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Evolutionary algorithms for multi-objective optimization Applied for reactive dispatch problem.

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Abstract
An Evolutionary Algorithms as a technique of optimization presented in this paper to solving the reactive dispatch problem RDP. This reactive dispatching RD consists to minimize three objectives functions which are respectively the voltage deviation function, the power losses in transmission lines and the function cost for the reactive power compensation device in electrical power system. This recent technique based on Evolutionary Algorithms, in particular the NPGA (Niched Pareto Genetic Algorithm) and the NSGA-II technique (non-dominated sorting genetic algorithm) are used to solve this reactive dispatching problem RDP. In order to demonstrate the advantage of this approaches, a classical technique called weight method is used. Results simulation are obtained from the application of all methods cited on test system 20-bus-6-units using matlab Simulink.

Keywords: Evolutionary Algorithms, reactive dispatching problem RDP, NPGA, NSGA-II, power losses, voltage deviation, cost function for compensation device.

Introduction

In the last decade, the control of active distribution problems to improve the economy and operational safety of the power system has received a lot of attention. As a general rule, the load bus voltages can be kept within their allowable limits by reallocating the reactive power generations in the system. This can be accomplished by adjusting the processing taps, sources of switchable VAR and generator voltages. Indeed, reactive power compensation can participate on the one hand in minimizing active losses in transmission lines and on the other hand in reducing voltage deviations for consuming nodes. Several research works in the literature have focused on solving this type of optimization problem.

In general, three techniques to solving this complex optimization problem. The first method uses the nonlinear programming algorithm [1]. But, nonlinear programming-based techniques have many disadvantages, such as unsafe convergence properties, execution time, and algorithmic complexity. The second optimization technique analyze, we use the sensitivity and gradient-based technique to linearize the objective function and the constraints of the system around an operating point [2]. But, methods based on gradients are likely to be trapped in local minima and the resulting solution will not be the optimal solution.

The third approach utilizes the heuristic methods to search for the optimal solution in the problem space [3]. These heuristic techniques have been used to solving this complex optimal dispatch problem with success. The multiobjective problem was transformed to mono objective problem by technique called a weighted sum [4].

Unfortunately, in problems with a non-convex Pareto-optimal front, the best compromise solutions cannot be guaranteed and also the execution time will be quite long. In order to accomplish these drawbacks, Reference [5] presents the e-constraint technique for solving multi-objective problems.

Problem formulation

Solving the problem of optimal reactive power dispatching consists in optimizing three objective functions, which represent the function cost of reactive energy compensation devices, transmission losses and voltage deviation, under certain constraints.

Objectives functions

Solving the problem of optimal reactive power dispatching consists in optimizing three objective functions, which represent the function cost of reactive energy compensation devices, transmission losses and voltage deviation, under certain constraints.

A. Cost of compensation devices:

The cost function of the compensation reactive power devices is formed by the cost of installation and the cost per MVAR. This function can be considered to a linear function [6, 7, 8]:

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

With:
Cfi: fixed cost of installing reactive power sources at node i in ($).
Cgi: cost per MVAR of the compensation reactive power devices at node i in ($ / MVAR).
Qgi: compensation at node i (MVAR).
Nc: number of possible nodes for installing the compensation devices.

B. Total active transmission losses:

The total active losses in the transmission lines are given by the following equation [9]:

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

With:
Y_{Nij}, θ_{Nij}: respectively modulus and argument of element ij of the nodal matrix.
Vi: voltage at nodes i.
Vj: voltage at node j.
N: number of nodes in the network.

C. Voltage deviation:

The deviation of the voltage in a bus i is represented by the following expression [1]:

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

V_i^{ref} represents the desired voltage at bus i

Problem constraints

The constraints of reactive dispatching are of four types:

A. Constraints linked to the voltages of the consuming buses:

The voltages of the consuming nodes are limited by an upper limit and a lower limit:

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

B. Constraints linked to the reactive production of the banks located at the consumer buses:

The reactive production Q_{gi} of the banks of capacitors located at the consumer bus i is bounded by an upper limit Q_{gi}^{max} and a lower limit Q_{gi}^{min}
.

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

C. Constraint related to the cost of compensation systems:

The cost for compensation reactive power devices is limited by the maximum cost available for the investment:

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

D. Constraints linked to active losses of transmission and transmission lines:

The active losses in the transmission and transmission lines of energy is positive:

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

Multi-objective function

The weight method

The original multi objective problem POM is converted to mono objective problem POU using a linear combination of the objectives:

$$\text{Minimiser } y = f(x) = \omega_1 f_1(x) + \omega_2 f_2(x) + \ldots + \omega_{N_{obj}} f_{N_{obj}}(x)$$
$$\text{sachant que } x \in X_f \quad (8)$$

The ω_i are called weights, they are chosen as $\sum \omega_i = 1$.

NPGA method (Niched Pareto Genetic Algorithm)

It is a multi-objective optimization method proposed by Horn and Napfliotis in 1994, which uses a tournament based on Pareto-solution dominance [10, 11] It compares two individuals taken at random with a small subpopulation also chosen from the hazard. If only one of these two individuals dominates the subpopulation, it is then positioned in the next population. In other cases, a sharing function is applied to select the individual.

Selection procedure:
Entrance :
Pt (Population).
(Niche radius).
A (Comparison set).
Ncompare (Size of the comparison set).
Exit :
P '(Breeding population)
Step1: Set i = 1 and P '= {}.

Step2: Randomly choose two candidates $x_1, x_2 \in P_t$ for selection.
Step3: Randomly choose a comparison set A formed by Ncompare individuals of the population Pt.
Step4: Compare each of the candidates x1 and x2 with the set A using the dominance conditions defined in II.2 (definition 4).
Step5: If candidate x1 dominates set A and x2 does not dominate by this set, then P '= P' + {x1} and go to step 7. If candidate x2 dominates set A and x1 does not dominate by this set, then P '= P' + {x2} and go to step 7. In the other cases, that is to say, x1 and x2 dominate Pcompare or both do not dominate A, we go to step 6.
Step6: Use the sharing method for the selection.
Step7: If i = N, stop the procedure. Otherwise i = i + 1 and go to step 2.

Sharing procedure:
Step1: Set j = 1.
Step2: Determine the distance d_{ij} between individuals i and j of the current population.

$$d_{ij} = \sqrt{\sum_{k=1}^{N_{obj}} \left(\frac{J_k^i - J_k^j}{J_k^{\max} - J_k^{\min}} \right)^2} \quad (9)$$

With $J_k^{\max}$ et $J_k^{\min}$ are the minimum and maximum values of the objective function J_k.
Step3: Compared d_{ij} with the radius σ_{share}. The share function has the following form:

$$Sh(d_{ij}) = \begin{cases} 1 - \left(\frac{d_{ij}}{\sigma_{share}} \right)^2 & si\ d_{ij} \leq \sigma_{share} \\ 0\ sinon & \end{cases} \quad (10)$$

Step4: j = j + 1; if $j \leq N$ return to step 2, otherwise calculate the niche count corresponding to candidate i using the following procedure:

$$m_i = \sum_{j=1}^{N} Sh(d_{ij}) \quad (11)$$

Step5: Repeat the previous steps for the second candidate.
Step6: Compare m1 and m2 corresponding respectively to the first and second candidate. If $m_1 \leq m_2$, choose the first candidate, if not, choose the second.

NSGA-II

Multiobjective evolutionary algorithms that use non-dominated sorting and sharing, such as NSGA and NPGA (NPGA-Niched Pareto Genetic Algorithm) [12, 13, 14], have been criticized for their complexity, high computation, lack of elitism, and the need for specifying the sharing parameter. For this reason, the second version of NSGAII is considered among the most efficient algorithms for solving several optimization problems related to power grids. In this technique, the sharing parameter is replaced by the crowding distance. At an iteration t, a child population Qt with a number of Npop individuals is created from the parent population Pt of the same number of Npop individuals. These two child and parent populations will be combined to form a new Rt population.

$$R_t = P_t \cup Q_t \quad (12)$$

The population Rt of size 2Npop is then sorted according to a criterion of non-dominance in r fronts Fj, as indicated by equation (13).

$$R_t = \bigcup_{j=1}^{r} (F_j) \quad (13)$$

The selection of the Pt + 1 population will be based on the degree of non-dominance and the distance from the crowding.
Two individuals having the same degree of non-dominance, that is to say being in the same front Fj, will be sorted according to their crowding distances. The first Npop individuals of the population Rt + 1 will be the individuals of the population Pt + 1. An iteration t of the NSGAII algorithm is shown in Figure 1 [15, 16].

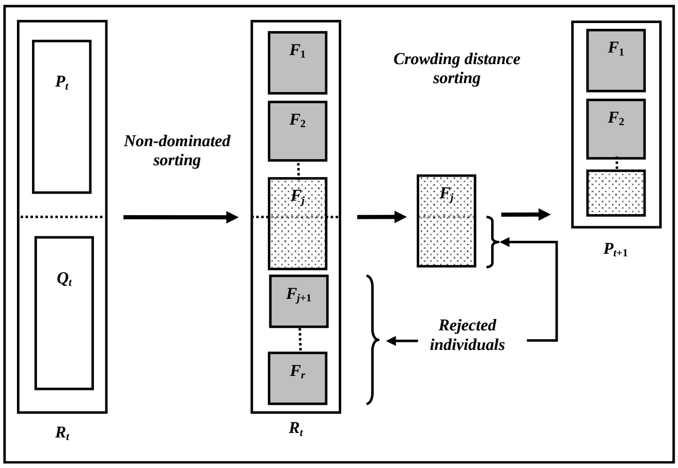

Fig 1: An iteration of the NSGAII

The crowding distance of an individual (i) is calculated according to the perimeter formed by the points closest to him for each objective. The process of selection by crowding distance within the same front favors the individuals furthest from each other. For a front Fi, the procedure for calculating the crowding distance of a solution Xi of the front Fj is detailed in [17, 18].

Simulation results

The network studied in this part is the Tunisian network version 1981 contains 20 bus, 6 thermal generators and 26 lines [9]. The structure of this network is represented by figure 2, the data of the buses and the lines are given by Tables 1 and 2 in appendices. While the cost coefficients of the device and the desired voltage values are given by table 3.

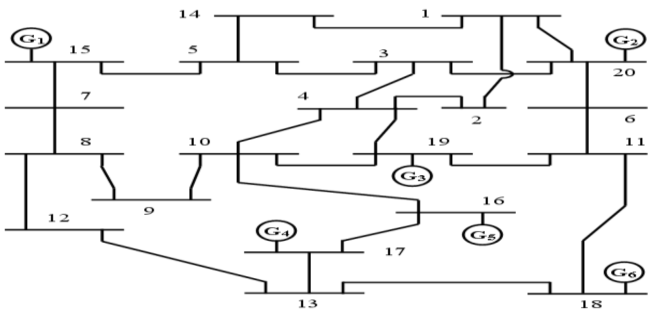

Fig 2: Tunisian network test system.

Bi-Objectves optimization

Figure 3 represents the optimal Pareto fronts for a bi-objective optimization of the loss / deviation functions by the three approaches NPGA, NSGAII and the weight method.

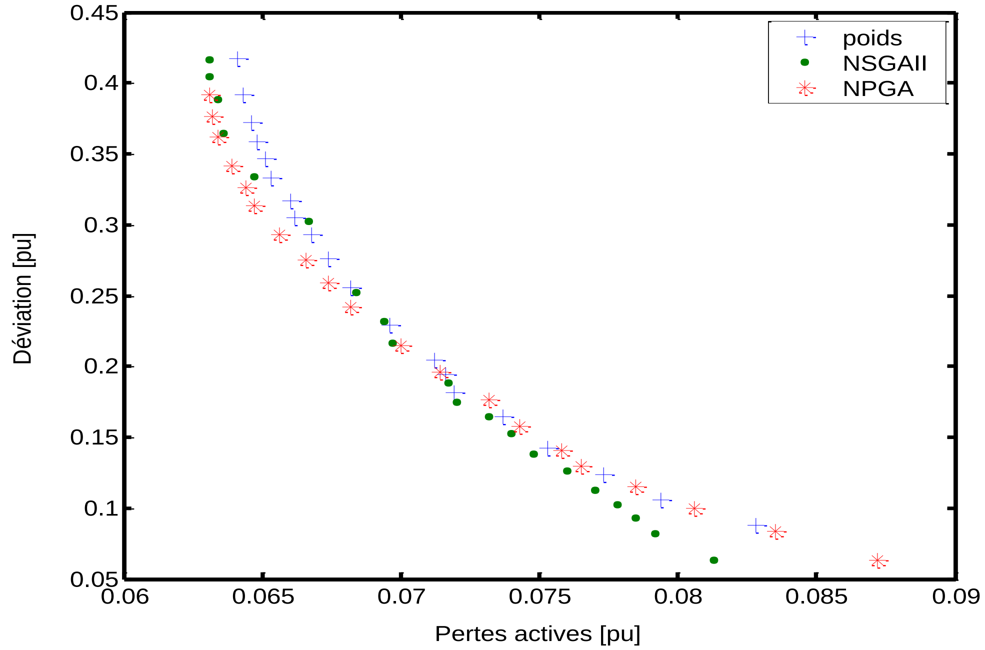

Fig 3: Front Pareto deviation / losses.

From Figure 2, we can derive the limit values for each approach with minimum active losses and minimum deviation. These values are summarized in Tables 4 and 5.

Table 4: Limit values with minimum active losses.

	NPGA	NSGAII	weight method
Q_{g1}[pu]	-0.0600	-0.1309	-0.0607
Q_{g2}[pu]	0.1080	0.2913	0.1288
Q_{g3}[pu]	-0.2189	-0.1621	-0.0705
Q_{g4}[pu]	0.4743	0.2680	0.2722
Q_{g5}[pu]	-0.0334	-0.0130	-0.0073
Q_{g6}[pu]	0.1261	0.1857	0.1134
Q_{g7}[pu]	-0.0820	-0.0946	-0.0510
Q_{g8}[pu]	0.1144	0.0189	0.0190
Q_{g9}[pu]	-0.0182	0.0676	-0.0205
Q_{g10}[pu]	-0.2676	-0.2881	-0.2297
Q_{g11}[pu]	-0.1081	-0.0709	0.0621
Q_{g12}[pu]	0.1787	0.1652	0.1273
Q_{g13}[pu]	-0.0470	-0.0388	-0.0103
Q_{g14}[pu]	0.3557	0.3302	0.3695
Minimum active losses [pu]	0.0631	0.0631	0.0640
Corresponding Deviation [pu]	0.3767	0.4166	0.4224

From Tables 4 and 5, we can see that the reactive production is important for a minimum deviation, it is low when the losses are minimal. We can also notice that the methods based on evolutionary algorithms (NPGA and NSGAII) give the best solutions than the classical methods (weight method) and we admit that the NSGAII method offers the best results despite its calculation time which is a little slow compared to the others.

Table 5: Limit values with minimum deviation.

	NPGA	**NSGAII**	**weight method**
Q_{g1}[pu]	0.2768	0.3105	0.1828
Q_{g2}[pu]	0.3056	0.1168	0.1366
Q_{g3}[pu]	0.7257	0.0003	0.4377
Q_{g4}[pu]	0.1811	0.4494	0.4730
Q_{g5}[pu]	0.0613	0.1927	0.1545
Q_{g6}[pu]	0.1954	0.1215	0.1614
Q_{g7}[pu]	0.3523	0.3661	0.3139
Q_{g8}[pu]	0.1409	-0.0832	0.0418
Q_{g9}[pu]	-0.2560	0.0016	-0.1890
Q_{g10}[pu]	-0.3035	-0.2872	0.0181
Q_{g11}[pu]	0.2653	0.2363	0.1173
Q_{g12}[pu]	0.1155	0.2108	0.1991
Q_{g13}[pu]	0.0849	0.0410	-0.0051
Q_{g14}[pu]	0.4309	0.4179	0.4174
Minimum deviation [pu]	0.0618	0.0621	0.0834
Corresponding active losses [pu]	0.0876	0.0818	0.0845

The voltage profile at the load buses corresponding to the minimum active losses determined by the three approaches is shown in figure 4.

Similarly, the voltage level at the load buses corresponding to a minimum deviation is shown in figure 5.

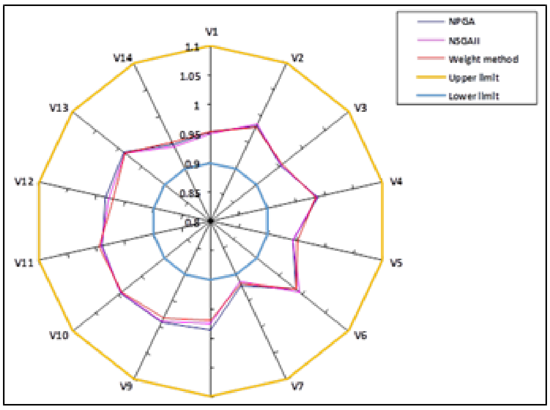

Fig 4: Voltage profile with minimum active losses.

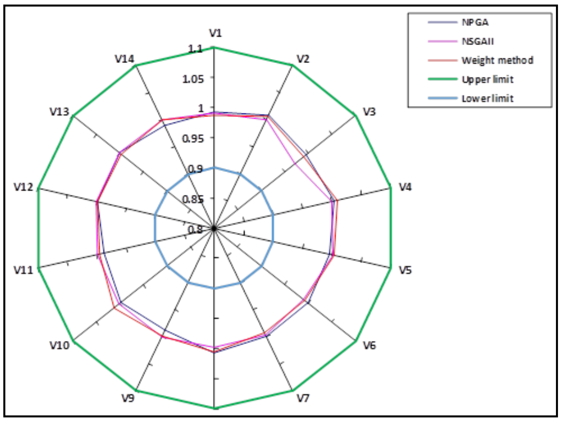

Fig 5: Voltage profile with minimum deviation.

Figure 5 shows that at minimum deviation the voltage values at the consuming buses are too close to the desired value (1 pu).

Tri-Objectves optimization

Figures 6 illustrate the Pareto surfaces Voltage deviation / Cost of compensation devices / Active losses in transmission and power transmission lines in four different views.

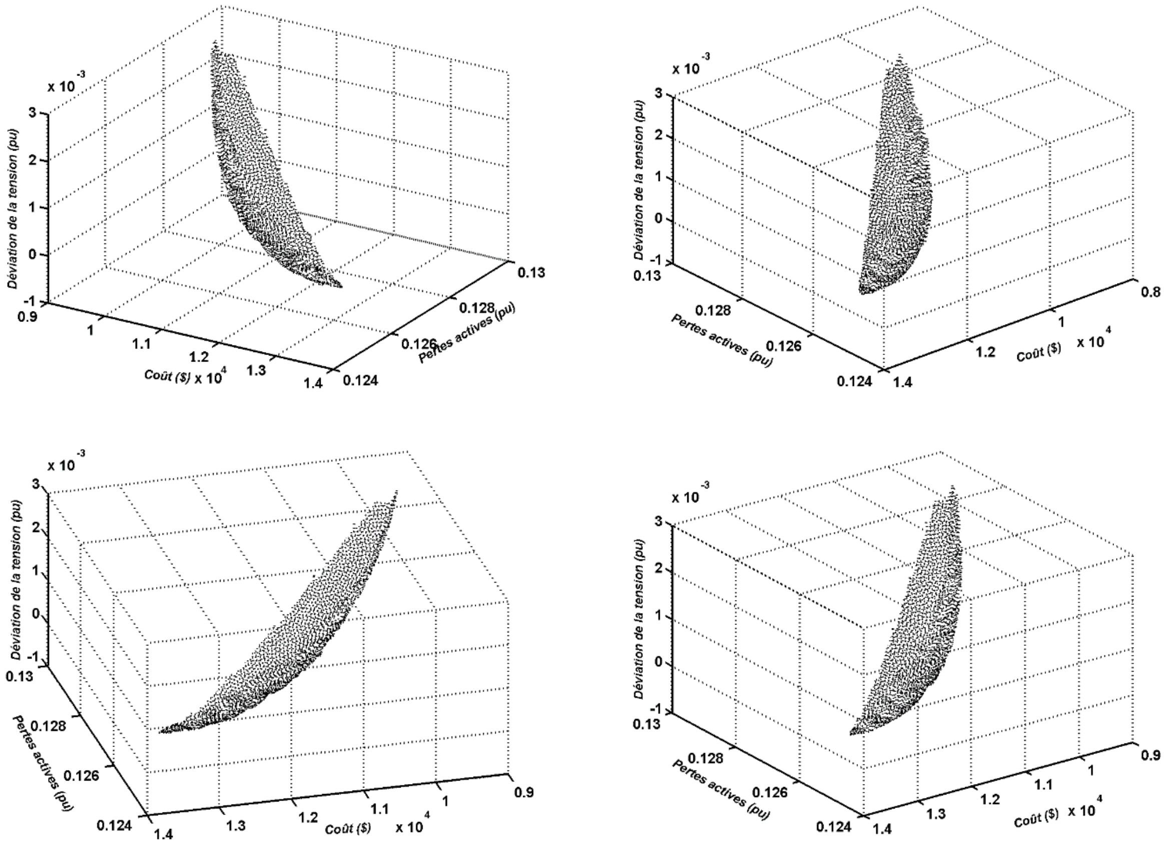

Fig. 6: Deviation / Cost / Loss Pareto Surface.

Table 6 gives the limit values of the Pareto surface of figure. 6.

Table 6: Limit values of the Pareto surface Deviation / Cost / Losses.

	Minimum cost	Minimum losses	Minmum deviation
Cost ($)	$9.0939\ 10^{3}$	$1.3435\ 10^{4}$	$1.3013\ 10^{4}$
Losses (pu)	0.1296	0.1247	0.1259
Deviation (pu)	$32\ 10^{-4}$	$5.7883\ 10^{-4}$	$32.65\ 10^{-4}$

Conclusion

In this paper, the problem reactive Dispatch problem of the Electric Power Network has been defined and resolved. The methods proposed for the resolution are mainly based on Evolutionary Algorithms. First, we defined the Dispatching (DR) problem and then we applied three methods for its resolution. These are the NPGA, NSGAII and the weights method. The simulations are made on a test network, the Tunisian network version 1981 contains 20 nodes, 6 thermal generators and 26 lines. A comparative study on the Pareto fronts of these methods is carried out. The NSGAII method offers the best results. This is the reason why we chose this method for solving the problems of tri-objective optimization of the DR. Then we were interested in the determination of the pareto surface of the problem with three objectives (cost of the device of compensation / deviation / total active losses). The methods proposed for the resolution of Dispatching problems show that the solutions provided are encouraging in the case of complex nonlinear problems, having a large number of variables and under several constraints.

Appendices

Table 1: Buses data.

Buses data						
Buses	**Nominal voltage (KV)**	**Operable voltage (KV)**	**Pg (MW)**	**Qg (MVAR)**	**Pc (MW)**	**Qc (MVAR)**
1	90.00	0.00	0.00	0.00	50.00	11.00
2	225.00	0.00	0.00	0.00	0.00	0.00
3	90.00	0.00	0.00	0.00	70.00	30.00
4	225.00	0.00	0.00	0.00	0.00	0.00
5	90.00	0.00	0.00	0.00	0.00	0.00
6	150.00	0.00	0.00	0.00	0.00	0.00
7	90.00	0.00	0.00	0.00	20.00	12.00
8	150.00	0.00	0.00	0.00	0.00	0.00
9	225.00	0.00	0.00	0.00	0.00	0.00
10	225.00	0.00	0.00	0.00	5.00	1.00
11	150.00	0.00	0.00	0.00	50.00	20.50
12	150.00	0.00	0.00	0.00	42.00	15.00
13	150.00	0.00	0.00	0.00	3.00	1.00
14	90.00	0.00	0.00	0.00	50.00	20.00
15	90.00	81.90	10.00	0.00	15.00	5.00
16	225.00	229.50	25.00	0.00	0.00	0.00
17	150.00	149.25	40.00	0.00	20.00	10.00
18	150.00	147.90	35.00	0.00	25.00	15.00
19	225.00	224.10	200.00	0.00	0.00	0.00
20	90.00	86.04	0.00	0.00	20.00	10.00

Table 2: Line's data

Line's data					
Connection	**Resistance (Ω)**	**Reactance (Ω)**	**Connection**	**Resistance (Ω)**	**Reactance (Ω)**
1→2	0.00	70.88	9→10	9.00	42.50
1→20	3.30	9.70	10→16	17.00	98.50
2→4	3.50	16.70	10→19	9.20	43.80
3→4	0.00	35.44	11→18	15.00	42.00
3→20	1.50	5.00	11→19	0.00	17.72
4→10	9.80	46.70	13→12	16.90	47.60
4→19	9.90	46.70	13→17	14.60	41.00
5→3	6.70	19.30	14→1	9.60	21.20
6→11	29.80	83.20	14→5	7.70	16.00
6→20	0.00	45.75	15→5	21.90	60.70
7→8	0.00	68.63	15→7	8.70	24.20
8→9	0.00	73.91	16→17	0.00	70.88
8→12	27.70	77.70	18→13	15.20	42.60

Table 3: Cost coefficients of the compensation device and desired voltage values.

Bus N°	C_{fi} ($)	C_{gi} ($/MVAR)	$V_{desired}$ (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
6	1771.59	5314.8	1
7	1771.59	5314.8	1
8	1771.59	5314.8	1
9	1771.59	5314.8	1
10	1771.59	5314.8	1
11	1771.59	5314.8	1
12	1771.59	5314.8	1
13	1771.59	5314.8	1
14	1771.59	5314.8	1

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