A Multi-objective Planning Framework for Analysing the Integration of Distributed Energy Resources

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This thesis is the result of the author's original research. It has been composed by the author and has not been previously submitted for examination which has led to the award of a degree.

To my parents Hector and Maria Hilda

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Abbreviations

ANM	Active Network Management
BFS	Backward Forward Sweep
CHP	Combined Heat and Power
CO_2	Carbon Dioxide
DER	Distributed Energy Resources
DG	Distributed Generation
DP	Dynamic Program
DSO	Distribution system Operator
EP	Evolutionary Programming
ES	Evolutionary Strategies
GA	Genetic Algorithms
gCO_2	Grams of Carbon Dioxide
HV	High Voltage
kW	Kilowatt
kWh	Kilowatt-hour
LCA	Life Cycle Analysis
LV	Low Voltage
MCDM	Multi-criteria Decision Making
MCS	Monte Carlo Simulation
MOEA	Multi-objective Evolutionary Algorithms
MOGA	Multi-objective Genetic Algorithm
MV	Medium Voltage
MW	Megawatt
MWh	Megawatt-hour
NPGA	Niched Pareto Genetic Algorithm
NSGA	Non Sorting Genetic Algorithm
NSGA-II	Non Sorting Genetic Algorithm-II
O&M	Operation and Maintenance
OPF	Optimal Power Flow
PAES	Pareto Archived Evolutionary Strategy
PCA	Principal Component Analysis
PLF	Probabilistic Load Flow
PV	Photovoltaic
R/X	Ratio of Resistance (R) over Inductance (X)

ROC	Renewable Obligation Certificates
SA	Simulated Annealing
SPEA	Strength Pareto Evolutionary Algorithm
SPEA2	Strength Pareto Evolutionary Algorithm 2
SPGA	Stochastic Pareto Genetic Algorithm
TS	Tabu Search
TVM	Time Value of Money
UK	United Kingdom
UKGDS	United Kingdom Generic Distribution System
VEGA	Vector Evaluated Genetic Algorithm

Abstract

The electricity industry faces the challenge of adapting to new circumstances where environmental concerns and the optimal use of resources are crucial. In this scenario, Distributed Energy Resources (DER) are recognised as one of the possible solutions for sustainable economic development. The optimal integration of DER in the distribution networks is essential to maximise DER benefits and minimise the cost of DER integration. An adequate DER planning method is required to obtain valuable information for the best deployment of these resources.

The integration of DER has several drivers, such as the minimisation of cost, the reduction of carbon emission and the reduction of energy losses, among others. At the same time, several stakeholders are involved in DER research, development and management. Consequently, a flexible and multi-objective planning method that considers technical, environmental and economic impacts of DER integration can provide a deep insight into the advantages and drawbacks of DER, and can reflect the different perspectives on the problem.

Most renewable DER have a variable output. Hence, the planning of DER integration must consider the stochastic nature of DER. Likewise, the active management of DER and the network has been recognised recently as one of the new paradigms for the integration of larger penetrations of DER. As a result, an appropriate planning technique for DER integration must consider the simultaneous interaction of controllable and stochastic DER to provide an adequate evaluation of DER impacts and benefits.

Novel multi-objective optimisation techniques, known as Multi-objective Evolutionary Algorithms (MOEA), have been developed recently. MOEA are able to analyse complex objective functions and offer a "true" multi-objective approach. Consequently, MOEA are able to handle complex multi-objective problems such as DER planning effectively.

This thesis proposes to use multi-objective planning to analyse the optimal integration of stochastic and controllable DER. It presents the design, development and demonstration of a planning framework based on a state-of-the-art MOEA. Results from two relevant case studies show that the multi-objective planning method proposed is a novel and valuable tool for the analysis of DER integration. The framework proposed is generic and can be applied to other energy planning problems.

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Chapter 1

1. Introduction

This chapter introduces the new paradigms and techniques that motivated this research. It outlines the objectives and methodology of the thesis. Also, it enumerates the main contributions of this thesis, and describes in detail the chapter structure.

1.1. *Thesis Background*

1.1.1. Distributed Energy Resources

In recent years, climate change has prompted international awareness about the impacts that electricity generation and, more generally, the use of energy have on the environment. Cleaner ways of generating energy and a more efficient use of it are required to ensure a sustainable economic development. For instance, the countries of the European Union have committed to supply 20% of their energy from renewable sources by 2020 [1.1]. Besides these environmental concerns, the steady rise of fossil fuel costs, coupled with concerns over security of supply, are encouraging the use of a more diverse energy mix.

In this context, local generation of heat and electricity and the local use of renewable energy resources are considered as some of the most promising options to provide a more secure, clean and more efficient energy supply [1.2]. The traditional centralised structure of power systems is being challenged and new concepts proposed. New government policies and regulations, the aforementioned environmental targets and technological innovation are allowing, and in some cases encouraging, the gradual shift from large centralised power plants to smaller and more distributed generators. These generators are connected to the distribution system and typically supply energy to a small number of local customers.

Distributed Generation (DG), also known as Embedded Generation, is defined as "an electric power source connected directly to the distribution network or on the customer site of the meter" [1.3]. The most common DG technologies include Combined Heat and Power (CHP) generators, micro-turbine generators, solar photovoltaic generators (PV), wind generators and micro hydro schemes [1.4]. At present, DG is considered within the broader concept of Distributed Energy Resources (DER), which also includes responsive loads and energy storage [1.5].

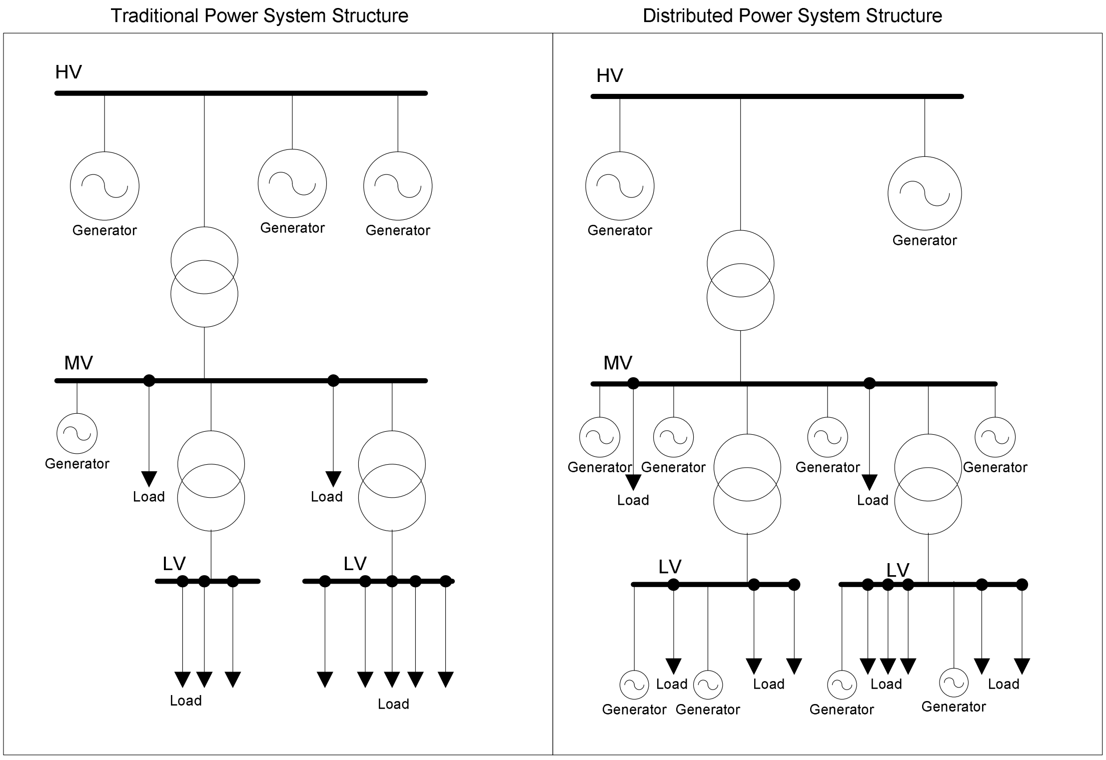

Figure 1-1 Change from Centralised Structure to Decentralised Structure of Power Systems

The structural change of power systems is illustrated in Figure 1-1. Distributed Generation capacity sizes range from a few kW connected to the low-voltage network (LV micro-generation) to tens of MW connected to the medium-voltage network (MV large scale DG) [1.4]. Distributed generators supply local loads and also interact with the wider system. In addition, in the distributed power system a number of large generators remain connected to the high voltage network (HV).

In the particular case of the United Kingdom (UK), the 2006 Energy Review [1.6] recognised that renewable DER could help to reduce carbon emissions and that it could increase the security of supply by having a more diverse generation mix. Consequently, it proposed a set of measures to encourage the use of low-carbon and distributed technologies, such as easier access to renewable energy incentives for micro-generators. More recently, the 2007 UK Energy White Paper [1.2] acknowledged the potential of DER to contribute to the achievement of environmental targets and energy security challenges and proposed measures to facilitate DG connections, including more flexible licensing arrangements and clearer exports rewards for smaller generators. As a result, it can be expected that DER, and particularly DG, will play an important role in the future UK electricity system [1.7].

1.1.1.1. DER Impacts and Benefits

The use of Distributed Energy Resources is proposed as one of the possible solution for today's energy challenges. Consequently, the main technical, economic and environmental effects of DER have been extensively investigated in recent years. For instance, the book of Jenkins *et al.* [1.4], published in 2000, provides an in-depth discussion of the issues related to embedded generation. Similarly, the doctoral theses of Ochoa [1.8] and Thong [1.9], both presented in 2006, study in detail the technical impacts of DG on the distribution network. Also, several research papers review DER impacts and benefits [1.5],[1.7],[1.10] or study a single impact, such as investment deferral [1.11] or line losses [1.12].

Table 1-1 Summary of DER Benefits and Impacts (Varied Sources)

	Benefits	**Impacts**
Technical	• Improvement of voltage profile • Reduction of distribution losses • Reduction of transmissions losses • Increased reliability • Reduction of peak loads	• Voltage rise • Increase of line losses • Reverse power flows, which might exceed thermal limits of equipment • Increase of network fault levels • Unbalance • Transient voltage variations • Injection of harmonics • Network instability
Environmental	• Reduction of carbon emissions • High overall efficiencies (e.g. micro-CHP)	• Noise and visual pollution (e.g. wind farms) • Effect on the ecosystem and fishery (e.g. micro-hydro) • Increment of localised emissions (e.g. micro-CHP)
Economic	• Reduction of DSO operating costs (by line losses reduction) • Investment deferral • Increased reliability • DER developer revenues, less up-front capital costs and reduced financial risk of investment	• Need for grid reinforcements • Increased DSO costs (by increasing losses and fault levels) • Increased uncertainty in demand prediction

The main benefits and impacts of DER identified in the literature are summarised in Table 1-1. Some effects depend on the DER location, size and pattern of output [1.7]. For example, DER located close to load centres and with a production coincident with demand reduces power flow in lines. This reduction in power-flows results in an improvement of voltage profile, and in a decrease in the line losses [1.4]. Moreover, if DER produces power at peak times, network investments can be deferred. Similarly, the reliability of the network can be increased by DER with constant production (e.g. gas generators) and connected to meshed grids, or by DER that are allowed to operate in islanded mode while connected to radial networks. In contrast, DER with a variable output, such as wind generators, or DER connected to radial networks and not allowed to work in islanded mode do not increase the reliability of the network [1.4].

Many of these technical effects translate to economic benefits for the Distribution System Operator (DSO) (e.g. reduction of line losses, investment deferral), or for the customer (e.g. increased reliability). The economic benefits for the DER owner arise from energy sales. Hence, for a DER developer maximising the amount of energy traded, while keeping the system within technical operation limits, is paramount.

Distribution networks were designed deterministically for unidirectional power flows, from higher voltages to lower voltages, rather than to accommodate large penetrations of DER. As a result, wrongly located DER, DER whose production is not coincident with demand or DER whose capacity largely exceeds the capacity of the network, has negative effects, such as reverse power flows, increment in line losses and voltage rise. DER located close to fault points contribute to the fault currents and might require the replacement of switchgear equipment. Other impacts of DER include the degradation of voltage quality, by injecting power electronic harmonics, and an increase in network instability, because of the low inertia of DER [1.9].

1.1.1.2. The Need for an Optimal DER Integration

The distribution network must be kept within operational and design limits at all times to provide good-quality energy and avoid damage to the equipment (i.e. voltage and thermal constraints, fault level limits). Hence, the technical impacts of DER can limit the installation of DER and restrict the associated economic and environmental benefits. In weak rural networks, where large amounts of renewable resources are located, the voltage rise is the impact limiting the integration of DER [1.10]. In meshed urban networks, where large numbers of micro-CHP units could potentially be installed, thermal limits and fault levels are also constraining factors [1.4].

There are two management philosophies to keep the network within operational limits and to minimise the steady state impacts of DER: “fit-and-forget” and Active Network Management (ANM). Under a traditional “fit-and-forget” connection philosophy, the grid is reinforced to keep the system within deterministic operational limits. Hence, the operational problems are solved at the planning stage. Strbac *et al.* [1.7] identifies that the "fit-and-forget" approach would require extremely costly reinforcements in the network to accommodate large penetrations of DER. Similarly, Pecas-Lopes *et al.* [1.5] recognise that this management philosophy is limiting for the integration of DER. As a result, "a fundamental shift from passive to active network management" was proposed in recent years [1.13]. Under this management philosophy the operational problems are solved with the active management of the network and the DER (i.e. DER curtailment and/or dispatch). ANM has been shown to considerably increase the amount of DER that can be connected to the network without the need of reinforcements [1.5]. In this thesis, actively managed DER is also referred to as "controllable DER".

Under either management approach, the optimal integration of DER in the distribution grid is fundamental to guarantee the best use of resources, i.e. maximise benefits and minimise costs. The sub-optimal integration of DER under a fit-and-forget management will result in a requirement for additional and unnecessary transmission and distribution grid reinforcements, network sterilisation, increased line losses and/or unattainable development and environmental targets, as demonstrated by other researchers [1.11], [1.12], [1.14]. Likewise, the sub-optimal integration of DER under active DER management will result in excessive energy curtailment, which could convert an economically feasible project into an unfeasible one, as demonstrated in Chapter 6 of this thesis.

1.1.2. Distributed Energy Resources Planning

Planning can be succinctly defined as "the process of identifying alternatives and selecting the best from among them" [1.15]. Distributed Energy Resources planning can be defined as a structured approach to optimise the type, location, number and size of distributed resources in a particular distribution system given a set of objectives and constraints. The most common objective pursued is minimisation of total cost. However, other main drivers are not unusual, for example: maximisation of DER capacity, minimisation of active line losses or amelioration of voltage profile. Constraints are usually defined by the technical limits of DER and network components, and by the power flow equations.

DER planning can provide valuable information to stakeholders and market players involved in DER development, management and regulation. DER developers can obtain information about the most promising locations for DER investments to maximise revenue. For example, it is now possible to perform an initial evaluation of DER connection via a web-based tool [1.16]. Similarly, DSOs can identify which locations, sizes and types are beneficial (or detrimental) for their system operation [1.17]. From a high-level perspective, DER planning can provide valuable information about the potential and the impacts of large penetrations of DER, identifying the targets that can be reached with an optimal use of resources. Consequently, the analysis of optimal integration of DER can inform incentives and policies to encourage DER developments in the places, sizes and types that ensure benefits and minimise the impacts of DER.

As a result, in recent years the DER planning problem has been studied from varied perspectives, and under different denominations. Diverse methods for optimising the location, size and/or type of DER have been proposed, with particular emphasis on DG placement and sizing. Chapter 3 provides an extensive review and discussion of DER planning methods, with related references. This review highlights that most of the proposed techniques are based on assumptions that restrict their application to the planning and analysis of stochastic and controllable DER. The term "stochastic DER" is used in this thesis to refer to variable energy resources such as wind and solar energy, and heat-lead CHP.

Most DER planning methods focus on the optimisation of a single objective, usually the minimisation of total costs, or the minimisation of line losses. A single-objective approach is practical from a DER developer or a DSO point of view. Nonetheless, the integration of DER technologies has a wider spectrum of environmental, technical, and economic benefits and impacts, as shown in Table 1-1. DER planning is in essence a multi-objective planning problem, as discussed next. A multi-objective DER planning method able to evaluate stochastic and controllable DER can provide valuable information for the optimal integration of DER.

1.1.3. Multi-objective Approaches in Power Systems Planning

Until the 1970s energy planning was predominantly aimed at finding the most efficient solution at the least cost; it was regarded as a single criteria problem. However, in the 1980s the need to incorporate environmental and social concerns resulted in an increased use of multi-criteria approaches for energy planning. Moreover, after the oil embargo of 1973, developed nations became interested in energy efficiency and the use of a diverse pool of energy sources. As a result, multi-criteria approaches were particularly popular for renewable energy planning and energy resource allocations. The wide use of multi-criteria approaches for energy planning beyond 1990 was recognised as a "paradigm shift" in energy planning [1.18].

In the particular area of power systems planning, the identification of this task as a multi-objective problem is not recent. For example, Kavrakoğlu *et al.* [1.19] mentions that "new dimensions" were emerging in power systems planning early in the 1980s. It identifies some reasons for this "metamorphosis", these were: the interest in a clean environment, the concern over nuclear technology, the sudden increase in energy prices because of the 1973 oil embargo, supply risks and the threat of energy shortages. It is no coincidence that most of these reasons overlap with the drivers for DER.

In addition, in the 1980s and 1990s a large number of electricity companies around the globe were privatised. The new liberalised structure included several different market players, and it required the explicit inclusion of additional drivers for planning, mainly performance and environmental constraints and reliability targets. Liberalisation also produced the decentralisation of the decision making process. Planning was no longer a centralised task. Different market players were now involved each one with a different perspective and often with conflicting objectives. Planning was no longer targeted at minimising the total overall cost but at maximising each utility's profit [1.20]. Similarly, the deregulated environment increased the uncertainty and associated risk for each of the new market players.

Consequently, it was recognised that power systems planning is in essence a multi-objective problem, or that "it is often not possible to identify a single plan which simultaneously optimises all objectives" [1.21]. Moreover, Schweppe *et al.* [1.22] discussed the advantage of considering attributes in their "natural" units. Since this change of paradigm, various multi-objective approaches for power systems planning and operation have been proposed [1.18], [1.23], [1.24].

1.1.3.1. Multi-objective DER planning

In an optimisation problem with multiple conflicting objectives the solution is not a unique element but instead a group of non-dominated solutions: the Pareto set [1.25]. This new concept of optimality was initially proposed by Francis Ysidro Edgeworth in 1881 and later generalised by Vilfredo Pareto in 1896. A solution belongs to the Pareto set if it cannot improve in one objective without detriment to other objectives. A very common example of this conflict is the cost versus performance dilemma faced by every buyer on a daily basis, illustrated in Figure 1-2.

In this illustrative example, a planner wants to determine the best energy source for a community minimising cost while simultaneously maximising performance, measured in this case by the reduction of carbon emissions. The two objectives are conflicting: high performance solutions are costly, while cheap solutions have a poor performance. Several cost/performance solutions belong to the Pareto set. Since performance can only increase to the detriment of cost, the problem is multi-objective and a trade-off is necessary. The planner will settle for the cheapest solution that provides his desired level of performance, or alternatively, his budget will limit the performance he can obtain.

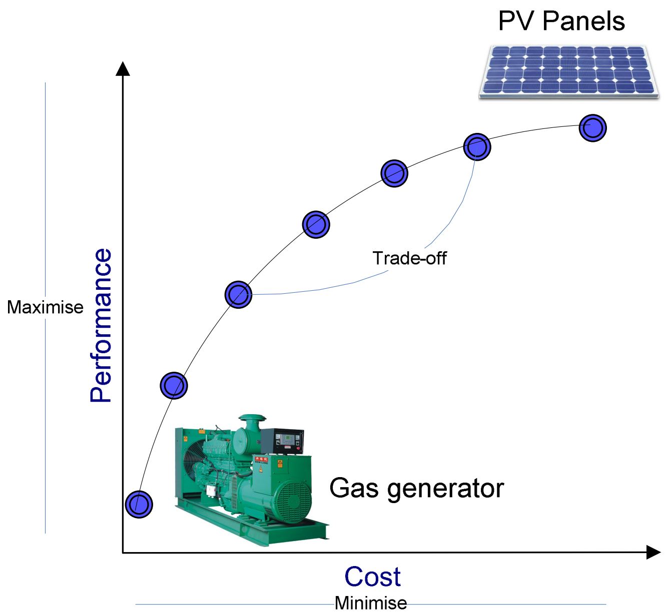

Figure 1-2 Example of a Multi-objective Problem

This simple example can be extended to more complex DER planning problems. Diverse economic, technical and environmental impacts of DER integration can be formulated as planning objectives. It is not necessary to convert all objectives to cost, and technical and environmental impacts can be formulated in their natural units. The multi-objective optimisation of objectives other than total cost can expand the knowledge about the optimal DER integration. An analysis of the Pareto front can decipher the extension of the objectives and the correlation and trade-offs between objectives. In addition, a multi-objective analysis can express different points-of-view (e.g. DER owner, DSO, regulators, customers, environmentalists) facilitating the identification of compromise solutions [1.26].

In spite of the value of a multi-objective analysis, only a small number of multi-objective DER planning methods have been proposed, particularly in the last three years. These techniques are also reviewed in Chapter 3. Most of these approaches are unable to deal with several types of stochastic and controllable DER simultaneously, as already mentioned for single-objective DER planning techniques. Also, few of these methods include environmental objectives and almost none considers probabilistic constraints in the analysis. These two elements are important because the environmental benefits of DER need to be fully evaluated, and recent regulations [1.27] encourage the use of probabilistic constraints.

Consequently, this thesis identified a clear need for a comprehensive multi-objective planning method that includes current drivers of DER integration, and that is able to evaluate controllable and stochastic DER. The complexity of DER planning and the specifications for a DER planning method are discussed extensively in Chapter 4.

1.1.3.2. The Optimisation/Modelling Dilemma

DER planning is a multi-objective optimisation problem, with nonlinear and non-convex objectives and constraints, and with discrete and integer variables. The solution to this complex optimisation problem usually requires simplifying assumptions, and/or the use of novel optimisation techniques. However, if the problem is over-simplified, for example by considering a single snapshot analysis of stochastic DER, the optimal solutions found are in fact sub-optimal, or as phrased by Irving *et al.* [1.28]: “a real solution to a non-problem”. Similarly, a realistic model of DER is worthless when optimised with an inaccurate optimisation method, i.e. “a non-solution to a real problem” [1.28]. This illustrates the optimisation/modelling dilemma faced in the solution of real optimisation problems, which is discussed further in the next chapter.

In order to generate useful results, the DER planning problem must be solved by an optimisation method able to provide an optimal or near-optimal solution and able to evaluate a realistic model of DER. A new group of multi-objective optimisation techniques developed in recent years, known as Multi-objective Evolutionary Algorithms (MOEA), provide these two conditions.

1.1.4. Multi-objective Evolutionary Algorithms

A large number of multi-objective optimisation techniques have been developed since the 1950s [1.29]. Until recently, multi-objective techniques suggested converting the multi-objective problem to a single-objective optimisation problem, by emphasising one particular solution at a time [1.30]. This is referred to as the "classical" approach to multi-objective optimisation [1.25]. A limitation of this approach is that the solutions found are susceptible to the shape of the Pareto front and several runs of the optimisation are required to find the Pareto set, as illustrated in Chapter 2. This strategy is time-consuming and implies a loss of useful information about the optimisation process and about the shape and extension of the Pareto set. This type of multi-objective optimisation techniques has already been applied for DER planning in recent years, for example by Ochoa [1.8], Celli *et al.* [1.17] and Harrison *et al.* [1.26]. All of these works are reviewed in Chapter 3.

In the last two decades, different researchers have proposed a new group of multi-objective optimisation techniques. These techniques are based on the principles of natural evolution. As a result, these techniques are referred to as Multi-Objective Evolutionary Algorithms. One of the main advantages of MOEA is that they deal with multi-objective problems in an "ideal" way, without aggregating all objectives into a single measure of performance [1.25]. MOEA handle groups of possible solutions simultaneously. Consequently, they are able to find several solutions of the Pareto set in a single "run". Furthermore, MOEA are a powerful search method for problems with discrete and integer variables, such as the DER planning problem. In addition, MOEA optimisation process does not require derivative information, and can optimise objective functions that are discontinuous, non-convex and nonlinear. Consequently, MOEA can provide a flexible platform for the analysis of stochastic and controllable DER. This capability is exploited in this thesis.

Since the first MOEA were developed in the mid-1980s, MOEA has become a very active research area, as illustrated in Figure 1-3. Several specialised algorithms have been proposed and applied to diverse multi-objective problems of engineering, industry and science [1.25]. At present, the Strength Pareto Evolutionary Algorithm 2 (SPEA2), developed in 2001 by Ziztler *et al.*[1.31], is one of the most advanced and recognised MOEA. Its suitability for dealing with multi-objective problems is well verified, and it has been demonstrated to outperform other counterparts both in theoretical and practical problems [1.31], [1.32], [1.33]. The concepts and development of MOEA, and the SPEA2 algorithm, are discussed extensively in the next chapter.

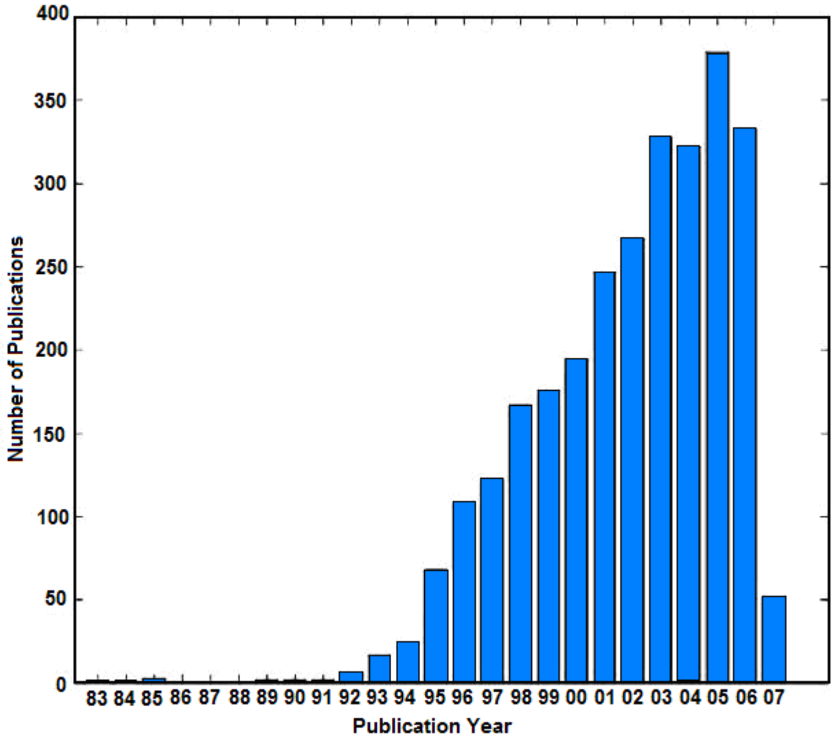

Figure 1-3 MOEA Publications per Year (Up to Early 2007) (Source [1.34])

Despite the increased attention on MOEA, the power systems engineering research community only recently began to pay attention to these optimisation techniques [1.23]. Specifically, the application of MOEA to DER planning problems has not yet been widely studied [1.35]. Nonetheless, this trend is changing. The comprehensive review of multi-objective DER planning conducted for this research, and presented in Chapter 3, shows that the interest of DER planning researchers in MOEA has increased, especially in the last two years. One of the contributions of this thesis is to facilitate the understanding of MOEA and their use in DER planning.

1.2. *Thesis Objectives and Methodology*

This research is based on the hypothesis that a MOEA-based multi-objective planning tool can provide valuable information for the optimal integration of DER in distribution networks. Consequently, the main objective of this thesis is to design, develop and test a flexible multi-objective planning framework to analyse the integration of Distributed Energy Resources.

In order to provide a useful analysis of DER integration, the planning framework must make it possible to answer the following questions:

- What are the best configurations for DER in a given distribution network in order to achieve multiple objectives?
- What are the correlations between these objectives when DER is integrated optimally in a particular network?

The following methodological steps are essential to achieve the main objective of this thesis, and evidence of this approach is provided throughout this thesis:

- Gain an understanding of multi-objective optimisation and MOEA to select an optimal algorithm for the planning framework.
- Undertake a critical review of the state of the art of techniques for DER and DG planning and optimisation, with particular emphasis on multi-objective DER planning and optimisation.
- Explore in detail the complexity of the DER planning problem and determine the specifications for a multi-objective planning framework for DER that considers current drivers of DER integration.
- Develop a flexible and modular DER planning framework that includes the most important issues identified. Also, outline how the remaining challenges can be handled.
- Finally, demonstrate the ability of the developed framework to answer the questions proposed by applying it to a set of relevant case studies.

This thesis aims to provide a powerful analytical tool for DER integration. It is not intended to develop a DER planning tool to find the single least-cost solution from a particular point of view.

1.3. *Contributions to Knowledge*

This thesis presents a novel multi-objective planning framework to analyse the optimal integration of stochastic and controllable DER. This framework includes current drivers of DER integration. It integrates a state-of-the-art MOEA, a stochastic simulation algorithm, an AC power flow algorithm and an optimal power flow algorithm into a flexible analysis platform. The principal contributions of this thesis are discussed fully in Chapter 7, and are summarised next:

1. It presents a comprehensive review of DER planning techniques. A similar review of the research area has not been published. This review identifies the trends in the research area, and identifies gaps for future research.
2. It provides a deep examination of the DER planning problem and the specification for a flexible multi-objective planning framework for DER integration analysis. This specification discusses the type of techniques that should be used for the analysis of stochastic and controllable DER.
3. It describes in detail the development of an analytical tool for stochastic and controllable DER. The detailed development process and the practical details provided are a contribution for future researchers that might face similar challenges.
4. It provides a comprehensive description of the concepts of multi-objective evolutionary algorithms applied to the DER problem, and contributes to the future use of these techniques in DER planning.
5. It expands the knowledge about the impacts and benefits of DER integration, by discussing the detailed calculation of sixteen different planning attributes and exposing findings of optimal DER plans with two specific case studies.

1.4. *Thesis Structure*

The structure of this thesis is a reflection of the methodological steps and the contributions of this work. The thesis is divided in seven chapters. The chapter interrelation is illustrated in Figure 1-4. A detailed description of each chapter is provided next to facilitate the understanding and use of this thesis.

Chapter 1 introduces this thesis. It discusses the background and motivation of this thesis. Also, it lists the research objectives and the methodological steps followed.

Chapter 2 has four main sections. The first section covers basic concepts of optimisation, and reviews the most common single-objective optimisation techniques used in power systems. This section is necessary as it provides adequate background for the review of DER planning technique presented in Chapter 3, and helps to understand the advantages of using a MOEA for DER planning. The second section of Chapter 2 describes the principles of Genetic Algorithms (GA). The basic GA structure constitutes the base for MOEA. Hence, each step of GA optimisation is discussed in detail. The third section of this chapter introduces the key concepts for multi-objective optimisation, and describes the main types of techniques used in this area, with particular emphasis on multi-objective evolutionary algorithms. Finally, the Strength Pareto Evolutionary Algorithm 2 (SPEA2), which is used in the planning framework implemented in Chapter 5, is described in detail.

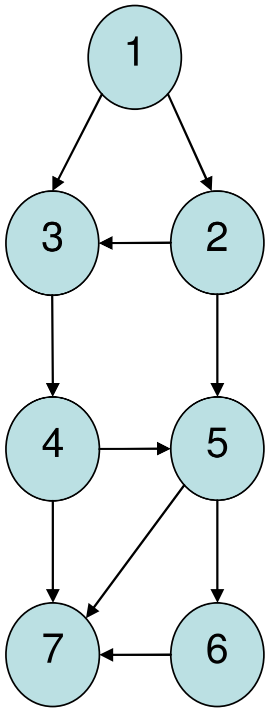

Figure 1-4 Chapter Interrelation

Chapter 3 presents a critical literature review of the state of the art of Distributed Generation and Distributed Energy Resources planning. Initially, the process of power systems planning is briefly recalled. Next, a representative sample of single-objective DER planning techniques is analysed. This review demonstrates that DER planning objectives are diverse and sometimes conflicting and that most techniques cannot handle diverse types of stochastic DER simultaneously. It also illustrates the mathematical complexity of DER planning as an optimisation problem. Next, a comprehensive review of multi-objective planning techniques is examined. This review discusses in detail the latest developments in the area. Importantly, this review highlights the possibilities for further research and places this thesis in the context of the research area.

Chapter 4 has two sections. In the first section, the DER planning problem is studied in detail. This examination illustrates the complexity of the DER planning problem. In addition, the main aspects that must be handled when optimising DER are identified. This study determines the specifications for the multi-objective planning framework, considering current drivers of DER integration and the characteristic of modern planning techniques. In the second section of the chapter, the methods to handle each one of these specifications are discussed. The structure of the planning framework is proposed, and each component described in detail. Moreover, multi-objective visualisation and analysis techniques, such as Principal Component Analysis, are presented.

In ***Chapter 5,*** the implementation of the planning framework, based on the specifications of Chapter 4, is described. The planning framework has four main components: a multi-objective evolutionary algorithm, a stochastic simulation algorithm, a power flow algorithm and an optimal power flow algorithm. The implementation of each one of these components is detailed. Moreover, the calculation procedure for each one of the planning attributes is explained. In addition, practical aspects of the framework development (platform, code, speed) are discussed.

In ***Chapter 6,*** the multi-objective planning framework is applied to two relevant case studies. The first study examines the integration of micro-generation in an urban low-voltage network. Results illustrate the usefulness of the multi-objective approach proposed, and demonstrate the ability of the planning framework to deal with a complex stochastic problem. The second case study analyses the integration of wind turbines in a medium-voltage network. Results demonstrate the use of probabilistic constraints. Also, results demonstrate that the approach proposed is able to optimise the integration of controllable units. The discussion from both case studies provides useful information about DER impacts and benefits.

Chapter 7 presents the conclusions from the framework specification and development and from the case studies. The contributions of this work are discussed and further work for the development of this research is proposed.

1.5. *Associated Publications*

The requirements for a planning technique for distributed energy resources and highly distributed power systems are discussed in depth and appropriate examples given in:

- **Alarcon-Rodriguez, A.D.**, Ault, G.W., Curie, R.A.F., McDonald, J.R., *"Planning the Development of Highly Distributed Power Systems"*, 2nd International Conference of Distributed Energy Resources, Napa, USA, December 2006.

- **Alarcon-Rodriguez, A.D.**, Ault, G.W., McDonald, J.R., *"Planning the Development of Highly Distributed Power Systems"*, 19th International Conference on Electricity Distribution, CIRED 2007, Vienna, Austria, May 2007.

- **Alarcon-Rodriguez, A.D.**, Ault, G.W., Curie, R.A.F., McDonald, J.R., *"Planning Highly Distributed Power Systems: Effective Techniques and Tools"* International Journal of Distributed energy Resources, Vol. 4, No. 1, January 2008.

The development of a multi-objective planning framework for stochastic and controllable Distributed Energy Resources and the analysis of a relevant case study are presented in:

- **Alarcón-Rodríguez, A.D.,** Haesen, E. Ault, G.W., Driesen, J., Belmans, R., *"Multi-objective Planning Framework for Stochastic and Controllable Distributed Energy Resources"*, IET Renew. Power Gener., 2009, Vol. 3, Iss. 2, pp. 227–238

The extension of the planning framework to analyse network reinforcements as a planning option and a case study that studies the conflict between DSO and DER developers objectives were presented in:

- Haesen, E., **Alarcón-Rodríguez, A.D.**, Driesen, J., Belmans, R., Ault, G.W., *"Opportunities for Active DER Management in Deferral of Distribution System Reinforcements"*, 2009 IEEE Power Systems Conference & Exposition, Seattle, USA, March 2009

Additionally, the author has contributed to the following published papers:

- Burt, G.M., Tumilty, R.M., Lincoln, R.W., **Alarcon-Rodriguez, A.D.**, Ault, G.W., Finney, S.J., Infield, D.G., *“An Overview of the Highly Distributed Power System”*, 1st International Conference and Workshop on Micro-Cogeneration Technologies and Applications, Micro-Gen 2008, Ottawa, Canada, April 2008.

1.6. *Summary*

This chapter presents the background to the thesis and introduces the new ideas that motivate this investigation. The objective and methodology followed are outlined. In addition, the work is put into context and a list of main contributions presented. Finally, the structure and scope of the thesis is presented.

The impacts and benefits of DER are already well covered in literature. Therefore, an extensive and detailed discussion of each DER benefit/impact is unnecessary in this chapter. For a more comprehensive discussion of DER impacts, the book of *Jenkins et al.* [1.4], and the PhD thesis of Vu Van Thong [1.9] are two helpful references.

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Chapter 2

2. Multi-objective Optimisation with Evolutionary Algorithms

2.1. *Introduction*

The previous chapter discussed the need for an optimal DER integration. It also mentioned that multi-objective DER planning can provide valuable information for the optimal integration of DER. The process of DER planning is analysed in-depth in the next two chapters. This analysis shows that the optimal integration of DER is a complex optimisation problem. Consequently, this chapter discusses the main concepts and techniques of multi-objective optimisation.

Optimisation is the task of finding the set of design parameters that maximises a desired attribute or minimises an undesirable attribute subject to a group of constraints [2.1]. In other words, it involves finding the "best solution" from a set of candidate choices [2.2]. Some optimisation methods were developed some time ago; for example, the Lagrange constrained minimisation was proposed in 1750. Nonetheless, it was not until the use of computers that optimisation techniques became popular and began to be applied to a diversity of practical purposes. George Dantzig, who developed the Simplex Method in 1947, is considered the "father" of modern optimisation. Since this milestone a variety of mathematical and heuristics optimisation methods have been proposed.

When an optimisation problem has a single objective the problem is scalar; the definition of "best solution" is one-dimensional and there is only a single best solution (or none, eventually). Powerful single-objective optimisation methods based on mathematical approaches are available, such as the Simplex method. Similarly, most heuristic optimisation techniques have been applied to solve single-objective optimisation problems. Therefore, it is common for optimisation problems to be framed in the single-objective paradigm. Nonetheless, some practical optimisation problems, such as DER planning, have multiple (and usually conflicting) objectives that must be optimised simultaneously. These problems are multi-objective problems. The solution to multi-objective optimisation problem is based on the multi-dimensional concept of "best solution": the concept of Pareto optimality, explained in this chapter. In a multi-objective problem there is no single solution, but a set of optimal solutions known as the Pareto set.

A large number of multi-objective optimisation techniques have been proposed. Initially, most of these techniques were based on the iterative resolution of a single-objective optimisation problem; this is known as the "classical" approach to multi-objective optimisation [2.3]. This approach has been used extensively, mainly because of the existence of powerful single-objective optimisation techniques. Nevertheless, this approach has some limitations: it produces only a single solution at each iteration, it requires subjective information and its success depends on the shape and the continuity of the Pareto front [2.3],[2.4],[2.5]. Consequently, in the last two decades a new group of heuristic multi-objective optimisation techniques has been developed to overcome these limitations. These techniques are denominated Multi-objective Evolutionary Algorithms (MOEA), and were briefly introduced in the previous chapter.

The DER planning problem, examined in the next two chapters, is a complex optimisation problem. It is multi-objective, nonlinear, and non-convex, with integer and discrete variables. MOEA are able to handle these types of problems effectively. Hence, the multi-objective planning framework presented in this thesis makes use of one of these MOEA: the Strength Pareto Evolutionary Algorithm 2 (SPEA2). An adequate system model and a flexible and modular approach were identified as requirements for the planning framework, as will be discussed in Chapter 4. SPEA2 provides a modular and flexible multi-objective approach that allows the interaction of stochastic and controllable DER to be modelled, as exposed in Chapters 4 and 5.

Before embarking on the description of the SPEA2 algorithm, an introduction to optimisation and a detailed explanation of Genetic Algorithms (GA) is necessary. Also, in order to give a background for the review of DER planning techniques presented in the next chapter a brief discussion of other optimisation techniques commonly used in power systems is required. This discussion helps to understand the choice of a MOEA approach for DER planning.

This chapter is structured as follows: Initially, the generic formulation of the optimisation problem is introduced and key concepts discussed. The different types of optimisation problems and the main groups of single-objective optimisation techniques are enumerated. The working principles, advantages and drawbacks of GA are examined in detail. Then, the concepts of multi-objective optimisation are studied and the advantages of a multi-objective formulation are discussed. Finally, MOEA are introduced and the SPEA2 method is described in detail.

2.2. *Optimisation: Key Concepts*

2.2.1. Problem Formulation

An optimisation problem can be generically expressed as:

$$\min \mathbf{F}(\mathbf{x}) = \min\left(\left[f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_m(\mathbf{x})\right]\right) \tag{2-1a}$$

$$\mathbf{x} \in \Omega \tag{2-1b}$$

$$\mathbf{g_j}(\mathbf{x}) = 0 \quad j = 1, 2..p \tag{2-1c}$$

$$\mathbf{h_k}(\mathbf{x}) \leq 0 \quad k = 1, 2..q \tag{2-1d}$$

$\mathbf{F}_{(\mathbf{x})}$ is a vector of m objective functions $f_i(x)$. For a single-objective problem m=1. In this case, all objectives are expressed as minimisation. A maximisation objective can be formulated by minimising the negative of the objective function: min-$f_i(\mathbf{x})$. $\mathbf{x}$ is the decision vector that includes the set of n decision variables [x_1,x_2, x_3, … ,x_n]. The decision domain Ω is defined by the possible values that the decision variables can take. It is also known as the "search space". The decision variables x_i can be continuous, discrete or integer in nature. A particular case of integer variables are binary variables, which only take two values: 0 or 1.

The optimisation problem is bounded by equality and inequality constraints, $\mathbf{g_j}$ and $\mathbf{h_k}$ respectively, which can be linear or nonlinear. For example, constraints can be simple limits for the decision variables (e.g. $x_l \leq x \leq x_u$), or more complex functions that depend on several decision variables (e.g. h(x) $= x_1 + (2x_2 - x_3)^2 \leq 0$). Problems without constraints are referred to as unconstrained optimisation problems. Objective functions and constraints are categorised depending on their mathematical nature as linear, quadratic and nonlinear. Quadratic objective functions are typically separated from the nonlinear classification because special tailored solution methods can be applied to this type of problems when the constraints are linear, as examined later in this chapter.

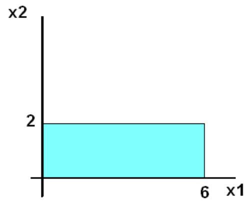
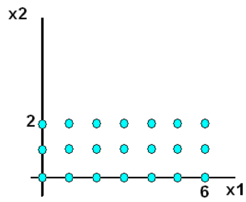
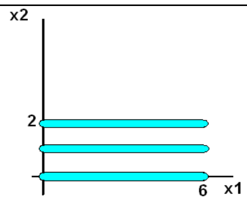
2.2.2. Decision Domain, Decision Space and Objective Space

The decision domain Ω and the constraints $g_j(x)$ and $h_k(x)$ define a *feasible* region A [2.6]:

$$A = \{\mathbf{x} \in \Omega : \mathbf{g}(\mathbf{x}) = 0 \wedge \mathbf{h}(\mathbf{x}) \leq 0\} \tag{2-2}$$

such that all the points that do not belong to *A* constitute the *infeasible* region. Table 2-1 shows some examples for a decision vector with two variables, and illustrates the feasible decision domains in each case.

Table 2-1 Decision Domain Examples

Decision domain Ω	Example	Feasible decision domain (A)
Continuous	$0 \leq x_1 \leq 6$ $0 \leq x_2 \leq 2$ $x \in \Re$	
Discrete Integer	$0 \leq x_1 \leq 6$ $0 \leq x_2 \leq 2$ $x \in Z$	
Mixed Integer – Continuous	$0 \leq x_1 \leq 6$ $x_1 \in \Re$ $0 \leq x_2 \leq 2$ $x_2 \in Z$	
Binary Integer	x_1=[0,1] x_2=[0,1]	$\Omega = \begin{bmatrix} 00 \\ 01 \\ 10 \\ 11 \end{bmatrix}$

The objective function **F(x)** maps the decision vector from the *decision space* to the *objective space*. Thus, a feasible region is also defined in the *objective space*. Figure 2-1 shows an example of an optimisation problem with two decision variables (x_1,x_2) and two objective functions defined by:

$$F(\mathbf{x}) = \min\left(\left[f_1(\mathbf{x}), f_2(\mathbf{x})\right]\right) \tag{2-3a}$$

$$f_1(\mathbf{x}) = x_1 + x_2 \tag{2-3b}$$

$$f_2(\mathbf{x}) = x_1^2 - x_2^2 \tag{2-3c}$$

$$\mathbf{x} \in \Re \tag{2-3d}$$

$$0 \le x_1 \le 2 \tag{2-3e}$$

$$0 \le x_2 \le 1 \tag{2-3f}$$

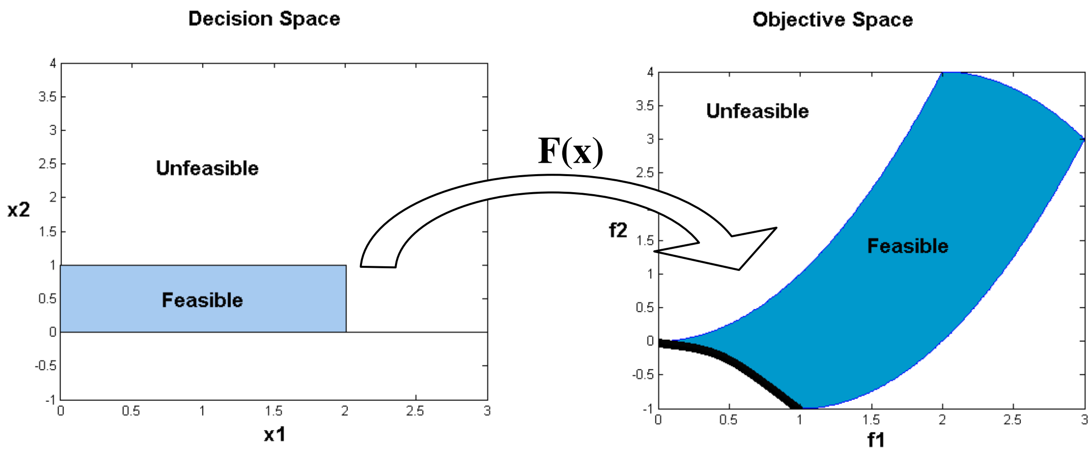


Figure 2-1 Two-objective Example

The figure illustrates how the function **F(x)** maps the constrained decision space in the objective space. In addition, it is possible to see that both objectives (f_1, f_2) are incompatible because there is no single solution that minimises both objectives at once. The problem is multi-objective: instead of a single solution, there is a set of optimal solutions (depicted as a bold line in the objective space). Multi-objective problems are developed further later in this chapter. Also, the objective space of Figure 2-1 is non-convex, while the decision space is convex. The concept of convexity is clarified next.

2.2.3. Convexity

The concept of *convexity* is crucial in defining the difficulty of an optimisation problem and the method for solving it. A set *C* is convex if a line segment between any two points in *C* lies in *C* [2.2]. A function *f(x)* is convex if the line between two points $f(x_1)$ and $f(x_2)$ always lies above the graph of f(x), in other words: a function *f(x)* is convex in an interval if and only if its second derivative is always positive or zero in this interval. Figure 2-2 illustrates this concept.

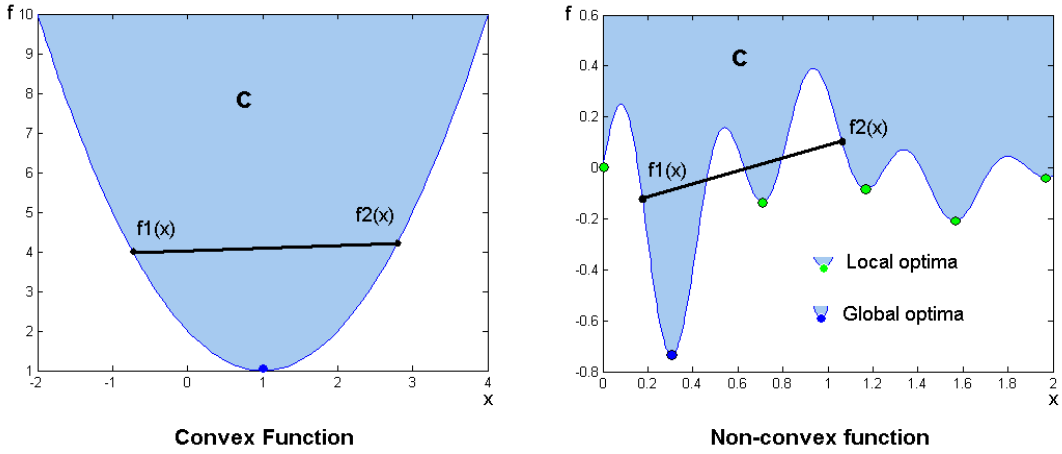


Figure 2-2 Non-convex and Convex Functions

The definition of convexity permits the following observations and statements:

- Discontinuous sets are non-convex by definition (e.g. discrete variables). Therefore, integer or mixed integer problems have a non-convex feasible region [2.1]
- Convex objective functions have a single optimal point. This is the global optima. In contrast, non-convex objective functions have more than one optimal point. These are local optima. A non-convex function has also only a single global optimal point.
- Any nonlinear equality constraint is non-convex by definition [2.1].
- Nonlinear objective functions can be either convex or non-convex, as seen in Figure 2-2. So, convexity is a more accurate measure of the difficulty of a problem than nonlinearity.

Optimisation problems differ greatly in their level of difficulty depending on: the nature of the variables (e.g. continuous, discrete, integer), the existence of constraints (constrained, unconstrained), the shape/nature of the objectives and constraints functions (e.g. linear, nonlinear), the number of objectives (single-objective, multi-objective) and the convexity of the problem [2.2]. There is no single method that can solve them all efficiently.

A comprehensive review of all optimisation methods or an exhaustive explanation of the methods is not in the scope of this chapter. Therefore, the next section presents a brief description of single-objective mathematical and heuristic optimisation methods commonly used in power systems. This description is intended to provide an adequate background for the review of DER planning techniques made in the next chapter, and to support the choice of a MOEA approach for DER planning.

2.3. *Single-objective Optimisation*

Single-objective optimisation methods are usually classified as mathematical methods and heuristic methods [2.7]. These two groups have completely different theoretical bases and contrasting benefits and drawbacks. Mathematical methods are designed to solve specific types of problems. So, when applied to the right problem, a mathematical method can provide an accurate optimal solution in a relatively short period. Linear and convex problems can be solved by an appropriate method even when thousands of variables are involved. Furthermore, mathematical methods are able to provide proofs for the optimality of the solution in these cases. Table 2-2 presents the main groups of mathematical optimisation methods. These are classified according to the nature of the variables, objectives and constraints.

Table 2-2 Mathematical Optimisation Techniques

Optimisation Techniques	Variables	Objectives	Constraints
Analytical methods (calculus)	Continuous (Real)	Continuous and differentiable twice	Continuous and differentiable twice
Linear Programming	Continuous (Real)	Linear	Linear
Quadratic Programming	Continuous (Real)	Quadratic	Linear
Nonlinear Programming	Continuous	Linear/Nonlinear	Nonlinear
Integer Programming	Integer	Linear/Nonlinear	Linear/Nonlinear
Mixed – Integer Programming	Discrete, Continuous	Linear/Nonlinear	Linear/Nonlinear
Zero-one programming	Binary integer	Linear/Nonlinear	Linear/Nonlinear
Dynamic Programming	Discrete	Any, but it should be able to split into sub-problems	Implicit (non-feasible solutions are not considered)

Non-convex (nonlinear, discrete and combinatorial) problems present a great level of difficulty for mathematical methods, even with small numbers of variables [2.2]. Mathematical methods are based on a local search approach [2.8]. So, even if a mathematical approach finds an optimal solution for a non-convex problem, there is no guarantee that this solution is the global optima. In this case, a compromise is needed, either in terms of finding a suboptimal (local) solution, or in terms of a high computation time to determine the true global optima [2.2].

Table 2-3 Heuristic Optimisation Methods (Source [2.8])

Heuristic Methods	**Natural Principle**
Evolutionary Algorithms	Genetics and Evolution
Simulated Annealing	Thermodynamics of metal cooling
Tabu Search	Human memory
Ant colony search	Ants' behaviour to solve problems
Neural networks	Brain functions
Fuzzy Programming	Human linguistic categorisation
Bacterial Foraging	Baceria behaviour to look for food

In contrast, heuristic optimisation techniques are very good at solving the type of problems difficult for traditional methods, such as combinatorial, nonlinear and non-convex problems. Most heuristic methods are based on principles taken from nature (Table 2-3) and they are sometimes referred as "heuristic search" methods. They conduct a "global search" and usually find a good approximation of the global optima in a limited period of time [2.8]. However, these methods do not *guarantee* discovery of the *absolute* global optima. Some heuristic methods (e.g. Evolutionary Algorithms) work with a group of solutions simultaneously, instead of the point-by-point local search of mathematical approaches. This makes them particularly robust for "noisy" objective evaluations [2.9] and ideal to solve multi-objective problems in an effective way. Noisy objective evaluations are discussed further on a later chapter.

2.3.1. Mathematical Optimisation Methods

2.3.1.1. Analytical Methods

Analytical methods are based on the principles of calculus. Extreme points (maximum/minimum) of a function *f(x)* can be found by setting the derivative of the function to zero:

$$\frac{\partial f}{\partial x} = 0 \qquad (2\text{-}4)$$

Moreover, it is possible to determine whether an extreme point is a maximum or minimum by using the second derivative. Minimum points occur when the second derivative is greater than zero, while maximum point occurs when the second derivative is negative. If the second derivative is equal to zero, it is an inflection point.

$$\frac{\partial^2 f}{\partial^2 x} > 0 \qquad x_{\min} \tag{2-5a}$$

$$\frac{\partial^2 f}{\partial^2 x} < 0 \qquad x_{\max} \tag{2-5b}$$

Convex functions have a single optimal solution (e.g. Figure 2-2). In contrast, non-convex functions can have several local optima. An analytical method has no information about which points are global or local optima, only local behaviour can be determined. Therefore, to find the global optima all the optimal points must be identified and classified.

The analytical procedure can be extended to multi-variable problems by taking the gradient of the function, which now includes the partial derivatives of the function in terms of each variable, and equate that to zero:

$$\nabla f(x, y) = 0 \tag{2-6a}$$

$$\text{where } \nabla = \left(\frac{\partial}{\partial x}, \frac{\partial}{\partial y} \right) \tag{2-6b}$$

This results in a set of equations that, when solved, identifies the extreme points of the multi-variable function.

An extension of this method permits the optimisation of constrained problems. Equality constraints **g(x)** are included using Lagrange multipliers λ, so that the new function to optimise is [2.10]:

$$L(x, \lambda) = f(x) - \lambda g(x) \tag{2-7}$$

Non-equality constraints **h(x)** can be included by using the Karush-Kuhn-Tucker (KKT) conditions [2.1].

Analytical methods require continuous objective functions that can be differentiated twice. Moreover, when a large number of variables is involved resolving the system of equations by determining the gradient becomes complex, especially when equations are non-convex. Most nonlinear optimisation methods are based on these principles [2.10], and they use gradient information to guide the local search, first and second derivatives as proof of optimality and Lagrange multipliers to include constraints.

2.3.1.2. Linear Programming

Linear programming problems are convex optimisation problems with a linear objective function, linear constraints and continuous decisions variables. Powerful optimisation methods are available to solve this type of problem [2.1]. These methods are based either on the Simplex method, or on some sort of interior-point approach. An example of a linear problem written in Standard form is:

$$\min \mathbf{f}(\mathbf{x}) = \mathbf{ax} + \mathbf{b} \tag{2-8a}$$

$$\mathbf{g_j}(\mathbf{x}) = \mathbf{cx} + \mathbf{d} = 0 \quad j = 1, 2..p \tag{2-8b}$$

$$\mathbf{h_k}(\mathbf{x}) = \mathbf{rx} + \mathbf{s} \le 0 \quad k = 1, 2..q \tag{2-8c}$$

$$\mathbf{x} \in \Re \tag{2-8d}$$

$$\mathbf{a}, \mathbf{b}, \mathbf{c}, \mathbf{d}, \mathbf{r}, \mathbf{s} \in \Re \tag{2-8e}$$

Where **x** is the vector of decision variables, **f(x)** is the objective function, **g(x)** and **h(x)** the equality and inequality constraints, respectively, and **a**, **b**, **c**, **d**, **r** and **s** are the vectors of real numbers that define the linear relationships of the problem.

The Simplex method is based on the knowledge that the optimal point is always found at a corner point (or vertex) of the constraint set [2.1]. So, the Simplex method consists of the iterative resolution of sets of linear equations, defined by constraints equations and the objective function (Figure 2-3). The Simplex method is computationally efficient, and can solve optimisation problems with large numbers of variables.

The Simplex method guarantees an optimal solution. However, in the theoretical worst-case scenario, the number of iterations of the Simplex method can grow exponentially with the size of the problem [2.1]. Consequently, “interior point” methods have been proposed. These methods usually provide faster computation by iteratively computing solutions in the interior of the feasible region and moving towards the optimal point, as illustrated in Figure 2-3.

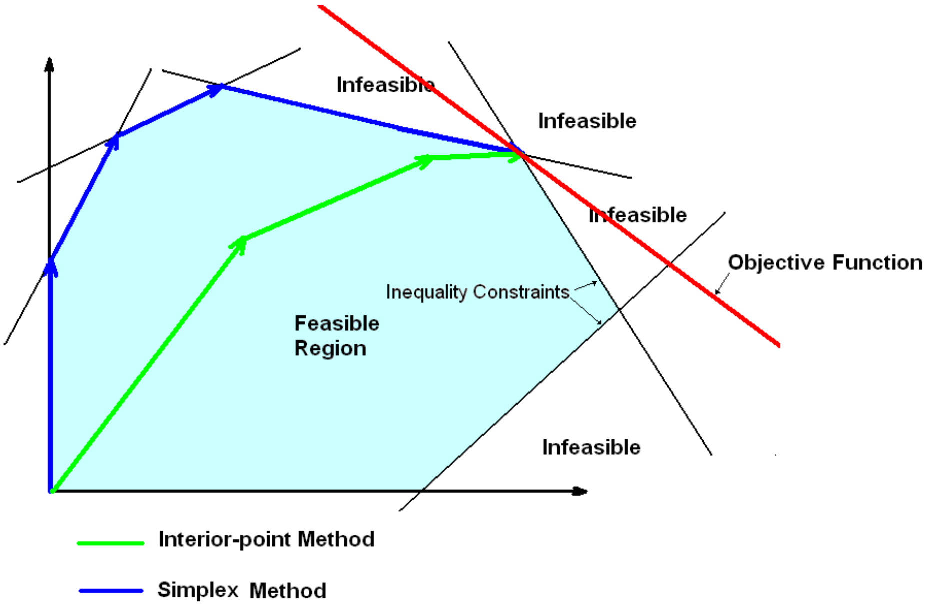


Figure 2-3 Simplex and Interior-point Method (Maximisation Problem)

Linear programming methods can also be used to solve problems with quadratic objective functions [2.1], because quadratic functions are convex. However, the constraints must be linear. These problems are usually called 'quadratic programming', and follow a similar solution philosophy. In this case, the solution is not guaranteed to be in a vertex, and can be located in the interior of the feasible region [2.11].

Duality Theory

The formulation of the problem presented in equations (2-1) is known as the primal problem. The concept of duality states that that every primal problem formulation has an associated formulation known as the dual problem [2.11]. For example, if the primal problem is:

$$\min f(\mathbf{x}) = \mathbf{cx} \tag{2-9a}$$

$$s.t. \quad \mathbf{Ax} \le \mathbf{b} \tag{2-9b}$$

$$\mathbf{x} \ge 0 \tag{2-9c}$$

The dual problem is expressed as:

$$\max g(\mathbf{y}) = \mathbf{by} \tag{2-10a}$$

$$s.t. \quad \mathbf{Ay} \ge \mathbf{c} \tag{2-10b}$$

$$\mathbf{y} \ge 0 \tag{2-10c}$$

The duality theorem states that the solution to the primal problem provides the solution to the dual problem, and vice-versa [2.11]. Both formulations represent essentially the same problem. Though, sometimes it is easier to solve the dual problem, for example, when the problem has a large number of constraints and few objectives [2.11]. A large part of optimisation theory is devoted to the study of duality. However, a review of duality theory is beyond the scope of this chapter. Extended explanations can be found in [2.2] and [2.11]

2.3.1.3. Nonlinear Programming

Nonlinear programming involves problems with nonlinear objectives and/or nonlinear constraint functions. Some authors consider "nonlinear problems" only as those not known to be convex [2.2]. Convex nonlinear problems have a single feasible region, bounded by constraints, and have a single optimal solution, as illustrated in Figure 2-2. Since the optimal solution for a convex problem is located in the convex feasible space, it can be iteratively approximated from an initial point. Hence, convex nonlinear problems can be efficiently solved by interior-point or analytical methods whose working principles were explained in the previous sections.

In contrast, nonlinear non-convex problems have several local optima. This makes these problems extremely difficult to solve, because the search can be easily misguided to wrong regions of the search space, i.e. local optima, and become trapped there. Moreover, in non-convex problems the decision and objective space are not necessarily continuous or bounded in the same region. Nonlinear (non-convex) problems are usually solved by iterative methods. An initial solution is estimated, and then the algorithm iteratively approximates to the (local) optima solution. This "hill climbing" (or descending) process requires derivative or gradient information to choose the direction of ascent/descent, and a convergence criterion to recognise when an optimal point has been found. This process has its basis in the analytical resolution, explained in section 2.3.1.1. As in analytical methods, constraints can by dealt with by using Lagrange multipliers. In the cases where function derivatives or gradient information is not available, the function gradient is approximated from previously computed iterations. Other popular nonlinear programming methods approximate the nonlinear problem to a quadratic problem, and apply a Quadratic Programming algorithm sequentially (i.e. sequential quadratic programming [2.1]).

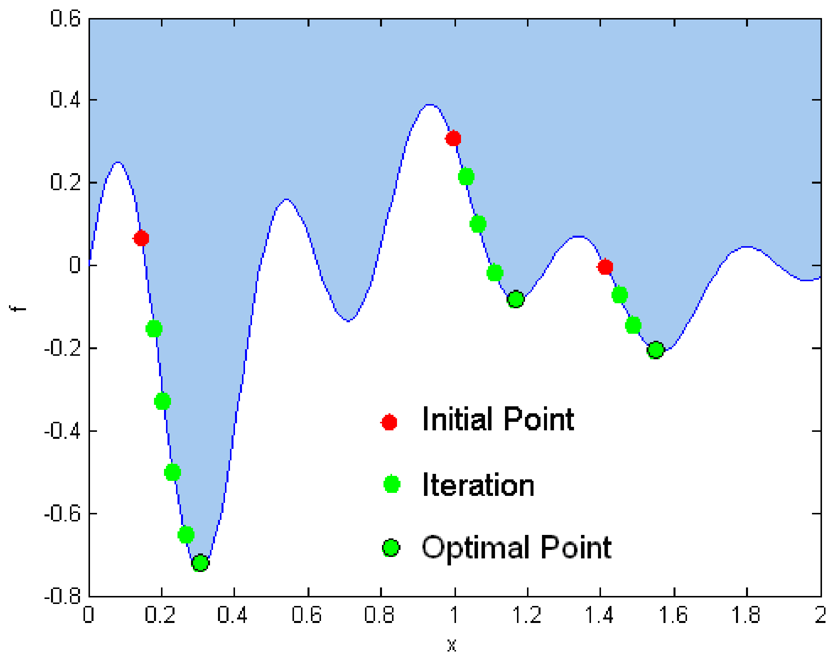


Figure 2-4 Nonlinear Optimisation Problem ($\min f(x) = \cos(10x) \cdot \sin(5x) \cdot e^{-x}$)

The “hill climbing” process guarantees the discovery of a local optimal solution. However, in any non-convex problem there is no certainty that a local optimal solution is the global optima. As a result, the search must be repeated from varied starting points to find the global optimal, as illustrated in Figure 2-4. This procedure can be extremely time-consuming when the shape of the objective function is intricate or unknown. In extremely difficult problems, the global optima cannot be found in a limited time. Hence, to solve a nonlinear non-convex problem requires some degree of compromise: accuracy is sacrificed in favour of computing time, or vice versa. Heuristic techniques, such as Genetic Algorithms, are particularly effective in solving these types of combinatorial nonlinear problems. This will be evident from the detailed explanation of GA provided later in this chapter.

2.3.1.4. Integer and Mixed-integer Programming

Integer and Mixed-integer Linear Programming

Integer programming problems occur when the decision variables can only take integer values. For example, when the solution sought is made up of a combination of investment alternatives (e.g. in which locations should DER be installed?) or when fractional units are not an option (e.g. how many DER should be installed?). When some of the variables are continuous, the problem is mixed-integer. Although at first glance these problems might seem simpler than linear programming, they are actually more complex. Variables in the search space can only take particular values and the problem is non-convex. Two main approaches are popular to solve these problems: Branch and bound and cutting plane methods [2.1].

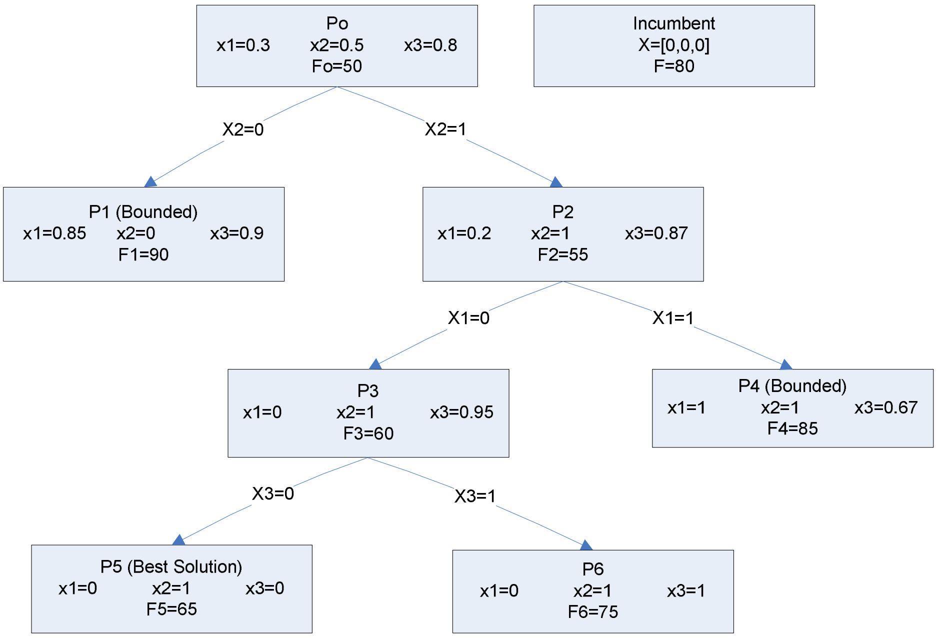


Figure 2-5 Branch and Bound Method (Adapted from [2.1])

Branch and bound methods start with a relaxed version of the integer problem. All variables are assumed as continuous and a linear programme is solved. In addition, a trial solution for the problem of interest is generated, assuming integer values for the decision variables in this case. The initial trial is kept as the best solution so far; thus, it is called the "incumbent" solution. Next, a variable (for example x_2 in Figure 2-5) is branched in its possible integer values. The problem is solved again for each case. If any solution performs worse than the incumbent solution, this branch is closed off. For example, in Figure 2-5, P_1 is bounded; solutions with integer values for x_1 and x_3 can only perform worse than the continuous version of the problem. On the contrary, if an integer solution performs better than the incumbent solution, it becomes the new best solution. The branch and bound procedure is repeated until all possibilities have been analysed. Note that this doesn't mean that an exhaustive search is made, as the bounding step prevents the algorithm of analysing solutions that are known to be suboptimal.

Cutting plane methods are based on a similar approach [2.1]. The problem is solved iteratively as a continuous linear programming problem. In this case, linear constraints that "cut the plane" of the decision variables are included in the optimisation at every iteration. These constraints permit the best integer solution to be found, by disregarding unfeasible non-integer solutions.

Integer and Mixed-integer Nonlinear Programming

Nonlinear mixed-integer problems combine the difficulties of solving combinatorial problems with the complexity of nonlinear (and non-convex) objectives and constraints. Usually an attempt is made to linearize the problem objectives and constraints in the first instance, as powerful linear programming methods are available. However when this is not possible, the solution philosophies used to solve these types of problems are similar to those of their linear counterparts. Namely, branch and bound and cutting-plane methods are used. Nonetheless, each iteration is made more difficult by the need to solve a nonlinear problem.

Another approach commonly used to solve nonlinear mixed integer problems is Benders' decomposition. In this technique, the problem is divided into a master (integer or mixed integer) and slave problem (nonlinear programming) which are solved independently [2.12]. Initially, the variables of the slave problem(s) are fixed to solve the master problem. Once a solution is found for the master problem, the optimal solution for the slave problem(s) is updated. The process is repeated iteratively, until an optimal solution is reached. An example of this approach in power systems can be found in the simultaneous optimisation of distribution network investments (master problem, integer programming) and operation (slave problem, nonlinear programming) [2.13].

2.3.1.5. Dynamic Programming

Dynamic programming provides a very general methodology for problems that can be separated into smaller solvable problems. It is based on the principle of optimality, which states that "a sub-policy of an optimal policy must be an optimal sub-policy by itself" [2.1].

A dynamic programming problem involves a sequence of stages. At each stage one of the optimisation sub-problems is solved, considering the optimisation history (i.e. the stages previously visited). This particular feature prevents the method from evaluating all possible options. The optimal solution corresponds to the "optimal path" created by determining the optimal sub-policies. These characteristics make dynamic programming quite attractive for solving problems that involve sequential decisions, for example: the network development process [2.7], or generation dispatch [2.1]. However, this technique suffers from the curse of dimensionality, that is, the computational complexity of the problem grows exponentially with the size of the problem. Therefore, its direct applicability to large problems is limited [2.1].

2.3.2. Heuristic Optimisation Methods

2.3.2.1. Evolutionary Algorithms

Evolutionary Algorithms are global search methods based on the principles of evolutionary theory. There are three main groups of Evolutionary Algorithms: Genetic Algorithms (GA), Evolutionary Strategies (ES) and Evolutionary Programming (EP). These were developed independently, but share common characteristics. These algorithms are based on stochastic search using groups of potential solutions. The best performing solutions are iteratively chosen and combined (GA) or modified (EP, ES) to find better solutions, until a stopping criterion is met. An example of an EA based optimisation is illustrated in Figure 2-6.

GAs base their search on the combination of good solutions, by means of a crossover operator. In addition, a random search operator (mutation) with low probability of occurrence is used to expand the search. GA put an emphasis on the "genetics" of each solution; so, the GA theory assumes that exchanging genes between good solutions will eventually create better solutions. In contrast, ES and EP base the search on changing good solutions by means of the mutation operator. In this case, the asexual evolution process by mutation is mimicked.

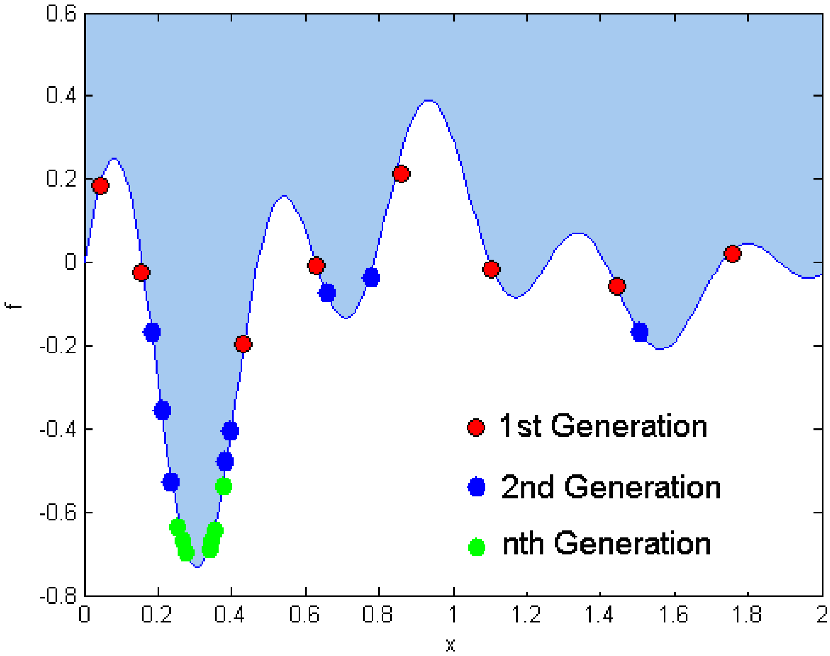


Figure 2-6 Evolutionary Algorithm Example ($\min f(x) = \cos(10x) \cdot \sin(5x) \cdot e^{-x}$)

Genetic Algorithms are the most popularly used Evolutionary Algorithm [2.14], and these terms are sometimes used interchangeably. Most of the applications of heuristic methods to power systems are based on GA. The reason is that GAs are very good at dealing with combinatorial nonlinear problems, such as the ones encountered in power engineering (e.g. generation planning). A detailed explanation of Genetic Algorithm principles, benefits and drawbacks is given later in this chapter (section 2.3.4), and their use in multi-objective optimisation is discussed in section 2.4.2.2.

2.3.2.2. Simulated Annealing

Simulated Annealing (SA) is a search method based on the principles of metal annealing [2.8]. When metal melts, molecules have high energy and move freely. As they cool down, they gradually lose energy and form crystals. If the cooling process is slow enough to permit the formation of perfect crystals, the metal will find its state of minimum energy (the optimal state). In contrast, if the cooling process is too fast the metal will solidify in a sub-optimal crystal formation; thus becoming brittle. The SA analogy is used to optimise a solution through a number of "cooling" stages until an optimal state is achieved (Figure 2-7).

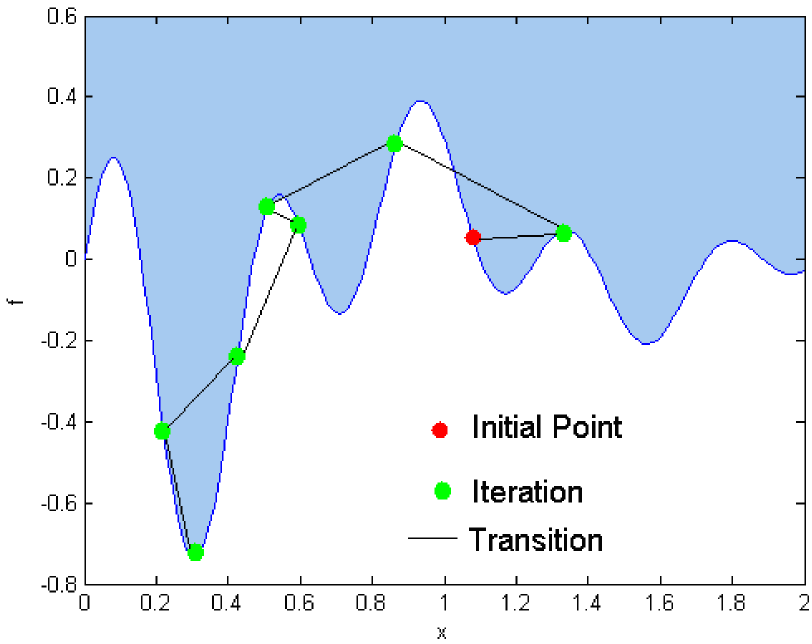


Figure 2-7 Simulated Annealing Example ($\min f(x) = \cos(10x) \cdot \sin(5x) \cdot e^{-x}$)

So, SA conducts a pseudo random search where potential solutions move from one point to the other. Changes to suboptimal solutions are permitted with a probability that diminishes with the search. This allows SA to initially escape from local optima. However, gradually the search will cool down and only moves to better solutions are permitted, to find the optimal point. The advantages of SA are that it can deal with any type of objective functions and that its implementation is very simple [2.8], which is also the case with GA. In contrast, SA cannot recognise when it has found an optimal solution, so, it is commonly used as an approximation method.

2.3.2.3. Hybrid Techniques

A particular characteristic of heuristic techniques is their ability to combine easily with other heuristic or mathematical techniques. These hybrid techniques combine the ability of each technique into powerful search methods. Song *et al.* [2.8] mention some of these combinations:

- Tabu Search (TS) and Simulated Annealing (SA): TS is an algorithm that bases the search on a “memory” process. It keeps a short-term memory “tabu list” of regions of the search space known to be sub-optimal, and a long-term memory of transition strategies that improved the search. SA, in contrast, conducts a probabilistic search, reducing changes in time. A hybrid of both permits SA to remember regions of the search space that were already explored and to apply optimal strategies that help to improve convergence towards global optima.

- SA and GA: SA evaluates a single solution each time while conducting the search. However, some attempts have been made to parallelise SA using groups of solutions. Similarly, the "cooling" principles of SA have been used in GA to reduce the acceptance rate of new populations, enhancing the GA exploration of the search space.
- GA and local search: GAs are very good at searching for the region of the global optima, but they often fail to converge to the global optima. Therefore, in this hybrid GA a local search algorithm (e.g. "hill climbing") is started from the optimal solution obtained by the GA.
- GAs and local search: GAs are very good at solving combinatorial problems. Therefore, another hybrid application of GAs is nonlinear combinatorial problems. In this case, the problem is decomposed and a GA is used to solve the combinatorial master problem while a nonlinear mathematical approach is used to solve the slave problem.

2.3.3. Single-objective Optimisation in Power Systems

A large number of power engineering problems require the use of optimisation methods. These problems are usually difficult to solve for a number of reasons: objective functions include nonlinear terms (power losses, quadratic cost equations); equality constraints are frequently defined by the power flow equations, which are nonlinear and non-convex; decision vectors include integer (switching operations, investment decisions), discrete (capacity) and continuous (operation set points) varuables. Problems are also characterised by a large search space in relation to the standards of most optimisation methods [2.1].

Song *et al.* [2.8] suggests that whenever a power systems optimisation problem can be mathematically formulated, it should be solved by mathematical optimisation. However, given the complexity of most problems, simplifying assumptions must be included in the model of the problem [2.15]. The most common applications of traditional mathematical methods to power systems problems are summarised in Table 2-4.

Table 2-4 Application of Mathematical Optimisation Methods to Power Systems (Source [2.16])

Optimisation Method	Applications
Linear programming	Load Flow Optimal Power Flow (OPF) Reactive power planning Active and reactive power dispatch
Nonlinear programming	OPF Hydrothermal scheduling
Integer and Mixed integer programming	Optimal reactive power planning Power systems planning Unit commitment Generation scheduling
Dynamic programming	Reactive power control Transmission planning Distribution Planning Unit commitment

Conversely, Deb [2.3] recognises that engineering optimisation applications usually involve major simulations to compute the objective function, and that consequently classical methods are not well suited to solve these practical optimisation problems "without major fix-ups". As an example, Neimane [2.7] mentions that the application of mathematical optimisation techniques to real distribution system planning case studies is limited. Similarly, Silva *et al.* [2.17] mention that even if mathematical methods provide an accurate optimal solution, they require simplified models. Hence, only sub-optimal solutions are provided in a practical sense. Lee *et al*. [2.18] recognise that when the simplifications violate the principles of the mathematical methods (e.g. linearization of nonlinear constraints to apply a linear programming method) the solutions found are "certainly" incorrect or even infeasible. This trade-off exemplifies the optimisation/modelling dilemma, introduced in the previous chapter, and expressed by Irving *et al.* [2.1]: "It is too easy to fall into the trap of finding accurate solutions for 'non-problems', or 'non- solutions' to real problems." (Figure 2-8).

Heuristic methods are particularly good at solving nonlinear and combinatorial problems, and it has been proven that they can outperform classical methods in non-convex problems [2.18]. Hence, the application of heuristic methods to power systems problems has gained considerable attention in recent years, especially the use of Evolutionary Algorithms. Mathematical accuracy is sacrificed to some degree because finding the absolute global optimum is not guaranteed. However, modelling accuracy can be increased and any type of objective functions or intricate constraints can be included.

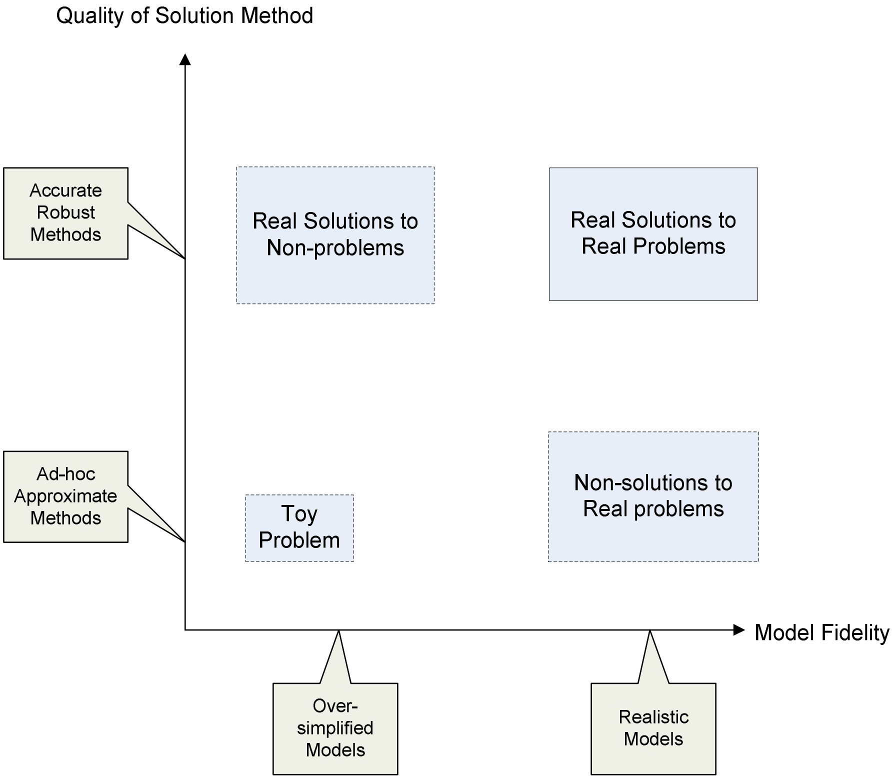


Figure 2-8 Optimisation/Modelling Dilemma (Adapted from [2.1])

An early publication of Miranda *et al.* [2.19] identified the first applications of GA to power systems planning, including capacitor placement, voltage optimisation and load flow analysis. Later, Miranda *et al.* [2.14] reviewed 135 publications recording applications of evolutionary computation to power systems. The range of purposes is extensive and it includes network expansion planning, operation planning, analysis and control of power systems. More recently, Silva *et al.* [2.17] reviewed 85 publications, and identified that generation scheduling and network expansion planning are the most popular applications. Silva *et al.* [2.17] references a case study in which a GA finds a solution 8% cheaper than the one found by conventional optimisation for the transmission expansion problem of the north-north-eastern network in Brazil. This problem is so complex that the actual optimal is not known. The result demonstrates the applicability of GAs to large and complex problems. Next, the working principles and structure of GAs is described in detail.

2.3.4. Genetic Algorithms

Initially developed by Holland in the 70's and popularised by Goldberg [2.20], Genetic Algorithms are a search method based on the mechanics of natural selection and genetics. Most of GA terminology is based on concepts and terms from genetic science. GAs use a population of chromosomes, also known as individuals, each one representing a possible solution to the optimisation problem. Each chromosome is assigned a fitness value, based on its performance. The fittest individuals are combined through a crossover process to produce offspring, which share some features ("genes") taken from each parent. The worst individuals do not reproduce and do not spread the genes into new offspring. Also, from time to time, some individuals undergo mutation, which introduces new characteristics to the population.

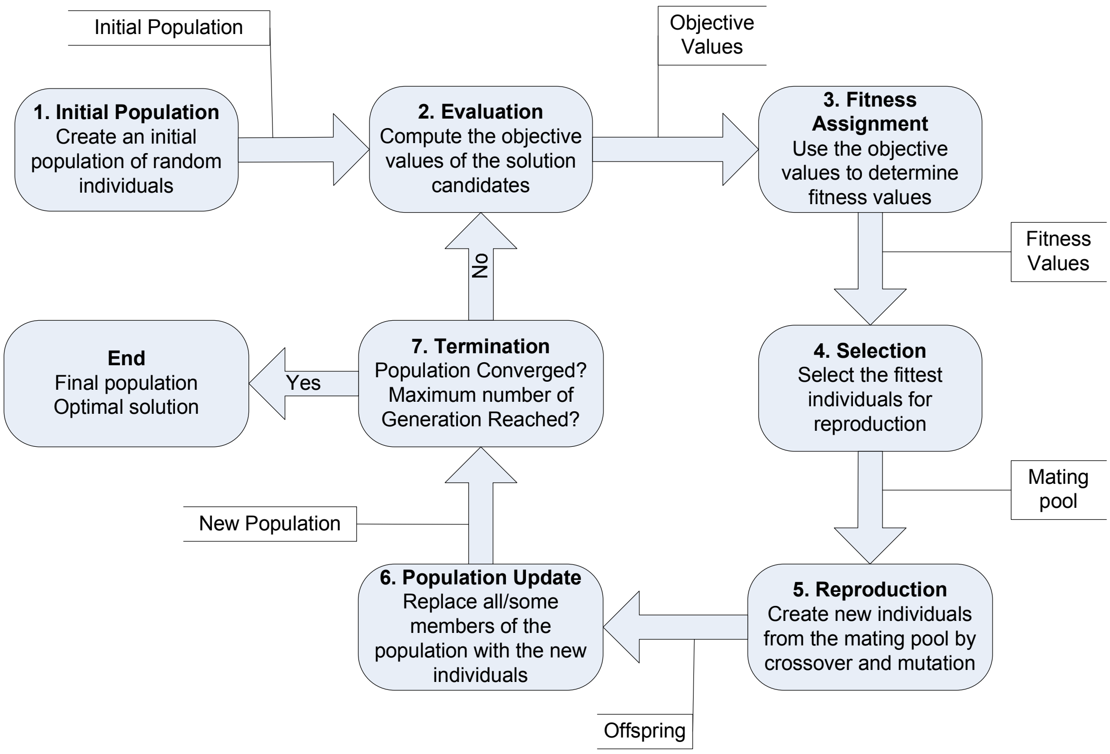


Figure 2-9 Basic Genetic Algorithm

The selection/crossover/mutation process is repeated across generations, with the intention of eventually creating individuals fitter than their predecessors are. The population size is usually kept constant by removing either bad or old individuals; therefore, the average fitness of the population will increase in time. Also, the fittest individuals will eventually approximate the global optima. The process continues for a specified number of generations or until all the population converges to a single chromosome.

The basic Genetic Algorithm can be summarised using steps identified in Figure 2-9. Depending on the author, the number of steps attributed to a canonical GA varies, but the process is the same. Each step is explained in detail next. First, the working principles of GA are discussed.

2.3.4.1. How Do GAs Work?

GAs are based on very simple principles; nonetheless their behaviour is highly nonlinear, stochastic and complex [2.3]. Some hypotheses explain some of the reasons why GAs perform well in a number of difficult optimisation problems [2.21]. Efficient optimisation algorithms must make use of two processes to find the global optima: exploration (cover the whole search space) and exploitation (make use of information already known). For instance, exhaustive search is good at exploration. In contrast, traditional optimisation methods are good at exploitation: they conduct local search based on one-point information. The genetic operations of GAs, described next, perform both exploration and exploitation simultaneously, in an optimal way. Selection and crossover make use of several solutions already known to be good and exploit this information. Afterwards, the mutation operator explores the whole search space for better solutions. Moreover, since a GA work with groups of solutions simultaneously, it conducts a wider exploration of the search space at every iteration.

The "Schema theorem" [2.20] suggests that fit individuals have chromosomes with particular patterns of gene that perform well, called "schemata". Since fit individuals have more chances of reproduction, these schemata are propagated in the population, and the chance of finding better solutions increases. Also, since every chromosome has a large number of gene patterns, GA implicitly conducts a parallel search over a large number of schemata. This *implicit parallelism* is one of the reasons for the good performance of GA [2.21]. Goldberg [2.20] points out that GA have the ability to find good "building blocks", consisting of schemata of short length which work well together and tend to improve the fitness of an individual when incorporated to it. GA can successfully search, find and combine good "building blocks" to create optimal solutions. So, by combining these building blocks and propagating them the fitness or solution quality of the population increases.

2.3.4.2. Encoding

To solve an optimisation problem using GAs it is necessary to encode the decision variables into chromosomes. Each decision variable is represented as one gene in the chromosome (Figure 2-10). Each chromosome defines a "genotype" which corresponds to a unique set of variables in the decision space, the "phenotype".

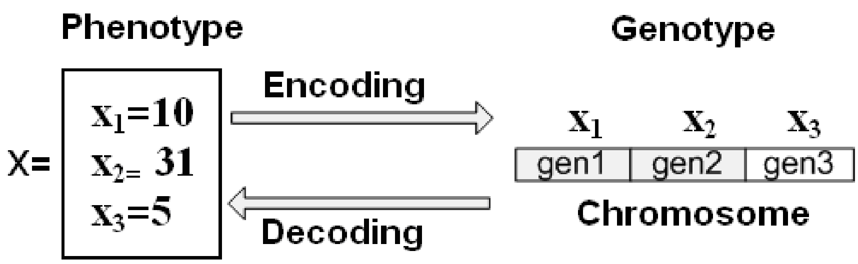


Figure 2-10 Chromosome Encoding

Initially, Goldberg [2.20] suggested the binary alphabet to be the most appropriate encoding system, as it provides the largest amount of schemata. This is the "traditional way" of encoding [2.21]. Even so, it is possible to use other encoding systems, for example, integer numbers, sequences, or real numbers. Recently, it has been proven that there is no "best choice" for the encoding system and that a single given problem can be solved efficiently using different encoding philosophies [2.18]. The crucial aspect is that the algorithm, i.e. the encoding and the genetic operators, promote the processing of good "building blocks" [2.3].

	Phenotype	Chromosome	Genotype
Bynary encoding	**X=[10,31,5]**	01010 | 11111 | 00101	**010101111100101**
Integer encoding	**X=[10,31,5]**	10 | 31 | 5	**103105**

Figure 2-11 Binary and Integer Encoding

Figure 2-11 illustrates two possibilities for encoding a three variable problem: using a 5-bit binary representation or an integer representation with an alphabet of 32 values ($0 \leq x \leq 31$). Each gene is represented with a different colour.

2.3.4.3. Initial population

Creating the first population is not a trivial step, as it can strongly influence the efficiency of the algorithm. The first population consists of a number of trial solutions to the optimisation problem, which are encoded into chromosomes. A good first population can reduce the evaluation time and prevent premature convergence to local optima [2.10]. In contrast, a bad initial population makes the GA search process longer, as this will rely too heavily only on the exploration (mutation) operator to find the global optima, resembling an exhaustive search.

So, the first population must provide the algorithm with varied and good schemata to conduct the search. The most common approach is the creation of "random" individuals [2.3],[2.21]. Nonetheless, if the random parameters are not correctly set, the initial population will leave regions of the search space unexplored; thus affecting the efficacy of the search efficiency. Consequently, some authors suggest a uniform creation of individuals in the decision space instead [2.10]. In addition, if specialised information on the problem is known beforehand, for example regions of the decision space that might be optimal, some good solutions can be "seeded" in the initial population.

The population size is also a key factor to achieve an efficient GA. Some authors recommend population sizes between 30 and 100 individuals [2.8],[2.22]. However, Deb [2.3] demonstrated that the optimal size of the population depends on the difficulty of the problem (e.g. solution space landscape, number of variables) and that there is no single recommendation that applies to all problems. The more "difficult" the problem, the larger the population should be. Goldberg [2.20] provides some discussion on the effects of the relative size of the population. It shows that a small population has good initial performance and it converges more quickly. Nonetheless, if the population is too small the lack of diversity in schemata can cause the algorithm to converge to local optima.

Hence, the population size must be large enough to provide the GA with a good number of schemata to conduct the search. The diversity of schemata will result in convergence of the GA towards the global optima. However, there is a trade-off between the speed and the accuracy of the algorithm. A large population has greater inertia, so, evolution towards the optimal regions will be slower.

2.3.4.4. Evaluation and Fitness Assignment

The evaluation and fitness assignment is sometimes considered as a single step, it consists of the translation of the chromosome's genotype to a fitness value. The fitness value must accurately reflect the ability of the individual to achieve the optimisation objective (or objectives) [2.21]. The fitness value is used in the next step of the GA (selection) to choose the best performing individuals for reproduction.

The evaluation and fitness assignment consists of three sequential steps, as shown in Figure 2-12. First, the chromosome needs to be decoded into the decision variables (**X**). Then, the objective(s) values (**O**) are obtained through the objective evaluation. In basic single-objective GA, the objective value is directly used as the fitness value (*F*). However, normally the objectives are translated to the fitness value using a fitness function [2.22]. Problem constraints are usually included as penalties in the fitness functions [2.3]. These penalties can be proportional to the degree of constraint violation. Individuals that violate the problem constraints have lower fitness compared to feasible individuals. As a result, the exploration is directed towards feasible regions of the search space. Figure 2-12 also provides a power system application in DER as an example to provide realism for the three generic steps illustrated.

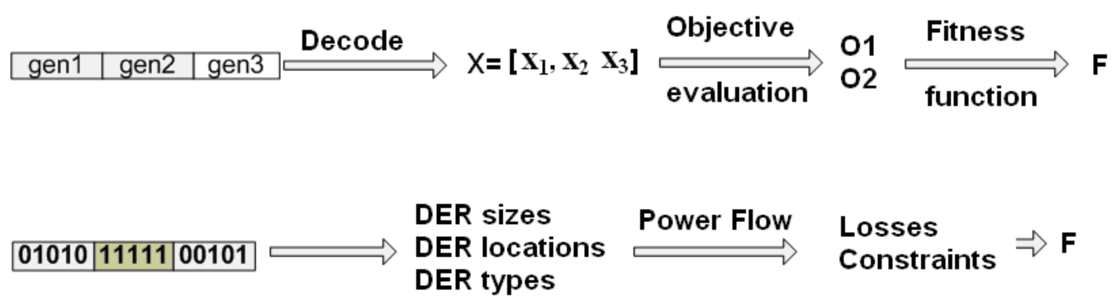


Figure 2-12 Evaluation and Fitness Assignment

To assign the fitness of each individual, quantification of the performance of each solution is needed. Since only the objective values are used to determine the fitness of every individual, the objective functions do not need to be continuous or differentiable. They can be anything from a simple mathematical function to a complex system simulation based on the decision variables, or even subjective values based on preference. This characteristic is fundamental because it permits GA the optimisation of complex, non-continuous, non-differentiable objective functions. Moreover, this mapping permits the formulation of multi-objective problems, explained later in this chapter.

2.3.4.5. Selection

Fit individuals have good schemata. The GA approach means that these schemata must be kept in the population, and must be combined to create even better individuals. GAs ensure this by a selection process in which fit individuals are given higher chances of reproduction. A "mating pool" is created and used in the next step (crossover) to create new solutions. Individuals are selected from the population and "copied" to the mating pool. Several copies of a fit individual are possible. The most common selection processes are 'roulette wheel selection' and 'tournament selection' [2.21].

In roulette wheel selection the mating pool is filled by successively choosing individuals from the population using a random number generator. Each individual is assigned a chance of selection proportional to its fitness. The higher its fitness, the greater chance of selection an individual gets. This process guarantees that better individuals are chosen more often. However, Deb [2.3] recognises that roulette wheel selection methods have a disadvantage; they depend on the absolute value of fitness. So, scaling problems can occur. Two extremes are exemplified, one in which a single individual has considerably higher fitness than the rest of the population. In this case, its chances of selection are close to one, and the mating pool is filled with copies of this single chromosome. The other extreme is when all individuals have roughly the same fitness. In this case, the chances of selection are approximately the same, which is equivalent to not performing the selection process.

In contrast, tournament selection mimics the natural process of competition for mating [2.10]. A small set of individuals (usually two or three) are picked from the population and compared in terms of fitness. The best individual is selected and copied to the mating pool (Figure 2-13). Individuals are compared until the mating pool is full. Fitter individuals win more tournaments and therefore receive more chances of reproduction. One advantage of the tournament selection method is that the number of individuals that are compared in each tournament can be adjusted to increase the selection pressure and speed the convergence of the algorithm. Also, since the selection depends on a relative comparison of fitness, tournament selection does not suffer from the scaling problem identified in roulette wheel selection. Moreover, it has been demonstrated that the tournament selection has better or equivalent convergence and computational properties than any other reproduction operator [2.3].

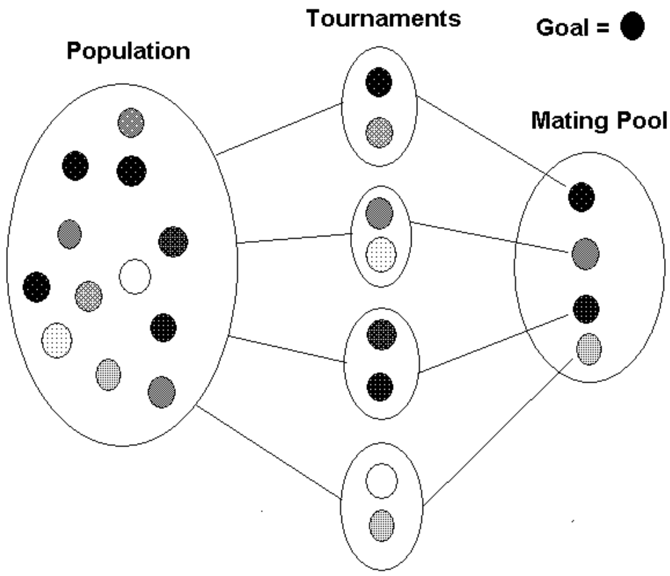


Figure 2-13 Binary Tournament Selection

2.3.4.6. Crossover

Crossover is the key operator of GA. It guarantees that information is interchanged between good chromosomes, eventually leading to the production of better chromosomes. It consists of combining pairs of chromosomes from the mating pool (called "parents") by "swapping" their genes to produce a pair of new chromosomes (called "offspring"). The process of crossover is repeated until all pairs of chromosomes of the mating pool have been picked. However, not all parents are combined. The crossover operator is applied with a probability called the crossover rate. Normally this rate is between 0.6 and 1.0 [2.21], although some empirical studies suggest that the best crossover rate is between 0.65 and 0.85 [2.8]. The parents that are not combined are directly copied to the next population; or with identical result, each offspring is an exact copy of each parent.

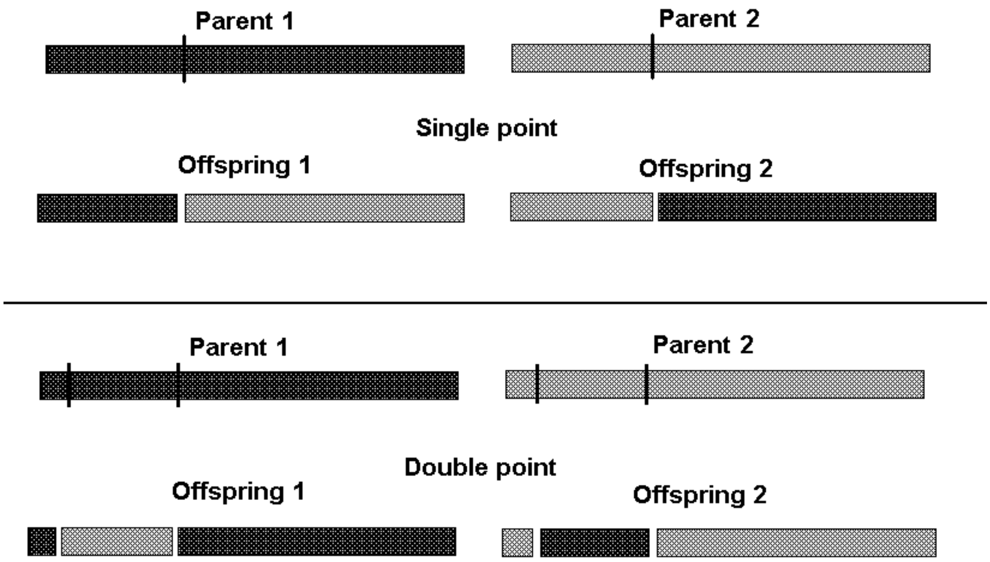


Figure 2-14 Single and Double-Point Crossover

The simplest way of crossover is "single-point crossover". In this case, the two parent chromosomes are split at a single random point, and the segments are interchanged to produce the new offspring. So, each offspring inherits one sequence of genes from each parent. Another possibility is to cut the parent chromosomes at two points ("double-point crossover"). The segment between the two cutting points is swapped between the parent chromosomes. Both crossover techniques are illustrated in Figure 2-14. Researchers agree that two-point crossover is usually better than single point crossover [2.23], as it permits a higher exploration rate of the search space.

Ultimately, the chromosome can be split at multiple points ("multi-point crossover") and the corresponding segments between parents are exchanged to produce two new offspring. A generalisation of multi-point crossover leads to uniform crossover. In this case, a "crossover mask" is created using a uniform probability distribution. The crossover mask determines which bits (if a binary representation is used) or genes (if an integer or real representation is used) from each parent are passed to each offspring (Figure 2-15). Multi-point and uniform crossovers might be regarded as more disruptive than single and double point crossover because building blocks are more likely to be destroyed [2.23]. However, they favour the exploration of the search space, and it has been shown that uniform crossover performs better than two-point and single-point crossover [2.10].

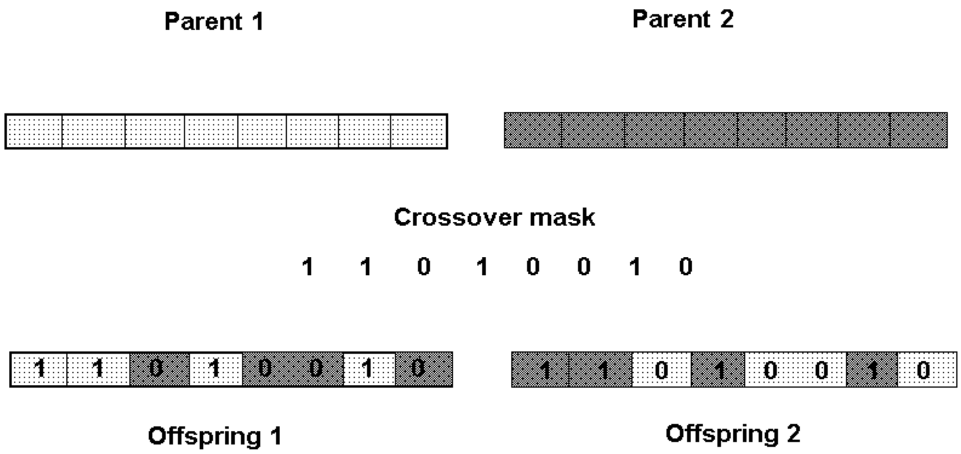


Figure 2-15 Uniform Crossover

In terms of DER planning problems, the building blocks are DER (or a combination of DER) installed in particular nodes of the network. Hence, the crossover operator exchanges DER units between successful topologies. More elaborated crossover operators are possible, for example to prevent unfeasible chromosomes to be formed or to enable repair operations. However, this implies an additional step of evaluation after the crossover operator. If this evaluation is fast, it could speed up convergence. In contrast, if this evaluation is lengthy the convergence benefits result in detrimental impact on the algorithm speed.

Several crossover techniques have been proposed for real encoded GA [2.3],[2.10]. These techniques propose the arithmetical combination parent genes to create offspring genes. However, these are not employed in this thesis and are not discussed here.

2.3.4.7. Mutation

The mutation operator provides a search element to the GA. It is very important because it keeps the diversity of the population by exploring regions of the decision space that were not previously explored [2.3], or by bringing back genes that were removed through selection [2.23]. This operator is applied to the offspring after crossover. For a binary encoding GA, the mutation operator is a "bit-swapping" operation. For a real encoding GA the mutation operator consists of assigning a random value in the search space region to the gene being mutated [2.3] (Figure 2-16). Other possibilities have been proposed. An example of a mutation approach is to use normally distributed random numbers (instead of a uniform distribution), to ensure that the new gene value is closer to the one being mutated.

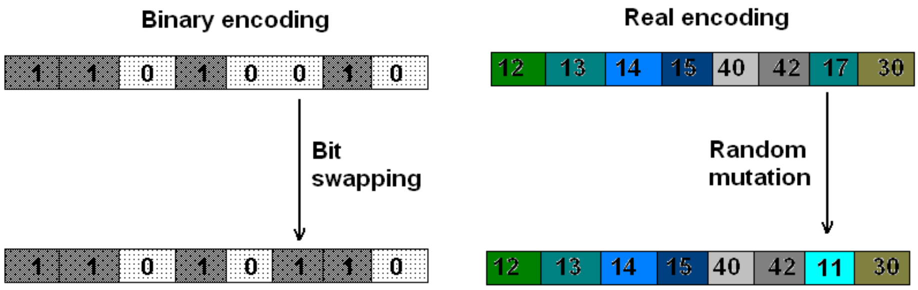


Figure 2-16 Mutation

For DER planning problems changing the gene value means modifying the type or size of the DER unit, or adding a new DER if there is none installed in the node. In addition, shifting two DER locations (within the same chromosome) has been proposed as a specialised mutation operator [2.24].

As is the case with the crossover operator, mutation has a probability of occurrence known as the mutation rate. This rate is expressed as the probability of each bit/gene being mutated. Since mutation is a disruptive operator, a low mutation rate is suggested. A value of 1/n (where n is the number of bits) has been found to be ideal for binary encodings [2.10]. Beasley *et al.* [2.23] states that the optimal mutation rate is more important than an optimal crossover rate. A key aspect of ensuring an appropriate GA search is a diverse set of solutions. Haupt *et al.* [2.10] proved that this diversity could be provided either by a large population, or by the mutation operator. So, as the optimal population size decreases, the mutation rate must increase. However, Goldberg [2.20] demonstrated that too high a mutation rate (>0.5) converts the search into a random search. Another possibility is to adapt the mutation rate with time, starting with a high (exploratory) mutation rate in early generations that will change to a low (fine-tuning) mutation rate at later generations.

2.3.4.8. Population Updating: Reinsertion and Elitism

The last step of the GA is to reinsert the newly created offspring into the population. Usually the population size is kept constant across generations; so, a replacement process is necessary. In a "generation replacement" process, all the old population is replaced by the offspring. So, the number of offspring created must be equal to the population size. This is the most common replacement method [2.21]. In "steady-state" replacement only some members of the population are replaced, usually two. Typically, the worst members of the old population are replaced by the new offspring. Then, only a couple of offspring are created every generation. Beasley *et al.* [2.21] recognise that there are no conclusive results that prove this strategy to be better.

Elitism

A key concept in the population update step is elitism. Elitism gives an opportunity to the best performing individuals from the old population to survive directly in the new population [2.3]: in this sense it is "survival of the fittest". It is applied either by comparing offspring and parents and choosing the best from them for the new population, or by copying directly a number of the best performing individuals from the old population to the new population [2.22]. This simple process ensures that a good solution is never lost by crossover or mutation and is deterministically kept in the population until a better solution replaces it [2.3]. Elitism has been proved to help the convergence of GA to global optima [2.3]. Moreover, elitism is a key concept in Multi-Objective Evolutionary Algorithms. MOEA based on elitist strategies outperform the non-elitist techniques. [2.15]. The SPEA2 technique, used in the planning framework and explained later in this chapter, is an elitist technique.

2.3.4.9. Convergence

If the GA is correctly implemented, the population eventually evolves and finds solutions in the region of the global optima [2.21]. Since GA is an iterative process, it needs a stopping criterion. The most common convergence criteria for single-objective GA are [2.10],[2.21]:

- All the genes of the population have converged. A gene is said to converge when 95% of the population shares the same value.
- A target value for the objective has been reached
- The fitness of the best individual does not change in a number of continuous generations.
- A predefined number of generations has been reached.

2.3.4.10. GA Advantages and Drawbacks

Advantages

The main advantage of GA is that these methods can successfully solve optimisation problems that traditional optimisation methods find difficult. For example, they can readily cope with integer variables, non-convex and non-differentiable functions [2.3],[2.14]. Moreover, the addition of constraints does not increase the difficulty of the optimisation problem for GA.

The GA search process is separated from the model and the objective evaluation. Hence, GA can be implemented modularly [2.25]. Also, the GA objective evaluation does not require functions, only objective values are required. Therefore, separate simulations can be used to evaluate objectives. This permits the GA to interface with existing simulation models [2.22] and with local search optimisation methods. It will be evident in the subsequent chapters that this thesis exploits GA modularity and the possibility of complex objective evaluations.

GAs are powerful search techniques. Nonetheless, they are based on simple concepts [2.25]. The algorithm can be coded without deep mathematical knowledge [2.22]. This particular characteristic makes GAs quite attractive to engineers, as it permits employing most time and effort in the modelling of the problem itself and not on coding the optimisation problem. This in turn is also a benefit. When deep knowledge of the application is available, the GA implementation can be enhanced, for example by providing specific first population, crossover and mutation operators. Such bespoke GA operators can improve the GA performance greatly [2.23].

GA work with a group of potential solutions at each iteration step. This provides several benefits at the same time. First, the search occurs in several regions of the search space simultaneously and it is less likely to be trapped in local optima [2.16]. Second, since GA works with sets of solutions simultaneously, it provides a natural way of dealing with multi-objective problems [2.25]. Finally, the search is robust to variations in single-objective evaluations, because it depends on the whole population. Therefore, GA is good for "noisy" objective evaluations [2.9],[2.25].

GA algorithms require the evaluation of several solutions simultaneously; they are parallel algorithms in essence. This particular characteristic makes possible the implementation of

GA over several distributed processors [2.25]. Parallel GAs overcome one of the major criticisms of GA, the large associated computing time.

Disadvantages

GA does not guarantee finding the global optima in a set or limited time. This restricts the application of GA to real time (i.e. online) optimisation problems [2.22]. Nonetheless, GA solutions improve with simulation time [2.25]. Therefore, when a complex optimisation problem is approached and computing time is not critical (e.g. planning), GA can provide a good compromise between the accuracy of the optimisation method and the detail of the model. GA can analyse more detailed models of the optimisation problem. Thus, the accuracy lost by GA in terms of providing the absolute global optima is regained by permitting a more truthful representation of the problem.

A large computational time is required in some GA applications and this is mentioned as one of the drawbacks of evolutionary approaches. Nonetheless, Miranda *et al*. [2.14] puts this large computational time in context: GA approaches produce results not easily obtained before, in terms of the quality of the solutions and in terms of the additional knowledge gained about the problem.

The correct implementation of a GA depends on a number of problem-specific parameters (initial population, population size, crossover rate and mutation rate). Some guidelines and discussion of these parameters were provided in the previous section. However, generally these parameters are problem specific. If the algorithm is not well implemented, premature convergence to local optima can occur. This effect is called “genetic drift” [2.22] and it occurs when the population is too small to provide diverse schemata and all the genes converge prematurely in a wrong region of the search space. In this case, mutation becomes the only search operator. The genetic drift can be reduced by increasing the mutation rate [2.21], however, if the mutation rate is too large the search becomes a random search [2.20]. The genetic drift can also be reduced by a large and diverse population, which is the usual procedure for intricate optimisation problems [2.10]. However, when the population is too large, the algorithm becomes slow, due to the large number of objective evaluations required. Moreover, when each objective evaluation is highly complex (e.g. a simulation) this can result in an extremely long computing time.

Finally, GA is not an effective optimisation method for all types of problems. Some objective functions might be very difficult or even impossible to optimise by GA. This occurs when the combination of two good building blocks (genes) create a bad chromosome. This effect is called "deception". The underlying theory of GA doesn't work with deceptive functions [2.22]. Therefore, a crucial step to apply GA to a problem is to recognise if the problem being tackled provides building blocks that, when combined, produce good chromosomes. Also, in the case of linear and convex functions, there are methods that outperform GA in performance and accuracy. Consequently, it is necessary to have a good understanding of the problem to be solved in order to choose an adequate solution method.

2.4. *Multi-objective Optimisation*

So far, the principles and most common techniques of single-objective optimisation have been introduced. However, real problems seldom have a single objective of interest. A common example of this dichotomy is the cost versus performance decision faced by any investor who wants the best solution at the cheapest price, illustrated in the previous chapter. A trade-off exists between cost and performance: how much is an increase in performance worth? Or alternatively, how much performance can be sacrificed to save a given amount of money? Although real problems are more complex, similar decisions are faced daily by engineers and planners.

Finding a single solution for a multi-objective problem involves two stages: optimisation and decision-making. Two contrasting philosophies can be applied, depending on the order in which these stages are applied. In the first approach, the decision-making process precedes the optimisation process. The problem is modified to fit a single-objective optimisation framework. This is called a "preference-based" multi-objective optimisation, and it is illustrated in Figure 2-17. The process requires preference information about the problem. However, the quantification of subjective preferences is not an easy task, especially if little information about the problem is available beforehand. More importantly, this solution process is a "black box": given a set of parameters, a single subjective solution is obtained. Hence, valuable information about the problem is lost [2.26].

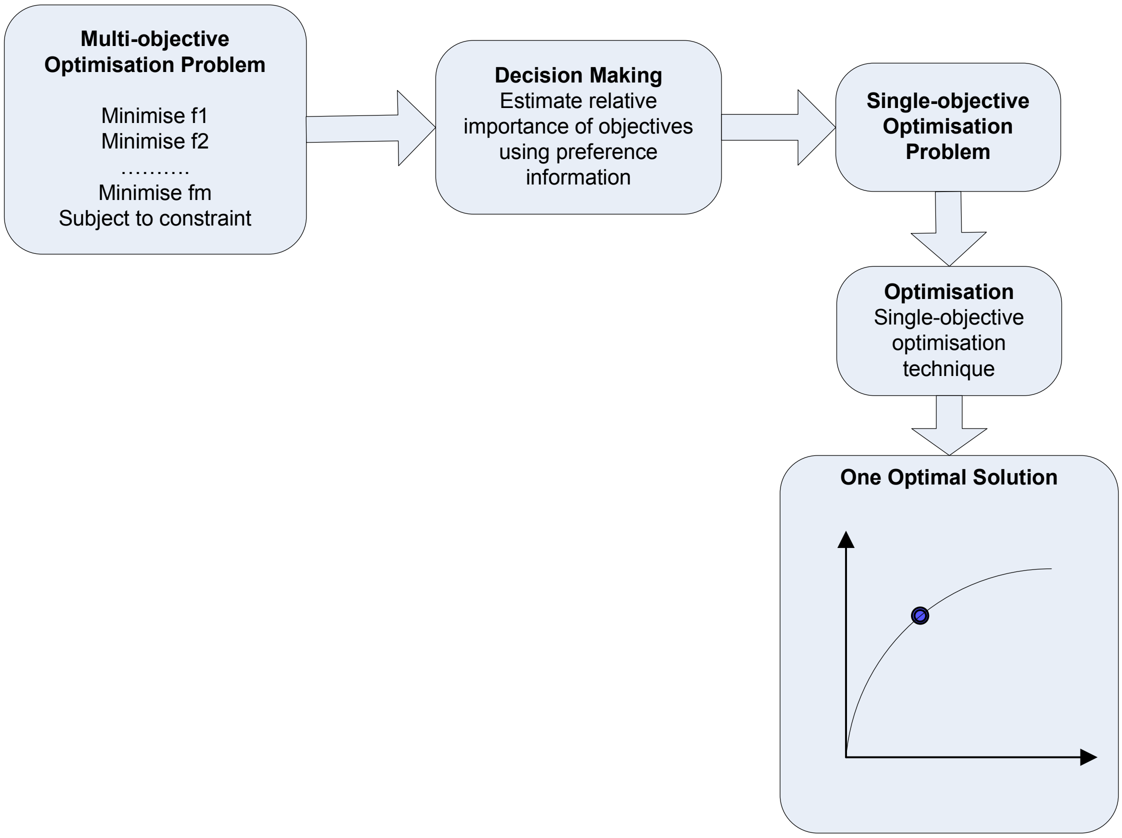


Figure 2-17 Preference-based Optimisation (Adapted from [2.3])

In contrast, in the second approach a multi-objective optimisation technique is applied first, followed by the decision-making process, as illustrated in Figure 2-18. Some authors believe this to be an "ideal" multi-objective optimisation approach for the following reasons:

- The method is more methodical, more practical and less subjective [2.3].
- It provides a wider range of alternatives to choose from; therefore, it permits more informed decisions [2.27].
- Since real problems are usually multi-objective, this approach permits a more realistic representation of practical problems [2.27].
- It permits the generation of useful information about the problem being studied [2.28]; it is possible to know the scope of every objective and to analyse the correlations between objectives.

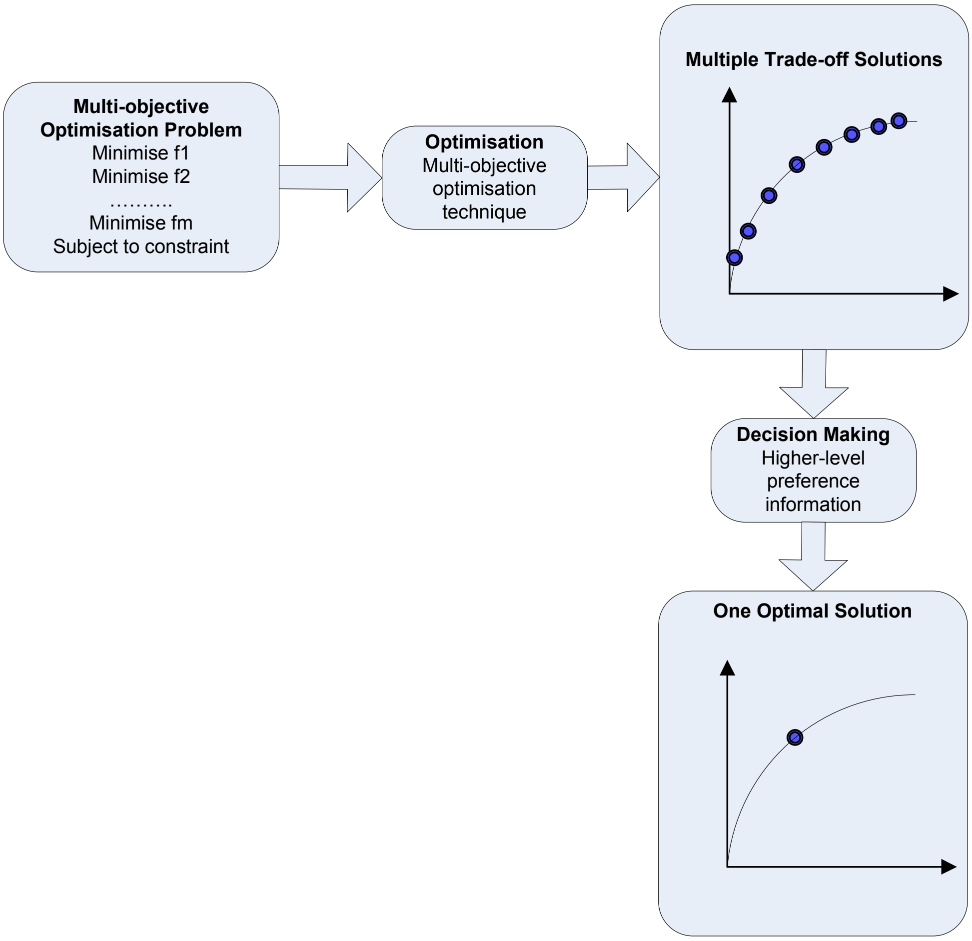


Figure 2-18 "Ideal" Multi-objective Optimisation (Adapted from [2.3])

The last two points are of particular significance for the research presented in this thesis, because a more accurate representation of the DER planning problem is possible and a deep understanding of DER integration can be obtained by means of a multi-objective optimisation technique.

In the next section, multi-objective optimisation techniques used to generate the set of optimal alternatives are presented. In the absence of any preference information, all solutions must be considered equivalent: they are all optimal [2.29]. Since this research does not focus on the choice of a single solution, the decision making stage is not studied. Several techniques for the decision making process to choose a single solution exist. Multi Criteria Decision Making (MCDM) is a vast research field. A broad review of MCDM techniques is provided in Espie's doctoral thesis [2.30]. In addition, the application of MCDM to energy planning problems is studied by Hobbs and Meier [2.31].

Before describing the most common multi-objective optimisation techniques, it is necessary to introduce key concepts of multi-objective optimisation.

2.4.1. Pareto Optimality

In multi-objective problems, the concept of "dominance" is used to determine if one solution is better than others are. A solution *x* is said to dominate a solution *y* if the following two conditions are true [2.3]:

- *x* is no worse than *y* in all objectives and
- *x* better than *y* in at least one objective

In this case *y* is said to be "dominated" by *x*, or alternatively, *x* is said to be "non-dominated" by *y*. The concept of dominance is exemplified in a two objective minimisation example shown in Figure 2-19.

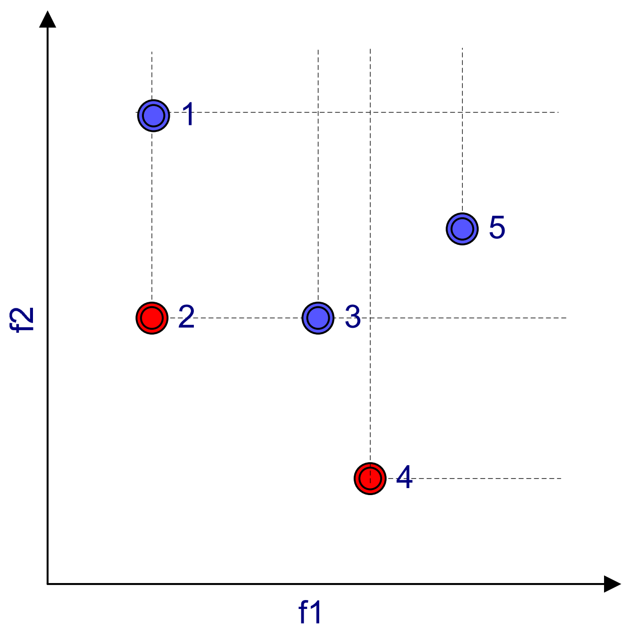


Figure 2-19 Pareto Dominance Example

Since both functions are to be minimised, the following dominance relationships can be observed: solution 2 dominates solutions 1, 3 and 5; solution 3 only dominates solution 5 and solution 4 only dominates solution 5. Conversely, solutions 2 and 4 are non-dominated because there is no solution that dominates them. Note that even if solution 2 is equal in one objective to solutions 1 and 3, it still dominates them, given the concept of dominance.

The non-domination relationship determines the concept of Pareto optimality. A solution is said to be Pareto optimal if it is non-dominated by any other solution [2.3]. In other words, a Pareto optimal solution cannot be improved in one objective without losing in another one [2.15]. So, in this case, solutions 2 and 4 are Pareto optimal. All solutions that are Pareto optimal constitute the Pareto set. The objective values of the Pareto set in the objective space constitute the Pareto front.

The concept of dominance explained in this section is known as "weak dominance" and it is the most widely used. Hence, in this thesis "dominance" refers to "weak dominance". Other concepts of dominance exist, such as "*strict dominance*" [2.3] and "significant dominance" [2.32], which are not used in this work.

2.4.2. Multi Objective Optimisation Techniques

A multi-objective problem that has conflicting objectives has no single solution. Normally, multi-objective problems have a large number of solutions defined by the Pareto set. Since obtaining all Pareto solutions is practically impossible, a subset of the Pareto front is usually looked for. Therefore, solving a multi-objective problem involves satisfying three areas [2.3][2.15]:

- **Accuracy:** To find a set of solutions as close to the real Pareto front as possible.
- **Diversity:** To find a set of solutions as diverse as possible
- **Spread:** To find a set of solutions that "capture the whole spectrum" of the true Pareto front

These requirements are exemplified in Figure 2-20. The first case (Case 1) is able to obtain solutions that are accurate and capture the extent of the objectives; nonetheless, the set of solutions is not diverse. In the second case (Case 2), a diverse set of well-spread solutions is obtained, although these are not accurate. The solutions in the third case (Case 3) are accurate and diverse; however, the edges of the Pareto front are not explored. Finally, the fourth case (Case 4) illustrates the solution of an ideal algorithm.

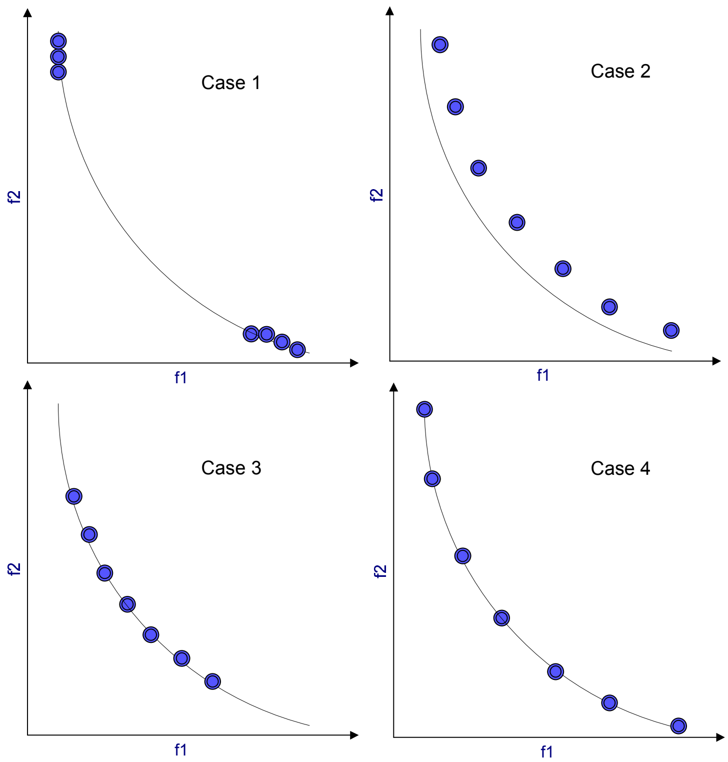


Figure 2-20 Requirements of a Multi-objective Optimisation Problem

Methods to obtain several Pareto set solutions are discussed next. These methods are divided into two groups. The first makes use of single-objective techniques, therefore is commonly referred to as the "classical approach". In contrast, the second group is based on Evolutionary algorithms and permits identification of several solutions of the Pareto front at once.

2.4.2.1. Classical Approach

Classical multi-objective approaches are based on single-objective optimisation methods. Single solutions are found using a preference-based approach, illustrated on top of Figure 2-17. Several solutions of the Pareto front are obtained by solving single-objective problems iteratively. Since this approach constitutes a repeated single optimisation, it must deal with all the complexities of solving a single-objective problem, discussed at the start of this chapter. The two most common classical approaches are described next.

Weighted-sum Method

The weighted-sum method converts the multi-objective problem into a single-objective problem by changing the multi-objective function into a weighted-sum of the objectives:

$$\min F(x) = \sum_{i=1}^{m} w_i f_i(x) \tag{2-11}$$

Weights w_i indicate the relative importance of each objective f_i. Objectives are usually normalised so the weight vector w_i can take values in the range [0,1]. Similarly, it is usual practice to assign weight values so that all weights add to one: $\sum_{i=1}^{m} w_i = 1$ [2.3].

This method is exemplified next with a two objective minimisation in Figure 2-21. The single-objective function *F(x)* is a straight line with a slope equal to $-w_1/w_2$, depicted as a dashed line in Figure 2-21. The position of the line in the objective space depends on the value of *F(x),* as all points in the line have the same value for the objective function *F(x)*. Moving the line towards the origin minimises the value of *F(x)*. As a result, the optimal point A is located where the objective function is tangential to the Pareto Front [2.3].

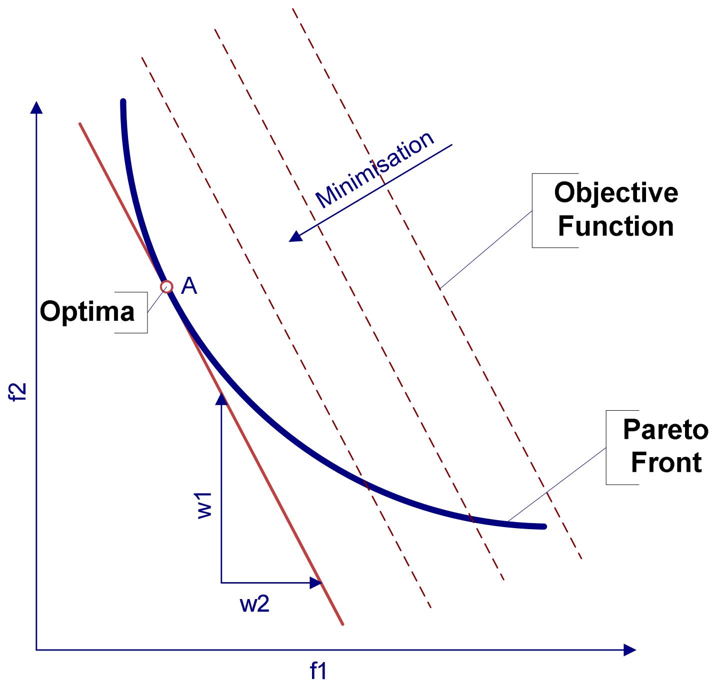


Figure 2-21 Weighted-sum Minimisation

In a convex Pareto Front, multiple solutions can be found by changing the set of weights iteratively [2.3]; that is, changing the slope of the objective function. This is exemplified in Figure 2-22, where points B, C and D are the optimal points corresponding to different set of weights (slopes).

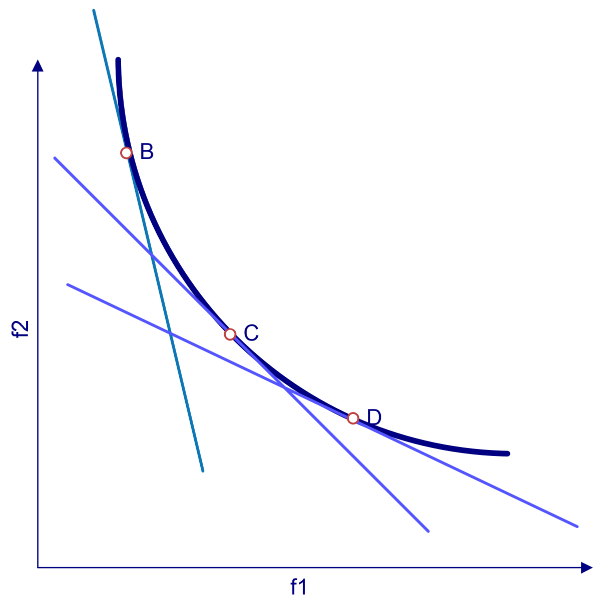


Figure 2-22 Weighted-sum Minimisation – Different Solutions

This method is simple and easy to implement, and in convex problems it has been demonstrated that it can find all Pareto front solutions [2.3]. Nonetheless, it has two main disadvantages. First, choosing a good set of weights is not an easy task, especially when the shape of the Pareto front is not known. Objectives usually do not have the same scales and therefore a normalisation is required. Also, different sets of weights may not lead to different solutions [2.3].

For example, in Figure 2-23 the extreme points *e* and *f* are the optimal solution for several set of weights. Moreover, when the mapping is not linear, uniformly distributed set of weights do not produce uniformly distributed Pareto solutions. In complex (i.e. nonlinear and non-convex) problems, it is even possible that a single set of weights leads to more than one solution. This case is also illustrated in Figure 2-23, where E and F are the optimal solutions for the same tangential line.

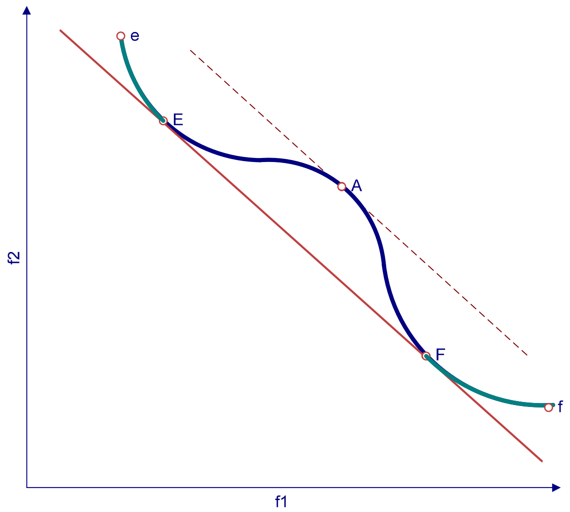


Figure 2-23 Weighted-sum Method with Non-convex Pareto Front

The second disadvantage of the weighted-sum method, and perhaps the most limiting, is that this method is unable to find all solutions when the Pareto front is non-convex. This can easily be observed in Figure 2-23. The weighted-sum minimisation will never find point A. Points E and F are tangential to the objective line that is also tangential to A; though E and F have a lower value for the objective function F(x). In general, no point within E and F can be found by the weighted-sum method, because tangential lines of greater gradient or lesser gradient will first find points with lower objective values in the segments eE and Ff respectively. Since it is not easy to know the shape of the Pareto front, or its convexity, beforehand, the weighted-sum method needs to be applied with caution [2.3].

ε -constrained method

The ε-constrained method was introduced to overcome the difficulties of the weighted-sum method with non-convex Pareto fronts. In this case, the multi-objective problem is simplified by keeping a single-objective function (f_μ), usually the most important objective. The other objectives are expressed as inequality constraints. The vector of constraints ε defines upper bounds for these objectives. So, the multi-objective function of equation (2-1) now becomes:

$$\min f_\mu(\mathbf{x}) \tag{2-12a}$$

$$\mathbf{f_j}(\mathbf{x}) \le \boldsymbol{\varepsilon} \qquad j = 1, 2, ..m \quad j \ne \mu \tag{2-12b}$$

The value of the constraint vector represents the trade-off between the objectives. Obtaining a good solution for $f_\mu(x)$ requires relaxation of the constraints for the rest of the objectives. Several solutions of the Pareto Front can be found by changing the ε-constrained vector.

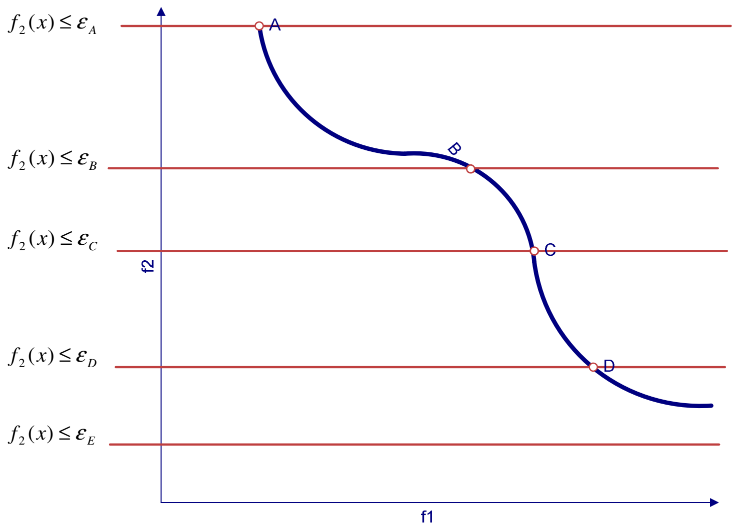


Figure 2-24 ε-constrained Method

For example in Figure 2-24, f_1 is kept as the objective function, while f_2 is constrained. A loose constraint (e.g. ε_A) permits the lowest possible value for f_1 to be found. In fact, any constraint above ε_A will still result in the algorithm finding A as the optimal point. In contrast, a tight constraint (e.g. ε_D) will produce a very high value for f_1. However, if the constraint is too tight (e.g. ε_E), there might be no feasible solution for f_1.

The benefit of the ε-constrained is that it can deal with convex or non-convex Pareto fronts. However, it requires the same amount of information as the weighted-sum methods. Also, the constraint vector must be in the feasible region of each objective, as illustrated in Figure 2-24. Therefore, previous knowledge about the characteristics of the Pareto front is necessary [2.3]. Moreover, when the problem has several objectives, a large amount of information is required, and a large number of iterations are needed to find several solutions that belong to the Pareto front.

2.4.2.2. Evolutionary Approach

The concepts of multi-objective optimisation and the most common classical multi-objective optimisation methods have been introduced in the previous section. The disadvantages of the classical approach were also discussed. This subsection examines the evolutionary approach of multi-objective optimisation.

Evolutionary Algorithms work with a number of solutions at any given time. When they were developed their potential to solve multi-objective problems was recognised [2.20]. Early attempts to use EA to solve multi-objective problems were based on the classical approach (e.g. weighted-sum GA or ε-constrained GA); nonetheless, researchers soon started to propose novel algorithms that exploited the nature of EA. These Multi-Objective Evolutionary Algorithms are based on the same GA structure discussed in depth in section 2.3.4 and they involve the same steps. However, the fitness assignment and selection operators are modified to handle the multi-objective problem; this is explained next. All the advantages and drawbacks discussed for GA in previous section are shared by MOEA. So, MOEA are ideal for dealing with non-convex, nonlinear combinatorial multi-objective problems. Moreover, it has been demonstrated empirically that a single run of MOEA is more effective than several runs of classical methods [2.28].

Next, an introduction to the development history of these techniques is outlined, discussing its origin, the first generation of MOEA and the second generation of MOEA, to which SPEA2 belongs to. This elaboration is necessary to illustrate the recent development of the area and to show the advantages of SPEA2 over other MOEA.

MOEA Origins

The Vector Evaluated Genetic Algorithm (VEGA) developed in 1984 is considered the first multi-objective evolutionary algorithm. It is a standard GA, in which the selection stage is modified. In this case, the mating pool is divided in m subpopulations (m being the number of objectives) and parents are selected according to how well they perform in a single objective. Then, the subpopulations are shuffled together and crossover and mutation is performed as usual. Although this approach generates individuals close to the Pareto, the algorithm fails to retain them [2.4]. Moreover, eventually this algorithm converges to the extreme of each individual objective (Figure 2-25) [2.15].

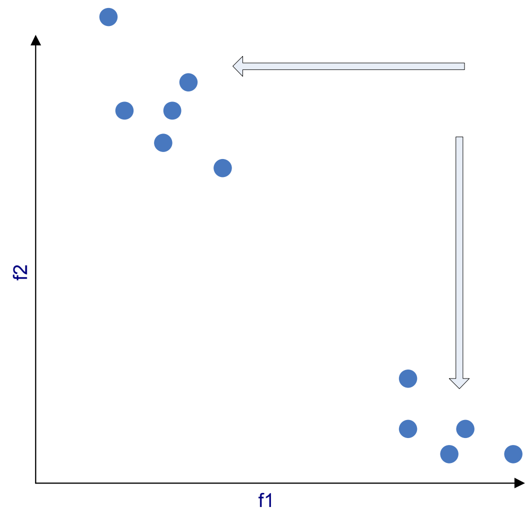


Figure 2-25VEGA Search Directions

First Generation MOEA

After VEGA, the next decisive milestone is the proposal by Goldberg [2.20] for the use of Pareto optimality as fitness criteria. In this case, the population is ranked in fronts (Pareto ranking). The non-dominated solutions obtain the highest rank (associated with highest fitness) the next front is given the second highest rank and so on, as illustrated in Figure 2-26.

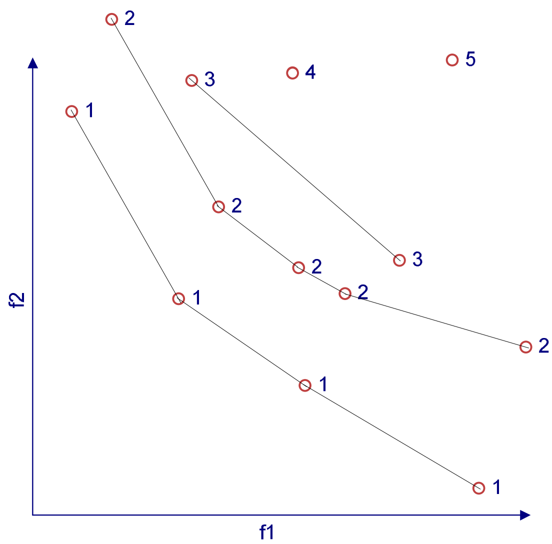


Figure 2-26 Goldberg's Pareto Ranking

In the selection step, solutions with a higher rank are selected more often for crossover and mutation. As a result, the search is pushed towards the Pareto front. Goldberg [2.20] also proposed the use of a "niching mechanism" to maintain the diversity of the solutions along the Pareto front, in order to obtain a more well spread Pareto front. In this niching mechanism, the fitness of each individual is modified according to the distance to its neighbours [2.5]. Individuals that are too close together have their fitness reduced. Therefore, this approach is also called "fitness sharing". It is applied as follows:

$$f_{Si} = \frac{fi}{\sum_{j=1}^{N} \phi(d_{ij})} \tag{2-13a}$$

$$\phi(d_{ij}) = \begin{cases} 1 - \dfrac{d_{ij}}{\sigma_{sh}} & d_{ij} < \sigma_{share} \\ 0 & otherwise \end{cases} \tag{2-13b}$$

where f_{Si} is the shared fitness of f_i, N is the number of neighbouring solutions, and $\Phi(d_{ij})$ is a niche count. d_{ij} indicated by the distance between solutions i and j and σ_{share} is the niche radius.

Goldberg's theoretical background served as the base for several MOEA developed in later years. These are considered the "first generation" of MOEA and include the Multi-Objective Genetic Algorithm (MOGA) proposed in 1993, the Non-dominated Sorting Genetic algorithm (NSGA) published in 1994, and the Niched Pareto Genetic Algorithm (NPGA) also from 1994 [2.4]. One of the first comparative studies found MOGA to outperform NSGA, NPGA and VEGA. However, one of the major criticisms of all the first generation techniques is that their performance depends on the size of the niche (σ_{share}) [2.29], which is usually a difficult parameter to set correctly [2.15].

Second Generation MOEA

The Strength Pareto Evolutionary Algorithm (SPEA) proposed by Zitzler *et al.* [2.33] in 1999 started the second generation of MOEA. In this publication, the authors proposed two key concepts: the use of elitism to preserve non-dominated solutions and a novel fitness assignment that avoids using the niching mechanism. In SPEA, non-dominated solutions are kept in a secondary elite population, called the "external archive". This method guarantees that these solutions won't be lost through crossover or mutation. Moreover, the elite population participate in the selection and crossover process; therefore, the convergence towards the Pareto front is speeded.

The SPEA fitness assignment considers not only dominance relationships, but also the distribution of the solutions. The SPEA fitness assignment is different for non-dominated (i.e. elite) or population solutions:

- Solutions in the external archive P' (i.e. elite solutions) are given a *fitness* value equal to the number of solutions in the population P they dominate, divided by the number of solutions in the population.

- Solutions in the population (P) are given a fitness value equal to the number of solutions from the archive (P') by which they are dominated, plus one.

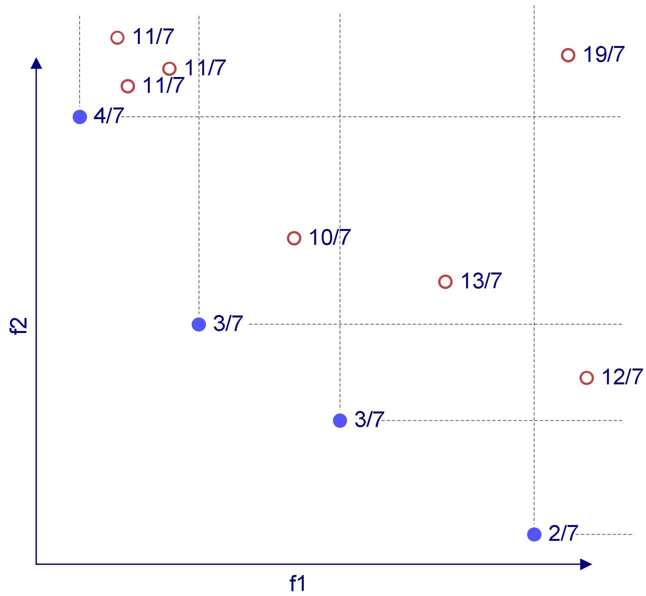


Figure 2-27 SPEA Fitness Assignment Process

Hence, SPEA fitness assignment guarantees that non-dominated solutions have a lower fitness (fitness is to be minimised). Also, solutions in crowded regions of the Pareto front and the search space have worse fitness, pushing the search towards less crowded regions and helping to obtain a well-spread Pareto front by exploring non-explored regions [2.33]. It is possible to observe these effects in the example illustrated in Figure 2-27

After SPEA was proposed, the use of elite populations (or external archives) in MOEA became the norm. It is now a defining characteristic of state-of-the-art MOEA. It was later demonstrated that elitism is a theoretical condition to guarantee the convergence of MOEA towards the Pareto front [2.4].

Most elitist MOEA are based on a framework similar to SPEA and only differ in the way they perform fitness assignment and selection (clustering) [2.34]. The generic structure of MOEA is illustrated in Figure 2-28. Figure 2-29 shows the typical evolution of a MOEA towards the Pareto front.

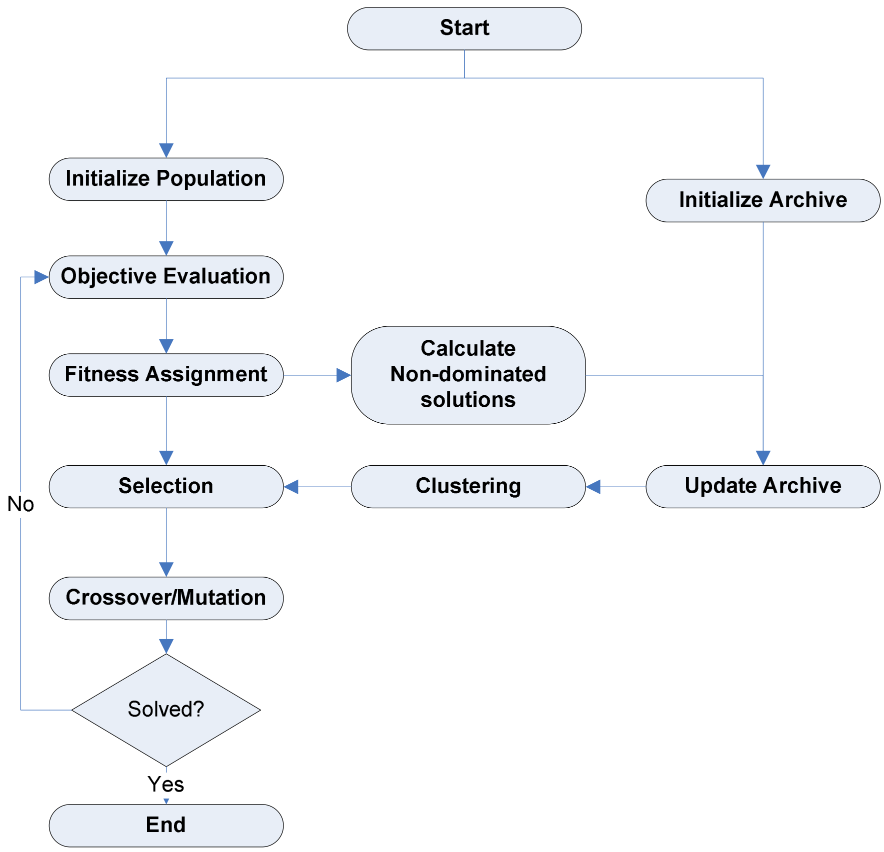


Figure 2-28 Typical Structure of an Elitist MOEA (Adapted from [2.35])

Coello-Coello [2.4] considers the most representative MOEA of the second generation to be the Strength Pareto Evolutionary Algorithm (SPEA), published in 1999; the Pareto Archived Evolutionary Strategy (PAES) proposed in 1999; the Nondominated Sorting Genetic Algorithm II (NSGA-II) developed in 2000 and the Strength Pareto Evolutionary Algorithm 2 (SPEA2) from 2001.

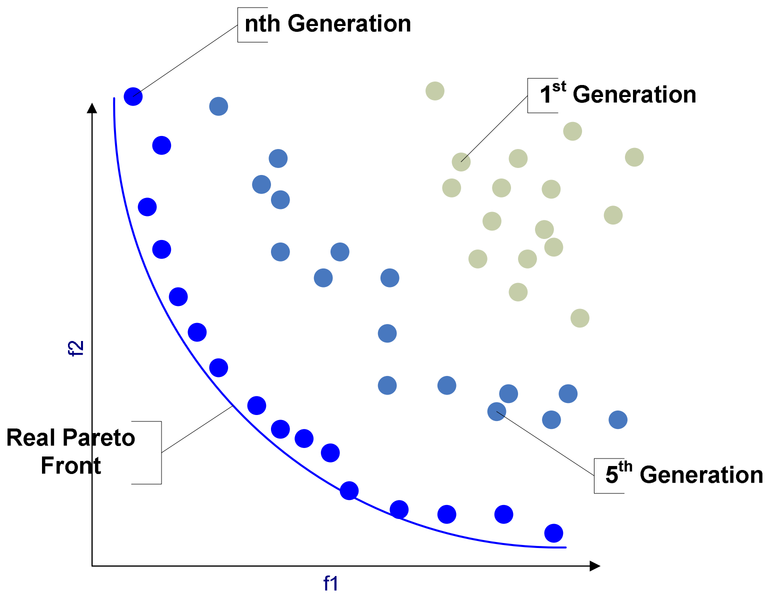


Figure 2-29Typical MOEA Evolution towards the Pareto Front

The last two (NSGA-II and SPEA2) have gained widespread attention and have begun to be applied to a diversity of practical problems, including now DER planning as demonstrated in the next chapters. NSGA-II in particular is considered by some authors as "the most popular method" [2.34] because of its simplicity and effectiveness. NSGA-II is based on three concepts [2.29]:

- It includes elitism by maintaining non-dominated solutions in the population (it doesn't use an external archive explicitly).
- Fitness assignment is based on dominated ranking (Figure 2-26). Hence, solutions closer to the Pareto front receive a better fitness.
- It uses a "crowding distance" estimation as a second comparator in the tournament selection. So, when solutions of the same rank (or front) are compared, the one from the less crowded region is selected for reproduction.

In contrast, SPEA2 is based on a slightly more complicated fitness assignment and clustering mechanism, explained in detail in the next section. SPEA2 has been verified to perform better than PAES and as well as NSGA-II in the problems studied [2.36]. It has also been demonstrated that SPEA2 outperforms NSGA-II in problems with large number of objectives [2.34]. Furthermore, Mori *et al.* [2.37]compared SPEA2 and NSGA-II in a practical problem (distribution network expansion planning) and demonstrated that SPEA2 outperformed NSGA-II in terms of the quality of the solution and the computational time, in the particular problems studied.

The MOEA research area is very active and the development of a history of MOEA is an ongoing process. It can be expected that new developments will be proposed in the coming years. The multi-objective planning framework presented in this thesis uses SPEA2. SPEA2 is a well-tested algorithm that has been demonstrated to outperform other state-of-the-art counterparts. Nonetheless, the development of the planning framework presented in later chapters is based on the concept of modularity. Therefore, any fitness assignment or selection procedure can be included without the need to upgrade the entire planning framework.

MOEA Constraint Handling

Most real optimisation problems involve constraints. Thus, the satisfaction of constraints is a crucial aspect for solving optimisation problems effectively. Konak *et al.* [2.15] list four different approaches to constraint handling in single-objective problems using EA:

- Discard unfeasible solutions
- Reduce the fitness of infeasible solutions using a penalty function
- Use genetic operators to ensure that only feasible solutions are produced
- Repair unfeasible solutions

The second approach is the one most commonly used [2.3]. The implementation of this approach in single-objective problems is simple, although it requires the choice of appropriate penalty factors. Consequently, Deb *et al.* [2.29] proposed a parameter-less constraint handling. This “constrained tournament selection” was proved to perform better than other constraint handling methods [2.29]. Therefore, Deb *et al.* [2.29] extended this concept to the multi-objective case and proposed the concept of “constraint dominance”: A solution x is said to “constraint-dominate” a solution y, if any of the following conditions is true:

- Solution x is feasible and solution y is not

- Solution x and y are both infeasible, but solution y has a smaller overall constraint violation.
- Solution x and y are feasible and solution x dominates solution y

In this case, feasibility is defined over all m optimisation objectives. Similarly, constraint violation is defined over all objectives; thus, a solution that marginally violates a single objective is preferred to a solution that violates all objectives. Deb *et al.* [2.29] proved this constraint handling approach to be better than others found in the literature. This modified dominance concept is simple and logical; more importantly, it maintains the modularity of MOEA and can be generalised and applied to other MOEA.

MOEA in Power Systems to Date

For many years, the resolution of multi-objective problems was based on classical multi-objective approaches, with their associated difficulties. This was also the case for multi-objective power systems problems. For example, in a state-of-the-art survey published in 2007, Rivas-Davalos [2.38] recognised that power systems engineering "has been scarcely touched" by MOEA (Figure 2-30). This is also evident from the multi-objective DER planning review conducted in the next chapter: until recently, the weighted-sum method and the constrained method were the most common approaches.

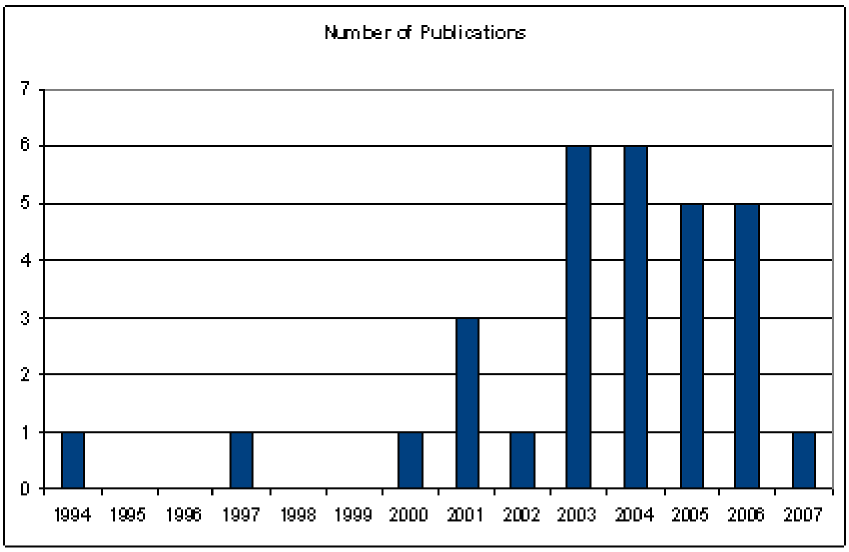


Figure 2-30 Application of MOEA to Power Systems Problems (Source [2.38])

Nonetheless, MOEA can effectively solve the types of problems to which multi-objective power systems problems belong. Moreover, MOEA are based on straightforward concepts and provide modular solutions. Consequently, in recent years an increase in their application to power systems of MOEA has been observed (Figure 2-30). It is likely that MOEA will stimulate more interest in the power systems engineering community in the coming years. This thesis intends to contribute to motivate this interest and to facilitate the future use of MOEA in DER planning and other applications.

2.5. *The Strength Pareto Evolutionary Algorithm 2 (SPEA2)*

The SPEA2 algorithm [2.36] is an elitist MOEA developed in response to criticisms of the first SPEA algorithm. It has been demonstrated that SPEA2 outperforms most state-of-the-art algorithms in test problems and outperform them in practical applications. As in any other MOEA, SPEA2 is based on the fundamental GA structure described in detail in section 2.3.4. SPEA2 uses a population (**P**) of size N and an external archive (**A**) of size $\overline{N}$ that stores non-dominated solutions.

The overall algorithm is repeated for T generations as follows:

Input:	N:	Population size
	$\overline{N}$:	Archive size
	T:	Maximum number of generations
Output:	$\mathbf{A_F}$:	Final non-dominated set

Step 1: **Initialisation:** Generate an initial population $\mathbf{P_t}$ and create the empty archive external $\mathbf{A_t}$**.** Set the generation count t to zero t=0,

Step 2: **Fitness assignment:** Evaluate the population $\mathbf{P_t}$. Determine the fitness values of individuals in $\mathbf{P_t}$ and $\mathbf{A_t}$.

Step 3: **Environmental selection:** Copy all non-dominated individuals of $\mathbf{P_t}$ and $\mathbf{A_t}$ to $\mathbf{A_{t+1}}$. If size of $\mathbf{A_{t+1}}$ exceeds $\overline{N}$ then reduce $\mathbf{A_{t+1}}$ by means of a truncation operator, otherwise if size of $\mathbf{A_{t+1}}$ is less than $\overline{N}$ then fill $\mathbf{A_{t+1}}$ with the fittest dominated individuals in $\mathbf{P_t}$ and $\mathbf{A_t}$.

Step 4: **Termination**: If $t \geq T$ then the final solution is the non-dominated set $\mathbf{A_F}=\mathbf{A_{t+1}}$. Stop.

Step 5: **Mating selection**: Perform a binary tournament selection on $\mathbf{A_{t+1}}$ in order to fill the mating pool.

Step 6: **Variation**: Create the new population $\mathbf{P_{t+1}}$ by applying crossover and mutation operators to the mating pool. Increment generation counter ($t = t + 1$) and go to Step 2.

Any multi-objective algorithm has three main goals: accuracy, diversity and spread, as illustrated in section 2.4.2. SPEA2 achieves these goals by implementing an enhanced fitness assignment procedure that increases selective pressure. Also, this fitness assignment includes density information that encourages the exploration of the less dense regions of the objective space. Moreover, by means of the truncation operator applied in Step 3 a diverse and well-spread set of non-dominated solutions is kept. Another particularity of SPEA2 is that only members of the elite archive (non-dominated set) participate in the reproduction step.

Steps 1, 5 and 6 are similar to those of a GA. The termination of the algorithm (Strep 4) is usually defined by a limiting number of generations. Steps 2 and 3 are exclusive to SPEA2 and are explained next

2.5.1. SPEA2 Fitness Assignment

SPEA fitness assignment was criticised because individuals dominated by the same Pareto members received the same level of fitness, and because Pareto front solutions that dominate a large amount of solutions are assigned worse fitness [2.3], as illustrated in Figure 2-27.

Hence, Zitzler *et al*. [2.36] proposed an improved fine-grained fitness assignment for SPEA2. In this case, the fitness of an individual depends both on how many solutions it dominates and by how many solutions it is dominated. Initially, a strength value (S) is assigned to each element in the combined set **P** and **A**, corresponding to the number of solutions it dominates, as illustrated on the left-hand side of Figure 2-31. Then, the raw fitness value (R) of each solution is calculated as the sum of all the strengths of its dominating elements in **P** and **A**, as shown on the right-hand side of the same figure. This fitness assignment process ensures that solutions dominated by many individuals (which in turn dominate many individuals) are assigned the worse fitness.

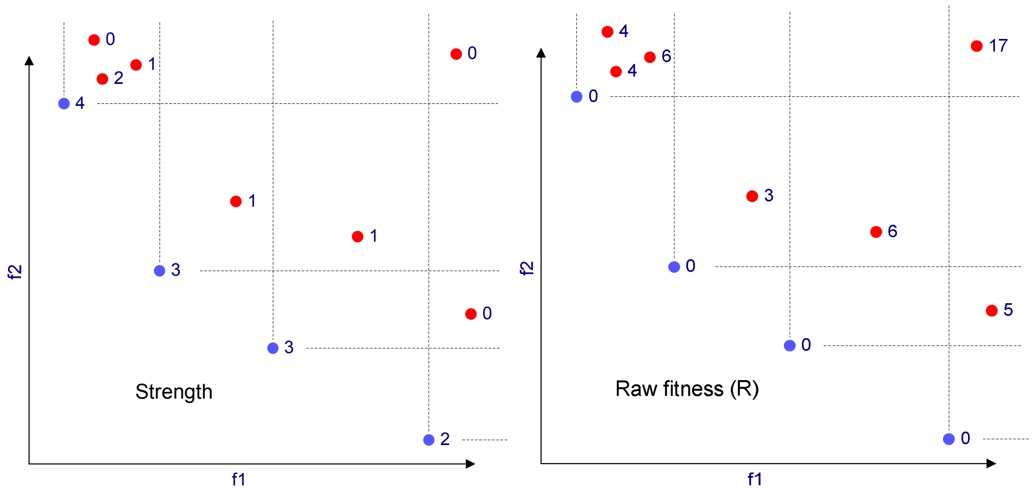


Figure 2-31 SPEA2 Fitness Assignment

Moreover, it is possible to see that with this fitness-assignment all Pareto solutions get a similar raw fitness. In addition, solutions dominated by the same individual (e.g. the cluster of three solutions on the top-left corner) are assigned different levels of fitness, according to their dominance relationships. Therefore, the solutions closer to the Pareto front, in less crowded regions and dominated by fewer individuals, are assigned better fitness. In this form, the search is pushed towards the Pareto front, and towards less crowded regions of the search space.

To discriminate between individuals that have identical raw fitness *R*, *R* is corrected using a local density estimation *D*. SPEA2 uses the inverse of the distance to the k^{th} nearest neighbour as an estimation of density:

$$D(i) = \frac{1}{\sigma_i^k + 2} \qquad \text{(2-14)}$$

where σ_i^k is the distance to the k^{th} nearest neighbour. Normally, k is assumed to be the square root of the population size ($k = \sqrt{N + \overline{N}}$). A two is added to the denominator to ensure its value is greater than zero and that that $D(i)<1$, so it doesn't affect the domination count of R. Consequently, the resulting fitness F is the sum of the raw fitness R and the density estimation D:

$$F(i) = R(i) + D(i) \tag{2-15}$$

This fitness value is used to choose the solutions that will be copied to the external archive (environmental selection). Only the fittest solutions survive to be combined and mutated.

2.5.2. SPEA2 Environmental Selection

In SPEA2, the size of the external archive is kept constant. When the non-dominated solutions in the sets $\mathbf{P_t}$ and $\mathbf{A_t}$ are copied to the archive ($\mathbf{A_{t+1}}$), three possibilities exist:

- The set of non-dominated solutions ($\mathbf{A_{t+1}}$) is exactly the same size as the archive ($|\mathbf{A_{t+1}}| = \overline{N}$). In this case, the environmental selection step finishes.
- The set of non-dominated solutions ($\mathbf{A_{t+1}}$) is smaller than the archive ($|\mathbf{A_{t+1}}| < \overline{N}$). In this case, the archive is filled with the best $\overline{N} - |\mathbf{A_{t+1}}|$ dominated solutions until it is full.
- The set of non-dominated solutions ($\mathbf{A_{t+1}}$) is larger than the archive ($|\mathbf{A_{t+1}}| > \overline{N}$). In this case, a truncation operator is applied to $\mathbf{A_{t+1}}$ to remove solutions until the non-dominated set fits in the archive.

The truncation operator of SPEA2 guarantees that solutions kept in the external archive are well spread, and that boundary solutions are not lost. The truncation operation removes solutions iteratively. At each iteration, the individual in $\mathbf{A_{t+1}}$ with the closest distance to another individual is chosen. If there are several individuals with minimum distance, the second minimum distance is used, and so forth.

Figure 2-32 illustrates the selection of the alternative to remove (left) and the order of truncation of three solutions (right), assuming N=7.

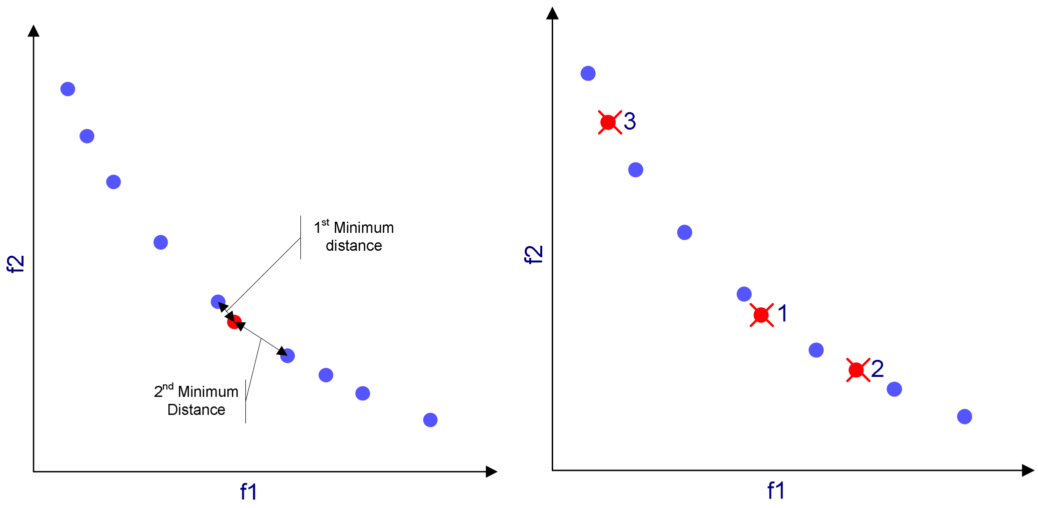


Figure 2-32 SPEA2 Truncation Operator

Finally, Figure 2-33 illustrates the interaction between the population and the archive in a two-generation SPEA2 example. The size of the population is assumed to be N=10, while the size of the archive $\overline{N}$ =5. The steps of objective evaluation, fitness, selection, crossover and mutation are not discussed or illustrated, as they were already discussed in-depth previously in this chapter.

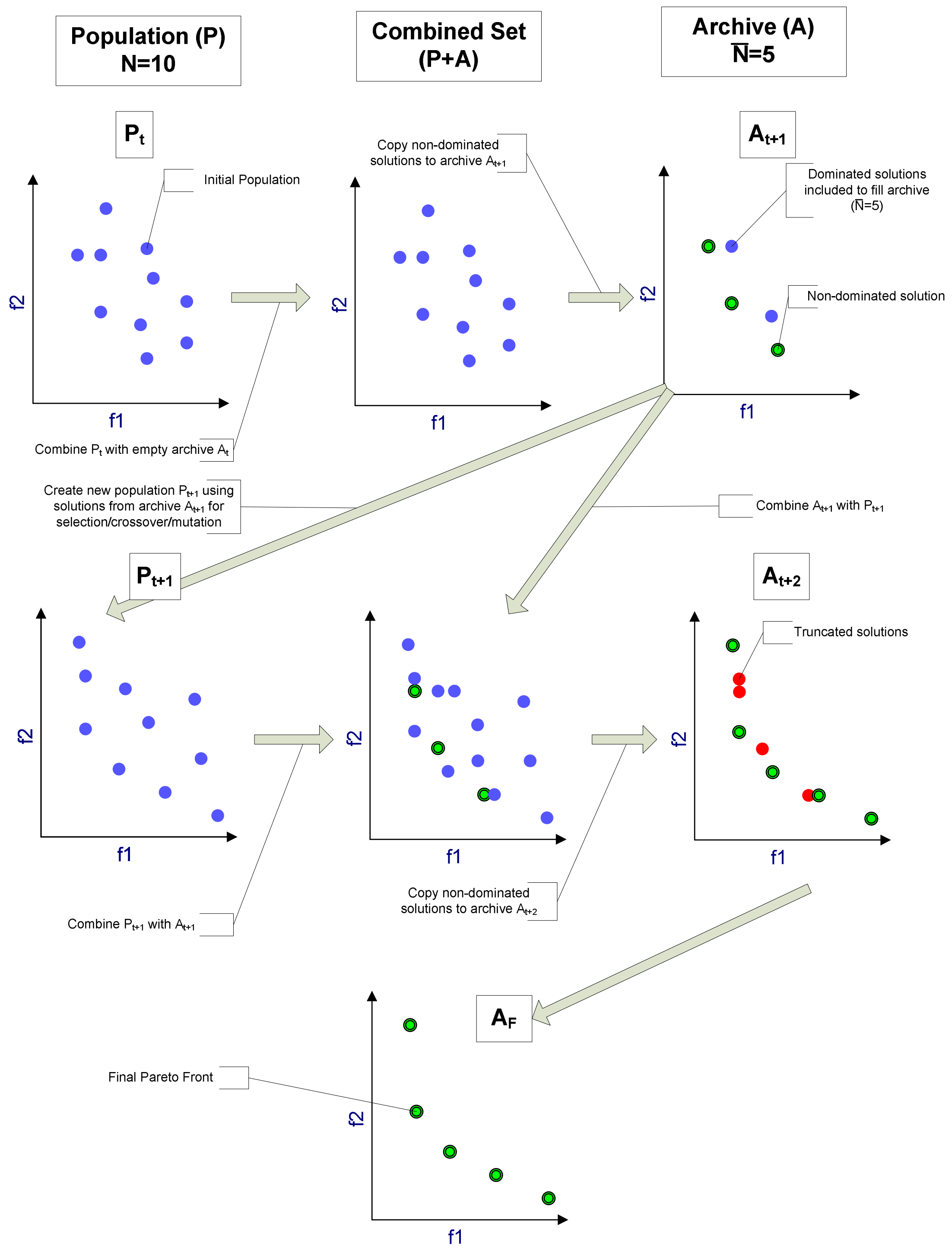


Figure 2-33 SPEA2 Population Interaction

2.5.3. SPEA2 in Power Systems

MOEA are only now starting to gain attention in the power systems community. Nonetheless, two applications of SPEA2 to power systems problems can be found in literature. Both publications explore the distribution network-planning problem. In [2.39] Rivas–Davalos *et al.* propose the optimisation of two objectives: total cost and energy not supplied. The encoding uses an integer number representation. In this case, a chromosome of variable length represents the lines used in each solution. Problem-specific crossover and mutation operators are used. The authors conclude that SPEA2 is able to tackle complex problems such as distribution systems planning. Mori *et al.* [2.37] present a similar problem. In this case, three objectives are proposed: installation cost, cost of losses and network voltage profile. The author proposes a binary encoding to represent the investment decisions. This paper compares SPEA2 with the NSGA-II and it concludes that SPEA2 performs better in terms of the solution's quality (accuracy, spread) and computational speed, in this particular application. Finally, an application of SPEA2 to financial portfolio optimisation is found in [2.40]. This paper is not directly related to power systems, although an analogy to generation portfolio optimisation could be made. It compares SPEA2 to other MOEA (NSGA-II, MOGA and VEGA). The authors demonstrate that SPEA2 is the best for this application, "even in small number of generations".

2.6. *Summary*

In this chapter, the key concepts that define an optimisation problem and its complexity have been discussed. Initially, single-objective optimisation techniques were reviewed. The working principles of the most common single-objective techniques applied in power systems were discussed. Mathematical techniques provide high mathematical accuracy, although they have to sacrifice model detail in complex problems. In contrast, heuristic techniques are able to deal with complex application models, though they have to forgo mathematical accuracy in doing this. The optimisation/modelling dilemma was illustrated. A particular type of heuristic techniques, Genetic Algorithms, is able to efficiently solve combinatorial nonlinear problems. Thus, they have been successfully applied to a number of power system problems.

GAs are based on simple principles: a population of potential solutions that is iteratively combined using probabilistic rules until it converges to the global optima. This chapter presented Genetic Algorithms in detail. Each step of the algorithm is discussed. Moreover, the advantages and drawbacks of GA are analysed. One advantage of GA is that they permit the solution of multi-objective problems in an ideal way. As a result, they are the base for a completely new family of multi-objective optimisation techniques.

Multi-objective optimisation problems have a different concept of optimality: Pareto optimality. These problems do not have a single solution, but a group of optimal solutions: the Pareto set. In some cases, a single solution of the Pareto set is required. Then, a decision-making process is necessary, either to convert the multi-objective problem to a single-objective problem, or to choose a single solution from the Pareto set. This second approach has been recognised by researchers to provide several benefits, including a more truthful representation of multi-objective problems. In this case, before the final stage of decision-making, it is necessary to find a large number of accurate and well-distributed Pareto set solutions. This multi-objective optimisation process by itself can provide a lot of useful information about the problem, and this is emphasised in this thesis.

Two different types of multi-objective optimisation techniques are used to find the Pareto set. The first type is based on the iterative use of single-objective optimisation techniques to find several solutions. This methodology requires a deep knowledge of the problem, it can be computationally complex and, in some cases, it cannot deal with non-convex Pareto front. In contrast, multi-objective techniques based on the principles of Genetic Algorithms are able to find several solutions of the Pareto set simultaneously. These techniques are known as Multi-Objective Evolutionary Algorithms. The research presented in thesis makes use of one of these techniques: the Strength Pareto Evolutionary algorithm 2 (SPEA2). SPEA2 has been demonstrated to outperform other algorithms in practical problems and has been described in this chapter. The following chapter introduces the mathematical formulation of the DER planning problem and provides a comprehensive review of single and multi-objective DER planning techniques.

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Chapter 3

3. Distributed Energy Resources Planning

3.1. *Introduction*

The optimal integration of DER in the distribution grid can provide several benefits. For example, it can reduce power losses, improve voltage profiles or decrease carbon emissions. In contrast, a sub-optimal integration of DER can have the opposite effects, resulting in increased costs, network reinforcements, energy curtailment or even in unsustainable system operation conditions. Consequently, DER planning -understood in this work as optimising DER type, size and/or location - is crucial to obtain maximum DER benefits, and minimise its impacts. DER planning is not just an economic optimisation of resources; it is a powerful analytical tool. Each DER benefit or impact can be translated to a planning objective. The information of what is "optimal" in each case deepens the knowledge about DER. Furthermore, when the problem is formulated as a multi-objective optimisation, a profound analysis of DER integration is possible.

This chapter presents a comprehensive and critical literature review of DER planning techniques. Initially, this chapter describes the process of power-systems planning. The link between power systems planning and optimisation techniques is discussed. Afterwards, the mathematical formulation of the DER planning problem is presented. The mathematical complexity of this optimisation problem, and the difficulties associated with solving it, are illustrated. Then, relevant single-objective DER planning techniques are analysed. This analysis emphasises the different planning objectives proposed, and identifies some of the main shortcomings of the single-objective techniques reviewed. Subsequently, a critical analysis of multi-objective planning approaches for DER is made. This comprehensive review highlights the contributions of different authors and the possibility for further developments in the area. Finally, a timeline of multi-objective DER planning and the context of this research are discussed.

3.2. *Power Systems Planning*

Power systems' planning is the process of finding the best energy sources and equipment, together with their location, manner of interconnection and schedule of deployment to serve a future demand [3.1], [3.2]. It is a process of optimisation and decision-making and the optimal solution depends on the planner's goals and preferences: what needs to be achieved? What defines the best solution? Traditionally, the main goal of power systems' planning is to minimise the total cost. However, planning is not just restricted to economic goals. Other planning goals are possible; for example, to find a clean energy supply; to improve the system performance; to maximise energy exports or to minimise dependence on energy imports, as will be reviewed later in this chapter. In this wider perspective, planning becomes a powerful analytical tool. The knowledge of what are "optimal" configurations can guide not only adequate investments but also incentives, research and innovation.

Willis and Scott [3.1] study the *investment* planning process for Distributed Generation. The planning process is considered as a five-step procedure (Figure 3-1). These steps are discussed next in the context of this work.

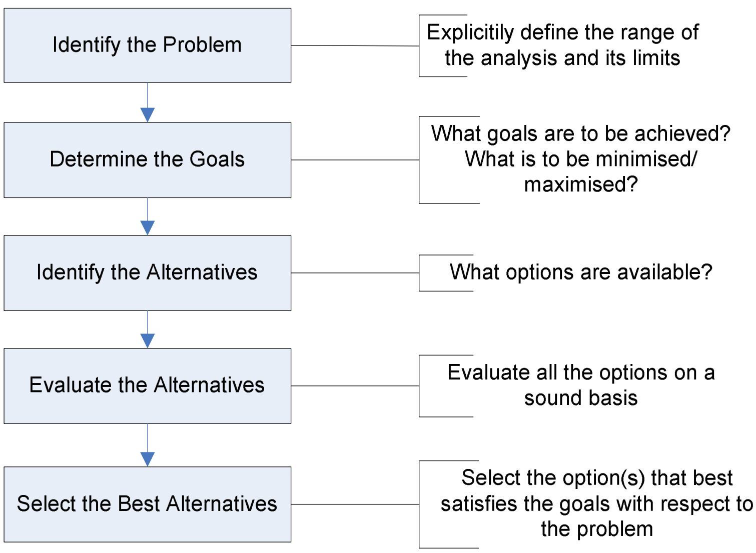

Figure 3-1 Five steps of Planning (adapted from [3.1])

This chapter reviews the planning of DER in the long term (years), i.e. investment planning. Operational planning, in contrast, refers to the optimisation of the power system's *operation* in the short term (hours, minutes) to minimise costs and technical impacts. It is not discussed in this chapter. The operational planning of controllable DER is discussed briefly in the next two chapters.

3.2.1. Defining the Planning Problem (Step 1)

The first step of the planning process is to define the scope of the planning problem: the boundaries of the system being studied and the period of the analysis.

Optimising the whole power system is extremely difficult, if not impossible. Therefore, it is decomposed in smaller problems: generation; transmission; sub-transmission and distribution planning. Local distribution networks that are weakly connected are analysed separately. When vertically integrated DSOs are allowed to invest in DER, these resources are included as part of the distribution system planning process. Willis [3.3] and Neimane [3.4] provide a comprehensive explanation of the investment planning process of distribution networks; these works consider DER as one of the options of the network planner.

Yet, vertical integration of utilities is not permitted in liberalised electricity markets. In this scenario, DSOs are not allowed to invest in DER and are required to provide unrestricted access to DER developments, subject to compliance with connection and technical guidelines, such as [3.5]. In this case, DER developers determine the most favourable investments for maximising revenues by means of DER planning. Likewise, DSOs and regulators can identify optimal locations, sizes and types for DER integration. With this information, they can provide incentives to improve system performance [3.6], achieve environmental targets making an adequate use of existing network assets [3.7] or minimise negative DER impacts [3.8].

Planning ranges for investment planning are defined as short-term or long-term. Short-term plans aim at guaranteeing that immediate demand growth can be served while keeping the system within operational limits and standards. So, short-term plans are “project oriented” and look for the schedule of additions or projects that the system requires in the near future. The minimum period of study for a short-term plan is the time necessary for the plan to be approved and the equipment to be purchased, installed and tested: the lead-time [3.1]. A guide of lead-times is provided by Willis and Scott [3.1], though it is noted that modern power plants can be constructed in shorter times.

Long-term plans look further ahead into the future. Thus, they are able to include a wider range of options in the analysis. Traditionally, in regulated utilities long-term plans aim at providing solutions with lasting value: a true minimal cost throughout the useful life of equipment (e.g. DSOs). On the contrary, in competitive markets, long-term plans aim at recovering capital investments in the shortest period possible or at maximising revenues over the lifetime of investments (e.g. a private DER developer). In both cases, the analysis must consider the useful life of alternatives to provide an adequate assessment. In the case of distributed generation, the useful life of the equipment is normally considered 20 years [3.3].

In a long-term plan, it is crucial to take into account all the possible changes that might occur in the power systems and its economic environment within the analysis period. These changes include:

- Load growth of existing load points
- Changes in demand behaviour and profiles (e.g. energy efficiency measures)
- New loads and/or generation connection
- Changes in the network infrastructure (e.g. ageing of equipment, interconnections)
- Technical characteristic of equipment (e.g. increase of efficiency, reduction of emissions)
- Equipment and fuel costs
- Energy market prices
- Changes in the regulatory environment (taxes, incentives)

The trends in these parameters are determined by projections and forecasts. Uncertainty in the forecasts increases the further one looks into the future. So, it is crucial for long-term plans to consider relevant uncertainties. The scenario technique is the most common approach for planning in the presence of uncertainty [3.9]. In this case, uncertainties are modelled as a set of possible futures/scenarios, each one representing a possible outcome of uncertain parameters (e.g. low, medium and high load growth). Next, optimal plans are produced for each one of these scenarios. Then, appropriate techniques are used to choose plans that are robust (i.e. perform well in all possible futures [3.10]), or that produce the least regret for the planner if an undesirable future occurs (Risk analysis [3.11]). Willis [3.3] considers the scenario method to be the only valid way to handle uncertainty, especially when multiple-objectives are involved.

3.2.2. Planning Goals, Objectives and Constraints (Step 2)

Planning goals are expressed in terms of objectives and constraints. Objectives target the maximisation/minimisation of an attribute. Objectives are open-ended; each solution is always challenged to do better, the feasible plan with the best attributes must be found. On the contrary, constraints only need to be met rather than exceeded [3.3]. Attributes measure the quality of a plan in terms of the goals of the planner. So, it is crucial to define planning attributes that accurately reflect the goals targeted. Attributes can be technical, economic or environmental. Table 3-1 presents this set of key concepts that define the planning problem, with relevant examples.

Table 3-1 Planning Key Concepts

Concept	Definition	Example
Goal	To achieve a set of objectives subject to a set of constraints given the problem and time frame defined	To find the minimal cost solution to serve the projected demand for feeder X subject to environmental constraints and current regulations considering an horizon of 10 years
Objective	The minimisation/maximisation of an attribute	Minimise cost Maximise energy exports
Constraint	The minimum/maximum value for an attribute to make a plan feasible or worth of consideration	Maximum voltage deviation Minimum rate of return
Attribute	The measure of the goodness of a plan	Installation cost (£) CO_2 emissions (Tonnes) Maximum voltage deviation (V) Probability of voltage violation (%) Energy losses (kWh)

Some common planning attributes are presented in Table 3-2. In traditional planning approaches, all relevant attributes are converted to cost and the total cost is minimised subject to a set of technical constraints. However, analysing an attribute in its natural units can provide valuable information, for example by means of a multi-attribute formulation of the problem. This possibility is explored in Alarcon-Rodriguez *et al.* [3.12] and developed further in this thesis.

Table 3-2 Planning Attributes

Technical	Economic	Environmental
Voltage Energy produced Energy not supplied Energy exported Power losses Line loadings Harmonic distortion Fault level Installed capacity	Cost of equipment Cost of operation and maintenance of equipment (O&M) Outage cost Cost of energy produced Revenue Profit Rate of return	Green house gas emissions CO_2 emissions Radioactive waste Noise

3.2.3. Solving the Planning Problem

The first two steps define the scope of the planning problem. Steps 3 to 5 provide a structured way to find a solution: identify all alternatives, evaluate them, and select the best. These steps constitute essentially an optimisation algorithm. Consequently, efficient planning methods combine them into a single process [3.3], and make use of some sort of optimisation method. Optimisation techniques were already studied in Chapter 2. So, a discussion of Steps 3 to 5 in the context of this thesis is provided next.

3.2.3.1. Selection and Evaluation of Alternatives (Steps 3 and 4)

In the third step, the possible alternatives for solving the planning problem and achieving the goals are identified. In terms of an optimisation problem, this means setting the boundaries of the search space: what alternatives are going to be considered? What is the decision domain? Willis and Scott [3.1] judge this stage to be the most critical and where most planning mistakes are made. The most common mistakes are:

- Failing to consider all relevant options
- Not including the "do-nothing" case as one of the options.

In addition, another perspective is possible. An analysis of only a set of alternatives permits the separation and study of the effect of these in the planning attributes. For example, Alarcon-Rodriguez *et al.* [3.13] propose to analyse only DER and not network reinforcements to examine the isolated effect of DER in the planning objectives.

Alternatives must be evaluated to determine the degree of achievement of objectives, and the compliance of constraints. Every attribute must be quantified. In power systems planning this stage involves a techno-economic analysis. Normally, technical attributes are quantified by power system analyses (load flow, reliability and fault studies). Economic attributes require an analysis of cash flows (expenditures and incomes) over the period of the analysis. In this case, it is crucial to take into account the time value of money to provide a fair comparison of present and future spending and incomes. The time value of money is discussed in Appendix A. Some technical attributes are converted to environmental and economic ones using appropriate conversion factors (e.g. CO_2 emitted by energy generation, cost of energy losses). A key aspect in this stage is to evaluate all alternatives using *the same procedure*, to avoid bias in the comparison of alternatives.

Willis and Scott [1.15] consider it crucial to evaluate *all* alternatives. However, the exhaustive evaluation of all alternatives can be inefficient or practically impossible when the search space is very large. A vast search space is usually produced by alternatives that have a combinatorial nature, for example the placement of different type of DER in a distribution network. In this case, optimisation algorithms or heuristic searches must be used to guarantee an implicit evaluation of all alternatives. Traditional mathematical optimisation techniques find the optimal solution using information from the analytical expression of objectives (derivatives, gradients). In some cases, planning objectives cannot be expressed as continuous and differentiable mathematical functions. Then, heuristic optimisation algorithms, such as genetic algorithms, can be used to find a good approximation of the optimal solution. GAs need only to evaluate a limited number of solutions to find a (near) optimal solution. In conclusion, optimisation algorithms do not require the evaluation of all possible alternatives but they must guarantee the exploration of the whole search space.

3.2.3.2. Selection of the Best Alternative (Step 5)

Power system planning is a multi-objective problem in essence [3.10]. It aims at resolving multiple objectives at once. Objectives are frequently in conflict with each other: improving one objective will worsen other(s), (e.g. Figure 3-2). A common example of this conflict is the line losses versus reinforcement cost trade-off. Investing in line reinforcements will reduce losses; in contrast, a low reinforcement cost will lead to high line losses.

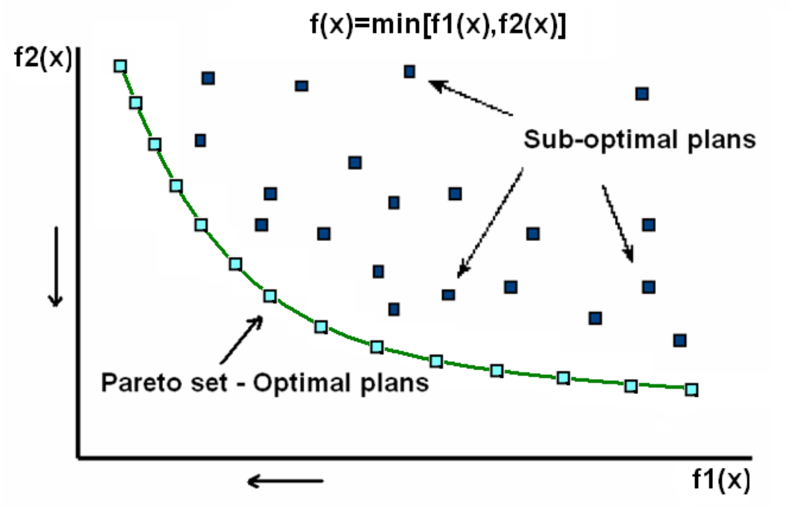

Figure 3-2 Pareto-set for a Two-objective Optimisation

A single-objective formulation of the problem is possible when there is no conflict between objectives (e.g. Figure 3-3), when a single objective is more important than the rest or when preference information permits the accurate combination of objectives into a single-objective function, as examined in the previous chapter.

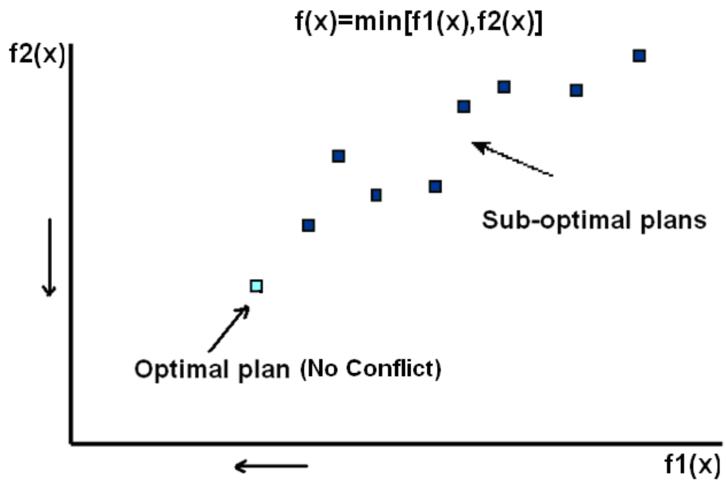

Figure 3-3 Two-objective Optimisation - No conflict

Commonly, power system planning is regarded as a single-objective problem: to minimise total cost, subject to technical constraints. Translating several attributes to cost and minimising the total cost is essentially a weighted-sum minimisation. In this case, the selection of the best alternative is uncomplicated, because there is only one best alternative (or none). However, in the absence of preference information, i.e. cost, to aggregate objectives, and when objectives are incompatible, there is no single plan which optimises all objectives at once, nor a single objective that is more important than the rest. In this case, all optimal solutions must be considered equivalent. The solution of the multi-objective planning problem is a set of non-dominated solutions: the Pareto set. This multi-objective set of solutions provides rich knowledge about the planning problem, the extension of the objectives, the correlation between them, and the possible trade-offs that the planner can make. The possibility to study the DER integration problem in depth by means of a multi-objective formulation is explored in this thesis.

Decision Making

This thesis is focused on the multi-objective analysis of DER integration. Hence, the choice of a *single* optimal solution based on preference information is not contemplated in this work. Even so, for the purpose of completeness, the decision making stage is briefly introduced.

Traditional planning problems *do* require a single solution. In this case, two approaches are possible. They both need unambiguous preferences from the planner. The first approach requires *a-priori* preference information to translate the problem to a single-objective optimisation problem. The second uses *a-posteriori* preference information to choose a single optimal solution from the Pareto set [3.14]. Both approaches are illustrated in Figure 3-4.

When deep knowledge of the problem and reliable information is known *a-priori,* it is possible to formulate the multi-objective problem as a single-objective optimisation, and obtain a single solution, as seen in the left-hand side of Figure 3-4. This is commonly done by using a weighted-sum method or choosing a primary objective and setting the rest as constraints. In this case, the single optimal solution represents a specific point of view (costs, weights or objectives) of the multi-objective problem. When specific attributes are aggregated in the weighted-sum, the scope of each planning attribute is obscured and information about the possible trade-off between objectives is lost [3.15].

In the absence of *a-priori* preference information, all non-dominated solutions are initially considered equivalent. A multi-objective optimisation technique is used to find the Pareto front. In some cases, the number of optimal solutions belonging to the Pareto front is very large, so only a sub-set of solutions is actually found. The solutions of the Pareto front provide rich knowledge about the planning problem. This information helps the planner determine the preferred solution *a-posteriori*, either by means of simple exploration or ideally by means of appropriate decision-making techniques. There are a number of Multi Criteria Decision Making (MCDM) techniques that can be applied for this purpose [3.16],[3.17]. However, a thorough review of MCDM techniques is beyond the scope of this chapter.

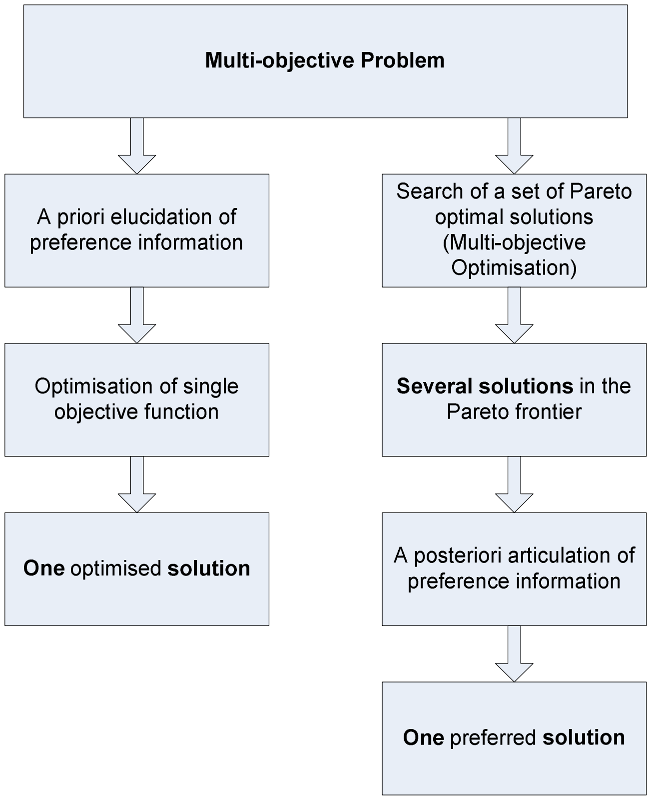

Figure 3-4 Finding a Single Solution for a Multi-objective Problem (Adapated from [3.14])

3.3. *Distributed Energy Resources Planning*

3.3.1. Problem Formulation

DER planning is the process of optimising DER type, size and/or location in order to achieve a set of objectives and subject to a set of constraints. The DER planning problem can be generically expressed as:

$$\min \mathbf{F}(\mathbf{x}) = \min\left(\left[f_1(\mathbf{x}), f_2(\mathbf{x}), ..., f_m(\mathbf{x})\right]\right) \tag{2-1a}$$

$$\mathbf{x} \in \Omega \tag{2-1b}$$

$$\mathbf{g_j}(\mathbf{x}) = 0 \quad j = 1, 2..p \tag{2-1c}$$

$$\mathbf{h_k}(\mathbf{x}) \leq 0 \quad k = 1, 2..q \tag{2-1d}$$

Where:

f_i : the i^{th} objective function.

m: the number of objectives. m=1 for a single-objective problem

x*:* the decision vector of DER location, sizes and types

Ω: the decision domain that defines the possible locations, sizes and types of DER (search space)

$\mathbf{g_j}$: the j^{th} equality constraint, usually defined by the power flow equations of the network (power balance), discussed in the next chapter.

$\mathbf{h_k}$: the k^{th} inequality constraint, usually technical limits of the equipment (e.g. voltage constraints, thermal constraints, short circuit limits, etc), operating limits of DER (e.g. maximum capacity) or performance targets (e.g. reliability, emissions).

DER planning is a non-convex optimisation problem, because it has nonlinear equality constraints defined by the power flow equations. It also has some nonlinear optimisation objectives, such as line loss minimisation, discussed in the next section. DER planning variables are discrete and integer. These variables are the discrete locations, sizes and types of DER and the topology of the network. As a result, DER planning is a non-convex combinatorial problem, with several local optima, and one global optimal solution. Non-convex, nonlinear, combinatorial problems are usually difficult to solve using traditional mathematical methods since these methods are designed to find local optima solutions

[3.18], as discussed in the previous chapter. The problem is manageable when a small number of DER units are analysed, though its complexity is significantly increased when a large number of DER units is studied, given the combinatorial nature of the problem. Likewise, difficulty is increased greatly when the time variability of DER production and demand is considered.

The complexity of this optimisation task is dealt with using two approaches. The first is to apply simplifying assumptions to the formulation of the problem. For example, linearization of the objective functions and constraints, reduction of the dimension of the search space, assumption of the discrete nature of DER units as continuous, simplification of the time variability of load and DER into snapshot analyses. In this way, it is possible to solve the optimisation problem using traditional mathematical programming methods, for which powerful computer methods are available (e.g. Linear Programming), as reviewed in the previous chapter.

The second approach is based on the use of heuristic optimisation techniques (e.g. Genetic Algorithms) which are well suited to deal with non-convex combinatorial problems [3.19] and can handle discontinuous search spaces and non-differentiable objective functions. Though, the drawback of these techniques is that they only find an approximation of the global optimal solution in a limited time. This optimisation/modelling dilemma was already introduced in the previous chapter (Figure 3-5). An ideal formulation of the problem should be as close to the upper-right corner of the figure as possible. Thus, much care should be taken when modelling the problem and choosing an appropriate optimisation method.

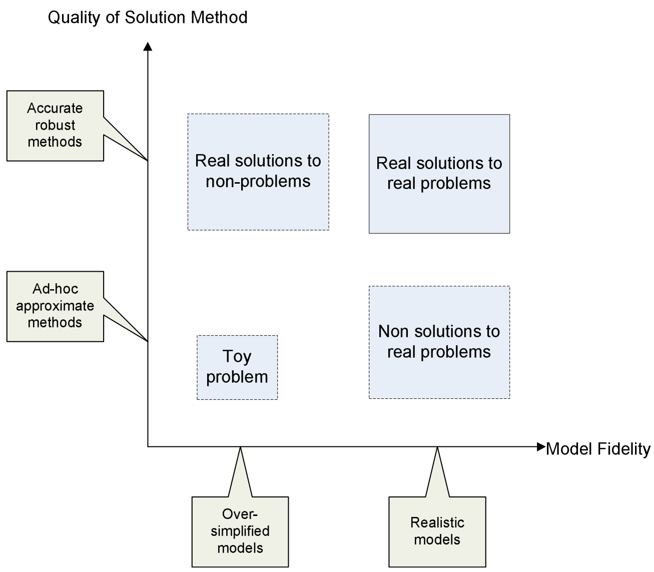

Figure 3-5 The Optimisation/Modelling Dilemma (Adapted from [3.20])

3.3.2. DER Planning Techniques

In the last fifteen years, diverse approaches and optimisation methods have been proposed to address the DER planning problem, under a variety of denominations:

- DG Planning
- DER Planning
- DG Optimisation
- Optimal Accommodation of DG
- Optimal DG Parameters
- Optimal Sizing and Siting of DG
- Optimal DG Allocation
- DG Capacity Evaluation
- Evaluation of DG using a Multi-objective Index
- Optimal DG Placement
- Optimal Utilisation of Distribution Networks

These approaches differ in the search space, objectives, constraints and assumptions considered. Nonetheless, they all fit in the broad definition of DER planning: to find the optimal size, location or type of DER in order to achieve one or more objectives, subject to a set of constraints.

Initially, most of these methods focused on single planning objectives, typically cost minimisation or power losses minimisation. However, in the last five years, some authors recognised that a multi-objective formulation of the problem better reflects the conflicting planning objectives and provides a clearer picture of the conflicts between benefits and impacts of DER. Single-objective and multi-objective methods are reviewed in the next two subsections. The publications reviewed are those cited frequently and those considered relevant for the research presented in this thesis. The denomination used by each author (DG or DER) is conserved in the description below.

3.3.2.1. Single-objective DER Planning Methods

Single-objective DER planning methods predominantly target four objectives:

- Minimisation of power losses
- Minimisation of power losses taking into account cost

- Minimisation of total cost
- Maximisation of DG capacity (or DG energy)

These techniques tend to be grouped together in literature reviews. However, in this review they are analysed separately, as they lead to very different results. For example, minimisation of power losses aims at finding optimal DER installations to reduce flows in lines as much as possible. In this case, voltage profiles are ameliorated and thermal constraints are not violated. On the contrary, DER capacity maximisation aims at installing the maximum capacity possible without breaking any system constraint. In this case, including all relevant constraints in the problem formulation is crucial. When DER capacity is maximised, line power flows increase and as a result losses are not minimised; quite the opposite, in some cases losses with the maximum DER capacity possible could be even higher than in the case of no DER.

Minimisation of Power Losses

Active energy losses are caused by the flow of electric current through equipment in the network. They are proportional to the electric resistance of equipment and the square of the current flow. Electrical energy is not always produced where or when it is consumed. Therefore, electric energy needs to be transmitted from the generation to the consumption point (disregarding the possibility of electric storage in this analysis). Consequently, electrical losses cannot be avoided. To give an idea of the magnitude of distribution system losses, in the UK these have been estimated as 7% of all energy generated [3.21].

Some level of loss reduction can be achieved by reducing power flows in lines, by network reinforcements, local generation or energy efficiency measures. A reduction in power flows and losses increases the spare transfer capability of the equipment. So, a reduction in losses helps to achieve a more efficient use of system capacity and defer network upgrades, all of which can provide indirect financial benefits for the DSO. Moreover, energy losses must be purchased (and/or produced) by the DSO. Therefore, a reduction in losses also results in direct financial benefits. Power loss minimisation is a common goal in academic power systems planning, although it is rarely considered in practical planning problems.

DER installations tend to produce power close to where it is consumed and, as a result, power flows in lines and power loss in the system can be reduced. In contrast, DER located in sub-optimal places or DER wrongly sized have a detrimental effect on system losses, as already shown by several studies such as [3.22] and [3.23]. In addition, DER production must be coincident with demand behaviour, as the opposite would result in an increase of line losses, as demonstrated by Alarcon-Rodriguez *et al.* [3.12]. So, to achieve loss reduction, three elements are essential: optimal DER location, DER size and coincidence between demand and production. A number of authors have proposed techniques to find the best location, size and/or type of DER to reduce losses. Yet, not all of them consider the time variability of load and demand, as discussed next.

Narayan *et al.* [3.24], published in 1994, is one of the first publications to acknowledge the need to develop methods to determine optimal DER installations. It proposes an iterative second-order numerical method (nonlinear programming) to find the best sizes of DER in predefined locations. The objective is to minimise systems losses, or alternatively reduce a particular line loading, subject to a maximum injection of power by DER. The paper makes no specific mention of DER and the issue of load variability. However, it presents some conclusions that are mentioned by other publications in later years. For example, that large reductions in system losses can be obtained with small penetrations of DER.

Kim *et al.* [3.25] criticises the use of the second order method, as this method could fail to find the global optimal solution by being easily trapped in local optima. So, it proposes a modified genetic algorithm (GA) to find the best size allocation of DG at selected nodes of a meshed network. The maximum injection of power from DG is constrained. The paper shows that the GA-based method finds better solutions than the iterative method presented previously by Narayan *et al*. [3.24]. However, the technique considers only a snapshot (maximum demand) of the system, and losses are treated as power instead of aggregated energy, so it fails to take into account the dynamic nature of DG and demand.

Griffin *et al.* [3.26] tackles the loss minimisation problem from a different perspective. It proposes a heuristic iterative method to find the best locations and sizes for distributed generators in the sub-transmission system. The objective is to minimise the power losses during periods of high power transfer to maximise power exports, subject to voltage and thermal constraints. Initially the locations where DG has more effect in loss reduction are identified. Then, DG is increased at these locations until losses no longer decrease. Because of the approach used, only a near optimal solution is found. The work also analyses the siting of DG on "practical distribution feeders", and it proposes to use an exhaustive search algorithm in this case. This type of search can be computationally expensive for large systems or a large number of DG units, reducing its applicability to real size problems. Although Griffin *et al.* argue that the entire load profile should be integrated to truly minimise losses, it only considers peak demand and one snapshot of generation. Consequently, the method is not appropriate for diverse types of stochastic DG.

Haesen *et al.* [3.27] proposes the use of a GA to find the best location of Distributed Generators in a residential distribution grid. This publication recognises that the variability of load and generation must be considered when analysing DG. As a result, it proposes the evaluation of daily profiles for different types of generators. The objective function is the minimisation of losses over a period of 24 hours; voltage constraints are considered a penalty in the objective function. The minimisation of daily energy losses is a simplification of the problem; nonetheless, the approach proposes a way to deal with multiple types of time-variant DG. This work is the first step towards a more comprehensive multi-objective formulation for DER planning, discussed in section 3.3.2.2.

Analytical techniques have also been proposed to solve the problem of loss minimisation. For example, Wang *et al.* [3.28] proposes an analytical method to find the best location for a single DG unit of fixed size. Losses are minimised while the system is kept within voltage limits. An advantage of the proposed approach is that it handles time-variant load and DG, as well as radial and meshed networks. Similarly, Acharya *et al.* [3.8] proposes an analytical approach to optimise not only the location but also the size of a single DG unit. The approach uses an '*exact loss formula*'. Yet, this analysis is based on peak demand. Therefore, the quantification of losses is still inaccurate, even using an exact loss formula, because load varies over time. The advantage of such analytical techniques is that they are not iterative algorithms. Therefore, convergence problems are avoided and a fast solution can be obtained [3.28]. However, given the complexity of the problem, these techniques can usually only be used to find the best location and size for a small number of DG units. Therefore, its applicability to diverse scenarios of multi-type DER penetrations is limited.

Minimisation of Power Losses and Cost

Losses are effectively an operational cost, so their reduction leads to economic benefits. However, a complete minimisation of losses is not desirable if it is not economically efficient. So, loss reduction benefits must always be weighed against the cost of achieving them.

Borges *et al.* [3.29] recognises that DG loss-minimisation is usually a cost-benefit problem. It proposes a GA to find the best location and sizes for DG in order to maximise a cost-benefit index. This index is calculated as the ratio of losses cost-reduction over the annualised cost of installing and maintaining DG ($TotalCost_{DG}$):

$$f = \max\left(\frac{CostLosses_{NODG} - CostLosses_{DG}}{TotalCost_{DG}}\right) \tag{3-2}$$

where $CostLosses_{NODG}$ is the cost of losses in the base case and $CostLosses_{DG}$ is the cost of losses with the optimal DG installations. Optimal DG sites and sizes are optimised from a list of candidate solutions. Voltage constraints are considered and the best solution is expected to have a minimum reliability index. The technique considers DG always available. Therefore, this technique cannot be applied to optimise wind generators or PV. Moreover, losses are calculated for a single load-level (peak). Then, the quantification of reduction in losses is not always accurate, especially when the load factor is low and the DG capacity factor high, or if there is no coincidence between DG production and demand. In these cases, the optimal solution found by the algorithm is sub-optimal.

The problem is approached from a different perspective by Le *et al.* [3.30]. It proposes a sequential quadratic programming algorithm to maximise the reduction of losses, translated to cost, minus the annualised cost of DG investment and O&M. In other words, the monetary benefit of loss reduction is maximised:

$$f = \max\left(CostLosses_{NODG} - CostLosses_{DG} - TotalCost_{DG}\right) \tag{3-3}$$

Some network constraints are considered (e.g. voltage constraints), and the number of DG units, DG unit sizes, and maximum DG penetration level are considered as constraints. An advantage of this approach is that it acknowledges that the time variation of load may have an impact on the optimisation, so a load profile is analysed. Also, the approach proposed can handle different types of DG (constant output or intermittent). In contrast, the technique proposed can only optimise a single type of DG at one time. Therefore, no simultaneous optimisation of different types of DG is possible. Le *et al.* apply the technique iteratively to obtain the trade-offs between line loses and DER penetration. A multi-objective formulation of the problem would be more effective for this task. Moreover, the technique is effective to optimise a limited number of DG. However, when the number of units is large the number of iterations required by the sequential quadratic programming to analyse all the possible combinations becomes extreme.

When the loss minimisation analysis is made in terms of cost, the optimal solution is no longer the one that achieves the absolute minimum system losses. In this case, the optimal solution depends on the economic parameters chosen (i.e. costs of energy, DG installation costs, operation and maintenance costs, discount rate, period analysed). More importantly, the optimal solution depends on the way costs and benefits are compared. This is clarified next.

For instance, Borges *et al.* [3.29] uses a cost-benefit ratio (Equation 3-2), while Le *et al.* [3.30] looks for the solution that maximises the net benefits (Equation 3-3). Taking the simple illustrative example of Table 3-3, it is possible to observe that these two metrics lead to very different optimal solutions. Alternative 1 is the one that provides the best cost-benefit ratio (1.5), although it is the one that produces the least net-benefits (£60k). In contrast, Alternative 3 produces the most net-benefits (£200k), but it has the lowest cost-benefit ratio (0.5). Using the benefit instead of the net benefit in the cost-benefit ratio calculation produces comparable results.

Table 3-3 Cost-benefit Example

Alternative	**Costs (k£)**	**Benefit (k£)**	**Net Benefit (k£) Benefit-Cost**	**Cost-Benefit Ratio Net Benefit / Cost**
1	40	100	60	1.5
2	100	200	100	1
3	400	600	200	0.5
4	100	160	60	0.6
5	80	160	80	1
6	80	180	100	1.25

The use of a cost-benefit ratio has some advantages because the optimal solution is the one that maximises the benefit for each monetary unit spent. In other words, it ensures an efficient use of resources. So, this metric can be used to prioritise investments when there is a limited budget [3.31]

Minimisation of Total Cost

The benefits of DER are not only limited to reduction of losses. So, a number of studies propose planning approaches where all relevant benefits, impacts and costs are analysed and compared on a fair basis to choose the best solution. Two types of publications are reviewed next. The first group [1.15], [3.32] provide guidelines for a structured approach to the DG planning problem. They do not describe the use of specific optimisation methods; instead, they extend traditional power systems planning concepts to the problem of DER planning. On the other hand, in the second group of publications [3.33], [3.34], [3.35], [3.36] optimisation techniques proposed for cost minimisation DER planning are described.

Willis and Scot [1.15] explores in detail the DG planning problem. Some of the concepts of this book have already been reviewed at the beginning of this chapter. The problem is addressed from a DG developer's point of view. The developer in this case can either be a DSO that can own and operate DG or a private investor that invests in DG to supply its own energy at the lowest cost or to make a profit. The optimal DG solution is defined from an economic point of view where investment alternatives are analysed in-depth and compared on a fair basis. Therefore, all relevant attributes and the time value of money must be included in the analysis. Moreover, complying with several technical criteria (constraints) is also crucial. The final decision can be made based on different economic criteria (e.g. maximisation of revenue, minimisation of total cost, maximisation of a cost-benefit index, etc). The book provides a comprehensive study of the issues that must be considered by a private DG developer. The approach proposed can be seen as an extension of well-established traditional power system planning approaches.

Dugan *et al.* [3.32] also extends traditional distribution planning concepts into DG planning. In this case, DG is considered an investment option for the utility-planner, and a total cost minimisation analysis is used for finding the best DG investment plan. Based on the simulation of yearly profiles, the planner computes the cost of pre-selected alternatives and finds the best plan. All relevant attributes need to be converted to cost (reliability, losses, power quality, unserved energy) and the authors recognise that "decisions will be significantly affected by which costs are included in the analysis". So, a careful analysis of all the relevant attributes is necessary.

In the two previous approaches, a limited number of pre-defined alternatives are compared, taking into account all the relevant aspects. However, in some DER planning problems there are no pre-defined alternatives; only a search space is defined by objective functions and decision variables (Equation 3-1). In this case, the planner needs to find the best locations, sizes and types of DG to address a problem (e.g. load-growth, substation overload) at the minimum total cost. All investment alternatives are not explicitly enumerated as their number is very large. Also, finding the best solution by simulating all alternatives would be prohibitive in terms of the number of alternatives to be compared. Therefore, in this case the use of optimisation techniques is mandatory, as already explained earlier in this Chapter, and discussed next.

El-Khattam *et al.* [3.33] considers DG as an investment option for the DSO. It proposes the use of a mixed integer nonlinear optimisation technique to find the best size and site of DG, in order to minimise the total cost. The costs considered include DG, reinforcement investments, O&M costs, losses and additional energy bought from the transmission system connection. The analysis proposed considers only a snapshot of demand. DG is assumed to always be available and to have no time variability in relation to the load. Therefore, the cost quantified for attributes that depend on DG and load variability is not accurate (e.g. cost of losses, energy bought from the transmission system). Moreover, as the method cannot account for time-variant DG it would need to be adapted to analyse distributed energy resources such as wind, PV or heat-led CHP.

Teng *et al.* [3.34] uses a slightly different perspective: ‘value-based planning’. The ratio of benefits over costs is maximised by means of a genetic algorithm that optimises DG locations and DG types from a predefined list of possible investments. The cost-benefit index used as the objective function includes “benefits received by the utility and its customers” and the costs incurred by DG installation, operation and maintenance. The benefits taken into account are reduction in power costs, reduction in the cost of losses and reduction in the customer interruption cost, as a measure of reliability. Although some of the constraints that *should* be included are mentioned, there is no explicit indication of the way these are handled by the GA algorithm. Moreover, load and DG variability is not acknowledged.

In the publications reviewed so far, the problem is addressed from the perspective of the DER developer. However, some authors consider the problem from the point of view of a DSO that cannot invest in DER.

Celli *et al.* [3.35] proposes the use of a genetic algorithm to find the best location and optimal sizes for DG units. The objective function is the minimisation of the total cost of network reinforcements, network operation and energy losses. Some of the power system constraints are included (voltage rise, fault currents). The analysis considers the peak load, and it uses an '*utilisation factor of energy losses*' to correct the value of losses from peak load to give a better approximation of the real cost. So, the technique finds the solution with the minimal operational cost for the DSO. However, there is no discussion of whether the information found (best location/sizes) could serve the DSO as a guideline to promote attractive DG investments. Moreover, only the network costs are determined, the analysis does not consider the cost of installing or operating DG. Therefore, it is probable that the minimum cost solution for the DSO is extremely expensive for the DG developer. A multi-objective approach to this problem could illustrate compromise solutions that minimise both the DSO costs and the DG developer costs, as examined later.

This approach is extended in Carpinelli *et al.* [3.36]. In this case, the sizing and siting of DG is considered under uncertainty. The uncertainty of wind energy production is modelled in a number of different scenarios. For each scenario, wind farm production is calculated by means of Monte Carlo Simulation. Then, the best locations and sizes for DG for each scenario of wind production are found using the single-objective method developed by Celli *et al.* [3.35]. Each optimal solution found is evaluated in all the scenarios; a matrix of objective values for every alternative/scenario is produced. Decision theory is used to find the overall optimal solution. The paper suggests the use of different decision theory paradigms (e.g. least regret, probabilistic) to choose the final solution. Though, Miranda et al. [3.11] already demonstrated that the use of probabilistic choice leads to riskier decisions, Carpinelli *et al.* acknowledges that the planner could benefit from the knowledge of which locations are more convenient to have private DG units to minimise losses, keeping the system under statutory limits. Moreover, it provides a method for considering uncertainties in the selection of the optimal solution.

Maximisation of DG Capacity and DG Energy

In some developed countries, including the UK, environmental targets promoted the development of policies and incentives that encourage the connection of vast amounts of renewable generators. These type of generators need to be located wherever the renewable resources are available therefore, in many cases they will be connected to distribution networks. Since distribution networks were designed primarily to feed loads and not to accommodate large amounts of distributed generation, many operational and planning challenges arise, such as reverse power flows, voltage rise, and increased fault currents. The impacts of DG on the networks will trigger the need for network reinforcement or, alternatively, for some operational solutions such as reactive compensators or active network management [3.37]. Consequently, total costs will be increased.

However, if an efficient use of resources is looked for, it is rational to maximise the use of the existing network before costs are incurred in reinforcements, regardless of who is charged for these costs. Therefore, it is essential to determine first the maximum capacities of DG that can be connected in the network without degrading system operation [3.38]. Hence, in this case, including all relevant constraints in the problem formulation is crucial. The next group of papers propose optimisation methods to deal with this problem. Some of these methods have been later adapted to examine other objective functions or even to provide multi-objective formulations. However, they are all discussed in this section, to expose the evolution of the approaches.

Harrison and Wallace [3.38], [3.39] present an Optimal Power Flow (OPF) approach to maximise DG capacity installed in predefined locations without violating network constraints (voltage, thermal) and without reinforcement of the network. The method is based on an established approach for load shedding. It is adapted to the DG case by considering DG as negative load; consequently, minimisation of load curtailment cost becomes maximisation of DG installation benefits. This paper enlightens about the effect of considering DG connections on a "one by one" basis instead of a whole network approach. It shows that in the first case, some network capacity is sterilised. Consequently, it demonstrates that a more ample planning approach is needed, where system-wide implications are taken into account.

Installed capacity is an attribute that does not vary with time so, the use of a single load scenario (worst case) is correct. The time variability of load and generation is not explored; the technique is a "single deterministic optimisation". Nonetheless, the authors point out that it could be implemented sequentially to handle time-variant load and energy resources; in this case, it could handle aggregated objectives such as DG energy, losses or CO_2 emissions. A limitation of the proposed approach is that it does not find the best location for DG installations; the possible DG locations for which sizes are optimised are pre-defined. Therefore, to find the best locations for a number of DG installations, an OPF must be run for each combination of possible locations.

In [3.40] Harrison *et al.* use the OPF approach to evaluate the incentives provided to DSOs and DER developers for loss reduction and reinforcement deferral. Two different objective functions are analysed. Each objective function reflects the point of view of a DG developer and a DSO, respectively, both trying to maximise their net benefits. A multi-objective formulation based on the ε-constrained method is presented. Moreover, a multi-period OPF is proposed, which evaluates a load duration curve to provide a better estimation of losses. Harrison *et al.* show that DG developers and DSOs have conflicting objectives and that a multi-objective formulation can effectively replicate different perspectives for the DG planning problem. Moreover, this work demonstrates that incentives do have a major impact on stakeholders' optimal locations and sizes for DG. For example, DG developers are not directly exposed to the effect of losses, so they try to maximise capacity and profit. On the other hand, DSOs have a loss reduction incentive that outweighs the benefit of connecting DG. Subsequently, they would prefer smaller DG investments that provide a larger reduction in losses, to the detriment of a DG developer's profit. A trade-off analysis enables the identification of several possible compromise solutions. A similar analysis is made for reinforcement deferral incentives. Nonetheless, a limitation of the proposed approach is that DG is considered as a firm supply of energy, operating constantly at rated power. This restricts the analysis of time-variant generators such as renewable DG and heat-led CHP. In addition, the ε-constrained method has some drawbacks, such as the requirement for a large number of iterations to find several solutions of the Pareto front, and a need for previous information on the problem, which were already discussed in the previous chapter.

Harrison *et al*. [3.7] recognises that most DG planning approaches attempt either the optimisation of DG sizes (for predefined locations), or the optimisation of DG locations (for predefined DG sizes), but not both simultaneously. So, this work [3.7] upgrades the OPF approach to simultaneously optimise both optimal locations for DG connections and the sizes of DG. The optimisation objective is the maximisation of the connected capacity of DG. A "Hybrid GA and OPF" technique is proposed. In this case, the ability of GA to solve complex combinatorial problems is used to find the best locations for DG. At the same time, the OPF approach previously described is used in the GA evaluation step to determine the maximum capacity of DG that can be connected in each of the selected locations. So, the approach makes use of two powerful optimisation methods, exploiting their strong points. A limiting aspect is that the number of DG units to connect must be known beforehand. In Harrison *et al.* [3.6], the applicability of this approach to a different objective function is demonstrated. In this case, the objective is to maximise DSO's benefits including DG connection charges and loss reduction incentives. In this paper, Harrison *et al.* recognise that the approach is still a single snapshot analysis and that, as a result, the effects of load variation are not explored. So, they identify that a multi-period approach is required to analyse different types of time-variant generation or include probabilistic constraints.

Keane *et al.* [3.41] explores a similar problem: the maximisation of total DG capacity installed, subject to power system constraints. In this work, the approach is based on the linearization of the problem. A linear relationship between capacity added and constraints is approximated for each node by adding incremental capacities of DG at each node in turn. Similarly, the interdependence between different nodes' constraints is calculated. Once constraints have been linearized, a linear programming algorithm is used to find the maximum DG capacity that can be added without violating them. The constraints included are voltage rise, thermal limits of equipments, short circuit limits, and short circuit ratios. In addition, an energy resource constraint can be added to each node, adding realism to the analysis.

A drawback of the linearization of the problem is that the optimal solution could actually be sub-optimal, or even unfeasible, if inappropriate ranges of DG capacities are used to determine the linear equations for the optimisation problem formulation. The reason for this is that the solution of a linear programming problem lies always on a corner point of the constraint set, as already illustrated in Figure 2-3, in the previous chapter. Hence, if constraints are not linearized properly, the optimal solution is actually infeasible. In addition, the paper mentions that wind energy is one of the most common energy sources for DG. However, it fails to mention that the use of probabilistic analysis for this type of energy sources could give a better picture of constraint violations and foster larger renewable energy production, as demonstrated in Chapter 6 of this thesis.

In a more recent publication, Keane *et al.* [3.42] presents an iterative linear programming optimisation to allocate non-firm DG capacity in order to maximise energy harvesting and at the same time minimise voltage constraint violations. So, in this case the analysis goes beyond the worst-case scenario, and considers the possibility of allowing some voltage constraint violations in order to maximise the energy produced by DG (non-firm capacity allocation). Keane *et al*, propose a novel objective function: a cost-benefit index which considers the ratio of energy produced by DG over the connection cost. This objective function also considers a voltage sensitivity factor for each network node. This factor is calculated using the methodology explained in a previous paragraph (reference [3.41]), and it reflects the voltage rise caused by power injections in other nodes. So, the energy is maximised while the connection cost and voltage rise are minimised. Moreover, other network constraints (thermal constraints, short circuit limits) are explicitly considered by the optimisation, using the approach described in the previous paragraph.

Keane *et al.* [3.42] demonstrates that non-firm allocation can increase the energy production of different types of DG, compared with the firm allocation approach. Furthermore, the authors compare the results with a non-firm allocation approach that does not consider voltage rise minimisation. This comparison confirms that the approach with the voltage sensitivity factor in the objective function minimises the amount of curtailed energy. However, this comparison does not offer an explicit trade-off analysis of energy produced vs. energy curtailed, which could be obtained by a multi-objective formulation of the problem. Moreover, care must be taken with the linearization of constraints because solutions could be sub-optimal or fall in the unfeasible region of the solution space, as aforementioned.

Further Comments on Single-objective Techniques

DG as a firm supply of Energy

Most of the papers reviewed mention the growing interest in renewable generation as one of the drivers for the increase in DG. However, few of them present approaches that can actually deal with the time-variability of these types of energy resources which is one of their most prominent characteristics from a power system viewpoint. Most approaches consider DG to be a firm supply of energy. As a result, most analyses are based on a single-scenario analysis, commonly worst case or peak demand. In some cases, this analysis can be accurate, for example in capacity maximisation, as capacity is an attribute that does not vary over time. However, in other cases it will lead to inaccuracies in the attribute evaluation (e.g.

losses), sub-optimal solutions, or eventually result in the inapplicability of the proposed techniques to time-variant DER.

Publications that acknowledge that the variability of DG and load has considerable effects on attribute calculation deal with the problem using three different methods:

- Simulation of load and DG production profiles
- Use of a Load duration curve
- Use of correction factor for losses or for capacity factor of DER

Complexity is increased when different types of DG interact at the same time, or when the controllability of some units is considered. A snapshot of the system is unable to capture all the benefits and impacts of DG. As a result, the applicability of these techniques to time-variant or controllable DER is limited. This important issue is summed up well by Dugan *et al.*: "Methods for including DER into the planning process must be able to capture time and location specific benefits" [3.43].

Planning Constraints

The number of constraints considered by the different approaches reviewed above varies significantly. These constraints can be divided in two groups, as seen in Table 3-4.

Table 3-4 DER Planning Constraints

Power System Constraints	DER Constraints
Maximum voltage deviation	Maximum power injected
Maximum thermal loading of equipment and lines	Total amount of DG
Short circuit levels	Maximum size of DG units
Short circuit ratio	Maximum energy resource per node
Reliability levels	Maximum DG penetration

The first group of constraints (power system constraints) determines the feasibility of a solution, while the second group determines the search space. The best solution could be found in terms of other objectives, but if this solution violates the technical constraints of the power system, it might not be acceptable. Special attention should be given to voltage constraints when analysing rural or weak networks, which is a common case with distributed generation.

Moreover, deterministic network constraints provide only one view of the problem, and could sometimes limit more in-depth analyses. A probabilistic analysis of time-variant DG and load permits the assessment of the probability of constraint violation. This in turn better reflects the effects and costs of possible decisions to be taken, and could lead to a more objective decision-making process [3.44] and provide a better tool for accurate cost-benefit analysis [3.6]. Probabilistic constraints are discussed extensively in the next chapter.

Dynamic Planning

All of the publications reviewed consider the power system as a static entity and planning as a single-stage task. Possible changes in the network topology and/or the possibility of timing DER investments are not dealt with. Dynamic planning formulations are known for having the "curse of dimensionality", where the size of the problem increases exponentially to the number of stages considered. While it cannot be denied that 'a dynamic problem formulation results in a dramatic increase of computational efforts' [3.4], it is also necessary to remember that sub-optimal plans are caused not only by wrong capacities or wrong location of equipments, but also by poor timing of the investments [3.45]. So, if the DER planning task is aimed at optimising investments, the possibility of timing them must be considered, either by dynamic or pseudo-dynamic approaches, for example Neimane [3.4].

3.3.2.2. Multi-objective DER Planning Methods

DER planning is a multi-objective problem in essence. The benefits and impacts of DER are various, and each one can be translated to a planning objective, or alternatively expressed as a constraint. In the last section, it was possible to see that this problem is commonly formulated as a single-objective problem. However, a multi-objective formulation of the problem provides several advantages:

- It provides a more realistic model of the problem [3.46], clearly a prerequisite to provide realistic solutions, as already explained in section 3.3.1.
- It permits the formulation of different perspectives on the problem (e.g. different stakeholders' goals), helping to achieve a compromise solution [3.40], as already reviewed in the previous section.

- The information obtained from the whole Pareto front (the extent of objectives and their correlations) can inform the planner's decision-making process as already illustrated in section 3.2.3.2.

Multi-objective optimisation problems are solved by two fundamentally different groups of techniques. These techniques are either based on preference information and the repetition of a single-objective optimisation (e.g. classical methods such as the weighted-sum, ε-constrained) or on a true multi-objective formulation of the problem (e.g. SPEA2). The advantages and drawbacks of both types of methods were already explained in the previous chapter.

Only a small number of authors have proposed multi-objective approaches for the DER planning problem, especially in the last five years. Initially, classical multi-objective optimisation techniques were used. Then, the recognition that a true-multi objective approach provides a better way of solving the problem encouraged the use of specialist genetic algorithms such as the ones described in the previous chapter. In the next sections, these multi-objective DER planning approaches are reviewed. They have been grouped based on authors (or research groups) and this can be read as the 'schools' from which this thinking on DER planning optimisation is emerging. A chronological sequence is followed to emphasise the recent evolution of this research area.

University of Cagliari

Celli *et al*. [3.47] presented in the 2003 Power Tech Conference one of the first works to discuss the advantages of a multi-objective formulation for DG planning. This work proposes the use of a GA based ε-constrained method to find the best sizes and locations for DG to minimise several objectives: cost of reinforcements, cost of energy non-served, cost of power losses, cost of energy bought and a harmonic distortion index. In addition, technical constraints of the network are taken into account (voltage, line current and short circuit limits). The problem is analysed from the point of view of a DSO that has no control over DG investments. Hence, Celli *et al.* mention that the information produced by the planning tool can be used to determine any incentives the utility could offer to DG developers.

This work was later improved and published in 2005 [3.48]. In this second publication, Celli *et al.* acknowledge load and DG variability. So, the objective function is evaluated by means of a simplified probabilistic load-flow, previously developed by *Celli et al.* [3.49]. This probabilistic load flow assumes linear correlations among DG units, and between loads and DG units. Therefore, controllable DG units cannot be analysed.

Later, Carpinelli *et al.* [3.50] extends the multi-objective approach in order to include uncertainties in DG energy production. Each one of the possible futures is formulated as a scenario. Subsequently, a "double trade-off method" is used. This method can be summarised in five steps:

1. Formulate the problem as a single-objective problem: use one objective of interest for the planner as the master objective, and the rest of the objectives as constraints.
2. For each objective chosen and for each scenario, apply the e-constrained method [3.48] to find several Pareto solutions.
3. Evaluate the set of optimal solutions of each scenario in the remaining scenarios.
4. For each scenario, determine the set of non-dominated alternatives (conditional set).
5. Finally, find the global decision set: the alternatives that are not dominated in at least one future, that is, the union of the conditional sets.

The robustness of each of the alternatives in the global decision set is calculated and used to choose the best plans. The robustness of an alternative is defined as the proportion of scenarios where it belongs to the conditional set. That is, the alternatives with the highest robustness are those which belong to the Pareto front in most of the possible futures (scenarios). The method is based on the trade-off analysis proposed by Burke *et al.* in 1988 [3.10] and it is a practical way to deal with uncertainties under a multi-objective perspective.

Carpinelli *et al.* [3.50] analyses three minimisation objectives: cost of energy losses, voltage profile and total harmonic distortion. The voltage profile objective is calculated as the mean deviation of voltage across the network. This might obscure localised benefits of DG, or alternatively, hide problems that are not solved by DG. Moreover, the work failed to recognise that in radial networks (as the case study presented) voltage deviation and line losses are positively correlated. Reduced line flows produce lower voltage deviations, and lower line losses.

The double trade-off approach is applied in Carpinelli *et al.* [3.51] to the optimal sizing and siting of power-electronic interfaced (controllable) DG. An inner optimisation is used in every evaluation step of the GA to determine the best operation mode of the power electronic interface. This inner optimisation has the objective of reducing harmonic distortion and improving voltage profile by managing reactive power. In this approach, the variability of DG is not addressed. Though, importantly, this paper illustrates the possibility of GA to accommodate inner optimisation algorithms to handle controllable DER. It proposes the use of reactive power management to control voltage profiles. Nonetheless, because of the high R/X ratio of distribution lines, voltage magnitudes are also dependant on active power injections, as illustrated in Chapter 5. Hence, active power management of DG/DER should also be considered to manage voltage profiles. An inner optimisation for active power management for DER within the planning framework is proposed later in this thesis.

Until 2008, all the multi-objective formulations proposed by the power systems research group of the University of Cagliari were based on the ε-constrained method. The method is presented by this research group as a "multi-objective evolutionary algorithm"; yet, it actually is a single-objective GA that obtains a number of multi-objective solutions iteratively. This process has been classified as a "naïve" approach for multi-objective optimisation [3.52] and has been criticised for needing strong *a-priori* knowledge of the problem [3.53], being time consuming (each single solution of the Pareto front requires several iterations) and not being appropriate for a large number of objectives [3.52].

In Carpinelli *et al.* [3.50] the authors already recognised that *a-priori* preferences could notably affect the final solutions. Moreover, in the 2008 PMAPS conference [3.54], Celli *et al.* acknowledged that the use of true multi-objective approaches "seems more effective than the previous one adopted", in reference to the ε-constrained method. So, in this latter work the planning approach previously proposed in [3.48] is updated to a state-of-the-art Multi Objective Evolutionary Algorithm (NSGA-II). Also, this work proposes a problem formulation that can handle different types of generators simultaneously. Moreover, in this recent publication *Celli et al.* [3.54] recognises that one of the drivers for DG is the environmental benefits that some of these technologies can provide; so, an environmental objective (CO_2 emissions) is explicitly included. So, in their most recent work, the authors provide a comprehensive formulation of the problem from the DSO perspective, including technical, economic and environmental objectives. DG and load time-variability are acknowledged, and DG production and load is treated probabilistically. Although, in the case study proposed only simplistic daily load curves are used, ignoring seasonal variations of DG and load.

In summary, though all the publications reviewed Celli, Carpinelli *et al.* highlight the advantages of using a multi-objective approach; they recognise that a multi-objective approach permits a better simulation of reality and that it can help in the decision-making process. They mention a key aspect: "a (planning) tool should leave the planner the faculty of choosing which aspects to consider in his search of the optimal solution" [3.48]. These publications brought the research community's attention towards the multi-objective nature of the DER planning problem. As a result, [3.48] is frequently cited in recent works in the area.

Conversely, these approaches have some limitations. For example, the probabilistic approach used [3.49] cannot handle controllable DER units. So, when controllable units were analysed (for instance in [3.51]) the variability of DG was not included. Furthermore, probabilistic information is available. However the use of the probability of constraint violation as a planning objective/constraint is not investigated, even when new regulations favour the use of probabilistic treatment of constraints, for example the European Standard EN 50160 [3.55]. In these works, the great potential of presenting multi-objective results in a graphical way is never explored in depth. Most importantly, the correlation between the different objectives is not analysed. Finally, since the problem is formulated from a single perspective (DSO), some objectives are not evaluated (e.g. DG cost). As a result, the optimal solutions from the DSO perspective are not compared with the cost of installing and operating DG, which would provide an overall (social) least-cost solution.

Ochoa et al.: A Multi-objective Performance Index

The work of Ochoa *et al.* [3.56] focuses on the technical impacts of DG. It proposes the use of a "multi-objective performance index" to evaluate various technical impacts of DG in unbalanced distribution networks: active power losses, maximum voltage drop and short circuit currents. This performance index is calculated as a weighted-sum of these technical impacts. In order to find the best locations for DG connections in distribution networks, Ochoa *et al.* propose to use a GA, and employ the weighted-sum index as the objective function. So, the best locations that minimise DG impacts are determined. This publication recognises that DSOs might not have control over DG investments, but that information about optimal DG locations could shape the nature of the contract between the DSO and the DER developer.

Subsequently, Ochoa *et al.*demonstrate the applicability of the multi-objective performance index to single DG/Load scenarios [3.57] and to time-varying generation [3.58]. The analysis of two additional impacts is added: reserve capacity of conductors and reactive power losses. However, in both of these publications, the approach is limited to an evaluation of possible DG connections (exhaustive location of DG units in diverse nodes), rather than applying an optimisation algorithm to find the best locations/sizes for DG. Even so, the approach is a powerful tool for DG impacts evaluation as it considers unbalanced networks, load and DG variability. Moreover, it acknowledges that other impacts (economic, environmental) could be included in the evaluation.

The multi-objective index evaluates several impacts. However, in the case of radial networks (as most distribution networks in normal operation), it can be demonstrated that most of the impacts have a high positive correlation. For example, active and reactive line losses are concurrent. Similarly, line losses (active and reactive) and reserve capacity of conductors both depend on line flows. Likewise, line losses and maximum voltage levels have a positive correlation. As a result, the weighted-sum is measuring several times the same basic effect, i.e. the reduction of line flows. A multi-objective formulation of the problem and an adequate analysis of objectives correlation (e.g. by means of Principal Component Analysis, explained later in this thesis) could identify these relationship and determine the minimum number of impacts that need to be analysed [3.59].

The multi-objective index is a weighted-sum of the technical impacts; that is, a single value that represents not only the technical impacts of DG but also the point of view of the planner. The implications of using this weighted-sum are discussed in Ochoa's doctoral thesis [3.23]. In this work, he recognises that the major drawback of the weighted-sum approach is the difficulty of determining appropriate values for the weights when there is not enough information about the problem. So, he proposes a true multi-objective formulation of the problem. In this case, the NSGA is used to locate a small number of fixed size wind turbines in order to maximise/minimise energy exports (for profit or energy independence, respectively) and minimise energy losses and short circuit limits. In this way, it is possible to investigate a compromise between DG benefits, and impacts. Moreover, Ochoa mentions that while more objectives could be included in the MO formulation (NSGA), care must be taken to guarantee that objectives are not concurrent. However, the same should be applied to the single-objective weighted-sum, as was already explained in the previous paragraph.

Haesen et al.: Multi-objective Planning of Stochastic DER

The work of Haesen *et al.* provides a comprehensive examination of the DER planning problem. First, the use of single and multi-objective optimisation techniques for the DER planning problem is examined in [3.15]. Next, the application of a traditional mathematical approach is analysed and compared with a GA-based approach [3.60]. The authors identify that a multi-objective formulation able to optimise different types of stochastic DER is required. Consequently, they propose a multi-objective approach based on SPEA and yearly profile simulation [3.61]. This approach is extended further with the analysis of controllable storage units [3.62] and the use of a state-of-the-art multi-objective optimisation algorithm [3.63]. A detailed discussion of these publications is provided next.

Initially, Haesen *et al.*[3.15] discusses the drawbacks of single-objective formulations and recognise the advantages of a true multi-objective approach. Accordingly, a multi-objective DER optimisation based on the SPEA algorithm is proposed. The objective function evaluation includes the simulation of daily DER production and load profiles; this method permits the optimisation of several types of DER simultaneously. The SPEA multi-objective DER planning approach is compared with the iterative use of a single-objective method, previously proposed by Haesen *et al.*[3.27]. The comparison shows that single weighted-sum solutions are better than the ones found in the Pareto front by SPEA, but that in contrast the whole Pareto front provides a wider range of possible solutions. Also, each weighted-sum solution is highly sensitive to the set of parameters chosen. Therefore, if a single solution is looked for, inaccuracy in any parameter will lead the search towards mistaken regions of the Pareto set and produce a sub-optimal plan. As a result, Haesen *et al.* suggest the use of both methods to gain insight into the planning problem. However, finding each single weighted-sum solution requires as many iterations as finding the whole Pareto front (using SPEA).

Importantly, in this work, Haesen *et al.* recognise that in cases when attributes cannot be converted to cost accurately, or when a larger number of objectives are analysed, the true multi-objective optimisation becomes essential. Finally, this publication proposes the use of bi-objective plots to examine correlations or conflicts between objectives. This visualisation technique becomes extremely useful when the number of objectives is greater than three.

In the next publication of Haesen *et al.* [3.60], the use of traditional mathematical optimisation techniques for planning time-variant DER is studied. The DER planning problem is formulated as an iterative Mixed Integer Quadratic Programming problem. Traditional optimisation techniques require mathematical formulations of the objective functions. These formulations can only include deterministic profiles. As a result, the authors conclude that traditional optimisation techniques cannot model the stochastic aspects of DER and load effectively. In addition, the authors identify that some objectives (e.g. voltage sags, reliability) cannot be formulated as a mathematical function of DER type, placement and size.

As a result, Haesen *et al.* highlight that GA can handle objectives that are too complex to be formulated in an analytical expression. So, the use of Monte Carlo Simulation (MCS) in the objective evaluation is suggested, instead of the daily profiles simulation used in [3.15]. The MCS method produces an accurate evaluation of the stochastic performance of DER and load without the need for an analytical formulation. Moreover, it permits the evaluation of other objectives (i.e. reliability) that are difficult to formulate analytically. In the approach proposed, MCS consists of the simulation of a number of different yearly profiles. The planning methodology for stochastic DER is summarised in a further publication [3.61]. In this work, the authors recognise that an optimisation approach should be as adapted to the problem as possible, a clear allusion to the optimisation/modelling dilemma already discussed in section 3.3.1.

The GA-MCS approach provides a practical way of evaluating topologies with stochastic DER although two trade-offs can be identified. First, the optimisation/modelling trade-off [3.20]: GA permit the evaluation of more realistic models, but the convergence towards global optima cannot be reached in limited time. In contrast, analytical expression are able to find the global optima (with appropriate parameters), yet, they are limited to evaluate simplified models. The second trade-off relates to the accuracy of the MCS. The accuracy of MCS evaluations depends on the number of trials or years simulated. So, accuracy improves but to the detriment of the speed of the GA, and vice versa.

The SPEA planning approach is used by *Haesen et al.* in [3.62] to analyse the incorporation of a single controllable energy storage unit into a distribution grid with stochastic DER. In this case, an inner optimisation algorithm is used in the objective evaluation stage of the GA to optimise the operation of the storage unit. Simultaneously, the external multi-objective optimisation is used to optimise the rating (power) and capacity (energy) of the storage unit.

This inner optimisation offers a practical method to optimise a controllable DER in a stochastic environment. This method can be modified to optimise controllable and stochastic DER simultaneously, as demonstrated later in this thesis.

In the CIRED 2007 conference presentation [3.64], Haesen proposed the use of Principal Component Analysis (PCA), a powerful method to reduce the dimensions of a multi-objective problem and analyse multiple objectives correlations. Finally, after CIRED 2007, the approach based on the SPEA algorithm was upgraded to an improved version of this algorithm: SPEA2 [3.63]. Previous studies had shown that the SPEA algorithm is outperformed by both the NSGA-II [3.65] and SPEA2 [3.66], as already discussed in the previous chapter.

In summary, the method proposed by Haesen *et al.*permits the multi-objective optimisation of diverse types of time-variant DER or controllable energy storage. However, it has some limitations:

- The work focuses on stochastic DER, including renewable generation. However, no attempt is made to quantify environmental benefits, or formulate an environmental objective.
- MCS provide rich probabilistic information. Haesen *et al.* [3.62] proposes the use of the 95% percentile of maximum voltage deviation as an objective, targeting the amelioration of voltage profile according with the EN50160 regulation [3.55]. Still, the trade-offs between the probability of constraint violation and other objectives are not investigated. For example, an analysis of the trade-off between risk of voltage violation and environmental benefits (CO_2 emissions) could determine if current probabilistic regulations should be modified to obtained larger greenhouse gasses emissions reductions.
- A practical method to evaluate controllable storage units is proposed. The approach can optimise controllable energy storage *when DER units are already installed*. However, the approach is not able to optimise stochastic units that can be controlled (e.g. curtailment of wind generators, dispatch of CHP units), or the simultaneous optimisation of stochastic and controllable units.
- Finally, it is not possible to infer from the works published how network constraints are treated in the multi-objective formulation. No constraint management under the multi-objective formulation is proposed.

The work of Haesen *et al.* has some parallels with the research presented in this thesis, particularly the proposal of a true-multi-objective formulation and an appropriate method to evaluate several types of stochastic DER units. A timeline presented later in this chapter demonstrates that both pieces of research occurred simultaneously. The coincidences in the approach were identified early in the development of this research. This in turn made it possible to establish contact with the ESAT research group at KU Leuven, particularly with Edwin Haesen, and pursue a collaborative approach to push forward the research in this area jointly. An inner optimisation algorithm for controllable DER units, initially proposed by Edwin Haesen was integrated into the flexible planning framework proposed in this thesis. This resulted in the planning methodology for stochastic and controllable DER units summarised in Alarcon-Rodriguez *et al.* [3.13].

A fundamental difference exists in the way Haesen *et al.* studied the problem and the way it is accomplished in this thesis. Haesen *et al.* followed an inductive approach, starting from a single-objective formulation [3.27] to determine the best approach to handle multiple objectives [3.15] and stochastic DER units [3.60]. In contrast, the research presented in this thesis first established the characteristics of the problem to be solved, described in Alarcon-Rodriguez *et al.*[3.12], and then deduced the best techniques to be used. The DER planning problem was recognised to be multi-objective so, the use of an appropriate and state-of-the-art multi-objective optimisation algorithm was proposed. DER was recognised to be time-variant; consequently, a suitable approach to handle stochastic generation (and demand) was ascertained. This reasoning is explained in detail in the next chapter.

Other Multi-objective Approaches

The methods presented next are limited for the problem studied in this thesis; nonetheless, some key contributions are highlighted.

Pelet *et al.*[3.67] study the optimisation of the design parameters of an integrated energy system (diesel and PV generators) for a remote community. Detailed analytical formulations are used for the diesel engines and PV operation, cost and emissions calculation. Two objectives are used: total cost and CO_2 emissions. This approach underlines that a true-multi objective formulation permits more informed decisions. Moreover, the conflict between cost and environmental benefits is recognised: clean solutions are more expensive.

Mori *et al.* [3.68] present an approach based on SPEA2 to optimise *distribution network expansion*. This approach considers DG as an option for the planner, together with possible substations and lines. It aims at minimising three objectives: power losses, cost of new equipments and voltage deviation. The cost objective only considers installation costs and it does not take into account operating costs of DG (fuel, O&M). So, the optimal solution could be more expensive in the long-term. In addition, the problem is approached like a capacitor placement problem, disregarding the time variability of DG. The whole planning exercise is made in terms of peak power. As a result, only a single type of DG (constant power) can be handled by the formulation. Nonetheless, an important point of this work is that it demonstrates that SPEA2 provides better solutions than NSGA-II in the case study presented, although SPEA2 computational time is slightly higher than NSGA-II.

Haghifam *et al.* [3.69] also assumes that DG is a constant power source. The authors propose an approach based on NSGA-II. The planning objectives include total cost (net present value of energy bought from the transmission system, DG installation and operation), technical and economic risks. The novelty of this work is that it proposes to minimise the maximum risk of constraint violation as one of the planning objectives. In this case, load behaviour uncertainty is modelled using fuzzy numbers. The risk of voltage constraint violations is calculated as the fuzzy possibility of voltage constraint violation. The economic risk is treated similarly: the uncertainty of market price of energy is modelled using fuzzy numbers. Then, the fuzzy possibility of DG being a more expensive solution is calculated and minimised. Fuzzy numbers permit the representation of uncertain variables for which limited information is available. Therefore, a quasi-probabilistic formulation of the problem is possible. An analogy can be made between the fuzzy "possibility" of constraint violation and the more elaborated "probability" of constraint violation. However, the calculation of this latter requires more detailed information about the load behaviour (e.g. load curve duration, load profile, load model).

Multi-objective DER planning: A Timeline

The most important advances in the area of multi-objective DER planning are illustrated in the timeline of Figure 3-6. This timeline shows that most advances were proposed in the last three years. Some trends can be identified:

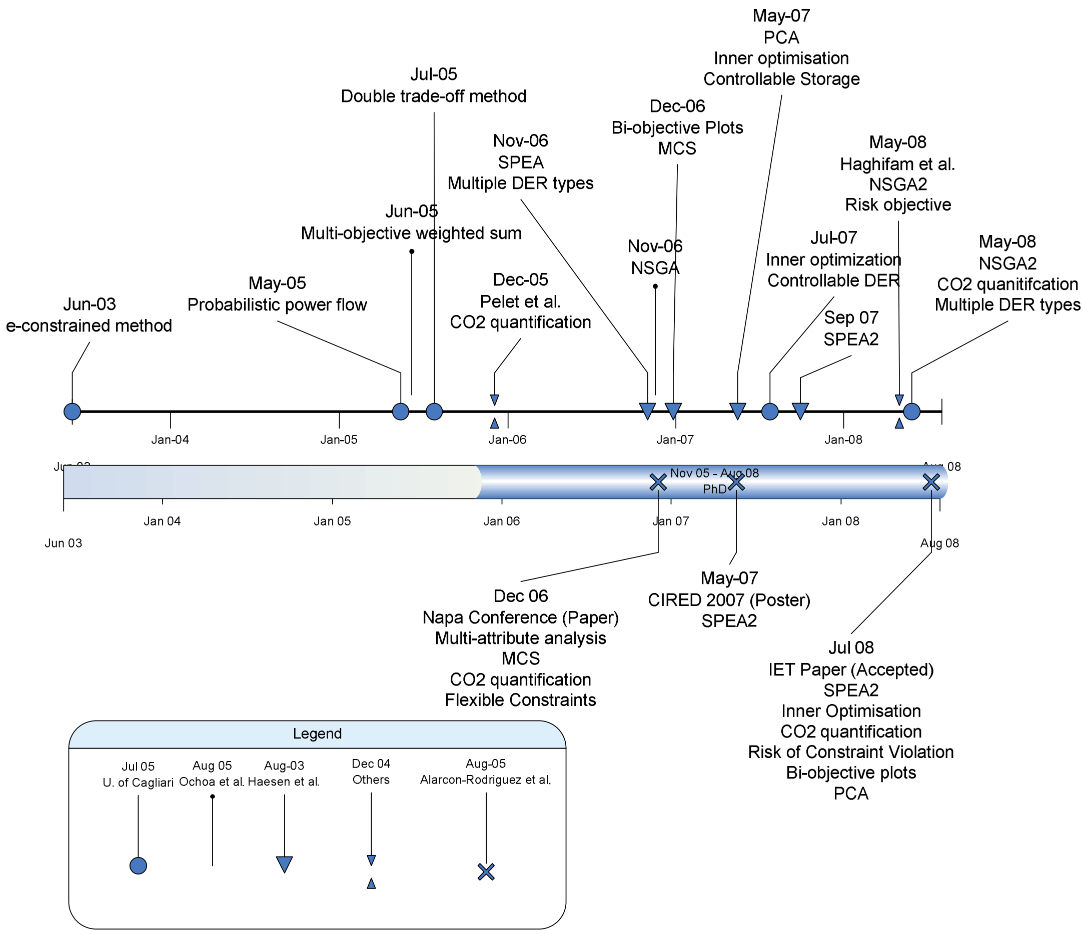

Figure 3-6 Multi-objective DER Planning Timeline

- The gradual adoption of state-of-the-art MOEA, instead of *preference* optimisation techniques.
- The stochastic analysis of DER and load is prevalent, either by means of probabilistic load flow or simulation of profiles. Though, few authors propose to evaluate constraints probabilistically.
- The use of GA permits the incorporation of inner optimisation algorithms in the objective evaluation, which in turn permits the simulation of controllable energy storage and DER units. It is expected that the possibility of inner optimisation will be used more widely, as the concept of active management of DER and networks becomes widespread.
- Most of the authors recognise the benefits of a multi-objective formulation. However, only Haesen *et al.*propose effective ways to illustrate results (when the number of objectives is larger than three) and analyse the objectives correlation.

- Finally, most of the authors recognise that one of the drivers for DER development is the environmental benefits that can be obtained from an adequate integration of these technologies. As a result, new approaches must incorporate explicitly environmental objectives.

A second timeline is included in Figure 3-6 to place the development of this thesis in the context of the papers examined. Key milestones of the development are provided in terms of relevant publications and presentations. It is demonstrated in the next chapters that this work incorporates and expands the latest developments of the area. A multi-objective planning framework for diverse types of DER is proposed, making use of a state-of-the-art multi-objective optimisation algorithm. Technical, economic and environmental objectives are considered. In addition, a flexible treatment of constraints is included. Finally, emphasis is made in the appropriate analysis of results.

3.4. *Summary*

DER planning is defined as finding the optimal DER size, type and/or location to achieve a variety of objectives. It is a complex optimisation problem, whose solution requires the use of simplifying assumptions or heuristic algorithms. A trade-off exists between the detail of the model and the accuracy of the optimisation method used. Much care should be taken when modelling the problem and choosing an appropriate optimisation method.

A large number of techniques have been proposed for DER planning. Most of these techniques are focused on single-objective optimisation. In recent years, the multi-objective nature of the problem has been recognised, and the specific area of multi-objective DER planning has rapidly evolved.

A review of a representative sample of single-objective DER planning techniques is presented in the chapter. The review shows that objectives pursued by single-objective techniques are diverse, and it attests that these objectives can be conflicting in nature. Moreover, it is illustrated that the DER planning problem can be approached from several perspectives. The analysis of techniques confirmed that most of the single-objective techniques cannot adequately handle several types of stochastic or controllable DER simultaneously.

In addition, a critical review of literature devoted to multi-objective planning of DER is presented. The analysis demonstrates the evolution in the nature of the optimisation techniques used for the problem; state-of-the-art MOEA have been gradually adopted by different researchers. Moreover, the different approaches to handling time-variant and controllable DER are enumerated. Finally, a timeline illustrates the recent and rapid development of this particular research area and, most importantly, places the research presented in this thesis in the context of the publications discussed.

The next chapter analyses in detail the DER planning problem. This analysis identifies the requirements for a DER planning technique for the analysis of DER integration. Consequently, the specifications, structure and techniques for the planning framework are proposed.

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Chapter 4

4. Specification of the DER Planning Framework

4.1. *Introduction*

Chapter 1 discussed the importance of an optimal DER integration. Chapter 2 presented key concepts of single and multi-objective optimisation techniques. Particular emphasis was made in describing multi-objective evolutionary algorithms (MOEA). Chapter 3 provided a critical review of single and multi-objective DER planning techniques. This evaluation identified some of the shortcomings of DER planning techniques in relation to the objectives proposed in this research. Similarly, it recognised the possible further developments in the area.

This chapter presents the specification of a planning framework for DER integration analysis. First, the DER planning problem is examined from the perspective of this research's objective. In this context: What constitutes the DER planning problem? What are the degrees of complexity of this analysis? The answers to these questions determine the structure and the appropriate type of techniques required for the planning framework. Similarly, it establishes which simplifications are possible. This analysis also elucidates the reasons behind the choice of a *flexible* and *multi-objective* platform, explicitly included in the title and objectives of this research.

The chapter is structured as follows. Initially, the objective and scope of the DER planning framework are described. Next, the complexity of the DER planning problem is examined in the context of this research. In addition, relevant characteristics of modern planning techniques are reviewed. This analysis determines the high-level structure of the framework and the particular characteristics of the optimisation method and evaluation techniques used. Additionally, the planning attributes for the analysis of DER integration are selected. Subsequently, the structure of the planning framework is described in detail. Throughout this chapter possible improvements are discussed where appropriate.

4.2. *Planning Framework Objective and Scope*

4.2.1. Objective

The main objective of the DER planning framework is to analyse DER integration. Hence, the planning framework must answer the following questions:

- What are the best configurations for DER in a given distribution network in order to achieve multiple objectives?
- What are the correlations between these objectives when DER is integrated optimally in a particular network?

The framework provides a better understanding of DER integration by finding several Pareto optimal DER configurations and analysing the relationship between multiple objectives of DER integration. Planning objectives reflect relevant benefits and impacts of DER integration. The selected planning attributes are listed in Table 4-1, later in this chapter.

4.2.2. Scope

This thesis proposes a high-level analysis of DER integration in which a large number of alternatives and varied attributes are evaluated, as opposed to an exhaustive technical analysis of a single alternative. The high-level analysis proposed is based on the evaluation of DER impacts over a long-term. Hence, the planning framework includes only steady-state impacts of DER integration. The analysis of the impacts of DER on the transient behaviour of the power system is beyond the scope of this work. Stability studies of the distribution power system are usually conducted as a second stage in the planning process [4.1], and they require detailed dynamic models of loads, DER and network components [4.2].

This research encloses both: the specification and development of a DER planning framework, described in this chapter and the next; and the analysis of relevant case studies to illustrate the proposed approach, presented in Chapter 6.

4.3. *The DER Planning Problem*

Neimane [4.3] analysed the complexity of the distribution network-planning problem and identified that this complexity is caused by multiple and conflicting objectives, the dynamic nature of the planning problem, the large number of variables and uncertain information. This analysis is taken as starting point. It is extended to the DER planning problem, and adapted to the context of this thesis. Hence, in the context of the objectives of this research, the DER planning problem is characterised by:

- Multiple and conflicting objectives
- Multiple perspectives on the problem and the need for a flexible approach
- DER diversity and the stochastic nature of the power system
- The dynamic nature of the planning problem
- Uncertainty in information

Each one of these aspects is examined in detail next. The large number of variables, identified by Neimane [4.3] as an issue in distribution systems planning, is not studied in this work. A large number of variables are inherent to any complex planning problem. Consequently, a platform and optimisation technique capable of handling large problems is considered essential for the planning framework.

4.3.1. The Need for A Flexible Multi-Objective Approach

This section discusses the requirement for a *flexible* and *multi-objective* approach in detail. Three fundamental aspects are analysed: Section 4.3.1.1 discusses the inadequacy of a single-objective approach to answer the questions proposed in this thesis, and summarises the advantages of a proper multi-objective approach, already introduced in the previous chapters. Section 4.3.1.2 emphasises that the technical constraints of the network must be included in the analysis of DER integration. This section shows that planning constraints can be formulated in different ways to provide a deep analysis of DER integration. Finally, the discussion of section 4.3.1.3 highlights that a useful analytical tool requires a flexible approach, both in terms of planning objectives and constraints and in terms of the decision variables of DER integration.

4.3.1.1. Multiple and Conflicting Objectives

The multi-objective nature of the DER planning problem is evident from the discussion of previous chapters. DER impacts and benefits are numerous, and each one can be potentially formulated as a planning objective. Single-objective DER planning approaches, reviewed in Chapter 3, focus on either the optimisation of technical impacts or economic attributes. Three main groups are recognised:

- A single technical impact/benefit is optimised (e.g. line loss minimisation, energy harvesting maximisation) subject to the technical constraints of the network
- A single technical impact/benefit is translated to cost and minimised/maximised (e.g. maximisation of line losses economic benefit, maximisation of installed capacity benefits) subject to the technical constraints of the network
- Several impacts/benefits are aggregated into a single cost attribute or a performance index which is minimised/maximised (e.g. Ochoa's performance index, total cost minimisation). Similarly, in terms of *investment* planning of DER, minimisation of total cost (or maximisation of revenue) is the sole objective, the other attributes are either translated to cost or regarded as constraints.

A single-objective approach is adequate when there is a single impact/benefit of interest, when all costs represent a single point of view [4.4], or when there is strong preference-information to aggregate technical impacts into a single performance index [4.5].

Nonetheless, many of the DER planning objectives are contrasting in nature. Moreover, several perspectives of the problem are possible since several stakeholders are involved in DER research, planning and development. Subsequently, there is no single-optimal solution, but a Pareto set of optimal solutions. If each attribute is combined into a single measure of performance, the specific impacts and benefits of DER (or the different perspectives of the problem) are hidden and the analysis of DER integration is limited significantly. Consequently, a single-objective approach is not appropriate to provide a deep analysis of DER integration.

The advantages of a multi-objective formulation were already introduced in chapters 2 and 3. For example, a multi-objective approach provides a more realistic representation of the DER problem and expresses different perspectives on it. In addition, the whole scope of each benefit and impact and the correlations between them can be investigated. Thus, a multi-objective approach permits a deeper analysis of DER integration, which is the key objective of the DER planning framework.

Moreover, a multi-objective formulation allows attributes to be expressed in their natural units, differing from traditional single-objective approaches that require conversion of all attributes to cost or to a dimensionless measure of performance. So, a multi-objective analysis can include objectives that cannot be easily translated to cost (e.g. voltage deviation, probability of constraint breaches), making trade-offs among fundamental concerns more explicit [4.6]. Consequently, the possibilities for the analysis of DER integration are extended.

This section clarified the reasoning behind a crucial requirement for the planning framework: a *multi-objective* approach. The need to analyse multiple objectives determines not only the nature of the optimisation method, it must be multi objective, but also the requirement for an evaluation procedure able to compute the relevant benefits and impacts of DER integration. Additionally, in this section the need for a f*lexible* approach is introduced. The planning framework must be flexible not only in terms of the analysis of several different objectives, but also by permitting the analysis of non-cost objectives. The need for a flexible approach is extended later in section 4.3.1.3, when planning goals and decision variables are discussed.

4.3.1.2. DER Planning Constraints

Equality and Inequality Constraints

Planning constraints are part of most planning and optimisation problems, and are as important as planning objectives. Mathematically, constraints are expressed as equality and inequality constraints. In power systems planning, equality constraints are determined by the requirement for power balance in the nodes and in the system: the active and reactive power injected to a node must be similar to the active and reactive power withdrawn from it [4.7]:

$$\sum_{g}(P_{gi}+Q_{gi})+\sum_{t}(P_{ti}+Q_{ti})+\sum_{d}(P_{di}+Q_{di})=0 \tag{4-1}$$

where g represents generators, t represents lines and d the loads connected to node i. P and Q stand for the power injected to bus i.

The set of power balance equations for all nodes is known as the *power flow equations*. The resolution of the power flow equations determines voltages and line flows. These equality constraints are not flexible, i.e. this condition must be satisfied, as they model the natural behaviour of energy flows.

Technical limits of the network and equipment define the inequality constraints of the optimisation. Traditionally, these are used as planning constraints. The technical constraints commonly considered are maximum and minimum node voltage deviation, maximum thermal loading of equipment and maximum fault levels. In addition, limits to the size of DER equipment are imposed to reflect energy resource availability and technical connection restrictions, as well as constraints in operation conditions (e.g. fixed power factor). The most common technical constraints are expressed next:

$$V_i^{\min} \le V_i \le V_i^{\max} \tag{4-2a}$$

$$DER_i \le DER_i^{\max} \tag{4-2b}$$

$$S_k \le S_k^{\max} \tag{4-2c}$$

$$S(sc)_k \le S(sc)_{k_i}^{\max} \tag{4-2d}$$

where *V* is the voltage at the i^{th} node, *DER* is the *DER* installed at that node, *S* is the apparent power flow at the k^{th} line (or equipment) and *S(sc)* is the short circuit current in that equipment.

Some flexibility can be permitted in the analysis of inequality constraints, as explained in a later section. This flexible treatment of planning constraints, referred as to Multiobjectivisation, permits a wider analysis of DER integration.

Voltage and Thermal Constraints: AC and DC Power Flow Formulations

The resolution of the power flow equations permits the calculation of node voltages and line power flows. Two formulations are possible for the power flow equations: AC or DC. AC power flow equations are nonlinear, and their resolution requires an iterative process, where convergence sometimes cannot be achieved [4.8]. In addition, nonlinear equality constraints are non-convex and increase the difficulty of the optimisation problem, as already explained in previous chapters. In contrast, DC power flow equations are linear; thus, they can be integrated into linear optimisation formulations for which powerful optimisation packages are available. Nonetheless, DC power flow looks only at active power flows, its formulation assume power lines to be purely inductive, and voltage nodes to be one per unit. DC power flow formulation disregards active line losses and cannot determine voltage rise impacts. Consequently, the use of DC power flow to DER planning is limited to networks with high X/R ratios and particular scenarios where voltage rise is not of concern [4.9].

Voltage constraints are of particular interest in DER planning. This constraint is often the limiting factor in the installation of more DER capacity [4.10],[4.11], especially in weak networks such as rural networks [4.12]. For this reason, an AC power flow formulation is essential for attribute valuation in the planning framework. The non-convexity of an AC power flow formulation determines the need for an optimisation method able to handle nonlinear equality constraints. The particular AC power flow calculation used in the planning framework is described in the next chapter.

Thermal loading of lines can be determined by either approach (AC or DC). Thermal loadings are initially reduced by increasing penetration of DER; consequently, these constraints tend to be disregarded when analysing low penetrations of DER. Nonetheless, it has been demonstrated that the thermal limits of equipment can be exceeded by reverse power flows with high penetrations of DER [4.13]. Hence, thermal constraints must be considered when analysing large penetrations of DER.

Probabilistic Voltage Constraints

Until recently, voltage constraints of the network were expressed deterministically, for example, +10%/-6% for low-voltage networks and ±6% for medium-voltage networks [4.10]. Consequently, traditional DER planning approaches used these deterministic limits. Nonetheless, this approach has been recognised to restrict the potential of DG [4.12],as variable DG only produce its maximum output for a limited period. New regulations propose the use of stochastic constraints. These constraints permit the violation of technical limits for a maximum established amount of time. For example, the European standard EN 50160 requires a voltage magnitude with a maximum variation of +10/-10% for 95% of the week, considering mean 10 minutes rms values [4.14].

The use of stochastic voltage constraints permits a "more objective" evaluation of the potential of DER [4.12]. In addition, when probabilistic constraints are combined with the flexible approach described later in this section (Multiobjectivisation), a powerful analysis of

DER integration is possible. So, a probabilistic treatment of voltage constraints must be possible within the DER planning framework. This requires the stochastic evaluation of DER integration, which is discussed in section 4.3.2.

Fault Level Constraints

Fault levels are usually a concern with large penetrations of DER in high and medium-voltage urban networks [4.13]. These networks are usually meshed and provide several low impedance paths for the fault currents. DER increase the fault levels in the system, and therefore prompt the requirement for larger switchgear equipment. Some planning methodologies consider fault level constraints [4.7], [4.15]. In these approaches, the limits imposed by switchgear equipment are included as constraints in the planning formulation to limit DER integration. Other approaches include short circuit currents in the optimisation objective to restrict the effect of DER in fault currents [4.5]. In contrast, in low-voltage and rural networks (i.e. radial networks), voltage and thermal limits are the main constraining factors [4.13],[4.16].

The case studies presented in Chapter 6 focus on radial networks, where fault levels are usually not considered a constraining factor, as discussed in the previous paragraph. Thus, a fault level calculation was not implemented in the planning framework. In this case, fault level calculation and protection design are assumed as a step conducted after planning. As part of further work, a fault level calculation could be included in the multi-objective planning framework to make sure that the switchgear in the network is capable of dealing with the expected fault currents. The modular approach of the planning framework, discussed in the next chapter, facilitates the addition of new analyses such as fault level calculation

A Flexible Treatment of Constraints: Multiobjectivisation

In traditional planning approaches, if a solution violates the technical constraints of the network it is “unfeasible” and it cannot be accepted, regardless of its performance in other planning objectives. Nonetheless, a more flexible analysis permits the quantification of the effect of constraints on other planning objectives. This approach is known as “Multiobjectivisation” [4.17] and it consists in formulating the technical impacts that define planning constraints as planning objectives, for example: minimise maximum voltage deviation, minimise maximum thermal loading of lines, minimise the probability of voltage violation, minimise fault level, etc. A multi-objective formulation of this problem permits the evaluation of the benefits in other objectives from relaxing some of the constraints.

Following a similar reasoning, it is also possible to convert any planning objective into a planning constraint. Alternatively, the maximisation/minimisation of an attribute can be formulated as an objective with a minimum/maximum attainment level (i.e. a "constrained objective"). Multiple objectives and constraints can be analysed simultaneously. This degree of *flexibility* in the analysis reflects either planning conditions (e.g. to minimise total cost constrained to a budget limit), scenario conditions (for example to constrain the maximum penetration of DER), or determines minimum attainable conditions for the planning task (e.g. maximum allowable CO_2 emissions that any plan can have).

Summarising the discussion presented in section 4.3.1.2, the following requirements for the planning framework are identified:

- The objective evaluation must quantify relevant technical impacts of DER integration. These include voltage rise. Hence, the use of an AC power flow formulation is mandatory
- The optimisation method must be able to handle any type of equality and inequality constraints (linear and nonlinear)
- A probabilistic treatment of voltage constraints must be possible
- A flexible approach is needed: any attribute should be able to be formulated as a planning constraint or a planning objective

4.3.1.3. Flexibility

The requirement for a flexible approach in terms of objectives and constraints has already been introduced in the previous sections, and it is summarised next. Additionally, the need for a flexible approach to the decision variables of DER integration is discussed.

Flexibility in Terms of Planning Goals, Objectives and Constraints

In traditional, centralised power systems planning the planning goal is unique: to find the set of investments that minimises total cost subject to a set of technical and environmental constraints. With the decentralisation of energy markets, planning is no longer a centralised task. Several market players are involved and each one has different planning goals, usually still related to economic optimisations. The need for flexible planning approaches in this liberalised market environment is evident. For example, Dugan *et al.* [4.18] recognise that a planning tool must be flexible and adaptable. Planning goals differ from one planner to the next, and even different projects from the same planner can require a different perspective. Similarly, Celli *et al.* [4.19] propose that a planning tool should let the planner select which aspects to include in his search for the optimal solution.

Nonetheless, the concept of flexibility proposed in the previous sections is not restricted to *investment* analyses from different perspectives. The optimisation of the varied technical, environmental and economic benefits and impacts of DER integration can provide a deeper analysis, and produce valuable information for DER integration. So, the flexibility of the approach in terms of objectives and constraints is essential to create a useful analytical tool.

Flexibility in Terms of Decision Variables

Flexibility is also required in terms of the type of decision variables included in the optimisation analysis. For instance, an analysis of DER integration can consist of optimising the size and location of a single unit; or finding the optimal size and location for varied numbers of DER units of different types. Eventually, the analysis can consist of finding the best configuration of DER in the whole network, assuming that every node is a potential location for DER installations. Thus, a question arises, is it possible to implement a planning framework flexible enough to handle all these possibilities? This thesis tries to answer to this question. Again, the need for flexibility is critical in determining the most adequate optimisation method. A crucial requirement is the ability of the optimisation algorithm to handle discrete and integer variables characteristic of DER siting and sizing planning problems. In addition, the DER planning framework should be able to optimise diverse types of DER simultaneously.

Hence, the requirements for a flexible planning framework discussed in section 4.3.1.3. are:

- Include any planning attribute as objective or constraint
- Permit different types DER integration analyses: sizing and/or siting of single unit, various units or eventually considering the whole network as the search space.

4.3.2. DER diversity

DER are characterised by a high degree of diversity on:

- Geographical distribution: Diverse connection points in the network
- Energy sources: Variable, constant
- Technologies: Generation technology, control technology

Each one of these has a considerable effect on planning attributes, objectives and constraints. Simplified approaches, some of which were reviewed in the previous chapter, tend to focus only on the geographical distribution of DER. In these approaches, DER (typically only DG) is assumed to be a constant supply of energy and a single snapshot of the power system is analysed, usually the worst-case scenario of maximum generation and minimum load. This simplification is adequate in some cases and it permits the use of powerful optimisation methods to obtain mathematically accurate results for the set problem.

However, DER diversity in terms of energy sources requires particular attention. The benefits of DER depend not only in the location and size of the generation, but also in the complex relationship of generation and demand over time. The interaction of diverse time-variant energy sources and demand is a stochastic problem. The problem becomes more complex when the evaluation of controllable technologies is proposed. A simplified deterministic approach limits the analysis of time-variant energy resources (e.g. wind and solar energy), or the consideration of controllable technologies. Hence, adequate stochastic evaluation techniques are required to handle this type of problem.

4.3.2.1. Stochastic Nature of DER

Variable Energy Sources

From a modelling point of view, energy resources are differentiated by their variability [4.2]:

- Variable or uncontrollable energy sources (e.g. wind, solar, tidal)

- Constant or controllable energy sources (e.g. hydro, gas, diesel, biomass)

Variable energy sources depend on external or non-controllable weather parameters (e.g. wind, irradiation, tides) that vary according to time and location. These resources are stochastic and characterised by hourly and seasonal variations. Since the primary energy resource cannot be stored, electrical energy generation cannot be pre-scheduled to match electrical energy demand. Therefore, the electrical power generated reproduces the stochastic nature of the energy source. Hence, these DER are known as stochastic DER or intermittent DER [4.12].

The electrical output of stochastic DER at any point in time is uncertain. Nonetheless, the characteristic hourly and seasonal patterns of the primary energy resources can be known, given historic data or appropriate weather models. So, DER production fluctuations are usually modelled using time-series of historical weather data and DER models [4.2][4.5], [4.20],[4.21], [4.22] or alternatively, historical time series data of a similar DER is used directly if available [4.22].

In contrast, when the primary energy sources can be stored (e.g. oil storage, gas tanks, hydro dam, biomass storage), the production of energy can be prescheduled, i.e. dispatched, according to demand, market signals and/or the availability of the resource. Power generation is modelled as a constant source, or as an output whose pattern is known beforehand. A special case is CHP generation. CHP generation depends on a constant energy source (e.g. gas, diesel or biomass); however, in some cases CHP generation aims at supplying the heat demand, and electricity is regarded as a non-controllable by-product. In this case, CHP electricity production is modelled based on the demand of thermal energy [4.23].

Demand Fluctuations

Electrical demand is determined by the end-uses of electrical energy. These are domestic appliances (such as white goods, computers, air-conditioning and heaters), lights and industrial processes (mainly electrical motors). At the domestic level, each single household demand is characterised by sharp needle peaks and high variability [4.1]. Nonetheless, at an aggregated level (e.g. a distribution transformer, a substation) demand is the result of multiple small decisions by individuals. Hence, demand peaks and valleys interleave and the resulting aggregated demand is smoother. The same analysis can be applied to commercial and industrial energy uses [4.1].

Demand varies over time; thus, it is also a stochastic process. At an aggregated level, demand fluctuations are caused by the variations of weather and the main end uses of energy, such as lighting, cooling, cooking, heating and industrial processes. Demand at any point in time cannot be predicted with certainty; however, the long-term behaviour of hourly, daily (weekday/weekend day) and seasonal variations can be estimated. Demand variation over time is usually represented by load curves. Load curves provide a time-series of demand, spaced uniformly (15, min, 30 min, 1h) for a given a time span (a day, a week, a year, etc). Commonly, load curves are classified according to customer class (domestic, commercial, industrial, etc). Distribution networks are commonly planned to supply the maximum coincident demand of all customers (i.e. the coincident peak load) [4.24]. Nonetheless, when DER is included in the analysis, the problem becomes more complex, as the network impacts depend not only on the coincident peak loads but also on the interaction of DER and load over time.

Dugan *et al.* [4.18] recognise that a single snapshot power flow is not able to capture all the issues that must be addressed when planning DER. Mendez *et al.* [4.22] analysed extensively the effect of different penetrations of different stochastic DG on distribution system losses. Results of this analysis showed that the variability of the energy source and the correlation with load are key factors. A similar analysis is made in Alarcon-Rodriguez *et al.* [4.25], where different load and DER profiles are analysed using a multi-attribute analysis (line losses, CO_2 emissions, energy generated). This analysis concluded that DER production and load profiles have a large effect on the quantification of planning attributes and optimal solutions.

One snapshot of the power system is unlikely to adequately capture the stochastic nature of DER and load, and reflect the benefits and drawbacks of DER. In addition, some of the attributes are stochastic in nature, for example the probabilities of constraint violation, discussed previously. Therefore, the DER planning process requires a stochastic evaluation of planning attributes to capture the effect of variations of DER and demand.

Electrical Energy Storage

The addition of electrical energy storage results in an apparent alteration of the demand and DER production profiles. For example, the time variability of load can be smoothed to avoid peaks [4.1]. Similarly, stochastic DER production can be stored to produce a more constant output. Also, electrical energy storage makes it possible to provide energy when the primary energy resource is not available, for example at night for photovoltaic systems. Alternatively, it is possible to control storage units to maximise energy exports [4.21] or respond to other market signals. In all cases, the size of the storage must be optimised evaluating cost and benefits [4.26]. Additionally, the control of the storage units requires an operational short-term optimisation. Barton *et al.* [4.27] showed that electrical storage (particularly flywheel storage) can permit the harvesting of larger amount of wind energy "given reasonable storage cost assumptions". In contrast, Foote *et al.* [4.26] performed detailed cost-benefit studies and concluded that the short and medium term cost of electrical storage units remain too high to make it viable.

Most DER planning approaches do not consider storage units in their analysis, mainly because the cost effectiveness of these technologies has not yet been fully demonstrated. Stand-alone DER applications (e.g. PV panels for isolated communities) represent a different situation, where storage units are cost effective. The DER planning framework presented in this thesis does not consider electrical storage units. Nonetheless, it will be clear from the implementation presented in the next chapter that an optimisation of storage units could be integrated within the planning framework if required.

4.3.2.2. Controllable DER Technologies

Distribution networks were designed primarily to feed loads and not to accommodate large amounts of distributed generation. As a result, the sub-optimal integration of DER results in operational and planning challenges such as reverse power flows, voltage rise, and increased fault currents. These impacts trigger the need for network equipment reinforcement. Consequently, some authors, reviewed in the previous chapter, propose planning methodologies to determine the optimal location and sizes to maximise the penetration of DER without the need for reinforcement solutions. These approaches model DER as a passive element in the network, similar to a negative load.

Nonetheless, an alternative approach is possible to enable large penetrations of DG without degrading system operation: active network management (ANM). ANM consists of the active management of DG and the network to overcome the negative impacts of DG, mainly voltage rise effect. Liew *et al.* [4.28] present different active management philosophies to maximise the penetration of wind generation in distribution networks. These include power generation curtailment, reactive compensation and on load tap changing (OLTC) coordination. Mutale [4.29] demonstrated that these active management philosophies can permit the connection of large amounts of DG without network reinforcements. In addition, a extensive report [4.30] studies the possibility of distributed generation to provide ancillary services and support system operation. It concludes that, although at present few distributed generators are equipped with the necessary infrastructure to provide ancillary services, the opportunity for DG to provide these services will surely increase as DG penetration and availability increase.

The active management of DG effectively involves short-term operational planning. The curtailment/dispatch of DG is optimised given a set of objectives (minimise cost, minimise curtailed energy, maximise energy export) and subject to network constraints. AMN requires coordination with centralised voltage regulation schemes, together with communication and control technologies challenges. In addition to DG, other DER are active in nature. For example, responsive loads react to overload conditions to guarantee network operation, or storage units that are operated according to technical and/or market conditions in the power system.

In this research, the possibility of including some controllable DER technologies is considered. Particularly, the possibility of DG to be dispatched or curtailed to keep the system within operational constraints (voltage/thermal) is explored. Although responsive loads are not modelled in this work, the algorithm proposed in the next chapter can handle the simulation of this DER. A description is provided in the next chapter. The technological challenges of implementing these active management schemes are not examined. Currie *et al.* [4.31] outlines some of these challenges. Storage units are not considered, as aforementioned.

4.3.3. Dynamic Nature of the Planning Problem

The focus of traditional power system planning in a deregulated environment is to find the best schedule of investments to serve future demand achieving a set of objectives and complying with a set of constraints. Hence, *investment* planning is essentially a dynamic optimisation problem: the best scheduling of investments must be found in order to maximise the associated benefits. Nonetheless, the complexity of dynamic optimisation is such that, although most of the literature reviewed recognises that the planning problem is a dynamic task, few of the techniques proposed incorporate dynamic or pseudo-dynamic approaches. For example, Skok *et al.* recognise that "dynamic planning has never been a definite success" [4.32]. Planning is usually regarded as a static optimisation task [4.3]. Plans are produced assuming that equipment will be installed in a single year, usually the first, to cover a future demand. Pseudo-dynamic approaches divide the analysis period into a number of sub-periods and solve the static planning problem for each sub-period.

In the case of DER planning, analysing the dynamic nature of the planning problem is realistic if the analysis is conducted from a developer's point of view (e.g. a DER developer, or a DSO that can invest in DER) and the plan will be used as an investment decision. The optimality of plans in this case is defined by a single economic objective. A dynamic formulation of the problem dramatically increases the computational effort required [4.3]. The number of decision variables increases proportionally with the number of stages considered and the size of the search space increases exponentially. So, considering even a few stages can convert a manageable problem to a very complex and unsolvable optimisation task. However, sub-optimal plans are caused not only by wrong investments or wrong location of equipments, but also by poor timing of the investments [4.33]. So, dynamic planning should be considered if the extra effort and computation of the analysis is outweighed by the benefits of knowing the optimal timing of investments.

Miranda *et al.* [4.34] proposes the use of a GA to solve the problem of network expansion planning; in this case, the timing of investments is directly coded into the GA chromosome. Skok *et al.* [4.32] also propose the use of a GA based approach to solve a similar problem. In this case, a "master" GA is used to find the best location for investments, while a "slave" GA is used to determine the optimal timing of each investment. Mitra *et al.* [4.35] propose a dynamic programming (DP) formulation to find the best development plan for a micro-grid. However, as was mentioned in Chapter 2, this method cannot be successfully applied to large problems. Neimane [4.3] proposes the use of a hybrid GA-DP formulation for the problem of distribution system planning. A DP stage is used in the evaluation stage of the GA to find the best timing of investments. Any of these formulations could be adapted to the DER planning problem, if finding the best timing of investments is required.

In contrast, if DER planning is used to analyse the benefits and impacts of DER on a network where DER installations are considered as arbitrary (e.g. private DER investments, domestic micro-generation), the increased complexity of a dynamic planning formulation is not outweighed by the usefulness of the information provided by the results. In this case, i.e. when the planner is not responsible for the timing of the DER investments, the timing issue is effectively an exogenous factor in the planning problem. Moreover, if the analysis is multi-objective, considering the dynamic nature of the problem becomes even more complex, as optimality is defined in a multi-dimensional space. In that case, aggregation of objectives (or choosing a chief objective) is necessary to solve the dynamic problem, adding subjectivity to the analysis. The drawbacks of this subjective analysis were discussed in previous chapters. What is more, the increased number of decision variables results in an enlarged Pareto set. A large number of optimal solutions may result in "information pollution", i.e. the generation of so much data that it cannot be successfully analysed to produce useful conclusions [4.6].

Given the nature of the analysis proposed in this thesis, dynamic planning will not be included. The complexity of the problem-formulation would be significantly increased without a proportional increment in the quality of the information obtained. Yet, even if the framework doesn't take into account the dynamic nature of planning, it is essential to consider the time value of money (in the form of discount rates), load growth and the possible changes in the network over the period of the study, even for a single stage analysis. Moreover, it must be emphasised that if the framework will be extended to produce an *investment* planning tool, considering the possibility of timing investments is essential to provide more optimal results.

4.3.4. Uncertainty

Chapter 3 already mentioned that long-term plans must take into account all the possible changes that might occur in the power system and its economic environment within the analysis period. Projections and forecasts determine the trends in these parameters. Uncertainty in the forecasts increases the further into the future one looks. A high degree of uncertainty results in planning decisions of low quality that produces sub-optimal solutions [4.3], as illustrated in the second case study of Chapter 6. Nonetheless, traditional planning techniques are often deterministic and static. Information is assumed to be certain, known and unchanging. This assumption is commonly made to simplify the resolution of the planning problem.

In the case of DER *investment* planning, producing an optimal solution that is *robust* and/or *flexible* to uncertainty is essential. Robustness implies that the solution will perform well no matter which future scenario occurs, while flexibility in this case means that the planning solution can be easily adapted if an undesirable future occurs [4.3]. Choosing such a solution requires a decision making stage in the planning process. The preference of the planner (or decision maker) towards risk is reflected in the single optimal solution chosen. The scenario technique, explained briefly in the previous chapter, is the most common approach for planning in the presence of uncertainty. This method is considered as the only valid method to handle uncertainty, especially in multi-objective problems [4.1]. A key aspect is to define relevant uncertainties, i.e. those that have a large effect on the outcome of the planning process. In the case of DER planning the main sources of uncertainty are related to load growth, load profiles, the future availability (and cost) of DG technologies, and fuel and energy prices.

In this work, DER integration is analysed under a high-level multi-objective perspective. In this analysis, all solutions are considered equivalent and there is no need for a decision-making stage to choose a single investment solution. Hence, considering uncertainty as a risk based decision-making stage is not included as an explicit requirement for the DER planning framework. Nevertheless, the effects of key uncertainties in the multi-objective analysis can be evaluated using a "scenario" approach, illustrated in Figure 4-1 and explained next.

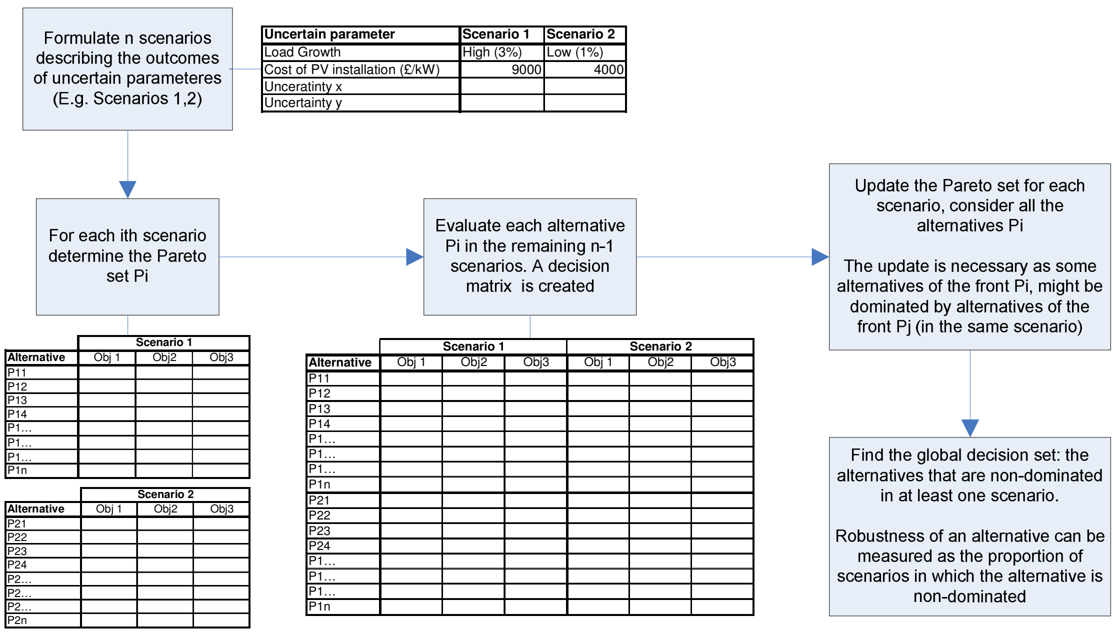

Figure 4-1 Multi-objective Scenario Analysis

In the Scenario analysis, the multi-objective optimisation is repeated using different assumptions for uncertain parameters (e.g. load growth, DER revenue, load profiles). Then, the optimal solutions (of each scenario) are evaluated in all scenarios to determine solutions that are robust, i.e. perform well in all futures. Thus, the scenario approach Figure 4-1 consists of the sequential combination of multi-objective optimisations (one for each future) and further objective evaluations. This scenario analysed is briefly demonstrated in one case study of Chapter 6. It is considered more important to demonstrate in detail other key features of the planning framework, such as the analysis of multiple solutions and multiple objectives, in diverse problems of DER integration.

This section focused on the analysis of uncertainty in forecasted parameters, i.e. long-run uncertainties. Another degree of uncertainty exists due to the stochastic evaluation of DER attributes, in which models are used and only a limited number of DER/demand events are evaluated (e.g. evaluation of a limited number of samples or a set of typical DER and demand days within the whole planning period). In this case, the evaluation of attributes is only an approximation with an established accuracy. This uncertainty is discussed further in section 4.5.2.2 and in the next chapter.

4.4. *Specification of the DER Planning Framework*

The analysis performed in the previous section identified the required characteristics of the DER planning framework. In summary, the DER planning framework must:

1. Deal with multiple objectives
2. Provide a flexible approach in terms of objectives and constraints
3. Provide a flexible approach in terms of the possible analyses of DER integration
4. Consider the stochastic nature of the power system
5. Permit the analysis of diverse types of DER

4.4.1. Specification of the Optimisation Method

The requirements for the planning framework determine the specifications for the optimisation method. The optimisation method must effectively deal with:

- Multiple objectives
- Any type and number of constraints and objectives
- Integer and discrete variables
- The optimisation of several types of DER simultaneously

4.4.2. Specification of the Planning Attributes

Planning objectives focus on the minimisation or maximisation of attributes, while planning constraints determine the limits for them. Hence, the selection of the attributes is a key step; these must reflect relevant impacts and benefits of alternative solutions. The planning attributes included in the framework are listed in Table 4-1. They were determined from the review of planning techniques described in the previous chapter, the analysis of the DER planning problem presented in this chapter and from discussions with researchers across different disciplines. The calculation of each attribute is discussed in detail in the next chapter.

Table 4-1Attributes - DER Planning Framework

Technical	Units
Line Losses	MWh/year
Network over voltage Probability	%
Maximum voltage deviation	V
Network overload probability	%
Maximum thermal loading	%
Imported Energy	MWh/year
Exported Energy	MWh/year
Grid dependency (total energy flow through network connections)	MWh/year
DER Energy penetration	%
Curtailed energy	MWh/year
Dispatched energy	MWh/year

Environmental	Units
CO_2 emissions factor (load)	gCO_2/kWh
CO_2 emissions factor (total)	gCO_2/kWh

Economic	Units
Annualised cost of DER	£/year
Levelised cost per kWh of DER	£/kWh
Annualised DER net benefits	£/year

An increase in the power system reliability is also recognised as one the potential benefits of DER, as already discussed in Chapter 1. A key aspect of increased reliability is the availability of DER. Jenkins *et al.* [4.2] demonstrated that low capacity factor DER (e.g. solar, wind) have only a small positive effect on reliability. In addition, when installed in radial networks, DER only increase reliability indices if it is permitted to work on an "islanded" mode [4.2]. In contrast, DER can reduce network reliability by adding internal failures [4.36]. The focus of case studies presented in Chapter 6 is on radial distribution networks and on DER with low capacity factor. The possibility of DER working in "islanded mode" is not contemplated in these case studies. Hence, reliability indices are not increased by the presence of DER, and reliability indexes are not included as planning attributes. In this thesis, the reduction of network reliability by DER internal failures is considered negligible and it is not evaluated. Some methods to quantify reliability indices of distribution networks with DER units are proposed by Jenkins *et al.* [4.2], and Sun *et al.* [4.37].

The list in Table 4-1 provides a wide range of technical, economic and environmental attributes. It demonstrates that the planning framework can handle diverse types of objectives. Moreover, it will be evident from the specification and development presented next that the planning framework could analyse other attributes if necessary, such as harmonic distortion, fault levels, total DSO cost, fossil fuel use and reliability.

4.4.3. Specification for the Attribute Evaluation

From the specifications for the planning framework enumerated at the start of section 4.4 and the list of attributes presented in Table 4-1, it is determined that the attribute evaluation must:

- Consider the stochastic nature of the power system. Characteristic fluctuations in DER production and demand must be analysed
- Be based on an AC power flow formulation to quantify relevant impacts of DER integration (e.g. voltage rise, probability of voltage violation)
- Evaluate several types of DER simultaneously
- Analyse controllable DER

Next, the desired characteristic of modern planning techniques, summarised by Ault *et al.* [4.33], are examined briefly. Some of these determine additional requirements for the planning framework, and lead to the structure proposed in section 4.5.

4.4.4. Desired Characteristics of Modern Planning Techniques

Ault *et al.* [4.33] explore the desired characteristic of modern power systems planning techniques. These are grouped according to their relation with the planning activity. Three groups are of particular interest for this research: the planning activity scope, the planning framework structure and planning data and information. For these groups, Ault *et al.* [4.33] determine that effective planning approaches should:

a) In terms of the planning active scope:

   - Deal with multiple-criteria
   - Enable consideration of multiple and diverse solutions
   - Provide whole system solutions: optimise the system rather than particular components

b) In terms of the planning framework

   - Be modular in terms of access to analytical components

- Provide means of integrating analytical modules and interfacing with other applications
- Be as automated and interactive as appropriate

c) In terms of planning data and information:

- Provide bulk data-handling facilities
- Provide auditable planning records
- Enable data and model reuse
- Enable reuse of solutions
- Facilitate the use of planning rationale

Some of these requirements are similar to those identified for the DER planning framework. For example, the requirement for multiple criteria in the analysis, already discussed in a previous section, and the need for multiple and diverse solutions, which is an essential condition for a multi-objective optimisation. In addition, Ault *et al.*'s work suggests that the planning framework must be able to produce whole-system solutions. The importance of a whole system planning analysis, instead of a one-by-one optimisation, has been demonstrated by Harrison *et al.* [4.38]. Whole-system analyses achieve more optimal solutions, and avoid undesirable impacts and network sterilisation, as discussed in the previous chapter.

Also, Ault's analysis adds a key requirement for the planning framework: modularity. A modular implementation of the planning framework will permit the use of "the most appropriate analytical functions and applications for the planning task" [4.39]. Modularity also provides a solution to some of the requirements enumerated in the previous section. A planning framework based on a modular approach permits the evaluation of any number and type of attributes, because each particular evaluation can be implemented as a module if necessary. Moreover, it is possible to incorporate new objective evaluations easily, without the need for a whole reformulation of the framework.

Finally, the requirement for appropriate data handling is essential in providing a useful analytical tool. Only a careful recording of optimal solutions will permit an adequate analysis of DER impacts and benefits. Moreover, input information must also be correctly stored. In this way, it will be possible to repeat analyses or evaluate different scenarios by changing some of the assumptions. Similarly, if the optimal solutions are properly stored, these can be reused; either to compare them with a new set of results or as the starting point for a new analysis.

4.5. *Planning Framework Structure*

The requirements for the planning framework were summarised in the previous section (4.4). In addition, following Ault *et al.*'s analysis of modern planning techniques, the requirements of *modularity* and a proper *recording of input and output information* were incorporated in this work. Consequently, the structure of the planning framework is designed according to these specifications. Figure 4-2 illustrates the high-level structure of the proposed planning framework and the information flow and interrelation of the building blocks. The multi-objective optimisation and the objective evaluation are the key components and are explained first. The stochastic objective evaluation is one part of the multi-objective optimisation. Nonetheless, given its importance, it is considered separately.

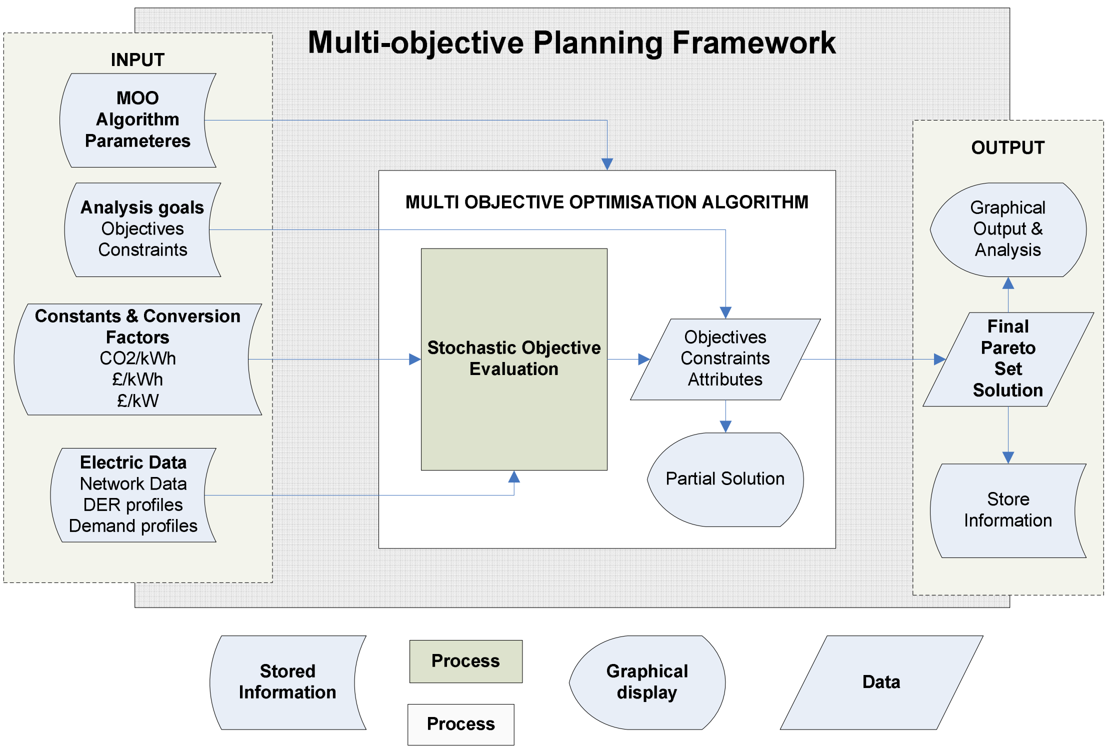

Figure 4-2 Multi-objective Planning Framework - High-level Structure

4.5.1. Multi-objective Optimisation Algorithm

The analysis of the DER planning problem determined that the planning framework must make use of an optimisation method that:

- Can optimise multiple objectives simultaneously
- Can handle any type of constraints and objectives
- Can handle integer and discrete decision variables
- Can optimise several types of DER simultaneously

Moreover, an explicit need for a modular approach is identified. Multi Objective Evolutionary Algorithms (MOEA), extensively discussed in Chapter 2, offer all of these characteristics. MOEA allow the simultaneous optimisation of several DER types, with an appropriate chromosome encoding, as demonstrated in the next chapter. Additionally, the fitness assignment procedure permits the selection of any attribute as a planning goal and/or planning constraint, providing the framework with the flexibility required. The treatment of any type of constraints, also required by the planning framework, is facilitated by the concept of constraint dominance, discussed in Chapter 2.

Hence, it is determined that the planning framework will be based on a MOEA. Particularly, the Strength Pareto Evolutionary Algorithm 2 (SPEA2) is selected, as it outperforms other MOEA in practical applications and it performs well in problems with a large number of objectives. Even so, the framework structure presented in this chapter is generic, and can be applied to any MOEA.

Figure 4-3 shows the basic structure of the SPEA2 algorithm and illustrates the input and output information flow and the interaction with the stochastic evaluation module discussed in the next section. Input information is required in terms of the SPEA2 algorithm parameters (population and archive size, crossover and mutation rates, maximum number of generations). In addition, information about which attributes are assigned as objectives and/or constraints is required to calculate the fitness of each solution using the concept of constraint dominance. The key element of the framework, and therefore of the SPEA2 algorithm, is the evaluation of attributes. This evaluation is performed by means of a stochastic simulation, consisting on the repetition of power flow analysis for diverse situations of DER production and demand. The evaluation of attributes is discussed in detail next.

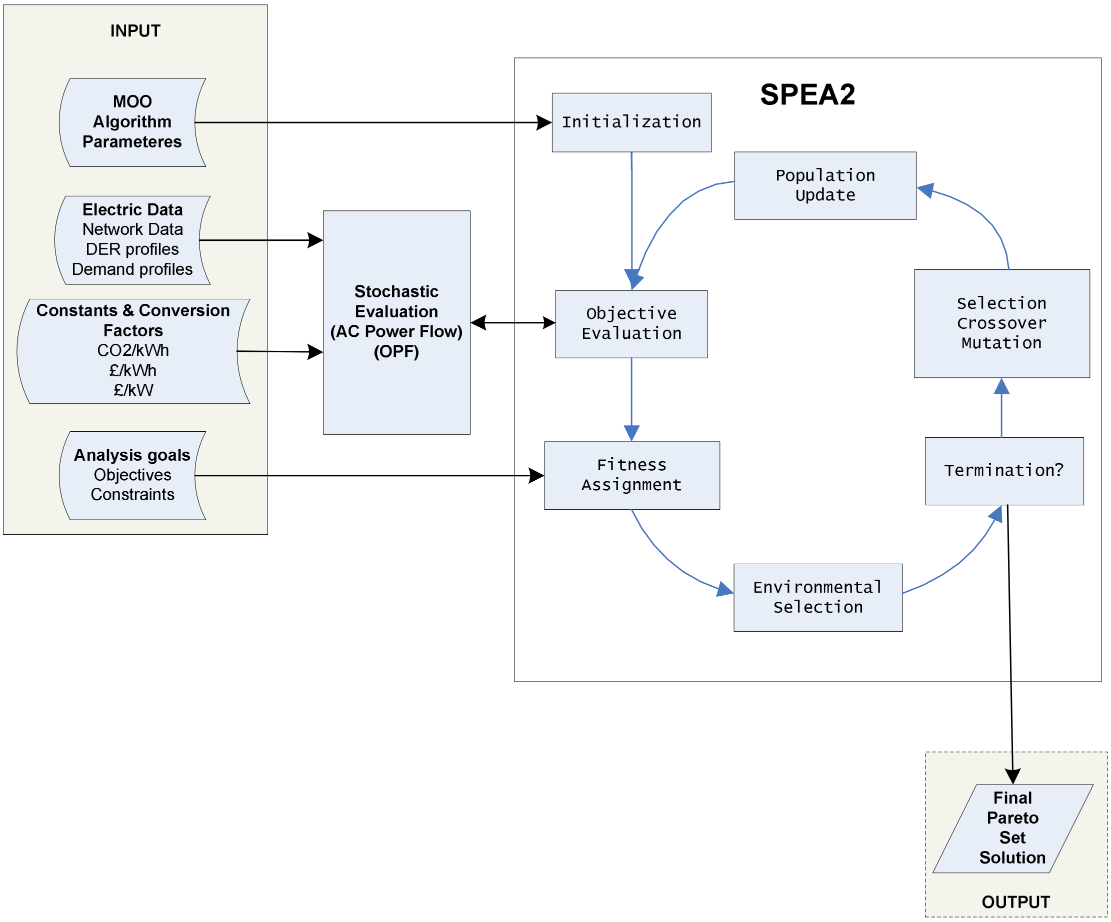

Figure 4-3 SPEA2 Basic Structure with Input and Output Information

4.5.2. Attribute Evaluation

The analysis of the DER planning problem determined a key requirement for the planning framework: the need for a stochastic evaluation of planning attributes. Three other requirements in relation to the evaluation of attributes were also identified. First, the explicit need for an AC power flow formulation to quantify voltage rise and probabilistic voltage constraint violations. Also, an appropriate procedure to evaluate controllable DER units is required. Finally, the evaluation of attributes must be able to evaluate different types of DER simultaneously. A stochastic evaluation process that complies with all of these requirements is discussed next.

4.5.2.1. Evaluation of Stochastic Processes

A stochastic process is a model of a system that "develops randomly in time according to probabilistic rules" [4.2]. The power system is a stochastic process. As such, the state of the power system at a particular point in time cannot be predicted accurately. Nonetheless, the long-term behaviour of DER and demand follows well-studied trends, and can be modelled using time series or probabilistic approaches. These models permit the estimation of the long-term behaviour of the power system and to quantify the planning attributes. Two general approaches exist to evaluate stochastic attributes: direct analytical techniques and stochastic simulation techniques [4.40].

Analytical Approach

Analytical approaches represent the system by a mathematical model and use convolution techniques to find the expected values of the stochastic variables (mean and standard deviation). They usually provide a fast solution, although they require simplifications and assumptions. An example commonly found in power systems applications is the analytical resolution of probabilistic load flow (PLF) [4.41]. This type of PLF is based on the linearization of the power flow equations and probability theory. PLF calculates the stochastic network variables (power flows and voltages) given the probability distribution of each load and generator. Although it provides a fast solution, its assumptions are limiting for the analysis stochastic and controllable DER. Analytical PLF assumes total independence or linear correlations between input variables (loads and generation). This restricts the analysis of controllable units. Moreover, PLF was initially developed to be used in transmission systems and the linearization of power equations results in larger mistakes when applied to distribution systems, due to the larger voltage deviations that exist at the distribution level [4.42].

The assumptions required by analytical methods restrict the scope of the analysis. Hence, the evaluation attributes of the proposed planning framework is based on stochastic simulation.

Simulation Approach

Stochastic simulation techniques estimate the attributes by simulating the actual process and the stochastic nature of the variables [4.40]. These techniques are widely used for the estimation of reliability indices in power systems. It is also possible to use them to evaluate the effect of the stochastic behaviour of DER and demand in the planning attributes [4.40]. In this case, a series of deterministic power flow calculations, each one for a possible condition of DER production and demand, is conducted. The attributes are estimated from these observations. The accuracy of the information obtained increases with the number of evaluations. For this reason, stochastic simulations require a large computational time, although with the capabilities of modern computers this need not be excessive. Nonetheless, they are able to provide rich information about the problem being studied. Moreover, stochastic simulations do not require an over-simplified model of the system studied; thus, they can take into account "virtually any aspect" [4.40]. This is a key feature as it allows the consideration of controllable units, as explained later in this chapter and demonstrated in the next chapters.

Stochastic simulation techniques are loosely referred as Monte Carlo Simulation (MCS), although strictly MCS only applies to completely random processes [4.40]. Moreover, an important feature of MCS techniques is the generation of random numbers. In this work, the generation of random numbers is not studied. Hence, the evaluation step is referred only as "stochastic simulation".

4.5.2.2. Stochastic Simulation

The generic structure for the stochastic simulation proposed is presented in Figure 4-4. Deterministic power flow calculations for possible conditions of the power system (DER production/ demand) are performed in succession. Events are sampled using information of DER production and demand profiles. The network variables (voltages, power flows) permit the calculation of other electrical attributes (e.g. line losses, imported and exported power). This in turn permits the calculation of economic and environmental attributes. The process is repeated for a number of simulations or until a convergence condition based on a required degree of precision is achieved.

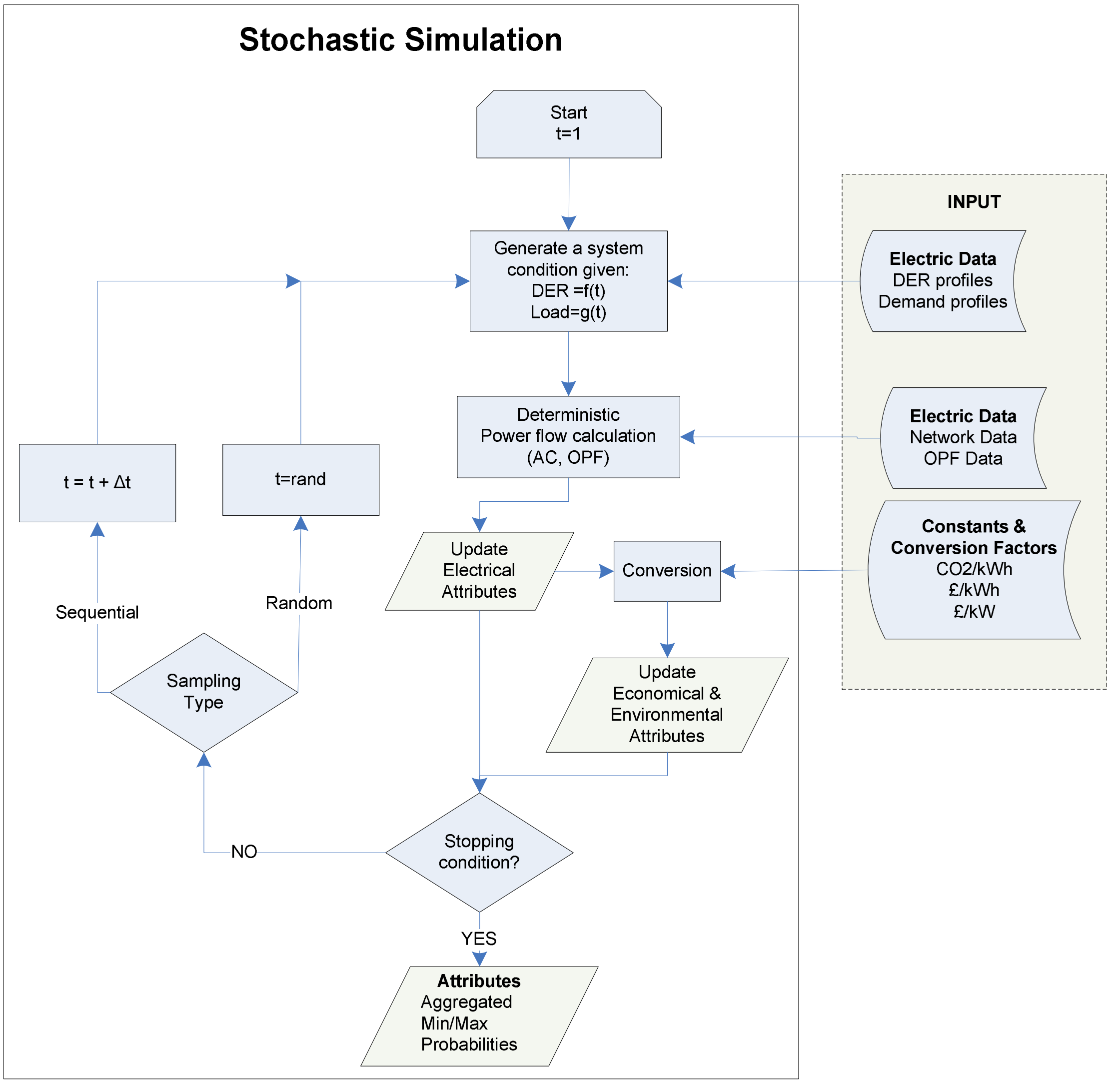

Figure 4-4Stochastic Simulation

Sampling Techniques

The sampling of simulation periods (or events) can be conducted in two forms: random or sequential. Random sampling is based on simulating any interval randomly. Sequential sampling follows a chronological order of intervals during the simulation. The use of either approach depends on whether the history of the simulation has any effect on the present conditions (e.g. energy storage optimisation, hydro generation). Billiton and Allan [4.40] recognise that the sequential approach always works, while the random approach is more restrictive, although generally faster.

In this work, events are sampled from time-series of DER and demand, as discussed in the next section and illustrated in the next chapter (Figure 5-19). Random sampling refers to pick randomly events from the time series, while sequential sampling refers to simulate events at regular intervals. The implementation of both approaches is illustrated and practical implications are discussed extensively in the next chapter.

A key aspect for the MOEA objective evaluation is that in every generation *all* solutions must be evaluated using the same procedure, as the contrary could result in an erroneous dominance comparison. Hence, when sequential sampling is used the same sequence of events must be evaluated to evaluate *all* solutions. Similarly, if random sampling is used, the same sequence of random numbers must be used to evaluate *all* individuals. This technique is known as “correlated sampling” and it helps to reduce the variance introduced by the random sampling [4.40].

Stochastic Simulation - Input

The stochastic simulation requires information about the stochastic behaviour of DER and load. It is not uncommon in DER planning techniques to evaluate a single “characteristic” day, disregarding weekday and seasonal variations for simplicity. Nonetheless, this simplification hides some of the most important impacts of DER. Hence, hourly, daily and seasonal fluctuations of DER must be evaluated. The use of annual simulation is common to determine the impact of several DER solutions [4.18]. Longer term fluctuations are not taken into account.

It is assumed that the input information for the stochastic simulation is in the form of time series of data of demand and DER production (also known as profiles or load curves). The use of this format has been chosen because information in this format is readily available, either from historical records of weather, demand and DER production or from profiles produced specifically for research purposes from simulation and/or laboratory testing. Moreover, time series of DER and data can be created using appropriate statistical models. The use of load-curve methods is encouraged by Rackliffe *et al.* [4.43] in their guidelines for planning DG, as “statistical and load duration curve methods are not nearly as accurate in estimating cost and reliability”.

The data available for the cases studies, described in detail in Chapter 6, consists of two sets of yearly and seasonal profiles with resolutions of 30 and 5 minutes respectively. These profiles represent varied DER and load types with 17,520 samples (one year of half hours) or 6,048 samples (three characteristic weeks with five minutes samples) for each profile, according on the data set. For the purposes of the case studies, it is assumed that each set of profiles is synchronised. An important aspect of the evaluation of attributes is to take into account the correlation between loads, and between loads and DER. Therefore, with both sequential and random sampling the interdependence between DER types and load types is taken into account by sampling all profiles at the same time [4.41].

The simulation of attributes in the case studies of Chapter 6 is based on the set of time series of DER production and load available. This is a simplification in terms of the *strict* principles of stochastic simulation. A more comprehensive evaluation of attributes would be based on the creation of a wider range of simulation events, either by a statistical analysis of DER and demand production or by using a larger set of data (e.g. several years). However, more detailed modelling of time series of DER production and load from larger statistical data is not within the scope of this work. The author is not aware of DER planning approaches based on simulation periods longer than one year of hourly data (8760 samples). Therefore, the approach proposed is sufficient to demonstrate the planning framework and provide a good estimation of the attributes, with a reasonable evaluation speed. The trade-offs between the evaluation accuracy and the algorithm speed is elaborated in a later section. A comparison of the attribute evaluations with results from larger data sets might be a worthwhile future exercise to quantify the error introduced.

Power Flow Calculation and Inner Optimisation

The key element of the stochastic evaluation is the power flow calculation. This calculation is based on the resolution of the power flow equations (Equation 4-1), and determines the electrical variables (voltages and flows) for every simulated event. Most attributes are calculated based on these variables. Since the power flow calculation must be repeated numerous times, it is crucial to have a fast and reliable algorithm. Moreover, the type of networks evaluated (radial, balanced) determines the need for a specific type of power flow approach. The particular algorithm used and its implementation are described in the next chapter.

The control of DER represents a short-term operational planning of the power system. As such, it can be implemented in the stochastic evaluation of attributes. The methodology illustrated in Figure 4-5 is applied in each time step evaluation, when the evaluation of controllable units is required. The particular Optimal Power Flow (OPF) formulation used and its practical implementation are described in the next chapter. If only un-controllable units are evaluated then only a power flow is performed without the OPF correction of constraints violations. Similarly, a single power flow evaluation is required to evaluate worst scenario conditions (min demand/ max generation).

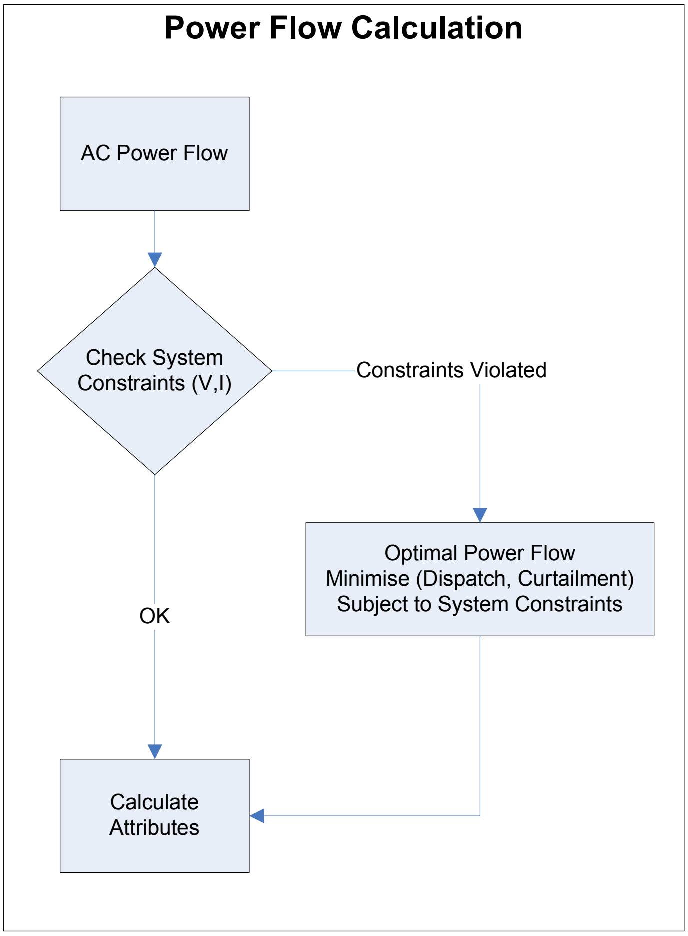

Figure 4-5 Power Flow Calculation

Stochastic Simulation - Output

For every event t and for every attribute Ai, an observation a_{it} is produced. Then, the attributes can be estimated. Commonly, attributes are calculated as the mean of the observations:

$$A_1 = \frac{1}{n}\sum_{t}^{n} a_{1_t} \tag{4-3}$$

where n is the number of evaluations. Eventually, a conversion factor can be used to transform units (e.g. generated energy to CO_2 emissions), or to provide average daily, monthly or annual values. Moreover, obtaining other type of information is possible. For example, it is possible to capture the extreme occurrence of the simulated attributes:

$$A_2 = \max[a_{21}, a_{22}, ..., a_{2n}] \tag{4-4}$$

This is not exactly the same as performing a worst-case scenario analysis, although it provides a good approximation with enough samples. It is also possible to estimate the probability of an event occurring (e.g. a constraint violation) by keeping a count of these occurrences:

$$A_3 = P(a_3 > constraint) \approx \frac{count(a_{3t} > constraint)}{n} \tag{4-5}$$

The three approaches presented permit the estimation of the attributes presented in Table 4-1. It is evident that the accuracy of the attributes increases with the number of evaluations. This is discussed next. In addition, the stochastic simulation is able to provide more detailed information on each attribute if required, such as standard deviation, median, percentiles and histogram.

Stopping Criteria

Two types of stopping conditions are commonly used. One is to evaluate a predefined number of samples. This condition is normally used with sequential sampling or with random sampling when the behaviour of the system is well understood. The second type of stopping condition is based on setting a pre-defined precision for the attributes. The simplest form of this condition is the use of the relative uncertainty R as stopping criterion [4.44]:

$$R = \frac{s}{\bar{x}\sqrt{n}} \tag{4-6}$$

where s is the standard deviation of the sample, $\bar{x}$ the mean value of the sample, n the number of simulations. The relative uncertainty decreases with the number of evaluations. Hence, there is a clear trade-off between the speed of the algorithm and the accuracy of the attributes.

MOEA must evaluate hundreds of alternatives over hundreds of generations. Thus, a small saving in the simulation time represents a large amount of computation time. The production of fast evaluations of the alternatives is crucial. Nonetheless, fast evaluations have reduced accuracy. This trade-off is illustrated in Figure 4-6.

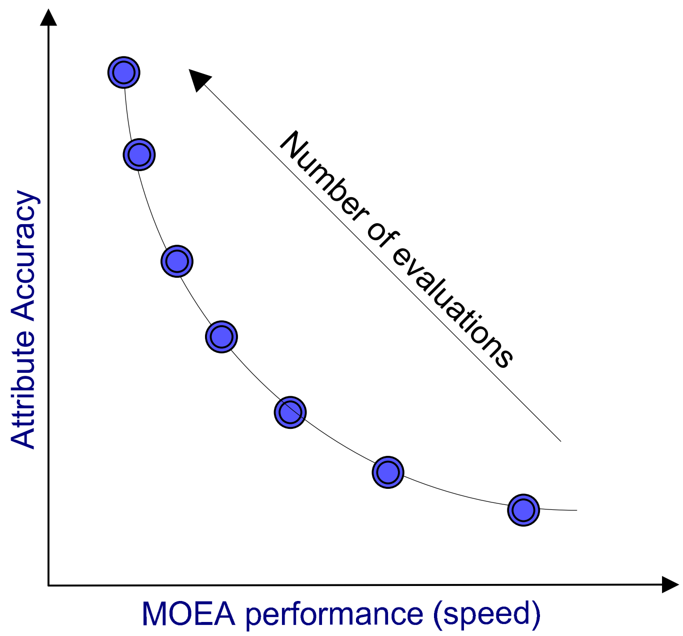

Figure 4-6 Simulation Accuracy vs. MOEA Speed Trade-off

A more elaborated stopping criterion generates attributes that have a certain confidence level of the estimate, given a required precision or confidence interval. Evaluations with guaranteed confidence levels and confidence intervals could be used when the interest lies in a particular solution, or a small group of solutions. However, the use of the relative uncertainty is sufficient for the high-level analysis proposed and for the purpose of the stochastic evaluation. The goal of the stochastic evaluation is to provide an estimate of each alternative's performance, to permit dominance comparisons and guide the search towards optimal regions of the search space.

Noisy Objective Evaluations

When random sampling is used, attributes values for the same DER topology could vary between consecutive evaluations, unless the same sequence of random intervals is used every time. This variation is commonly referred as a "noisy" objective evaluation. Evolutionary Algorithms search principles assume deterministic objective evaluations. Although, single-objective EA shows "remarkable robustness to all noise levels" [4.45], this is not the case for multi–objective EA. Noise has a negative effect on the accuracy of the Pareto set found, depending on the noise level. This problem is obviously non-existent when sequential sampling is used, as the attribute values for the same DER topology is constant over consecutive evaluations in this case.

Bui *et al.* [4.46] conducted a comprehensive study of the SPEA2 and NGSA-II algorithms in noisy evaluations. Results showed that the SPEA2 algorithm is robust to small amounts of noise ($R<0.10$). In this case, it produces a good approximation of the Pareto set, and outperforms NSGA-II. As can be expected, the accuracy of results improves with longer simulation runs (larger number of generations). However, for larger noise in the evaluations ($R\geq0.10$) the performance of both algorithms, especially SPEA2, is greatly affected.

Consequently, when random sampling is used, it is essential to guarantee a given accuracy to permit consistent comparisons ($R<0.10$). When this required degree of accuracy cannot be achieved in realistic time, the use of sequential sampling is indispensable. The effect of different number of evaluations in the computational speed and in the relative precision of the estimated attributes is investigated in the next chapter. Results from this investigation are used as a guideline to define the sampling technique to use, the stopping criteria R and the maximum number of evaluations.

The optimisation of noisy objective functions is recognised as one of the current challenges of the MOEA research area [4.17]. Recently, specialised algorithms for the optimisation of noisier problems have been proposed. For example, Eskandari *et al.* [4.47] propose the concept of "Stochastic Pareto dominance" and present the Stochastic Pareto Genetic Algorithm (SPGA, April 2008). The implementation of these specialised algorithms is not contemplated in this research; nonetheless, it is recognised as one of the possible avenues for further work.

Stochastic Simulation – Information Flow

Finally, the information flow between the stochastic evaluation of attributes and the multi-objective algorithm is illustrated in Figure 4-7.

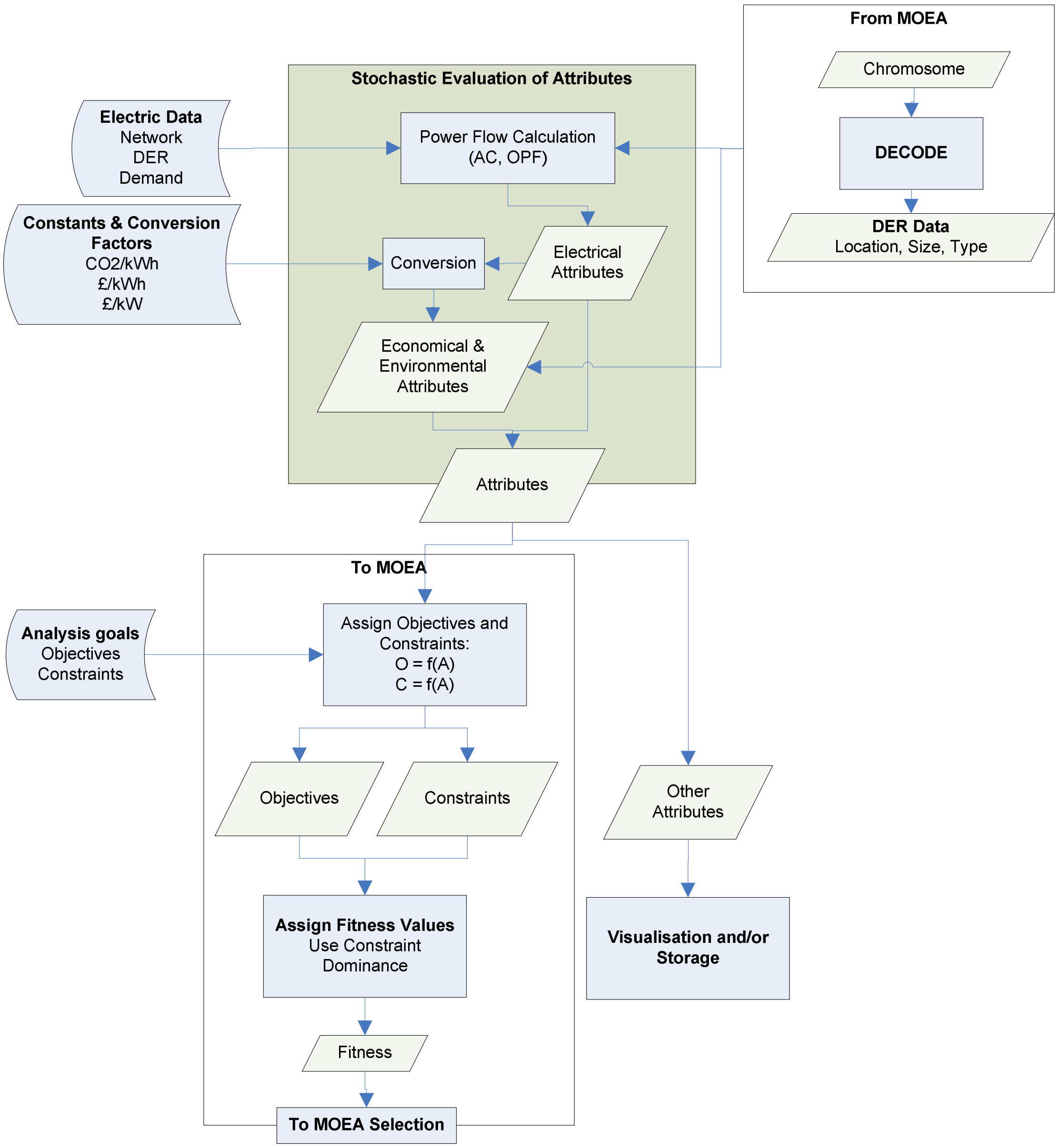

Figure 4-7 Stochastic Evaluation - Information Flow

The MOEA chromosome, once decoded, informs about each alternative configuration of DER locations, sizes and types. The stochastic simulation performs several power flows using this information and information on DER production and load profiles as an input. Also, power flows involve a model of the electric network studied, which is discussed in the next chapter. Conversion factors are required to transform electrical attributes into economic and environmental variables; thus, they must be provided as input information. Some economic attributes are calculated directly from the chromosome information.

The stochastic evaluation calculates attributes values for each alternative configuration of DER. MOEA determines the fitness of each alternative given the attribute values, and using the constrained dominance concept and the chosen objectives/constraints of the particular analysis. The stochastic evaluation can evaluate attributes that are neither objectives nor constraints. Hence, it is also possible to visualise the effect of the optimisation on other attributes of interest. This process is clarified with the explanation and examples provided in the next two chapters.

4.5.3. Planning Framework- Input Information

The input data required for the analysis is divided into four groups as seen on the right hand side of Figure 4-8. This information is stored in “input files”, which permit the reuse of information and the reproduction of analyses.

A MOEA is used in the planning framework. The parameters for the MOEA must be provided. These are population(s) size, crossover and mutation rate and maximum number of generations. A discussion on the effect of these parameters was provided in Chapter 2. Usually these parameters are problem specific. Some further discussion is provided in the next two chapters. Moreover, a problem specific first population creation, which also requires input information, is proposed in the next chapter.

The second group of input information refers to the goal of the analysis: what are the benefits and impacts that are going to be analysed? So, the planning objectives and constraints must be selected. Any attribute can be a planning objective, a planning constraint or both. In addition, the planning framework calculates attributes that are neither objectives nor constraints, permitting a wider analysis of DER integration.

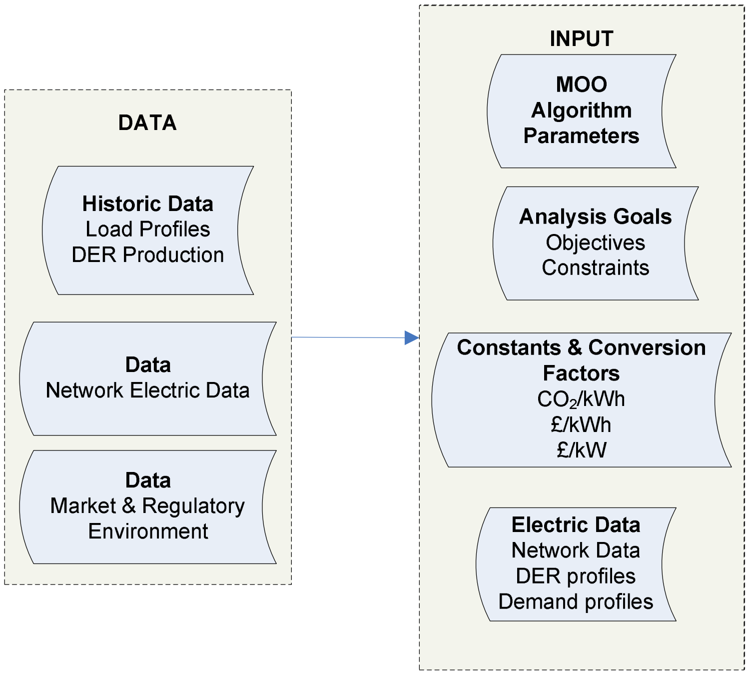

Figure 4-8 Planning Framework Information Input

The third group of input information is related to economic and environmental conversion factors. This information depends on market conditions and the DER technologies. These include:

- DER emission rates (gCO_2/kWh)
- Grid equivalent emission factor (gCO_2/kWh)
- DER installation cost (£/kW)
- DER O&M cost (£/kWh or % of installed cost)
- DER benefits (£/kWh)
- Discount rate for DER (%)
- Time frame analysis for DER (years)

The fourth set of input information provides the data to perform the objective evaluation:

- Network Electrical Data
    - Network topology
    - Circuit impedance

- Operating limits:
  - Maximum and minimum voltage limits
  - Thermal limits
- Load
  - Load type of each node
  - Load maximum value per node
  - Load profiles per load type
- DER
  - DER production profiles per DER type
  - DER maximum capacities per DER type

The main goal of the case studies presented in Chapter 6 is to demonstrate the flexibility and applicability of the planning framework and to produce conclusions about DER benefits and impacts. Hence, these case studies use historic data of load profiles. Some case studies include historic data of DER production while others are based on profiles produced by means of weather data and DER models. Detailed information is provided on each case study. The use of historic and modelled data is reasonable for the purposes of the case studies. A similar approach can be found in other studies that consider the time-variability of DER and load [4.5][4.22].

In addition, in the case studies of Chapter 6 load profiles and DER production profiles are considered invariant over the years; hence, no efficiency measures or climate change effects are included in the analysis. The use of more elaborated forecasting techniques for load and DER is essential for a practical study. Load forecasting techniques are well covered in the literature (see for example [4.1[) and are not included in this thesis. The study and development of other parts of the planning framework are more important to demonstrate the novelty of this research. Hence, most time was spent in the research and development of the flexible multi-objective approach proposed and on the analysis of different problems of DER integration.

4.5.4. Planning Framework – Output Information

The output of the planning framework must generate an answer the two questions proposed in section 4.2. The first question is related to the decision space (what are the best configurations to achieve several objectives?) while the second one is related to the objective space (what are the correlations between objectives?). The MOEA solution provides the answer to the first question. The optimal configurations are known, and it is possible to analyse trends in DER deployments (e.g. nodes and DER sizes) or particular configurations, as illustrated in Chapter 6. Answering the second equation requires a further step of analysis and visualisation.

4.5.4.1. Multi-objective Visualisation and Analysis

A two objective trade-off can easily be visualised in a two-dimensional graph. In the case of a tri-objective analysis, a useful visualisation technique is the scatter plot, where the two chief objectives are plotted in the main axes (x and y) while the third objective determines the colour (or size) of the data points. An example is illustrated in Figure 4-9.

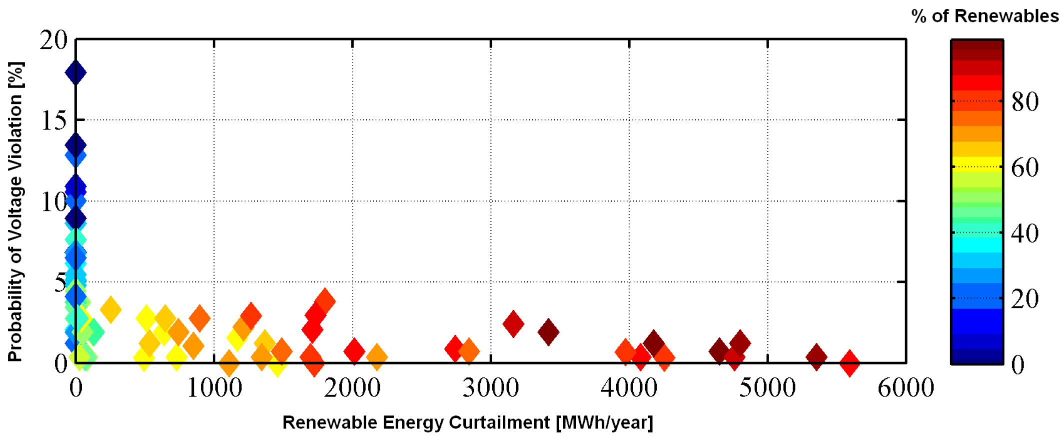

Figure 4-9 Example of a Scatter Plot

Nonetheless, illustrating a set of solutions with a large number of objectives is more difficult. The simplest option is to use bar plots [4.48]. First, the solutions are arranged in terms of one of the objectives. Then, each objective for each solution is plotted with a bar (usually of different colour). Since objectives ranges usually vary (i.e. different units and different magnitudes), normalised scales are used. The bar plot is useful to illustrated a small number of solutions. Even so, visualisation of trends becomes harder for larger sets.

In this case, the set of results P of the optimisation of *m* objectives can be visualised by projecting it in every two-objective plane. This gives a set of m(m-1) bi-objective plots, each one illustrating the trade-offs between a pair of objectives. Only *m(m-1)/2* plots are necessary if only one plot is produced for every pair of objectives (instead of two).

Moreover, since the diagonal of the graph is not used, it is possible to plot the histogram for each objective, or other useful information, in this 'space' if required. This visualisation method is referred to as a "scatter plot matrix" method. This method permits the visual identification of conflict or correlation between pairs of objectives. Moreover, maximum and minimum attainment levels (and therefore the range) of each objective are identified. Figure 4-10 illustrates an example using a set of results with three objectives.

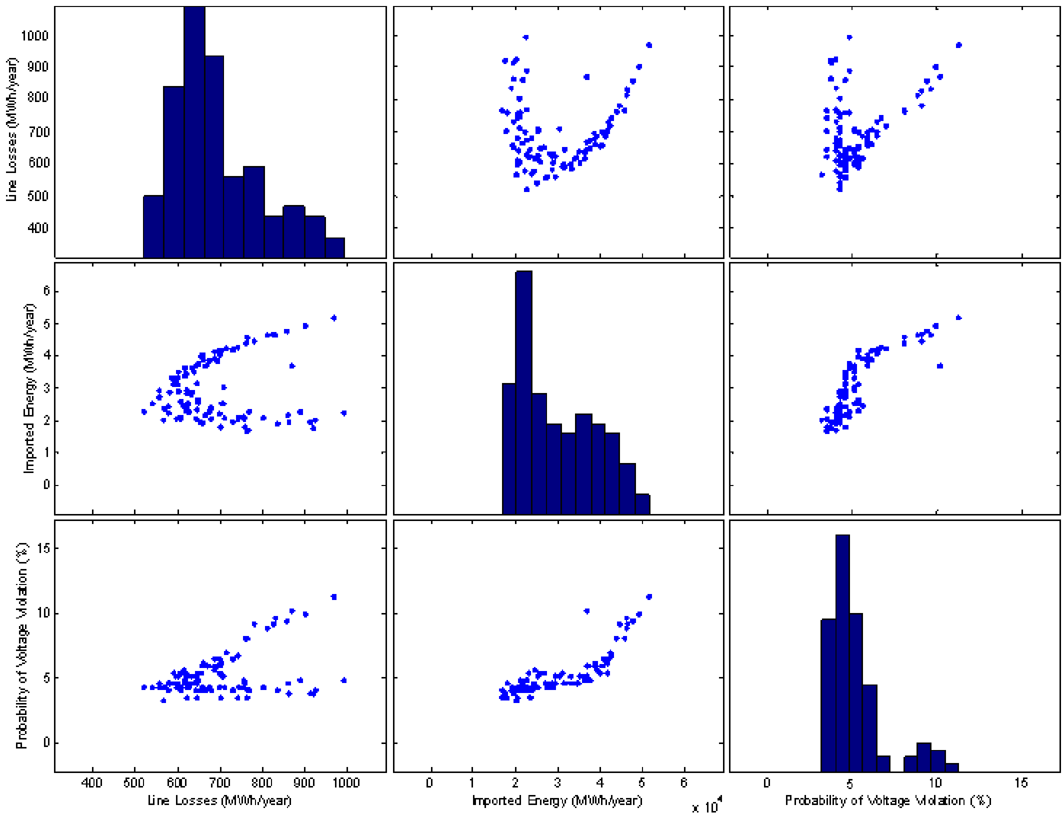

Figure 4-10 Scatter-Plot Matrix Method

The determination of correlations between pairs of objectives is very important. Strong negative correlation between two objectives indicates a conflict between them. In contrast, when two objectives have a high positive correlation, they represent the same causal effect. Hence, only one of the objectives needs to be studied. Reducing the number of objectives in the study facilitates the analysis of results.

Linear correlations can be determined by Principal Component Analysis (PCA) [4.49]. In a PCA all elements in P undergo a linear transformation along the eigenvectors of the covariance matrix of P^TP. The eigenvector corresponding to the largest eigenvalue represents the direction that exhibits the largest variance in P; the second largest eigenvalue corresponds to the second orthogonal direction of largest variance in P and so on. In other words, the axes are rotated to coincide with the orthogonal directions of largest variance in the data. Commonly only two or three principal components are visualised [4.3]. Projection along the two eigenvectors (or principal components) corresponding to the two largest eigenvalues of the original objective directions gives a set of two-dimensional axes in which linear correlations are visualised. It was confirmed by test cases in this thesis that the reduction of an m-dimensional trade-off set to the two principal components still maintained over 80% percent of the total variance in the original set, given the attributes proposed in Table 4-1.

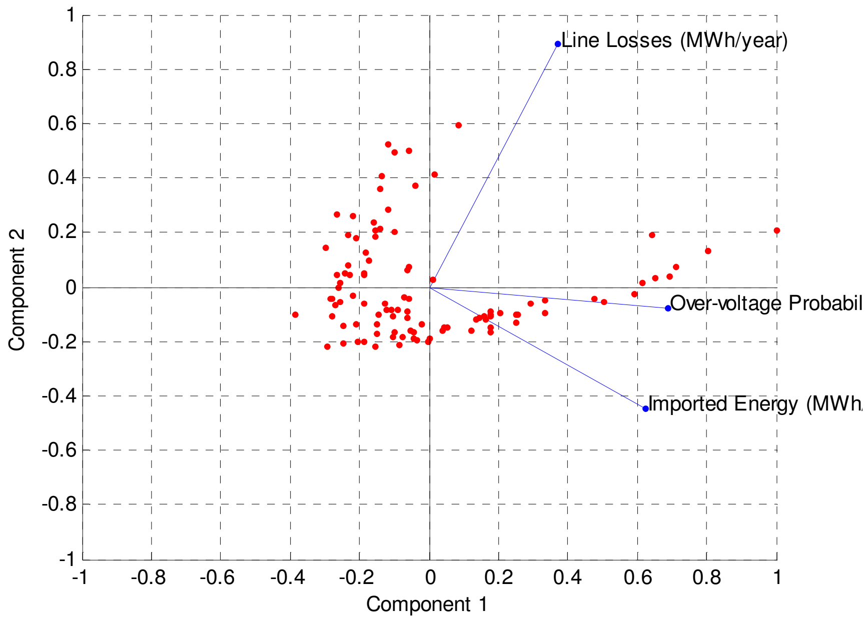

Figure 4-11 Principal Component Analysis

In the PCA plot, the x-axis corresponds to the largest variance in objective values, while the y-axis corresponds to the second largest orthogonal variance. The vectors illustrate the direction and magnitude of variation on the objectives. The angle between vectors indicates the linear correlation between objectives. A small angle means a strong linear correlation; a square angle means no linear correlation in the analysed data. A negative correlation results in opposite vectors. Three vectors separated by 120 degrees show objective interdependence, each objective is negatively correlated with the remaining two. PCA is a statistical analysis method, which includes the calculation of the covariance between objectives. Hence, objectives correlations are also quantified numerically, besides being illustrated in the PCA plot.

The PCA plot illustrates only linear correlations. Therefore, care must be taken when nonlinear correlation exists between objectives. For example, the U-shape at the top of Figure 4-10 results in a very small linear correlation in Figure 4-11. Consequently, it is advisable to analyse the PCA plot together with the Scatter-Plot Matrix plot to get a better understanding of the problem. Other multi-objective visualisation methods were studied, such as the Value Path and the Star Coordinate method [4.48]. Nonetheless, these methods could not illustrate correlations as clearly as the combined use of the Scatter-Plot Matrix and PCA plot, for a large number of solutions.

4.5.4.2. Decision Making

It is not the objective of the planning framework to provide a single solution. Nonetheless, the high-level structure of a further "Decision making" module is proposed in Figure 4-12. As explained in Chapter 2, the multi-objective formulation of the problem permits a deep understanding of it. Then, it is possible for the planner to express preferences using appropriate decision-making techniques and choose a single solution. Several publications review Multi Criteria Decision making techniques (see for example Hobbs and Meier [4.6] and Deb [4.48]). Once a single solution is chosen further engineering, design and financial studies must be conducted to produce an investment plan. The information obtained by means of the planning framework could also support further refinement of the analysis (e.g. study other objectives, change constraint limits, analyse a different scenario) to gain more understanding of the problem or a given sub-set of solutions of particular interest.

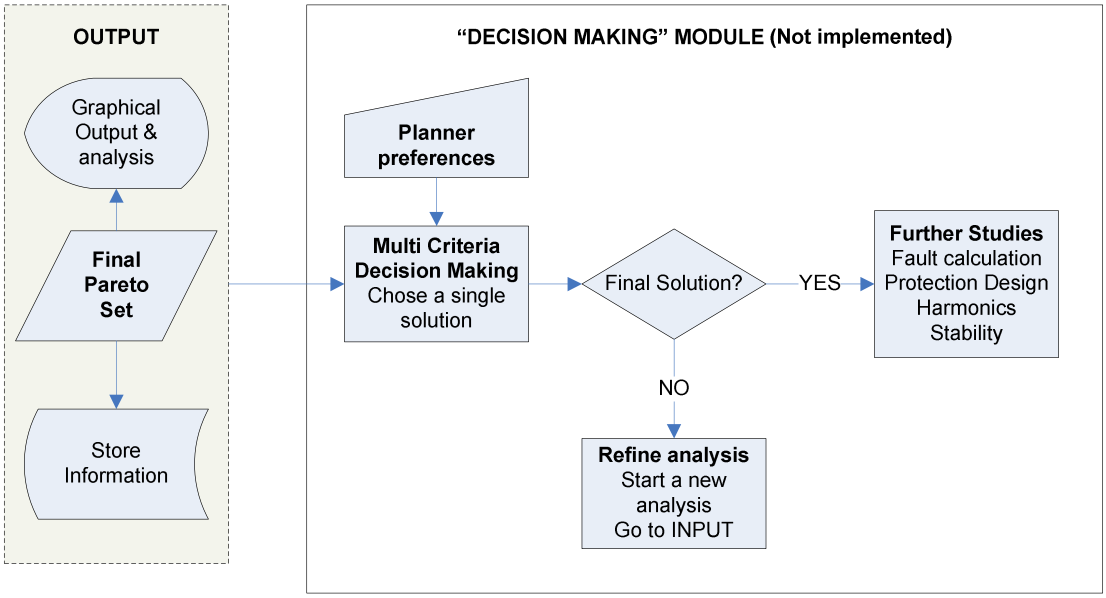

Figure 4-12 Decision Making Module

4.6. *Summary*

Based on an analysis of the DER planning problem under the perspective of this work, the key requirements for the planning framework have been identified. The DER planning problem is characterised by multiple and conflicting objectives. Also, many perspectives for a DER integration analysis are possible. Therefore, the DER planning framework must be based on an appropriate multi-objective optimisation technique. Moreover, a crucial degree of flexibility is required in terms of planning objectives and constraints.

DER is also characterised by a high degree of diversity in technologies and energy sources. These have a determinant effect on planning objectives and constraints. Thus, simplified methods for evaluating the time variability of DER would undermine the very nature of the proposed study. An appropriate approach for the analysis of diverse types of stochastic and controllable DER is required.

Based on these requirements, which include an explicit need for a modular approach, the structure of the planning framework is proposed. It is based on a state-of-the-art MOEA and has an inner module for DER stochastic simulation. The proposed structure provides a flexible approach in which different stochastic attributes can be evaluated. In addition, the structure of the optimisation and simulation modules permits the selection of different attributes as planning objectives and constraints. The solution enables the incorporation of other attributes evaluations and further modules to process input information and/or analyse output information.

The specific techniques implemented in the next chapter have been outlined. The optimisation is based on the SPEA2 algorithm. The objective evaluation is based on a stochastic simulation, which includes an inner loop AC power flow. Controllable units are analysed using an OPF. Some of the issues and assumptions surrounding the implementations of these techniques have been introduced. Simplifications to the planning framework, and relevant methods to handle them, have also been mentioned. In the next chapter, the practical implementation of the planning framework is discussed in detail.

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Chapter 5

5. Development of the DER Planning Framework

5.1. *Introduction*

The previous chapter discussed the complexity of the DER planning problem. Based on this analysis, it identified the requirements and proposed the structure for a planning framework for DER integration analysis. The planning framework is based on the SPEA2 algorithm, whose structure and working principles were described in detail in Chapter 2. The evaluation of the objectives within the SPEA2 algorithm is based on the stochastic simulation of potential DER configurations. The structure of this stochastic evaluation was described in the previous chapter. This stochastic evaluation makes use of a power flow algorithm and of an optimal power flow optimisation when controllable units are being evaluated.

This chapter explains the implementation of the planning framework into a multi-objective analytical tool. Each one of the techniques on which the framework is based is discussed. The chapter describes essential assumptions and decisions on which the implementation is based. Moreover, it discusses the platform in which the framework was implemented and the reasons why this platform was chosen.

This chapter is structured as follows: Initially, the platform and structure of the planning framework are introduced. Next, the development of SPEA2 operators for the DER planning problem and the choice of SPEA2 parameters are detailed. Afterwards, the power flow algorithm used is explained. Then, the optimal power flow optimisation, and its implementation as a linear programming problem are discussed. In a subsequent section, the detailed calculation of each of the planning attributes is explained, discussing the importance of each planning attribute in the context of DER planning. Finally, the sampling procedure within the stochastic evaluation is explained. In particular, different sampling techniques are examined, and their effect on the speed and accuracy of the stochastic evaluation illustrated.

5.2. *Platform and Structure*

The choice of an adequate software platform and structure for the planning framework is a key aspect. The software platform has a determinant effect on computation speed. Also, it decides the time spent on the software coding. In addition, an adequate software platform and structure will ensure the future use and development of the framework by other researchers, and its integration with other existing models/simulation frameworks.

5.2.1. Platform

The planning framework was implemented in Matlab. This software platform was chosen for the following reasons:

- It is a well-known software platform, widely used in the power systems research community
- It has built-in functions for matrix algebra and complex number manipulation
- It has advanced graphical visualisation techniques for multi-dimensional data
- It can be linked to Excel for information input and output
- It provides an optimisation tool-box with a linear programming solver, used in the resolution of the inner OPF
- It provides built-in functions for Principal Component Analysis
- Its ease of use and the author's familiarity with it

The planning framework uses a large number of matrix and vector calculations. As a result, all matrices are stored as sparse matrices, to reduce the use of RAM memory, and increase computation speed. The Profiler function of Matlab was used extensively to enhance the computation speed of every single procedure.

5.2.2. Structure

Each element of the planning framework is implemented as a Matlab function with the form:

$$(output_1, output_2, ..., output_n) = function(input_1, input_2, ..., input_n)\ .$$

Figure 5-1illustrates the main functions implemented within the planning framework.

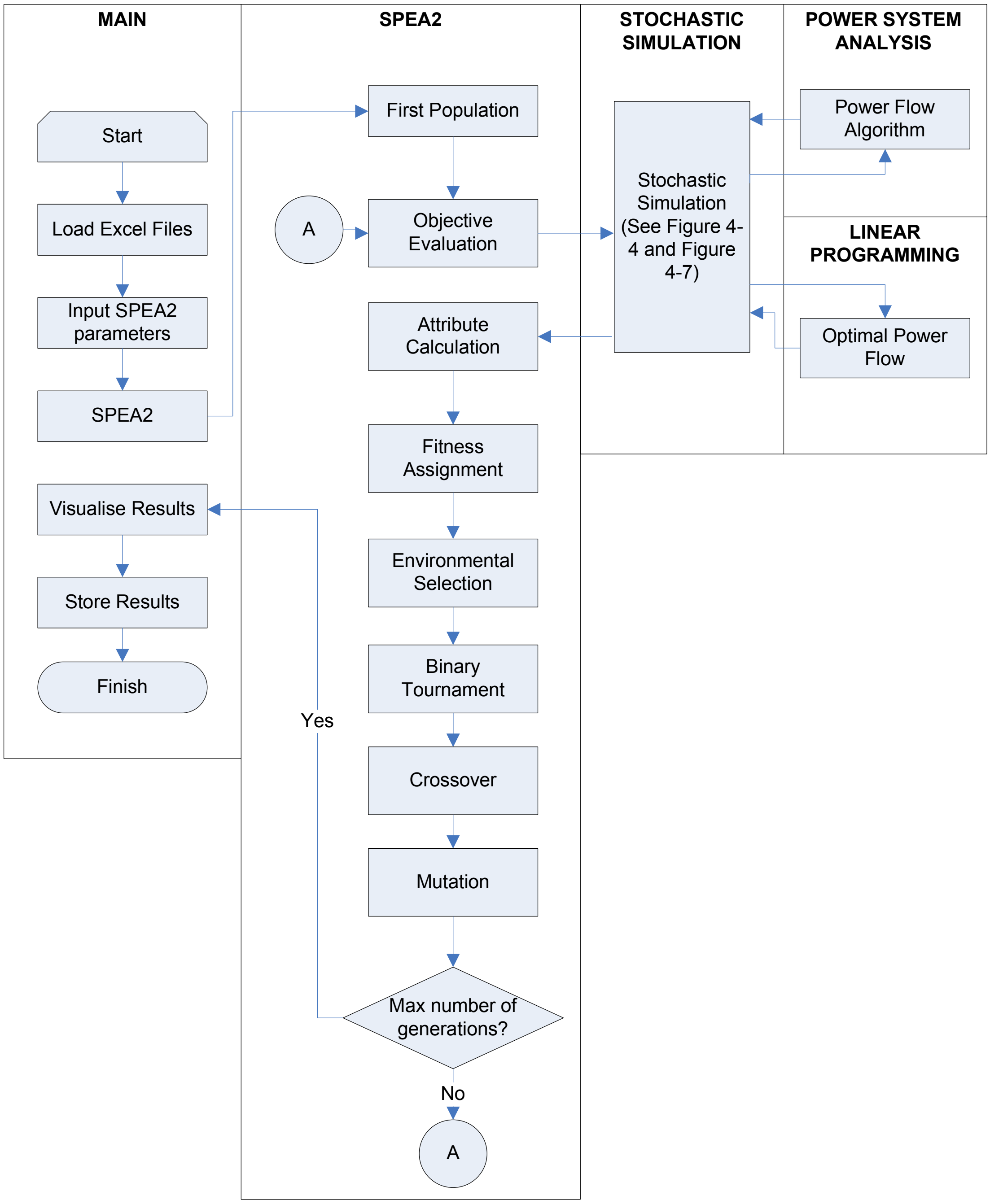

Figure 5-1Planning Framework Structure

These functions are grouped into five main procedures, as illustrated in Figure 5-1. Each function is independent and only linked to the rest of the code through the *input* and *output* arguments. Functions operate with variables within their own workspace, as opposed to scripts that use global variables. As a result, functions can be modified, extended or replaced when necessary without updating the rest of the code. This ensures the modularity of the planning framework. Modularity facilitates the inclusion of new objective evaluations (e.g.

fault calculations, reliability) and the test and development of different SPEA2 operators (e.g. first population, crossover and mutation operators).

5.2.3. Input and Output Information

Input information is provided in three Excel files. The first file stores the objectives and constraints of the study. This file also contains input data on each DER type considered in the study such as: maximum DER sizes and numbers, the controllability of the DER unit (curtailment/dispatch); emissions factor; capacity costs; dispatch and curtailment costs; operation and maintenance costs; and benefits per unit of energy of each DER type. The second file provides the production profiles for each DER type and demand profiles linked to each network node by the load type. The third file provides the network impedances, the network topology data, the load installed in each node and the corresponding load type. The UKGDS format [5.1] is used for the profiles and network files. The SPEA2 algorithm parameters are provided in the Matlab command line. Output information consisting of the optimal configurations and their objectives values are stored in Excel files once the SPEA2 provides an optimal solution.

5.3. *SPEA2 Applied to the DER problem*

The working principles of evolutionary algorithms and the structure of the SPEA2 algorithm were discussed in detail in Chapter 2. In this section, the practical implementation of the SPEA2 algorithm for the DER planning problem is described.

5.3.1. Decision Variables and Chromosome Structure

A key step in the solution of a problem by means of EA is the adequate encoding of the decision variables. An appropriate encoding philosophy must reflect the building blocks of the problem. Four types of decision variables are considered by the planning framework. These are the optimal number of DER units to install, the optimal locations where DER units should be installed, the optimal DER types and the optimal DER capacities to install in each location. Given these decision variables, the basic building block of the DER planning problem is the DER unit. DER units installed in each node are encoded as genes, as explained next. The network configuration is used as the structure of the chromosome. The network is assumed unchanged during the period of analysis.

5.3.1.1. Encoding

Every DER installed in each node is encoded as one gene in the chromosome. The chromosome is represented by a vector with a number of elements equal to the number of network nodes. Each network node is represented as concatenation of integer numbers, as illustrated in Table 5-1.

Table 5-1Chromosome Encoding

Network Node	**Node 1**	**Node 2**	**Node 3**	**Node i**	**Node n**
Chromosome Genes	$G_{1j}G_{12}G_{11}$	$G_{2j}G_{22}G_{21}$	$G_{3j}G_{32}G_{31}$	*GijGi2Gi1*	*GnjGn2*G_{j1}

Each integer number G_{ij} in the gene corresponds to jth DER type installed in the ith node. By default, it is assumed that every node in the network is a possible location for a DER installation. If only some nodes are studied, a reduced network structure is used as the base of the chromosome. Similarly, the installation of specific DER types in particular nodes can be restricted to reflect existing technical constraints, as illustrated in one case study in the next chapter.

The planning framework must analyse several types of optimisation problems, as discussed in the previous chapter (section 4.3.1.3.). Hence, flexibility is required in the encoding system. Table 5-2 shows three different types of analysis that the planning framework supports, and the encoding for G_{ij} used for each analysis.

The total number of units in the *whole system* can be limited for each DER type, as in the examples provided in Table 5-2. The procedures for first population creation, crossover and mutation explained next include routines to guarantee that the maximum number of DER units per type is not exceeded. Alternatively, the analysis can be targeted at finding the optimal configuration *for the whole network*. In this latter case, the maximum number of units per type in the whole network is not limited. Still, the maximum number of DER units of a type *per node* is limited (analysis 2 in Table 5-2), or the maximum size of DER units is restricted (analysis 3 in Table 5-2). These possibilities are clarified with the two case studies presented in the next Chapter.

Table 5-2 Gene Encoding

	Analysis Type	G_{ij}	Decoding	Example
Analysis 1a	**Optimisation of the location for DER units of predetermined size:** A number of DER units per type must be optimally located in the network. A single unit of each type can be installed per node. This problem is a sub-category of the one expressed in the next row.	1 or 0	1 if unit of type i is installed in node j, 0 otherwise.	Find the best locations for two 500 kW CHP installations and three 200 kW wind turbines. Only one unit of each type can be installed per node.
Analysis 2	**Optimisation of the location of DER installations and the number of installations per node:** A number of DER units per type must be optimally located in the network. Each node can have up to n_{type} DER installations per type. The size of each DER type is predefined.	0,1,2….,n_{type}	The number represents the number of units of type i installed in the node j, from 0 to a maximum of n_{type}.	Find the best location for 20 PV systems of 1 kW each one and 5 micro-wind turbines of 2 kW each one. Each node can have a maximum of 3 systems of each type.
Analysis 3	**Optimisation of the location and size of DER installations:** A number of DER units must be optimally located in the network. Also, the size of each unit is optimised (per type). A maximum capacity is defined for each DER type.	0,1,2,…,99	The number represents the size of the DER unit of type i installed in node j in % of maximum capacity.	Find the best size and location for 40 systems of each DER type. Each node can have PV installation up to 50 kW and CHP units up to 20 kW.

The second and third type of analysis are based on the assumption that DER units are scalable and that capacity factors are constant for all DER sizes installed in the same area. In this case, the same production profile can be applied to all DER sizes. This assumption is solid for modular systems such as PV installations and some gas generators. In contrast, this assumption is weak for wind turbines, as normally the capacity factors of wind turbines of different size vary. Hence, for a more adequate sizing analysis of non-scalable technologies, such as wind turbines, each generator size should be considered as a different DER type, with an appropriate production profile applied. Then, the first analysis type should be used to determine the optimal sizes.

5.3.1.2. Decoding

The decoding procedure translates the chromosome vector into a matrix of installed capacities of DER (**CDER**). Each element $CDER_{ij}$ in the i[th] row and j[th] column corresponds to the size of the DER of type i installed in the node j:

$$\begin{array}{ccc} & Nodes & \\ CDER = & \begin{bmatrix} CDER_{11} & CDER_{12} & \ldots & CDER_{1j} & CDER_{1Node} \\ CDER_{21} & \ldots & \ldots & \ldots & \ldots \\ CDER_{i1} & \ldots & \ldots & CDER_{ij} & CDER_{iNode} \\ CDER_{Type1} & \ldots & \ldots & CDER_{Typej} & CDER_{TypeNode} \end{bmatrix} & Types \end{array} \qquad (5\text{-}1)$$

The matrix **CDER** permits the direct calculation of some basic attributes of the configuration represented by the chromosome, such as installed capacities and installation costs. These basic attributes are used to determine some of the planning attributes discussed in the previous chapter. The calculation of all of the attributes is explained in section 5.6.

5.3.2. First Population Creation

The creation of a diverse first population is essential to guarantee the exploration of the whole search space, as discussed in Chapter 2. Most GA-based DER planning techniques are based on the creation of random but feasible topologies for the first population. In the planning framework, two methodologies are used to create the first population.

First, a user-defined fraction of the first population is created by adding random DER units. Each initial solution is restricted to a maximum penetration level for each DER type. This maximum penetration level is defined depending on the conditions of the analysis, such as DER sizes, maximum number of units, size of the network and loading level of the feeders. This limit prevents the algorithm from creating unfeasible topologies. The remainder of the population is created by adding increasing penetrations of each DER type to all the nodes that are considered for DER installations, deterministically, up to the maximum penetration limit set for each DER type. This procedure is a "uniform" first population creation, as suggested by Haupt *et al.* [5.2]. The "do-nothing" case (i.e. no DER) is also included in the first population, as it is known to be Pareto optimal in some objectives (e.g. DER installation cost, DER penetration level).

These three procedures provide the SPEA2 algorithm with varied topologies to start the search. In addition, if there are solutions that are known to be near optimal, for example from a previous study or from an examination of the problem objectives, these should be "seeded" in the initial population to increase the search speed.

5.3.3. Objective Evaluation and Constraint Handling

In every evolutionary generation, planning attributes are computed for every potential solution by the stochastic evaluation process. A matrix of planning attributes is created. Each column of the matrix corresponds to a planning attribute, listed in Table 4-1 of the previous chapter. Each row corresponds to a potential solution, i.e. a chromosome of the population. The calculation of each attribute is detailed later in this chapter (section 5.6).

The objectives and constraints of the analysis are defined in an input file for each particular study. Any attribute can be selected as a planning objective, planning constraint or both. Given the specific objectives, a matrix of objectives **O** is created by copying the respective columns of the attribute matrix, as illustrated in Figure 5-2. Since *all the attributes* are computed and stored in the attribute matrix, planning attributes that are not planning objectives can still be studied and visualised. Next, given the constraints defined for the analysis, an overall constraint violation C_j is calculated for every j^{th} chromosome, as the sum of the relative constraint violations:

$$C_j = \sum_i \left| \frac{a_{ij} - c_i}{c_i} \right| \tag{5-2}$$

where a_i is the i^{th} attribute of the jth chromosome and c_i is the respective constraint value. Constraints can be defined for all, some or none of the planning attributes. A check routine prevents errors when the constraints are set to zero. The constraint-dominance concept, explained in Chapter 2, is used to include planning constraints in the SPEA2 algorithm. This method ensures a flexible approach as an attribute that is an objective can also be constrained, attributes can be constrained even if they are not planning objectives, and if no constraints are defined (C=0) the usual concept of dominance is applied.

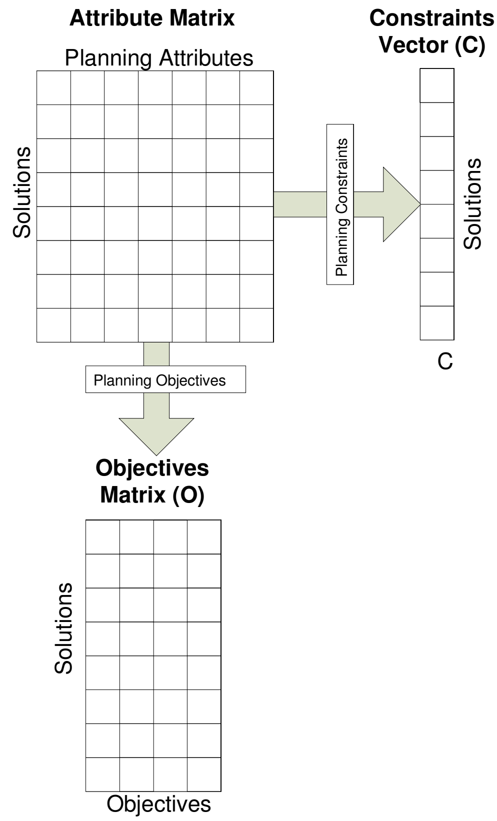

Figure 5-2 Attributes, Objectives and Constraints

Finally, once the dominance relationships between all solutions have been computed, the fitness of each solution is calculated according to the specific fitness assignment procedure of SPEA2, explained in Chapter 2.

5.3.4. Selection

Binary tournament has better or equivalent convergence and computational properties than any other reproduction operator [5.3]. Hence, for the selection step, a binary tournament procedure has been implemented, as illustrated in Figure 5-3.

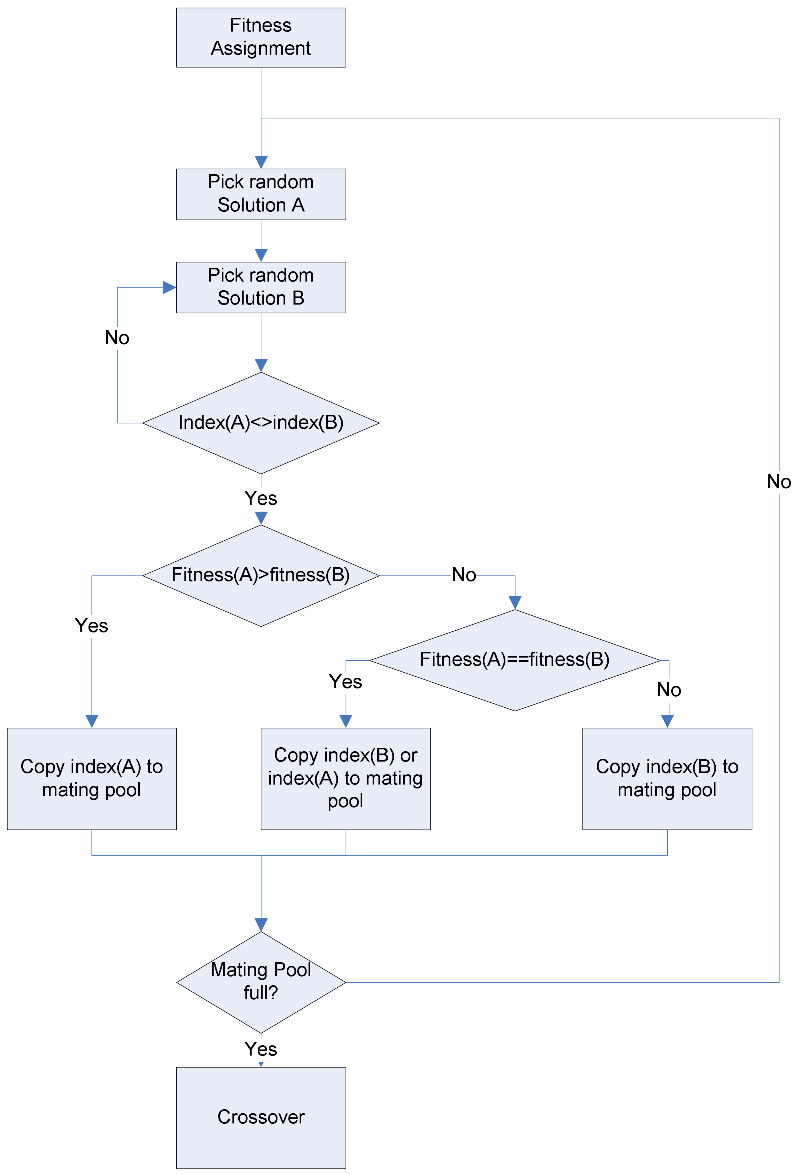

Figure 5-3 Binary Tournament

Pairs of solutions are chosen and their fitness compared. The index of the fittest solution is stored in a mating pool vector. In the unlikely case that two solutions have exactly the same fitness value, one of them is chosen randomly and its index copied to the mating pool. The procedure is repeated until the mating pool is full, that is when enough “parents” have been chosen to create a completely new population. Since each parent creates a new member, the size of the mating pool is equal to the size of the population.

5.3.5. Crossover

In the DER planning problem the 'crossover' procedure exchanges groups of DER units between two successful topologies to eventually find optimal DER mixes and configurations that perform better in one or more objectives. Different crossover types were reviewed in Chapter 2. Uniform crossover has been demonstrated to perform better than two-point and single-point crossover in other problems [5.2]. In the DER planning problem, uniform crossover facilitates the search for optimal DER mixes in the nodes, as explained next. Hence, this crossover type was implemented in the planning framework.

The single-point and double-point crossover operators exchange *large groups* of adjacent *genes* at once, as illustrated in Chapter 2. These operators are less disruptive, and groups of genes (i.e. DER) from the initial solutions are likely to remain together for several evolutionary generations. As a result, when using single or double-point crossover the search for optimal DER mixes in the *nodes* relies heavily in the mutation operator, which usually has a low probability of occurrence. Tests conducted in this research showed that "building blocks" created in the first population remained in the final solution after hundreds of generations. On the contrary, uniform crossover exchanges each gene *independently*, not in groups, according to a 'crossover mask' created using uniform random numbers. Because this crossover method is more disruptive, it favours the exploration of the whole search space [5.4]. Hence, new DER mixes are created in the nodes at every evolutionary generation, and uniform crossover is more likely to find optimal DER mixes in the nodes. Optimal solutions are kept in the elite population for the next generation. Therefore, these solutions are not destroyed.

5.3.5.1. Crossover Operator Implementation

Two different uniform crossover approaches are necessary, depending on whether the number of DER units per type is limited or not.

Whole Network Analysis

When any number of DER units per type can be installed in the network, the crossover process is exactly as discussed in Chapter 2 and illustrated in Figure 2-15. A crossover mask vector of the same length of the chromosomes is created. Then, genes between two parent chromosomes are exchanged to create two offspring chromosomes. The process is repeated iteratively; pairs of parents are chosen from the mating pool, until a whole new population has been created.

Limited Number of DER

If the number of DER units per type is restricted for the whole network, the previous procedure might result in configurations that exceed the maximum number of DER units per type. For example, imagine that the limit of DER is half of the network nodes, and that the first parent has DER installed in all odd nodes, while the second parent has DER in all even nodes. Then, it is possible that one of the offspring could exceed the limit of DER (half of the network nodes), unless the crossover mask perfectly balances the exchange of genes/DER. Therefore, to avoid exceeding the limit of DER per type, an additional step is added.

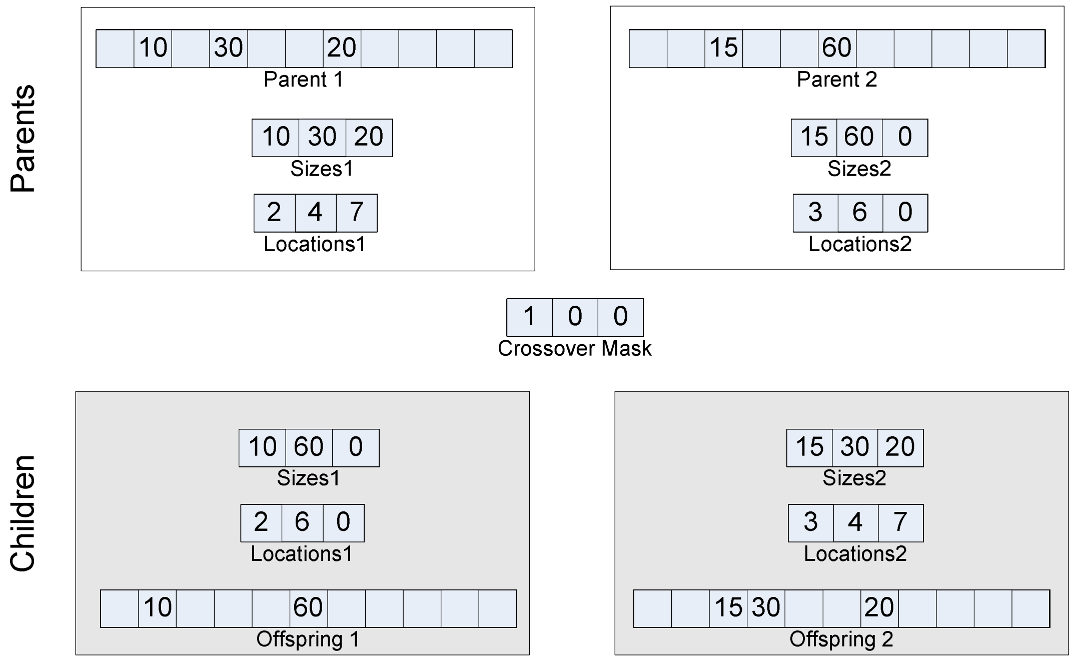

Figure 5-4 Crossover for Limited Number of DER Units

For each chromosome, and for each DER type, two vectors are created. The first vector stores the DER sizes and the second vector the DER locations of the chromosome. The length of each vector is the maximum number of DER units for that type. Then, *both* DER sizes and DER locations are exchanged between the parent chromosomes, using the *same* crossover mask. This can be understood as "moving" a DER unit from one topology to the other, depending on the crossover mask values. This method prevents a topology from exceeding the limit of DER. Moreover, it supports the crossover between solutions with different numbers of units (of the same type), as seen in the example illustrated in Figure 5-4. Also, since this procedure is performed independently for each DER type, different maximum number of units can be defined for each DER type. Once the crossover process is performed for all DER types, the full chromosome is "reconstructed".

In the example of Figure 5-4, only a DER type is illustrated. The limit of DER units is three. A parent with three DER units and a parent with two DER units are mated. The crossover mask indicates whether a unit is being exchanged or not (0 if it is exchanged).

Finally, a "check" routine is implemented to prevent a child chromosome being assigned two units in the same node. For example, if the second unit of parent 1 (30 in node 4) was located in node 3 instead, and given the crossover mask, offspring 2 will be assigned two units in node 3 (15 and 30) simultaneously. The check routine prevents this problem occurring, impeding the exchange of the gene.

5.3.6. Mutation

The mutation operator provides the population with new genes, and favours the exploration of the whole search space. Even if it has a low probability of occurrence, it is important for maintaining the diversity of the population, as discussed in Chapter 2.

5.3.6.1. Mutation Operator Implementation

As in the case of crossover, two different mutation procedures were implemented, depending on whether the number of DER units per type is restricted or not.

Whole Network Analysis

In the case that only a placement analysis is carried on (Analysis 1 in Table 5-2), and if the number of DER units is not restricted per type, the mutation operator simply consists of a "bit-flipping" operation. Therefore, if a gene is being mutated, its binary value is flipped.

When the analysis includes sizing of DER units (Analysis 2 and 3, Table 5-2), and with a probability equal to the mutation rate, each gene is mutated as follows:

- If a generator of type j exists in node i (G_{ij}>0):
  - It is removed with a low probability (p_1)
  - Its size is changed to a random value with a high probability (1-p_1).
- If there is no generator of type j in node i (G_{ij}>0):
  - A generator of random size is added to node i

A probability p_1 is added to allow the mutation operator to delete DER units. Deletion is necessary as test cases showed that DER penetrations tend to increase rapidly in this type of analysis, because of the crossover operator. Therefore, the '0' gene must be re-included in the chromosomes from time to time to preserve diversity. The value of p_1 was determined empirically (10-20%).

Limited Number of DER per Type

When the number of DER per type is limited in the network, two vectors for each DER type and for each chromosome are created, as illustrated for the crossover operator in the previous section (Figure 5-4). Then, if the gene is being mutated, values from each vector are changed as follows:

- If a generator of type j exists in node i (G_{ij}>0) either:
  - Its location is changed and the size maintained, with 50% of probability.
  - Its size is changed (or bit flipped to zero) and the location maintained, with 50% of probability.
- If there is no generator of type j in node i (G_{ij}=0):
  - A generator of random size is added (or bit flipped to one) in a random location

5.3.7. SPEA2 Parameters

Four parameters must be set for the SPEA2 algorithm. These are the population size, the archive size, the crossover rate and the mutation rate. It was already discussed in Chapter 2 that the size of the population depends on the difficulty of the problem. The more "difficult" the problem, the larger the population should be, because small populations do not provide enough diversity [5.5]. However, if the population is too large the computation time could be extremely large, without a proportional increase in the quality of the solution [5.6].

Similarly, the archive size is one of the more influential parameters in SPEA2. The archive solutions have a direct participation in the fitness assignment procedure, and only solutions from the archive participate in the selection, crossover and mutation procedures. Ziztler et al. [5.7] mention that too many non-dominated solutions (i.e. a large archive) might reduce selection pressure, as most solutions will have a similar fitness. In his doctoral thesis, Ziztler [5.5] used archive sizes between 25% and 80% of the population size for test problems using the SPEA algorithm. For SPEA2 [5.8], the authors used an archive size equal to the population size in all the test problems they conducted and they used population sizes between 250 and 400. A similar approach was applied by Mori *et al.* [5.9] in a power systems application reported in Chapter 2: the archive size was set equal to the population size, and population sizes of 100 and 200 were used. On the contrary, Rivas-Davalos *et al.* [5.10] used a population size of 200 and archive size of 50 for other power systems application.

In the test studies conducted in this thesis, population sizes between 100 and 400 members were used. The archive size was set equal to between 25% and 75% of the population size. The implementation of SPEA2 in Matlab was validated using both test functions for which the Pareto front is known [5.8], and using the DER planning problem. In this latter case, and because the Pareto front is not known, the results obtained by SPEA2 were contrasted with results obtained by exhaustive random trials. In the problems studied, and given enough generations (>300), the SPEA2 satisfactorily approximated the Pareto front.

An appropriate mutation rate is important to maintain the diversity of the population. Ziztler *et al.* [5.8] used a mutation rate of 0.006 for the SPEA2 binary test problems. Deb *et al.* [5.11] employed a mutation rate of *1/n* for NSGA-II for real coded problems, where *n* is the number of decision variables. Man *et al.* [5.4] reported some guidelines that suggest using a mutation rate of 0.001 for large populations (100) and a mutation rate of 0.01 for small populations (30). In this work, the mutation rate is set equal to 1/n, where *n* is the number of genes, as suggested by Deb *et al.* [5.11]. Hence, on average one gene of each chromosome will be mutated in every generation.

SPEA2 is an elitist algorithm. Optimal solutions are preserved for the next generation in the external archive. Hence, a high crossover rate (0.8-1.0) is commonly used in elitist MOEA [5.7], [5.12], [5.13]. In this work, a crossover rate between 0.90 and 0.95 is applied. So, between 5% and 10% of the parents are not combined, but are mutated at every generation to produce new offspring. The implementation of dynamic mutation and crossover rates in the DER planning problem, as suggested in [5.14], is recognised as an interesting possibility for further work.

5.4. *Power Flow Algorithm*

The case studies presented in Chapter 6 are concentrated on radial distribution networks. Radial networks represent the instance where vast amounts of DER will potentially be integrated (e.g. rural areas, LV networks with micro generation) and where DER impacts have been recognised to limit DER integration [5.15]. Moreover, almost all MV distribution networks are operated radially [5.16]. In the case studies, networks are assumed to be balanced. The study of balanced radial networks requires the use of particular power-flow techniques. Newton-Raphson methods, commonly used in interconnected transmission system studies, are not appropriate for the analysis of distribution networks because of the high R/X ratios and the weakly meshed or radial structure of these networks [5.16] [5.17]. Instead, a number of algorithms have been proposed specifically for the analysis of radial distribution systems. These methods exploit the radial structure of the network and provide a simple formulation. In addition, they are quite robust for heavy loads and less sensitive to high R/X ratios [5.18].

The power-flow calculation implemented in this work is based on the method proposed by Bombard *et al.* [5.17]. It is a backward/forward sweep (BFS) method for *balanced* radial distribution systems. The BFS algorithm implementation is explained in detail in Appendix B. Next, some key assumptions of its implementation are discussed.

5.4.1. Power Flow Algorithm: Input and Output

The input arguments required for the power flow algorithm are the grid voltage, the network topology and impedance and the active and reactive load injected in each node. A node-to-branch-incidence matrix **L** is determined from the topology of the network, as explained in Appendix B. A diagonal matrix **Z** is used to represent network impedances. The radial distribution circuits are modelled as a series impedance z=r+j*x. Each i^{th} diagonal element of **Z** corresponds to the complex impedance of the i^{th} branch. Capacitance effects are ignored. This model is adequate for most radial distribution systems, except in the cases of long lines where a π model is required [5.16].

The vectors of power withdrawn at each node $\mathbf{P_{node}}$ and $\mathbf{Q_{node}}$ are the difference between the load power ($\mathbf{P_{Load}}$, $\mathbf{Q_{Load}}$) and the total power injected by DER units ($\mathbf{P_{DER}}$, $\mathbf{Q_{DER}}$):

$$\mathbf{P_{node}} = \mathbf{P_{Load}} - \mathbf{P_{DER}} \tag{5-3a}$$

$$\mathbf{Q_{node}} = \mathbf{Q_{Load}} - \mathbf{Q_{DER}} \tag{5-3b}$$

The BFS is a deterministic calculation for a single snapshot of the system. Therefore, the load power ($\mathbf{P_{Load}}$, $\mathbf{Q_{Load}}$) and the DER injected power of each node ($\mathbf{P_{DER}}$, $\mathbf{Q_{DER}}$) are sampled from the load profile of each node load type and from the DER profile of the installed DER in each node. The sampling implementation is discussed later in this chapter (section 5.7). Constant power models are assumed for both loads and DER. This model is commonly used for loads in distribution systems planning [5.19], and it is also appropriate to model most distributed generators in steady state operation [5.20], [5.21].

The output arguments of the BFS algorithm are the vectors of node voltages, line and node currents.

Node voltages: $\mathbf{V_{node}}=[V_1, V_2,\ldots,V_i,\ldots V_n]^T$

Line currents: $\mathbf{I_{line}}=[I_{line1}, I_{line2},\ldots,I_{linei},\ldots,I_{linen}]^T$

Node currents: $\mathbf{I_{node}}=[I_{node1}, I_{node2},\ldots,I_{nodei},\ldots,I_{noden}]^T$

The analysis is single phase; all node voltages are phase voltages. It is assumed that the grid voltage V_{grid} is constant. The BFS power flow is implemented as an independent function. Therefore, other power flow calculation for unbalanced or meshed networks can be integrated when required, provided that the output arguments maintain the format and structure mentioned.

5.4.2. Accuracy and Performance

Because of the stochastic evaluation of attributes and the use of an Evolutionary Algorithm, the power flow analysis is performed millions of times in a single DER integration analysis. Therefore, the power flow calculation must be accurate and fast. Three different radial networks were analysed (19, 83 and 355 nodes). Node voltages and power flows were compared with result obtained using two commercial packages: PSS/E and PSCAD. In all cases, the relative errors obtained were less than 0.1%. A single power flow calculation takes between 2 and 3 milliseconds. A whole year simulation (17520 samples) of a 355-node network is performed in around 40 seconds with a voltage resolution of 1e-5 volts in a desktop computer with a 3GHz core-duo processor and 4GB of RAM. It was not possible to find *recent* references to the performances of other power-flow algorithms. Nonetheless, to the knowledge of the author this speed is comparable with other open source power-flow packages, such as PSAT [5.22].

5.5. *Optimal Power Flow (OPF)*

In transmission systems, voltage magnitudes are strongly linked with reactive power flows [5.23]. Hence, voltage control in transmission networks relies mostly on reactive power control. However, in distribution systems the case is different. Distribution networks are characterised by higher R/X ratios and mainly active power flows. As a result, the voltage drop depends both on the active current flowing and the resistance, and also on the reactive power flow and the inductance, as illustrated in Figure 5-5. Consequently, the control of active power generation can provide effective voltage support [5.21] [5.23][5.24].

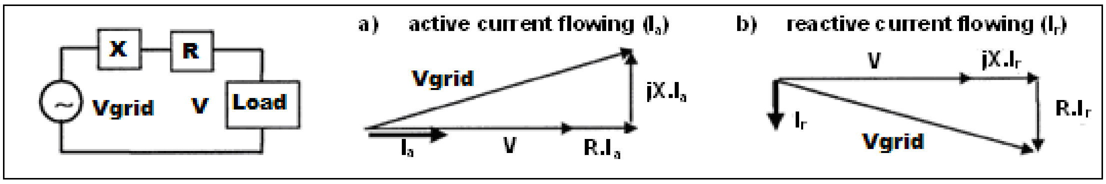

Figure 5-5 Phasor Diagrams for Active and Reactive Power Flows (Adapted from [5.24])

In the centre of Figure 5-5 (case a) it can be observed that when power flows are mainly active and circuits have a high R/X ratio, the voltage drop can be managed by controlling the active power. Hence, in this thesis the possibility to control active DG power to keep the system within operational constraints (voltage/thermal) is explored. Specifically, it is assumed that active power from renewable DER generators can be curtailed, while CHP units can be re-dispatched to support network operation. CHP production is assumed to be heat lead; thus, it must satisfy heat loads and cannot be curtailed. This active power control of DG can be formulated as an optimal power flow (OPF) problem, explained next. A discussion on the technology and implementation of the DG control scheme is not in the scope of this thesis.

5.5.1. OPF Formulation

The objective function of the OPF is:

$$\min f(\mathbf{P}) = C_{dispCHP}\mathbf{P_{disp}} + C_{curtDG}\mathbf{P_{curt}} \tag{5-4}$$

Subject to:

$$\mathbf{V_{min}} \le |\mathbf{V_{node}}| \le \mathbf{V_{max}} \tag{5-5a}$$
$$|\mathbf{I_{line}}| \le \mathbf{I_{max}} \tag{5-5b}$$
$$\mathbf{0} \le \mathbf{P_{disp}} \le \mathbf{CHP_{max}} - \mathbf{CHP_{out}} \tag{5-5c}$$
$$\mathbf{0} \le \mathbf{P_{curt}} \le \mathbf{DER_{out}} \tag{5-5d}$$

where $C_{dispCHP}$ and C_{curtDG} represent the costs of dispatch and curtailment, and $\mathbf{P_{disp}}$ and $\mathbf{P_{curt}}$ represents the vectors of active power dispatched and active power curtailed per node, respectively. $\mathbf{V_{min}}$ and $\mathbf{V_{max}}$ are the constraints for the vector of node voltages $\mathbf{V_{node}}$. $\mathbf{I_{max}}$ is the maximum current transfer capacity of each line, and $\mathbf{I_{line}}$ is the vector of line current flows. $\mathbf{CHP_{out}}$ is the vector of CHP production in each node, while $\mathbf{CHP_{max}}$ is the vector of installed CHP capacities per node.

The difference between $\mathbf{CHP_{max}}$ and $\mathbf{CHP_{out}}$ vectors determine the margin of dispatch per node. $\mathbf{DER_{out}}$ is the vector of renewable power production per node and constrains the maximum power that can be curtailed in each node. These concepts are illustrated for one node in Figure 5-6. Each element of the vectors $\mathbf{DER_{out}}$ and $\mathbf{CHP_{out}}$ varies for every simulated event. The sampling of events within the stochastic simulation is discussed later in this chapter. Only those CHP units with dispatch margin and those renewable generators with curtailable energy are considered as decision variables in every OPF optimisation.

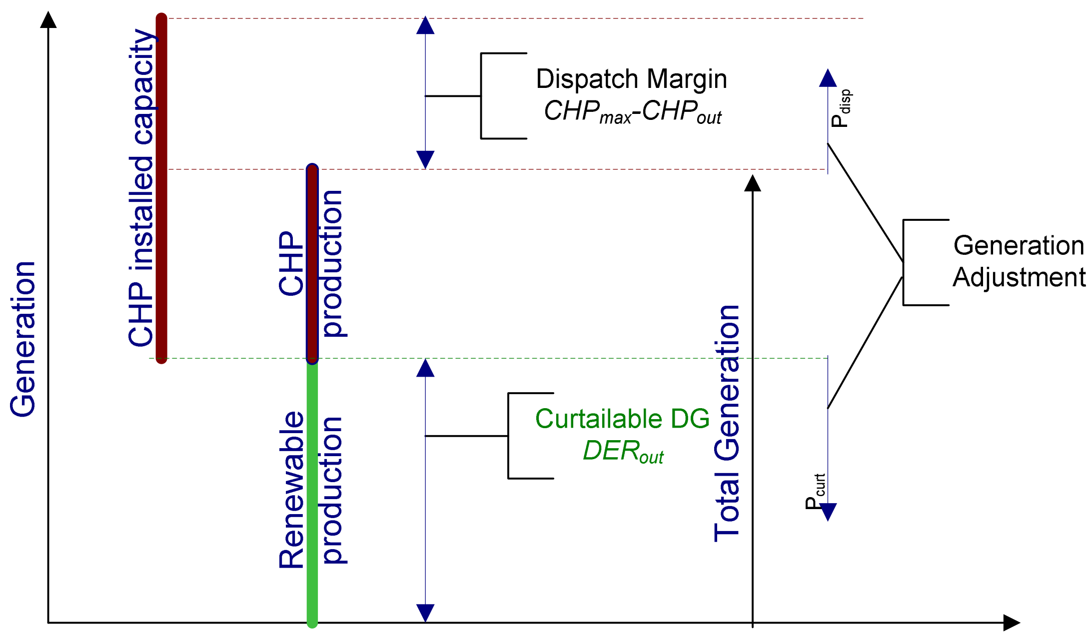

Figure 5-6 CHP Dispatch and Renewable DG Curtailment

The goal of the optimisation is to minimise the total cost of dispatch and curtailment subject to thermal and voltage constraints. This aims at reducing the additional use of fossil fuels and maximising the energy from renewable sources. It is possible to formulate the objective as a pure *power* dispatch/curtailment minimisation, by making costs C_i equal to one. Furthermore, the curtailment and dispatch costs C can be represented as vectors to provide nodal, i.e. localised, price signals for CHP dispatch and DER curtailment. Similarly, it is also possible to use a cost matrix **C** in the stochastic simulation. In that case, the matrix **C** provides localised and time dependant costs for curtailment and dispatch.

5.5.2. Linear Programming OPF

The OPF formulation has a linear objective (5-4) and nonlinear and linear constraints (5-5a and 5-5b; 5-5c and 5-5d, respectively). The nonlinear constraints are based on the AC radial power flow equations, explained in Appendix B. It is possible to linearize these constraints by approximating the voltage and current phasors magnitudes by their real part. The approximation of the voltage magnitude $|V|$ by its real part V^r leads only to small errors when node voltage angles are small with respect to the substation reference voltage ($V^r >> V^i$) [5.16], as illustrated in Figure 5-7. This is the case in normal load flow conditions in distribution systems [5.16].

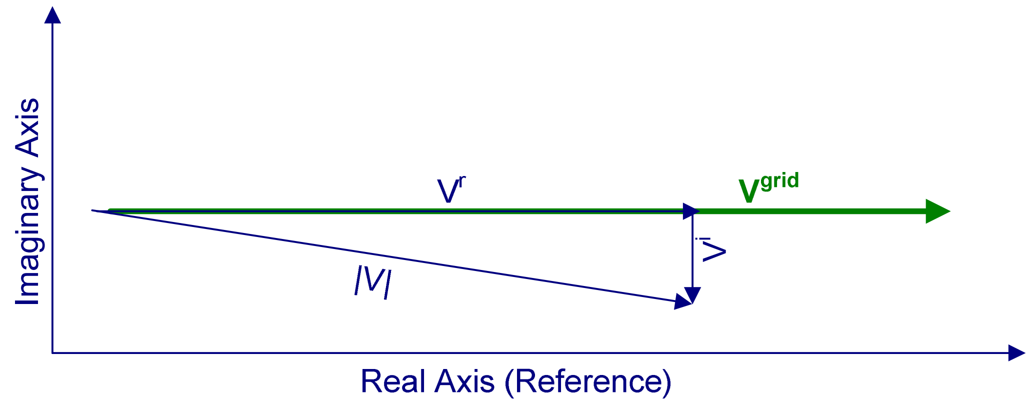

Figure 5-7 Voltage Phasor

These approximations permit the formulation of all objectives and constraints as a linear combination of the decision variables $\mathbf{P_{disp}}$ and $\mathbf{P_{curt}}$. As a result, the OPF can be formulated and solved as a linear programming problem in a standard form, such as:

$$\min f(\mathbf{X}) \tag{5-6}$$

Subject to:

$$\mathbf{AX} \leq \mathbf{b} \tag{5-7a}$$

$$\mathbf{LB} \leq \mathbf{X} \leq \mathbf{UB} \tag{5-7b}$$

Where the decision vector **X** is the dispatched and curtailed power vectors $\mathbf{P_{disp}}$ and $\mathbf{P_{curt}}$. The cost function f(**X**) is formulated by the cost vectors C of equation (5-4). Upper bounds **UB** are defined by equations (5-5c) and (5-5d); lower bounds **LB** are zero. Matrices of coefficients **A** and vectors of limits **b** are a linear function of the voltages and currents vectors *before* the optimisation.

Voltage constraints are expressed as:

$$\mathbf{A}_V\mathbf{P_{disp}} - \mathbf{A}_V\mathbf{P_{curt}} \le \mathbf{b}_{V\mathbf{max}} \tag{5-8a}$$

$$-\mathbf{A}_V\mathbf{P_{disp}} + \mathbf{A}_V\mathbf{P_{curt}} \le \mathbf{b}_{V\mathbf{min}} \tag{5-8b}$$

Where:

$$\mathbf{A}_V = \left(\mathbf{R_T}\left(\frac{\mathbf{V_{node}}^{\mathbf{r}} + \gamma\mathbf{V_{node}}^{\mathbf{i}}}{\left|\mathbf{V_{node}}\right|^2} \right) - \mathbf{X_T}\left(\frac{\mathbf{V_{node}}^{\mathbf{i}} - \gamma\mathbf{V_{node}}^{\mathbf{r}}}{\left|\mathbf{V_{node}}\right|^2} \right) \right) \tag{5-9a}$$

$$\mathbf{b}_{V\mathbf{max}} = (V_{max} - V_{grid})1 + \mathbf{R_T}\mathbf{I^r}_{\mathbf{load}} - \mathbf{X_T}\mathbf{I^i}_{\mathbf{load}} \tag{5-9b}$$

$$\mathbf{b}_{V\mathbf{min}} = (V_{grid} - V_{min})1 - \mathbf{R_T}\mathbf{I^r}_{\mathbf{load}} + \mathbf{X_T}\mathbf{I^i}_{\mathbf{load}} \tag{5-9c}$$

Current flow constraints are expressed as:

$$\left(-\mathbf{A_I}\mathbf{P_{disp}} + \mathbf{A_I}\mathbf{P_{curt}}\right) \le \mathbf{b_{Imin}} \tag{5-10a}$$

$$\left(\mathbf{A_I}\mathbf{P_{disp}} - \mathbf{A_I}\mathbf{P_{curt}}\right) \le \mathbf{b_{Imax}} \tag{5-10b}$$

Where:

$$\mathbf{A_I} = \mathbf{T}\left(\frac{\mathbf{V_{node}}^{\mathbf{r}} + \gamma\mathbf{V_{node}}^{\mathbf{i}}}{\left|\mathbf{V_{node}}\right|^2} \right) \tag{5-11a}$$

$$\mathbf{b_{Imin}} = \mathbf{I_{max}} - \mathbf{T}\mathbf{I^r_{load}} \tag{5-11b}$$

$$\mathbf{b_{Imax}} = \mathbf{I_{max}} + \mathbf{T}\mathbf{I^r_{load}} \tag{5-11c}$$

$\mathbf{V_{node}}$ and $\mathbf{I_{load}}$ are the node voltages and node currents in the network *before* the optimisation. The superscripts r and i denote the real and imaginary parts of the vectors' elements. $\mathbf{R_T}$ and $\mathbf{X_T}$ are resistance and impedance matrices, explained in Appendix C. **T** is the topology matrix, explained in Appendix B and γ is the power factor of the generators (Q/P). The complete derivation of the matrices **A** and **b** is explained in Appendix C.

After the optimisation, node power injections of equation (5-3) are updated with $\mathbf{P_{disp}}$ and $\mathbf{P_{curt}}$ and voltage and power flows are re-calculated by means of the AC power flow algorithm (BFS), as illustrated in Figure 5-11 later in this chapter. Since the problem is nonlinear (voltages and currents depend on the injected powers $\mathbf{P_{disp}}$ and $\mathbf{P_{curt}}$, which in turn depend on voltage and currents), the linear OPF only provides approximations of the optimal dispatched and curtailed powers. A more accurate solution could be obtained by an iterative linear programming formulation, in which voltage and currents in equations (5-9) and (5-11) are updated after each run of the OPF. The accuracy is increased to the detriment of the speed of the algorithm. In contrast, a single iteration provides a fast approximation of optimal dispatch and curtailment. The computation time of the OPF is a key factor for the analysis of controllable DER. This aspect will be discussed further at the end of this chapter.

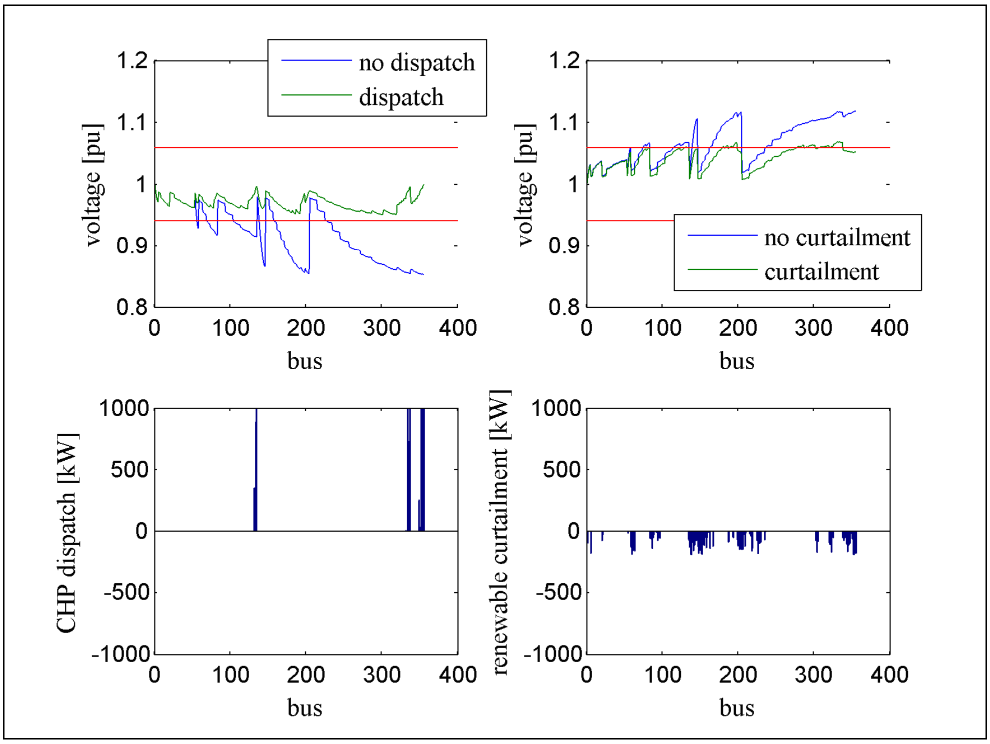

Figure 5-8OPF Example

Figure 5-8 illustrates two examples of optimal CHP dispatch and DER curtailments. Voltage limits are set at +/- 6%. In both cases, voltage constraints were only monitored at critical nodes of the network. Checking only critical nodes of the network reduces the computation time, as explained in the next section. Depending on the particular voltage profile and thermal loading of the grid, optimal DER adjustment solutions can simultaneously include curtailment and dispatch in different parts of the network. As only some node voltages are checked, it is possible that some node voltages will result in small constraint violations, as seen in the right-hand side of Figure 5-8. Hence, it is important to select adequate points in the network to check the voltages, for example, the end of feeders for heavily loaded circuits.

In the planning framework, the OPF is solved using the Linear Programming function of Matlab (*linprog*). Nonetheless, since the problem is expressed in standard form, any commercial optimisation package can be used to solve it. Also, other formulations for this OPF problem are possible, such as a sequential linear programming formulation aforementioned or a nonlinear AC OPF formulation, such as the one proposed by Zhou *et al.* [5.21], in which voltage sensitivities are calculated using the Jacobean matrix.

5.5.3. OPF Validation

The OPF was evaluated under a large and diverse set of DER production and demand situations. A large network was used in the analysis (UKGDS rural network with 355 nodes [5.1]). Twenty thousand different scenarios of under-voltage (dispatch), over-voltage (curtailment) and excessive thermal loading were simulated. This is a comprehensive validation, as situations of over and under-voltage occur only in a small percentage of events (<5%) when a whole year (17520 samples) is simulated.

In cases where an optimal solution is known to exist (i.e. DER can be curtailed or dispatched), it was confirmed that the OPF algorithm corrects the problem and provides a feasible solution. For example, Figure 5-9 and Figure 5-10 show the minimum/maximum voltage before and after the OPF, for cases of dispatch and curtailment, respectively. It can be seen that even in extreme situations of under/over voltage the OPF produces a solution. The maximum thermal loadings in these cases were also analysed and confirmed to be within limits.

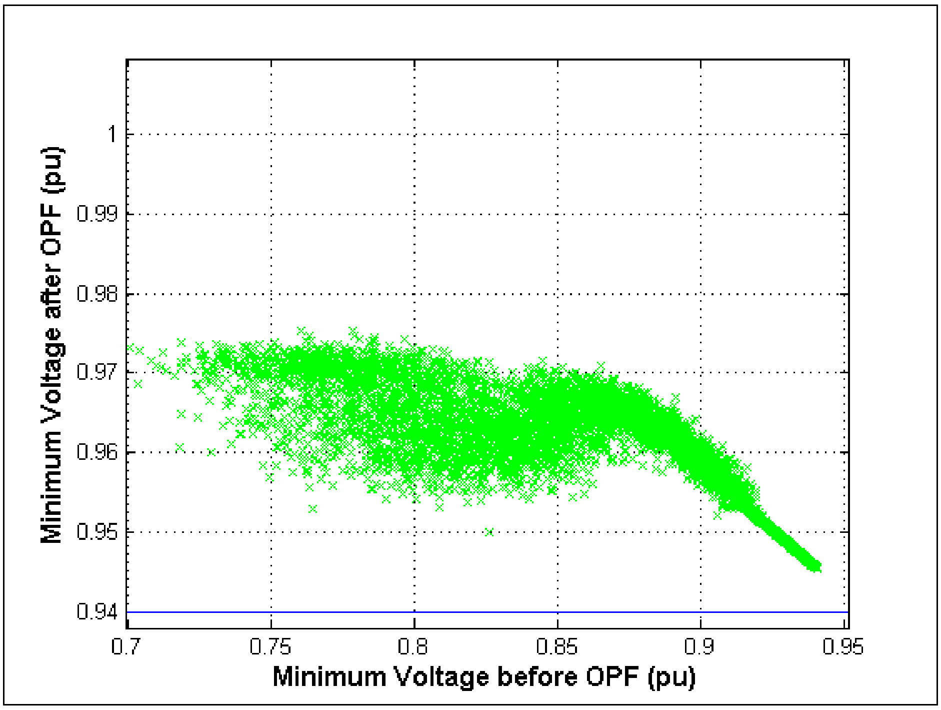

Figure 5-9DER Dispatch – Minimum Voltage Before and After OPF

Several of these cases were studied individually to confirm that the solutions provided are (near) optimal. This verification consisted of placing renewable and dispatchable generators of different costs in the same node or region of the network and confirming that a merit order was followed in the curtailment/dispatch. Finally, diverse scenarios where DER cannot provide network support were simulated. The analysis included scenarios where there is not enough generation to dispatch or when generation cannot be curtailed (e.g. CHP). It was confirmed that in these cases the OPF algorithm couldn't find any optimal solution, because the problem is mathematically unfeasible.

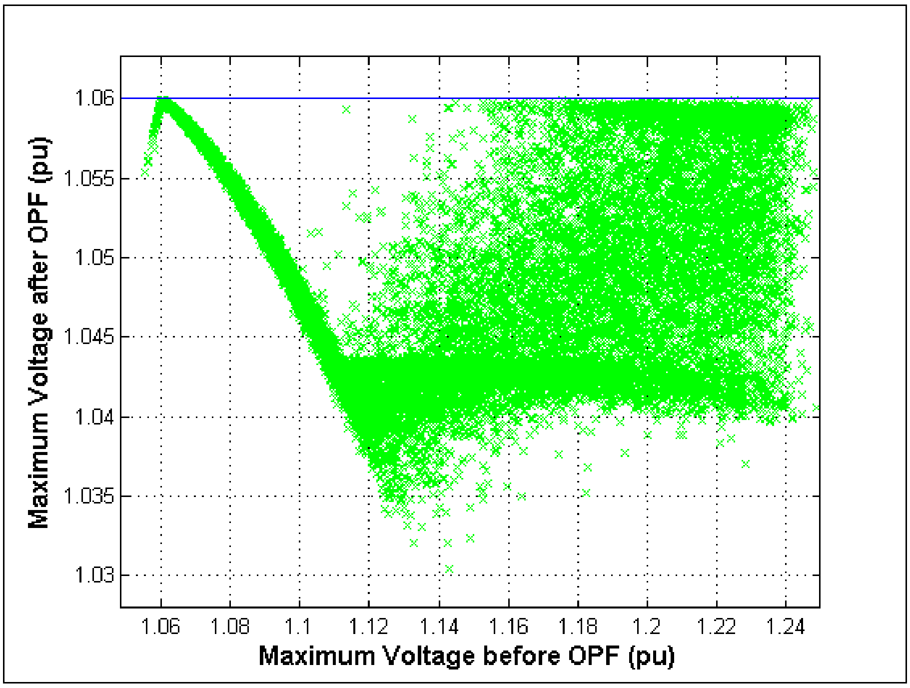

Figure 5-10 DER Curtailment – Maximum Voltage Before and After OPF

5.5.3.1. Post OPF Attribute Calculation

When the network problem can be solved by DER, the OPF produces a dispatch/curtailment solution ($\mathbf{P_{disp}}$ and $\mathbf{P_{curt}}$). Using the solution vectors, the DER power injected in each node is corrected and power flows recalculated using the AC power flow, as already mentioned. In contrast, if DER cannot provide network support, the OPF fails to produce an optimal solution. In this case, planning attributes are calculated based on the initial conditions, as illustrated in Figure 5-11.

Following this procedure, a true multi-objective analysis of the problem is provided. Solutions that can provide network support are suboptimal in terms of dispatched and curtailment energy (assuming these are to be minimised), but have improved values of line losses, voltages and thermal loadings. In contrast, solutions that are not able to provide network support in extreme situations have zero dispatch or curtailment power and cost; they are optimal in these attributes. Nonetheless, these solutions are penalised in other technical attributes such as line losses, probability of voltage violations and maximum voltages and thermal loadings.

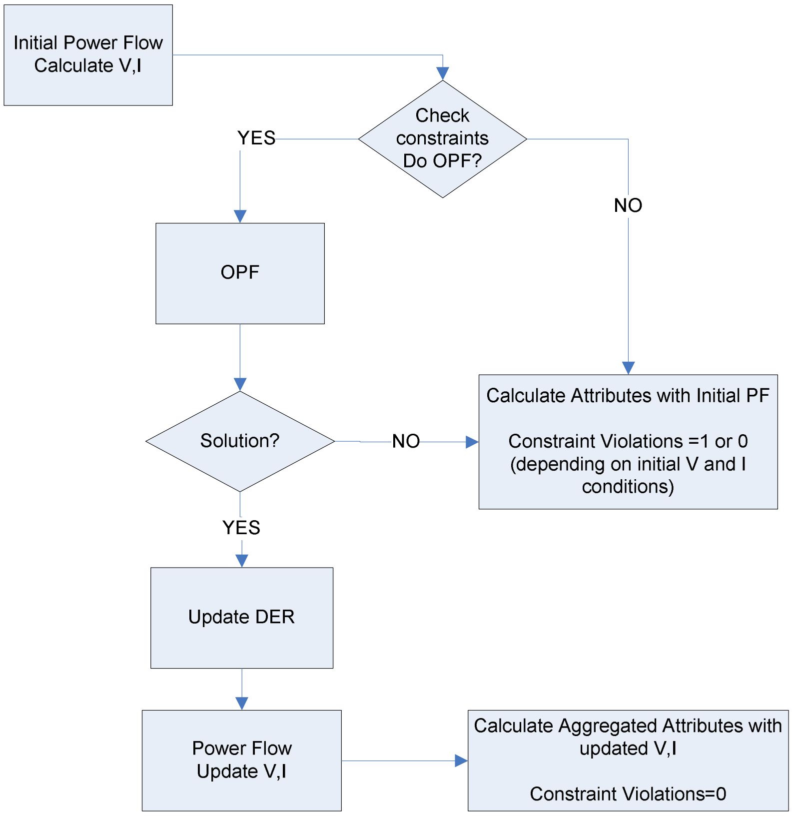

Figure 5-11 Post OPF Attribute Calculation

5.5.4. OPF Performance

The resolution of one OPF for the 355 node UKGDS network takes between 5 and 20 seconds, depending on the number of DER units analysed and if all nodes voltages are considered as optimisation constraints, in a desktop computer with a 3GHz core-duo processor and 4GB of RAM. The *linprog* algorithm uses more time when it is unable to find an optimal solution (i.e. the optimisation problem is unfeasible), as iterations are performed until a maximum limit is reached. A lengthy evaluation can be acceptable when the interest lies in a single solution. However, when hundreds of solutions need to be evaluated, reducing the computation time is crucial. Therefore, additional steps to reduce the computation time are proposed.

First, computing unsolvable optimisation problems requires the most computation, and it is unnecessary. Therefore, an "OPF check" routine is implemented to identify unfeasible optimisation problems prior to the execution of the OPF. Only two power flows are necessary to check these conditions, as seen in Figure 5-12. Hence, the OPF is only performed if there is at least one generator to dispatch or one generator to curtail and if one of the following conditions applies:

- The problem is only an over-voltage problem, and it can be solved by curtailing all curtailable generation (i.e. a feasible solution exists).
- The problem is only an under-voltage problem and it can be solved by dispatching all dispatchable generators (i.e. a feasible solution exists).
- There exists problems of over and under-voltage simultaneously.
- There exists a problem of thermal congestion in lines

Second, the OPF computation time depends on the number of variables and constraints included in the formulation. Thus, as a simplification, voltage constraints are only checked at certain ‘nodes of interest’, usually critical nodes of the network: end of laterals, main feeders. Reducing the number of voltage constraints enhances greatly the performance of the algorithm. For example, considering only six nodes in the 355-node network reduces the computation time of each OPF to an average of 0.4 seconds. The assumption is solid, as voltages in adjacent nodes of the network are interrelated. Checks that are more extensive could be made, to the detriment of the speed of the algorithm. Thermal constraints are still checked in all lines.

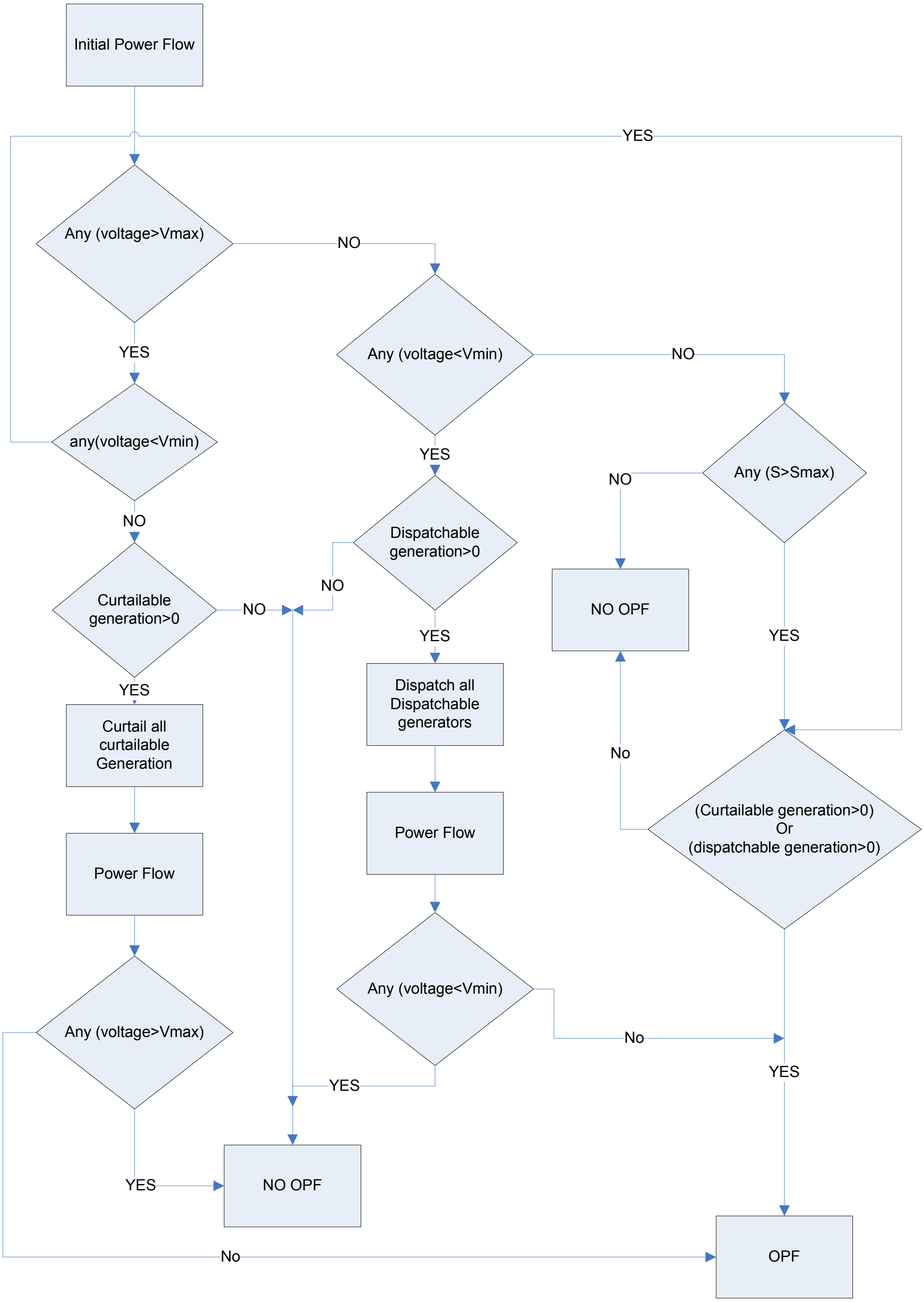

Figure 5-12 OPF Feasibility Check

5.6. *Planning Attributes*

5.6.1. Technical Attributes

The calculation of the technical attributes, listed in Table 5-3, is based on the vector outputs of the BFS power flow ($\mathbf{V}_{\mathbf{node}}$, $\mathbf{I}_{line}$, $\mathbf{I}_{node}$), the OPF algorithm ($\mathbf{P}_{curt}$, $\mathbf{P}_{disp}$), information about DER sizes and locations provided by the chromosome (**CP**), and a vector of capacity factors of each DER type (**CF**). Attributes have been divided according to their calculation procedure, and each one is explained next.

Table 5-3Technical Attributes

Attributes	Units
DER Energy penetration	%
Line Losses	MWh/year
Imported Energy	MWh/year
Exported Energy	MWh/year
Grid dependency (total energy flow trough network connections)	MWh/year
Curtailed energy	MWh/year
Dispatched energy	MWh/year
Network over voltage Probability	%
Maximum voltage violation	V
Network overload probability	%
Maximum thermal violation	%

5.6.1.1. DER Energy and DER Penetration Level

The ratio of DER installed over the system load is a measure of the level of DER penetration. Some authors define this ratio in terms of installed DER capacity over peak load (e.g. [5.25]). Nonetheless, when several types of DER are integrated and each type has a different capacity factor it is more illustrative to express the penetration level as the ratio of annual DER energy to annual load. The total DER energy produced in the whole network can be determined by:

$$E_{Total} = k \cdot \mathbf{CF} \times \mathbf{CP} \tag{5-12}$$

where **CF** is a horizontal vector of the capacity factor of each DER type. Each element of **CF** corresponds to the average of the production profile of each DER type normalised in terms of the capacity. **CP** is a vertical vector of installed DER per type, calculated as the sum of the rows of the **CDER** matrix (equation 5-1); *k* is a conversion factor to obtain daily, monthly or annual energy values. In this work annual values are analysed, so, k=8760 hours/year.

The penetration level of DER in terms of total DER energy is calculated as:

$$penetrationLevel_{DER} = \frac{\mathbf{CF} \times \mathbf{CP}}{\mathbf{LF} \times \mathbf{LP}} \times 100 \tag{5-13}$$

LF is a horizontal vector of the load factor of each load, calculated as the average of each load profile; and **LP** is the vertical vector of peak loads at each node. The annual conversion factors *k* in the numerator and denominator cancel each other.

The energy produced by each DER type is calculated as the dot multiplication of the capacity vector **CP** by the transposed of the vector **CF**:

$$\mathbf{E}_{\mathbf{Type}} = k \cdot \mathbf{CF}^{T} \cdot \mathbf{CP} \tag{5-14}$$

$\mathbf{E}_{\mathbf{Type}}$ is a vertical vector; therefore, each row is the energy produced by each DER type. The annual energy production per type is used to determine the CO_2 emissions, explained later in this chapter. If required the penetration level of each type of DER can be calculated using the $\mathbf{E}_{\mathbf{type}}$ vector, or for each type of energy resource (e.g. renewable, fossil fuel, CHP, etc) using a similar approach.

In some single-objective analyses reviewed in Chapter 3 DER penetration level, or a similar attribute (e.g. DER capacity, DER energy), is formulated as a maximisation objective, subject to network constraints. In those cases, DER penetration level is maximised to make the most of the associated benefits of DER (e.g. reduction of CO_2 emissions, renewable energy production). Nonetheless, in a multi-objective analysis the impacts and benefits of DER are explicitly formulated as objectives. Hence, two perspectives are possible. These are explained next.

DER Penetration Level Minimisation

When DER penetration level is formulated as a minimisation objective, it is possible to find the minimum DER penetration level required to achieve a certain value in other planning attributes. Or expressing this trade-off analysis from another perspective: the optimal attainment level of other planning attributes for each level of DER penetration is determined. The discussion is illustrated in Figure 5-13, with a DER penetration level minimisation and loss-minimisation optimisation example. The calculation of annual power losses is explained in later section.

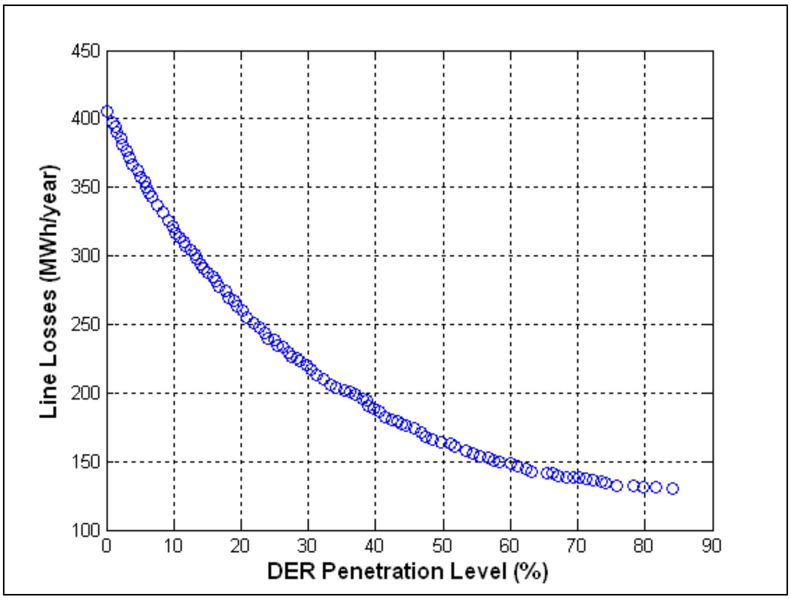

Figure 5-13 DER Penetration Level Minimisation Example

DER Penetration Level Maximisation

If DER penetration level is maximised, and objectives are contradictory, the analysis determines the maximum DER penetration level that can be installed without degrading the system technical, environmental or economic performance, reflected in the other objectives. The analysis is illustrated in Figure 5-14; in this case, DER penetration level is maximised. Line losses are still being minimised subject to network constraints. Hence, it is possible to determine the maximum amount of DER that the system can absorb with a determined amount of losses.

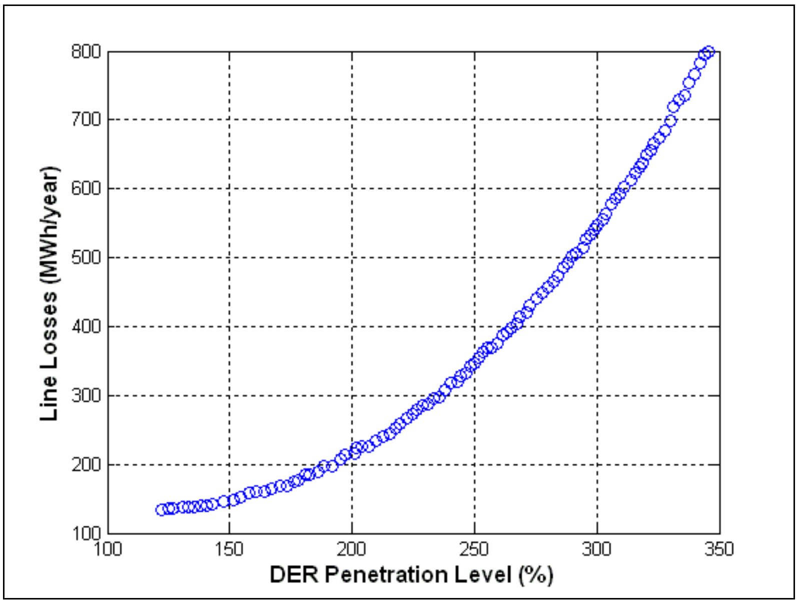

Figure 5-14 DER Penetration Level Maximisation Example

If there is no contradiction between DER penetration maximisation and other objectives (e.g. maximisation of energy exports and minimisation of CO_2 emissions, when only renewable DER is considered), the problem is no longer multi-objective. In that case, only a single optimal solution exists: to install as much generation as the system can technically accept. Single-objective problems or problems with non-conflicting objectives are not considered in this thesis or in the case studies of the next chapter.

5.6.1.2. Aggregated Energy Attributes

Aggregated energy attributes are calculated by means of a stochastic simulation of the power system. The stochastic simulation consists of a repetition of n deterministic power flows, referred as samples. The samples are averaged and by means of conversion factors, the planning attributes over a *simulated period* (e.g. a year) are estimated.

Line Losses

The minimisation of active line losses is one of the chief objectives of DER planning, as already discussed in Chapter 3 (section 3.3.2.1). Active line losses depend on the magnitude of the current and the line resistance. At every simulation event t, the total line losses in the system are calculated as:

$$Losses_t = 3\left|\mathbf{I_{line}}\right|^2 \times \mathbf{R} \tag{5-15}$$

$|\mathbf{I_{line}}|$ is a horizontal vector of line current magnitudes; $\boldsymbol{R}$ is a vertical vector of line resistances, calculated as the real part of the diagonal of the impedance matrix **Z**. The system is assumed to be 3-phase balanced; so, a factor of 3 is added to compute the system losses. If the network is single phase (phase and neutral) a factor of 2 must be used instead [5.16].

The yearly losses are calculated by aggregating the losses determined for each event:

$$YearLosses = \frac{8760}{n}\sum_{t}^{n} Losses_t \tag{5-16}$$

where n is the number of simulations. 8760 is the conversion factor (hours/year) used to translate average power losses (W) to annual energy losses (Wh/year).

Losses caused by the current and impedance of the lines are known as variable line losses or "cooper losses" [5.16]. From these, only active energy losses are computed, as these are the ones of most interest for DSOs. Reactive line losses (the product of the current magnitude and the reactance X) are not analysed. Iron losses, also known as fixed losses, caused by the magnetisation currents in the transformers and reactors, are not computed.

Imported and Exported Energy

When a radial distribution system is analysed, the active power flow in the network connection at any instant t can be calculated as:

$$GridPower_t = 3Re\left(V_{grid}(I_{grid})^*\right) \tag{5-17}$$

where I_{grid} is the current flowing through the network connection and V_{grid} is the fixed voltage of the network connection (phase voltage).

I_{grid} can be calculated as the sum of all the elements of the vector of node currents I_{node}:

$$I_{grid} = \sum_{node} \mathbf{I_{node}} \tag{5-18}$$

$\mathbf{I_{node}}$ is computed by the BFS algorithm. A positive element in $\mathbf{I_{node}}$ represents current flowing to the node (load); while a negative element represents current flowing from the node (DER). Thus, if the net sum I_{grid} is positive, active power is being imported from the grid connection and vice versa.

The energy flow through the grid connection *GridPower* is calculated for every simulation event *t*. Then, it is possible to aggregate imported and exported energy over the simulated period:

$$ImportedEnergy = \frac{8760}{n}\sum_{t}^{n} GridPower_t \qquad \forall GridPower_t > 0 \tag{5-19a}$$

$$ExportedEnergy = \frac{-8760}{n}\sum_{t}^{n} GridPower_t \qquad \forall GridPower_t < 0 \tag{5-19b}$$

Imported and exported energy are always positive values. Imported energy is formulated as a minimisation objective to maximise the use of local resources. Exported energy can be formulated either as a minimisation or maximisation objective, depending on the perspective of the study. If the exploitation of local renewable energy resources is encouraged, exported energy is formulated as a maximisation objective (e.g. [5.26]). In contrast, if the objective is to achieve the best energy balance between local DER production and demand, exported energy and imported energy should both be minimised. Consequently, a further objective of “grid dependency” minimisation can be formulated by minimising the sum of imported and exported energy:

$$GridDependancy = ImportedEnergy + ExportedEnergy = \frac{8760}{n}\sum_{t}^{n} \left|GridPower_t\right| \tag{5-20}$$

This attribute quantifies the degree of independence of the studied grid by measuring the total amount of energy interchanged with the main system.

Dispatched and Curtailed Energy

Whenever an OPF is successfully performed, a vector of optimal power curtailment $\mathbf{P_{curt}}$ and a vector of optimal power dispatch $\mathbf{P_{disp}}$ are produced. The aggregation of the sum of these vectors' elements over the simulation determines the yearly curtailed and dispatched energy in the network, respectively:

$$CurtailedEnergy = \frac{8760}{n}\sum_{t}^{n}\sum_{node}\mathbf{P}_{\mathbf{curt}t} \tag{5-21a}$$

$$DispatchedEnergy = \frac{8760}{n}\sum_{t}^{n}\sum_{node}\mathbf{P}_{\mathbf{disp}t} \tag{5-21b}$$

Both objectives are formulated as minimisation in the multi-objective planning framework. The minimisation of curtailed energy aims at maximising renewable energy production. The minimisation of dispatched energy aims at minimising the additional use of fossil fuels. Note that these objectives are technical and formulated in terms of energy. Cost objectives are discussed in a later section.

Energy Balance

The energy balance requires that at any moment in time, and hence over any time period, the energy generated within and imported to the system (IN) must be equal to the energy consumed within the system plus energy exports and losses (OUT), as illustrated in Figure 5-15. Hence, the following equality must always be satisfied:

$$\begin{aligned} E_{Total} + DispatchedEnergy - CurtailedEnergy + ImportedEnergy = \\ ExportedEnergy + TotalLoad + YearLosses \end{aligned} \tag{5-22}$$

Where *TotalLoad* is the annual energy demand, calculated as $8760 \times \mathbf{LF} \times \mathbf{LP}$, and the rest of the variables have been explained previously. This condition was used to verify the correct implementation of the stochastic evaluation. Moreover, the energy balance is used later to determine the emission factors.

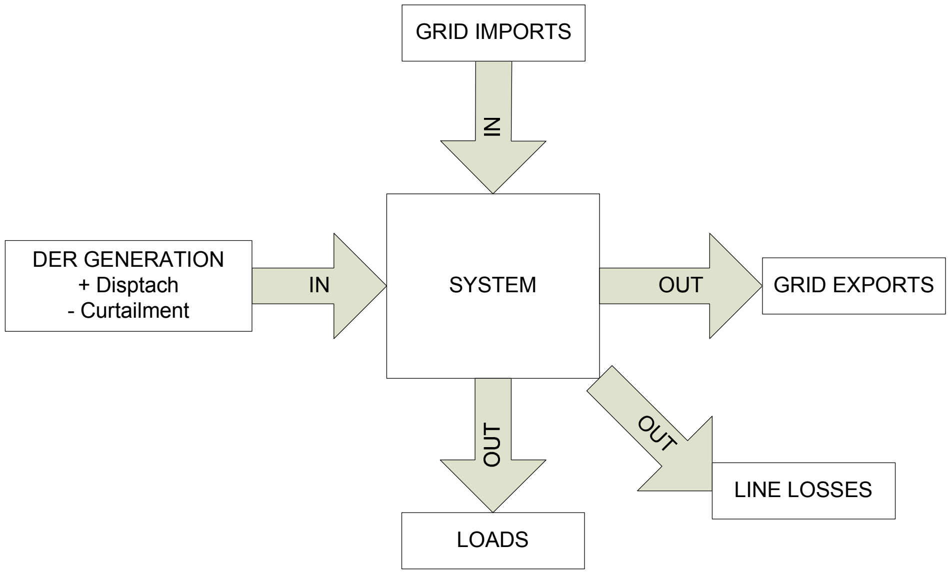

Figure 5-15 System Energy Balance

5.6.1.3. Voltage Impacts and Thermal Loading Attributes

DER optimally located and sized can reduce node voltages and power flows, as long as DER production is coincident with demand. In contrast, DER suboptimally located or sized, or whose production is not coincident with demand, increases voltages and power flows. The second group of technical attributes measure these benefits and impacts of DER installation. Deterministic and probabilistic measures of voltage profile improvement and power flow reduction are proposed as attributes, as explained next.

Maximum Voltage Deviations and Maximum Thermal Loading

As a deterministic measure of DER impact, the network maximum voltage deviation and the maximum line loadings over the *whole* simulated events are recorded:

$$VDeviation_{\max} = \max_t \left[\max_{node} \left(\frac{\left|\mathbf{V}_{\mathbf{node}_t}\right| - V_{reference}}{V_{reference}} \right) \right] \times 100 \qquad (5\text{-}23a)$$

$$TLoading_{\max} = \max_t \left[\max_{line} \left(\frac{\left|\mathbf{I}_{\mathbf{line}_t}\right|}{\mathrm{I}_{max}} \right) \right] \times 100 \qquad (5\text{-}23b)$$

Both variables are expressed as percentages. Voltage deviations are measured from a reference voltage, $V_{reference}$, usually one per unit. The thermal loading of each line $\mathbf{I_{line}}$ is compared with the maximum current carrying capacity of the conductors $\mathbf{I_{max}}$. The attributes proposed can be used either as planning objectives to provide a measure of DER impacts, or as deterministic planning constraints to restrict DER sizes using the technical limits of the network.

These attributes are not exactly the same as performing a worst-case scenario analysis. A worst-case scenario analysis consists in two power flow calculations: minimum generation/maximum load and maximum generation/minimum load. It provides a measure of the worst *possible* event, which can have a very low probability of occurrence. In contrast, the attributes proposed provide a measure of the worst *likely* event, given the number of samples simulated and the period of the analysis. The values provided by the proposed attributes are a less extreme measure than a worst-case scenario analysis.

Probabilistic Attributes of Voltage and Thermal Violation

The attributes proposed in the previous section measure an extreme occurrence in a single node or line, without indicating what the probability of this occurrence is. Consequently, a set of probabilistic attributes is proposed in this section to quantify the probability of constraint violations. These attributes are formulated as minimisation objectives, as an increment in the network quality is looked for. The probability of voltage constraint violation is calculated as the ratio of the number of simulation events in which *any* node had a voltage violation over the number of total simulated events *n*.

$$VDeviation_{prob} = \frac{\sum_t Vbreak_t}{n} \times 100 \tag{5-24a}$$

$$Vbreak_t = \begin{cases} 1 & if\left(\left(any(\mathbf{V_{node_t}} > V_{\max}\right) or \left(any(\mathbf{V_{node_t}} < V_{\min}\right)\right) \\ 0 & otherwise \end{cases} \tag{5-24b}$$

Similarly, the probability of thermal limit violations is calculated as the ratio of the number of simulation events where *any* line was outside limits over the total number of simulation events *n*:

$$TLoading_{prob} = \frac{\sum_{t} Ibreak_{t}}{n} \times 100 \tag{5-25a}$$

$$Ibreak_{t} = \begin{cases} 1 & if \left(any(\mathbf{I}_{\mathbf{line}_t} > I_{\max}) \right) \\ 0 & otherwise \end{cases} \tag{5-25b}$$

These attributes measure the probability of *any* node/line in the sy*stem* being out of bounds. The probability of *a particular node/line* being out of bounds is equal or lower to the probability *of the system* being out of bounds. Thus, the attributes proposed provide a measure of the *worst* performance of a node/line in the system. If a particular set of nodes/lines are the interest of the study, the probability of them being out of bounds can be formulated as a separate attribute, using a similar approach. Likewise, in large systems it is possible to divide the network into zones, and calculate separate probabilistic attributes for each zone.

These attributes can be used as planning objectives or planning constraints, as mentioned in the previous chapter. As objectives, they provide a more comprehensive measure of DER technical performance than the deterministic attributes proposed in the previous section or than a worst-case scenario analysis. As constraints, the probabilistic attributes allow the study of probabilistic limits, such as the ones proposed by the EN 50160 regulation, already discussed in the previous chapter. These constraints avoid restricting DER penetration based on extreme situations with low probability of occurrence, such as a worst-case scenario analysis.

5.6.2. Environmental Attributes

One of the main drivers behind DER installation is the possibility of minimising the environmental impacts of energy production. Hence, two attributes are proposed to measure these environmental benefits: a total CO_2 emission factor ($Total_{CO2}$) and a load CO_2 emission factor ($Load_{CO2}$).

Table 5-4 Environmental Attributes

Attributes	Units
CO_2 emissions factor (load)	gCO_2/kWh
CO_2 emissions factor (total)	gCO_2/kWh

$Total_{CO2}$ quantifies an equivalent emission factor for the total energy flow in the system (in or out). In contrast, $Load_{CO2}$ quantifies the emission factor attributable *only* to the energy consumed within the system. The calculation procedure of each attributed and the key differences between them are explained next.

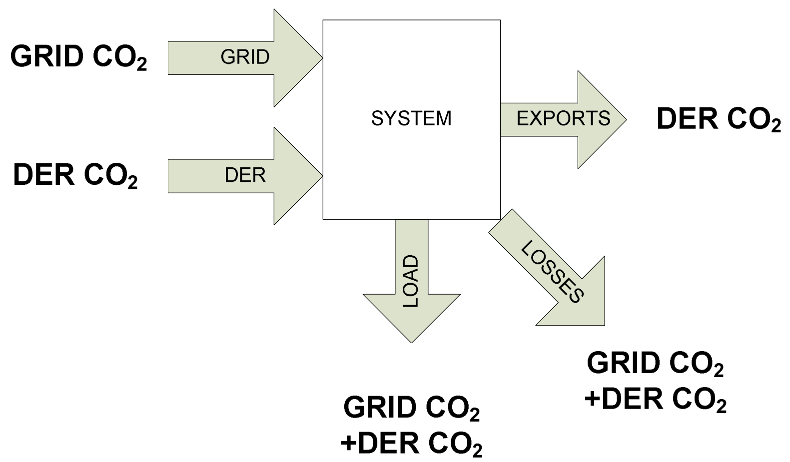

Figure 5-16 System CO_2 Emissions Balance

The attributes are calculated based on the energy balance of the system, previously illustrated in Figure 5-16. The energy imported from the grid to the system can be allocated direct CO_2 emissions, based on the 'carbon intensity' of the grid energy ($grid_{CO2}$). Similarly, the energy generated by DER can be attributed an average carbon emissions factor (DER_{CO2}). The grid carbon intensity depends on the central system energy mix and the system losses. In the UK, this factor is expressed as a yearly average value of grams of CO_2 per unit of energy, currently set as 430 gCO_2/kWh [5.27] (long-term marginal emissions factor). This factor is assumed constant and not affected by DER penetration. Nonetheless, if large penetration of DER will reduce the dispatch of central units, the grid carbon intensity should be modified accordingly [5.28].

The energy generated by DER has an average emission factor DER_{CO2}, calculated as the ratio of the total CO_2 emissions of DER over the total energy generated and dispatched:

$$DER_{CO2} = \frac{8760 \cdot \mathbf{EF} \times (\mathbf{CF}^T \cdot \mathbf{CP}) + DispatchedEnergy \times EF_{CHP}}{E_{Total} + DispatchedEnergy - CurtailedEnergy} \tag{5-26}$$

CF and **CP** have already been introduced. **EF** is a horizontal vector of the emission factor of each type of DER, provided in the input file. The DER emissions factor of each DER unit installed depends on the technology and fuel used. Renewable units are assumed to be carbon-free [5.28] ($EF_{renewable} = 0$). So, in this case the emissions are only attributed to the CHP units. In the case of CHP units, the analysis is more complex, as the emissions apportioned to the electrical energy generated depend also on the heat production, and on the alternative energy supplies. Pout *et al.* [5.29] studied extensively different conventions used for apportioning carbon emissions from CHP systems. This study concluded that the only valid convention is that carbon intensities of electricity and heat production should be proportional to those of the alternative supplies. For example, if the total CHP emissions are 67% of the combined emissions of alternative sources, the CHP intensities for electricity and heat should be 67% of the respective emission factors of the alternative sources. [5.29]. The emission factors of the CHP units considered in the case studies of next chapter are EF_{CHP}=300 gCO_2/kWh, and EF_{CHP}=326 gCO_2/kWh. Details of the CHP units are provided in the next chapter.

5.6.2.1. Total Energy Emission Factor

An equivalent emission factor for the *total* energy flow can be calculated by dividing all the carbon emissions (imported and generated by DER) by the total energy flow (input or output, as these are equal):

$$Total_{CO2} = \frac{ImportedEnergy \times grid_{CO2} + TotalDEREnergy \times DER_{CO2}}{ExportedEnergy + TotalLoad + YearLosses} \tag{5-27}$$

The imported energy is calculated using equations (5-16a). *TotalDEREnergy* is the denominator of equation (5-26), which accounts for the energy generated by DER plus the energy dispatched minus the energy curtailed. All carbon emissions imported and generated are accounted in the numerator of equation (5-27), while the denominator includes all the energy in the system (in this case, consumed and exported). So, $Total_{CO2}$ calculates an equivalent emissions factor for the *total* energy flow. This emissions factor does not represent the load emission factor (explained next) or the exported energy emissions factor, as only DER energy is exported, as seen in Figure 5-16.

5.6.2.2. Load Emissions Factor

The CO_2 emissions attributed to the load and the losses ($Load_{CO2}$) depend on the total energy imported from the grid and the fraction of the DER energy that was not exported. Hence, the load emissions factor is:

$$Load_{CO2} = \frac{ImportedEnergy \times grid_{CO2} + (TotalDEREnergy - ExportedEnergy) \times DER_{CO2}}{TotalLoad + yearLosses} \qquad (5\text{-}28)$$

All the terms of the equation have been already explained. This attribute is only an approximation, as it could occur that only some types of DER are exported. Nonetheless, it is sufficient for the purposes of the planning framework.

There is a key difference between $Total_{CO2}$ and $Load_{CO2}$. $Load_{CO2}$ provides an indication of the carbon intensity of the energy *consumed within* the system. This attribute does not consider energy exports. Hence, its minimisation looks for the best energy mix to provide a low-carbon supply for the load of the studied system only. The optimal energy mix will be highly dependent on the coincidence of low-carbon DER production and demand. In contrast, $Total_{CO2}$ considers energy exports. It assumes that all energy is consumed not only in the system but also elsewhere. Hence, the minimisation of $Total_{CO2}$ results in the installation of as much low-carbon DER as possible, subject to the system constraints. The use of either attribute depends on the objectives of the analysis.

Both attributes ($Total_{CO2}$ and $Load_{CO2}$) provide an indication of the total carbon reduction, and can be expressed as a percentage of the initial grid carbon intensity. Moreover, the total carbon emissions (in tonnes per year) could also be used as a planning attribute. Only direct CO_2 emissions are taken into account in the attributes proposed. Direct CO_2 emissions are the ones produced when generating energy. In contrast, life cycle analysis (LCA) emissions include the total CO_2 emitted during the manufacturing, transport, installation and disposal of the DER units (a "cradle to grave" analysis [5.30]). The calculation of lifecycle emissions of different distributed generation technologies and DER has gained attention recently and it is still ongoing research. LCA emissions could be included as a planning attribute once information is available for the DER technologies analysed.

5.6.3. Economic Attributes

In an analysis of DER integration, it is essential to compare the technical and environmental benefits of DER with the cost of obtaining them and with the negative impacts of DER. In a multi-objective analysis, technical and environmental benefits can be explicitly formulated in their natural units, as demonstrated throughout in this chapter. Hence, it is possible to explicitly visualise the trade-offs between DER costs and these technical and environmental benefits. Similarly, the technical impacts of DER integration can be compared against the technical or economic benefits that could be obtained when integrating DER.

Economic benefits and costs of DER can be analysed from several perspectives, depending on which costs/benefits are included in the analysis, how these are aggregated and which point of view is included in the analysis (e.g. DSO, DER developer). In this thesis, three economic attributes have been chosen as a representative sample. These are presented in Table 5-5. The first two attributes analyse the costs of DER integration, using two different approaches. No assumption is made about who incurs in the costs. The third attribute provides a measure of net economic DER benefits, from a DER developer perspective.

Table 5-5 Economic Attributes

Attributes	Units
Annualised cost of DER	£/year
Levelised cost per kWh of DER	£/kWh
Annualised DER net benefits	£/year

The calculation of attributes in Table 5-5 includes the capital cost of DER installations plus future operation and maintenance costs. In addition, future benefits are considered in the third attribute. Installations costs are assumed to happen at the beginning of the evaluation period (or year zero) while other costs and benefits occur at different times in the future (Figure 5-17). To accurately compare these costs and benefits, it is necessary to translate them to comparable values. Two methods are commonly used. The first is to convert all cash flows into present values. In the second method, used in this thesis, all investments and cash flows are converted into annuities (i.e. equal annual values). Both methods are based on the concept of the time value of money (TVM). A succinct introduction to TVM is provided in Appendix A.

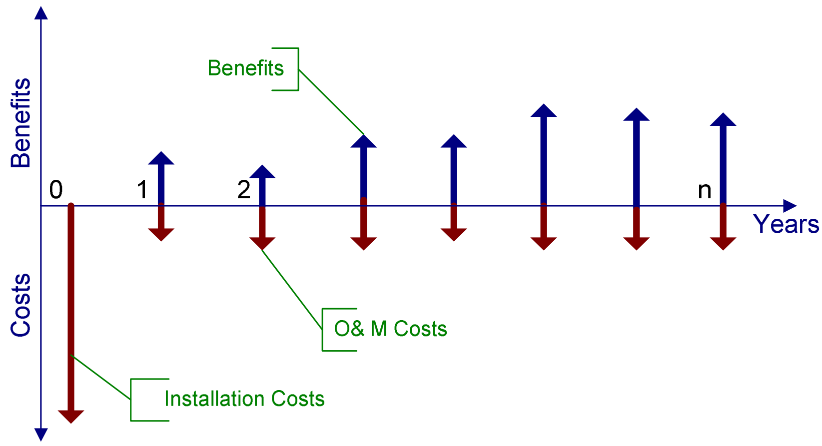

Figure 5-17 Costs and Benefits of a DER Installation

5.6.3.1. Annualised Cost of DER

Cost is "the total sacrifice that must be expended or traded in order to gain some desired product or end result" [5.19]. The first economic attribute ($Cost_{DER}$) provides a measure of the spending required by the DER configuration to gain the technical and environmental benefits provided by DER. $Cost_{DER}$ includes the installation costs of DER plus all future operation, maintenance and fuel costs. The costs of all DER installations are aggregated into a single attribute; hence, a high-level perspective on the total DER cost is provided without making any assumption of who incurs in the costs. All costs are expressed as annual values:

$$Cost_{DER} = Annuity(Cost_{Inst}) + Cost_{O\&M} \tag{5-29}$$

Installation costs ($Cost_{Inst}$), include the cost of all the DER equipments plus costs of installing each DER system (e.g. infrastructure, connection, land). Commonly, installation costs are expressed per unit of capacity (i.e. £/kW). Therefore, the total installation costs can be determined by multiplying the total installed DER (per type) **CP** by the installation cost per kW of each DER type **IC**:

$$Cost_{Inst} = \mathbf{IC} \times \mathbf{CP} \tag{5-30}$$

IC is a horizontal vector of unit cost of capacity of each DER type, which is provided in the input file. This calculation assumes a similar installation cost per capacity unit for all units of the same type, regardless of size. Nonetheless, economies of scale can be included by separating the rows of the vector **CP** according to capacity size ranges for which different unit prices are defined. Then, the expanded vector **CP** is multiplied by the respective installation costs per unit **IC** to obtain the total installation cost.

All installations are assumed to happen at year zero. Installation costs are translated to annuities using the annuity conversion factor described in Appendix A. The useful life of DER is assumed as 20 years; a discount rate of 7% was chosen to calculate the annuities [5.31]. Representative installation costs for different DER types are presented in the next chapter.

Operation and maintenance costs ($Cost_{O\&M}$), include the non-fuel operation and maintenance costs of DER installations, such as: plant labour, inspection, replacement and repair of system components and consumables. Also, in the case of fossil-fuelled DER, fuel costs are included. Operation and maintenance costs are commonly expressed per unit of energy produced (£/kWh) or as a percentage of capital costs (%) [5.32]. Therefore, this attribute is calculated using the values obtained in equation (5-21) or equation (5-29), depending in which way unit O&M costs are expressed. Although in practice these costs vary from year to year, they are normally considered constant for every year.

Curtailment and Dispatch Costs

In Figure 5-18 the bulk costs and revenues of energy provision and dispatch/curtailment are illustrated. The energy supply costs are incurred to deliver energy to the system, as seen in the bottom centre of Figure 5-18. In addition, if the active management of DER to manage voltage and thermal constraints is considered, extra costs are incurred to provide these ancillary services, as seen in the top of the same figure. If DER units are assumed controllable, the cost of the installation of the DER management scheme has to be added to the installation costs. This cost includes voltage measurement schemes, communication links between DER and DSO control and communication between DSO control and substation. These costs have been estimated at £10,000 per DER unit for rural systems, and £100,000 per substation for urban grids [5.31].

Moreover, the dispatch of generators to overcome under-voltage and overflow situations requires the generation of an extra amount of energy. The generation of this energy has a higher cost per unit than the energy produced in normal operation, as the wear-off of equipment due to the cycling of the units must be considered [5.33] on top of the normal fuel and O&M costs.

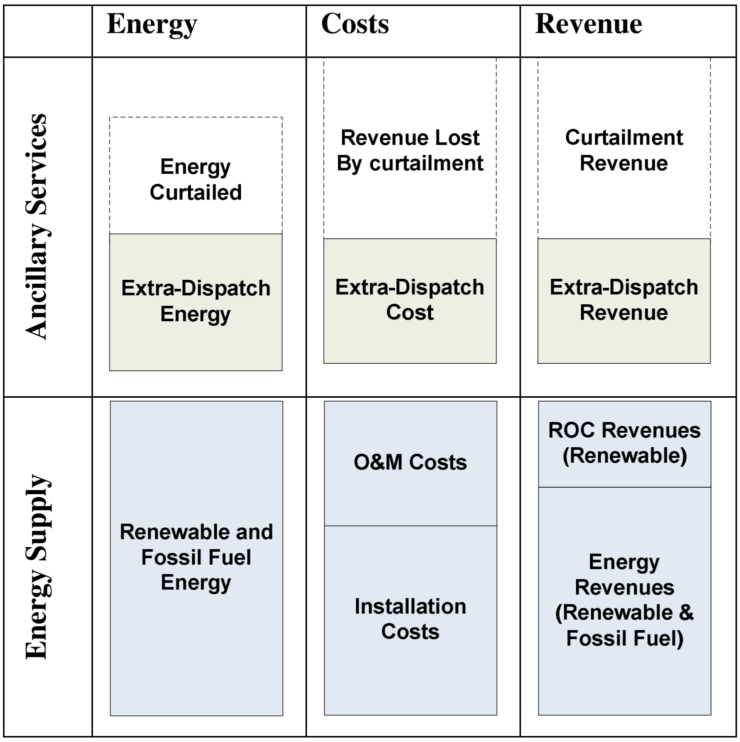

Figure 5-18 Energy, Costs and Revenues

On the other hand, the curtailment of energy to reduce over-voltages and excessive power flows requires a reduction in the energy produced, as seen on the top-left corner of Figure

5-18. If the generator has firm access to the network, i.e. "the generator has the right to export its energy onto the grid in all reasonable conditions" [5.34], the curtailment of energy represents a loss of benefit to the DER owner, because this energy will not be traded. In this case, the benefit lost is considered as a cost that must be compensated. Normally, the "cost of curtailment" equals the different between the market price and the generation cost multiplied by the volume of energy curtailed [5.34].

In contrast, if the generator owner has non-firm access and an output greater than the firm amount at which it is allowed to operate, the revenue lost is not compensated [5.35]. Hence, in this case, the energy curtailment is not included as a cost. In this work, and given that the analysis of controllable DER units is proposed, *it is assumed that all generators have non-firm access*. Hence, curtailment costs are not included in the annual cost terms. The implications of firm and non-firm access in the costs per unit delivered are discussed in the next section.

5.6.3.2. Levelised cost of DER

The annualised cost of DER ($Cost_{DER}$), already explained, provides a measure of the spending required in absolute terms. Hence, this attribute, when minimised, favours the solutions with the least overall spending. Nonetheless, the attribute does not measure the cost efficiency of solutions, and can be misleading when comparing solutions of different scale [5.36]. Therefore, a cost-benefit attribute is proposed. In this case, the attribute calculates the levelised cost of DER energy [5.36]:

$$Cost_{kWh} = \frac{Cost_{DER}}{TotalDEREnergy} \tag{5-31}$$

Annualised costs required for the production of energy, explained in the previous section, are compared with benefits, measured in terms of energy delivered. Total DER energy is the denominator of equation (5-26). So, it accounts for all the energy generated and dispatched minus the energy curtailed. The minimisation of this attribute favours alternatives that provide cost-effective solutions, i.e. less spending for each kWh delivered. Consequently, if energy is curtailed (i.e. the amount of energy delivered is reduced) the cost per unit delivered is higher than the no-curtailment case.

In this work, non-firm access for DER is assumed. Hence, the revenue lost for curtailment is not included as a cost. Nonetheless, if firm access was considered, and the revenue lost was added as a yearly cost of DER, revenues must cover not only the production (and dispatch) cost, but also the revenue that the DER owner lost. Hence, each energy unit delivered will have two cost components: one that represents the cost of production of energy, and a second one that accounts for the cost of lost revenue. Therefore, when curtailment costs are considered, the unit costs of energy are higher than when these costs are not considered. Moreover, in this case, the higher the curtailment level, the higher the cost of each unit of energy delivered.

5.6.3.3. DER Benefits

Finally, an attribute that estimates the annual net benefits of DER installations is proposed. This attribute take account of benefits from the perspective of a DER owner. Nonetheless, it provides only a high-level analysis of the net economic benefits of DER, as all the DER installations benefits are aggregated into a single attribute. A complete financial evaluation of a DER investment project requires a detailed analysis of the benefits and costs over the whole life of the project.

Net benefits are calculated by deducting the annual costs from the annual revenues that are obtained from DER installations. Two sources of revenue are considered, as illustrated in the bottom-right corner of Figure 5-18. These are the revenues from the direct sale of energy (i.e. energy revenues) and the incentives received from producing renewable energy (i.e. Renewable Obligation Certificates, ROC revenues). Hence, benefits are calculated as:

$$\begin{aligned} Benefits_{DER} &= \mathbf{Price_{type}} \times \mathbf{TotalDEREnergy_{type}} \\ &+ \mathbf{ROC_{type}} \times \mathbf{TotalDEREnergy_{type}} - Cost_{DER} \end{aligned} \tag{5-32}$$

$\mathbf{TotalDEREnergy_{type}}$ is a vertical vector that accounts the annual energy generation per DER type (**Etype**), plus energy dispatch minus curtailment reductions. $\mathbf{Price_{type}}$ and $\mathbf{ROC_{type}}$ are horizontal vectors of energy prices and ROC revenues obtained by each type of energy. Although in practice these benefits vary from year to year, they are considered constant for every year. In the case of self-generation (e.g. micro-generation), the avoided costs of energy purchase should be included as the benefits of DER installations [5.30].

Dispatched energy is remunerated, as it is included in the total energy computation. Two possible analyses are possible. In the first, a net benefit is not generated by dispatch because the revenue received for energy dispatch is intended to cover only the extra costs of dispatch. In the second, dispatched energy receives an extra remuneration as an ancillary service for the DSO. If the revenue lost by curtailment was included in the analysis (i.e. firm access contract), this is received only to cover exactly the amount of revenue lost, that is the income for energy sales and the ROCs that would have been received.

5.7. *Stochastic Simulation*

So far in this chapter, the implementation of the SPEA2 algorithm for the DER planning problem was described. Also, the power-flow calculations and the valuation of attributes were discussed. It was shown that some of these attributes are calculated by means of a stochastic simulation, embedded in the objective function of the SPEA2 algorithm. The structure of the stochastic simulation has been described and illustrated in the previous chapter. In this section, some aspects of its practical implementation are examined. First, the sampling of events in the simulation is explained. Next, the effect of different sampling techniques in the accuracy of the attributes is illustrated and the effect of random sampling in the SPEA2 algorithm discussed. This discussion identifies appropriate sampling techniques for the analysis of controllable and non-controllable DER units.

5.7.1. Sampling of DER and Demand Profiles

The stochastic simulation consists of the repeated evaluation of events, as explained in section 4.5.2.2 of the previous chapter. Yearly DER and demand profiles corresponding to each DER and load type are provided in input files. For every event simulated, a vector **SP** is sampled from the production profile of each DER type, as illustrated in Figure 5-19. Each element of **SP** is a value between 0 and 1 that indicates the proportion of active power generated by each unit in terms of its installed capacity in the node. If the power factor of

DER units is different than one, each element of **SP** is corrected by $(1+j.\gamma_{type})$, where γ_{type} is the ratio of reactive to active power of the DER units (*Q/P*).

Then, the **CDER** matrix (equation 5-1) is left-multiplied by the vector **SP** to obtain the horizontal vectors of DER active and reactive power injections per node **($\mathbf{P_{DER}}$, $\mathbf{Q_{DER}}$)**:

$$\mathbf{P_{DER}} + j\mathbf{Q_{DER}} = [(1+j\gamma_1)sp_1 \quad (1+j\gamma_2)sp_2 \qquad (1+j\gamma_{Type})sp_{Type}]\times\mathbf{CDER} \qquad (5\text{-}33)$$

The same procedure is used to determine node loads ($\mathbf{P_{load}}$, $\mathbf{Q_{load}}$); that is, for every simulated event the load profile of each load type is sampled and multiplied by the load capacity installed **LP.** The vectors ($\mathbf{P_{DER}}$, $\mathbf{Q_{DER}}$) and ($\mathbf{P_{load}}$, $\mathbf{Q_{load}}$) are used in the power flow algorithm to calculate the nodal power vectors, as seen in equation (5-3).

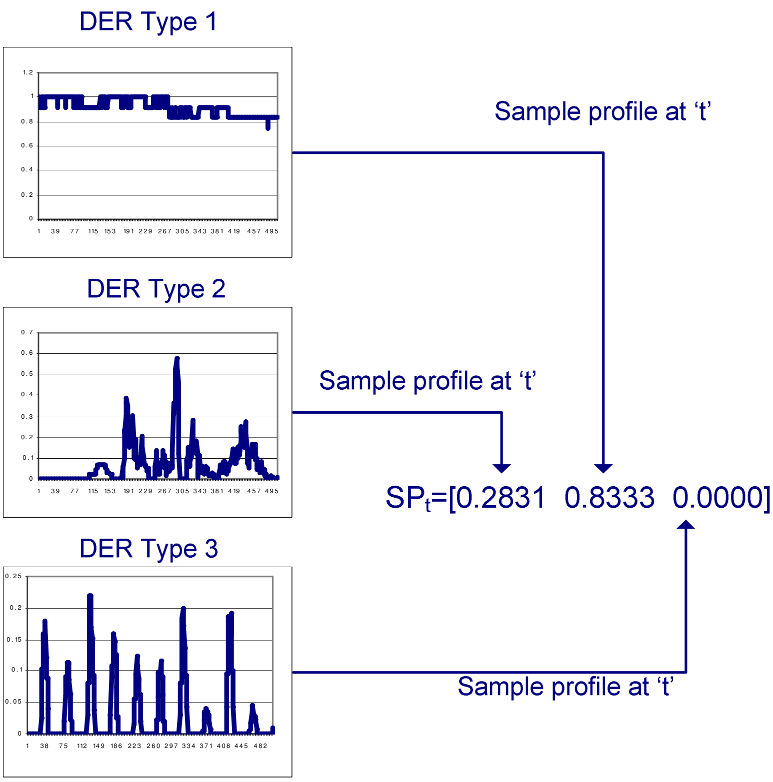

Figure 5-19Sampling Procedure for DER

DER Production and Demand Correlation in Small Networks

In a small area, the output of stochastic generation of the same type shows similar fluctuations, as these generators depend on the same prime mover (i.e. the wind, solar radiation). As a result, a complete linear correlation between the power generated by units of the same type can be assumed [5.37]. The same analysis applies to system loads of the same type; similar load types "show similar stochastic behaviour" [5.37]. Hence, a perfect positive correlation is a valid assumption when considering load-load relationships [5.38]. Papaefthymiou *et al.* [5.37] concludes that this methodology can provide a realistic approach in physically small systems. In contrast, assuming total independence between the production of DER of the same is regarded as a "non-realistic" assumption for small areas [5.37].

Therefore, when the system is small it is assumed that the same production profile can be used for all DER units of the same type, and the same demand profile applies for loads of the same type. This assumption implies that the wind profile that drives wind turbines affects all installations at unison. Similarly, the solar radiation that powers PV installations has a correlated effect in all installations. CHP generation is based on heat demand. Hence, it is assumed that the heat demand on a small region is correlated for the heat loads of the same type. The micro-CHP profiles used in the next chapter were created using ESP-r building simulation tool [5.39]. The production profile of each CHP unit in each node was modified adding a +/- 30 min variation, as explained by Kelly *et al.* [5.40], to account for different occupancy characteristics and add realism to the analysis.

In order to account for the interdependence between the production of different DER types and between DER production and load, all profiles are sampled at the same event t for every simulation event [5.41]; all profiles are assumed to be synchronised.

DER Production and Demand Correlation in Large Networks

In larger systems the behaviour of DER production of the same type vary across different zones of the network, and it is more complex to model. Complete positive correlation between DER production profiles for the same DER type cannot be assumed. Likewise, it is not possible to assume total independence between the DER production in different zones, as some interdependence exists between DER production in adjacent regions and nodes. These correlations are hard to model for some stochastic generators, such as wind [5.42]. Nonetheless, this situation can be dealt with by dividing the network in different zones, as proposed by Ochoa *et al.* [5.43]. Following this approach, the system is divided in different areas taking into account geographical characteristics, the topology and the size of the system under analysis and the availability of information (e.g. historical production profiles, weather measurements). Then, appropriate profiles for each DER type in every zone are determined, either based on historical records; or alternatively, produced using weather data and models and DER production models, as in [5.42]. The same approach can be followed to model similar load types in different zones of the network, if there are significant differences between their behaviours.

5.7.2. Sampling Technique: Accuracy and Performance

In the stochastic simulation, the events are sampled either sequentially or randomly. The sampling technique and the number of events simulated have an effect both in the accuracy of the attribute evaluations and in the time required for the whole analysis. Therefore, the relationship between the evaluation speed and the accuracy of the attributes was quantified for the framework implementation. The study was based on large penetrations of three types of DER and it estimated the upper limit for the evaluation time of controllable and non-controllable DER units. Moreover, it provided some general guidelines to choose the best sampling technique to use. Also, some of the limitations of the framework implemented were recognised. No previous studies of sampling techniques for the analysis of DER were found in the literature. Hence, the analysis presented next is a contribution to this research area.

5.7.2.1. Non-Controllable DER

In this analysis, groups of Wind, PV and CHP generators with sizes ranging from 10kW to 500kW were randomly located in the 355-node UKGDS network [5.1]. The penetration level of each technology was limited to the range 0 to 50%. The configurations were evaluated using sequential and random sampling; the UKGDS profiles were used in these analyses [5.1]. The relative uncertainty (R) of all the technical attributes discussed in section 5.6.1.2 and 5.6.1.3 was computed using equation (4-6) of the previous chapter. The average time needed for each chromosome evaluation was recorded. As measure of MOEA performance, the number of days to evaluate 300 generations of a population of 300 chromosomes was calculated.

Sequential Sampling

A thousand different topologies with non-controllable DER were simulated. The complete profiles (17520 samples) were sampled sequentially. Three distinctive levels of relative uncertainty can be recognised in the attributes of all the chromosomes evaluated, as shown in Table 5-6. The maximum measures of voltage and thermal loading have very low relative uncertainty, and converge very fast. Aggregated energy such as line losses and imported energy also converge very fast and achieve a very low relative uncertainty after a few hundred samples (<1000). In contrast, exported power and the probability of voltage violations have a slower convergence and higher relative uncertainty. A similar order between the attributes' relative uncertainties was observed throughout all the simulations explained in the following sections. Figure 5-20 illustrates a typical convergence of the attributes in the sequential simulation.

Table 5-6 Relative Uncertainty – Sequential Sampling - 17520 samples

R	Range	Attribute
Very Low	0.0002 – 0.0020	Maximum Voltage Violation, Maximum Thermal Loading
Low	0.0004 – 0.0100	Imported Energy, Line Losses
Medium	0.0230 – 0.0990	Exported Energy, Probability of Voltage Violation

The high relative uncertainty of annual exported power, and its slow convergence, is explained by the fact that exported power occurs only at some instances of the year in the topologies analysed. In some chromosomes, the probability of voltage violations has a similar behaviour. Only a few events per year have voltage violations (p=1) and a large number of the observations are zero. The standard deviation of the observations of these attributes is very high compared with their mean; and consequently the relative uncertainty of the measurements is high. The relative uncertainty decreases with the square root of the number of samples, hence, the number of samples must be quadrupled to halve the relative uncertainty (assuming that the standard deviation and the mean remain constant). Consequently, an extremely large number of samples would be needed to reduce further the relative uncertainty in these variables, as seen in Figure 5-20. A comparable effect occurs with dispatch and curtailment, when controllable units are analysed.

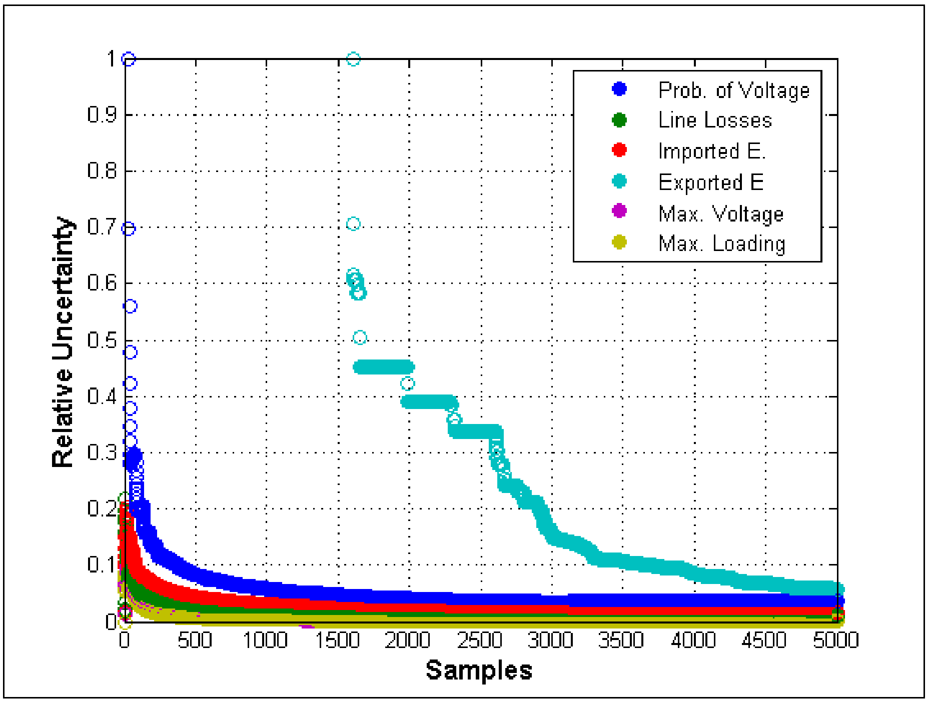

Figure 5-20 Typical Convergence – Sequential Sampling Example

The relative uncertainty obtained in the attributes is adequate for the high-level analysis of the planning framework. However, this accuracy is obtained to the detriment of speed. The evaluation of 17520 samples takes 40 seconds per chromosome on average. If a population of 300 chromosomes is analysed over 300 generations, 6 weeks are necessary. Shorter evaluation times are required. When controllable units are analysed, the evaluation times are much larger, as discussed later.

Sequential Sampling – Time Step

The stopping condition of sequential sampling is defined by the number of samples to evaluate. Hence, faster evaluations can be achieved by analysing a smaller number of samples. It is crucial that the stochastic evaluation considers the characteristics of seasonal, weekly and daily production and demand patterns. So, a larger time step (Δt) between samples is used to sample the whole profiles. Time steps equal to integer fractions of the number of samples per day minus one were used. In the profiles used, there are 48 samples per day; hence, the time steps studied were 2, 3, 5, 11, 23 and 47. The use of these time steps prevents the sampling procedure from continuously sampling only the same half hours every day (e.g. a time step of 12 samples would only sample the same 4 half hours of every day). It also ensures that at least one half hour is sampled from every day. As a result, daily, weekly and seasonal variations are still considered. Another possibility to reduce the number of samples is to analyse characteristics days for each month or season.

Results of different sampling steps are presented in Table 5-7. The attribute with the highest relative uncertainty (R) for each chromosome is presented, as it determines the minimum number of evaluations required. The average value of the highest R over the whole population is provided. Also, the maximum value over the whole population of chromosomes is provided to give an idea of the whole population performance. The estimated time to evaluate a 300-chromosome population over 300 generations is presented.

Table 5-7 Sequential Sampling – Non-controllable DER

Time step	# Samples	Relative Uncertainty			Days to evaluate (300x300)
		Attribute	Average	Highest	
1	17520	Exported Energy	0.0368	0.0998	41.7
2	8760	Exported Energy	0.0522	0.1403	17.2
3	5840	Exported Energy	0.0637	0.1753	11.0
5	3504	Exported Energy	0.0819	0.2118	6.3
7	2502	Exported Energy	0.0912	0.2390	4.7
11	1592	Exported Energy	0.1246	0.3406	2.8
23	761	Exported Energy	0.1735	0.4389	1.4
47	372	Exported Energy	0.2348	0.6431	0.7

In Figure 5-21 the average highest relative uncertainty over the simulations is compared with the number of samples. Also, in the secondary axis, the number of days to evaluate 300 chromosomes over 300 generations is illustrated. The average highest relative uncertainty has an exponential behaviour. It decreases fast up to 3000 samples. Then, only small decrements are obtained with considerably larger number of samples, as already mentioned.

From Figure 5-21 it is clear that the choice of sampling step (or number of samples) depends on two contrasting factors. If a short evaluation time is required, some attributes such as exported power have a high value for R. In contrast, if low relative uncertainty is required in all of the attributes, the whole optimisation process lasts several days. In this case, a time step of 7 (i.e. 2502 samples) is a good compromise. With a time step of 7 samples, the average highest relative uncertainty in the attributes is still reasonably low ($R<0.10$), while realistic evaluation times (<5 days) are obtained.

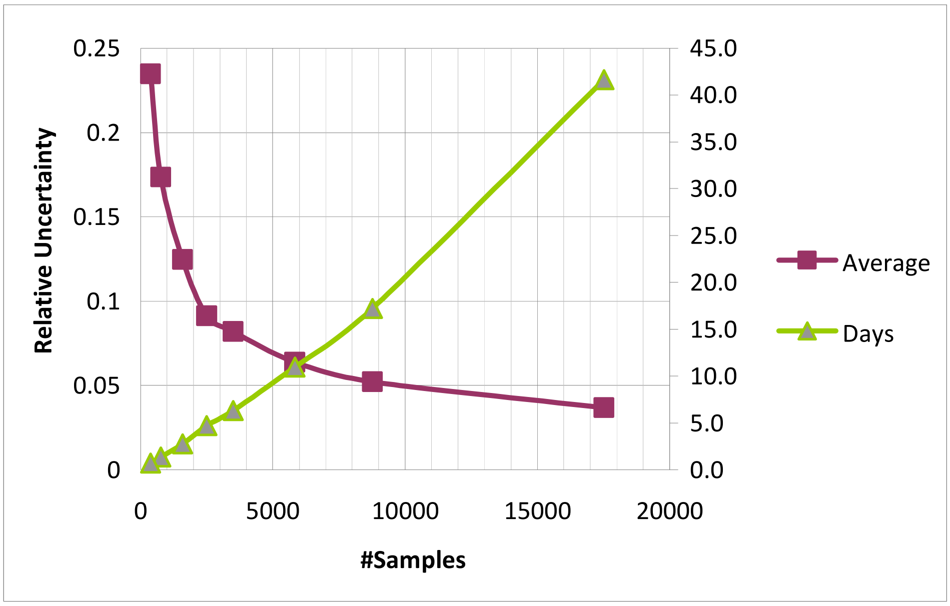

Figure 5-21 Sequential Sampling: Relative Uncertainty Vs. Number of Samples

It must be emphasised that only the attribute with the highest relative uncertainty is illustrated. Hence, the time estimation of Figure 5-21 is an upper limit. The rest of the attributes have faster convergence and much lower relative uncertainties, as illustrated in Figure 5-20. So, if the analysis focuses only on attributes such as line losses, or maximum voltages, the accuracy and speed of the planning framework is higher.

Random Sampling

A thousand random topologies with non-controllable DER were evaluated using random sampling. A minimum relative uncertainty was set as a stopping criterion. Three different values were used for this limit: 0.05, 0.10, and 0.20. The minimum, average and maximum number of samples that each evaluation required to achieve this relative uncertainty was recorded. Results are presented in Table 5-8. As in sequential sampling, the attributes with higher relative uncertainty were exported energy and the probability of voltage violations. Hence, these attributes determined the number of samples in each evaluation. The rest of the attributes had lower relative uncertainty, following the trend explained before (Table 5-6).

Table 5-8 Random Sampling - Non-controllable DER

Stopping Criteria	Samples Required			Days to evaluate (300x300)
	Min.	Avg.	Max.	
R<0.05	3380	7376	17393	18.1
R<0.10	762	2094	16561	4.9
R<0.20	221	707	9955	1.4

In Figure 5-22 the relative uncertainty is compared with the average number of samples (primary axis) and the estimated time to compute 300 generations (secondary axis). It can be observed that to decrease the uncertainty by half, the average evaluation time increases between 3 and 3.5 times. Results for random sampling are similar to the ones obtained using sequential sampling for non-controllable units. For instance, to obtain solutions with a worst relative uncertainty of R<0.10, 2094 samples per evaluation were required on average. Moreover, the evaluation of 300 generations of 300 chromosomes would also take approximately 5 days.

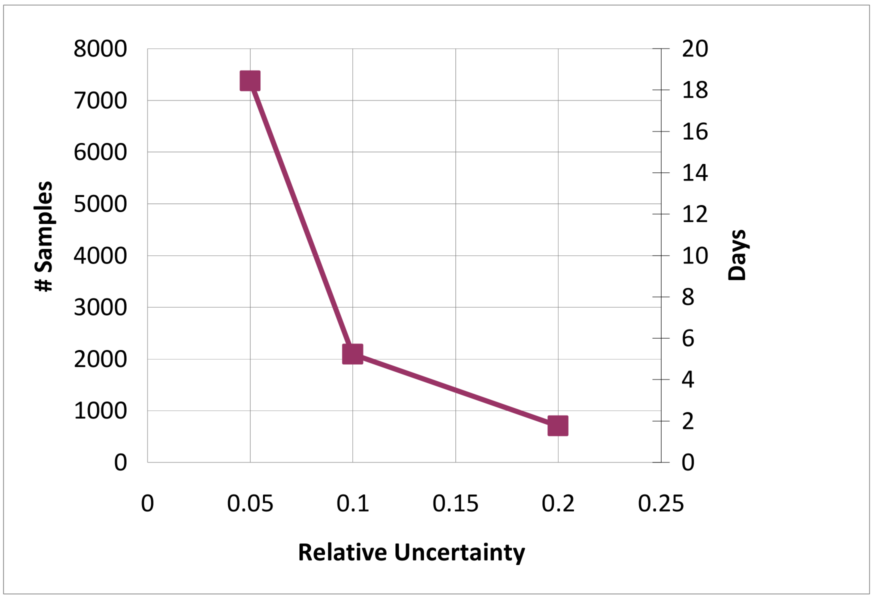

Figure 5-22 Random Sampling – Non-controllable DER

There is a key difference between random sampling and sequential sampling. The random sampling procedure *ensures* that all attributes have a maximum relative uncertainty. In contrast, in sequential sampling the stopping condition only depends on the number of samples, in the implemented framework. The average accuracy of attributes can only be estimated and eventually a complex topology will have higher relative uncertainty in some attributes, as seen in Table 5-7. Hence, random sampling is preferred for the analysis of non-controllable units.

When random sampling is applied, the value of each specific attribute of a chromosome could vary between consecutive evaluations. This variation is regarded as a "noisy" objective evaluation [5.13]. SPEA2 is based on the comparison of the objectives of potential solutions. Hence, accurate attribute evaluations ensure that comparisons between solutions over consecutive evaluations are consistent. This in turn ensures the convergence of the optimisation towards accurate and diverse Pareto front. Buche *et al.* [5.44] mentions that MOEA are "inherently robust to small amounts of noise" .Similarly, Bui *et al.* [5.13] and Goh *et al.* [5.45] show that SPEA2 is robust to small levels of variation in the objectives ($R<0.10$), but that with larger amounts of noise ($R>0.10$) the quality of the solutions is diminished. Therefore, when random sampling is used a maximum relative uncertainty of ($R<0.10$) is essential, as already mentioned in the previous chapter. Figure 5-22 shows that in the studied cases this level of accuracy can be achieved in realistic evaluation times (5 days).

5.7.2.2. Controllable DER

A similar analysis was repeated assuming all DER units to be controllable. Renewable generators were assumed curtailable while CHP units are dispatchable. In this case, the analysis included only 250 random topologies, as the evaluation time is much longer. Results are discussed next.

Sequential Sampling

Results from different time steps for sequential sampling are shown in Table 5-9. The attribute with the highest relative uncertainty is presented and the average highest relative uncertainty over the population listed. Also, the highest and lowest relative uncertainty of this attribute over all the chromosomes is presented, to illustrate the spread of solutions.

The attributes with the highest relative uncertainty in this case are dispatched and curtailed energy. Dispatch and curtailment only happen at some sampled events; specifically when a problem exists in the network and when DER can solve it. Hence, in some chromosomes there are only a few observations of dispatch/curtailment throughout the simulation. This results in a high standard deviation in relation to the mean, and a high relative uncertainty. Moreover, because of this variable characteristic, the relative uncertainty can only be reduced up to a point, even with an extremely large number of simulated events. For example, the lowest relative uncertainty that was obtained with 17520 samples for dispatched energy was 0.0234, compared with relative uncertainties on the range 0.0004-0.0100 for line losses.

Dispatch and curtailment are caused by localised problems, specific to each chromosome. Hence, the spread between different solutions' relative uncertainty is wide. This is can be evidenced in Table 5-9 and it is illustrated in Figure 5-23 by examining the histogram of the highest relative uncertainty for 17520 samples. In this histogram, it is possible to observe that the majority of relative uncertainties of attributes are spread in the range 0.0-0.6. Most solutions reach relative uncertainties lower than or equal to 0.3. In those cases, the convergence of curtailed energy and dispatched energy is similar to the one of exported energy presented in Figure 5-20. In particular cases, there is no convergence in the attributes, and the relative uncertainty equals 1. A relative uncertainty of 1 corresponds to a case where only one event different than zero was observed in the whole simulation. In this case, the solutions that didn't converge are only 2% of all the topologies

Table 5-9 Sequential Sampling – Controllable DER

Time step	# Samples	Relative Uncertainty				Number of Days to evaluate (300x300)
		Attribute	Avg.	Highest	Lowest	
1	17520	Dispatched Energy	0.2808	1.0000	0.0234	100.1
2	8760	Dispatched Energy	0.3777	1.0000	0.0331	45.5
3	5840	Dispatched Energy	0.3882	1.0000	0.0394	31.7
5	3504	Dispatched Energy	0.5156	1.0000	0.0523	19.2
7	2502	Dispatched Energy	0.4499	1.0000	0.0599	14.3
11	1592	Dispatched Energy	0.5489	1.0000	0.0722	10.3
23	761	Curtailed/Dispatch Energy	0.5216	1.0000	0.1122	6.7
47	372	Curtailed/Dispatch Energy	0.5860	1.0000	0.1456	4.3

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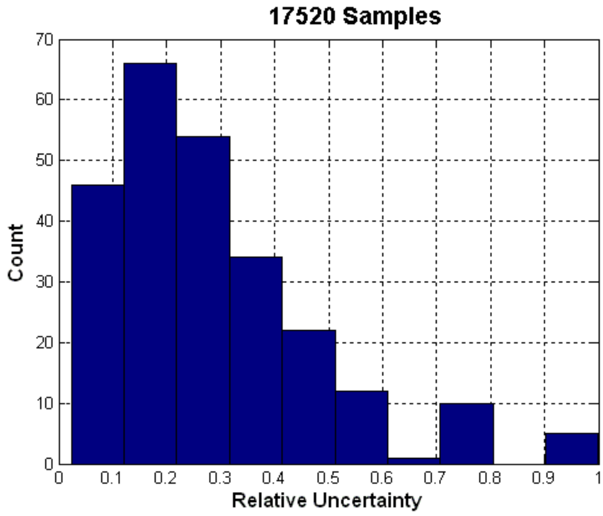

Figure 5-23Histogram – Sequential Sampling – Controllable DER

The histogram also demonstrates that because of the variable nature of dispatch and curtailment, these attributes do not achieve very low values for R, even with the evaluation of 17520 samples. Considering this characteristic is essential while choosing a realistic stopping criteria or sampling step for controllable units. In the studied cases, realistic evaluation times for large penetrations of controllable units were only obtained when considering a small number of samples per chromosome (<1500). This number of samples results in an average highest uncertainty of around 0.55.

When controllable units are analysed, the resolution of each OPF takes considerably more time than a power flow calculation. For example, a single power flow takes around 2-3 milliseconds, while an OPF resolution takes 400 milliseconds. When a large number of samples are evaluated, more instances of constraint violations must be solved, and the negative effect of lengthy OPF evaluations in the overall speed is multiplied. For instance, the evaluation of one chromosome with 17520 samples can take up to 250 seconds (100 seconds on average), even if only some events have OPF evaluations; compared with the 40 seconds used to evaluate a non-controllable DER topology. Since the SPEA2 evolutionary process involves thousands of chromosome evaluations (e.g. 90,000 evaluations for a 300 chromosome population over 300 generations), the overall estimated time is considerably large.

The estimated times of Table 5-9 and Table 5-10 (presented next) should be understood as an upper limit, or worst-case estimation. The chromosomes evaluated include large numbers of controllable DER units of three different types (10-100 units per type). Complex situations of over-voltage, under-voltage and overflow in lines were created. The OPF in each iteration included up to 300 optimisation variables and more than 900 constraints. Moreover, some of the OPF problems were unfeasible, such as overload problems caused by CHP units that are not curtailable. This presented a complex and large search space, and resulted in lengthy OPF evaluations. A simpler analysis, for example the placement of a handful of curtailable generators, results in faster OPF evaluations, as the linear programming variables are considerably reduced and all OPF problems are feasible. This is illustrated in the next section.

Random Sampling

Table 5-10 show the results from the evaluation of the same 250 chromosomes using random sampling. Again, it was observed that some solutions did not converge, and 17520 samples were evaluated without reaching the specified relative uncertainty in all attributes. Even so, random sampling showed to be faster than sequential sampling. When random sampling is used, the evaluation stops once all the attributes have reached a satisfactory relative uncertainty. Hence, the number of OPF evaluations is reduced, and the overall speed of the analysis is increased.

Table 5-10 Random Sampling – Controllable DER

Relative Uncertainty	**Samples**			**Number of Days to evaluate (300x300**
	Min.	**Avg.**	**Max.**	
R<0.10	930	14343	17520	84.6
R<0.20	268	9147	17520	52.8
R<0.30	201	5391	17520	31.7
R<0.40	201	2739	17520	8.5

The estimated time to obtain solutions with high accuracy (R<0.10) is still unrealistic as can be seen in Figure 5-24 (full line). Only R<0.40 represents a realistic stopping criteria in terms of evaluation time.

Though, Figure 5-25 also shows results obtained by analysing the integration of 10 curtailable DER units in the same network and using the same profiles (dashed line). The analysis included 250 chromosomes with random DER topologies with penetration levels varying from 0 to 50%. Results demonstrate that as the problem becomes simpler, the speed of the evaluations increases; or, equally, attributes with lower relative uncertainty can be obtained in the same evaluation time. In this case the evaluation time for attributes with relative uncertainty of R<0.10 is more realistic, although still considerably large.

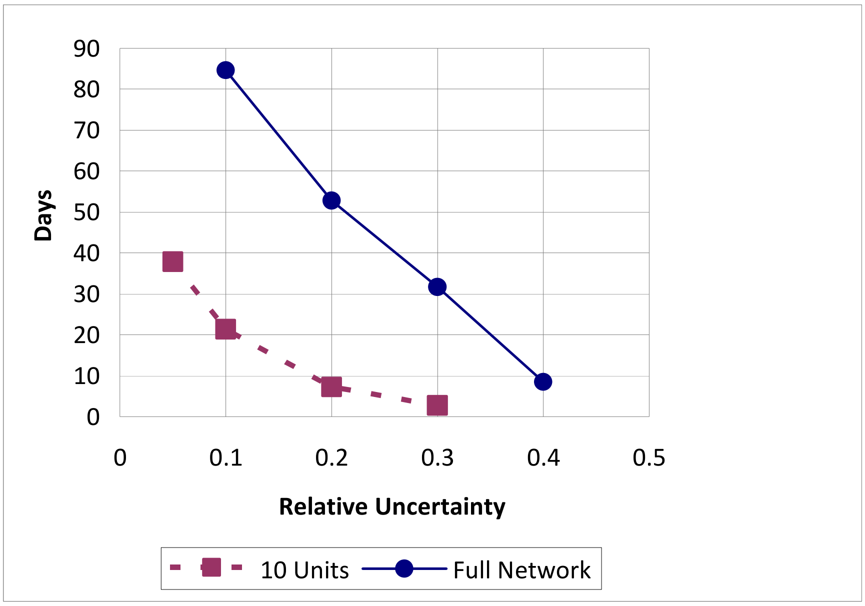

Figure 5-24 Random Sampling – Controllable DER

It was already discussed that attributes that vary a lot between consecutive evaluations (R>0.10) would have a negative effect on the SPEA2 optimisation process [5.44]. Hence, when accurate solutions cannot be obtained by random sampling in realistic time, the use of sequential sampling is mandatory. In sequential sampling, the same sequence of events is sampled in every evaluation. The attributes of a chromosome are constant from one evaluation to the next; and comparisons between chromosomes objectives are consistent over all the generations. Hence, by using sequential sampling, the assumptions in which SPEA2 is based are respected and the SPEA2 optimisation process is not affected. Though, the accuracy and quality of the solutions still depends on the number of samples used; some solutions will have low accuracy in some of their attributes (e.g. dispatched energy, curtailed energy) because these have high variance in the samples, while the rest of the attributes will be more accurate.

5.7.2.3. Sampling Techniques: Summary of Results

Figure 5-25 summarises the evaluation time required to achieve different levels of accuracy for controllable and non-controllable units. In the case of sequential sampling, the average highest relative uncertainty is plotted. For non-controllable units, random and sequential sampling gave similar results. Though, random sampling is preferred because it ensures the accuracy of all attributes in all chromosomes. In this case, relative uncertainties of R<0.10 can be achieved in realistic times. Moreover, it must be highlighted that this time estimation is based on the least accurate attribute (i.e. is an upper limit) and that with this stopping condition the rest of the attributes will have relative uncertainties lower or much lower than 0.10.

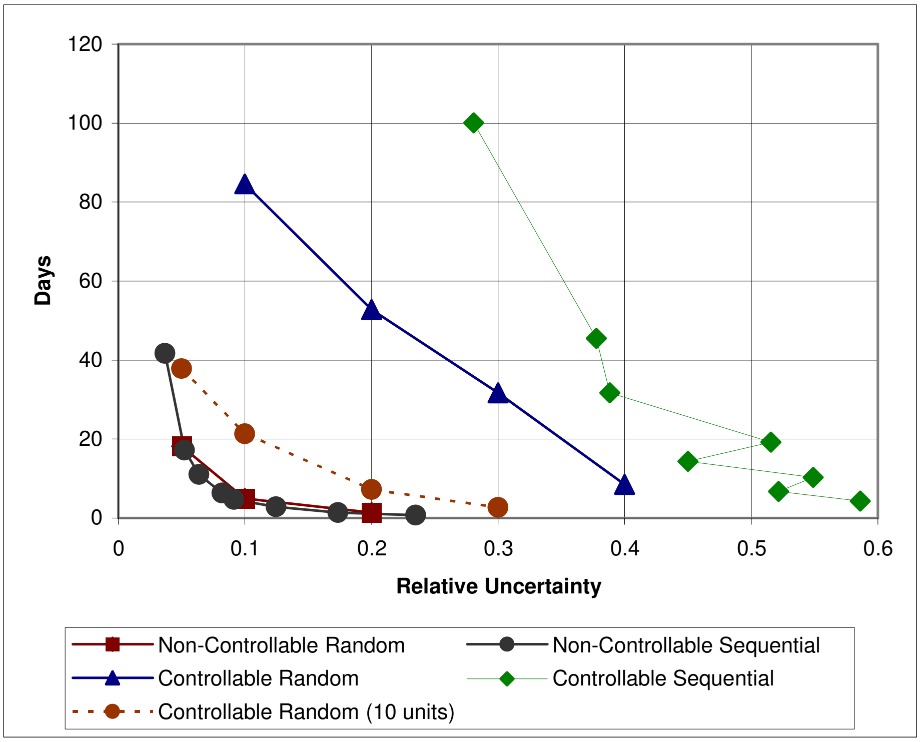

Figure 5-25 Sampling Techniques – Accuracy vs. Evaluation Time

When controllable units are analysed, random sampling is found to be a better choice in terms of evaluation speed. In terms of the estimated time to obtain given levels of accuracy, the analysis of a few controllable units resembles the study of non-controllable units. As the number of controllable units studied increases, OPF evaluations become longer; and more time is required to achieve accurate attributes. Consequently, in the case of controllable units, a realistic evaluation time is the limiting factor for the accuracy of attributes such as dispatched energy and curtailed energy. In problems that involve a large number of controllable units, attributes cannot achieve relative uncertainties lower than 0.10 in realistic time. Then, only sequential sampling is an option. In this case, the number of samples to evaluate would also be limited by realistic evaluation time.

The analysis of large numbers of controllable units presents a challenge in terms of the required evaluation time for two reasons. First, the attributes of dispatched energy and curtailed energy have a high variance. Consequently, a large number of samples are required to achieve accurate estimates. Second, the OPF resolution takes much more time than a normal power flow calculation. Hence, in this case the analysis of large penetrations of controllable DER can only achieved with a compromise; some chromosomes will have quantifications of curtailed energy and dispatched energy with high relative uncertainty, in a limited evaluation time. Note that the rest of the attributes will be more accurate, as already discussed in the previous section.

The parallel implementation of the SPEA2 algorithm over multiple processors [5.46] will considerably reduce the evaluation time of both controllable and non-controllable units. Hence, it is a valuable further work. The OPF resolution time (400 ms for a 355-node network) is comparable with the computational burden of other OPF formulations found in the literature [5.47]. Nonetheless, the OPF optimisation could be enhanced further by linking the linear OPF formulation with specialised optimisation packages (e.g. GAMS, Tomlab).

5.8. *Summary*

In this chapter, the implementation of a multi-objective tool for the analysis of DER integration is presented. This tool is based on the framework discussed extensively in the previous chapter, and it makes use of the SPEA2 algorithm, described in Chapter 2 and the stochastic simulation procedure illustrated in the previous chapter.

In the first part of the chapter, the use of the SPEA2 algorithm for the DER planning problem is described, and the implementation of each one of the steps of SPEA2 explained. Moreover, the reasons behind the choice of each one of the parameters of SPEA2 are discussed. One of the requirements identified for the planning framework is that it must be able to analyse different types of problems of DER integration. Hence, a flexible encoding system for SPEA2 is proposed. This encoding handles different types of problems with minimum changes to the rest of the optimisation algorithm. Similarly, the implementation of specific crossover and mutation operator for each type of problem is described.

The calculation of the attributes is based on a stochastic simulation, which makes extensive use of power flow calculation. Consequently, in the second part of this chapter, the power flow algorithm implemented is described. The algorithm used is specific to the type of networks analysed in the next chapter, and it provides a fast and reliable power flow calculation. Other power flow calculations can be integrated without difficulty, when the analysis of different types of networks is required. In the previous chapter, the use of an optimal power flow (OPF) for the analysis of controllable DER was proposed. In the third part of this chapter, the implementation of the OPF calculation is detailed. In this case, a linear OPF formulation is proposed. The derivation of the linear equations is described extensively in Appendix C. The OPF provides an approximation of curtailed and dispatched power, and can be extended for the analysis of controllable load.

In the fourth part of the chapter, each one of the planning attributes of the planning framework is described. The attributes are based on the outputs of the stochastic simulation. Hence, in the last part of the chapter, the practical implementation of the stochastic simulation is described. More importantly, the speed and accuracy of the tool implemented is quantified. The planning tool can provide highly accurate attributes when analysing non-controllable DER. In contrast, the analysis of controllable units is more challenging. The SPEA2 algorithm requires thousands of evaluations. Hence, the speed of the OPF was identified as a key factor for the analysis of controllable units. Further work is proposed to increase the speed of the planning framework.

In the next chapter, the planning framework is illustrated with a set of case studies. For brevity, not all the attributes presented in this chapter are used. Nonetheless, in each example some of the key features of the planning framework proposed in this thesis are demonstrated. Moreover, some conclusions obtained from the case studies are also discussed.

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Chapter 6

6. Case Studies in Optimal DER Planning

6.1. *Introduction*

In the previous two chapters the design and implementation of a planning framework for DER integration analysis has been extensively discussed. The planning framework evaluates diverse technical, economic and environmental benefits and impacts of DER integration. Each of these attributes can be used as a planning objective and/or as a planning constraint. Moreover, the optimisation of DER type, location and/or size is supported by a flexible encoding system. Hence, the range of studies of DER integration that can be carried out by the planning framework is very large. In this chapter, the planning framework is demonstrated with two relevant case studies. These case studies have been chosen because they represent current examples of DER integration in the UK.

In the first case study, the optimal integration of micro-generation in an urban low-voltage distribution system is examined. This case study illustrates the concepts of multi-objective optimisation and demonstrates the application and value of the multi-objective visualisation and analysis techniques discussed in Chapter 4. Moreover, results from this case study demonstrate that the impacts and benefits of DER are technology specific. The second case study explores the optimal integration of wind turbines in a rural medium-voltage distribution network. The first part of this case study illustrates the use of probabilistic objectives and constraints. The second part of the study demonstrates the planning of controllable DER. The results expand the knowledge of integration of stochastic DER in distribution systems, and illustrate the effects of enabling the curtailment of wind energy on the DER owner and the DSO across objectives of interest to them.

For brevity, not all attributes available in the analytical tool are presented in the case study. Those attributes presented are chosen to illustrate relevant economic, technical and environmental perspectives of DER integration and the important trade-offs across these diverse objectives.

6.2. *Case Study 1: Integration of Micro-generation in an Urban Distribution Network*

Micro-generation is defined as distributed generation with a capacity below 100kW [6.1]. The UK government's Micro-generation Strategy, presented in 2006, recognised these technologies to have the potential to contribute to achieve the UK's objectives of tackling climate change and at the same time ensure a reliable and affordable energy supply [6.2]. Renewable micro-generators (e.g. PV panels) and the combined production of heat and power (e.g. micro CHP) can increase the efficiency of energy production and help reduce CO_2 emissions. In addition, the local generation of energy could reduce losses in the distribution and transmission systems [6.1].

Some of the impacts of large numbers of micro-generators on the distribution system have already been studied [6.3], [6.4], [6.5], though, these investigations focused only on the study of a limited number of predefined DER configurations. In contrast, the first case study analyses the integration of micro-generation in an urban low-voltage network using the multi-objective planning approach proposed in this thesis. A set of optimal solutions is determined using three planning objectives. Also, several attributes of interest are analysed and compared.

6.2.1. Network and Demand Data

The network is a generic low-voltage network (0.4 kV, 3-phase, balanced), created by means of a statistical network design tool [6.6]. It has 83 nodes, covering an area of 0.25 km^2. It is connected to the medium-voltage network by means of a 1.2 MVA 11/0.4 kV transformer. Fifty nodes have connected loads. On average nine properties are connected to each load node. Figure 6-1 illustrates the network structure and the nodes that have connected loads.

Four customer types exist in the network: Domestic Unrestricted, Domestic Economy 7, Non-Domestic Unrestricted and Non-Domestic Economy 7. Eighty percent of the load-nodes have peak loads lower than 30 kW; all of these are Domestic Unrestricted. The biggest loads are non-domestic (90-261 kW) and are installed in the nodes illustrated as squares in Figure 6-1. The total installed load in the network is 1902.5 kW; the coincident peak load is 986.4 kW. Loads are assumed to have a power factor of 0.85 lagging. The annual demand of the network is 3789.6 MWh/year (including losses). Detailed data of the network and the loads is provided in Appendix D.

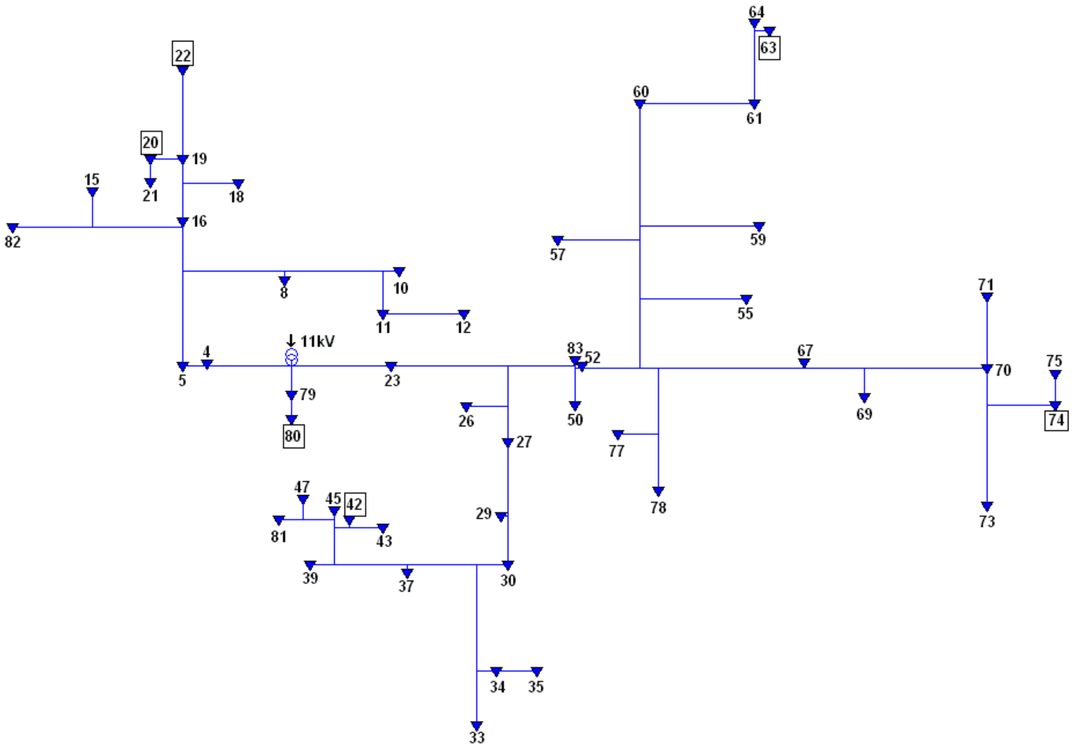

Figure 6-1 LV Network – Case Study 1

To provide a realistic analysis of a small-scale low-voltage network, each load node has a specific demand profile. Daily demand profiles with 5-minute intervals were derived from scaled England and Wales hourly year round demand profiles [6.7], [6.8]. To obtain demand profiles with five minute intervals, a normal variation with $\mu=0$ and $\sigma=5\%$ was added to each hourly value. This variability is characteristic of measured residential load profiles [6.8]. Profiles for three characteristic seasons (winter, summer and transition) were created. The total demand for the winter season is illustrated in Figure 6-2.

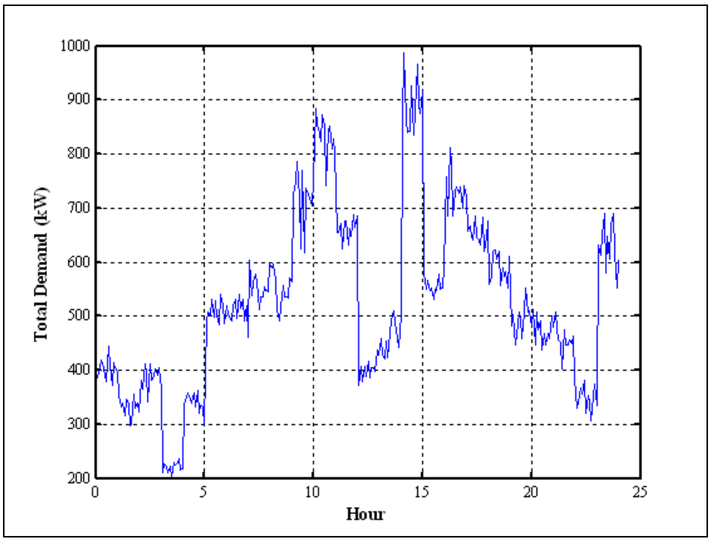

Figure 6-2 Case Study 1- Total Demand Winter

Table 6-1 shows the results from the evaluation of the base case using the 6048 samples (three characteristic weeks), without any DER installed. The highest voltage drop is experienced in node 63, affecting all nodes in the area (61, 62, 63, and 64). The highest thermal loading occurs in the transformer connected between nodes 1 and 2. The transformer is very close to its thermal limit. The line losses in the network represent about 2.1% of the imported energy.

Table 6-1Case Study 1 – Base Case

Attribute	Units	Value
Line Losses	MWh/year	81.10
Imported Energy	MWh/year	3789.60
Emissions Factor	gCO_2/kWh	430.00
Maximum Voltage Deviation	%	5.74
Over-voltage Probability	%	0
Maximum Thermal Loading	%	99.12
Overload Probability	%	0

6.2.2. Micro-generators Data

The integration of three types of micro-generators currently available in the UK market is analysed. The micro-generators considered are a Stirling engine micro-CHP [6.9], an internal combustion engine (ICE) micro-CHP [6.10] and a solar photovoltaic (PV) system [6.11]. The technical characteristics of these generators are listed in Table 6-2.

Table 6-2Micro-generators Data

Micro-generator	**Capacity (kW)**	**Capacity Factor (%)***	**CO_2 emissions factor (gCO_2/kWh)****	**Heat to Power Ratio**
Stirling micro-CHP	1	30.3	326	8:1
ICE micro-CHP	5.5	24.1	300	2.3:1
Solar PV System	1.2	11.2	0	----------

* from the production profiles used in the study
** from Pout *et al.* [6.12], assumes 90% efficiency, electricity and gas as alternative sources

Table 6-3Micro-generators Costs

Micro-generator	**Inst. Cost (£/kW)**	**O&M Cost Assumptions**	**Cost of Electricity (p/kWh)**
Stirling micro-CHP	3,500 [6.13]	• Fuel cost of 2.7p/kWh [6.13] • £110/year for maintenance [6.13]	4.5
ICE micro-CHP	2,080 [6.14]	• Fuel cost 2.7p/kWh [6.13] • £550/year for maintenance [6.13]	7.0
Solar PV System	5,000 [6.14]	• £60/year for a basic check and cleaning every year [6.14]	53.2

The costs of each micro-generation technology are summarised in Table 6-3. The installation and maintenance costs of the micro-CHP units are distributed proportionally between thermal and electrical energy generation, to provide a truthful measure of the cost of the electricity generated. The calculation of the unit costs is detailed in Appendix D. The Stirling micro-CHP units are the most cost-effective technology in terms of energy delivered. The most expensive technology in terms of energy delivered is PV generation.

6.2.2.1. DER Production Profiles

Time series of production for each micro-generator are available for three characteristic weeks of the year. The profiles have a resolution of 5 min, i.e. 6048 samples per profile. They were created by means of the ESP-r building simulation tool [6.15], which integrates a detailed thermal model of buildings and the energy generation systems, with end-user behaviours and real dynamic climate data [6.3]. In the case of micro-CHP four possible combinations of dwelling type (detached/semi-detached) and occupancy (intermittent/continuous) were considered [6.3]. A variation of +/-30 min was applied to each micro-CHP profile of the same type, to simulate differences in occupancy patterns

[6.3]. In the case of PV systems, five different roof orientations were modelled (East, Southeast, South, Southwest, West), assuming a panel inclination of 40 degrees. So, five PV generation profiles were created for each characteristic week [6.3]. Detailed data of each profile is presented in Appendix D.

Each load node of the network was assigned a house type (dwelling type, occupancy, orientation). The house type determines the profile applied to the micro-generators in the node. Installations are restricted only to load nodes. The micro-generators studied are assumed modular, i.e. a number of them can be installed in each node and the same production profile applied (Analysis 2, in Table 5-2 of the previous chapter). Some of the micro-generators are single-phase (e.g. Stirling engine, small PV installations); though, it is assumed that connections in each node are balanced over the three phases, and that voltage unbalance is not higher than the no-generation case [6.16]. Studies have shown that voltage rise and reverse power flows are the main impacts of these generators and that "voltage unbalance is unlikely to cause a problem" [6.1]. All generators are assumed to work at unity power factor. Micro-generation units are assumed uncontrollable and no dispatch or curtailment is considered.

6.2.3. Planning Objectives and Constraints

The planning objectives target a low-cost solution which minimises the carbon emissions attributed to the load and supplies local loads with local energy resources. Consequently, three planning objectives are defined:

1. Minimise the total annualised cost of DER (Equation 5-29)
2. Minimise the load equivalent emission factor (Equation 5-28)
3. Minimise the yearly energy imported from the grid (Equation 5-19a)

The planning objectives reflect economic, environmental and technical aspects of micro-generation integration that would be of interest to a regulator. The third planning objective is also of interest for the DSO, as the reduction in energy imports from the MV/LV could alleviate the use of the medium-voltage network and reduce network losses. Reducing energy imports could also defer network investments, although this depends on the reduction of peak loads, as examined later. Other objectives could be added to the analysis, for example to maximise benefits obtained by DER owners, to minimise line losses or to minimise grid dependency. Though, keeping the problem simple avoids “information pollution” and helps to demonstrate better the planning framework.

Voltage and thermal constraints in the network are considered deterministic, and limited to +/- 10% of the nominal voltage (400V). Thermal constraints are limited to a maximum of 100%. A limit is set to the maximum number of DER units that can be installed in each node. This limit considers the number of properties connected to each node. So, the search space is limited to a maximum of 10 Stirling engines (10 kW), 3 ICE generators (16.5 kW) and 10 PV installations (12 kW, ~90m^2) per node.

6.2.4. Case Study 1: Results and Discussion

The parameters used for the SPEA2 optimisation are shown in Table 6-4. Three characteristic weeks (6048 samples) and sequential sampling were used for the evaluation. All planning objectives have high accuracy (R<0.013). Each chromosome evaluation took an average of 6 seconds, and the total evaluation time was 100 hours.

Table 6-4 Parameters for SPEA2 Optimisation

Population Size	200
Archive Size	150
Generations	300
Crossover type	Uniform
Crossover rate	0.9
Mutation rate	0.004

The bi-objective plot from the optimal solutions is shown in Figure 6-3. The Pareto front is a plane in the three-dimensional objective space. Hence, each one of the plots corresponds to the projection of the plane on a bi-dimensional axis. Four optimal solutions are highlighted in the figure to facilitate the description of the Pareto Front (A, B, C and D). In addition, the cases of maximum penetration of each DER type are illustrated (S, ICE and PV) to show the area of the search space, and highlight the effect of each technology. Solution S is part of the Pareto front. In contrast, solutions PV and ICE are dominated solutions. The objectives and the penetration level of each DER type of these optimal solutions are presented in Table 6-5 and Table 6-6, respectively.

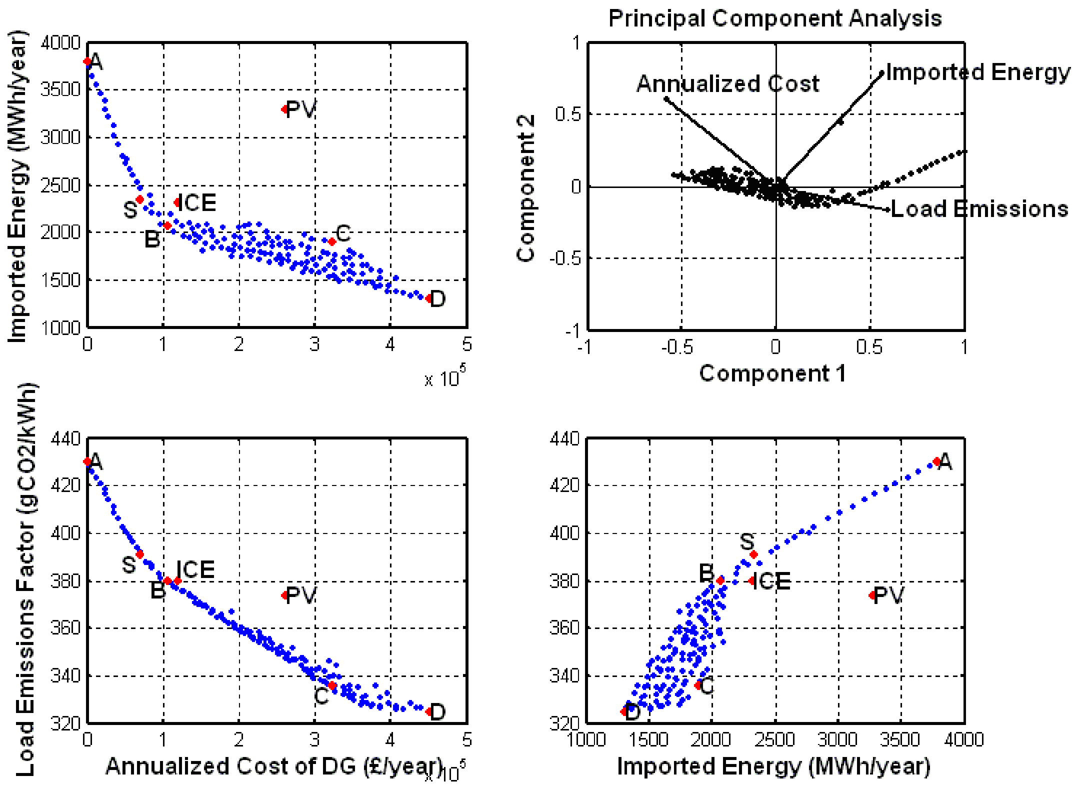

Figure 6-3 Optimal Solutions – Case Study 1

Table 6-5 Optimal Solutions – Case Study 1

Attribute		A	B	C	D	S	ICE	PV
Objectives	**Annualised cost (k£/year)**	-	105.72	323.06	450.8	70.32	119.49	260.98
	Emissions Factor (gCO_2/kWh)	430	379.88	335.75	324.89	390.42	379.91	373.65
	Imported Energy (MWh/year)	3,789.6	2,070.8	1,897.6	1,301.9	2,332.1	2,315.6	3,283.9
Other Attributes	**Exported Energy (MWh/year)**	-	262.0	89.4	1,201.2	84.3	200.2	9.3
	DER Energy Exported (%)	-	13.40	4.59	32.70	5.56	12.13	1.85
	Cost per kWh (£/kWh)	-	0.05	0.17	0.12	0.05	0.07	0.52
	Maximum Voltage (%)	5.7	6.6	5.8	8.7	5.6	6.5	5.7
	Maximum Loading (%)	99.1	88.5	89.9	90.1	90.8	97.9	98.2
	Line Losses (MWh/year)	81.1	56.1	49.2	65.5	56.5	58.4	70.6

Table 6-6 Optimal Penetration Levels – Case Study 1

Penetration Level (%)	A	B	C	D	S	ICE	PV
Stirling Engine	-	39.7	24.6	40.9	40.9	-	-
ICE	-	12.9	15.2	44.5	-	44.5	-
PV Systems	-	0.2	12.7	13.6	-	-	13.6
Total DER	-	**52.7**	**52.6**	**99.0**	**40.9**	**44.5**	**13.6**

The Principal Component Analysis (PCA) of the objectives is illustrated in the top-right corner of Figure 6-3. Annualised cost minimisation conflicts with the other two planning objectives (first PCA component is opposed). Particularly, the linear correlation between annualised cost and carbon emissions reduction is very strong (correlation coefficient of -0.97). A complete linear correlation (correlation coefficient of 1 or-1) indicates that the trade-offs between all solutions are constant. In contrast, the shape of the front annualised cost vs. imported energy (top-left plot) determines a less pronounced linear correlation (correlation coefficient of -0.85). This indicates that the trade-offs between solutions have a wide range of variation, as demonstrated later. CO_2 emissions minimisation and energy imports minimisation are not conflicting, the first PCA component has the same direction, and they show high positive correlation (correlation coefficient of 0.92).

The two extremes of the Pareto front can be easily recognised. They correspond to the “do-nothing” case (solution A), and the installation of the entire permitted DER in the network (solution D). Solution D has an annual cost of £450,000. A reduction of 25% on the load CO_2 emissions factor can be achieved. This means a reduction of around 400 tonnes of CO_2 per year. Generalising the emission reduction of the case study to UK domestic electricity demand (115 TWh [6.17]]), would result in a reduction of 12 $MtCO_2$/year or 2.2% of the total UK emissions (554 Mt CO_2 in [6.1]), though, the penetration levels of DER required for achieving these emission reductions are unlikely to be reached in the short or medium term. For instance, to generate 20% of the domestic demand by micro-generation requires 22 million PV systems of 1.2 kW or 9 million Stirling engines of 1kW. Hence, to achieve the UK CO_2 reduction targets (26% by 2020 and 80% by 2050 [6.18]), energy-efficiency measures, large-scale wind energy, nuclear power plants and/or Carbon Capture and Storage would be required, in addition to the use of micro-generation.

In solution D, imported energy can be reduced to a third of the initial value, with a DER penetration of almost 100%. Though, almost a third of the energy generated is exported to the MV grid, as can be seen in Table 6-5. The aggregated reverse flows (exports) of many domestic networks might cause overload problems in MV distributions systems, with such extreme penetration levels of DER.

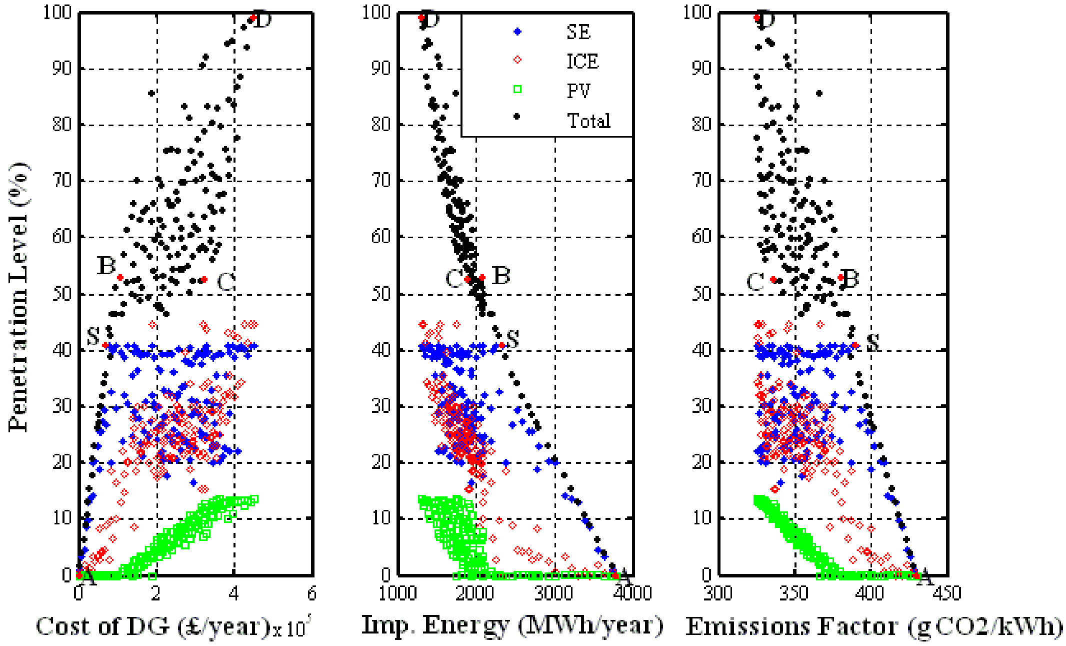

Figure 6-4 Optimal Penetration Level - Case Study 1

Figure 6-4 compares the optimal penetration level of each DER type with the planning objectives of each solution. This figure demonstrates that the proposed approach determines the optimal DER mix for each planning objective. Each point illustrates the penetration level of each technology (SE, ICE, PV), and the total penetration level of DER. Two different regions of the Pareto front can be characterised. The first region (A-S) corresponds to a group of solutions based mainly on increasing penetrations of Stirling engine micro-CHP (SE), with the annualised cost ranging from 0 to 100k£/year. Stirling engine micro-CHPs provide the most cost-efficient reduction in energy imports due to their low unit cost and higher capacity factor. Similarly, they provide cost-effective carbon reductions when the grid emission factor is high. These two aspects are examined in detail later.

In solution S the maximum penetration of Stirling engine micro-CHP is reached (40.9%). Hence, the second group of solutions have increasing penetrations of ICE micro-CHP and PV systems, with the penetration of Stirling engine micro-CHP ranging from 20-40%. These solutions correspond to the triangle-shaped region (BCD) of the Pareto front (Figure 6-3) and this is the second main region of interest. Three distinctive boundaries of this region can be identified (BC, BD and CD).

The solutions between B and C in the Pareto front (Figure 6-3) have an annual cost ranging from 100 to 300 k£/year. After solution S, these are the solutions that provide the most cost-effective carbon emission reductions, from 380 to 330 gCO_2/kWh. The energy imports corresponding to the front BC is ~2000 MWh. The second plot of Figure 6-4 shows that these configurations are based on mixes of Stirling engine micro-CHPs (20-40%), ICE micro-CHP (10-25%) and increasing penetrations of PV systems (0<10%), with total DER penetration ranging between 40-60%.

The front between B and D provides the most cost-effective reduction in energy imports from 2000 to 1300 MWh/year. The centre plot of Figure 6-4 shows that these solutions are based on mixes with large penetration of Stirling engines and ICE micro-CHPs. The maximum penetration of PV systems is included in the optimal DER mixes only when Stirling engines and ICE micro-CHP have almost reached their maximum penetration levels. This demonstrates that PV systems are the least cost-effective technology among the three studied (given the planning objectives). This is a reflection of high installation costs, low capacity factor and little coincidence with demand for the energy provided by PV systems, in the network studied.

6.2.4.1. Trade-off Analysis

Energy Imports and Annualised Cost

Figure 6-5 compares the levelised cost per kWh of each optimal solution according to the penetration level. It can be observed that the unit cost of the energy delivered of the optimal solutions is in the range 0.04-0.17 £/kWh. The costs for selected solutions are listed in Table 6-5. Up to 40% of DER penetration level, the cost of energy delivered is competitive with the grid energy, which costs 0.05 -0.08 £/kWh [6.1], and slightly higher than the unit cost of energy generated by large fossil-fuelled power plants, which costs 0.02-0.03 £/kWh [6.19]. After solution S, the increased penetration of PV systems raises the cost of the energy delivered. Solutions that provide large carbon savings with high penetrations of PV systems (e.g. solution C) have the highest cost per unit of energy.

Other studies have found that incentives of 0.40£/kWh for PV systems and 0.05£/kWh for micro-CHP would be necessary to stimulate a significant uptake of these technologies [6.1]. Currently “buy back” tariffs of between 0.05 £/KWh and 0.10 £/KWh are offered for micro-generation (PV systems, micro-CHP and wind) [6.20]. These tariffs reflect the production cost of the micro-CHP units included in this case study.

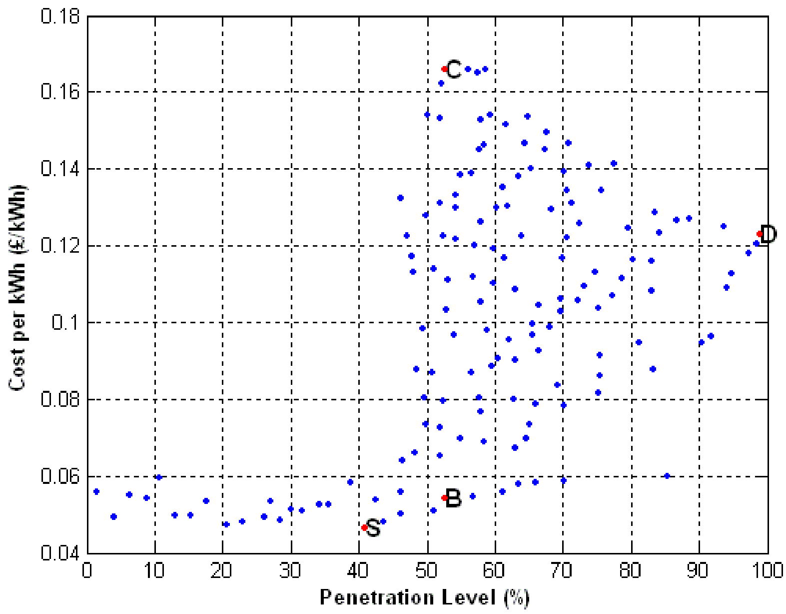

Figure 6-5 DER Penetration Level vs. Levelised Cost – Case Study 1

Micro-CHP units have a lower cost per kWh delivered. Consequently, solutions that are non-dominated in the objectives of imported energy and annualised cost (S, B and D) include higher penetrations of micro-CHP, as already illustrated. Though, the cost to reduce energy imports depends not only on the cost of the energy delivered but also on the coincidence between generation and demand, as discussed next.

Micro-CHP units have a high coincidence with domestic demand in winter, while PV system generation is prevalent in the summer when micro-CHP units have no output. As a result, after solution S, the installation of PV systems is required to obtain further reduction in energy imports (i.e. reducing summer demand), and ICE micro-CHP units are necessary to further reduce winter demand. Moreover, as the penetration of micro-generation increases, the energy imports reduced by every extra micro-generation unit installed decreases, i.e. the system saturates and more energy is exported. Consequently, further reductions in imported energy are more expensive, both because of the need for PV systems and because more units must be installed to obtain the same reduction in energy imports.

The cost efficiency of reducing energy imports can be determined from the trade-off between these two objectives. For example, solution S requires an annual spending of £70,320 to reduce 1,457 MWh/year of energy imports from solution A. This cost represents £48.2 for every MWh of energy imports reduced. Note that this cost is higher than the cost of energy delivered by Stirling engines (£45/MWh), as it reflects not only the unit cost of energy, but also the coincidence of DER production and demand in the grid, i.e. how much of the energy produced is used locally. If DER and demand were completely correlated in the grid, all the energy delivered by the DER units would be locally consumed, and the cost of reducing a unit of energy imported would be the same as the cost of producing it. Though, because a portion of the energy is exported, the cost of reducing every unit of energy imports is higher than the actual cost of production.

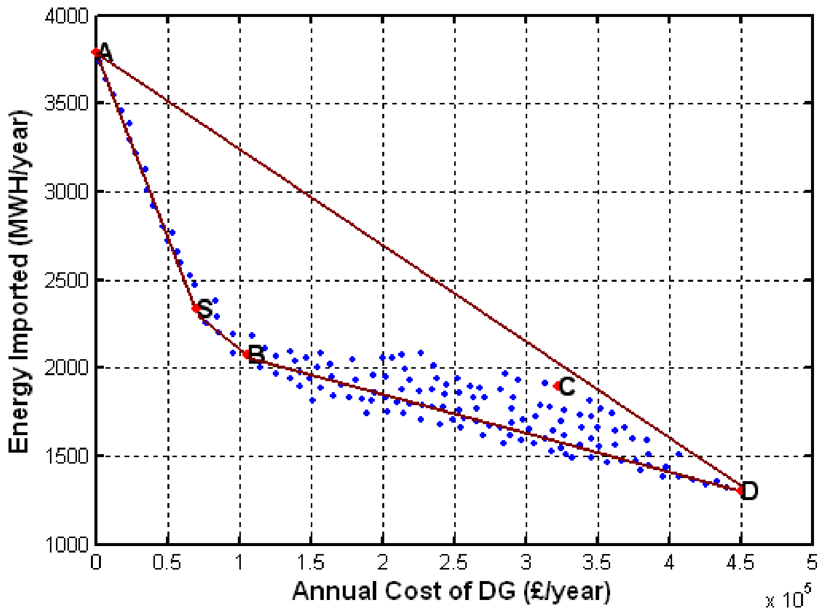

Figure 6-6 Trade Off – Annualised Cost vs. Imported Energy

Table 6-7shows the trade-offs between the optimal solutions in these two objectives (Figure 6-6). The results show that as the penetration level of DER increases, the cost of reducing energy imports grows exponentially. For instance, the trade-off between B and D is more than nine times larger than that of A and S, due to the reasons already discussed, i.e. the use of more expensive PV systems, and the requirement for more DER units to achieve the same reductions on energy imports.

Table 6-7 Trade Off – Annualised Cost vs. Imported Energy

Trade-off	Cost per MWh of Imports Reduced (£/MWh)
A-S	48.2
S-B	135.5
B-D	448.8
A-D	181.2

The incremental trade-offs show that self-sufficiency in this network cannot be achieved at a reasonable cost. Up to 40% of local load can be supplied cost-efficiently with the use of Stirling engines, or other types of micro-CHPs (e.g. the trade-off between A and ICE is £81.1/MWh), though this penetration level (40%) is unrealistic in the short and medium term. For example, solution S assumes that ~1 Stirling engine is owned by every property in the network. Furthermore, the main grid still has a major role in the provision of energy in a future with large penetration of DER. Even with 100% of DER penetration (solution D), a third of the annual energy demand must be imported from the grid, and a similar amount is exported back to the main system. Hence, the thermal loading of the equipment is not reduced drastically, as illustrated later in this section.

This analysis compared the costs of DER with the reduction in energy imports. In this case, the penetration of micro-generation was limited to provide a realistic picture of the integration of these technologies on a low-voltage/domestic power network. The results help to understand the importance of DER/demand coincidence. Moreover, the results demonstrate that the optimisation of varied types and numbers of DER is possible with the proposed approach. Consequently, the developed tool can be used to compare the impact of different technologies or to develop incentives to promote the uptake of some technologies (e.g. PV systems). Further analyses are promising, for example, it is possible to study the maximisation of the benefits obtained by DER owners (e.g. avoided purchases of energy, energy exports remuneration), and minimise the impacts in the networks, such as line loss minimisation. Moreover, the use of energy storage units, or load following micro-CHPs, which modify the trade-offs between costs, CO_2 emissions and imported energy, can be integrated within the planning framework.

Load Emission Factor and Annualised Cost

The cost of reducing carbon emissions by micro-generation depends on three factors: the carbon intensity of the DER unit, the cost per unit of energy produced and the capacity factor. An analysis of the trade-off between annualised cost and the carbon emission factor shows that Stirling engine micro-CHP provides a more cost-effective solution to reduce carbon emissions. For instance, solution S requires an annual expenditure of £ 1,776 for every gCO_2/kWh reduced in the load emissions factor. This is equal to £479 for every tonne of CO_2 reduced, as the annual load demand in the network is 3708.5 MWh/year. ICE micro-CHP is the second most cost-effective technology; the cost for every tonne of CO_2 reduced in solution ICE is £643/tonCO_2. PV systems are a zero-carbon technology; though, their higher installation cost and low capacity factor determine a high cost for carbon offsetting, which is £1248/tonCO_2.

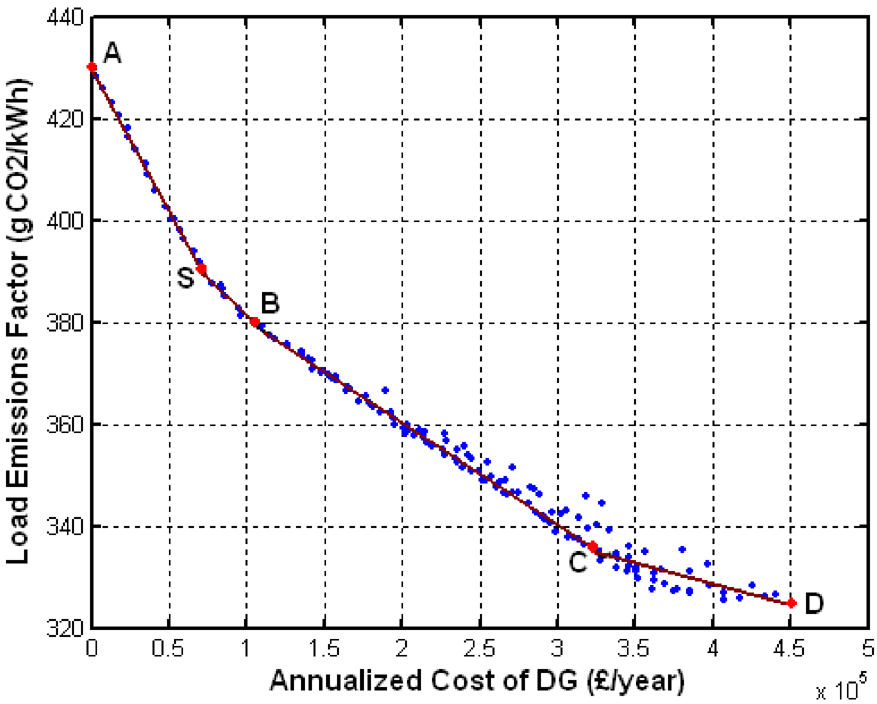

Figure 6-7 Trade Off – Annualised Cost vs. Carbon Emission Reduction

The trade-offs between the different segments of the Pareto front illustrated in Figure 6-7 are compared in Table 6-8. Note that in this case the load emission factor was used. The total emission factor, discussed in the previous chapter is up to 2% lower, as the energy exports are also carbon intensive.

Table 6-8 Trade Off – Annualised Cost vs. Carbon Emission Reduction

Trade-off	Cost per tonne of CO_2 (£/tonneCO2)
A-S	479
S-B	906
B-C	1,328
B-D	1,692
C-D	3,172

Table 6-8 shows that as the penetration level increases, the reduction in the load emissions becomes more expensive. On one hand, less cost-efficient technologies are used, while on the other hand more energy is exported.

A further key aspect must be considered: micro-CHPs provide environmental benefits only when the grid energy is very carbon-intensive (coal/gas based). Hence, micro-CHP generation reduce carbon emissions only up to a point (~320 gCO_2/kWh), after which only PV systems (or other zero carbon technologies) provide further environmental benefits. Hence, with larger penetrations of DER, or on a grid with a lower emissions factor, PV systems are the most cost efficient technology to reduce carbon emissions, among the three analysed.

The cost of offsetting carbon with micro-generation (PV systems or micro-CHP) is not competitive with large-scale zero-carbon technologies (i.e. hydro, nuclear, wind) that have a larger capacity factor and a lower cost per unit of energy. For instance, a 1MW Wind turbine, with a cost of £0.90M and a capacity factor of 27%, reduces approximately 1000 tonnes of CO_2/year, at a cost of £101/tonCO_2, assuming 430gCO_2/kWh avoided, a 20-year analysis, O&M costs of £18,000/year and a discount rate of 7%.

In this analysis, the micro-CHP emissions attributed only to electricity generation were accounted for, in order to compare them with the costs of generating electricity. An analysis of the thermal energy supply is not included in the case study. The installation of micro-CHP and CHP units is a multifaceted problem which includes impacts and costs of other types of energy demand and energy carriers (e.g. domestic heat provision and gas networks). The planning framework presented in this thesis supports the integration of other models and objectives. Hence, a comprehensive energy planning approach that considers thermal demand, gas and heating networks planning is a worthwhile further work and is described in more detail in the conclusions.

6.2.4.2. Other Planning Attributes

Selected attributes of the optimal configurations are plotted for all solutions in Figure 6-8. This figure shows that as DER penetration level increases, the imported energy is reduced, as was already discussed. The reduction of imported energy causes a decline of 12% in the maximum thermal loading in the network. Consequently, some upgrade investments can be postponed (e.g. transformer). Other studies found that PV systems alone would not reduce peak loadings, due to the lack of coincidence between production and demand [6.4]. In this case, the reduction of thermal loadings can be attributed to the optimal mixes of micro-CHP units, which reduce energy imports in peak times. Energy imports are highly correlated with thermal loadings in this network (linear correlation coefficient of 0.82).

From the point of view of the DSO an optimal penetration level of DER is 50-60%, where the benefits for the network operation are maximised (i.e. loss minimisation, thermal loading reduction), and the impacts are minimised. Line losses are reduced only up to 60% of DER penetration, after which they start to increase again. The maximum loss reduction is 40%. The increase in line losses beyond 60% DER penetration is caused by the increment of the reverse power flows, evidenced in the increment of exported energy. Energy is exported back to the MV grid with penetrations higher than 50%. With larger penetrations, the aggregated reverse flows can cause operational problems in the MV grid. Note that in this case line loss minimisation was not one of the planning objectives. It is possible that different DER configurations would provide a higher reduction in losses.

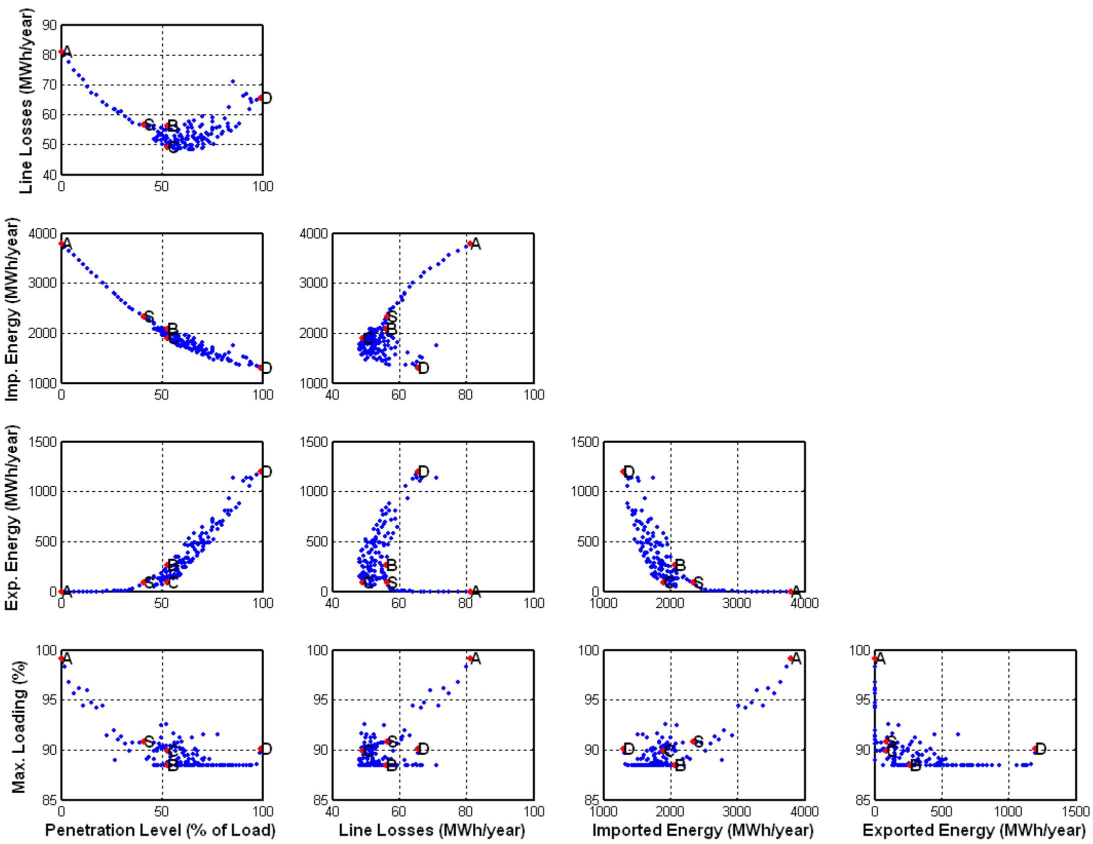

Figure 6-8 Planning Attributes – Case Study 1

None of the technical planning constraints was limiting for the development of DER, because in this case the DER penetrations were limited to provide a realistic analysis of micro-generation integration on an urban domestic network. Larger penetrations of DER were tested in the network, and it was found that a maximum penetration level of 110% could be reached without breaking technical constraints, provided that an optimal mix of DER technologies is integrated. Both voltage rise and reverse power flows in the main connection transformer were the limiting factor for further installations of DER in those cases. Nonetheless, it is unlikely that high levels of penetration (>10%) will be achieved with domestic micro-generation in the medium-term, unless a sharp drop in the cost of these technologies occurs, or adequate incentives are provided [6.1].

Micro-generation investments are decided by individual buyer initiative, and it is unlikely that the locations and sizes of these will be centrally planned. Moreover, in many cases, the installation of micro-CHP units is dictated by the thermal demand, and electricity is considered just a by-product. Nonetheless, an optimal use of the energy resources is essential to obtain a cost-effective and clean energy supply. The planning framework proposed in this thesis can be used to analyse the impacts of several types of micro-generation integration, and it can support the development of policies and incentives to encourage the adequate deployment of micro-generation.

6.3. *Case Study 2: Integration of Renewable Distributed Energy Resources in a Rural Distribution Network*

The use of renewable energy resources is recognised as a fundamental part of the UK government strategy to reduce CO_2 emissions. For instance, the UK government has set the target that 10% of electricity should come from renewable sources by 2010 and 20% by 2020 [6.20]. Currently, about 5% of UK's energy comes from renewable sources; mostly wind energy (3.7%) and hydro electricity (1.3%) [6.22]. Therefore, to achieve the government's target a substantial integration of renewable energy is required. A significant part of these renewable generators are going to be connected to the distribution system, due to their small capacity [6.23] and the existence of renewable energy resources in remote locations [6.24]. Distribution networks are usually not designed to accommodate large amounts of generators. Hence, the optimal location and sizing of DER is essential to guarantee an efficient use of resources, i.e. avoid unnecessary network reinforcements and prevent network sterilisation [6.24].

Network access for DER has been traditionally allocated on a firm access, namely a "worst-case scenario" analysis of maximum generation and minimum load. Some optimisation methods that maximise the connection of DER under firm access are reviewed in section 3.3.2.1 of this thesis (e.g. [6.24]). Nonetheless, some stochastic renewable generators, such as wind turbines, provide their maximum output only at very shorts periods of time [6.23], and as a result the use of a probabilistic analysis of DER integration provides a more objective evaluation of DER impacts and benefits [6.25]. Also, recent studies have shown that a non-firm integration of DER permits larger renewable energy production [6.26]. When non-firm access is considered, active management of the DER (i.e. DER curtailment) is essential to minimise the network impacts of DER and avoid expensive network reinforcements [6.25], [6.27]. Hence, the optimal integration of DER must consider not only the optimal number, size and location of DER units, but also the optimal operation of stochastic DER.

This case study analyses the optimal integration of wind turbines in a medium-voltage rural distribution network. The case study is divided into two parts. In the first part, the use of probabilistic objectives and constraints is demonstrated. The multi-objective approach illustrates the limitation of DER integration under a firm-access philosophy. In the second part, the possibility of curtailing renewable generation to increase the uptake of DER is included in the analysis, and the non-firm integration of wind turbines is optimised. The analysis exemplifies the conflict between the impacts of DER on the distribution network and the objectives of the DER developer. Also, the case study demonstrates that the multi-objective approach adopted in this work provides a deep insight into the DER integration problem, and that the frameworks proposed in this thesis include the current drivers of DER integration.

6.3.1. Network and Demand Data

The network studied is a 53-node medium-voltage rural network. It was derived from one feeder of the UKGDS generic rural overhead network 1 (HV OHa) [6.28]. The United Kingdom Generic Distribution Systems (UKGDS) provide resources for the study of the impacts of DG on distribution networks, including generic distribution networks, load and

DG profiles. UKGDS networks are based on statistical analysis of real networks. The generic parameters of these circuits are averaged values [6.29] that have been tuned to avoid overloads and voltage constraints breaches [6.30]. Therefore, the feeder was modified to provide a more realistic analysis of a rural network where voltage rise is often the constraining factor for DER integration [6.31]: the length of the conductors was doubled, the load was multiplied by a factor of 2.2 and the capacity of conductors was doubled.

The network studied is radial, and has long overhead lines (40 km in total) with high R/X ratios (in the range 1.4-2.7). Also, the network has a low customer density (0.20 MW/Km^2). The network is illustrated in Figure 6-9. Nodes were re-numbered from the UKGDS network to facilitate the description of optimal DER locations. Nodes 1 to 5 represent the main feeder, nodes 6 to 20 are the main branches and the rest of nodes are the secondary branches. Details of the network are provided in Appendix E.

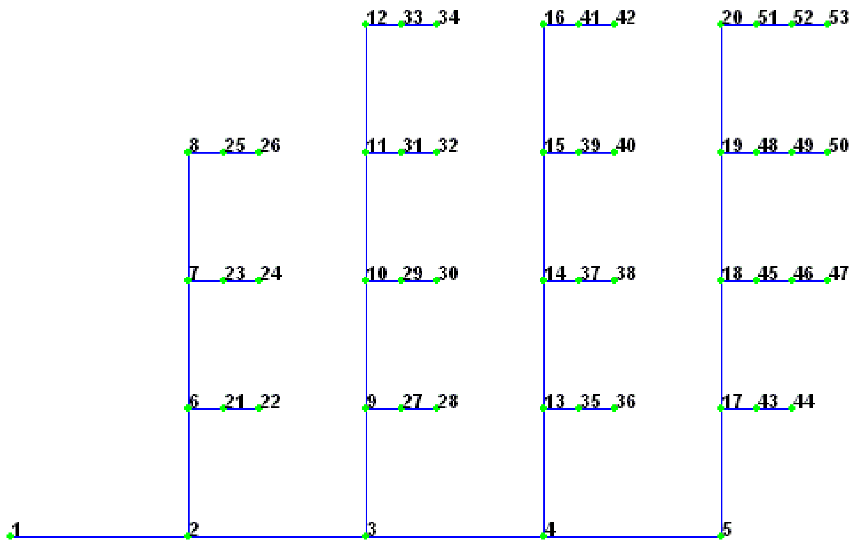

Figure 6-9 MV Network – Case Study 2

Four customer types are included in the network (Domestic Unrestricted, Domestic Economy, Industrial and Commercial). For each customer type, a yearly profile with half hour resolution is available from UKGDS [6.28]. All loads have a power factor of 0.98 lagging. The customer type and installed load of each node is detailed in Appendix E. The peak load of the feeder is 3.3 MVA; the minimum load is 0.34 MVA. Table 6-9 shows the results of the base case. The highest voltage drop is experience in node 53. The line losses represent 2.5% of the network load.

Table 6-9Case Study 2 – Base Case

Attribute	Units	Value
Line Losses	MWh/year	348.90
Imported Energy	MWh/year	14238.00
Maximum Voltage Deviation	%	5.99
Maximum Thermal Loading	%	29.85
Annual Load	MWh/year	13889.10

6.3.2. DER Data

The analysis will determine the optimal number of wind turbines to connect to the network and the optimal location of each one of them, given the multiple planning objectives, which are discussed next. It is assumed that a turbine with one MW can be connected to each node of the network. It has been concluded elsewhere that MV rural networks are not likely to support more than one to three MW of renewable generation [6.32]. Turbines are assumed to work at a power factor of 0.98 lagging. Installations are constrained in node 1.

Production profiles for a year with half hour samples are available from UKGDS [6.28]. These profiles are based on measured data and generation output models. The wind production profile has a capacity factor of 27.12% with the highest production achieved on March (42.07% capacity factor) and the lowest in January (16.14% capacity factor), as illustrated in Figure 6-10.

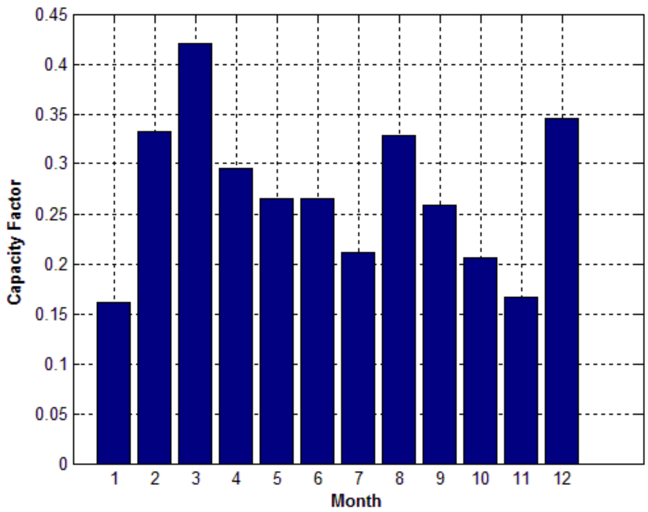

Figure 6-10 Monthly Capacity Factor - UKGDS Wind Profile

According to the UK Meteorological Office (Met Office) [6.33], January is the month when wind gales (>62 m/s) are more frequent in the UK. Extreme wind speeds are not used for producing energy as they can be damaging for the blades and structure of the wind turbine, and the cut out speed of wind turbines on the 1 MW range is around 25 m/s [6.34]. Therefore, the low production of January is due to wind speeds being too high.

The costs assumed for the wind turbine are listed in Table 6-10. These include the capital costs for installation and connection, and the costs for operation and maintenance. The costs of the active management scheme are included in the second part of the case study, when controllable units are analysed. The annuities of the capital costs are calculated using a 20-year period and a 7% discount rate. The combined benefits for energy revenues and Renewable Obligation Certificates are considered as £50/MWh [6.27]. The effect of varying this revenue is discussed in the case study.

Table 6-10Wind Turbine Costs

Installation* (£/MW)	**Connection* (£/MW)**	**Active Management Scheme* (£/MW)**	**O&M Costs** (%)**
750,000	150,000	£20,000	2% of Capital cost

*from [6.27]
**from [6.35]

The optimisation of the number of DER units and their locations is a combinatorial problem with an extremely large search space ($2^{52} = 4.5 \times 10^{15}$). Some methods have been proposed to optimise the locations and sizes for DER to maximise the penetration of DER and these were reviewed in Chapter 3. These methods have a drawback because the number of DER units must be predefined beforehand, and the study must be repeated to identify the optimal locations/sizes for different number of DER units. In contrast, the approach proposed in this thesis determines the optimal number of DER units, and their optimal location and size, in a single study, as demonstrated later in this chapter. The size of wind turbines is considered fixed; though, this also could be optimised if required, as the encoding system described in the previous chapter supports this decision variable.

6.3.3. Planning Objectives and Constraints

In the first part of the case study, referred as case 2a, the wind turbines are assumed uncontrollable. The planning objectives aim to maximise the economic benefits of DER integration, from a DER owner perspective, and to minimise the effect of DER in the network. Hence, the planning objectives are:

1. Maximise the benefits from a DER owner perspective (Equation 5-32)
2. Minimise the yearly line losses in the network (Equation 5-15)
3. Minimise the probability of voltage violation in the network (Equation 5-24a)

A fourth objective is added to determine the minimum penetration level required to achieve the best value in the three planning attributes, as discussed in section 5.6.1.1 of the previous chapter:

4. Minimise the DER penetration level (Equation 5-13)

By using this fourth planning objective, the framework will determine the optimal number of DER units for each level of DER benefits, losses and probability of voltage violation, as demonstrated later.

In the second part of the study (case 2b), the wind turbines are assumed to be controllable and OPF is performed when there is a voltage or thermal violation. Curtailment problems always have a mathematically feasible solution. Hence, the probability of voltage violation is zero for all optimal solutions in this case and the third objective is replaced with the minimisation of the curtailed energy, to optimise the operation of wind turbines. Hence, the planning objectives for case 2b are:

1. Maximise the benefits from a DER owner perspective (Equation 5-32)
2. Minimise the yearly line losses in the network (Equation 5-15)
3. Minimise the energy curtailed in the year (Equation 5-21a)
4. Minimise the DER penetration level (Equation 5-13)

The SPEA2 analysis includes both probabilistic and deterministic constraints. The probability of voltage violations is constrained to a maximum of 5% over the year. The voltage limits are set to +/-6% of the nominal voltage. Thermal constraints are assumed deterministic and set to a maximum of 100% of loading in all lines.

The OPF analysis considers deterministic voltage (+/-6%) and thermal constraints (100%). The curtailment problem is formulated in terms of energy [6.36], as under a non-firm analysis the revenue lost by energy curtailment is not included as a cost (see previous chapter).

6.3.4. Case 2a: Results and Discussion

The parameters used for the SPEA2 optimisation are shown in Table 6-11. Each chromosome evaluation took an average of 2.5 seconds to evaluate, and the total evaluation time was 34 hours. Sequential sampling was used to permit an unbiased comparison with the results of case study 2b. All planning objectives have high accuracy (R<0.05).

Table 6-11 Parameters for SPEA2 Optimisation

Population Size	100
Archive Size	50
Generations	500
Crossover type	Uniform
Crossover rate	0.9
Mutation rate	0.02
Sampling	Sequential
Stopping Criteria	3504 samples (Time step =5)

The objectives of the optimal solutions are illustrated in Figure 6-11. The base case scenario is identified (solution 0), together with four solutions which are labelled according to the number of wind turbines installed (3, 5, 6 and 8). The objectives for these solutions are detailed in Table 6-12.

The characteristic U-shape between line losses and DER penetration level is observed in the second row of plots. In this network, the losses are minimised to 60% of the initial value with 3 wind turbines installed in key locations. Optimal DER locations are discussed later. The optimal number of generators from a DSO point of view is between 2 and 6, as more installations increase the line losses in the system, and also the maximum voltages. With 8 turbines, the line losses are almost 140% of the base case.

Table 6-12 Planning Attributes – Optimal Solutions Case 2a

Attribute	Base Case	3WT	5WT	6 WT	8WT
Annual DER Benefits (£/year)	0	47,366	78,944	94,732	126,310
Line Losses (MWh/year)	349	201	244	298	482
Prob. of Voltage Violation (%)	0	0	0	0.06	3.99
Maximum Voltage Violation (%)	5.99	5.94	5.941	6.45	8.55
Maximum Thermal Loading (%)	29.85	29.25	36.80	44.6	60.6

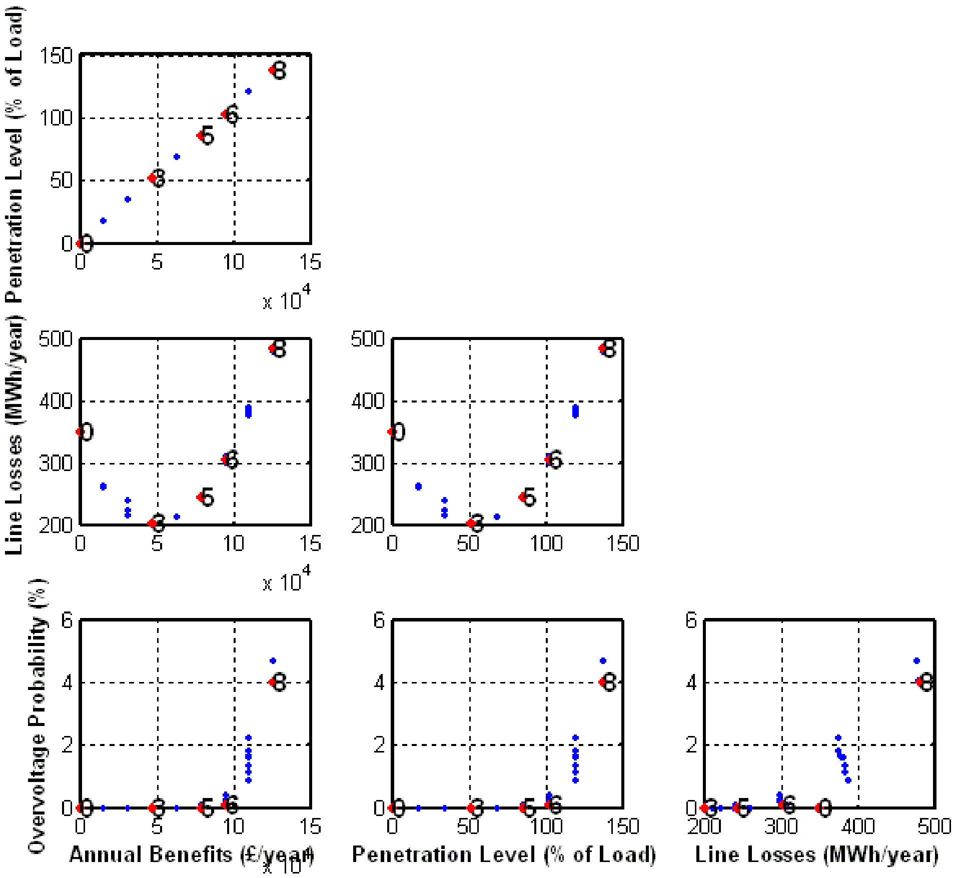

Figure 6-11 Optimal Solutions - Case Study 2a

The optimal siting of 5 wind turbines keeps the network within deterministic voltage limits. The 6th turbine, even when optimally located, causes a voltage rise outside the deterministic limits. Though, the maximum voltages with 6 turbines installed are only slightly above the deterministic constraints. These voltages are between 1.0645 p.u. and 1.0731 p.u. Consequently, the probability of constraint violation for the optimal solutions with 6 turbines is very small, between 0.06% and 0.4% of the year (4 - 35 hours). In contrast, if a suboptimal integration is followed, voltage constraint violations occur even with 3 turbines, as illustrated in Figure 6-12. As the number of turbines installed increases, their optimal placement becomes critical, because the impacts of the turbines on the voltage rise are aggregated. For instance, 8 turbines wrongly located can determine probabilities of voltage violation as high as 20%.

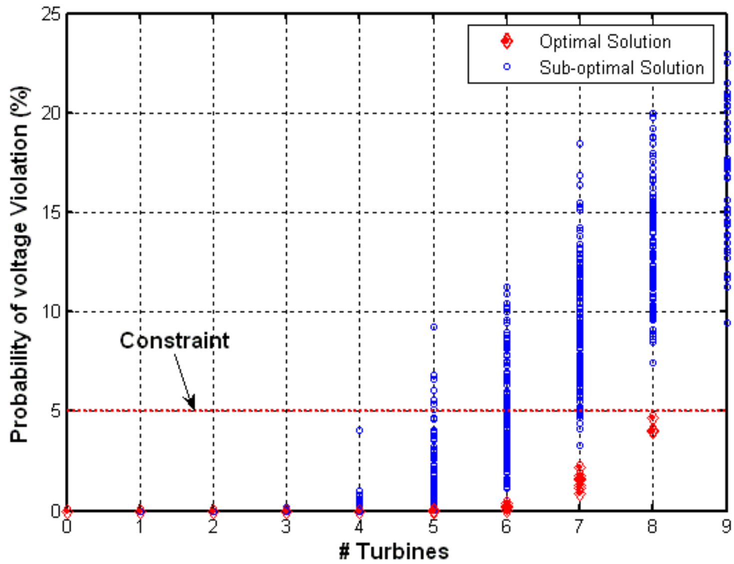

Figure 6-12 Probability of Voltage Violation with Optimal and Sub-optimal Integration

In a deterministic analysis even the smallest voltage violation is unacceptable, even if it happens just at a single instance or for a brief period of time. Hence, if deterministic constraints are applied (i.e. the probability of constraint violations must be zero), the DER owner net benefits are limited to around £ 79,000 per year, assuming an optimal location for 5 turbines. In contrast, using a probabilistic analysis and limiting the probability of voltage violation to 5%, up to 8 turbines can be installed. With 8 turbines, the net economic benefits increase to £126,000 per year, 60% more than in the best deterministic case. With 9 turbines installed, the probability of voltage violation exceeds 5%.

The increment in the DER owner benefits by installing 8 turbines is in conflict with the DSO objectives because line losses and maximum voltages would increase, as already discussed. However, an interesting compromise solution exists with the installation of 6 turbines. In that case, with 6 turbines the line losses are reduced from the base case, the probability of voltage violation is very small, the maximum voltages are not extreme and the benefits for the DER owner are 20% higher than when the deterministic constraints are used. This analysis demonstrates that a multi-objective approach is able to illustrate different perspectives of the DER integration problem.

Figure 6-13 shows the optimal locations for wind turbines for the selected optimal solutions listed in Table 6-12. In the case of 3 wind turbines, turbines are located strategically in the middle of the main branches. In these sites, the turbines can supply energy to the loads when production is coincident with demand, or export their surplus without increasing losses excessively when production exceeds demand. A simpler analysis that disregards the time-variability of DER would determine erroneous optimal locations, as losses are also time-variant, and would not be able to provide a probabilistic assessment of DER integration.

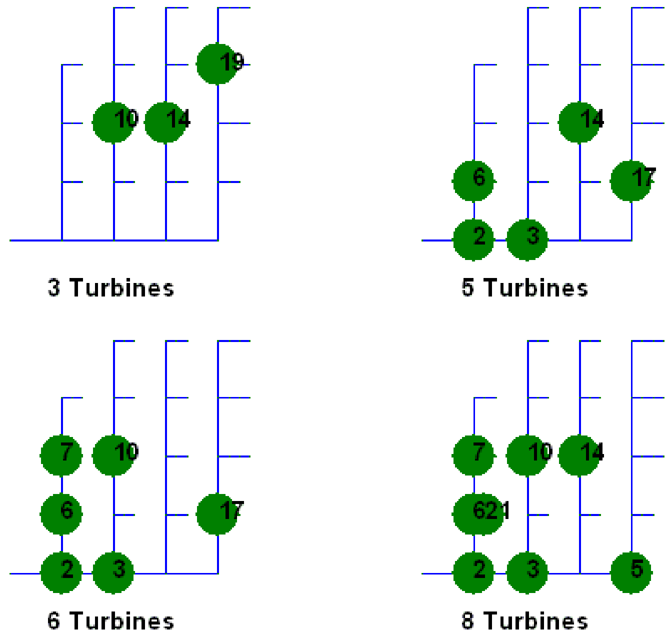

Figure 6-13 Optimal DER Locations - Case Study 2a

The case of 5 turbines shows most turbines located near the grid supply point, as other locations would lead to higher voltage rises and constrain the integration of DER. Two other turbines are located strategically in the main branches (nodes 14 and 17) to reduce the line losses. A similar distribution pattern is also observed when 6 or 8 turbines are installed: most of the optimal turbines are located near the grid supply point, and the rest of the turbines are strategically located between the grid supply point and the loads, to reduce the losses. For instance, turbines are installed in nodes 10 and 17 in the case of 6 turbines, and in nodes 5, 10 and 14 in the case of 8 turbines. The optimal locations achieve the two technical objectives chosen (minimise line losses, minimise probability of voltage violation), as the economic objectives are the same regardless of the location.

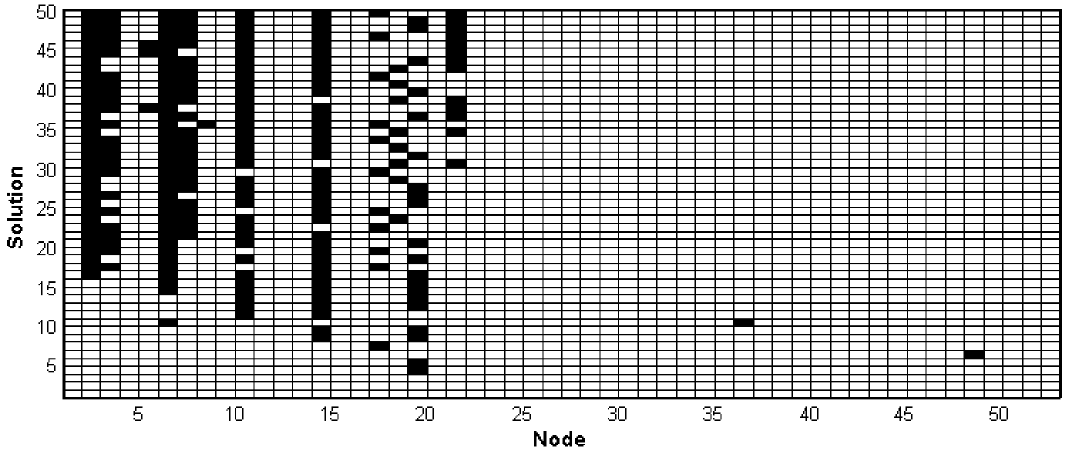

Figure 6-14 Optimal Solutions Chromosome – Case Study 2a

Additional information can be obtained by analysing the "chromosomes" of the fifty optimal solutions, illustrated in Figure 6-14. Solutions have been sorted from top to bottom according to the number of turbines installed. A black square indicates a turbine installed in the node. The optimal locations for DER turbines are predominantly in the main feeder (nodes 1-5) and in the primary branches (nodes 6-20). Strategic nodes can be identified; for instance, nodes 2, 7, 10 and 14 have a turbine installed in more than 50% of the solutions. Though, these nodes are not optimal locations when a single-turbine is optimised. These locations are optimal only when four or more turbines are installed, as they minimise the losses and the voltage rise problems. This is valuable information for a DSO, as it identifies key nodes to obtain the most benefits of DER installations. The information can be used to promote an optimal DER integration in the long-term.

The results presented in this study demonstrate that the approach proposed is able to find the optimal locations for different numbers of DER units in a single analysis. Moreover, it demonstrates that a multi-objective analysis of DER integration is able to illustrate different perspectives on the problem (e.g. DSO, DER owner). Also, by analysing each objective explicitly, the impacts constraining the development of DER can be identified, and locations that provide beneficial DER installations, for different penetration levels, are exposed.

6.3.5. Case 2b: Results and Discussion

The previous section showed that the deterministic analysis of DER integration restricts the integration of wind turbines. It illustrated that constraint violations of some solutions are very small and occur only for a very short period of time, and that a larger number of turbines can be installed if probabilistic constraints are used. In the second part of the case study, a different perspective is used. The possibility to curtail wind production to keep the system within deterministic constraints is analysed using a multi-objective approach.

The SPEA2 parameters used for the previous study were also used in this case (Table 6-11). The average evaluation time per chromosome was 5 seconds, and the total evaluation time was 69 hours. Curtailed energy is the least accurate attribute: 66% of the solutions have relative uncertainty lower than 0.10, and 86% of the solutions have a relative uncertainty lower than 0.2. The highest relative uncertainties correspond to the solutions with the lowest curtailment. The rest of the planning objectives have relative uncertainty lower than 0.05. The OPF voltage constraints were checked only in key nodes of the network, illustrated in Figure 6-15, to speed up the OPF optimisation.

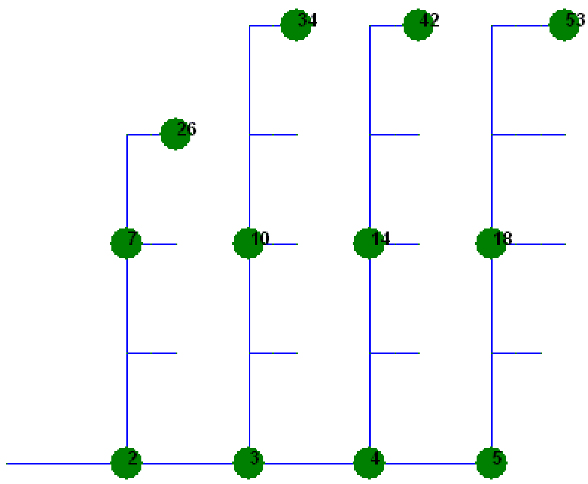

Figure 6-15 Nodes Used to Check OPF Voltage Constraints

Results are illustrated in Figure 6-16. Several solutions have been identified to facilitate the discussion of results. The labels of these solutions indicate the number of turbines connected (0, 3, 6, 7 and 8). The objectives of some of these solutions are detailed in Table 6-13.

The results confirm that the curtailment of the wind turbines is not necessary when there are no voltage constraint violations. Therefore, solutions with up to 5 turbines installed are similar to those in case study 2a. When the 6th turbine is installed, in an optimal location, a small amount of curtailment is necessary to keep the system within limits (1.7 MWh/year). In the previous case study it was observed that voltage violations with 6 turbines occur for a very small amount of time (0.06%); hence, the curtailment with 6 turbines is negligible (0.01% of the energy generated).

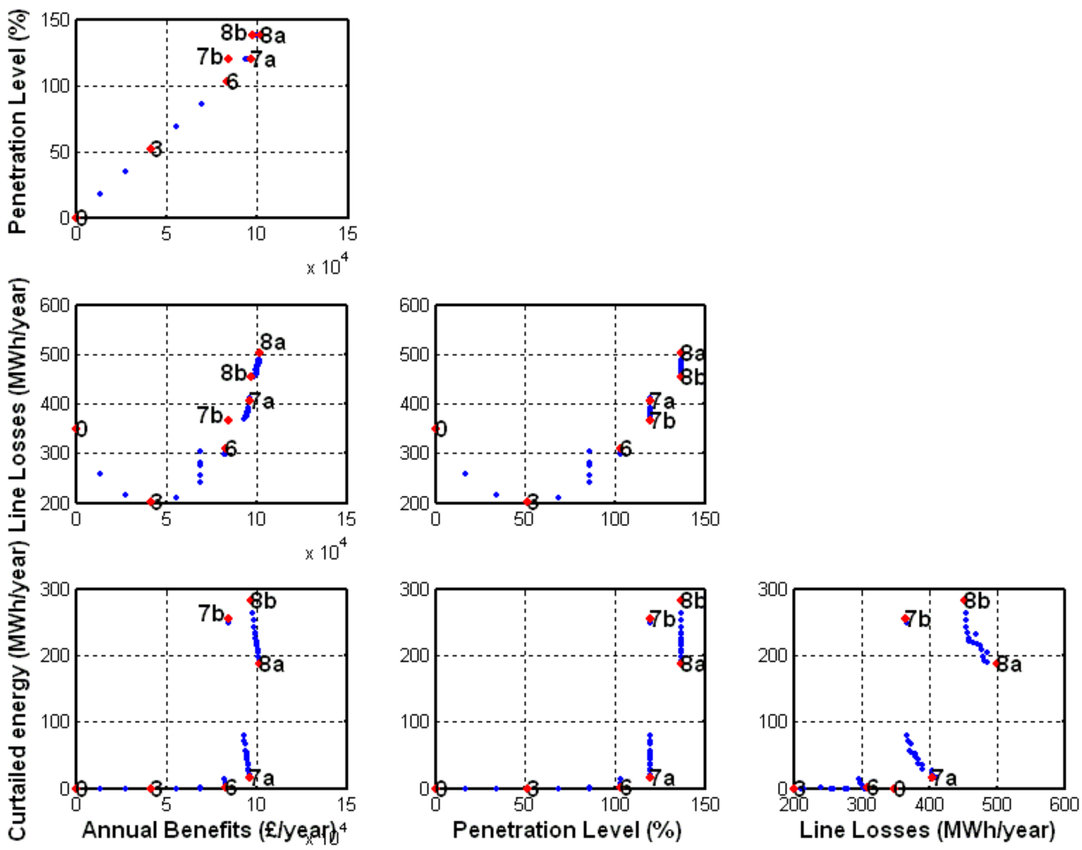

Figure 6-16 Optimal Solutions - Case Study 2b

The curtailment of energy to comply with network constraints increases considerably when more turbines are installed, as observed in the third row of plots of Figure 6-16. The amount of energy curtailed for 8 turbines is between 0.98% (8a) and 1.47% (8b) of the total energy available. The energy curtailed produces a reduction in the net benefit of 7.4% and 11.1% for solutions 8a and 8b, respectively, from the net benefits that would have been hypothetically obtained without curtailment with 8 turbines. The difference in the order of magnitude is because a large proportion of the revenues are used to cover the capital and operation costs. Hence, a relatively small amount of curtailed energy has a larger impact on the DER owner *net* economic benefits.

Though this "reduction" must be put in perspective; if deterministic constraints are used and curtailment is not applied, only 5 turbines can actually be installed and the benefits to the DER owner are restricted to £79,000/year, as discussed in the previous section. Hence, in reality the curtailment of energy permits an the increase in the net benefits to the DER owner by more than £20,000/year, an increase of 25%, and the renewable energy delivered increases by 58% (solution 8a compared with solution 5).

Table 6-13 Planning Attributes – Optimal Solutions Case 2b

Attribute	**Base Case**	**7a**	**7b**	**8a**	**8b**
Annual DER Benefits (£/year)	0	96,480	84,566	101,880	97,153
Line Losses (MWh/year)	349	405.9	366.0	500.8	453.8
Curtailed Energy (MWh/year)	0	16.53	254.81	186.52	281.07
Curtailed Energy (%)	0	0.10	1.53	0.98	1.48

The maximum amount of energy that can be curtailed before making the net benefits zero can be calculated using break-even economics, as proposed by Currie *et al.* [6.27]. For 8 MW (i.e. 8 turbines installed) and assuming a benefit per unit of energy of £50/MWh and the costs of Table 6-10, the maximum amount of energy that can be curtailed before incurring financial losses is 2167 MWh/year, or 11.4% of the total energy. Following a similar analysis, it can be determined that a maximum of 294 MWh/year (1.5% of the total energy) can be curtailed from the energy produced by the 8 turbines before the net benefits become £96,500/year, which is the revenue provided by solution 7a. Hence, if 8 turbines are installed and curtailment is larger than 294 MWh/year, it is economically more efficient to install 7 turbines, which cost less, avoid more energy curtailment, produce fewer line losses and provide the same or more net-benefits. This is confirmed by analysing the solutions; for instance, solution 8b has 281 MWh/year curtailed, and slightly higher net benefits than solution 7a.

Curtailment has contrasting effects on the planning objectives. For a given number of turbines installed, curtailment of energy reduces the DER benefits, which are to be maximised, as already demonstrated. Similarly, curtailment reduces the line losses, which are to be minimised, as less energy flows in the network. Consequently, a Pareto front can be distinguished for each bi-objective plot for each number of installed turbines. These fronts are 7a-7b and 8a-8b, for 7 and 8 turbines installed, respectively. Two of the bi-objective plots are illustrated in Figure 6-17. Solutions 7a and 8a have the least amount of curtailment, for 7 and 8 turbines respectively, and the higher losses and economic benefits. In contrast, solutions 7b and 8b have the higher curtailment, and lower losses and economic benefits.

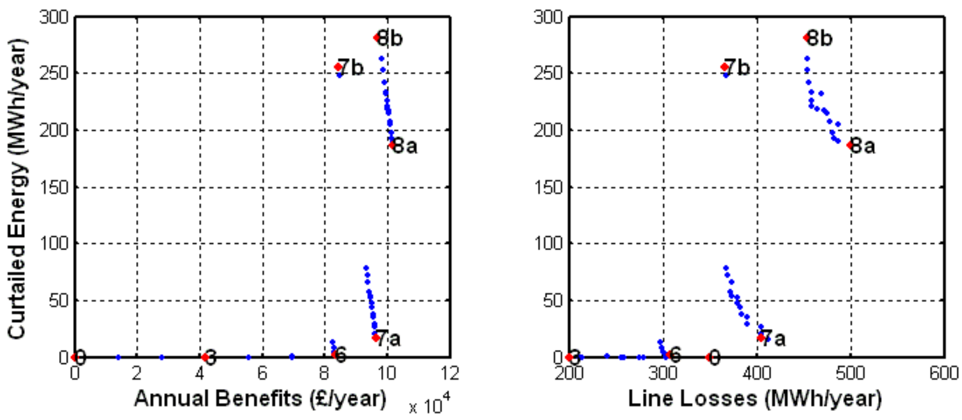

Figure 6-17 Bi-objective plots – Case Study 2b

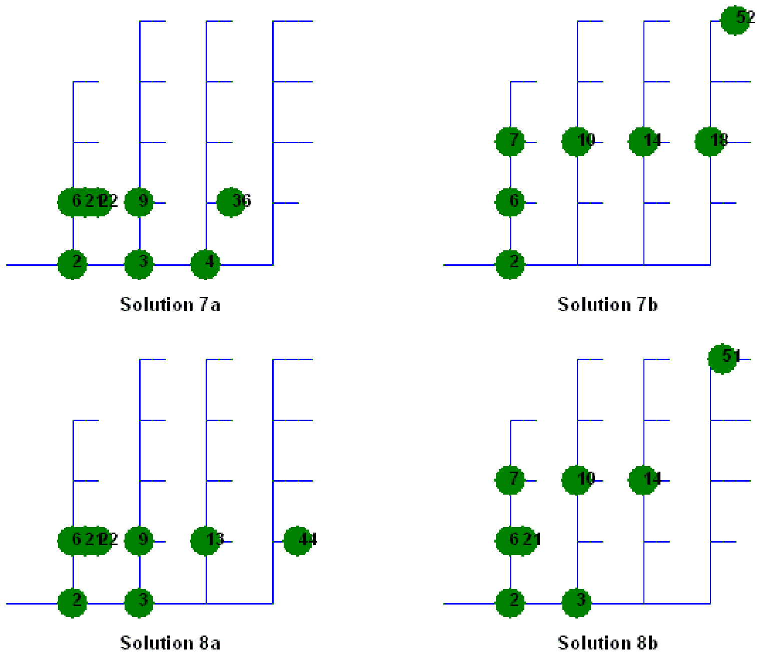

Figure 6-18 Optimal DER Locations - Case Study 2b

The optimal locations for turbines in solutions 7a, 7b, 8a and 8b are illustrated in Figure 6-18. Two trends can be recognised. Solutions 'a' (low curtailment, high benefits, high losses) have most generating units located close to the grid supply point. In this way, voltage rise effects, and consequently curtailment, are minimised. Additionally, some generators are located in the main or secondary branches to reduce some of the line losses. In contrast, in solutions ‘b’ (high curtailment, low benefits, and low losses) the generators are evenly distributed in the network, to minimise losses. In this case, more energy is curtailed due to the higher voltage rise. The analysis illustrates that in this network the locations that benefit the DER owner are not optimal for the DSO operator, and vice versa.

The importance of the optimal location of the turbines cannot be underestimated. Figure 6-19 compares the benefits obtained with optimal DER locations with the benefits obtained by sub-optimal configurations, for different numbers of turbines. As the number of turbines increases (>6) and when turbines are sub-optimally located a larger proportion of energy is curtailed to keep the system within constraints. Consequently, the amount of energy exported and the economic benefits received are reduced. With 9 or more turbines wrongly situated, it is possible that the benefits received will not be enough to cover the installation and operation costs (i.e. break-even point). With 12 or more turbines, it is not possible to obtain a solution that provides financial benefits, as the amount of energy curtailed reduces the revenue beyond the break-even point.

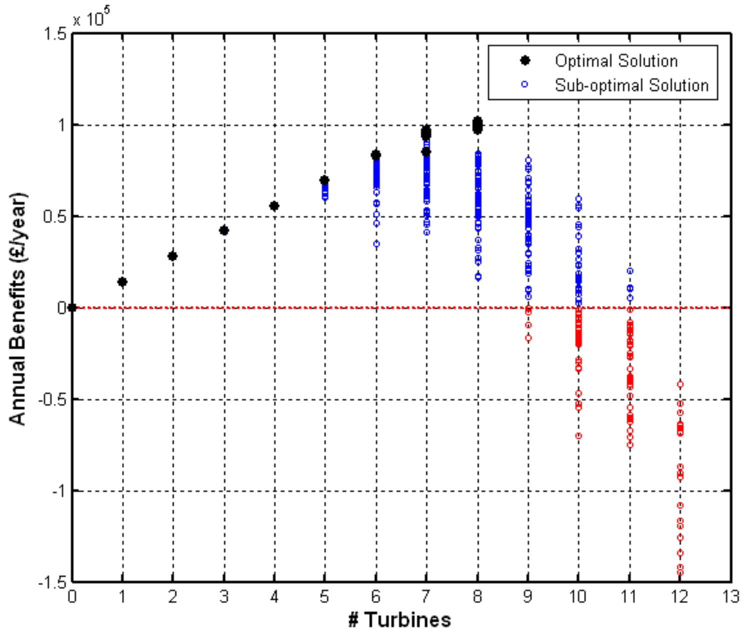

Figure 6-19 Annual DER Benefits with Optimal and Sub-optimal Integration

The additional benefits obtained with every extra turbine installed decrease (i.e. diminishing marginal benefits). In this network, and given the revenue defined (£50/MWh), the optimal number of turbines to maximise benefits is 8. When the 9^{th} turbine is optimally located, net benefits are still positive; however, the installation of 9 turbines is a dominated solution. The optimal installation of 8 turbines has larger net benefits, less curtailment and less line losses. Consequently, if all turbines belong to a single DER developer, i.e. using a centralised planning perspective, 8 turbines should be installed. In contrast, if each turbine/farm is developed separately up to 11 turbines can be installed profitably. Though, the benefits obtained by every installation are reduced, even if optimal locations are used, until no more turbines can be installed profitably in the network. This analysis highlights the importance of a comprehensive assessment for the network development of an efficient system, and for setting in place policy frameworks that will steer the outcome towards the most economically beneficial overall.

6.3.5.1. Scenario Analysis

The revenue received for every unit of energy sold is the factor that determines the optimal number of installations and the maximum economic benefits that can be achieved. For example, when the revenue is assumed £50/MWh, the optimal number of turbines to install to maximise benefits is 8, as already demonstrated (solution 8a). Nonetheless, in a liberalised energy market uncertainty exists in the price at which energy and accompanying renewable certificates can be sold. Hence, the analysis was repeated considering four additional scenarios for the revenue per unit of energy, from £45/MWh to £65MWh. In each scenario, the optimal solution that maximises the benefits was determined. The optimal solutions are listed in Table 6-14. The curtailment of energy increases with more turbines installed, though, the higher revenue received for the energy traded compensates for this curtailment. Hence, as the revenue per unit of energy increases, the optimal number of turbines to install also increases.

Table 6-14 Optimal Solutions in Diverse Scenarios - Case Study 2b

Scenario	Optimal Solution		
	# of Turbines	Annual Benefits (£/year)	Energy curtailed (MWh/year)
£65/MWh	10	407,5004	1368
£60/MWh	9	301,790	628
£55/MWh	9	197,770	628
£50/MWh	8	101,880	187
£45/MWh	7	13,268	13

The performance of each of the four optimal solutions was analysed in all the scenarios. The annual benefits obtained in each case are listed in Table 6-15 and illustrated in Figure 6-20**.**

Results illustrate the effect of uncertainty in the optimal solutions. For example, the optimal installation of 10 turbines maximises benefits when the revenue per unit of energy is £65/MWh. Though, if the benefit per unit sold drops to £45/MWh, the installation of 10 turbines results in a net financial loss. Similarly, installing 7 turbines guarantees some gain when the price of energy is low, but is not the optimal solution when the price of energy rises.

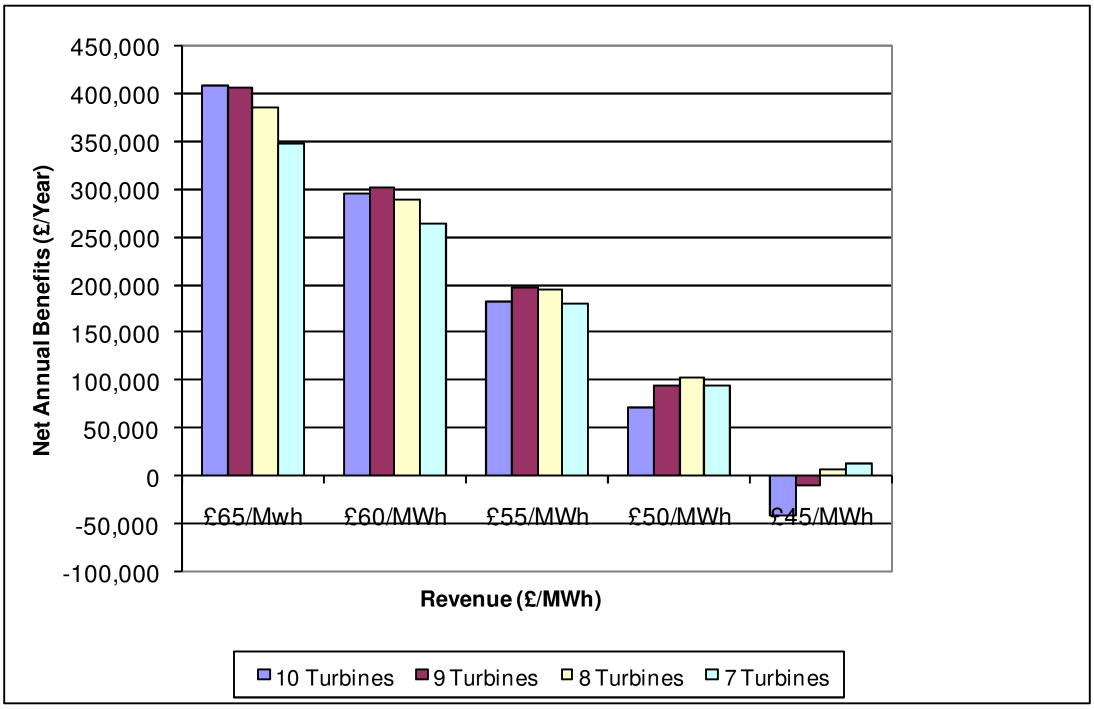

Figure 6-20 Scenario Analysis

Figure 6-20 and Table 6-15 show that there is no solution that is optimal in all scenarios. If the future price of energy was certain, or could be accurately predicted, the choice of an optimal solution would be straightforward. Nonetheless, this is not always the case and uncertainty is present in this and other parameters. The choice of a single solution is not the main objective of the planning framework presented in this thesis. Though, for completeness of this case study it is demonstrated next.

Table 6-15 Scenario Analysis - Case Study 2b

Scenario	Annual Benefits (£/year)			
	10 Turbines	9 Turbines	8 Turbines	7 Turbines
£65/MWh	**407,500**	405,940	384,290	346,583
£60/MWh	295,118	**301,790**	289,903	263,254
£55/MWh	182,890	**197,770**	195,640	179,925
£50/MWh	70,593	93,687	**101,880**	94,566
£45/MWh	- 41,765	-10,451	6,944	**13,268**

The choice of one solution over the others requires a Scenario Analysis. Two techniques are commonly used. The first, referred as to Probabilistic Choice, consist of maximising the weighted-sum of the benefits, given the probability of each scenario occurring [6.37]. Following this method and assuming a similar probability of occurrence of all scenarios (0.20), the optimal solution is the installation of 9 turbines, as this solution maximises the sum of the benefits over all scenarios, as seen in Table 6-16.

Table 6-16 Probabilistic Choice – Case Study 2b

Optimal Solution	**10 Turbines**	**9 Turbines**	**8 Turbines**	**7 Turbines**
Average Benefits (£/year)	182,867	**197,747**	195,731	179,519

However, probabilistic choice has been criticised, as it provides the optimal solution for an average future, which is unlikely to occur, and as a result it provides "riskier" solutions [6.38]. The second method, known as Risk Analysis, proposes a 'mini-max' approach where the maximum regret is minimised. Regret is the cost suffered for having chosen a different alternative than the optimal one for a future that really occurred [6.37]. Regrets for each one of the solutions in each one of the scenarios are shown in Table 6-17. In this case, the installation of 8 turbines minimises the maximum regret (i.e. risk).

Table 6-17 Risk analysis – Case Study 2b

Scenario	**Regret (£/MWh)**			
	10 Turbines	**9 Turbines**	**8 Turbines**	**7 Turbines**
£65/MWh	0	1,560	**23,210**	**60,917**
£60/MWh	6,672	0	11,887	38,536
£55/MWh	14,880	0	2,130	17,845
£50/MWh	31,287	8,193	0	7,314
£45/MWh	**55,033**	**23,719**	6,324	0
Maximum Regret	55,033	23,719	**23,210**	60,917

This analysis demonstrates that the multi-objective planning framework is also a useful tool for single-objective problems. The multi-objective approach provides the advantage that it can include other objectives explicitly, and hence, reflect other perspectives of the problem.

6.4. *Summary*

This thesis proposes the use of multi-objective optimisation to analyse DER integration. The development of a multi-objective planning framework has been presented in previous chapters. This chapter presented the application of the multi-objective planning framework to the analysis of two case studies of DER integration. These cases were selected to reflect current issues of DER integration in the UK. Moreover, the analyses presented are completely different, and illustrate the flexibility of the planning framework developed in this thesis.

The first case study analyses the integration of three types of micro-generators in an urban low-voltage network. Three planning objectives reflect technical, environmental and economic aspects of the problem. This case study demonstrated that the planning framework is able to optimise several types of stochastic DER simultaneously. Furthermore, the analysis illustrated that the impacts of DER are technology specific, and that different DER mixes have contrasting impacts on the distribution network and on the cost of DER integration. Moreover, the case study showed that large reductions in carbon emissions will be hard to achieve with micro-generation in the short or medium term, as the cost efficiency of using micro-generators to reduce carbon-emissions is not comparable with larger technologies. The analysis of diverse planning attributes showed that the main constraint for the integration of micro-generators is not technical, but economic.

The second case study focused on the integration of wind turbines in a medium-voltage network. The case study demonstrated that the multi-objective planning framework includes current challenges for the integration of wind turbines, such as probabilistic constraints, non-firm access and the analysis of generation curtailment. The limitations of firm access principles for the development of further wind turbine integration were examined under a multi-objective perspective. The results showed that the planning framework can also be a useful tool for single-objective planning. The multi-objective planning approach provides the advantage that other objectives can be explicitly included in the analysis, and different perspectives analysed.

In the next chapter, the conclusions of this thesis are presented. Also, the contributions to knowledge of this work are identified. Finally, further work that arises from this thesis is discussed.

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Chapter 7

7. Conclusions, Contributions and Future Work

7.1. *Conclusions*

This chapter presents the conclusions of this thesis. These have been divided into three groups: conclusions from the problem formulation, conclusions from the specification and development of the planning framework and conclusions from the case studies. This chapter also summarises the contributions of this thesis, and proposes further work for the improvement and development of the planning framework presented in this thesis.

7.1.1. Conclusions from the Problem Formulation

The comprehensive review of DER planning techniques presented in Chapter 3, and the detailed analysis of the DER planning problem of Chapter 4 showed that the concepts of DER planning have evolved in recent years. Some aspects of this evolution were discussed in Alarcon-Rodriguez *et al.* [7.1], and are summarised next:

- Traditionally, the integration of DER in distribution networks was considered as a single-objective problem, where the main concerns were the minimisation of cost subject to the technical constraints of the network or the minimisation of line losses. However, **DER integration has a wide range of technical and economic objectives**. These objectives include for example: to maximise the generation of renewable energy, to minimise voltage rise in the network, to maximise the net economic benefits or to minimise the thermal loading of equipments. Some economic objectives can be formulated from several perspectives, as **diverse stakeholders participate in DER research, development, management and operation** (e.g. the DER developer, the DNO, the regulator, the customer). Also, **there is an evident need to include environmental objectives in the analysis of DER integration,** i.e. carbon emissions minimisation, because DER is recognised as a possible solution to reduce the environmental impacts of energy generation. Most of these planning objectives can also be formulated as planning constraints, depending on the analysis. Consequently, **the DER planning problem is in essence a multi-objective problem where every impact**

and benefit of DER integration can be formulated as a planning objective or a planning constraint.

- Until recently, most DER planning techniques considered DER as constant and uncontrollable power sources. These techniques regarded a single-snapshot analysis of the system as sufficient for the evaluation of DER impacts. Nonetheless, **most DER technologies are stochastic in nature**. In addition, the **active management of DER and the network is recognised as one of the new paradigms for the integration of larger penetrations of DER** in the distribution systems. In a low-carbon future, several types of uncontrollable and controllable DER will interact simultaneously with an active power network. The analysis of this interaction cannot be oversimplified. In contrast**, a stochastic and probabilistic assessment of controllable and uncontrollable DER is necessary** to provide an adequate evaluation of DER impacts and benefits.

- Most traditional DER planning methods handle only one or two decision variables: DER size and/or DER location. Nonetheless, **the optimal integration of DER often has a combination of decision variables,** which, besides the optimal DER locations and sizes, includes the optimal number of units and the best DER types to install in the network. A **method that can simultaneously optimise some or all of these decision variables** will become a valuable tool for the analysis of DER integration.

So, appropriate methods are required to analyse the multiple impacts and benefits of DER. These methods must consider the new paradigms in DER operation and technology and analyse the stochastic interaction of DER and load. A flexible method is required to permit the analysis of diverse planning objectives and constraints, and to optimise varied decision variables of DER integration. This thesis presents an approach with these characteristics, as demonstrated in the previous chapters, and discussed next.

7.1.2. Conclusions from the Specification and Development of the Planning Framework

This thesis proposes a flexible multi-objective planning framework to analyse the benefits and impacts of the optimal integration of DER in the distribution networks. A novel aspect of this thesis is that the framework provides **a flexible analytical platform** that **is able to optimise simultaneously controllable and stochastic DER,** for the first time, and that **includes technical, environmental and economic planning objectives and constraints**. Also, the framework is able to provide a **probabilistic analysis** of DER integration in an optimisation environment.

The planning framework uses three primary techniques: a **multi-objective evolutionary algorithm (MOEA)**, **a stochastic simulation algorithm** and an **Optimal Power Flow (OPF)** algorithm for the analysis of controllable units. Analogous techniques have already been used individually by other researchers of the field. Nonetheless, **the strength of this present work is that it integrates them all into a single framework**. Results from two case studies included in the thesis and from an additional case study published in a journal paper [7.2] show that the framework is able to answer the two questions proposed at the start of this thesis (section 1.2), and that it **is a valuable tool to analyse the optimal integration of DER**, for the reasons discussed next:

- MOEA are an effective method to solve an optimisation problem such as DER planning, which is multi-objective, with integer and discrete variables, and nonlinear objectives and constraints. **MOEA do not require linear functions, analytical expressions, derivatives or continuous functions to perform the optimisation.** This aspect is important because the optimisation objectives and constraints are not limited by the optimisation technique. As a result, any impact, or number of impacts, of DER integration can be formulated as planning objective(s) or planning constraint(s). Also, **MOEA are able to optimise different types of decision variables of DER integration, such as DER size, location, number and type, without major changes to the framework structure.** These two features provide flexibility in terms of the types of analyses of DER integration that can be carried out, because **any number of objectives and constraints** of any mathematical nature can be chosen as planning goals, and diverse decision variables optimised. **This flexibility was demonstrated** with the two case studies of the previous chapter and the case study published in [7.2]: the objectives, constraints and decision variables of each case study are completely different. Nevertheless, they can be analysed effectively using the same framework.

- The objective evaluation of MOEA supports any type of objective evaluation, as aforementioned. Hence, a stochastic simulation algorithm for the evaluation of DER is integrated within the planning framework. **Stochastic simulation provides a more accurate evaluation of the interaction of stochastic DER and load, than a single**

snapshot analysis of the system. For instance, the first case study of the previous chapter showed that the planning framework is able to optimise the integration of three types of stochastic DER in a low-voltage network with fifty different load profiles. This analysis would not be possible with a simplified approach. Moreover, **the stochastic simulation supports the probabilistic analysis of DER integration.** Probabilistic measures permit a more objective evaluation of the impacts that limit the integration of DER, such as voltage rise. For example, the second case study demonstrated that in some cases the overvoltage problems that would limit the installation of wind turbines occur for a negligible amount of time. In addition, **the use of stochastic simulation has an advantage in that it can evaluate planning objectives that analytical expressions, or simplified approaches, cannot.** As a result, it is possible to incorporate an **inner optimisation algorithm** in the objective evaluation stage of MOEA. The inner optimisation algorithm is discussed in the next paragraph.

- **The framework includes a linear Optimal Power Flow for the analysis of controllable DER (inner optimisation algorithm).** OPF is one of the most used optimisation tools in power systems; it is applied to problems such as the economical dispatch of large-scale generation, the minimisation of transmission losses and the planning of the optimal development of generation. In this work, **the OPF is used to evaluate the optimal operation of controllable DER.** The OPF is applied repeatedly in the stochastic simulation, to optimise the curtailment of the output of renewable DER and the dispatch of controllable DER, in order to keep the system within operational constraints. The linear formulation of the OPF restricts its applicability only to radial networks with high R/X ratios and mostly active power flows. Nonetheless, the **modular structure** of the planning framework, discussed later, permits the replacement of this OPF with other inner optimisation algorithms. Therefore, **the analysis of storage units, responsive loads or active network management in meshed networks is possible within the planning framework.** The extension of the planning framework for the analysis of other DER and energy systems is discussed later as further work.

- **The framework is able to optimise both controllable DER and uncontrollable DER simultaneously,** as aforementioned. DER is recognised as one of the alternatives for a low-carbon future, and the active management of networks and DER is proposed as one of the new paradigms for the operation and planning of power systems. In such a scenario, tools that are able to analyse the benefits and impacts of the integration of many types of DER interacting simultaneously will be highly valued. Therefore, **a**

framework that supports the optimisation of type, size, location and number of stochastic and controllable DER simultaneously is a timely and novel contribution.

- **Flexibility** and **modularity** are recognised as two keys aspects to produce a useful tool that can be adapted to diverse environments (research, industry, regulatory). The framework is flexible, as already discussed. Also**,** the framework was developed based on a **modular structure,** as described in Chapter 5**.** In this structure **other impact evaluations, stochastic assessments and inner optimisations can be incorporated**. Therefore, the evaluation of other planning attributes (e.g. fault levels, reliability), DER types (e.g. storage) or network models (e.g. meshed networks) can be easily integrated within the planning framework. For instance, the second case study of Chapter 6 shows the optimisation of stochastic DER at first (case 2a), and later the analysis is expanded to optimise controllable DER (case 2b). Each one of these analyses uses a different module of the planning framework. Likewise, the sequential and random sampling evaluations discussed extensively in Chapter 5 are based on different analytical modules.

- The planning framework uses the Strength Pareto Evolutionary Algorithm 2 (SPEA2) fitness assignment and truncation procedures. The SPEA2 algorithm is one of the **state-of-the-art MOEA techniques**, as discussed in Chapter 2. Nonetheless, **the framework is based on a generic MOEA structure**. Each one of the MOEA steps is a module within the planning framework, as illustrated in Chapter 5. Hence, the framework is able to incorporate other MOEA fitness assignment or truncation procedures for the optimisation, if required. This flexibility is important, as the research area of MOEA is very active, and novel MOEA techniques that outperform SPEA2 are likely to be proposed in coming years. Moreover, the modular structure supports the research of different crossover, first population and mutation procedures, without major changes to the framework structure. Hence, **tailored MOEA operators for the DER planning problem can be developed and implemented**.

- MOEA deal explicitly with multiple objectives instead of aggregating all objectives into a single objective, as traditional multi-objective optimisation methods do. This aspect is important because diverse stakeholders are involved in DER development and operation, as aforementioned. Commonly, the objectives of one stakeholder are in conflict with the objectives of the other. Similarly, the impacts and benefits of DER are frequently conflicting. For example, the second case study of the previous chapter showed that increasing the DER owner's economic benefits would be to the detriment of the DSO objectives as line losses will increase and the voltage in the network will be outside operational limits. A true multi-objective approach permits compromise solutions to be found; in contrast, a single measure of performance obscures the analysis. **Consequently, the multi-objective approach provides a useful analysis in a market environment where many players are involved, where benefits and impacts must be explicitly visualised, and compromise solutions identified.**

The main impact of this thesis is that the structure of the framework proposed is generic and it can be applied to analyse diverse problems of power systems or energy systems planning. For instance, distribution network planning can benefit from this approach, as currently there is a requirement to analyse several perspectives of the problem explicitly (e.g. environmental, technical and economic planning attributes) and the active management of distribution networks is gaining widespread attention in the research community. As a first step, the framework proposed in this thesis has already been extended to include network reinforcements as one of the planning options [7.3]. **It is expected that the tool developed as part of this research will be extended to include other impacts and objectives of DER integration used for further research.**

In addition, **it is hoped that this thesis will serve as a base to develop analytical tools that can be used in diverse environments.** For example, the multi-objective approach can be a valuable tool for regulators to analyse the integration of different types of DER and micro-generation and develop appropriate incentives for their uptake. Similarly, the multi-objective approach can be used by DSO to evaluate the impacts of DER integration in a more comprehensive manner, or to find compromise solutions that maximise DSO and DER developer objectives simultaneously, as illustrated in the second case study. Moreover, **single-objective problems are a subset of multi-objective problems**. As a result, the multi-objective planning framework is able to provide an insight into more traditional single-objective problems, such as cost minimisation, line loss minimisation, or economic benefits maximisation, as illustrated in the second case study of the previous chapter. Additional dimensions of the problem, for example technical constraints, can be analysed explicitly, providing a deeper insight into the single-objective problem.

Also, it is envisaged that in the future, the generation, transport and use of energy (gas/heat/electricity) will be handled in a more comprehensive manner, to minimise the overall environmental impacts of energy generation. **A comprehensive view of the problem**

of energy provision using a multi-objective approach could enlighten some of the possible infrastructure solutions for a clean, diverse, and sustainable energy supply for economic development. Therefore, tools that are able to analyse the different perspectives of the problem explicitly, and that can evaluate the complex interaction of stochastic energy systems that include controllable DER, loads and networks, will be very helpful. **The flexible and modular structure of the framework proposed in this thesis can be applied to develop such tools.** This possibility is discussed later in this chapter as further work.

The main limitation of the proposed approach is that it is inherently computationally expensive. Each analysis is time consuming for three reasons:

- MOEA are based on the evaluation of hundreds of chromosomes over hundreds of generations; hence, tens of thousands of evaluations are performed to get good quality results. The accuracy of MOEA increase with the number of generations evaluated.
- When highly variable attributes are used as planning objectives (e.g. exported power, dispatched power, curtailed power) the stochastic simulations require hundreds or thousands of evaluations to get accurate results for every single chromosome.
- The OPF requires a long time to solve large optimisation problems, compared with the evaluation time for uncontrollable units.

Most evaluation times are realistic; for instance, an analysis can be completed within a couple of days. **This evaluation time must be put in perspective**. First, planning is not an "online" task, and the optimisation can be performed at the same time as other studies and duties. Second, it is possible to get results that otherwise would never have been obtained. Though, in some specific cases the multi-objective planning framework requires extremely long and unrealistic evaluation times to get accurate results. These cases occur when the integration of a large number of controllable DER in a large network is analysed, as demonstrated in Chapter 5. OPF problems that have large numbers of variables or OPF problems that are mathematically unfeasible (i.e. some instances of DER dispatch) require long evaluation times. Moreover, the integration of DER in a large network has a large number of decision variables; hence, a large MOEA population is required. **Nonetheless, the MOEA and the stochastic evaluation have an ideal structure to be implemented in**

parallel. The use of parallel processing can speed up the analysis considerably; therefore, it is suggested as further work, discussed later.

7.1.3. Conclusions from the Case Studies

The results from the case studies are discussed in the previous chapter. Although the results from the case studies are related to the specific DER technologies and network analysed, some general conclusions were identified. These are discussed next. The first case study discussed the integration of three types of stochastic micro-generation in a low-voltage urban network. The conclusions of this case study are:

- **It is not possible to analyse the effects of micro-generation with simplified approaches that do not consider the stochastic nature of DER and load, or that consider only a single DER type in each analysis**. There is a complex interaction between the stochastic generators and the stochastic loads. The impacts of micro-generation are technology specific and different mixes of micro-generators in the network provide different benefits.

- **Extremely large penetrations of micro-generation will be required to obtain significant carbon reductions from electricity consumption.** Moreover, carbon reductions provided by micro-generation are expensive compared with carbon reductions provided by larger technologies, which have a larger capacity factor and a lower cost per unit of energy. Hence, large-scale generators with zero or low-carbon emissions will be required to achieve large reductions of carbon emissions in the short or medium term at low cost.

- **Optimal mixes of micro-generation can provide some deferment of network investments**, as some reduction in the thermal loading of equipment is made possible. However, the reduction in thermal loading obtained is small (~10%) compared with the penetration levels of micro-generation required (>40%).

- **With large penetration of micro-generators, the role of the medium-voltage grid is not diminished.** With a 100% penetration of DER, almost a third of the energy generated by DER is exported back to the grid, and a third of the demand still must be imported.

- **A limitation of this case study is that it does not analyse the emissions and costs of the heat generated by micro-CHPs**. The case study only included the emissions savings and the costs attributed to the electricity generated by micro-CHPs. Nonetheless, the installation of micro-CHP units will provide larger emissions reductions, as it also offsets the emissions of gas boilers or other less efficient forms of heat generation. Hence, the comprehensive analysis of micro-CHP emissions and costs is suggested as further work.

The second case study examined the integration of wind turbines in a medium-voltage network. First, the use of probabilistic constraints was studied. Next, the curtailment of wind generation was compared with the benefits obtained under a multi-objective perspective. The conclusions from the case study are:

- **A multi-objective analysis provides an insightful and comprehensive examination of the problem of the integration of wind turbines in distribution networks.** On one hand, it is possible to compare the impacts and benefits of wind integration explicitly, on the other hand, different perspectives of the problem (DER developer, DSO) can be visualised. The DER developer objectives and the DSO objectives are in conflict but the multi-objective approach is able to identify solutions that benefit both stakeholders, i.e. a compromise solution.

- **The framework proposed is a useful tool to analyse the integration of wind turbines**, because it is able to include probabilistic constraints and to analyse the curtailment of wind turbines. Moreover, the framework is able to optimise the number of turbines to install, and their locations and sizes, in a single analysis.

- **The case study showed that there are diminishing marginal benefits with every extra turbine installed.** Hence, there are an optimal number of turbines to install to maximise the economic benefits. Beyond this optimal capacity, every extra installation decreases the total net benefits obtained by all the installations. The case study shows that the optimal number of turbines to install depends on the revenues that are received for every unit of energy traded. A scenario analysis, exemplified in the case study, could be used to choose the best solution.

- **The optimal location of wind turbines (already highlighted by the researchers in the field) cannot be underestimated.** Results showed that wrongly located turbines under a firm connection greatly increase the probability of voltage violations. Hence, a sub-optimal integration would considerably limit the penetration of wind energy. Moreover, turbines sub-optimally located under a non-firm connection would result in excessive curtailment that could convert a financially feasible project into an unfeasible one. Although a "centralised" planning philosophy is unlikely to be applied in a liberalised market such as the UK, results showed that a comprehensive analysis while planning the development of wind farms will increase the benefits that can be obtained, both for the DER developers (i.e. larger economic benefits) and for the environment (i.e. greater renewable energy production).

- **The multi-objective analysis confirmed that the curtailment of wind energy can foster a considerably larger integration of renewable energy without the need for network upgrades, when the turbines are optimally placed.** For instance, in the network studied a firm access connection would limit the penetration of wind turbines to 5 MW. In contrast, the curtailment of energy permitted the increment of the penetration of wind turbines in 60%, to 8 MW. Although some energy is curtailed, the benefits for the DER owner are increased. In the case study, an increment in the DER owner benefits of 25% was obtained with turbines optimally located, compared with the benefits obtained with a firm access connection. Larger penetrations (>8MW) could be integrated in the network studied with an active management, though, they would be sub-optimal from an economic point of view, because of the diminishing marginal benefits, discussed in a previous paragraph.

- **When wind turbines are actively managed, the optimal locations that benefit the DSO are not the same as the optimal locations that benefit the DER owner.** The DER owner wants to minimise curtailment, hence wind turbines must be located near the grid supply point. In contrast, the DSO wants to minimise the line losses, and to achieve this objective the wind turbines must be located strategically in the network between the grid supply point and the loads.

- **A limitation of this case study is that a complete correlation between the wind productions in the entire network was assumed.** However, the network analysed is small so the assumption can be considered valid. Moreover, the complete positive correlation provides the higher risk scenario. Nonetheless, a more detailed study should divide the network and apply different wind profiles to each area, as discussed in Chapter 5

7.2. *Contributions to Knowledge*

The following contributions of this thesis have been identified:

1. **It provides a comprehensive review of DER planning techniques (Chapter 3).** The review of Chapter 3 analysed new trends in the DER planning research area, identifying the evolution of DER planning techniques and the increased use of multi-objective approaches. Moreover, it recognised some of the shortcomings of current planning techniques in relation to the challenges of DER integration and identified potential area for this research. The author is not aware of a similar review of the research area.

2. **It presents a deep examination of the DER planning problem and the specification for a flexible multi-objective planning framework for DER integration analysis (Chapter 4).** This study highlights the complexity of the DER planning problem and discusses the techniques that can be applied to tackle it. It also defines the specifications for a tool for DER integration analysis. This specification considers current drivers of DER integration and the required characteristic for modern planning techniques. These specifications are a contribution for the development of DER planning tools.

3. **It presents the development of an analytical tool for stochastic and controllable DER (Chapter 5).** Chapter 4 enumerates and discusses a set of requirements for the development of a DER planning tool. Chapter 5 discusses the choice of each one of the techniques used to address these requirements, and demonstrates in detail the practical implementation of the planning framework into an analytical tool. This chapter discussed in detail the use of each planning attributed. The detailed development process and the practical details provided in Chapter 5 are a contribution for future researchers that might face similar challenges. Moreover, the tool implemented during the development of this thesis is also a contribution, as it can be used for further research.

4. **It provides a comprehensive description of the concepts of multi-objective evolutionary algorithms applied to the DER problem (Chapters 2 and 5).** Chapter 2 presents a comprehensive review of multi-objective optimisation, with particular

emphasis on the recent developments in area of multi-objective evolutionary algorithms. Chapter 5 presents the application of a MOEA to the DER planning problem, discussing in detail the use of each one of the MOEA procedures for the DER planning problem, and contributing to the future use of these techniques in DER planning.

5. **It expands the knowledge about the impacts and benefits of DER integration (Chapters 5 and 6).** Chapter 5 discusses the calculation of each of the technical, economic and environmental planning attributes included in the planning framework, and its use in DER planning. Hence, it facilitates the further implementation of these attributes in other DER planning approaches. Chapter 6 exposes findings of optimal DER plans with two specific case studies. The use of the multi-objective approach to illustrate the results and the discussion provided in this chapter helps to understand better the complex relationship between DER impacts and benefits. For instance, the first case study illustrated the technical impacts of the integration of micro-generation in the distribution network. Hence, it was possible to identified optimal penetrations that would benefit the DSO, and provide environmental benefits. In the second study, the contrasting objectives of the DSO and the DER developer were illustrated. The multi-objective approach permitted the identification of compromise solutions, and the analysis identified locations for wind turbines that would benefit both the DER developer and the DSO.

7.3. *Future Work*

Further work for the improvement and extension of the planning framework developed in this thesis has been identified. Two main avenues of research are suggested. One is related to the development and application of the planning framework for the analysis of other DER, power systems and energy systems. The other path proposes a strategy to overcome the main limitation identified in this research, which is a long computational time.

7.3.1. Further Development of the Planning Framework

A generic structure for a multi-objective DER planning framework has been specified. The planning framework has been implemented to analyse only radial distribution networks. A first step towards the implementation of a comprehensive planning framework for DER is to include the analysis of meshed networks, which would require a different power flow algorithm, and a different OPF algorithm (nonlinear). Moreover, impacts of DER in meshed networks must be included in the analysis, such as reliability and fault level calculations. The modular structure of the planning framework permits the integration of the analysis of meshed systems without major changes to the MOEA algorithm or the stochastic simulation.

The second step towards a more comprehensive DER planning framework is the inclusion of other DER types, including energy storage and responsive loads. The OPF supports the analysis of responsive loads, as has already been mentioned in Chapter 5. In the case of energy storage a different optimisation algorithm, which considers the dynamic nature of the energy storage optimisation, needs to be implemented. This development could be carried forward as a power engineering Master's thesis.

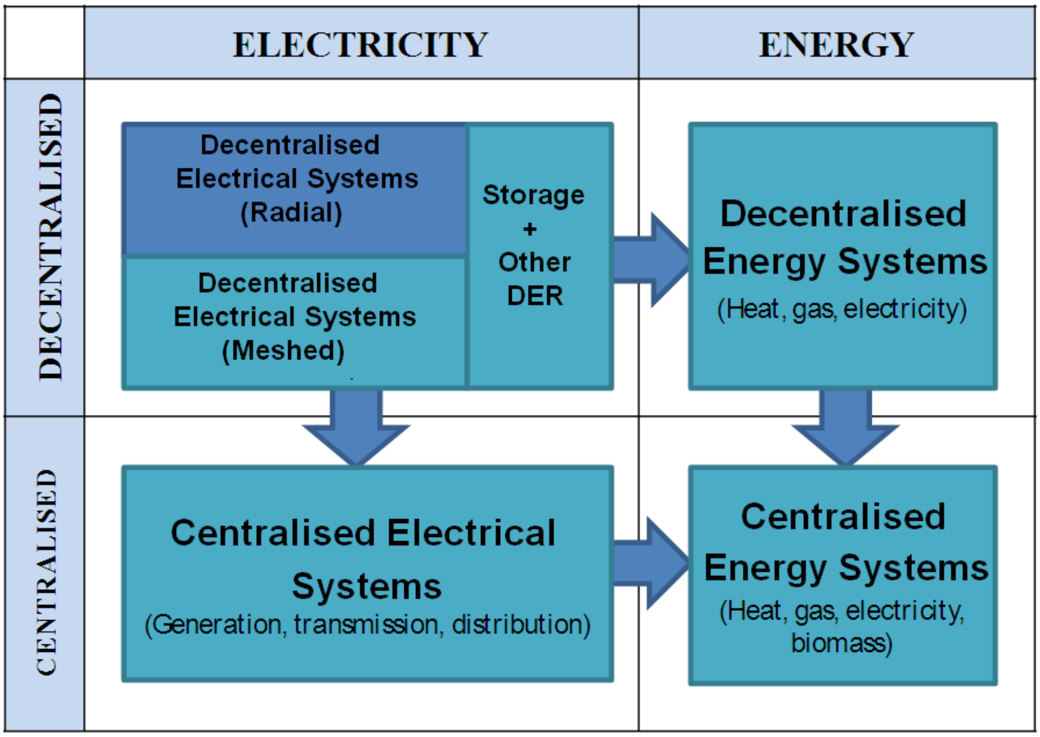

Figure 7-1Suggested Further Work

The analysis of decentralised electrical systems and DER is only one of the possible ways in which the planning framework can be implemented. As a result, the extension of the framework for the analysis of other power systems and energy systems problems is proposed, as illustrated in Figure 7-1. The first possibility is to focus on decentralised energy systems. In this case, it is necessary to consider the planning of gas networks, heat networks and include thermal demands in the analysis. The resulting tool would provide a comprehensive assessment of impacts in the provision of energy as a whole, on a decentralised level. It is worth noting that the study of decentralised energy systems in the UK has been recently awarded a research grant [7.4], proving the interest in this specific research area.

On a different path, the multi-objective approach can also be applied to the analysis of centralised electrical systems, such as transmission planning or centralised generation planning. The network, demand and generation models required for this purpose are different, and require different power flow algorithms, but the concepts of multi-objective planning and stochastic simulation are still useful. Ultimately, the framework can be implemented to analyse centralised energy provision. This refers to the analysis of the energy supply chain on a large scale (i.e. national, regional) including energy flows of diverse forms, such as gas networks, roads (for transport of biomass), electricity networks and generation and demand for electricity and heat on a large scale.

The development of the framework in these directions requires research in terms of adequate models for the energy systems, energy flow algorithms and inner optimisation algorithms, and each one could be carried out as a doctoral or postdoctoral study.

7.3.2. Improvement of the Planning Framework

One of the main limitations of the proposed approach is the large computational time. The use of a number of processors in parallel, known as parallel computing, offers a solution to this problem. The objective evaluation can be implemented in parallel in two different ways. The first is to code the chromosome evaluation procedure in parallel. Following this approach, the population of chromosomes is divided in n different groups (where n is the number of processors available), and each group is evaluated in parallel using a single processor. Once all objectives have been evaluated, the stages of selection, crossover and mutation, which are not time consuming, are performed on a single processor. The second possibility, which is slightly different, is to implement the stochastic evaluation in parallel. In this approach, a batch of simulation events is evaluated in parallel in each single processor; hence, the number of events simulated on a given period of time is multiplied by n. The attribute values of the chromosome are computed afterwards. In both cases, parallel computing will speed up the total evaluation time approximately by a factor of n. This study could be carried out as a Master's thesis on the area of electrical engineering or computational sciences.

7.4. *Thesis conclusion*

This thesis proposes the use of multi-objective planning for the analysis of the optimal integration of DER in distribution networks. It presents the research, specification, development and demonstration of a multi-objective planning framework that is based on three different analysis and optimisation techniques. Results demonstrate that the framework is a valuable tool for DER integration analysis. The work presented in this thesis can be used to develop planning tools for the analysis of decentralised electrical systems and integrated energy systems.

7.5. *References for Chapter 7*

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[7.2] **Alarcon-Rodriguez, A.D.**, Haesen, E. Ault, G.W., Driesen, J., Belmans, R., *"Multi-objective Planning Framework for Stochastic and Controllable Distributed Energy Resources"*, IET Journal of Renewable Power Generation, Vol. 3, Issue 2, pp. 227–238, June 2009

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[7.4] SUPERGEN HDPS – CORE, http://gow.epsrc.ac.uk/ViewGrant.aspx?GrantRef=EP/G031681/1, accessed March 2009

Appendix A: The Time Value of Money

A succinct introduction to the concept of the Time Value of Money is presented in this appendix. A more comprehensive explanation can be found in the references provided at the end of this section.

A.1 Present Value of a Future Sum of Money

The key concept of TVM is that "a pound today is more valuable than a pound in the future" [A.1]. A pound today can be invested at an annual interest rate (i). After one year, the pound will be equivalent to $(1+i)$ pounds. After two years, and assuming compound interest, the pound will be worth $(1+i)^2$, and after n years, $(1+i)^n$ pounds (Figure A-1).

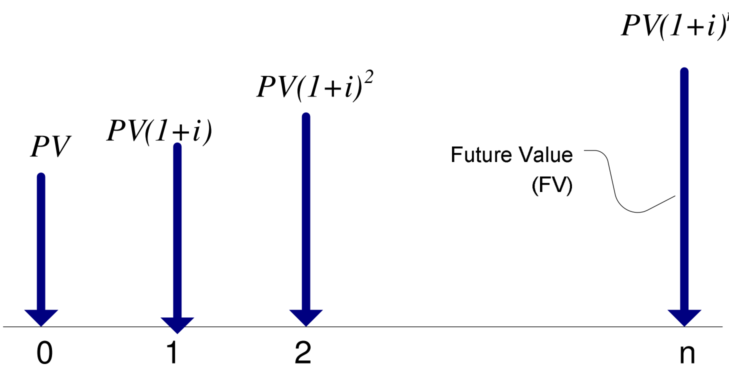

Figure A-1 Future Value of a Present Sum

Hence, the future value FV of a present sum PV is:

$$FV = (1+i)^n PV \tag{A-1}$$

Similarly, any future sum FV must be "discounted" to be translated into a present value PV:

$$PV = \frac{FV}{(1+i)^n} \tag{A-2}$$

The term $\frac{1}{(1+i)^n}$ is referred as the present worth factor and, in this case, i is referred as the "discount rate". The discount rate is the perceived rate of reduction of value from one year to next [A.2]. Using equation (A-2), all costs and benefits can be translated to present value and alternatives can be compared on a similar basis using the net present value (NPV). Alternatively, a cost-benefit ratio of net present benefits over net present costs can be used. If benefits are expressed in terms of energy, energy flows must be discounted, as failing to do so will result in a erroneous evaluation [A.1] [A.2].

In this investment analysis, the discount rate i must indicate the opportunity cost of capital, or rate of return [A.1]. That is: the return that the sum of money would have gained if invested elsewhere; for example, in other DER development. Discount rates also include other factors such as financial risk or the utilities' earning targets [A.2]. Low discount rates favour alternatives with low capital costs (and high operation and maintenance costs). Conversely, high discount rates favour alternatives with low operation and maintenance costs, but high investment [A.3]. In the case studies of Chapter 7 a discount rate of 7% was used. A full analysis of the choice of discount rates is beyond the scope of this work. Some discussion is available in [A.1] and [A.2].

A.2 Annuities of a Present Value

If a series of *equal* annuities (costs or benefits) is assumed to happen at the end of each period (e.g. every year), for n consecutive periods, the concept of present value permits to add them together into a present value PV (Figure A-2):

$$PV = \frac{A}{(1+i)^1} + \frac{A}{(1+i)^2} + ... + \frac{A}{(1+i)^n} \tag{A-3}$$

This equation can be rearranged as:

$$PV = \frac{A}{i}\left(1 - \frac{1}{(1+i)^n}\right) \tag{A-4}$$

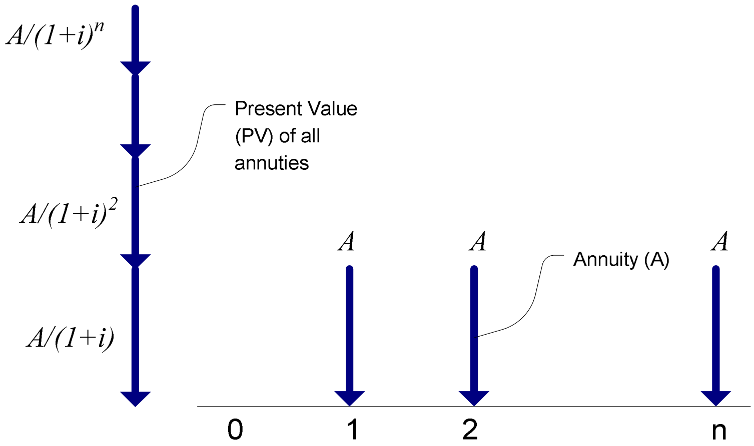

Figure A-2 Present Value (PV) of Equal Annuities (A) over n Periods.

Hence, it is also possible to translate a present value PV into a series of equal annuities A:

$$A = \frac{i(1+i)^n}{(1+i)^n - 1} PV \tag{A-5}$$

This formula is used to transform capital investments, assumed to happen in year zero, into a series of equal annual payments. This capital amortisation is added with the yearly costs and benefits of each alternative. Therefore, in this case it is possible to compare investment alternatives on a similar basis using annualised values.

A.3 References

[A.1] Khatib, H., *"Financial and Economic Evaluation of Projects with Special Reference to the Electrical Power Industry"*, Power Engineering Journal (February) (1996) 42-54.

[A.2] Willis H. L., *"Power Distribution Planning Reference Book"*, Ed. Marcel Dekker, New York, USA, 2004, ISBN 0-8247-4875-1

[A.3] Willis H. L., Scott, W. G., *"Distributed Power Generation. Planning and Evaluation"*, Ed. Marcel Dekker, New York, USA, 2000, ISBN 0-8247-0336-7.

Appendix B: Backward/Forward Sweep (BFS) Power Flow Algorithm

In this appendix the implementation of a backward-forward sweep power-flow calculation is presented. The algorithm is based on [5.17]. Assumptions in which the network, loads and generators have been modelled are mentioned.

B.1 Network Representation

The backward/forward sweep (BFS) algorithm uses three matrices to represent the network structure: a node-to-branch incidence matrix *L*, a line current summation (or topology) matrix *T* and an impedance matrix *Z*. These matrices are constructed using the network structure and line impedances data.

Consider the radial network illustrated in Figure B-1. Nodes are numbered sequentially, starting from the root node (0), in ascending order. Any path from the root node to a terminal node should encounter ascending numbers.

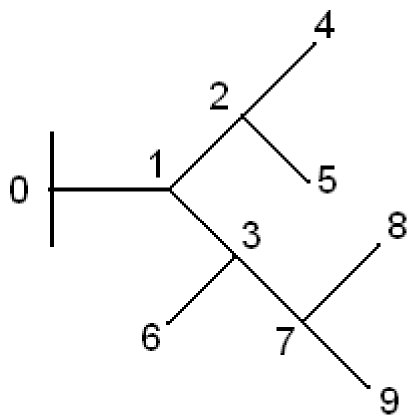

Figure B-1Radial Network Example (source [B.1])

From the network structure, the node-to-branch incidence matrix L is determined. Each row represents a branch, where 1 is assigned to the sending nodes, -1 to the receiving nodes and 0 otherwise. Columns represent the nodes and indicate the branches connected to each one. Note that the root node (0) is not included in the matrix. The node numbering procedure, explained lines above, produces a lower triangular matrix:

$$L = \begin{vmatrix} -1 & & & & & & & & \\ 1 & -1 & & & & & & & \\ 1 & & -1 & & & & & & \\ & 1 & & -1 & & & & & \\ & 1 & & & -1 & & & & \\ & & 1 & & & -1 & & & \\ & & 1 & & & & -1 & & \\ & & & & & & 1 & -1 & \\ & & & & & & 1 & & -1 \end{vmatrix}$$

From the node-to-branch matrix $\mathbf{L}$, a line current summation matrix $\mathbf{T}$ is determined as:

$$\mathbf{T} = \mathbf{L}^{-1} \tag{B-1}$$

The matrix $\mathbf{T}$ is also lower triangular:

$$\mathbf{T} = \begin{vmatrix} -1 & & & & & & & & \\ -1 & -1 & & & & & & & \\ -1 & & -1 & & & & & & \\ -1 & -1 & & -1 & & & & & \\ -1 & -1 & & & -1 & & & & \\ -1 & & -1 & & & -1 & & & \\ -1 & & -1 & & & & -1 & & \\ -1 & & -1 & & & & -1 & -1 & \\ -1 & & -1 & & & & -1 & & -1 \end{vmatrix}$$

The rows with non-zero elements of the j^{th} column of **T** represent the nodes belonging to the branches derived from the j^{th} node.

A diagonal matrix **Z** is used to represent network impedances. The radial distribution circuits are modelled as a series impedance z=r+j*x. Capacitance effects are ignored. This model is adequate for most radial distribution systems, except in the cases of long lines where a π model is required [B.2]. Each diagonal element z_{ii} corresponds to the complex impedance of the i^{th} branch:

$$z_{ii} = r_{ii} + j \cdot x_{ii} \tag{B-2}$$

The analysis is single phase; all node voltages are phase voltages. It is assumed that the grid voltage (node 0) is constant:

Grid voltage: V_{grid}

The electrical variables at every node and branches are represented by the vectors:

Node voltages: $\mathbf{V_{node}}=[V_1, V_2,\ldots,V_i,\ldots V_n]^T$

Line currents: $\mathbf{I_{line}}=[I_{line1}, I_{line2},\ldots,I_{linei},\ldots,I_{linen}]^T$

Node currents: $\mathbf{I_{node}}=[I_{node1}, I_{node2},\ldots,I_{nodei},\ldots,I_{noden}]^T$

Complex node power: $\mathbf{S_{node}}=[S_{node1}, S_{node2},\ldots,S_{nodei},\ldots,S_{noden}]^T$

B.2 Backward and Forward Sweeps

The algorithm consists of the initialisation and two steps, a backward sweep and a forward sweep, illustrated in Figure B-2. Each step is explained next.

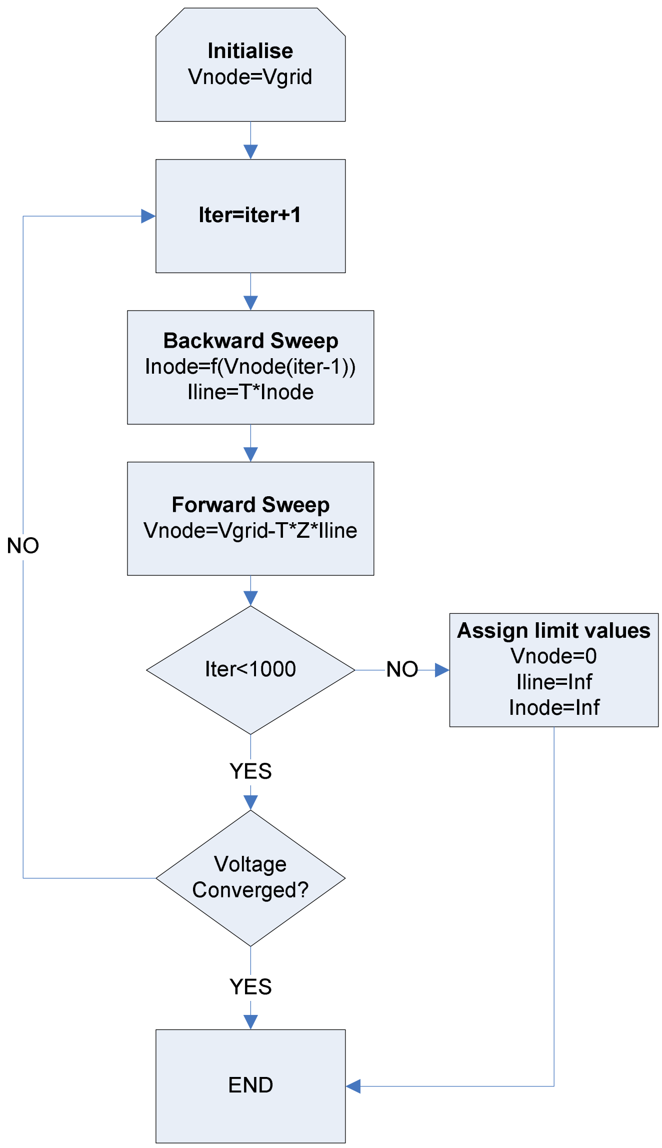

Figure B-2Backward/Forward Sweep algorithm

B.2.1 Initialisation

At the first step, all node voltages $\mathbf{V}_{\mathbf{node}}$ are assigned the grid voltage V_{grid}, by multiplying the value by a vector of ones $\mathbf{1}$:

$$\mathbf{V_{node}} = V_{grid}\mathbf{1} \tag{B-3}$$

B.2.2 Backward Sweep

In the backward sweep the node currents $\mathbf{I_{node}}$ and line current $\mathbf{I_{line}}$ are calculated based on the voltages $\mathbf{V_{node}}$ of the previous forward stage. Node currents depend on the power withdrawn at each node. This relationship is modelled according to the characteristic of the devices connected, usually a combination of resistive, inductive and constant power loads. In this work, all loads are modelled using the constant power model, as mentioned in Chapter 5. In the constant load model, the load power doesn't vary with the voltage magnitude ($S_{node}=P_o+jQ_o$=const.). Thus, when voltage drops more current is withdrawn, and vice versa:

$$\mathbf{I_{node}} = \left(\frac{\mathbf{P_{node}} + j\mathbf{Q_{node}}}{\mathbf{V_{node}}}\right)^* \tag{B-4}$$

If more detailed information about each load type (or mix of types) of each node is available, specific models for each load could be used, such as: constant impedance, constant current, exponential or polynomial load models, which can be found in [B.3] and [B.4].

Similarly, the current injected by each DER will vary with the voltage. The relation between injected current and terminal voltage depends on the type of generator. In this work all DER are assumed to work at a constant power factor and are modelled using a constant power model (B-4), as explained in Chapter 5. This model simplifies the inclusion of DER power in the calculation and allows the formulation of a linear OPF for active power control, explained later in this chapter.

The vectors of power withdrawn at each node $\mathbf{P_{node}}$ and $\mathbf{Q_{node}}$ is the difference between the load power **($\mathbf{P_{Load}}$, $\mathbf{Q_{Load}}$)** and the total power injected by DER units **($\mathbf{P_{DER}}$, $\mathbf{Q_{DER}}$)**:

$$\mathbf{P_{node}} = \mathbf{P_{Load}} - \mathbf{P_{DER}} \tag{B-5a}$$

$$\mathbf{Q_{node}} = \mathbf{Q_{Load}} - \mathbf{Q_{DER}} \tag{B-5b}$$

The BFS is a deterministic calculation for a single snapshot of the system. Therefore, the load power and the DER injected power of each node (equations B-5) are a sample of the load profile of each node load type and of the DER profile of the installed DER in each node, as discussed in chapters 4 and 5. The elements of the load power vectors ($\mathbf{P_{Load}}$, $\mathbf{Q_{Load}}$) are obtained by sampling the load profiles of each node's load type, and multiplying by each node's peak load. The calculation of the DER injected power per node ($\mathbf{P_{DER}}$, $\mathbf{Q_{DER}}$) was already explained in Chapter 5.

Knowing the power injected at each node, $\mathbf{I_{node}}$ is calculated using the constant power model (B-4). Then, the vector of line currents $\mathbf{I_{line}}$ is calculated using the current summation matrix:

$$\mathbf{I_{line}} = \mathbf{T}\mathbf{I_{node}} \tag{B-6}$$

B.2.3 Forward sweep

In the forward sweep, the vector of node voltages $\mathbf{V_{node}}$ is calculated using the line current $\mathbf{I_{line}}$ determined in the previous backward sweep. Node voltages depend on the network topology matrix $\mathbf{T}$, the impedance matrix $\mathbf{Z}$ and the vector of line currents $\mathbf{I_{line}}$:

$$\mathbf{V_{node}} = V_{grid}1 - \mathbf{TZI_{line}} \tag{B-7}$$

B.2.4 Convergence

The backward and forward stages are continued until a convergence criterion is met. This criterion in usually based on the convergence of the complex voltage [B.1] or the complex power [B.5]. In this work the voltage convergence criterion is used. Bombard *et al.* [5.17] demonstrated that for normal operation conditions, the BFS method provides "fast and reliable" convergence for any load model. Test cases conducted in this research showed that the power flow converged after 6 or 7 iterations in normal operation conditions. Nonetheless, in the extreme cases, when feeders are excessively loaded, convergence is never reached. Hence, a maximum limit of iterations is set equal to a thousand iterations. After this limit, extreme values will be assigned to the voltage ($\mathbf{V}_{\mathbf{node}}$=0) and the current ($\mathbf{I}_{\mathbf{node}}$=$\mathbf{I}_{\mathbf{line}}$=*Inf*) to penalise the performance of the solution that did not converge.

B.3 References

[B.1] Bompard, E., Carpaneto, E., Chicco, G., Napoli, R., *"Convergence of the Backward/forward Sweep Method for the Load-Flow Analysis of Radial Distribution Systems"*, Electrical Power Energy System No. 22, pp 521-530, 2000

[B.2] Lakervi, E., Holmes, E.J., *"Electricity Distribution Network Design"*, IEE Power Series 21, 2nd Edition, 2003, ISBN 0863413099

[B.3] Liu, J., Salama, M. M. A., Mansour, R. R, *"An Efficient Power Flow Algorithm For Distribution Systems with Polynomial Load"*, International Journal of Electrical Engineering Education, Volume 39 Issue 4, pp 371-386, Oct 2002

[B.4] Eminoglu, U., M. H. Hocaoglu, M.H., *"A Robust Power Flow Algorithm for Radial Distribution Systems"*, 2005 IEEE St. Petesburg PowerTech, St. Petesburg, Russia, June 27-30

[B.5] Ochoa, L.F., *"Desempenho de Redes de Distribuição com Geradores Distribuídos" (Performance of Distributions Networks with Distributed Generation)*, Doctoral Dissertation, Faculdade de Engenharia de Ilha Solteira, Universidade Estadual Paulista "Julio de Mesquita Filhio", November 2006

Appendix C: Optimal Power Flow (OPF) Formulation

In this appendix the formulation of a linear optimal power flow of is explained. The equations are based on the backward/forward power flow algorithm described in Appendix B. The use of an inner linear optimisation for controllable DER units was proposed by Edwin Haesen from KU Leuven University, and integrated into the planning framework as described in Alarcon-Rodriguez and Haesen *et al.* [C.1].

C.1 Symbols

The symbols used in this appendix are:

$\mathbf{I_{curt}}$:	Current curtailed in each DER (vector)
$\mathbf{I_{disp}}$:	Current dispatched in DER (vector)
$\mathbf{I_{line}}$	Line currents (vector)
$\mathbf{I_{load}}$:	Load current per node (vector)
$\mathbf{I_{max}}$:	Maximum current limit in each line (vector)
$\mathbf{I_{node}}$:	Node currents (vector)
$\mathbf{P_{curt}}$	Active power curtailed in each node (vector)
$\mathbf{P_{disp}}$:	Active power dispatched in each node (vector)
$\mathbf{S_{disp}}$:	Complex power dispatched in each node (vector)
$\mathbf{T}$:	Topology Matrix
V:	Voltage
V_{grid}:	Grid connection Voltage (constant)
$\mathbf{V_{max}}$:	Maximum voltage limit in each node (vector)
$\mathbf{V_{node}}$:	Node voltages (vector)
$\mathbf{Z}$:	Impedance Matrix
α:	Maximum voltage correction factor
β:	Maximum current correction factor
$\gamma_{disp:}$	Dispatched DER power factor (Q/P)

The superscripts r and i are used throughout this Appendix to represent real and imaginary part of complex phasors, vectors and matrices.

C.2 Linear Voltage Constraints

To linearise the voltage constraints in the OPF, the absolute value of *each node* voltage V is approximated by its real part:

$$\left|V\right| = \left|V^r + jV^i\right| \approx V^r \tag{C-1}$$

From the BFS algorithm (Appendix B) the node voltages can be calculated as:

$$\mathbf{V_{node}} = V_{grid}1 - \mathbf{TZTI}_{node} \tag{C-2}$$

Taking the real and imaginary part of the vector $\mathbf{I_{node}}$ and the matrix $\mathbf{Z}$, the vector $\mathbf{V_{node}}$ can be expressed as:

$$\mathbf{V_{node}} = \mathbf{V^r} + j\mathbf{V^i} = V_{grid}1 - \mathbf{T}(\mathbf{Z}^r + j\mathbf{Z^i})T(\mathbf{I}^r{}_{node} + j\mathbf{I^i}_{\mathbf{node}}) \tag{C-3}$$

If $\mathbf{TZ^rT}$ is replaced by $\mathbf{R_T}$ and $\mathbf{TZ^iT}$ by $\mathbf{X_T}$ respectively, the real elements of the vector of node voltages $\mathbf{V_{node}}$ are:

$$\mathbf{V^r} = V_{grid}1 - \mathbf{R_T I^r_{node}} + \mathbf{X_T I^i_{node}} \tag{C-4}$$

The real and imaginary parts of the node current vector $\mathbf{I_{node}}$ can be expressed as the sum of the vectors of current injections of load, dispatch, and curtailment $\mathbf{I_{load}}$, $\mathbf{I_{disp}}$ and $\mathbf{I_{curt}}$, respectively. Replacing these vectors in equation (C-4), the real elements of the voltage vector are:

$$\mathbf{V^r} = V_{grid}1 - \mathbf{R_T}(\mathbf{I^r_{load}} - \mathbf{I^r_{disp}} + \mathbf{I^r_{curt}}) + \mathbf{X_T}(\mathbf{I^i_{load}} - \mathbf{I^i_{disp}} + \mathbf{I^i_{curt}}) \tag{C-5}$$

Using the constant power model, the current injections $\mathbf{I_{disp}}$ due to CHP dispatch can be formulated in terms of CHP active power dispatch $\mathbf{P_{disp}}$ as:

$$\mathbf{I_{disp}} = \left(\frac{\mathbf{S_{disp}}}{\mathbf{V_{node}}}\right)^* = \frac{(1 - j\gamma_{disp})}{(\mathbf{V_{node}})^*} \cdot \frac{\mathbf{V_{node}}}{\mathbf{V_{node}}} \mathbf{P_{disp}} \tag{C-6}$$

where γ_{disp} is the ratio of reactive to active power of the CHP units (*Q/P*), assumed constant and similar for all generators, and $\mathbf{S_{disp}}$ is the apparent dispatched power.

Replacing the vector $\mathbf{V_{node}}$ in the numerator by its real and imaginary elements vectors $\mathbf{V^r}$ and $\mathbf{V^i}$, the real and imaginary expressions for the current $\mathbf{I_{disp}}$ can be formulated in terms of $\mathbf{P_{disp}}$:

$$\mathbf{I^r_{disp}} = \frac{\mathbf{V^r} + \gamma_{disp}\mathbf{V^i}}{\left|\mathbf{V_{node}}\right|^2} \mathbf{P_{disp}} \tag{C-7a}$$

$$\mathbf{I^i_{disp}} = \frac{\mathbf{V^i} - \gamma_{disp}\mathbf{V^r}}{\left|\mathbf{V_{node}}\right|^2} \mathbf{P_{disp}} \tag{C-7b}$$

Similar expressions are obtained for $\mathbf{I_{curt}}$ and $\mathbf{P_{curt}}$. Also, if load curtailment is analysed, a further vector of decision variables $\mathbf{P_{curt,load}}$ can be formulated using the same analysis.

Replacing the equations (C-7) in equation (C-5) and rearranging the expression, all voltages can be expressed as a function of the decision variables $\mathbf{P_{disp}}$ and $\mathbf{P_{curt}}$:

$$\mathbf{V^r} = V_{grid}\mathbf{1} - \mathbf{R_T I^r}_{\mathbf{load}} + \mathbf{X_T I^i}_{\mathbf{load}} + \left(\mathbf{R_T}\left(\frac{\mathbf{V^r} + \gamma_{disp}\mathbf{V^i}}{\left|\mathbf{V_{node}}\right|^2}\right) - \mathbf{X_T}\left(\frac{\mathbf{V^i} - \gamma_{disp}\mathbf{V^r}}{\left|\mathbf{V_{node}}\right|^2}\right)\right)\mathbf{P_{disp}} + \left(-\mathbf{R_T}\left(\frac{\mathbf{V^r} + \gamma_{curt}\mathbf{V^i}}{\left|\mathbf{V_{node}}\right|^2}\right) + \mathbf{X_T}\left(\frac{\mathbf{V^i} - \gamma_{curt}\mathbf{V^r}}{\left|\mathbf{V_{node}}\right|^2}\right)\right)\mathbf{P_{curt}} \qquad \text{(C-8)}$$

The values of $\mathbf{I_{load}}$, $\mathbf{V_{node}}$, $\mathbf{V^i}$ and $\mathbf{V^r}$ in the right-hand side of equation (C-8) are based on the currents and voltages *before* the optimisation. These values are considered constants. Hence, the voltage magnitudes approximated by $\mathbf{V^r}$ are a linear function of only the dispatched and curtailed power $\mathbf{P_{disp}}$ and $\mathbf{P_{curt}}$. Hence, the voltage constraint is linear. If the power factor of all dispatched and curtailed generators is assumed similar ($\gamma_{disp=}\ \gamma_{curt=}\ \gamma$), the expression can be simplified further and the coefficients $\mathbf{A_V}$, $\mathbf{b_{Vmax}}$ and $\mathbf{b_{Vmin}}$ can be determined:

$$\mathbf{A}_V = \left(\mathbf{R_T}\left(\frac{\mathbf{V^r} + \gamma\mathbf{V^i}}{\left|\mathbf{V_{node}}\right|^2}\right) - \mathbf{X_T}\left(\frac{\mathbf{V^i} - \gamma\mathbf{V^r}}{\left|\mathbf{V_{node}}\right|^2}\right)\right) \qquad \text{(C-9a)}$$

$$\mathbf{b}_{V\mathbf{max}} = (\mathbf{V_{max}} - \mathbf{V_{grid}})\mathbf{1} + \mathbf{R_T I^r}_{\mathbf{load}} - \mathbf{X_T I^i}_{\mathbf{load}} \qquad \text{(C-9b)}$$

$$\mathbf{b}_{V\mathbf{min}} = (\mathbf{V_{grid}} - \mathbf{V_{min}})\mathbf{1} - \mathbf{R_T I^r}_{\mathbf{load}} + \mathbf{X_T I^i}_{\mathbf{load}} \qquad \text{(C-9c)}$$

Such that voltage constraints can be expressed as:

$$\mathbf{A}_V\mathbf{P_{disp}} - \mathbf{A}_V\mathbf{P_{curt}} \le \mathbf{b}_{V\mathbf{max}} \qquad \text{(C-10a)}$$

$$-\mathbf{A}_V\mathbf{P_{disp}} + \mathbf{A}_V\mathbf{P_{curt}} \le \mathbf{b}_{V\mathbf{min}} \qquad \text{(C-10b)}$$

The matrix $\mathbf{A_V}$ quantifies the sensitivity of node voltages to power injections ($\mathbf{P_{disp}}$) and power curtailment ($\mathbf{P_{curt}}$). Each row *x* of the matrix $\mathbf{A_V}$ corresponds to the sensitivity of the voltage in the xth node to power injections in the y^{th} node, where *y* is a column of matrix $\mathbf{A_V}$.

The approximation of the magnitude of the voltages by their real part produces an underestimation of voltages. This underestimation of the voltage can be partially corrected by applying a correction factor α to the maximum voltage constraint:

$$\boldsymbol{\alpha} = \frac{\mathbf{V}^{\mathbf{r}}}{\left|\mathbf{V}_{\mathbf{node}}\right|} \tag{C-11}$$

Such that the maximum voltage constraint $\mathbf{V}_{\mathbf{max}}$ in equation (5-9b) is reduced accordingly:

$$\mathbf{V}^{\mathbf{r}} \leq \boldsymbol{\alpha}\mathbf{V}_{\mathbf{max}} \tag{C-12}$$

C.3 Linear Thermal Constraints

The line power flow constraint is expressed as:

$$\left|\mathbf{I}_{\mathbf{line}}\right| \leq \mathbf{I}_{\mathbf{max}} \tag{C-13}$$

From the BFS Algorithm, the line current vector $\mathbf{I}_{\mathbf{line}}$ can be expressed in terms of node currents $\mathbf{I}_{\mathbf{node}}$:

$$\mathbf{I}_{\mathbf{line}} = \mathbf{T}\mathbf{I}_{node} \tag{C-14}$$

The real part of the node current vector $\mathbf{I}_{\mathbf{node}}$ can be expressed as the sum of the real parts of the vectors of current injections of load, dispatch, and curtailment $\mathbf{I}_{\mathbf{load}}$, $\mathbf{I}_{\mathbf{disp}}$ and $\mathbf{I}_{\mathbf{curt.}}$ Therefore, the current flow constraint becomes:

$$-\mathbf{I}_{\mathbf{max}} \leq \mathbf{T}\left(\mathbf{I}^{\mathbf{r}}_{\mathbf{load}} - \mathbf{I}^{\mathbf{r}}_{\mathbf{disp}} + \mathbf{I}^{\mathbf{r}}_{\mathbf{curt}}\right) \leq \mathbf{I}_{\mathbf{max}} \tag{C-15}$$

$\mathbf{I}^{\mathbf{r}}_{\mathbf{load}}$ is the real part of the node current vector *before* the optimisation. Using equation (C-7a), $\mathbf{I}^{\mathbf{r}}_{\mathbf{disp}}$ and $\mathbf{I}^{\mathbf{r}}_{\mathbf{curt}}$ are expressed in terms of voltages and power; hence equation (C-15) becomes:

$$\textbf{-I}_{\textbf{max}}\ \textbf{-}\ \textbf{TI}^{\textbf{r}}_{\textbf{load}} \le \textbf{T}\left(-\left(\frac{\textbf{V}^{\textbf{r}} + \gamma_{disp}\textbf{V}^{\textbf{i}}}{\left|\textbf{V}_{\textbf{node}}\right|^{2}}\right)\textbf{P}_{\textbf{disp}} + \left(\frac{\textbf{V}^{\textbf{r}} + \gamma_{curt}\textbf{V}^{\textbf{i}}}{\left|\textbf{V}_{\textbf{node}}\right|^{2}}\right)\textbf{P}_{\textbf{curt}} \right) \le \textbf{I}_{\textbf{max}} - \textbf{TI}^{\textbf{r}}_{\textbf{load}} \qquad \text{(C-16)}$$

If the power factor of all dispatched and curtailed generators is assumed similar ($\gamma_{disp=}\ \gamma_{curt=}\ \gamma$), the expression can be simplified further and the coefficients $\mathbf{A_I}$, $\mathbf{b_{Imax}}$ and $\mathbf{b_{Imin}}$ can be determined:

$$\mathbf{A_I} = \mathbf{T}\left(\frac{\mathbf{V^r} + \gamma\mathbf{V^i}}{\left|\mathbf{V_{node}}\right|^2}\right) \qquad \text{(C-17a)}$$

$$\mathbf{b_{Imin}} = \mathbf{I_{max}} - \mathbf{TI^r_{load}} \qquad \text{(C-17b)}$$

$$\mathbf{b_{Imax}} = \mathbf{I_{max}} + \mathbf{TI^r_{load}} \qquad \text{(C-17c)}$$

Where the voltages and current values before the optimisation are considered constants, such that the maximum current constraints are expressed in standard form as:

$$\left(-\mathbf{A_I P_{disp}} + \mathbf{A_I P_{curt}}\right) \le \mathbf{b_{Imin}} \qquad \text{(C-18a)}$$

$$\left(\mathbf{A_I P_{disp}} - \mathbf{A_I P_{curt}}\right) \le \mathbf{b_{Imax}} \qquad \text{(C-18b)}$$

$\mathbf{A_I}$ determines the sensitivity of line currents to power dispatch and curtailment.

The approximation of the magnitude of the line currents by their real part produces an underestimation of the absolute current values. In this case, the underestimation is reduced by applying a correction factor β to the current constraint:

$$\boldsymbol{\beta} = \frac{\left|\mathbf{I^r}\right|}{\left|\mathbf{I_{line}}\right|} \qquad \text{(C-19)}$$

Such that the maximum voltage constraint $\mathbf{I_{max}}$ in equation (C-13) is reduced to make the constraint more binding:

$$\mathbf{I}^{\mathbf{r}} \leq \boldsymbol{\beta}\mathbf{I}_{\mathbf{max}} \tag{C-20}$$

Once the optimal DER adjustments are found, power flows and bus voltages are recalculated using the BFS power flow, as aforementioned.

C.4 References for Appendix C

[C.1] Alarcón-Rodríguez, A.D., Haesen, E. Ault, G.W., Driesen, J., Belmans, R., *"Multi-objective Planning Framework for Stochastic and Controllable Distributed Energy Resources"*, IET Renew. Power Gener., 2009, Vol. 3, Iss. 2, pp. 227–238

Appendix D: Supplementary Data for Case Study 1

D.1 Network Data

Sbase = 100kVA

Vbase=0.42 kV

Table D-1 Network data

Sending end	Receiveing end	R (p.u.)	X (p.u.)	Capacity (kVA)	Capacity (A)	length (m)
1	2	0.00118	0.00461	1200	1,650	5
2	3	0.00083	0.00056	550	756	44.04
2	79	0.00077	0.00052	550	756	27.26
3	4	0.00098	0.00065	80	110	2
3	5	0.00024	0.00016	550	756	12.92
5	6	0.00164	0.0011	550	756	86.67
6	7	0.00497	0.00207	233	320	53.49
6	13	0.00114	0.00077	550	756	40.24
7	8	0.00414	0.00275	80	110	8.42
7	9	0.00477	0.00199	233	320	51.36
9	10	0.00406	0.0027	80	110	8.26
9	11	0.00711	0.00153	160	220	39.19
11	12	0.00766	0.00165	160	220	42.21
13	14	0.00861	0.00185	160	220	47.44
13	16	0.00014	0.00009	550	756	4.84
14	15	0.00599	0.00129	160	220	33.03
14	82	0.00753	0.00162	160	220	41.53
16	17	0.00101	0.00068	550	756	35.56
17	18	0.00531	0.00114	160	220	29.28
17	19	0.00063	0.00042	550	756	22.1
19	20	0.00078	0.00032	419	576	16.87
19	22	0.00463	0.00312	306	421	81.65
20	21	0.00385	0.00082	160	220	21.2
2	23	0.00059	0.00039	1222	1,680	51.78
23	24	0.00069	0.00046	1222	1,680	61.26
24	25	0.00071	0.00048	550	756	37.63
25	26	0.00391	0.00084	160	220	21.54
25	27	0.00092	0.00061	550	756	32.37
27	28	0.00192	0.00129	550	756	67.8
28	29	0.00172	0.00114	80	110	3.5
28	30	0.00127	0.00085	550	756	44.68
30	31	0.00047	0.00031	550	756	16.44
31	32	0.01769	0.00381	160	220	97.53
31	36	0.00103	0.00069	550	756	36.31
32	33	0.00897	0.00193	160	220	49.45
32	34	0.00189	0.0004	160	220	10.39
34	35	0.00388	0.00083	160	220	21.4
36	37	0.0036	0.00238	80	110	7.31

Sending end	Receiveing end	R (p.u.)	X (p.u.)	Capacity (kVA)	Capacity (A)	length (m)
36	38	0.00177	0.00073	419	576	38
38	39	0.00625	0.00415	80	110	12.7
38	40	0.00158	0.00066	419	576	34.03
40	41	0.00037	0.00015	419	576	7.99
40	44	0.00068	0.00028	233	320	7.34
41	42	0.00043	0.00029	306	421	7.61
41	43	0.00851	0.00565	80	110	17.29
44	45	0.00415	0.00275	80	110	8.44
44	46	0.00292	0.00063	160	220	16.11
46	47	0.00958	0.00636	80	110	19.48
46	81	0.00631	0.00419	80	110	12.82
24	48	0.00066	0.00044	550	756	34.82
48	83	0.00251	0.00166	80	110	5.09
48	49	0.00004	0.00002	550	756	2
49	50	0.00623	0.00134	160	220	34.35
49	51	0.00008	0.00005	550	756	4.15
51	52	0.00098	0.00065	80	110	2
51	53	0.00056	0.00038	550	756	29.92
53	54	0.00294	0.00123	419	576	63.34
54	55	0.01015	0.00218	160	220	55.93
54	56	0.00249	0.00104	419	576	53.6
56	57	0.00774	0.00166	160	220	42.66
56	58	0.00063	0.00026	419	576	13.48
58	59	0.01136	0.00244	160	220	62.6
58	60	0.0052	0.00217	419	576	111.83
60	61	0.00279	0.00116	419	576	59.94
61	62	0.0038	0.00256	306	421	67.06
62	63	0.00045	0.0003	306	421	7.99
62	64	0.00371	0.00246	80	110	7.53
53	65	0.00045	0.00018	419	576	9.75
65	76	0.01103	0.00237	160	220	60.83
65	66	0.00354	0.00147	419	576	76.18
66	67	0.00256	0.0017	80	110	5.21
66	68	0.00146	0.00061	419	576	31.43
68	69	0.00488	0.00105	160	220	26.92
68	70	0.00298	0.00124	419	576	64.07
70	71	0.01193	0.00257	160	220	65.76
70	72	0.00194	0.0013	306	421	34.18
72	73	0.01682	0.00362	160	220	92.73
72	74	0.00201	0.00136	306	421	35.54
74	75	0.0052	0.00112	160	220	28.67
76	77	0.0039	0.00084	160	220	21.51
76	78	0.00935	0.00201	160	220	51.57
79	80	0.00063	0.00042	550	756	22.15

D.2 Load Data

Load density is 2.77 MW/km^2. The customers can be classified into 4 types as follows.

Table D-2 Customer category

Type no.	Type of consumers	Total number	Peak load (kW)
1	Domestic Unrestricted	40	11
2	Domestic Economy 7	4	30
3	Non-Domestic Unrestricted	4	52
4	Non-Domestic Economy 7	2	86

The type of customers in each node can be seen from the table below.

Table D-3 Profile Type of customers

Bus no	Type	Bus no	Type	Bus no	Type	Bus no	Type	Bus no	Type
4	1	20	3	35	1	57	1	73	1
5	1	21	2	37	1	59	1	74	3
8	1	22	3	39	1	60	1	75	1
10	1	23	1	42	4	61	1	77	1
11	1	26	1	43	1	63	3	78	1
12	2	27	1	45	1	64	1	79	2
15	1	29	1	47	2	67	1	80	4
16	1	30	1	50	1	69	1	81	1
18	1	33	1	52	1	70	1	82	1
19	1	34	1	55	1	71	1	83	1

In each node it is assumed that the house types are similar. The house type of each node is listed in Table D-4.

Table D-4 House Type of customers

Load Bus Number	**Orientation**	**Occupancy**	**House Type**
	S=1,E=2, W=3,SE=4, SW=5	**Continuous =1 Intermittent=2**	**Semi-detached=1 Detached=2**
4	1	2	1
5	1	2	1
8	2	1	1
9	1	2	1
10	4	1	1
11	2	2	2
12	2	2	1
15	1	2	1

Load Bus Number	Orientation	Occupancy	House Type
	S=1,E=2, W=3,SE=4, SW=5	Continuous =1 Intermittent=2	Semi-detached=1 Detached=2
16	4	2	1
19	4	1	2
20	1	1	1
21	1	2	1
22	3	2	2
23	5	1	1
26	1	1	1
27	4	1	1
29	2	2	2
30	3	2	1
33	2	1	1
34	5	2	1
35	5	1	1
37	4	2	1
39	3	2	1
42	2	1	1
43	5	1	1
45	1	1	1
47	3	1	1
50	3	2	2
52	3	2	2
55	5	2	2
57	4	2	1
59	1	2	2
60	2	2	1
61	3	2	1
63	1	2	2
64	3	1	1
67	5	1	1
69	3	1	1
70	2	1	2
71	3	1	2
73	4	1	2
74	2	1	2
75	1	2	1
77	4	2	1
78	4	1	2
79	2	2	1
80	1	1	1
81	4	2	1
82	5	2	1
83	3	1	1

D.3. Load Profiles

Power factor is assumed to be 0.85 p.f. lagging.

Table D-5 Load for 24 hour

	kW load at hour 1 - 24											
Bus no	1	2	3	4	5	6	7	8	9	10	11	12
4	0	0	2.81	0	0	0	4.04	12.95	6.4	5.43	2.38	0
5	3.72	5.12	0.56	4.56	4.09	5.07	9.3	2.62	8.59	11.48	5.28	9.59
8	0	3.67	0	6.7	0	0.24	5.81	17.69	1.1	5.81	8.25	0
10	5.25	1	0	0.97	2.13	3.67	0	13.56	15.73	7.86	2.14	1.16
11	8.49	3.97	3.99	0.11	1.22	6.67	4.25	5.98	3.93	14.58	4.15	9.31
12	38.55	1.02	49.77	50.6	59.39	8.67	26.76	30.33	7.5	0	17.9	2.12
15	0	0	2.17	0	5.81	5.98	4	9.91	1.77	4.17	0	5.5
16	1.9	0	1.83	3.73	4.71	8.83	0	3.06	0.02	0.82	5.26	8.31
18	0	0.69	1.52	0.72	2.35	3.21	0	1.07	9.99	2.92	8.93	0
19	0	0	0	0	6.65	0	5.1	10.88	2.42	5.42	5.18	0
20	11.16	30.09	0	30.02	24.64	0	0	0	0	123.38	92.5	155.22
21	20.53	22.66	40.81	30.14	0	0	40.7	33.06	17.92	0.57	3.07	3.84
22	15.74	0.7	0	23.02	0	25.56	34.83	23.59	65.99	0	31.76	76.53
23	4.16	4.17	5.34	1.88	2.77	4.47	0.63	0	6.92	3.73	2.81	5.78
26	1.06	0.06	0	4.12	0.49	4.45	0	0.1	9.37	0	0	4.92
27	4.55	0	2.95	3.81	0.3	7.04	7.56	9.55	12.23	4.09	8.53	11.66
29	4.49	0	0	2.84	2.99	2.85	6.8	12.85	10.01	4.09	4.52	5.36
30	5.46	0	3.22	1.02	3.37	0	7.3	8.44	2.56	3.03	0	6.77
33	6.14	3.26	2.81	0.77	1.05	0.32	11.79	7.56	2.71	0	1.82	17.81
34	1.46	0.27	1.68	0.82	3.85	0.96	2	0	9.23	6.28	12.23	2.81
35	7.29	0.77	1.53	3.66	0	5.98	0	1.72	6.75	0	5.53	7.62
37	9.13	0	5.92	1.65	0.59	2.36	0	7	3.72	9.94	5.5	5.51
39	2.06	2.94	3.91	0	0	4.92	3.75	20.32	7.71	0	4.4	1.98
42	63.69	38.32	129.42	0	0	0	0	22.8	90.82	78.78	137.45	47.85
43	6.23	1.63	3.97	4.22	3.61	0	1.71	8.58	8.36	5.48	0	9.32
45	0.04	0	0	4.44	2.85	1.22	0	8.11	2.52	8.51	4.14	1.82
47	37.94	0	0	54.78	0	40.45	25.92	5.93	17.49	3.22	6.49	7.86
50	6.96	3.11	6.5	0.24	7	0	1.06	10.11	9.56	0	13.18	5.78
52	0.27	2.03	0.84	6.85	2.99	0	6.1	13.21	14.41	6.65	2.47	2.72
55	0	0.73	0.23	3.64	0.99	0	6.23	15.79	0.87	2.16	0	6.9
57	2.87	5.45	8.04	1.59	0.92	3.88	2.35	5.41	6.01	0	9.12	5.14
59	7.08	9.46	0	2.21	0.81	0	0	0	8.07	10.15	18.95	8.36
60	2.89	3.86	0	2.01	3.43	0	1.8	4.48	0	7.28	3.87	8.16
61	3.83	1.26	3.74	0.83	0	6.47	2.3	16.89	0	0	9.43	1.69
63	22.96	2.52	0	33.12	20.13	0	5.43	0	17.76	80.86	96.3	153.2
64	0	9	2	3.84	5.34	7.43	0	10.83	5.7	0.56	0	2.41
67	0	0	1.67	0	5.13	1.31	0	3.35	5.08	8.04	5.49	14.1
69	6.23	4.66	0.5	5.34	0	3	5.38	5.47	0.91	10.59	2.61	0
70	4.08	0	0	4.21	3.75	1.87	3.03	8.8	0	13.6	0	14.73
71	6.07	2.2	3.13	0	2.22	1.52	2.11	0	6.79	0.3	10.45	4.5
73	0	0	0	2.58	0	0	1.46	10.17	0	0	8.44	6.6
74	9.37	26.05	0.34	0	11.66	0	24.77	27.19	50.63	0	17.46	56.25
75	0.86	0	0	0	0	3.32	4.12	9.29	12.37	10.37	11.32	11.74
77	2.07	1.52	2.6	5.73	0	0	5	9.46	11.05	4.79	0	5.69
78	0.94	0.72	0	6.94	7.55	1.13	1.07	4.76	0	3.32	5.63	7.13
79	47.41	14.95	8.7	0	0.76	29.35	37.67	0	15.18	4.02	9.12	7.12

	kW load at hour 1 - 24											
Bus no	1	2	3	4	5	6	7	8	9	10	11	12
80	237.44	183.56	31.39	58.68	10.76	124.55	191.79	42.1	0	49.13	116.97	73.16
81	0	2.28	1.05	3.08	2.46	1.95	0	15.27	20.78	4.23	0	10.61
82	5.31	4.4	1.13	2.11	3.36	5.98	2.82	11.82	17.5	3.43	3.18	13.58
83	1.2	3.95	6.75	5.78	0	4.74	4.83	3.41	9.42	8.12	5.39	2.33
Total	626.90	402.03	342.84	383.35	222.13	339.42	511.59	505.44	543.83	537.15	729.60	830.51

	kW load at hour 1 - 24											
Bus no	13	14	15	16	17	18	19	20	21	22	23	24
4	3.66	2.21	8.77	3.45	15.85	0.00	14.98	11.53	6.35	8.66	5.39	2.46
5	14.89	8.78	3.12	0.00	15.38	20.58	21.53	17.81	14.66	0.00	8.25	2.42
8	5.65	6.25	10.88	7.99	13.95	0.00	11.36	0.00	9.98	19.88	6.73	11.38
10	12.84	1.46	0.00	3.29	9.54	3.13	9.04	9.39	12.22	8.65	11.90	0.79
11	1.06	0.00	0.65	2.49	14.12	6.86	12.84	10.42	8.77	15.06	9.73	0.00
12	11.62	0.29	11.33	12.32	6.50	17.18	9.96	5.35	6.42	5.23	9.82	15.98
15	4.01	0.41	0.54	6.52	1.54	9.07	12.77	7.95	9.88	13.84	13.88	0.96
16	0.00	0.00	10.26	0.46	0.00	5.79	8.44	3.11	2.94	0.76	1.63	14.06
18	3.57	0.00	13.30	3.01	9.43	3.85	18.03	8.00	14.90	0.00	2.50	3.84
19	2.28	0.60	8.84	0.00	13.67	0.28	5.33	11.80	8.74	6.78	4.14	6.45
20	9.45	1.57	11.02	13.59	2.40	10.56	15.16	10.19	6.80	1.80	3.20	7.53
21	3.40	12.45	12.24	3.18	0.85	12.49	10.75	23.42	2.80	15.57	11.41	7.17
22	10.83	11.26	6.50	4.16	11.92	7.05	18.90	6.40	11.48	15.87	5.97	1.97
23	10.61	1.11	4.44	5.88	8.68	14.74	9.75	1.31	7.13	13.02	7.49	2.57
26	5.19	8.64	13.29	3.21	14.39	9.63	20.21	10.27	6.71	4.00	7.01	6.98
27	4.30	11.11	10.82	13.61	4.34	5.42	5.44	8.19	2.09	10.91	0.00	7.24
29	1.18	6.64	2.65	12.16	13.52	4.12	1.79	12.82	8.51	11.34	10.11	9.04
30	9.06	1.68	2.70	11.53	4.15	9.73	5.06	8.22	8.41	0.00	6.65	0.00
33	1.99	5.92	3.25	9.49	7.01	10.06	17.30	17.59	9.14	4.11	7.60	7.31
34	3.96	2.40	2.89	0.05	7.34	12.16	7.02	14.90	8.38	16.86	3.95	12.51
35	5.93	5.56	4.39	11.87	20.77	1.13	14.99	14.48	1.46	10.69	6.11	0.54
37	0.94	12.88	4.42	0.00	1.25	4.25	8.99	5.62	0.00	15.74	8.62	1.84
39	1.29	6.57	14.07	4.82	0.00	9.80	6.70	15.14	5.00	1.86	9.29	4.83
42	4.94	8.85	7.67	12.04	2.34	16.05	24.99	1.78	2.17	11.34	9.67	0.00
43	1.64	4.97	5.71	9.09	7.10	21.73	4.27	10.24	15.76	7.93	0.20	3.23
45	10.66	9.72	7.51	0.30	1.75	20.75	6.30	18.63	9.47	6.58	1.06	4.31
47	0.00	5.05	11.78	0.00	11.10	15.72	16.70	14.39	9.71	19.46	2.53	0.67
50	9.78	1.65	1.05	3.20	9.52	14.80	17.07	9.55	13.53	13.10	8.42	2.58
52	8.81	15.26	2.99	1.50	7.01	0.00	7.84	9.10	13.56	10.10	5.75	5.20
55	9.75	7.79	3.91	14.86	12.65	3.06	15.37	15.13	9.31	3.77	0.00	0.28
57	12.33	6.79	4.36	0.00	3.54	9.60	15.27	13.52	6.12	5.16	8.78	6.60
59	14.87	9.26	0.77	0.00	3.43	7.44	7.93	13.23	18.89	0.00	18.47	5.72
60	3.59	8.81	1.44	13.76	0.06	10.72	7.88	8.80	5.25	1.13	10.94	9.23
61	6.84	0.00	0.00	0.00	7.65	5.50	7.51	6.69	4.67	2.40	8.56	0.00
63	5.16	2.98	0.00	18.51	0.33	20.23	3.81	8.54	13.88	12.23	15.27	1.94
64	5.71	0.00	1.32	4.37	12.89	11.17	12.17	10.60	4.40	14.55	12.08	3.49
67	2.66	11.24	1.83	10.67	0.06	16.16	12.65	0.00	11.81	6.71	15.60	9.89
69	2.11	7.16	0.00	9.51	0.00	18.83	12.83	7.62	7.52	6.61	4.52	3.18
70	0.00	3.97	3.94	5.35	13.63	7.34	12.57	14.16	5.28	7.74	4.15	11.75
71	6.84	3.55	2.72	9.16	16.05	2.58	19.21	0.00	2.26	8.80	15.21	0.00
73	2.85	3.93	1.52	10.65	0.00	24.73	16.33	2.87	18.79	5.14	13.78	0.00
74	12.11	6.20	7.05	5.81	19.81	11.32	15.82	9.59	4.29	13.21	17.55	16.16
75	1.61	1.63	12.96	0.00	0.00	10.71	11.75	14.34	6.27	8.15	9.18	5.53

	kW load at hour 1 - 24											
Bus no	13	14	15	16	17	18	19	20	21	22	23	24
77	5.44	9.70	8.46	2.29	0.00	15.44	11.60	8.90	21.44	10.17	6.56	12.61
78	41.63	14.29	12.24	76.49	88.22	50.65	26.69	13.37	10.26	15.08	15.90	12.55
79	75.21	46.34	9.46	98.42	31.87	0.00	17.91	15.55	19.36	8.54	17.68	0.00
80	88.59	4.98	0.00	94.02	23.44	24.24	12.22	21.03	15.25	13.44	19.07	7.38
81	86.52	5.60	0.00	79.02	23.59	64.21	21.35	52.52	16.82	13.47	16.16	2.36
82	46.98	16.05	0.00	35.84	57.51	65.30	9.26	30.06	35.66	40.12	12.94	44.57
83	66.01	79.25	205.56	216.90	4.05	77.62	21.74	39.16	13.75	0.00	17.58	49.32
Total	660.35	402.81	474.63	864.81	554.19	723.79	635.39	603.28	488.24	465.56	449.02	346.37

D.4 DER Profiles

Detailed data of each profile capacity factor are presented in tables D-5 to D-7. More information about the tool used to create the profiles can be found in the references provided in Chapter 6. It was considered unpractical to reproduce the 13 DER profiles, as each one has 6084 samples.

Table D-6 PV System Capacity Factor (%)

Season	Duration (days)	Orientation					Average
		E	SE	S	SW	W	
Winter	**90**	1.39	1.91	2.09	1.78	1.25	1.68
Transition	**185**	9.91	12.99	14.48	13.45	10.55	12.28
Summer	**90**	16.55	20.07	21.12	21.96	19.11	19.76
Year Average	**365**	**9.45**	**12.00**	**13.06**	**12.67**	**10.37**	**11.51**

Table D-7 Stirling Engine micro-CHP Capacity Factor (%)

Season	Duration (days)	Detached House		Semidetached House		Average
		Continuous Occupancy	Intermittent Occupancy	Continuous Occupancy	Intermittent Occupancy	
Winter	**90**	63.89	39.58	50.74	39.58	48.45
Transition	**185**	43.45	35.86	34.72	30.70	36.18
Summer	**90**	0	0	0	0	0
Year Average	**365**	**37.78**	**27.94**	**30.11**	**25.32**	**30.28**

Table D-8 Internal Combustion Engine micro-CHP Capacity Factor (%)

Season	Duration (days)	Detached House		Semidetached House		Average
		Continuous Occupancy	Intermittent Occupancy	Continuous Occupancy	Intermittent Occupancy	
Winter	**90**	49.36	39.29	38.29	33.33	40.07
Transition	**185**	32.69	28.92	27.13	23.26	28
Summer	**90**	0	0	0	0	0
Year Average	**365**	**28.74**	**24.35**	**23.19**	**20.01**	**24.07**

D.5 Calculation of DER Costs per kWh

In the Table D-9 the calculation of the unit cost per kWh for the micro-generators is detailed. Installation and maintenance costs are proportionally distributed between electricity and heat generation.

Table D-9 Cost per kWh – Costs proportionally distributed

#	Costs Proportionally Distributed	Stirling Engine	ICE micro-CHP	PV Systems
A	Capacity (kW)	1.00	5.50	1.20
B	Heat to Power Ratio	8.00	2.30	-
C	Capacity Factor	0.30	0.24	0.11
D	Electrical Energy (kWh/year) D=8760*A*B	2,654.28	11,611.38	1,177.34
E	Total Installation Cost (£)	3,500.00	11,440.00	6,000.00
F	Installation Cost Attributed to Electricity F=E/(B+1)	388.89	3,466.67	6,000.00
G	Annuity of Installation Cost (£/year) G=F/10.594	36.71	327.23	566.36
H	Maintenance Cost (£/year)	110.00	550.00	60.00
I	Maintenance Cost Attributed to Electricity I=H/(B+1)	12.22	166.67	60.00
J	Fuel Cost Electricity (£/year) J=D*0.027	71.67	313.51	-
K	Total Annual Cost (£/year) = K=G+I+J	120.60	807.40	626.36
L	Cost per unit of electricity (p/kWh) L=K/D	4.54	6.95	53.20

D.6 Selected Optimal Solutions

Table D-10 presents the selected optimal solutions for Case Study 1. Only solutions B and C are presented. Solution A has no generators installed. Solution D has the maximum penetration in all load nodes (see Table D-5). Solutions S, ICE and PV have the maximum penetration of Stirling engines, ICE micro-CHP and PV systems in all load nodes, respectively. The numbers indicate the number of units installed in each node.

Table D-10 Selected Optimal Solutions for Case Study 1

	Solution B			Solution C		
Node	Stirling Engine	ICE Micro-CHP	PV systems	Stirling Engine	ICE Micro-CHP	PV systems
4	10			10		10
5	10					10
6			6			
8	10	2		10		10
10	10			10		10
11	10			10		10
12	10	2		10	1	10
15	10					10
16	10			10		10
18	10			7	3	10
19	10					10
20	10					10
21	10					10
22	10	3				
23	10	3		10		10
26	10	3		10		10
27	10			10		10
29	10			10		10
30	10			10	3	10
33	10	3		10		10
34	10					10
35	10					10
37	10			10	3	10
39	5				3	10
42	10			10		1
43	10			10	3	10
45	10			10	3	10
47	10			10		10
50	10				3	10
52	10				3	10
55	10			10		10
57	10			10		10
59	10					10
60	10	3				10
61	10	3				10
63	10			10	3	10
64	10			10		10
67	10	2			3	10
69	10	3		10	3	10
70	10	3			3	10
71	10			10	3	10
73	10	3		10		10
74	10			10		
75	10					10
77	10	3				10
78	10				3	10
79	10	3		10		
80	10	2		2	2	10
81	10			10	2	10
82	10			10		10
83		2		10	3	10

Appendix E: Supplementary Data for Case Study 2

E.1 Network Data

The network HV-OHa is a generic medium-voltage rural network (355 nodes, 11kV, 3-phase, balanced). The feeder was modified to provide a more realistic analysis of a rural network where voltage rise is the major impact of DER, as already explained in Chapter 6:

- The length of the conductors has been doubled.
- The load has been multiplied by a factor of 2.2
- The capacity of conductors has been doubled.
- The line between 1100 and 1101 has been replaced with a transformer.

Details of the studied feeder are provided in Table E-1.

Sbase = 100MVA

Vbase=11 kV

Table E-1Network Details – Case Study 2

Sending end	Receiving end	R (p.u.)	X (p.u.)	Capacity (MVA)	Length (Km)
1100	1101	0.835	1.179	12	-
1101	1102	0.2508	0.1698	8.92	1.104
1102	1103	0.2508	0.1698	8.92	1.104
1103	1104	0.2508	0.1698	8.92	1.104
1101	1105	0.248	0.178	6.66	1.104
1105	1106	0.248	0.178	6.66	1.104
1106	1107	0.248	0.178	6.66	1.104
1102	1108	0.186	0.1335	6.66	0.828
1108	1109	0.186	0.1335	6.66	0.828
1109	1110	0.186	0.1335	6.66	0.828
1110	1111	0.186	0.1335	6.66	0.828
1103	1112	0.186	0.1335	6.66	0.828
1112	1113	0.186	0.1335	6.66	0.828
1113	1114	0.186	0.1335	6.66	0.828

Sending end	Receiving end	R (p.u.)	X (p.u.)	Capacity (MVA)	Length (Km)
1114	1115	0.186	0.1335	6.66	0.828
1104	1116	0.186	0.1335	6.66	0.828
1116	1117	0.186	0.1335	6.66	0.828
1117	1118	0.186	0.1335	6.66	0.828
1118	1119	0.186	0.1335	6.66	0.828
1105	1120	0.3556	0.1331	4.5	0.792
1120	1121	0.3556	0.1331	4.5	0.792
1106	1122	0.3556	0.1331	4.5	0.792
1122	1123	0.3556	0.1331	4.5	0.792
1107	1124	0.3556	0.1331	4.5	0.792
1124	1125	0.3556	0.1331	4.5	0.792
1108	1126	0.3556	0.1331	4.5	0.792
1126	1127	0.3556	0.1331	4.5	0.792
1109	1128	0.3556	0.1331	4.5	0.792
1128	1129	0.3556	0.1331	4.5	0.792
1110	1130	0.3556	0.1331	4.5	0.792
1130	1131	0.3556	0.1331	4.5	0.792
1111	1132	0.3556	0.1331	4.5	0.792
1132	1133	0.3556	0.1331	4.5	0.792
1112	1134	0.3556	0.1331	4.5	0.792
1134	1135	0.3556	0.1331	4.5	0.792
1113	1136	0.3556	0.1331	4.5	0.792
1136	1137	0.3556	0.1331	4.5	0.792
1114	1138	0.3556	0.1331	4.5	0.792
1138	1139	0.3556	0.1331	4.5	0.792
1115	1140	0.3556	0.1331	4.5	0.792
1140	1141	0.3556	0.1331	4.5	0.792
1116	1142	0.3556	0.1331	4.5	0.792
1142	1143	0.3556	0.1331	4.5	0.792
1117	1144	0.2371	0.0887	4.5	0.528
1144	1145	0.2371	0.0887	4.5	0.528
1145	1146	0.2371	0.0887	4.5	0.528
1118	1147	0.2371	0.0887	4.5	0.528
1147	1148	0.2371	0.0887	4.5	0.528
1148	1149	0.2371	0.0887	4.5	0.528
1119	1150	0.2371	0.0887	4.5	0.528
1150	1151	0.2371	0.0887	4.5	0.528
1151	1152	0.2371	0.0887	4.5	0.528

E.2 Load Data

The peak load installed in each node, and the customer types are detailed in Table E-2. The following changes have been performed from the original UKGDS network:

- The customer types have been diversified.
- The load has been multiplied by a factor of 2.2.

Table E-2 Load Data

Node	Node (UKGDS)	Active Load (MW)	Reactive Load (MVAR)	Load Type
1	1100	0	0	0
2	1101	0.033	0.0066	1
3	1102	0.033	0.0066	1
4	1103	0.044	0.0088	1
5	1104	0.044	0.0088	1
6	1105	0.022	0.0044	2
7	1106	0.022	0.0044	2
8	1107	0.033	0.0066	1
9	1108	0.033	0.0066	1
10	1109	0.033	0.0066	1
11	1110	0.033	0.0066	1
12	1111	0.033	0.0066	1
13	1112	0.033	0.0066	1
14	1113	0.033	0.0066	1
15	1114	0.033	0.0066	1
16	1115	0.033	0.0066	1
17	1116	0.033	0.0066	1
18	1117	0.033	0.0066	1
19	1118	0.033	0.0066	1
20	1119	0.033	0.0066	1
21	1120	0.077	0.0154	4
22	1121	0.077	0.0154	4
23	1122	0.077	0.0154	4
24	1123	0.077	0.0154	4
25	1124	0.077	0.0154	4
26	1125	0.077	0.0154	4
27	1126	0.077	0.0154	4
28	1127	0.077	0.0154	4
29	1128	0.077	0.0154	4
30	1129	0.077	0.0154	4
31	1130	0.077	0.0154	4
32	1131	0.077	0.0154	4

Node	Node (UKGDS)	Active Load (MW)	Reactive Load (MVAR)	Load Type
33	1132	0.077	0.0154	4
34	1133	0.077	0.0154	4
35	1134	0.077	0.0154	4
36	1135	0.077	0.0154	4
37	1136	0.077	0.0154	4
38	1137	0.077	0.0154	4
39	1138	0.077	0.0154	4
40	1139	0.077	0.0154	4
41	1140	0.077	0.0154	4
42	1141	0.077	0.0154	4
43	1142	0.077	0.0154	4
44	1143	0.077	0.0154	4
45	1144	0.077	0.0154	4
46	1145	0.077	0.0154	4
47	1146	0.077	0.0154	4
48	1147	0.088	0.0176	3
49	1148	0.088	0.0176	3
50	1149	0.088	0.0176	3
51	1150	0.088	0.0176	3
52	1151	0.088	0.0176	3
53	1152	0.088	0.0176	3