Multiobjective Metaheuristics Optimization in Reactive Power Compensation

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Abstract: - An **e**fficient operation requires delimitation or optimization methods for the improvement of technical - economic indicators to achieve energy efficiency in industrial networks. This article proposes a multiobjective metaheuristic optimization using the metric of Tchebycheff in the objective function for the reactive power compensation, based on the modification of the variable integration method. An evolutionary algorithm is used to generate the initial population to achieve efficient solutions. To improve the solutions, refining algorithms are employed using random search conditions with flexible stopping criteria. The general algorithm was tested with satisfactory results in theoretical and real case studies.

Keywords: Multi-objective optimization, reactive power compensation, evolutionary algorithms, genetic algorithms, Tchebycheff distance, harmonic.

1 Introduction

Reactive Power Compensation is very often studied as a simple optimization problem with restrictions. The solution attends an objective function constituted by a linear combination of several factors, such as the investment and transmission losses and constraints in forms of limits of certain other parameters such as reliability and voltage profile. Reactive power optimization constitutes a sub-problem of the optimal power flow[1], which determines the proper adjustment of the reactive power variables like voltage magnitudes, transformers tap positions and the setting of reactive power compensation devices to optimize the objective functions while satisfying systems constraints.

The reactive power optimization problem solutions has been focused from conventional optimization techniques including the gradient method, quadratic programming], nonlinear programming, linear programming and interior point method, but the actual trends target to a multi-objective context through evolutionary optimization algorithm [4,7]. In general, these techniques are still associated with some difficulties, such as the handling of problems with characteristics of different nature, with solutions of the reactive power optimization problem not linear, discrete.

Genetic Algorithms (GA) is the most used heuristic method in the optimization of reactive power. The goal of GA is to look for the best solution within a series of possible solutions. By "best solution" we refer to those that optimize a predetermined metric for a given problem, that is, the value closest to this numerical value, once evaluated for a particular evaluation of a function [5]. The traditional optimization algorithms usually obtain an optimal solution, however with the application of evolutionary methods in the optimization, it allows the optimization of several simultaneous and independent solutions, originating a set of so-called optimally efficient solutions or Pareto solutions that satisfy the Preferences of the researcher.

Difficulties often arise in the solutions obtained with the AG optimization method, related to the nature of the function fitness, the form of coding solutions and the genetic diversity of the population. To overcome these shortcomings, other heuristic methods have been developed that maintain some common characteristics with genetic algorithms, among them is the one demonstrated by Arzola [2], based on the Method of Integration of Variables (MIV). It is a generalization of genetic algorithms that provide a family of evolutionary algorithms, where members of the population are not necessarily updated using a code to describe possible solutions, but several of them and any set of operators.
The conditional random search algorithm (CRS) [7] emerged as a modification to (MIV), and was developed to solve convergence problems when applied to very large populations. The modification adopted allows:

1. The search of the population by subintervals, according to (fig 3 and 4) allowed to have a greater diversity of the initial population, and its improvement in the whole range of solutions.
2. The search for efficient solutions in the environment of a previously calculated solution is achieved in order to improve the performance or characteristics of the solutions.
3. Searching for appropriate population samples, based on the best features of the already calculated population, selects a subpopulation that contains individuals with favorable segments of the code which can significantly accelerate the convergence of the method.

2. Reactive power compensation as a multi-criteria decision making system.

The characterization of reactive power compensation as a decision-making process lead to an external analysis, which should be realized in order to include the selection of implied variables, is shown in Fig.1 $u_1 \dots u_k$ coordination variables, $d_1 \dots d_r$ input data, $x_1 \dots x_n$ decision variable and $y_1 \dots y_m$ technical economic indicator.

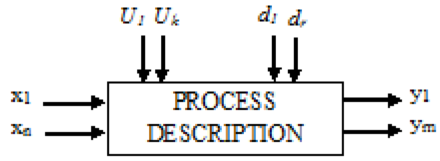

Fig. 1. Information classification of external analysis

The decision variables represent the connection options for: x_1 (transformers with bypass), x_2 (capacitors), x_3 (filters), and x_4 (synchronous motors overexcited). The technical - economic indicators (y_i) are selected according to criteria of the experts corresponding to: voltage in nodes, power factor, total harmonic distortion, total network energy losses and the economic variable through net present value. To obtain these indicators, appropriate modelling procedures are used as models in engineering systems. The nature of the method used allows all technical and economic indicators to be included, or even excluded, according to the characteristics of the networks.
In general, the synthesis of the system for decision-making includes the elaboration or selection of the necessary tools to:
1. Selection of the technical-economic indicators for given values of the decision variables.
2. Generation of solutions options close to the best compromise between the selected indicators
3. Graphic options that allow you to know the particularities of each solution option.
4. Complementary procedures of simulation that allow to study with more precision the particularities of each option generated.

3. Mathematical formulation of the problem.

The optimization method uses the metric of Tchebycheff that allows to reduce the weighted distance of the calculated value to the desired value of each indicator (y_i), included in the function;

$$\max_{i} \left\{ \omega_i \frac{\left| y_{c_i} - y_{d_i} \right|}{\left| y_{d_i} \right|} \right\} \tag{1}$$

Where:
ω_i - weight ratio, which gives greater or less importance to the objectives and i
y_{di}, y_{ci} - desired and calculated values of different objectives y_i.
By minimizing the equation (1) on a set of different combinations of values of (ωi), resulting in an efficient solution space, solutions that are not worse than the others belonging to the set of all possible, for at least one of the objectives. Given the advantages discussed above, it is assumed as a partial objective function (FO) at each node i = 1, m of the system, to the following expression:

$$Z_i = \max_j \left\{ w_{i,j} \left| \frac{Zc_{i,j} - Zd_{i,j}}{Zd_{i,j}} \right| \right\} \quad (2)$$

Where:
Z_i - Value of the partial function of node i; it accomplished that $0 \leq Z_i \leq 1$,
W_{ij} - Weight coefficient in node i for each indicator j, $0 \leq W_{ij} \leq 1$ and $\sum_{j=1}^{m} W_{ij} = 1$
$Zc_{i,j}$, $Zd_{i,j}$ - Calculated and desired value in node i for the objective or indicator j.
The W_{ij} coefficient can take different values depending on the evaluated objective. It also allows the optimization process to convert it from multiobjective to non-objective when the objectives in the function are overridden. The desired value of the objectives depends on each particular case, and is used as information directly associated with the general search, with the restrictions in each iteration.
Equation (2) includes only the objectives that will be analysed at node level: Z_1 (voltage), Z_2 (power factor) and Z_3 (voltage harmonic distortion). Finally for each node i is:

$$Z_i = \underset{i}{Max} \left\{ \lambda_i Z_{\max i} \right\} \quad (3)$$

Where:

- weight coefficient for node i.

- is the result of Z at the node for objective (i) with the worst value
Once Z_i is obtained, we search for the minimum of the Z_T function (4), including those indicators that were not evaluated in the nodes, but will be taken into account at the level of the entire network, Z_4 corresponding to the active losses associated with the compensation and Z_5 to the economic indicator evaluated by the previously calculated net present value.

$$Z_T = \max_i \left\{ \lambda_1 \; Z_1, .., \lambda_n Z_n , \quad \lambda_{n+1} \; Z_4 , \lambda_{n+2} Z_5 \right\}$$
(4)
Where:

- Value of the objective function for each configuration of the analysed network
$\lambda_1 \ldots \lambda_n$ - Weight constant for i node

- Weight constant for indicators (Z_4 and Z_5).

The weight constant for nodes i, (range is between 0 and 1) corresponds to the type of node and for the indicators that will depend on the importance of each particular case. For example it is necessary to highlight the economic indicator, in that case it is weighted with a weight equal to 1. This is possible, since as explained above, all weights are regulated between [0,1].
In addition, a set of constraints must be taken into account to ensure a feasible region of solutions. These restrictions are given by:

1. The capacitive reactive power of the node that must be between the allowed limits

2. Power factor of the input node

3. Power factor of load nodes

4. Net present value (NPV)
$$NPV \geq NPV_{min}$$

The mathematical model, which allows to calculate all the indicators and intermediate variables required from the decision variables and the input data, is given by the procedures of calculation of the load flow at the fundamental and harmonic frequency, designed for this research.

4. Implementation of the method for optimization

4.1 Variables Integration Method (VIM)

The population structure is determined by the set of decision variables involved in the optimization process. To have the possible solutions, there is a coding mechanism, which allows to assign a single value to each individual of the population, which is representative of its quality as a solution.

It is natural that an individual with a superior attitude represents a better solution to a problem and that, under specific conditions, can represent a correct or even optimal solution.

From an initial generation of candidate solutions for the process, which is iterative, new generations of individuals are produced, each time with better characteristics near the solution of the problem.

The stop criteria selection is due to, in general case, particularities of each concrete application, but predominating the followings:

1. Iterations quantity with no modifications in the population.
2. Difference distance between the best and worst solution inferior to a pre-established value in the population.
3. Predetermined number of generated solutions options.
4. Mixed conditions.

The algorithm of the VIM is showed in the Fig 2.

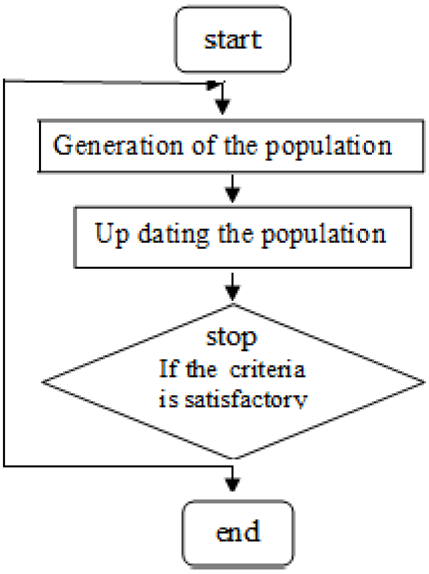

Fig. 2. Algorithm of Variables Integration Method

4.2 Random Conditional Search Algorithm.

The Random Conditional Search (RCS) method follows the basic ideas of the method (MVI) proposed by Arzola [4,5] Fig.2. This method is composed by a series of algorithms with which the search of the initial population, the improvement of the initial population and the selective reduction of the population are carried out.

4.2.1 Search Algorithm of the initial population

The initial population (IP) consists of a set K of elements, defined by the researcher. For each iteration, the best solution is included in the population, and this is done until the population size coincides with the one initially established.

There are two ways of obtaining this IP assuming that T represents the total of all possible solutions of the system:

1. Take k random integers between 1 and T
2. Divide the interval [1, T] into K subintervals and obtain a solution of the IP in each subinterval.

4.2.2 Initial Population Improvement

Afterward the IP has a fixed size, follows its improvements or updating; updating means, the comparison of the obtained solutions in the objective function; select the best among them all, i.e. the one that has a less value of *Z*; then this new solution is compared with the already calculated worst solution of the population and determining a possible replacement. At the moment which the foreseen accuracy δ is attained, the process of generation of random values of the population is restarted.

For each iteration two codes of variables are generated in an interval [A, B], obtaining three subintervals [A, x_1], [x_1, x_2] and [x_2, B]; the subinterval that contains a higher value of Z, which is the worst result [x_2, B], is eliminated (Fig. 2). Then, two other random values are generated within the subinterval obtained [A, x_2]. This process is repeated while the length of the interval x_1 - x_2 remains above a given precision (Fig. 3). While the population size is smaller than the established size, the solution of lower Z value is added to the population, at each step. Once the required population size has been reached, for a new Z-value calculated, this solution is compared to the worst solution and in the case of a smaller value of Z, it replaces the worst population solution already found until all the Solutions to the optimum.

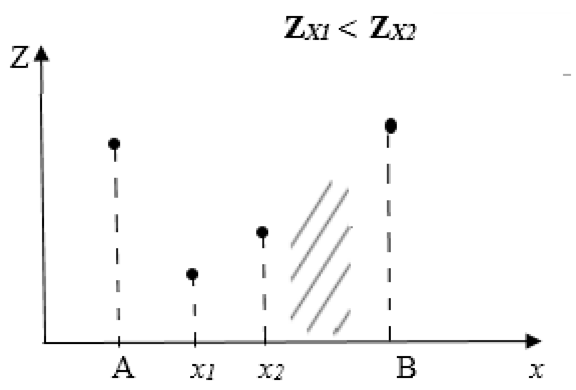

Fig. 3 First step for the initial population search in the interval [*A*, *B*], eliminating the interval [x_2, *B*].

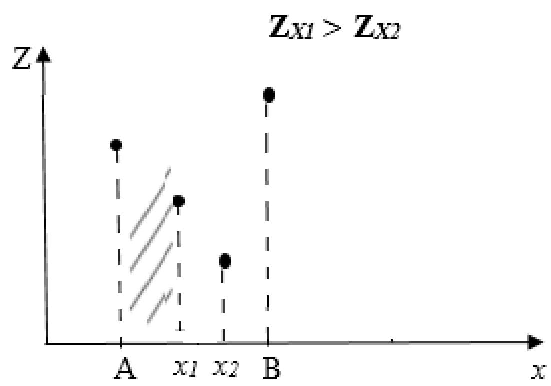

Fig. 4 Second step for initial population searching in the [A, X_1]

The algorithm leads to the search of individuals with decreasing values of Z, which means convergence of the algorithm, but it may happen that there are other solutions with values smaller than the calculated Zx_1, to remedy this problem, truncation possibilities have been implemented in the main algorithm, so that the new solutions are incorporated as appropriate. This algorithm has proven to be efficient when evaluated around 7% of all possible solutions (Fig. 5)

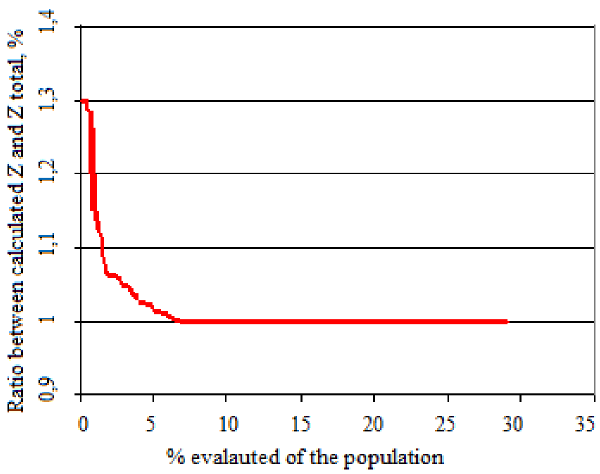

Fig. 5: Average ratio of calculated Z and percent of population evaluated

4.2.3 Variables Coding

The candidate variables to be encoded belong to the declared decision variables. The decision variables could take different connections or configurations, defined as the (x) chromosomes. This investigation assumed that an x chromosome is a string character, where each character represents a transformer, a bank of capacitors or a filter amongst others and every possible value of (x) depends on the definition of the analysed element. For example an electric system constituted by:

A transformer **T, with** two taps 1 and 2

A capacitor's bank **C,** with two switchable sections 1 and 2

A filter **F,** with two positions (connected or not connected).

Then, the number of independent combinations C_p, of the configurations, taken by these decision variables, would be;

$C_p = 2 \times 3 \times 2 = 12$

It is necessary to state out, the proposed codification is decimal, i.e., each digit of the code accepts decimal values. Because this code, a special but small algorithm is required to achieve the implemented codification in two functions providing knowledge about x_A.

With these two functions, it could be established that knowing sub code (x) warrants and univocal form of the corresponding codification for each electrical system and the reciprocal statement is also true; since the order of every element (transformer, filter and bank of capacitors) of the electrical system is invariant during each calculation.

4.2.4 Stop Criteria and validation of optimization algorithm.

The stop criteria used during optimization is a mixed condition, in which a number of solution codes are calculated without changes in the composition of the population; and the difference between the calculated Z values in the objective function should be less than a predetermined value (the worst and best solution).

The result of experiments to validate convergence of the algorithm shown in Fig. 5 were obtained for the system of Fig. 8. The system data for simulation and obtained efficient solutions are shown in Tables 1 and 2 respectively.

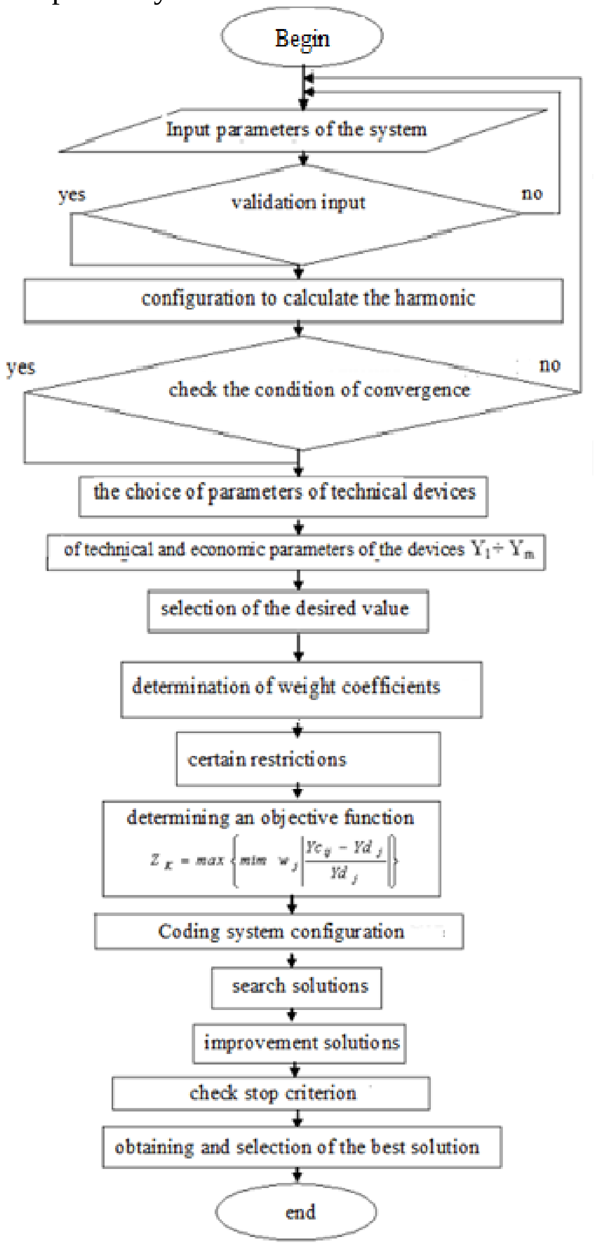

Fig 6. General Algorithm for efficient solutions achieving.

Each experiment is performed with an initial population that has a random character, obtaining good solutions from the evaluation of 7%, figure 5, 7. From this it can be deduced that for values of close to 10% of the set of all possible solutions is possible to obtain solutions that guarantee the requirements in the process of improvements and search of efficient solutions, which coincides with the one proposed by Arzola 2003 [7]. In these experiments the quality standard used to evaluate the solutions solutions corresponds to the best solution found in the exhaustive search represented through Zexa.

4.2.5 Convergence check

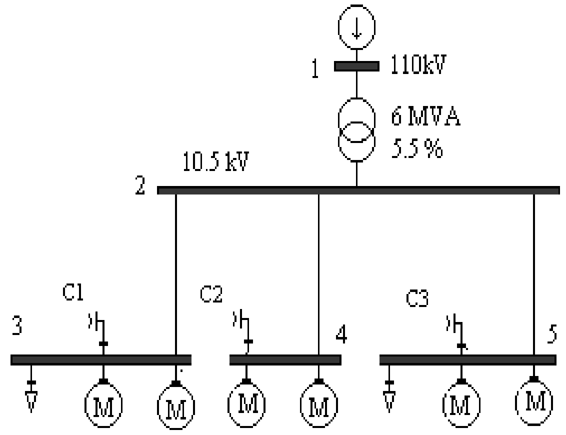

Fig.7. Power system to evaluate the convergence of the method.

Table 1: Qc and loads installed in the system of Figure 8 before optimization

Nodes	Active Power, kW	Reactive Power, kVAr	Capacitive Power, Qc kVAr
3	1053	390	450
4	81	34	34
5	2050	874	460

Table 1 shows the active and reactive power installed according to fig.7.The experimental simulation results show the convergence of the method and the emergence of efficient solutions shown in the table 2.

Table 2: Values of cos φ and losses for three of the efficient solutions found during optimization.

N^0	Calculated values Z	Cos φ			Qc, kVAr		
		4	5	6	C1	C2	C3
1	$0.736x10^{-2}$	0.96	0.94	0.94	472	27	375
2	$0.762\ x10^{-2}$	0.95	0.95	0.94	450	34	375
3	$0.771\ x10^{-2}$	0.95	0.95	0.95	450	34	469
4	$0.923\ x10^{-2}$	0.93	0.92	0.93	225	17	234

As can be seen in Table 2, the value of Z is the minimum in configuration 1, which is the best solution in terms of energy losses.

5. Study case

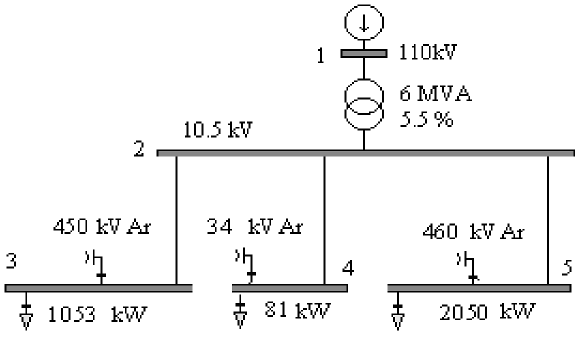

Fig. 8. Electric diagram

The graphical evolution of the proposed algorithm (RCS) is shown to find the solution of the electric scheme in Fig. 8. Tables 3 and 4 shows the results with three solutions 1, 2 and 3 (see fig.11), where the solution1 has a big value, solution 2 has an average value and solution 3 a small value.

Table 3. Value of losses and cos φ for different solutions

Calculated value of (Z) in the Objective Function		ΔE (kWh)	Cos φ		
			Node 3	Node 4	Node 5
Solution 1	0.025	298015	0.90	0.76	0.92
Solution 2	0.019	283824	0.94	0.89	0.92
Solution 3	0.009	276728	0.93	0.92	0.93

The variability of taps in the transformer and capacitors are shown in table 2.

Table 4. Transformers tap position and Qc in capacitors in kVAr

Calculated value of (Z) in the Objective Function		Transformer position and value of QC in kVAr			
		T1	C1	C2	C3
Point 1	0.025	2	472	17	234
Point 2	0.019	3	472	17	469
Point 3	0.009	6	225	17	234

Table 5. Calculated values of four of the selected optimal solutions

Solution	Calculated Values of (Z)	ΔE (kWh)	Cos φ in the load nodes		
			4	5	6
1	0.007	272471	0.96	0.94	0.94
2	0.007	274599	0.95	0.95	0.94
3	0.007	270342	0.95	0.95	0.95
4	0.009	276728	0.93	0.92	0.93

Table 6. Change in transformer taps and capacitive reactive power for optimal solutions

Solution	Transformer Taps	Qc in the capacitors in kVAr		
	T1	C1	C2	C3
1	6	472	27	375
2	6	450	34	375
3	6	450	34	469
4	6	225	17	234

In Tables 5 and 6, shows four of the selected solutions as optimal, over the 10% of all the possible solutions were calculated. This show off possible to finding optimal solutions (so-called Pareto solutions) from calculating between 7% and 10 % of the total population, if the proposed algorithm is used and also effectiveness warranties without exhaustive search, all of this, with no doubts permits the reduction of calculation time.

6. Conclusions

The reduction of harmonic distortion and reactive power compensation, can be evaluated as a problem of decision making under multiple criteria in discrete variables, with different technical and economic indicators associated, where includes the Tchebycheff weight distance in the objective function to analyse the network to determine efficient solutions

The character of the formulated task for compensation of reactive power permit the use of procedures for the generation of solutions based in codes evolution, that is, any one of the proper algorithms of Variables Integration Method. The conditional random search algorithm generates a number of correlated solutions with the optimization problem quickly and efficiently, it also facilitates evaluation of multiple connection options corrective elements in the network to facilitate decision making researcher

For the best selection of reserved indicators can be use weights in the objective function. In the case of large systems dimension, the values must be determined through experimental tests, considering the significance of analysed indicator, in order to reduce the number of weights coefficients the objective function.

It is seen in all cases obtaining efficient solutions when evaluating a number of population nearly 10% of all possible solutions. The obtained solutions could be considered efficient respect of those obtained with Exhaustive Search.

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