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A hybrid method for the optimal reactive power dispatch and the control of voltages in an electrical energy network

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Abstract: This paper presents the resolution of the optimal reactive power dispatch (ORPD) problem and the control of voltages in an electrical energy system by using a hybrid algorithm based on the particle swarm optimization (PSO) method and interior point method (IPM). The IPM is based on the logarithmic barrier (LB-IPM) technique while respecting the non-linear equality and inequality constraints. The particle swarm optimization-logarithmic barrier-interior point method (PSO-LB-IPM) is used to adjust the control variables, namely the reactive powers, the generator voltages and the load controllers of the transformers, in order to ensure convergence towards a better solution with the probability of reaching the global optimum. The proposed method was first tested and validated on a two-variable mathematical function using MATLAB as a calculation and execution tool, and then it is applied to the ORPD problem to minimize the total active losses in an electrical energy network. To validate the method a test was carried out on the IEEE electrical energy network of 57 buses.

Key words: electrical energy network, interior point method (IPM), optimal reactive power dispatch (ORPD), particle swarm optimization (PSO)

1. Introduction

The ORPD is a non-linear optimization problem, proposed by Carpenter in the early sixties and based on the economic power dispatch [1]. The ORPD is a special case of the optimal power flow (OPF) in which the active power control means are set while those of the reactive power are adjustable. The ORPD was usually considered as the minimization of an objective function representing the total active power losses in the electrical networks while respecting all nonlinear equality and inequality constraints.

Different conventional approaches have been developed to solve the ORPD problem, many of which are based on linear programming methods [2], others using nonlinear programming methods [3], quadratic programming [4, 5], the penalty method [6], the Newton method [7], the interior point method [8–10]. These conventional methods, good for deterministic quadratic objective functions with only one minimum, are generally based on successive linearizations using the first and the second derivative of the objective function and on its constraints as the search direction.

Currently, there are a variety of optimization techniques to overcome the ORPD problem, namely:

- Metaheuristics include the genetic algorithm (GA) [11], differential evolutionary algorithm (DE) [12], evolutionary programming [12] (PE), evolutionary strategy (SE) [13],
- Teaching-learning-based optimization (TLBO) [14],
- Grey Wolf optimizer (GWO) [15],
- Harmony search (HS) [16] and modified harmony search (MHS) [17],
- Gravitational search algorithm (GSA) [18, 19],
- Seeker optimization algorithm (SOA) [20],
- Moth-flame optimization technique (MFOT) [21],
- Gaussian bare-bones water cycle algorithm (NGBWCA) [22].

These global optimization techniques that do not require the convexity of the objective function have appeared with a high probability of converging towards the global optimum.

In this paper, we propose an improved optimization algorithm PSO-LB-IPM, which allows one to control and program batch hybridization, between the LB-IPM and the PSO method, to solve the problem of the ORPD and the control of voltages in an electrical energy network.

The proposed PSO-LB-IPM variant attempts to provide a better compromise between exploration and exploitation capabilities, as well as robustness and speed of computation for accelerated convergence towards the optimal solution.

The developed program has been validated on a two-variable test mathematical function, and implemented on a real problem of electrical network IEEE 57 buses. Satisfactory results were presented and discussed.

2. Formulation of the ORPD problem

The problem of the optimal reactive power dispatch and the control of the voltages is the search for the minimum of a certain objective function known as the total active power losses, subject to a limit number of the nonlinear constraints. In a general way the mathematical model to study must include an objective function, equality and inequality constraints, defined by:

$$\min f(x,u),$$

$$\text{subject to:}\quad \begin{aligned} g(x,\ u) &= 0,\\ h(x,\ u) &\le 0,\\ x_{\min} \le x &\le x_{\max},\\ u_{\min} \le u &\le u_{\max}. \end{aligned} \tag{1}$$

where f is the objective function that represents the total active power losses, x represents the state variables that contain the voltages at the load buses and u stands for the control variables that contain the generated voltages and the transformer tap ratios, g stands for the equality constraints that represent the power flow solution, h represents the inequality constraints, $u_{\min}$is the lower limit on the control variables and $u_{\max}$ is the upper limit on the control variables, $x_{\max}$ is the lower limit on the state variables and $x_{\max}$ is the upper limit on state variables.

3. Overview for particle swarm optimization method (PSO)

Particle swarm optimization is an optimization metaheuristics, invented by Russel Eberhart and James Kennedy in 1995. This algorithm was originally inspired by the living world. It is based on a model developed by biologist – Craig Reynolds – in the late 1980s, simulating the movement of a group of birds.

The method itself involves groups of particles in the form of vectors moving in the research area. Each particle is characterized by its position and a position change vector (called velocity or velocity vector). At each iteration, the particle moves. Socio-psychology suggests that individuals moving are influenced by their past behavior and that of their neighbors (neighbors in the social network and not necessarily in space).

Therefore we take into account, in the update of the position of each particle, the direction of its movement, its speed, its best position and the best position of its neighbors. The position of each agent is represented by its coordinates along the two axes, xy, and also the speed expressed by vx: speed along the x-axis and vy – speed along the y-axis. The modified position of each agent is realized by the information of its position and speed. Each agent knows its best value so far (*pbest*) and its position along the two axes xy. This information is obtained from the personal experiences of each agent. Moreover, each agent knows the best overall value of the group (*gbest*) among the *pbests*. Each agent tries to modify its position, using the current velocity and the distance from pbest and *gbest*.

The velocity of each agent can be modified by the following equation:

$$v_i^{k+1} = w.v_i^k + c_1 rand_1 \left(pbest - s_i^k\right) + c_2 rand_2 \left(gbest - s_i^k\right), \tag{2}$$

where v_i^k is the velocity of agent i at iteration k, w is the weighting function, c_1 and c_2 are the weighting factors, $rand_1$ and $rand_2$ represent the random number between 0 and 1, s_i^k is the current position of agent i at iteration k, *pbest* is the best position encountered by particle i, and *gbest* is the best position of the group.

The weight of the function used in Equation (2) is given by:

$$w(iter) = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} * iter, \tag{3}$$

where $w_{\max}$ is the initial weight, $w_{\min}$ is the final weight, $iter_{\max}$ is the maximum number of iterations, as well as *iter* represents number of iterations.

By manipulating Equation (3) we can gradually calculate a velocity near *pbest* and *gbest*. The current position can be modified by the following equation:

$$s_i^{k+1} = s_i^k + v_i^{k+1}, \tag{4}$$

where s_i^k is the current position and s_i^{k+1} is the modified position, v_i^k is the current speed and v_i^{k+1} is the modified speed.

Several applications of this method to overcome the problem of the optimal reactive power dispatch are reported in literature in the references [23, 24].

4. Overview for interior point method (IPM)

In this paper the primal-dual interior point method (PD-IPM) was used to solve the non-linear problem defined by the minimization of total active power loss in an electric power network, taking into account all the operational constraint control variables such as generator voltage and transformer tap ratios.

The inequality constraints of Equation (1) become equality constraints by introducing positive reduced (slack) variables $(x_l,\ x_u)$. Nonlinear problem (1) is written as:

$$\min f(x),$$

$$\text{subject to:}\quad \begin{aligned} g(x) &= 0, \\ x_u + x - x_{\max} &= 0, \\ x_l - x + x_{\min} &= 0, \\ x_l,\ x_u &\geq 0. \end{aligned} \tag{5}$$

The reduced variables are included in the function of the logarithmic barrier so we obtain a new non-linear problem (NLP):

$$f(x) - \mu \sum (\ln x_{ui} + \ln x_{li}),$$

$$\text{subject to:}\quad \begin{aligned} g(x) &= 0, \\ x_u + x - x_{\max} &= 0, \\ x_l - x + x_{\min} &= 0, \\ x_l,\ x_u &\geq 0. \end{aligned} \tag{6}$$

The barrier parameter "μ" is strictly positive during the convergence process progression and tends to be close to zero.

Lagrange's equation of (6) becomes:

$$L = f(x) - \mu \sum (\ln x_{ui} + \ln x_{li}) - \lambda^t g(x) - \alpha^t (x_u + x - x_{\max}) - \beta^t (x_l - x + x_{\min}), \tag{7}$$

where: λ, α and β are the vectors of the Lagrange multipliers.

From Karush-Kuhn-Tucker (KKT) conditions of the first order, a set of nonlinear algebraic equations is formed and solved by the Newton-Raphson algorithm [25]. The process of convergence of the IPM is stopped when the conditions of KKT are sufficiently lower than tolerance ε well specified:

$$\|L_x\| = \left\| \nabla f(x) - \nabla g^t(x)\lambda - \alpha - \beta \right\| \leq \varepsilon, \tag{8}$$

$$\|L_\lambda\| = \|g(x)\| \leq \varepsilon, \tag{9}$$

$$\|L_\alpha\| = \|x_u + x - x_{\max}\| \leq \varepsilon, \tag{10}$$

$$\left\|L_\beta\right\| = \|x_l - x + x_{\min}\| \leq \varepsilon, \tag{11}$$

$$\alpha^t x_u + \beta^t x_l \leq \varepsilon, \tag{12}$$

where x_l and x_u represent the lower and upper slack variables, and x represents primal variables, while λ, α and β are Lagrange multipliers that represent the dual variables.

The optimal solution is fulfilling the stopping criteria from (8) to (12).

The details and the implementation of this method to the optimal reactive power dispatch in the electrical energy network are presented in [25, 26].

5. The proposed hybridization for ORPD

In theory it is possible to hybridize all methods including exact method, so if it is possible to hybrid any method a priori, in practice one must be careful about the choice of methods used to obtain good cooperation between the constituents of the hybrid method. It is necessary to know how to characterize the strong points and the weak points of each method of research.

In this paper we are interested in hybridization based on batch modeling. The principle is a combination of an evolutionary method, such as metaheuristic population and a conventional method.

The proposed hybrid algorithm illustrated in Fig. 1 begins with the application of particle swarm optimization (PSO) that generates a solution population, the best solutions generated will be used as an initial solution for the interior point method (LB-IPM). The result obtained from the application of these two techniques represents the best solution.

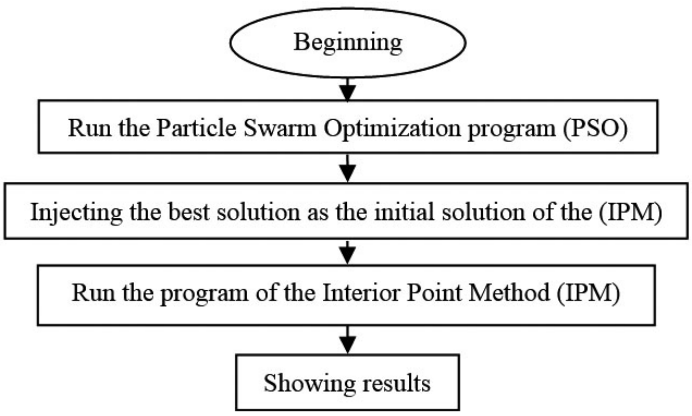

Fig. 1. Flowchart of the hybrid algorithm (PSO-LB-IPM)

6. Results and discussion

The resolution of the problem of the optimal reactive power dispatch (ORPD) and the control of the voltages in an electrical energy network was realized by the mathematical modeling presented previously. The hybrid algorithm PSO-LB-IPM was implemented in MATLAB R2013b as a computer tool, and simulation runs on an Intel (R) Core (Tm) CPU i3-3110M CPU with 4 GO RAM, The proposed hybridization is tested first on a two-variable mathematical function to justify robustness, performance and efficiency. Then it is applied to the ORPD problem using the IEEE57-bus electrical energy network.

6.1. Application on two-variable test function

The developed program has been tested and validated on the following function:

$$\min F(x) = \min\left((x_1-5)^2+(x_2-5)^2\right),$$

$$\text{subject to:}\quad x_1+x_2=10, \tag{13}$$

$$\text{with}\quad 0 \le x_1 \le 10,$$

$$0 \le x_2 \le 9,$$

where x_1, x_2 represent the variables of function “F”, and $F(x)$ is the objective function.

After several tests, the parameters of the hybrid method, best suited for guaranteed the best results, are shown as follows:

Table 1. Parameters of the hybrid method

Parameter name	Symbol	Value
Initial weight	$w_{\max}$	0.9
Final weight	$w_{\min}$	0.4
Maximum number of iteration for PSO	$iter_{\max}$	20
Weighting factor	C_1	1.9
Weighting factor	C_2	1.5
Size of the population (search space)	$nind$	150
Number of variables	$nvar$	8
Initial value of the Lagrange multiplier	λ	10
Initial barrier parameter	μ	100
Maximum number of iterations for LB-IPM	$\max_{iter}$	100
Convergence tolerance on barrier parameter “μ” for LB-IPM	tol	10^{-6}

The application of the hybrid algorithm (PSO-LB-IPM) gives the following results:

Table 2. Minimum objective function "*F*"

Iterations	$F(x)$	x_1	x_2
0	$1.23 \cdot 10^{-5}$	4.99	4.99
1	$1.01 \cdot 10^{-1}$	5.22	4.77
2	$7.39 \cdot 10^{-2}$	5.19	4.80
3	$1.97 \cdot 10^{-2}$	5.09	4.90
4	$8.61 \cdot 10^{-4}$	5.02	4.97
5	$1.27 \cdot 10^{-5}$	5.00	4.99
6	$3.39 \cdot 10^{-7}$	5.00	4.99
7	$1.03 \cdot 10^{-8}$	5.00	4.99
8	$5.89 \cdot 10^{-11}$	5.00	5.00
Time (s)		4.32	

The minimum of the "*F*" function was obtained after eight iterations with a run time of 4.32 seconds, thus it is possible to conclude that this hybrid method is fast and more accurate in terms of solution quality.

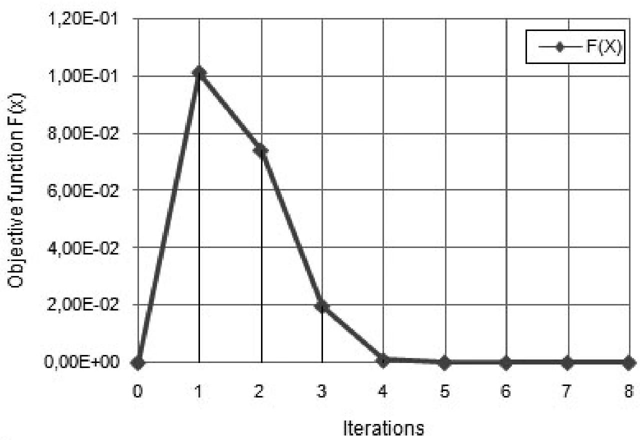

Fig. 2. Convergence of the function "*F*" according to number of iterations

Fig. 3 allows one to note that the choice of initial points (x_1, x_2) is very important in the computation process to ensure the fast convergence to the best minimum of the "*F*" function.

The values of the barrier parameter, Lagrange multiplier and the logarithmic barrier are shown in the following table (Table 3).

Fig. 4 shows, that the value of the barrier parameter "μ" tends to zero at the end of the convergence process.

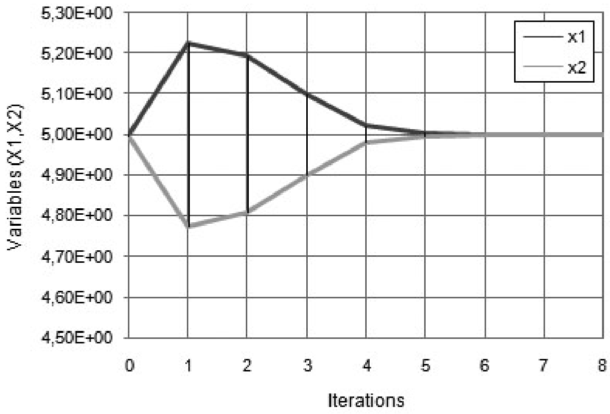

Fig. 3. Progression of variables “x” according to number of iterations

Table 3. Barrier parameter, Lagrange multiplier and the logarithmic barrier according to number of iterations

Iterations	Barrier parameter μ	Lagrange multiplier λ	Logarithmic barrier Log10 (μ)
0	$1.00{\cdot}10^{2}$	$-2.47{\cdot}10^{0}$	$2.00{\cdot}10^{0}$
1	$2.00{\cdot}10^{1}$	$-2.24{\cdot}10^{0}$	$1.30{\cdot}10^{0}$
2	$4.00{\cdot}10^{0}$	$-4.84{\cdot}10^{-1}$	$6.02{\cdot}10^{-1}$
3	$8.00{\cdot}10^{-1}$	$-1.11{\cdot}10^{-1}$	$-9.69{\cdot}10^{-2}$
4	$1.60{\cdot}10^{-1}$	$-2.28{\cdot}10^{-2}$	$-7.95{\cdot}10^{-1}$
5	$3.20{\cdot}10^{-2}$	$-4.14{\cdot}10^{-3}$	$-1.49{\cdot}10^{0}$
6	$5.72{\cdot}10^{-3}$	$-8.02{\cdot}10^{-4}$	$-2.24{\cdot}10^{0}$
7	$4.33{\cdot}10^{-4}$	$-1.43{\cdot}10^{-4}$	$-3.36{\cdot}10^{0}$
8	$9.01{\cdot}10^{-6}$	$-1.08{\cdot}10^{-5}$	$-5.04{\cdot}10^{0}$

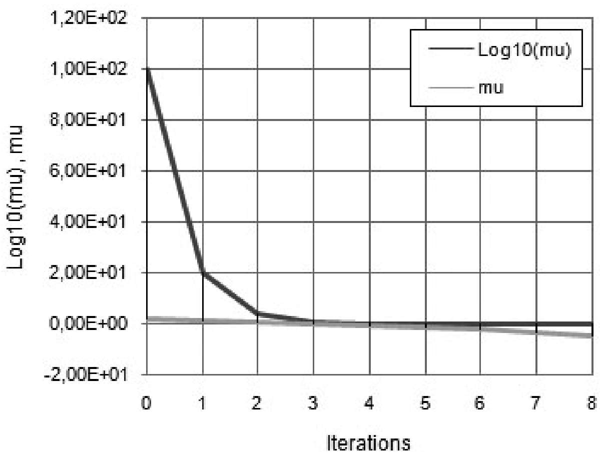

Fig. 4. Convergence of the mu (μ) barrier parameter

6.2. Application to the IEEE57-bus network

We will present different possible results and make the comparison between the two following cases:

– Case 1: initial case (power flow),

– Case 2: optimization by the hybrid PSO-LB-IPM.

The permitted operating limits of the voltages, and transformer taps, as well as reactive powers generated, and the reactive powers of the capacitors are summarized in Table 4.

Table 4. Limits

Bus	**Min**	**Max**
Transformers taps (*TLC*) (pu)	0.9	1.1
$V_1, \ldots, V_{57}$ (pu)	0.9	1.1
Q_1^g (Mvar)	−140	200
Q_2^g (Mvar)	−17	50
Q_3^g (Mvar)	−10	60
Q_6^g (Mvar)	−8	25
Q_8^g (Mvar)	−140	200
Q_9^g (Mvar)	−15	90
Q_{12}^g (Mvar)	−50	155
Q_{18}^c (Mvar)	0.0	20
Q_{25}^c (Mvar)	0.0	25
Q_{53}^c (Mvar)	0.0	10

– Case 1: initial case (power flow).

The electrical quantities at all the nodes of the IEEE57-bus electrical system must be known. The single-line diagram, illustrated in Fig. 5, is composed of 7 generation buses (1–3, 6, 8, 9 and 12), 50 buses of load, 3 shunt compensators (18, 25, 53), 15 transformers and 78 lines.

The power flow is then executed using the fast-decoupled load flow technique. We obtained the following results:

$$P_{GT} = 1279.82\ \text{MW}, \qquad P_{CHT} = 1250.8\ \text{MW}, \qquad P_{loss} = 29.02\ \text{MW},$$

where P_{GT} is the total generated active power, P_{CHT} is the total active power load and P_{loss} is the total active power loss.

These results show, that the voltages at the buses 30–36, 40, 42, 56, 57 exceeded their lower limits (0.9 pu) allowed for operation, while the rest of the buses presenting 80.71% of the total buses is found in their specified range (between 0.9 and 1.1 pu), which allows us to say that this operating point is a good basis for applying the optimization algorithm hybrid.

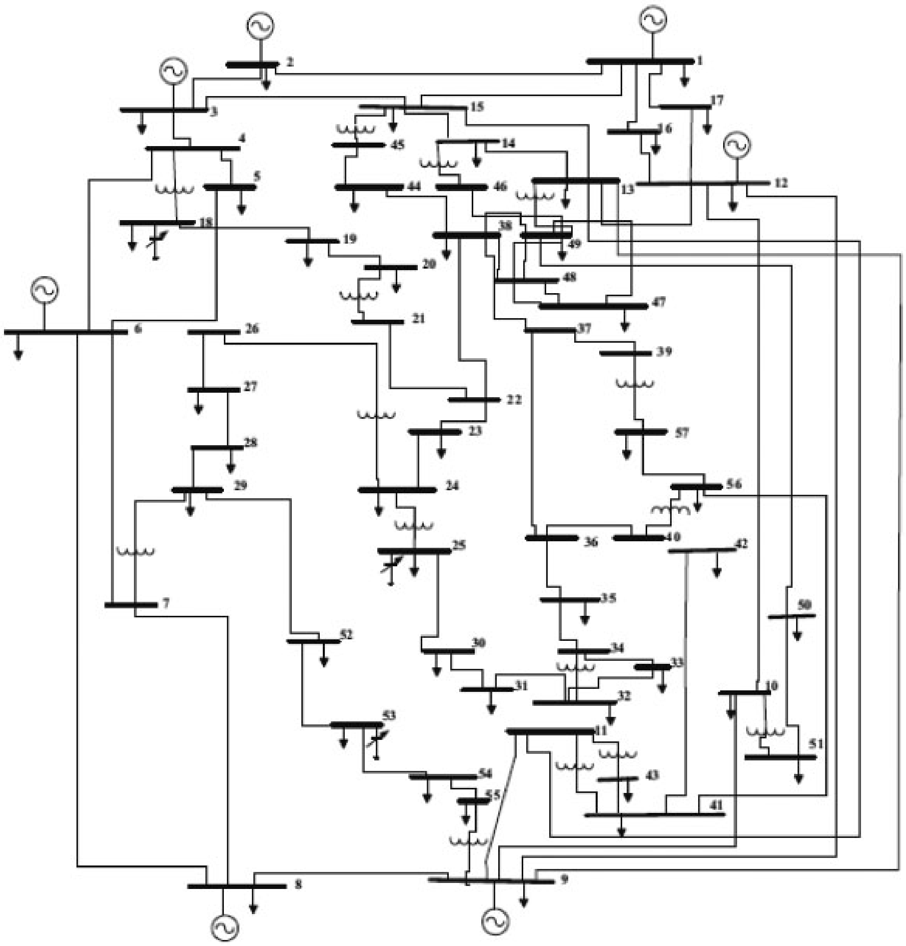

Fig. 5. Single-line diagram of IEEE57-bus power system [27]

Table 5. Generation voltages, active and reactive powers generated (case 1)

Bus	$|V_G|$ **(pu)**	θ **(...°)**	P_G **(MW)**	Q_G **(Mvar)**
1	1.04	0.00	479.82	128.81
2	1.01	−1.18	0.00	1.47
3	0.98	−5.97	40.00	−1.64
6	0.98	−8.61	0.00	−1.32
8	1.00	−4.44	450.00	61.01
9	0.98	−9.57	0.00	−3.06
12	1.01	−10.49	310.00	124.60

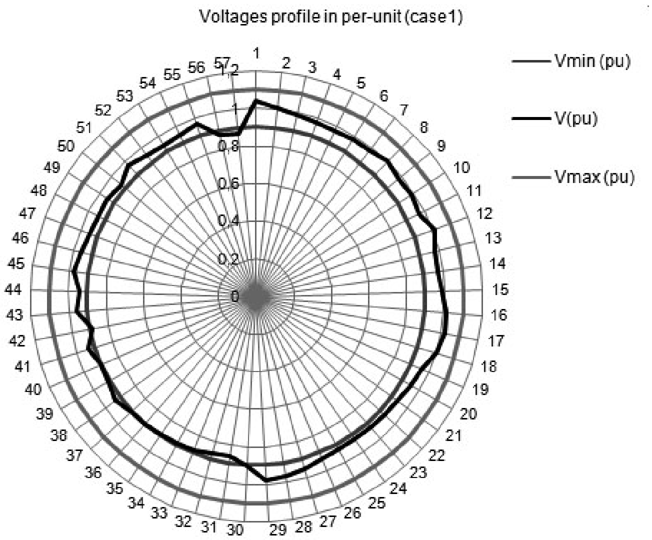

Fig. 6. Voltages profile before optimization (case 1)

– Case 2: optimization by the hybrid PSO-LB-IPM.

In this case, we made an application of the hybrid algorithm using 21 control variables (six generator voltages, fifteen transformer tap ratios) to solve the problem of the optimal reactive power dispatch and the control of the voltages in the IEEE57-bus network.

Regarding the choice of adjustment parameters of the hybrid algorithm PSO-LB-IPM, which is a very critical step for the convergence and the performance of the method, several executions and analyzes were made to make a judicious choice of these parameters for the problem studied. Then we chose:

Table 6. Parameters of the hybrid method

Parameter name	Symbol	Value
Initial weight	$w_{\max}$	0.4
Final weight	$w_{\min}$	0.2
Maximum number of iteration for PSO	$iter_{\max}$	10
Weighting factor	C_1	2
Weighting factor	C_2	2
Size of the population (search space)	*nind*	200
Number of variables	*nvar*	8
Initial value of the Lagrange multiplier	λ	10
Initial barrier parameter	μ	10
Maximum number of iterations for LB-IPM	$\max_{iter}$	10
Convergence tolerance on barrier parameter "μ" for LB-IPM	*tol*	10^{-6}

The new values of control variables after optimization by the PSO-LB-IPM are summarized in the following table:

Table 7. Modules and phase shift of the generated voltages (case 2)

Bus	Min (pu)	Max (pu)	$\lvert V_G \rvert_{\text{optimal}}$ (pu)	θ_{optimal} (...°)
1	0.9	1.1	1.10	0.00
2	0.9	1.1	1.10	−1.46
3	0.9	1.1	1.09	−5.79
6	0.9	1.1	1.09	−7.91
8	0.9	1.1	1.10	−4.37
9	0.9	1.1	1.09	−8.79
12	0.9	1.1	1.08	−9.06

The voltage profile and transformer tap ratios shown in Figs. 7 and 8, respectively, are within their allowable operating limits, which allows us to say that this hybrid optimization plays a large role in network security.

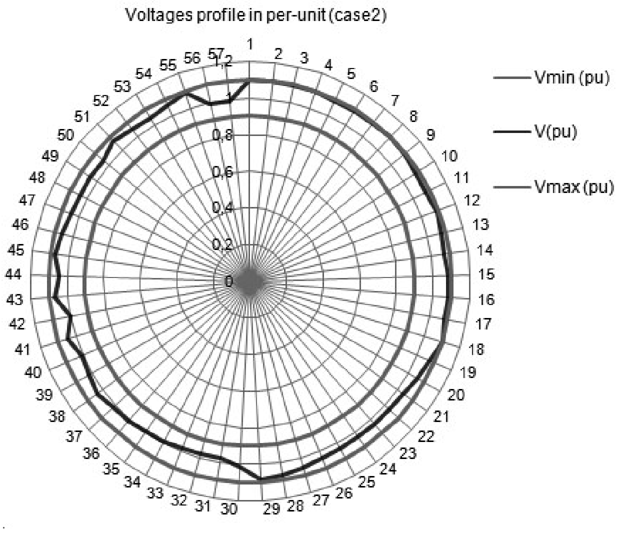

Fig. 7. Voltages profile after optimization by PSO-LB-IPM (case 2)

The overall voltage profile illustrated in Fig. 7 is high, this may be justified by the voltage control variables generated which are all close to their upper limits.

Fig. 9 clearly illustrates the rapid convergence of the hybrid method after 10 iterations that are necessary to reach the global optimal solution (better minimum of the active power loss), it can be said that the algorithm used is fast, very efficient and robust.

$$P_{GT} = 1274.02 \text{ MW}, \qquad P_{CHT} = 1250.8 \text{ MW}, \qquad P_{loss} = 23.22 \text{ MW}.$$

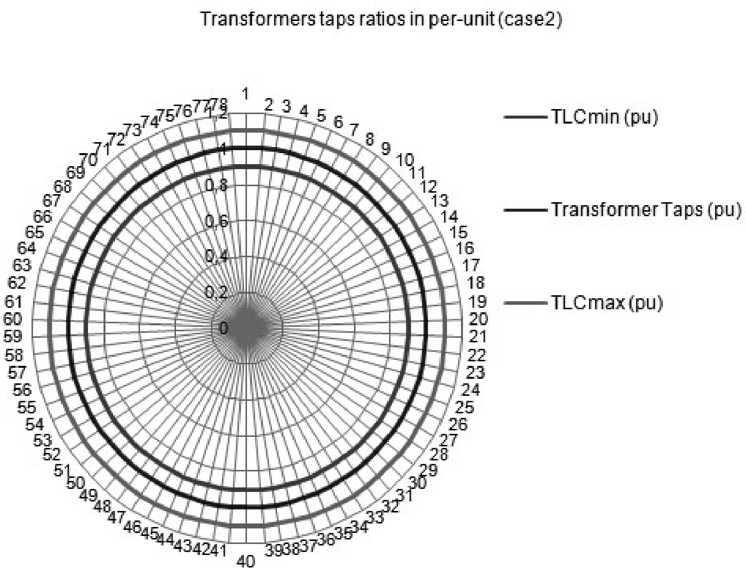

Fig. 8. Transformer tap ratios (case 2)

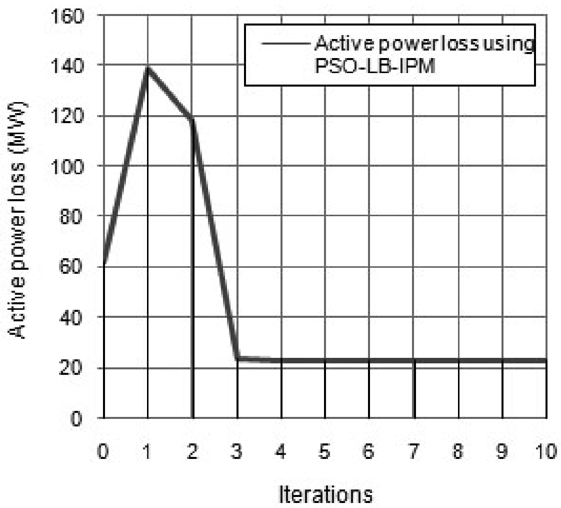

Fig. 9. Progression of total active power loss

The reading of the results obtained in Table 8 shows that the hybrid method used in case 2 always gives the best solution and the execution time is enormously large compared to the execution times of the power flow in case 1.

The active powers are fixed except balance bus "1". The reactive powers generated and the voltages are within their allowable limit for case 2, contrary to case 1.

The reactive powers of the shunt capacitors installed at the buses 18, 25, 53 respected their permitted operating limit as indicated in Table 9.

Table 8. Generation voltages, active and reactive power generated (cases 1 and 2)

Cases	**Case 1**			**Case 2**		
Bus	**$\|V_G\|$ (pu)**	**P_G (MW)**	**Q_G (Mvar)**	**$\|V_G\|$ (pu)**	**P_G (MW)**	**Q_G (Mvar)**
1	1.04	479.82	128.81	1.10	474.02	−34.29
2	1.01	0.00	1.47	1.10	0.00	50.00
3	0.98	40.00	−1.64	1.09	40.00	56.35
6	0.98	0.00	−1.32	1.09	0.00	09.52
8	1.00	450.00	61.01	1.10	450.00	−2.05
9	0.98	0.00	−3.06	1.09	0.00	90.00
12	1.01	310.00	124.60	1.08	310.00	59.01
Time (s)	8.81			24.51		

Table 9. Reactive powers of shunt capacitors

Bus	**Case 1 (Mvar)**	**Case 2 (Mvar)**
18	10.00	10.00
25	5.90	5.90
53	6.30	6.30

The active powers generated and the total active power losses following the execution of two cases (1 and 2) were compared to the original method of the PSO and LB-IPM, thus the results found in the literature by other metaheuristic approaches and hybrid are summarized in the following table:

Table 10. Total active power losses by different approaches

Active powers	**Cases**					
	Case 1	**PSO**	**LB-IPM**	**Case 2 PSO-LB-IPM**	**NGBWCA [22]**	**MICA-IWO [27]**
Total active power generated P_{GT} (MW)	1279.82	1274.24	1274.18	1274.02	1273.25	1275.06
Total active power load P_{CHT} (MW)	1250.80	1250.80	1250.80	1250.80	1250.80	1250.80
Active Power Loss P_{loss} (MW)	29.02	23.44	23.38	23.22	23.27	24.25
reduction in %		19.22	19.43	19.98	19.81	16.43

We found that the total active power loss 23.22 MW in case 2 (PSO-LB-IPM) is a decrease by 19.98% compared to the initial case (case 1), and it is a much better result than that found by the use of the original PSO method and LB-IPM.

In Table 10, a comparison between the results obtained with the proposed PSO-LB-IPM algorithm developed in the context of this work as well as with that found in the literature (for example, we take the optimization metaheuristics by Gaussian bare-bone water cycle algorithm reported in reference [22], and the hybrid approach (MICA-IWO) between the modified imperialist competitive algorithm and invasive weed optimization reported in reference [27]), was made concerning the minimization of the total active power losses.

The results found validate the proposed method and prove its performance from the point of view of the quality of the solution.

On the basis of the results obtained for the network model, it turns out that the voltage profile is respected. In fact, the smaller the active losses, the more voltages at the network nodes are close to their limits and vice versa.

On the other hand, if we are interested only in the objective function, which is the minimization of the total active power loss, our results show that the value of the loss obtained by the PSO-LB-IPM is better than that obtained by the initial case. Then the results prove the performance of the hybrid method in terms of the quality of the solution: minimum power losses, the limits imposed on the voltages, transformer taps, reactive powers generated and reactive powers of the capacitors have been respected.

7. Conclusions

In this paper, a robust, efficient and fast method called particle swarm optimization-logarithmic barrier-interior point method (PSO-LB-IPM) was presented to solve the ORPD problem and the control of voltages in an electrical energy system while respecting the nonlinear equalities and inequalities constraints.

The PSO-LB-IPM has been tested and implemented on the electrical energy network of IEEE 57 buses.

This technique proves the robustness and performance to maintain network security, and the efficiency of processing large scale nonlinear programming.

The simulation results obtained by the PSO-LB-IPM, have been proved satisfactory, and are better than that obtained in the initial case (case 1). The reactive powers generated, the reactive powers of the capacitors, the voltages and the regulators of the transformers (TCUL) are within their allowed limits of operation, and the total active losses have decreased by 19.98% compared to the initial case (case 1).

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