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Multi Objectives Reactive Dispatch Optimization of an Electrical Network

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Abstract

One of the problems of the responsible of energy production and distribution is the maintaining of an appropriate voltage profile.

This task can be done by the minimization of the active losses in the transportation and transmission lines by implantation of reactive power sources to the load buses. In addition to the minimization of the active losses, other criteria can be considered as the compensation devices cost and the voltage deviation. The problem to solve is multi criteria under constraints related to the voltages, the reactive productions, the compensation devices cost and the active losses. Its resolution requires the use of the advanced algorithms.

In this paper, we propose an approach based on the evolutionary algorithms (AE) to solve this problem multi criterion. It is about the SPEA2 method (Improving Strength Pareto Evolutionary Algorithm).

Keywords

Electrical network, Reactive dispatch, Multi objectives optimization, Evolutionary algorithms, Compensation devices cost, Voltage deviation, Active losses.

Introduction

Among the most important problems in the energy production and transportation systems is the maintenance of a voltage profile with an optimal operating and the security of the system.

An appropriate voltage profile can be maintained while minimizing three objective functions related to the total transmission active losses, the compensation devices cost and the voltage deviation of the load buses.

Different methods have been presented in the literature to solve the dispatch problems. Among these methods one can mention two families:

- The first based on the classic methods as the non linear programming technique [10], the weights method [11] and the ε-constraints method [12].
- The second based on the evolutionary techniques [1-4] as the NPGA method (Niched Pareto Genetic Algorithm) [5-6], NSGA (Non dominated Sorting Genetic Algorithm) [7], SPEA (Strength Pareto Evolutionary Algorithm) [8] and SPEA2 (Improving Strength Pareto Evolutionary Algorithm) [9].

The classic methods present some inconveniences as the non safety of convergence, the long time of execution, the algorithmic complexity and the generation of a weak number of non dominated solutions. Because of these inconveniences, the evolutionary algorithms took a bigger luck, thanks to their faculty to exploit vast spaces of research and don't require a pre recognition of the problem.

In this paper, the problem is formulated by three objective functions. The evolutionary optimization method used is the SPEA2. The simulations are made on the IEEE test network, 10 buses, 5 thermal generators and 13 lines.

Problem formulation

The resolution of the multi objectives problem of the optimal reactive dispatch, consist in minimizing three objective functions that represent the compensation devices cost, the transmission losses and the voltage deviation, under some constraints.

Compensation devices cost

The compensation devices cost function is formed by the fixed installation cost and the purchase cost.

This function is considered as a linear function [13-17]:

$$F_1 = \sum_{i=1}^{N_c} C_{fi} + C_{ci}\left|Q_{ci}\right| \quad (1)$$

with:

C_{fi} : fixed installation cost of the reactive power sources at the i^{th} bus ($).

C_{ci} : cost by MVAR of the compensation devices at the i^{th} bus ($/MVAR).

Q_{ci} : compensation at the i^{th} bus (MVAR).

N_c : number of possible bus for the installation of the compensation devices.

Total transmission active losses

The total losses in the transmission lines [18-20] are given by the following function:

$$F_2 = \sum_{i=1}^{N}\sum_{j=1}^{N} V_i V_j Y_{Nij} \cos(\alpha_i - \alpha_j - \theta_{Nij}) \quad (2)$$

with:

Y_{Nij} and θ_{Nij} are the size and the argument of the element *(i,j)* of the nodal admittance matrix.

V_i : voltage at the i^{th} bus.

V_j: voltage at the j^{th} bus.

N : number of buses in the electric network.

Voltage deviation

The voltage deviation at the i^{th} bus is represented by the following function [21-22]:

$$F_3 = \sum_{i=1}^{N_c}\left(V_i - V_i^{ref}\right)^2 \quad (3)$$

Problem constraints

Voltage and the reactive production at the load buses are restricted by upper and lower limits:

$$V_i^{min} \le V_i \le V_i^{max} \quad (4)$$

$$Q_{ci}^{min} \le Q_{ci} \le Q_{ci}^{max} \quad (5)$$

The compensation devices cost is limited by the maximum amount available for investment F_{1m}:

$$F_1 \le F_{1m} \quad (6)$$

The total transmission active losses are positive:

$$F_2 \succ 0 \quad (7)$$

Multi objectives optimization

Principle of multi objectives optimization

In general, a multi objectives optimization problem is formulated as follows:

$$\begin{cases} \text{Minimize } f(x) = \left(f_1(x), f_2(x), \ldots, f_{Nobj}(x)\right) \\ \text{Under :} \\ g_j(x) = 0 \quad , \quad j = 1,\ldots,M \\ h_k(x) \le 0 \quad , \quad k = 1,\ldots,K \end{cases} \quad (8)$$

with:

N_{obj} : number of objectives.

M, K : numbers of equality and inequality constraints, respectively.

x : decision vector.

Any two solutions x_1 and x_2 can have one of two possibilities: one covers or dominates the other or none dominates the other.

In a minimization problem, without loss of generality, a solution x_1 dominates x_2 if the following two conditions are satisfied:

$$\begin{cases} \forall i \in \{1, 2, \ldots, N_{obj}\}, \quad f_i(x_1) \le f_i(x_2) \\ \exists j \in \{1, 2, \ldots, N_{obj}\}, \quad f_j(x_1) \prec f_j(x_2) \end{cases} \quad (9)$$

X_f is the set of feasible solutions, i.e. $X_f = \{x \in X \mid g(x) = 0 \text{ et } h(x) \le 0\}$.

where $g(x) = (g_1(x), g_2(x), \ldots, g_M(x))^T$ and $h(x) = (h_1(x), h_2(x), \ldots, h_K(x))^T$.

A decision vector $x \in X_f$ is non-dominated with respect to a set $A \subset X_f$, if is only if:

$$(\text{non}\exists)\ a \in A \,/\, a \prec x \quad (10)$$

The set of non-dominated decision vectors is known as the Pareto optimal set, while the corresponding set of objective vectors constitutes the Pareto optimal front.

SPEA2 method (Improving Strength Pareto Evolutionary Algorithm)

The SPEA2 method is an improved version of the SPEA [9]. It defers of its predecessor in several aspects:

- The archive size P' is fixed.
- The calculation of the performance is refined more to the sense that it holds more counts the density of the solutions. The S_i value is calculated for all solution $i \in P_t \bigcup P_t^{'}$.
- Only the archive members participate to reproduction.
- A truncation method is used to control the archive size P'.

The SPEA2 method is defined by the following stages:

Input:

N (population size)

N' (archive size)

T (maximum number of generations)

Output:

A (non dominated set)

Algorithm:

Step 1: Initialization: generate an initial population P_0 and create an empty archive $P_0^{'} = \{\}$.

Step 2: Fitness assignment: calculate fitness values of individuals in P_t and $P_t^{'}$.

- $S(i) = \left|\left\{ j / j \in P_t \cup P_t^{'} \wedge i \succ j \right\}\right|$
- $R(i) = \sum_{j \in P_t \cup P_t^{'}, j \succ i} S(i)$
- Calculate the distances in the objectives space between every individual i and all others individuals $j \in P_t \cup P_t^{'}$, and stocked them in a list.
- Sorting the list in increasing order. The k^{th} element gives the distance sought, denoted as $\sigma_i^{(k)}$, $k = \sqrt{N + N^{'}}$.
- $D(I) = 1/(\sigma_i^{(k)} + 2)$
- $F(i) = R(i) + D(i)$

Step 3: Environmental Selection: copy all non dominated individuals in P_t and $P_t^{'}$ to $P^{'}_{t+1}$.

- $P^{'}_{t+1} = \{i / i \in P_t \cup P_t^{'} \wedge F(i) \prec 1\}$
- If $|P^{'}_{t+1}| \prec N^{'} : (N^{'} - |P^{'}_{t+1}|)$ better dominated individuals to the sense of F are copied in $P^{'}_{t+1}$.
- If $|P^{'}_{t+1}| \succ N^{'}$: reduce $P^{'}_{t+1}$ by means of the truncation operator; at each iteration that individual *i* is chosen for removal for which $i \le_d j$ for all $j \in P^{'}_{t+1}$

$$i \le_d j \Leftrightarrow \begin{cases} \forall\, 0 \prec k \prec |P^{'}_{t+1}| : \sigma_i^k = \sigma_j^k \\ \exists\, 0 \prec k \prec |P^{'}_{t+1}| : [(\forall\, 0 \prec 1 \prec k : \sigma_i^1 = \sigma_j^1) \wedge \sigma_i^k \prec \sigma_j^k] \end{cases}$$

Step 4: A tournament selection is applied to fill the mating pool.

Step 5: Apply recombination and mutation operators to the mating pool.

Numeric simulations and commentaries

In this part we present the results of the reactive dispatch (RD) problem. The simulations have been tested on the IEEE network (10 buses) [23].

Presentation of the studied network

The used network is an IEEE test network, including 10 buses, 5 thermal generators and 13 lines [23]. The network structure is shown in figure 1.

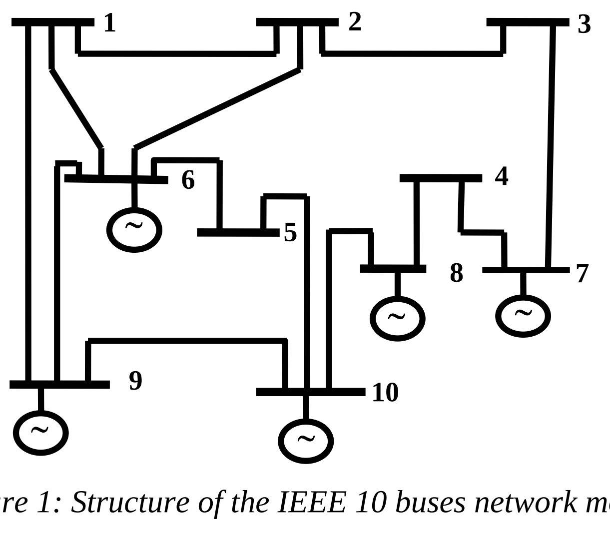


Figure 1: Structure of the IEEE 10 buses network modified

The data of the lines and buses are given in the tables 1 and 2. The coefficients of the compensation devices cost function and the voltage values wanted of the load buses are given in the table 3.

Table 1. Data lines

Line Number	Link	Impedance (p.u.)
1	1-2	0.02 + j0.08
2	1-6	0.06 + j0.24
3	1-9	0.04 + j0.16
4	2-3	0.06 + j0.24
5	2-6	0.06 + j0.24
6	3-7	0.06 + j0.24
7	4-7	0.04 + j0.16
8	4-8	0.06 + j0.24
9	5-6	0.04 + j0.16
10	5-10	0.06 + j0.24
11	6-9	0.01+ j0.04
12	8-10	0.04 + j0.16
13	8-10	0.08 + j0.32

Table 2. Data buses

Bus	Types	Active power loaded (p.u)	Reactive power loaded (p.u)	Voltages (p.u)
1	P-Q	0.20	0.097	-
2	P-Q	0.30	0.145	-
3	P-Q	0.20	0.097	-
4	P-Q	0.30	0.145	-
5	P-Q	0.20	0.097	-
6	P-V	0.30	0.145	1.00
7	P-V	0.15	0.0726	1.00
8	P-V	0.20	0.097	1.00
9	P-V	0.20	0.097	1.00
10	Slack	0.20	0.097	1.05

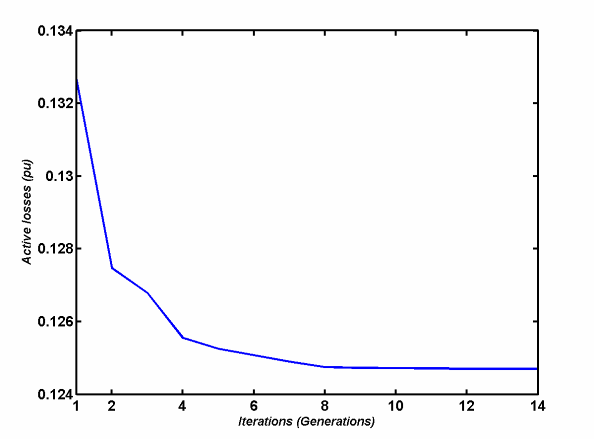
Table 3. Coefficients of the compensation devices cost and voltage values wanted

Bus	C_{fi} ($)	C_{gi} ($/MVAR)	V_i^{ref} (pu)
1	1771.59	5314.8	1
2	1771.59	5314.8	1
3	1771.59	5314.8	1
4	1771.59	5314.8	1
5	1771.59	5314.8	1

Simulation results

Mono objective optimization

The evolution of the mono objective optimization during the iterations of the active losses and the voltage deviation is shown in figures 2.



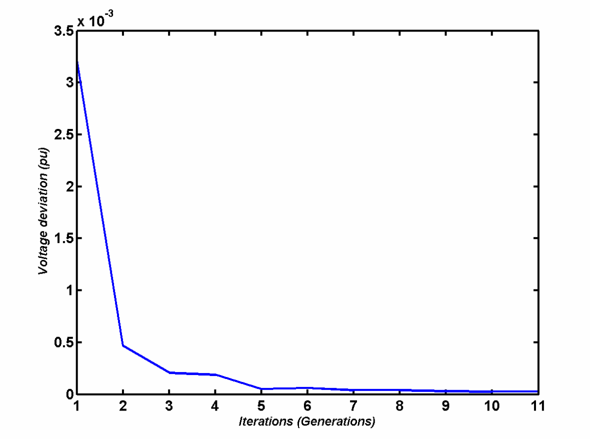


Figure 2. Convergence of the power losses and deviation objective functions according to the iterations

From the figures (2), we notice that the two functions active transmission losses and voltage deviation are decreasing according to the generations and convergent toward their minimal values. The active Losses function converge toward the value 0.1247 pu and the voltage deviation function converge toward the value 2.3946 10^{-5} pu.

Bi Objectives optimization

The optimal Pareto set for a bi objectives optimization of the functions of the compensation devices cost / deviation, losses / deviation and losses / compensation devices cost, are shown in figures 3, 4 and 5, respectively.

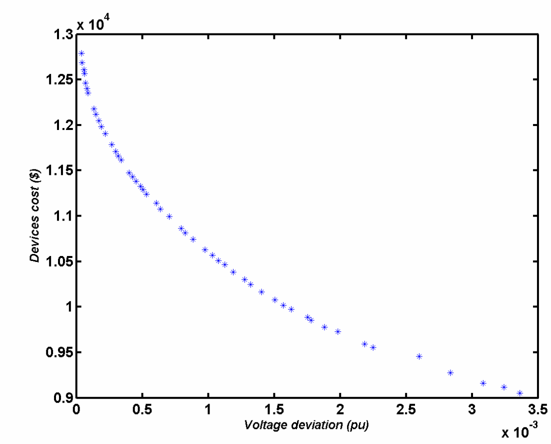


Figure 3. Pareto set cost /deviation

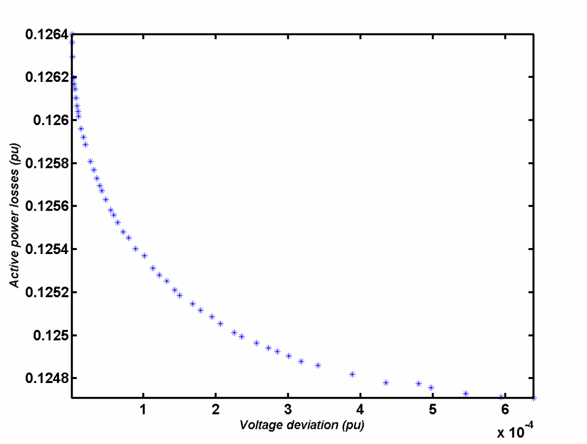


Figure 4. Pareto set losses /deviation

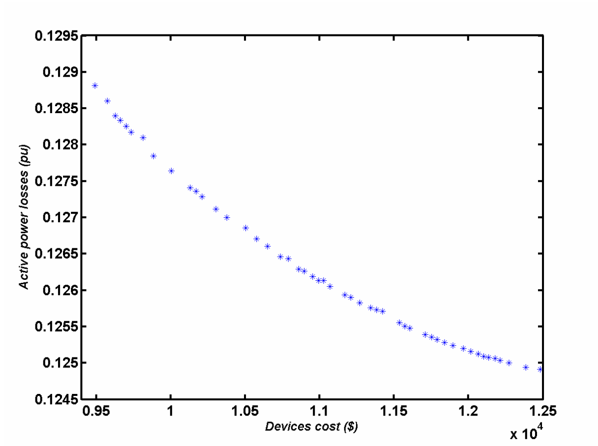


Figure 5. Pareto set losses /cost

From the figures 3, 4 and 5, we can pull the limit values of every case. These values are summarized to the tables 4, 5 and 6.

Table 4. Values limits of the Pareto set Cost/Deviation

Minimal devices cost Corresponding deviation	$9.0523\cdot10^{3}$ (\$) 0.0034 (pu)	Q_{g1}(pu)	Q_{g2}(pu)	Q_{g3}(pu)	Q_{g4}(pu)	Q_{g5}(pu)
		0.0071	0.0038	0.0110	0.0144	0.0002
Minimal deviation Corresponding cost	$3.7728\cdot10^{-5}$ (pu) $1.2788\cdot10^{4}$ (\$)	Q_{g1}(pu)	Q_{g2}(pu)	Q_{g3}(pu)	Q_{g4}(pu)	Q_{g5}(pu)
		0.0061	0.3427	0.1344	0.2560	0.0003

The table 4 shows that the reactive production of the compensation devices to the bus 5 is weak in relation to the productions of the other buses. It is due to the voltage value of this bus that is very close to the one desired. Therefore, the problem can be reduced while eliminating the variable Q_{g5}.

Table 5. Values limits of the Pareto set losses/Cost

Minimal losses	0.1249 (pu)	Q_{g1}(pu)	Q_{g2}(pu)	Q_{g3}(pu)	Q_{g4}(pu)	Q_{g5}(pu)
Corresponding cost	$1.2541\cdot10^{4}$ (\$)	0.0530	0.1523	0.0701	0.2128	0.2048
Minimal devices cost	$9.4927\cdot10^{3}$ (\$)	Q_{g1}(pu)	Q_{g2}(pu)	Q_{g3}(pu)	Q_{g4}(pu)	Q_{g5}(pu)
Corresponding losses	0.1288 (pu)	0.0072	-0.0039	0.0350	0.0642	0.0091

The table 5 shows that, for minimal losses, the total reactive production is important. For a minimal cost the total reactive production is weak.

Table 6. Values limits of the Pareto set losses/Deviation

Minimal losses	0.1247 (pu)	Q_{g1}(pu)	Q_{g2}(pu)	Q_{g3}(pu)	Q_{g4}(pu)	Q_{g5}(pu)
Corresponding deviation	$6.3865 \cdot 10^{-4}$ (pu)	0.1336	0.1605	0.1097	0.2517	0.2272
Minimal deviation	$1.0309 \cdot 10^{-6}$ (pu)	Q_{g1}(pu)	Q_{g2}(pu)	Q_{g3}(pu)	Q_{g4}(pu)	Q_{g5}(pu)
Corresponding losses	0.1264 (pu)	0.1512	0.2334	0.1480	0.2558	0.0047

The table 6 shows that the production of the bus 5 is weak for a minimal deviation, it is important when the active power losses are minimal.

Tri objectives optimization

The figures 6 illustrate the Pareto surface of Voltage deviation / Compensation devices cost / active Losses in the lines of transportation and transmission according to four different views.

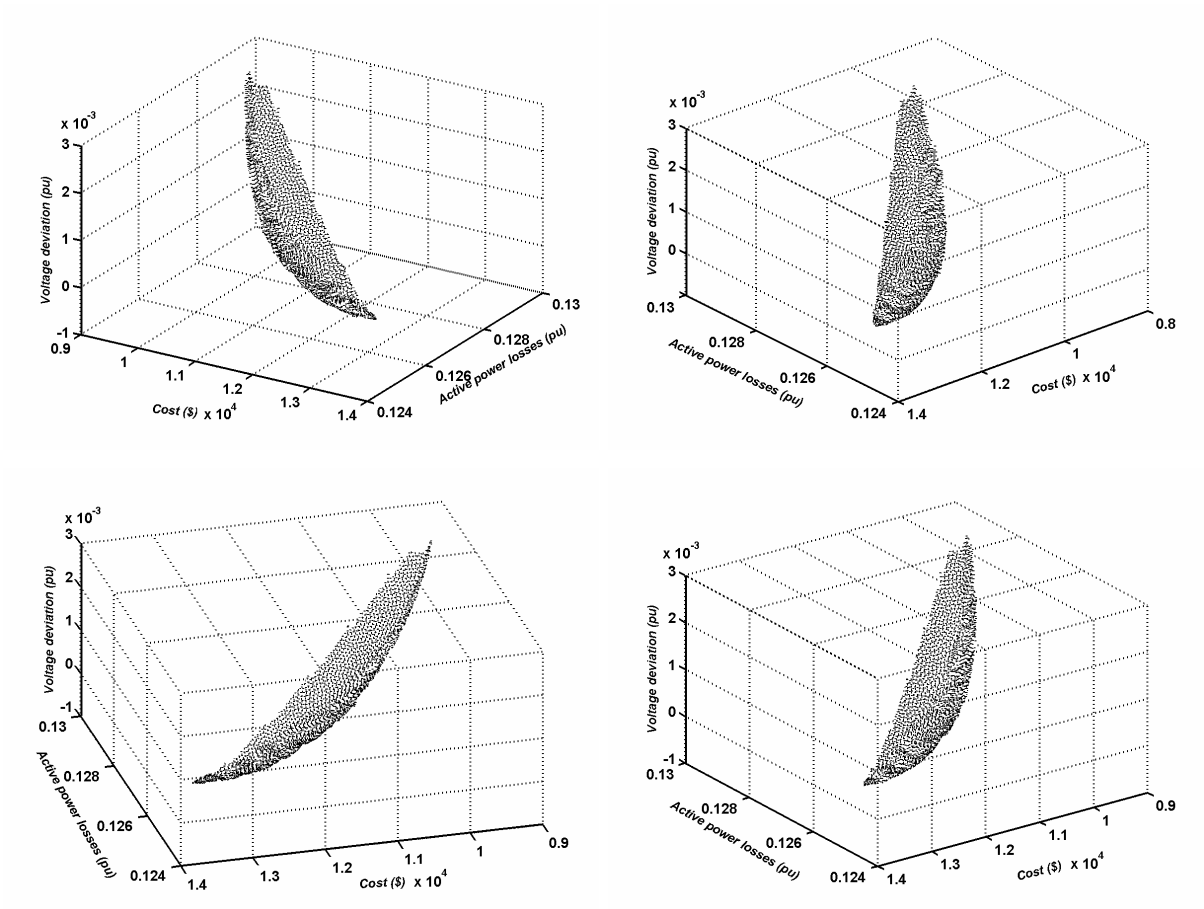


Figure 6. Pareto surface Deviation/Cost/losses

The table 7 gives the values limits of the Pareto surface of the figure 6.

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Table 7. Values limits of the Pareto surface Deviation/Cost/losses

	For the minimal cost		For the minimal losses		For the minimal deviation	
Cost ($)	$9.0939\ 10^{3}$		$1.3435\ 10^{4}$		$1.3013\ 10^{4}$	
losses (pu)	0.1296		0.1247		0.1259	
Deviation (pu)	$32\ 10^{-4}$		$5.7883\ 10^{-4}$		$0.3265\ 10^{-4}$	
	Q_{gi}	V_i	Q_{gi}	Q_{gi}	V_i	Q_{gi}
bus 1	0.0098	0.9763	0.1072	0.0098	0.9763	0.1072
bus 2	0.0099	0.9686	0.1786	0.0099	0.9686	0.1786
bus 3	0.0183	0.9680	0.1231	0.0183	0.9680	0.1231
bus 4	0.0000	0.9739	0.2326	0.0000	0.9739	0.2326
bus 5	0.0064	1.0000	0.2198	0.0064	1.0000	0.2198

From the table 7 one notice that the total production of the compensation devices is weak and voltages can have some values a little faraway of the values wanted for the minimal cost. Whereas this production becomes important and the values of voltages are very near of the values wanted for minimal losses and the minimal deviation. The staff responsible for the dispatch must choose a solution that is a compromise between the various objectives.

Conclusion

In this paper, an approach based on the SPEA2 method has been presented and applied to the multi objectives reactive dispatch problem of an electric network including a wind power station.

The problem has been formulated as a multi objectives problem, while taking into account the active losses, compensation devices cost and the voltage deviation functions.

The results show that the proposed approach is efficient for solving the multi objective reactive dispatch problem. The non dominated solutions obtained are well distributed and have satisfactory diversity characteristics.

Since this approach doesn't impose a limitation on the number of objectives, one can spread our problem while adding other objective functions as well as other constraints.

Annex

The per unit system (pu) is widely used in the power system industry to express values of voltages, currents, powers, and impedances of various power equipment. For a given quantity (voltage, current, power, impedance, torque, etc.) the per unit value is the value related to a base quantity.

For instance $O_{\mathbf{gi}}$ in (pu) = [Q_{gi} in (MVAR)]/[S_b in (MVA)] with S_b: Apparent power = 100MVA

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