# Multi-Objective Evolutionary Algorithms in Real-World Applications: Some Recent Results and Current Challenges

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**Abstract** This chapter provides a short overview of the most significant research work that has been conducted regarding the solution of computationally expensive multi-objective optimization problems. The approaches that are briefly discussed include problem approximation, function approximation (i.e., surrogates) and evolutionary approximation (i.e., clustering and fitness inheritance). Additionally, the use of alternative approaches such as cultural algorithms, small population sizes and hybrids that use a few solutions (generated with optimizers that sacrifice diversity for the sake of a faster convergence) to reconstruct the Pareto front with powerful local search engines are also briefly discussed. In the final part of the chapter, some topics that (from the author's perspective) deserve more research, are provided.

**Keywords:** evolutionary algorithms, multi-objective optimization, metaheuristics

## 1 Introduction

In real-world applications, most problems have several (often conflicting) objectives that we aim to optimize at the same time. Such problems are called "multi-objective" and their solution gives rise to a set of solutions that represent the best possible trade-offs amont all the objectives (i.e., the so-called *Pareto optimal set*). The image of the Pareto optimal set (i.e., the objective function values corresponding to this set) forms to so-called *Pareto front* of the multi-objective optimization problem being solved.

Starting in the mid-1980s, Evolutionary Algorithms (EAs) have become a popular search engine to solve multi-objective optimization problems, mainly because

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of their ease of use, and wide applicability (i.e., they require little domain-specific information to operate) [11, 15].

Modern multi-objective evolutionary algorithms (MOEAs) consist of two main components:

1. A selection mechanism that is normally (but not necessarily) based on Pareto optimality. Performance indicators can also be used for selecting solutions in a population and that has been, indeed, a relatively popular research trend in recent years [3].
2. A density estimator, which is responsible for producing different elements of the Pareto optimal set in a single run of a MOEA. Different options are available for this mechanism, such as: fitness sharing [16], entropy [82], clustering [79], adaptive grids [31] and crowding [17], among others.

Additionally, all modern MOEAs are *elitist*, which means that they retain the nondominated solutions generated at each iteration, so that at the end of a run, the user can have the globablly nondominated solutions that had been produced. Elitism is normally implemented through the use of an external archive, but the use of the main population for this purpose is also possible.

In spite of their popularity, one of the main limitations of MOEAs, when used for solving real-world problems, is their high computational cost, which is associated to the relatively high number of objective function evaluations that most current MOEAs require [62]. Although there are several remarkable efforts in this regard, several challenges still lie ahead, and the purpose of this chapter is precisely to review some of the most representative research that has been conducted in this area.

The remainder of this chapter is organized as follows. In Section 2, we present basic concepts related to multi-objective optimization. Then, in Section 3, we discuss the main schemes that have been proposed for dealing with expensive multi-objective optimization problems. In Section 4, we explore other ideas that havel also been used for dealing with real-world applications having objective functions that are computationally expensive. Section 5, provides some potential paths for future research in this area. Finally, the conclusions of this chapter are presented in Section 6.

## 2 Basic Concepts

We are interested in solving problems of the type[1]:

$$\text{minimize } \mathbf{f}(\mathbf{x}) := [f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_k(\mathbf{x})] \tag{1}$$

subject to:

$$g_i(\mathbf{x}) \leq 0 \quad i = 1, 2, \ldots, m \tag{2}$$

[1] Without loss of generality, we will assume only minimization problems.

$$h_i(\mathbf{x}) = 0 \quad i = 1,2,\ldots,p \tag{3}$$

where $\mathbf{x} = [x_1, x_2, \ldots, x_n]^T$ is the vector of decision variables, $f_i : \mathbf{R}^n \to \mathbf{R}$, $i = 1,...,k$ are the objective functions and $g_i, h_j : \mathbf{R}^n \to \mathbf{R}$, $i = 1,...,m$, $j = 1,...,p$ are the constraint functions of the problem.

To describe the concept of optimality in which we are interested, we will introduce next a few definitions.

**Definition 1.** Given two vectors $\mathbf{x}, \mathbf{y} \in \mathbf{R}^k$, we say that $\mathbf{x} \leq \mathbf{y}$ if $x_i \leq y_i$ for $i = 1,...,k$, and that **x dominates y** (denoted by $\mathbf{x} \prec \mathbf{y}$) if $\mathbf{x} \leq \mathbf{y}$ and $\mathbf{x} \neq \mathbf{y}$.

**Definition 2.** We say that a vector of decision variables $\mathbf{x} \in \mathscr{X} \subset \mathbf{R}^n$ is **nondominated** with respect to $\mathscr{X}$, if there does not exist another $\mathbf{x}' \in \mathscr{X}$ such that $\mathbf{f}(\mathbf{x}') \prec \mathbf{f}(\mathbf{x})$.

**Definition 3.** We say that a vector of decision variables $\mathbf{x}^* \in \mathscr{F} \subset \mathbf{R}^n$ ($\mathscr{F}$ is the feasible region) is **Pareto-optimal** if it is nondominated with respect to $\mathscr{F}$.

**Definition 4.** The **Pareto Optimal Set** $\mathscr{P}^*$ is defined by:

$$\mathscr{P}^* = \{\mathbf{x} \in \mathscr{F} | \mathbf{x} \text{ is Pareto-optimal}\}$$

**Definition 5.** The **Pareto Front** $\mathscr{PF}^*$ is defined by:

$$\mathscr{PF}^* = \{\mathbf{f}(\mathbf{x}) \in \mathbf{R}^k | \mathbf{x} \in \mathscr{P}^*\}$$

Therefore, we wish to determine the Pareto optimal set from the set $\mathscr{F}$ of all the decision variable vectors that satisfy (2) and (3). In practice, however, not all the Pareto optimal set is normally desirable or even achievable.

## 3 Dealing with Expensive Problems

In general, MOEAs can be unaffordable for an application when:

- The evaluation of the fitness functions is computationally expensive (e.g., it takes several hours).
- The total number of fitness function evaluations that can be performed is limited (e.g., we only have a certain computational budget available).

According to [29], there are three main schemes that can be used to deal with expensive problems:

**Problem approximation:** In this case, the idea is to replace the original (expensive) statement of the problem by another one which is easier (and less expensive) to solve.

**Functional approximation:** In this case, instead of using the original objective function(s) (which is/are expensive to evaluate), an alternative expression(s) is adopted. The new expression(s) is built based on the previous data obtained from evaluating the real objective function(s). The models that are obtained from the data that is currently available are called *meta-models* or *surrogates*.

**Evolutionary approximation:** This is an approach that is specific to EAs, and that aims to save fitness function evaluations by estimating the fitness of an individual using information from other (similar) individuals. The two main approaches in this class are: fitness inheritance and clustering.

Next, we will provide a short discussion of each of these schemes, as well as some real-world problems in which they have been adopted.

### *3.1 Use of Problem Approximation*

As indicated before, in this case, the idea is to replace the original problem by another one which is easier to solve. This sort of approach has been relatively popular in aeronautical/aerospace engineering, in which complex Computational Fluid Dynamics (CFD), Computational Aero-Acoustics (CAA) and Computational Structural Mechanics (CSM) are adopted. When using such tools, it is possible to approximate the original problem by using different resolutions in the flow or structural simulation, adopting either coarse or fine grids. For CFD simulations is also possible to rely on Euler flows instead of (the more expensive) Navier-Stokes flow simulations.

An example of this sort of approach is the work of Lee et al. [41, 42]. In this case, the authors applied the HAPMOEA (Hierarchical Asynchronous Parallel Multi-Objective Evolutionary Algorithm) [24] to the robust design optimization of an ONERA M6 wing shape. The authors considered uncertainties in the design environment, related to the flow Mach number, and the Taguchi method was used to transform the problem into one with two objectives to be minimized: (1) the mean value of an objective function with respect to variability of the operating conditions, and (2) the variance of the objective function of each solution candidate, with respect to its mean value. HAPMOEA uses an evolution strategy as its search engine, incorporating the concept of Covariance Matrix Adaptation (CMA). It also incorporates a distance-dependent mutation operator, and a hierarchical set of CFD models (varying the grid resolution of the solver). Small populations are evolved using fine mesh CFD solutions in order to exploit the search space, while large populations are evolved with coarse mesh CFD solutions for exploring the search space. Good solutions from the coarse mesh populations (in which evaluations have a low computational cost) are transferred to the fine mesh populations (in which evaluations are computationally expensive).

For more information on this topic, the interested reader must refer to: [62, 68, 6]

### 3.2 Use of Functional Approximation

The use of meta-models or surrogate models has been very popular in engineering. In order to build a meta-model, a set of data points that lie on the local neighborhood of the design is required. The accuracy of the meta-model relies on the number of samples provided (from the real objective function evaluations), as well as on the accuracy of the model that is used to approximate the objective functions. Such an approximate model must also have a low computational cost, since it will be evaluated many times during the search.

There are several techniques available for constructing surrogate models, from which the main ones are [62]: response surface methods, Gaussian processes (or Kriging), radial basis functions, artificial neural networks and support vector machines.

An example of this sort of approach is the work of Voutchkov et al. [81], in which the Nondominated Sorting Genetic Algorithm–II (NSGA-II) [17] was used to perform a robust structural design of a simplified jet engine model. The aim was to find the best jet engine structural configuration that minimized: the variation of reacting forces under a range of external loads, the mass for the engine and the engine's fuel consumption. The evaluation of the structural response was done in parallel by means of finite element simulations. The authors adopted a kriging based response surface method in order to reduce the computational time required to solve this problem. Four objectives were minimized: (1) standard deviation of the internal reaction forces, (2) mean value of the internal reaction forces, (3) engine's mass, and (4) mean value of the specific fuel consumption. The first two objectives were computed over 200 external load variations. Due to the many combinations of loads and finite element thicknesses, the multi-objective optimization problem would have taken on the order of one year of computational time on a single 1 GHZ CPU, if no effort had been made to perform a more efficient search. When using the surrogate model that they report, combined with parallel processing, the total optimization time was reduced to about 26 hours, in a cluster with 30 cores.

For more information on this topic, the interested reader must refer to: [32, 43, 45, 51, 53].

### 3.3 Use of Evolutionary Approximation

In this case, two main approaches are considered: clustering and fitness inheritance. Next, we will briefly discuss each of them.

Clustering is a term used to refer to the unsupervised classification of paterns into groups (which are called *clusters*). The idea is to partition data into different groups either in a hard way (i.e., into well-defined groups) or in a fuzzy way (i.e., using a certain degree of membership to each of the groups) [27].

Although clustering is normally not used as a specific technique to reduce objective function evaluations, this sort of technique is normally adopted in combination with surrogates in order to reduce the size of the training data set. This is an important task, since the use of very large training data sets makes prohibitive the cost of a surrogate method. Clustering is normally adopted in this context to split the data set into several small groups, and then an independent local model is built from each of them.

An example of the use of clustering is the work of Langer et al. [38], in which an integrated approach that adopts computer aided design modeling is combined with a MOEA for solving structural shape and topology optimization problems. The authors were interested in optimizing an instrument panel of a satellite, considering two objectives: (1) minimize the instrument panel mass, and (2) maximize the first eigenfrecuency. The authors solved the optimization problem for three shape and topology optimization cases: (a) a panel without instruments, (b) a panel with instruments at fixed positions, and (c) a panel with instrumental placing. They adopted polynomial based response surface methods in order to reduce the computational cost, and multiple local approximation models were constructed using a clustering technique. The use of parallel techniques was also required in this case (a cluster with 32 processors was adopted by the authors).

Fitness inheritance was originally introduced by Smith et al. [71], with the motivation of reducing the total number of fitness function evaluations performed by an evolutionary algorithm. The idea is that, when assigning fitness to an individual, some times we evaluate the objective function as usual, but the rest of the time, we assign a fitness value equal to the average of the fitness values of its parents. This saves one fitness function evaluation, and is based on the assumption of similarity of an offspring to its parents.

Evidently, fitness inheritance cannot be applied all the time, since it is required to have information from true fitness function evaluations in order to guide the search in a proper way. The percentage of time in which fitness inheritance is applied is called *inheritance proportion*. Clearly, this proportion should be less than one in order to avoid premature convergence [4].

A theoretical model of fitness inheritance was presented by Sastry et al. [69]. Such model was used to obtain the convergence time, the optimal population size and the optimal inheritance proportion (the authors found that values between 0.54 and 0.558 worked best for the inheritance proportion in problems of moderate and large size).

The work of Sastry et al. [69] was extended to the multi-objective case by Chen et al. [4]. In this case, the authors used fitness sharing to maintain diversity in the population with the aim of covering a larger extension of the Pareto front. The problem they solved was a bi-objective extension of the OneMax problem originally solved by Sastry et al. [69] in their study. The authors also presented a generalization (for the multi-objective case) of the theoretical work reported by Sastry et al. [69] regarding convergence time, optimal population sizing and optimal inheritance proportion. The experiments reported by the authors showed that savings of up to 40% of the total number of evaluations could be achieved when using fitness inheritnance alone. When combining fitness inheritance with fitness sharing, savings of up to 25% were obtained.

Reyes-Sierra and Coello Coello proposed the use of dynamic rules to assign the inheritance proportion in a multi-objective particle swarm optimizer [55]. Such rules produced savings that were from 19% up to 78% of the total number of evaluations. However, as expected, the greater the savings in the number of evaluations, the greater was the degradation in the quality of the results. Nevertheless, the authors showed it was possible to obtain savings of up to 49% without having a significant loss in the quality of the results. The authors adopted the Zitzler-Deb-Thiele (ZDT) test problems in their experiments [89].

It is worth mentioning that some researchers have considered fitness inheritance to be an inappropriate mechanism in complex or real-world problems (see for example [20], in which the authors concluded that fitness inheritance was not useful when the shape of the Pareto front is nonconvex or discontinuous). Such conclusions are valid for the proposal reported in [20]. However, in [56] it is shown that these limitations of fitness inheritance can be overcome, so that this approach can be applied to Pareto fronts having any kind of shape.

For more information on this topic, the interested reader must refer to: [19, 23, 52, 56, 37].

## 4 Other Approaches

There are some other ideas that can be used to tackle problems with computationally expensive objective functions, and which do not fall into any of the categories analyzed in the previous section. Here, we will focus on three types of approaches:

1. Cultural algorithms
2. Use of very small population sizes
3. Use of efficient search techniques

Next, we will briefly discuss each of these three types of approaches.

### *4.1 Cultural Algorithms*

Cultural algorithms were originally proposed by Robert Reynolds in the mid-1990s [57, 60]. The core idea behind cultural algorithms is to incorporate domain knowledge extracted during the search to an evolutionary algorithm. Cultural algorithms use, in addition to the population space commonly adopted in evolutionary algorithms, a belief space, which encodes the knowledge obtained from the search points that have been evaluated so far. The belief space is used to influence the evolutionary operators, with the aim of guiding the search in a very efficient way.

At each generation, a cultural algorithm selects some individuals from the population, in order to extract information from them. Such information will then be used to speed up the search. Evidently, the belief space requires some sort of scheme to represent the knowledge extracted during the evolutionary process and this representation is normally specific for each particular problem (or class of problems). It is also necessary to design mechanisms that allow to use this extracted knowledge to influence the way in which the evolutionary operators explore and exploit the search space.

Although cultural algorithms have been adopted for single-objective optimization by several authors (see for example [59, 58, 7, 28, 35]), its use in multi-objective optimization has been very limited until now.

The first proposal to design a cultural algorithm for solving multi-objective optimization problems is the framework described in [12], which uses Pareto ranking, and an approximation of the dimensions of the Pareto front in the belief space. In this proposal, the belief space works as a guide for the individuals to reach regions where nondominated solutions have been found. The belief space includes also a mechanism to obtain a good distribution of the resulting points along the Pareto front (i.e., a density estimator).

The earliest attempt to solve multi-objective optimization problems using cultural algorithms was based on the use of the $\varepsilon$-constraint method [36], since this sort of approach uses a single-objective optimizer rather than a MOEA (the cultural algorithm with differential evolution proposed in [35] was adopted for this sake). This approach turned out to be computational expensive, due to the high number of objective function evaluations required to generate a good approximation of the Pareto front. However, the authors showed that if the aim was to solve very difficult multi-objective optimization problems, then this additional computational cost was worth it. This was illustrated by solving several problems from the Deb-Thiele-Laumanns-Zitzler (DTLZ) [18] and the Walking-Fish-Group (WFG) [25, 26] test suites.

More recently, Best and his collaborators [1, 2] proposed a more general framework for using cultural algorithms with any sort of MOEA. This approach is interesting and incorporates several sources of knowledge, but it did not show a significant reduction of objective function evaluations, which is one of the main motivations for using cultural algorithms. Additionally, the results presented by the authors are not competitive with respect to those obtained by traditional MOEAs using the same number of objective function evaluations, which suggests that it is still required to conduct more research in this area. In fact, the incorporation of knowledge into MOEAs (using any sort of scheme), with the aim of making them more efficient is indeed a very promising research area [37].

### *4.2 Use of very small population sizes*

The use of small population sizes is unusual in the evolutionary algorithms literature in general, mainly because of the evident loss of diversity that is associated to small population sizes, and which normally leads to premature convergence. However, in the genetic algorithms literature, it is known that the use of very small population sizes is possible, if an appropriate reinitialization process is adopted (such approaches are called micro-genetic algorithms (micro-GAs) [34, 13, 14] and they use populations with no more than five individuals).

Krishnakumar [34] proposed the first implementation of a micro-GA. The first micro-GA for multi-objective optimization was introduced in [13, 14]. This approach uses a population size of four individuals, and three forms of elitism: (1) an external archive that adopts the adaptive grid from the Pareto Archived Evolution Strategy (PAES) [33], (2) a population memory, in which randomly generated individuals are replaced by evolved individuals, and (3) a mechanism that retains the two best solutions generated by each run of the micro-GA. The main advantage of this approach is its efficiency (its authors showed that their approach was up to an order of magnitude faster than the NSGA-II [17]). This is the reason why this approach has been used in computationally expensive real-world applications (see for example [9, 8]).

In a further paper, Coello Coello and Pulido introduced the micro-GA$^2$ [78], which is a fully self-adaptive MOEA that adopts a parallel strategy to adapt the crossover operator and the type of encoding (binary or real numbers) to be used. This approach can even stop automatically (it uses a mechanism based on a performance indicator to decide when to stop the search).

Over the years, other authors have adopted micro-genetic algorithms for solving a variety of problems (see for example [30, 47, 77, 72, 46, 76, 5, 61, 77]). Additionally, the use of very small population sizes has also been attempted with other bio-inspired metaheuristics, such as particle swarm optimization (see [22]).

## *4.3 Use of efficient search techniques*

During the last few years, some researchers have proposed schemes that allow a more efficient exploration of the search space through the use of aggressive search engines that produce a few points from the Pareto front and then adopt a local search engine to reconstruct the rest of the front. One example of this sort of hybrid MOEA is DEMORS (differential evolution (DE) for multi-objective optimization with local search based on rough set theory) [64]. This approach operates in two phases. In the first one, a DE-based MOEA produces a rough approximation of the Pareto front using a relatively low number of objective function evaluations (65% of the total number of objective function evaluations adopted by DEMORS are spent in the first phase). In the second phase, the remainder 35% of objective function evaluations still available, are spent on the use of a local search procedure based on rough set theory [49, 50], whose task is to reconstruct the missing parts of the Pareto front. DEMORS was validated using several standard test problems taken from the specialized literature, as well as in a real-world problem having 8 objective functions and 160 decision variables in which it was able to outperform NSGA-II.

The same authors experimented with other (similar) hybrids in which DE was replaced by particle swarm optimization [67, 66] or rough sets were replaced by scatter search [65]. All these approaches were found to be very efficient multi-objective optimizers, and seem particularly suitable for real-world applications in which the use of surrogates is not appropriate.

In further related work [63], the same authors compared different surrogate methods (namely, artificial neural networks, radial basis functions and support vector machines) coupled to a MOEA and combined the best performer of them (support vector machines) with rough sets. This sort of scheme was proposed as an alternative for dealing with multi-objective problems that are very expensive (computationally speaking).

## 5 Future Research Paths

There are a number of possible research paths in this area that are worth exploring:

- **Parallel Approaches:** Although parallel MOEAs have been used for several years [48, 11], most of the papers published in that area focus on discussing applications and normally, such papers put little emphasis on the development of innovative algorithmic designs. Nowadays, the use of grid computing and Graphics Processing Units (GPUs) opens new and promising venues for future research in this area (see for example [74, 21, 75, 70, 80, 88, 73]), particularly regarding the solution of real-world problems having computationally expensive objective functions. The incorporation of surrogate models into parallel MOEAs is another interesting topic that deserves more research and that has been only scarcely explored in the specialized literature until now (see for example [54]).
- **Hybridization:** Coupling gradient-based or direct search methods to MOEAs is another alternative way for dealing with computationally expensive problems. In recent years, several promising hybrids of this sort have been proposed (see for example [39, 44, 40, 83, 84, 85]). These approaches can also be combined with surrogates for further efficiency (see for example [86, 87]). However, the use of such hybrid approaches in real-world applications is still rare (see for example [8]). Nevertheless, this situation is expected to change as more research results in this area become available.
- **Sampling techniques:** Surrogate methods heavily rely on the sample and updating technique adopted. In many real-world applications that use surroages, latin hypercubes have been adopted for the initial sampling, with the aim of covering as much as possible of the design (i.e., decision variable) space. At later stages of the search, it may be more relevant to explore the neighborhood of a good solution (see for example [8]). However, sampling is also relevant in other approaches, such as when using small population sizes or when hybridizing a MOEA with a local search engine. Nevertheless, the impact of the sampling technique in the performance of such approaches has not been properly addressed so far, to the author's best knowledge.

## 6 Conclusions

This chapter has provided a quick overview of the most relevant research tools that are currently available to tackle computationally expensive problems using multi-objective evolutionary algorithms. Breadth has been emphasized over depth in the discussions provided herein. However, several additional references have been provided for those interested in getting an in-depth knowledge about any of the topics that have been addressed in this chapter.

One aspect that is worth mentioning is that the presence of computationally expensive objective functions is clearly not the only relevant aspect when solving real-world problems. Other issues such as scalability (in decision variable space or in objective function space, or in both), uncertainty and incorporation of user's preferences, just to name a few, have not been addressed here, mainly because of obvious space limitations. Readers interested in information about these and other relevant topics are invited to visit the EMOO repository [10], which is available at: `http://delta.cs.cinvestav.mx/˜ccoello/EMOO/EMOObib.html`.

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