A FUZZY MULTIOBJECTIVE APPROACH FOR OPTIMAL OPERATION OF DISTRIBUTION SYSTEMS USING EVOLUTIONARY ALGORITHMS

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1. INTRODUCTION

The actual and future development of distribution systems leads to new criteria and methods to reduce operating costs considering service quality constraints. According to our actual country regulations and UCPTE prescriptions, the reactive power compensation sources used in distribution systems are fixed/switched capacitors, which operate on the MV bus of substation or on the MV or LV buses of distribution transformers. Also, the voltage magnitudes of the system buses have to be within prescribed maximum and minimum limits.

A variety of methods have been devoted to solving locations, number and sizes of the capacitors. Conventional analytical methods in conjunction with some heuristics have been used in reactive power planning for many years, Kaplan (1). A gradient search based iterative procedure was proposed to deal with fixed/switched capacitor installation problem, Grainger et al. (2). Chung and Shaoyun (3) considered the capacitor placement as a linear programming problem and solve it by a recursive process with cost-benefit consideration. Chiang et al. (4) developed a solution based on an optimization technique, simulated annealing, to search the global optimum solution to the capacitor placement problem. Tabu Search strategy is used by Huang and Yang (5) for solving combinatorial optimization problem for capacitor placement in a radial distribution system. Carlisle and El-Keib (6) proposed a graph search based method for the optimal placement of fixed and switched capacitors on radial distribution systems. Many of these approaches are aimed at finding the optimum placement of reactive power sources with the minimum cost as the main objective. Inclusion of other objectives, such as electric power quality, makes it a multiobjective optimization problem.

The aim of this research is to propose a fuzzy multiobjective optimization technique based on evolutionary computation for voltage/reactive power control, on the case of distribution systems. Multiobjective optimization, also named Pareto optimization, extends optimization theory by permitting multiple objectives to be "optimized" simultaneously. It has been used in economics and management science for years and has gradually crept in engineering, Kagan and Adams (7). Process optimization are best viewed as a pareto optimal process seeking a consensus in which many objectives are balanced so that the improvement of any single objective will result in a negative impact on at least one other objective.

This paper makes use of fuzzy concepts in an evolutionary computation framework and proposes an efficient method based on the full integration of technical and economical aspects of the problem, namely:
1) technical aspect – concerned with the optimization of reactive power distribution, so to improve some quality indices such as the voltage profile of the network, for characteristic regimes;
2) economical aspect – concerned with the reduction of transmission line losses by considering the cost of reactive power sources (capacitor banks).

2. PROBLEM FORMULATION

In this section is formulated the general multiobjective problem taking into account a cost function (OF_1) and a performance function (OF_2):

1) OF_1 – update total cost (UTC)
The objective function OF_1 minimizing the overall cost is expressed as:

$$OF_1 = I + \sum_{t=1}^{T} M_{ct}(1+i)^{-t} + k_e \sum_{t=1}^{T} \Delta P_{peak\,t}(1+i)^{-t} + \sum_{t=1}^{T} C_{\Delta E_{loss}\,t}(1+i)^{-t} - V_{rem}(1+i)^{-T} \quad [\$] \qquad (1)$$

where: I is the investment cost; $M_{c\,t}$ - the maintenance cost; $\Delta P_{peak\,t}$ - the real power loss during peak load; k_e - the price of the kW-installed in an equivalent plant; $C_{\Delta E\,loss\,t}$ - the annual energy loss cost; V_{rem} - the remainder value of investment at the end of the study time; i - the discount rate; T – study time.

2) OF_2 – voltage irregularity (VI)
One of the power quality indices, which can be used to estimate the damages produced to the consumers because of the voltage variations, is the voltage irregularity, Pélissier (8). So, the objective function OF_2, which minimize the voltage irregularity, is:

$$OF_2 = \frac{1}{N} \sum_{i=1}^{N} \frac{\sum_{t=1}^{24} \left(\frac{U_i - U_n}{U_n} \cdot 100 \right)^2 \cdot P_{it}}{\sum_{t=1}^{24} P_{it}} \quad [\%^2] \qquad (2)$$

where: U_n, U_i – the nominal voltage and the voltage on bus i; P_{it} – the active power consumption on bus i, at time t; N – the total number of buses.
In addition, the optimization model verifies the following crisp constraints:
C1 - the voltage magnitudes of the system buses have to be within prescribed maximum and minimum limits;
C2 - no transmission of reactive power from the buses where there are capacitors to the power supply, in characteristic regimes;
C3 - no capacitor placement within nodes where there are distorting consumers.

In this optimization problem, it is attempted to minimize the operating cost and voltage irregularity. Using fuzzy programming, the multiobjective function is transformed into one with a single objective, fuzzy decision (FD), which satisfies the set of fuzzy objective, being defined as:

$$FD = OF_1 \wedge OF_2 \quad (3)$$

where $\wedge$ is the fuzzy "AND" operator. Any improvement of one objective function can be reached only at the loss of another. The optimal solution is searched from a population of admissible solutions using an evolutionary algorithm (EA).

3. FUZZY AND EVOLUTIONARY APPROACH

In the multiobjective optimization problem a fuzzy goal can be quantified by drawing out a corresponding membership function. To elicit a membership function μ_{OF_i} for each objective function OF_i, i =1, 2, ..., we first estimate (or calculate) the individual minimum OF_i^{min} and maximum OF_i^{max} of each objective function OF_i under the given constraints. Since our goal is to keep the operating cost and voltage irregularity as low as possible, a decreasing membership function, as depicted in Figure 1, is employed for each objective.

The membership function of each objective is calculated as follow:

$$\mu_{OF_i}(p) = \begin{cases} 1, & OF_i(p) \le OF_i^{min} \\ \dfrac{OF_i^{max} - OF_i(p)}{OF_i^{max} - OF_i^{min}}, & OF_i^{min} < OF_i(p) \le OF_i^{max} \\ 0, & OF_i(p) > OF_i^{max} \end{cases} \quad (4)$$

where p is an n-dimensional vector of variables. The fuzzy multiobjective problem, with membership function $\mu_{OF_i}(p)$ calculated for each of the i =1, 2, ... objective, can thus be defined:

$$\max \mu_{FD}(p) = \max\left(\mu_{OF_1}(p) \wedge \mu_{OF_2}(p) \wedge \cdots\right) \quad (5)$$

and represents the degree of achievement of the overall objective.

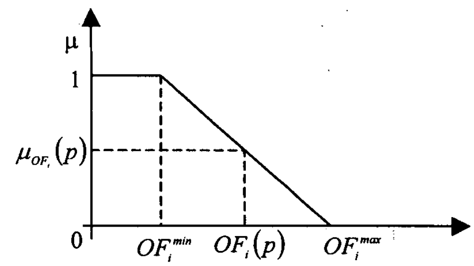

Figure 1 – Fuzzy membership function

So, fuzzy decision solution is defined as a crossing of all objectives, supposing that all objectives have the same importance. Though, there are some situations that are more important than others are. In these cases, the solution can be expressed like a convex combination of weighted aims:

$$\mu_{FD}(p) = \alpha \cdot \mu_{OF_1}(p) + \beta \cdot \mu_{OF_2}(p) + \cdots \quad (6)$$

with $\alpha + \beta + \cdots = 1$.

Using an EA the optimal solution is searched from a population of admissible solutions, named chromosomes, which change their structure from the actual to the next generation. The admissible solutions (initial population) are represented as strings of a fixed length, imposed by the number of buses where capacitors can be installed. In our study, each feeder is modelled by one chromosome and the elements of the strings (named genes) use integer numbers, each of them representing the number of capacitors placed in a bus (see Figure 2).

	Bus 1	Bus 2	Bus 3		Bus *n-1*	Bus *n*
Feeder i	2	0	10	...	7	12

Figure 2 - The chromosome structure

The randomly generated first population cannot meet the constraints of optimization model. Therefore, at the stage of generating the initial population, it is necessary to adopt some means by which each individual meets the constraints.

Our approach uses a combination of Genetic Algorithms (GAs) and Evolution Strategies (ESs) techniques; each individual competes with other individuals in a combined population of the old generation and the reproduced and mutated old generation. Figure 3 presents the mathematical approach based GAs and ESs.

The convergence is achieved when either the maximum fitness value does not decrease or the generations reach the maximum generation number. The solution is the chromosome with the best fitness function in the last generation.

- **GENERATION=1;**
- **Solution evaluation**: after ***m*** admissible solutions are randomly generated, the values of fitness function of this generation are calculated:

$$f_i = \mu_{FD}(p) = \alpha \cdot \mu_{OF_1}(p) + \beta \cdot \mu_{OF_2}(p) + \cdots, i = \overline{1, m}$$

Repeat

- **crossover**: recombine the chromosomes according to the "roulette wheel" selection method, Wong and Wong (9) and submitted to the crossover operation;
- **mutation**: modify at random one elements in the offspring chromosomes with a probabilistic mutation rate;
- **competition**: each individual in the combined population (***2m*** chromosomes – the old generation and the offsprings after crossover and mutation) has to compete with some other individuals to have a chance to be transcribed to the next generation. After all individuals will be ranked in descending order, the first ***m*** individuals are transcribed along with their corresponding fitness function to be the basis of the next generation;
- **elitism**: the best chromosome replace the chromosome with the minimum fitness value;
- **GENERATION=GENERATION+1;**

until {stop condition}

Figure 3 - Mathematical approach based GAs and ESs

The Figure 4 describes synthetically the fuzzy multiobjective decision-making.

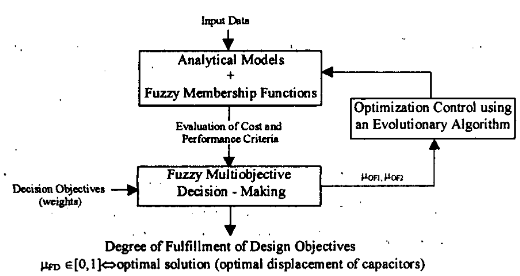

Figure 4 – Fuzzy Multiobjective Decision - Making

4. NUMERICAL RESULTS

The proposed method has been implemented using Delphi language and was tested on quiet a great number of distribution systems. Some synthetical results computed for the medium voltage (20 kV) distribution system shown in Figure 5 are presented bellow. The system has closed-loop configuration but operates as a radial one (the off-branches are represented with dashed line in Figure 5). In this paper we consider ten-year planning horizon (the life of the capacitor). A yearly load growth rate of 1% was assumed. The evaluation of the update total cost function has been made in \$. The cost of capacitor installation represents the initial investment (including circuit breaker and protection relay) and the maintenance cost.

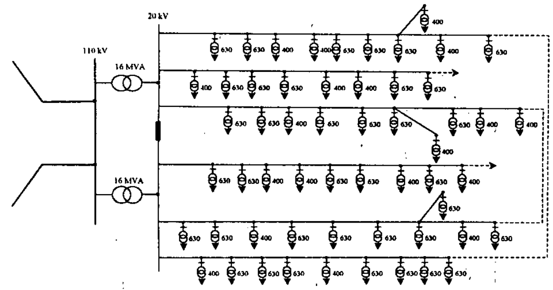

Figure 5 - Test distribution system

The tests have been made using 10 kVAr fixed capacitors (FC). We used ecological capacitors, with reduced specific losses (<0.25 W/kVAr). The discount rate is 10%. It has been taken into consideration the price of the kW-installed in an equivalent plant and also, the remainder value of the investment at the end of the period study (10% of the investment cost).

The multiobjective analysis is achieved for cost (OF_1) and performance (OF_2) criteria:

$$\mu_{FD}(p) = \alpha \cdot \mu_{OF_1}(p) + \beta \cdot \mu_{OF_2}(p), \ \alpha + \beta = 1 \quad (7)$$

The minimum and maximum of cost function was calculated for no capacitor placement within nodes and for maximum possible number of capacitors installation in each bus under the given constraints, respectively. The minimum and maximum of voltage irregularity has been estimated by experience.

Using the new algorithm based GAs and ESs the results emphasize that 10 individuals (ind.) ensure the global search area. Different values for crossover (cr) and mutation (mr) rate were tested with a view to determining the best solution. Table 1 shows the simulation results obtained for 10 individuals, 0.8 crossover rate and 0.1 mutation rate. We consider different combination of weighted aims, so that α+β=1. Also, we present the results obtained for a single objective function – update total cost – using the same input data.

Considering the cost criteria more important than performance criteria, we choose the solution with α=0.7 and β=0.3. Table 2 shows the optimal capacitor placement within buses.

TABLE 1 – Simulation results

	Objective Function						
	OF_1	$\alpha\mu_{OF_1} + \beta\mu_{OF_2}$					
	UTC [\$]	α	β	FC No.	UTC [\$]	VI [%²]	μ_{FD}
ind.=10, cr=0.8, mr=0.1,FC=74	234 873	0.3	0.7	304	250 339	0.420	0.5570
		0.4	0.6	299	249 532	0.426	0.4875
		0.5	0.5	294	248 766	0.430	0.4065
		0.6	0.4	270	246 181	0.480	0.3292
		0.7	0.3	226	242 691	0.550	0.2589

TABLE 2 – Optimal capacitor placement

Feeder 1		Feeder 2		Feeder 3		Feeder 4		Feeder 5		Feeder 6	
Bus	FC	Bus	FC	Bus	FC	Bus	FC	Bus	FC	Bus	FC
1	0	1	0	1	3	1	0	1	3	1	0
2	2	2	0	2	2	2	2	2	6	2	4
3	0	3	1	3	5	3	1	3	5	3	4
4	4	4	1	4	4	4	1	4	4	4	7
5	0	5	4	5	7	5	0	5	5	5	3
6	1	6	5	6	4	6	0	6	4	6	9
7	2	7	6	7	5	7	2	7	4	7	7
8	0	8	6	8	9	8	8	8	11	8	11
9	1	9	9	9	6	9	5	9	3	9	9
10	6			10	7			10	8		

Comparing these results with those obtained using only one objective function – update total cost – we can conclude that using the multiobjective analysis which include the performance criteria (voltage irregularity), the total number of capacitors is increased.

5. CONCLUSIONS

In this paper we have proposed a fast and efficient approach that integrates the fuzzy techniques with evolutionary algorithms for optimal capacitor placement. A multiobjective optimization technique which include an economical operating condition and voltage irregularity is presented. These two objectives are balanced so that the improvement of any single objective will result in a negative impact on other objective. The optimal solution is searched from a population of admissible solutions using a combination between GAs and ESs. The proposed approach has a high-speed computation and efficient search mechanism.

Future work in this area will involve extensions of the proposed approach to include objective functions related to the switched capacitors and their switching times. Also, as a constraint, may be considered the available stock of capacitors.

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