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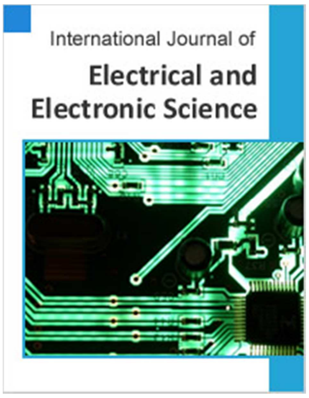

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Modified Imperialist Competitive Algorithm for Optimal Reactive Power Dispatch

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Abstract
This paper presents an improved imperialist competitive algorithm (ICA) for real power loss minimization using optimal VAR control in power system operation. In this paper, the modified imperialist competitive algorithm (MICA) is then offered for handling optimal reactive power dispatch (ORPD). The ORPD problem is formulated as a mixed integer, nonlinear optimization problem, which has both continuous and discrete control variables. The MICA is applied to ORPD problem on IEEE 30-bus, IEEE 57-bus and IEEE 118-bus test power systems for testing and validation purposes. Simulation numerical results indicate highly remarkable results achieved by proposed MICA algorithm compared to those reported in the literature.

1. Introduction

The problem of optimal reactive power dispatch problem (ORPD) has played an important role in optimal operation of power system; including generator reactive-power outputs and compensators for static reactive power, tap ratios of transformers, outputs of shunt capacitors/reactors, etc., with the aim to minimize interested objective functions such as real power loss, and summation of bus voltage deviation while at the same time satisfying a given set of operating and physical limitations. Since voltage of the generators are inherently continuous variables while the transformer ratios and shunt capacitors are discrete variables, the whole ORPD problem is considered as a non-linear multi-modal optimization problem with a combination of discrete and continuous variables [1–4].

In recent years many techniques ranging from conventional mathematical methods to computational intelligence-based techniques have been proposed to for application of optimal VAR control problem. Examples of the progress which has been made in this field are Khazali’s application of a harmony search algorithm (HSA) for achieving optimal reactive power dispatch and voltage control by reaching a global optimization of a power system [5]. Also in [6] Roy demonstrated higher ability of biogeography based optimization (BBO) technique introduced to solve multi-constrained optimal VAR control problem in power systems. In [7] Zhang introduced the mixture of dynamic multi-group self-adaptive differential evolution algorithm (DMSDE), as a solution for reactive power operational problems. Zhao in [8, 14] purposed a multi-agent based PSO for the ORPD problem. In [9, 15] a fuzzy adaptive PSO (FAPSO) for reactive power and voltage control is used and in [10] DE algorithm has been chosen to constitute the core of the solution for handling the optimal reactive power dispatch problem. In another reported case, Mahadevan and et al. in [11, 17] offers another method based on comprehensive learning PSO (CLPSO) for solving optimal VAR control problem. Other approaches for optimization of the above mentioned problem such as seeker optimization algorithm (SOA) and self-adaptive real coded genetic algorithm (SARCGA) are also presented in [12, 13-18, 19] and finally, the teaching learning algorithms (TLAs) are used for solving a stochastic in [14-18].

In 2007, Atashpaz-Gargari and Lucas introduced a novel with inspiration from social and political relations [21]. The performance of this evolutionary optimization algorithm has been continuously reinstated by successful utilization in many engineering applications such as optimal economic load dispatch [22], the multi-objective optimal power flow problems [23], and the electric power optimal planning [24-26].

The rest of this article is classified in four sections as follows: section 2 covers formulation of an optimal reactive power dispatch while section 3 explains the standard structure of the ICA and modified ICA (MICA) approaches, section 4 of the paper is allocated to presenting optimization results and undertaking comparison and analysis of the performance of the mentioned methods used to solve the case studies of optimal reactive power dispatch problem on standard IEEE systems and finally, in section 5, the conclusion of the implementation for the modified method is presented.

2. ORPD Problem

In general view, the goal of a solution of ORPD problem is to optimize the active power loss (P_{loss}) in the transmission network through optimal adjustment power system control parameters while satisfying equality and inequality constraints at the same time [1-4].

2.1. Problem Formulation

The ORPD problem can be mathematically formulated as follows:

$$\text{Minimize: } J(x,u) \tag{1}$$

$$\text{Subject to: } g(x,u) = 0 \tag{2}$$

$$h(x,u) \le 0 \tag{3}$$

In the above equation, *J(x, u)* is the objective function to be minimized, and x is the vector of dependent variables (state vector) consisting of:

1. Load bus voltage V_L.
2. Generator reactive power output Q_G.
3. Transmission line loading (or line flow) S_l.

Accordingly, the x vector can be illustrated as the following:

$$x^T = \left[V_{L1} ... V_{LNPQ}, Q_{G1} ... Q_{GNG}, S_{l1} ... S_{lNTL} \right] \tag{4}$$

where NG defines the number of generators.

u is the vector of independent continuous and discrete control variables consisting of:

1. Generation bus voltages V_G.
2. Transformer taps settings T.
3. Shunt VAR compensation Q_C.

Therefore, u can be expressed as:

$$u^T = \left[V_{G1} ... V_{GNG}, Q_{C1} ... Q_{CNC}, T_1 ... T_{NT} \right] \tag{5}$$

where NT and NC represent the number of tap regulating transformers and number of shunt VAR compensators, respectively.

2.2. Objective Function for ORPD Problem

The objective is of ORPD problem to minimize the real power transmission losses in the power system. The objective function is described as follow:

$$J(x,u) = P_{Loss} = \sum_{\substack{k=1 \\ k=(i,j)}}^{NTL} g_k \left(V_i^2 + V_j^2 - 2 V_i V_j \cos\delta_{ij} \right) \tag{6}$$

where P_{Loss} is the total active power losses of the transmission network. g_k is the conductance of branch k, V_i and V_j are the voltages of ith and jth bus respectively, NTL depict the number of transmission lines, NPQ depict the number of PQ buses, δ_{ij} phase difference of voltages between bus i and bus j.

2.3. Constraints

2.3.1. Equality Constraints

In the terms below, g is the equality constraints, illustrating typical load flow equations [1]:

$$\begin{aligned} & P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} V_j \left[G_{ij} \cos(\delta_{ij}) + B_{ij} \sin(\delta_{ij}) \right] = 0 \\ & \text{and } Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} V_j \left[G_{ij} \sin(\delta_{ij}) - B_{ij} \cos(\delta_{ij}) \right] = 0 \end{aligned} \tag{7}$$

where NB is the number of buses, P_{Gi} is the active power generation, Q_{Gi} is the reactive power generation, P_{Di} is the active load demand, Q_{Di} is the reactive load demand, G_{ij} and B_{ij} are the conductance and susceptance, respectively.

2.3.2. Inequality constraints

h is the inequality constraints that include:

i. Generator related constraints: the active power generation at slack bus, generation bus voltages, and reactive power outputs are restricted by their lower and upper limits as:

$$\begin{aligned} & P_{G,slack}^{\min} \le P_{G,slack} \le P_{G,slack}^{\max} \\ & V_{Gi}^{\min} \le V_{Gi} \le V_{Gi}^{\max}, \quad i = 1,...,NG \\ & Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max}, \quad i = 1,...,NG \end{aligned} \tag{8}$$

where $V_{Gi}^{\min}$ and $V_{Gi}^{\max}$ are the minimum and maximum generator voltage of ith generating unit; $P_{Gi}^{\min}$ and $P_{Gi}^{\max}$ the minimum and maximum active power output of ith generating unit and $Q_{Gi}^{\min}$ and $Q_{Gi}^{\max}$ are the minimum and maximum reactive power output of ith generating unit.

ii. Transformer limitations: transformer tap settings are restricted by their lower and upper limits as:

$$T_i^{\min} \le T_i \le T_i^{\max}, \quad i = 1,...,NT \tag{9}$$

where $T_i^{\min}$ and $T_i^{\max}$ define minimum and maximum tap settings limits of ith transformer.

iii. Shunt VAR compensator constraints: shunt VAR compensations are restricted by their limits as:

$$Q_{Ci}^{\min} \le Q_{Ci} \le Q_{Ci}^{\max}, \quad i = 1,...,NC \tag{10}$$

where $Q_{Ci}^{\min}$ and $Q_{Ci}^{\max}$ define minimum and maximum VAR injection limits of ith shunt compensator.

iv. Security constraints: include the constraints of voltages at load buses and transmission line loading as:

$$V_{Li}^{\min} \le V_{Li} \le V_{Li}^{\max}, \quad i = 1,...,NPQ \tag{11}$$

$$S_{li} \le S_{li}^{\max}, \quad i = 1,...,NTL \tag{12}$$

where $V_{Li}^{\min}$ and $V_{Li}^{\max}$ minimum and maximum load voltage of ith unit. S_{li} defines apparent power flow of ith branch. $S_{li}^{\max}$ defines maximum apparent power flow limit of ith branch.

Dependent variables are constrained using penalty terms to the objective function. Therefore, Eq. (1) is changed to the following form [5, 8 and 12]:

$$f = J(x,u) + \lambda_V \sum_{i \in N_V^{\lim}} (V_i - V_i^{\lim})^2 + \lambda_Q \sum_{i \in N_Q^{\lim}} (Q_{Gi} - Q_{Gi}^{\lim})^2 \tag{13}$$

where λ_V and λ_Q is the penalty terms, $N_V^{\lim}$ is the set of numbers of buses on which voltage is outside limits, $N_V^{\lim}$ is the set of numbers of generator buses on which injected reactive power outside limits, $V_i^{\lim}$ and $Q_{Gi}^{\lim}$ are defined as:

$$V_i^{\lim} = \begin{cases} V_i, & if\ V_i^{\min} \le V_i \le V_i^{max} \\ V_i^{\min}, & if\ V_i < V_i^{\min} \\ V_i^{max}, & if\ V_i > V_i^{\max} \end{cases} \tag{14}$$

$$Q_{Gi}^{\lim} = \begin{cases} Q_{Gi}, & if\ Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} \\ Q_{Gi}^{\min}, & if\ Q_{Gi} < Q_{Gi}^{\min} \\ Q_{Gi}^{\max}, & if\ Q_{Gi} > Q_{Gi}^{\max} \end{cases} \tag{15}$$

3. Modified Imperialist Competitive Algorithm

3.1. Imperialist Competitive Algorithm

ICA [21] is (the flowchart shown in Figure 1) purposed for general searching that is inspired from imperialistic competition. Each individual of the population this algorithm is called a 'country'. The countries in the population with the minimum cost (equal with elites in GA) are selected to be the imperialist states and the rest countries form the colonies of these imperialists. Note that the power of each country is inversely proportional to its cost [21].

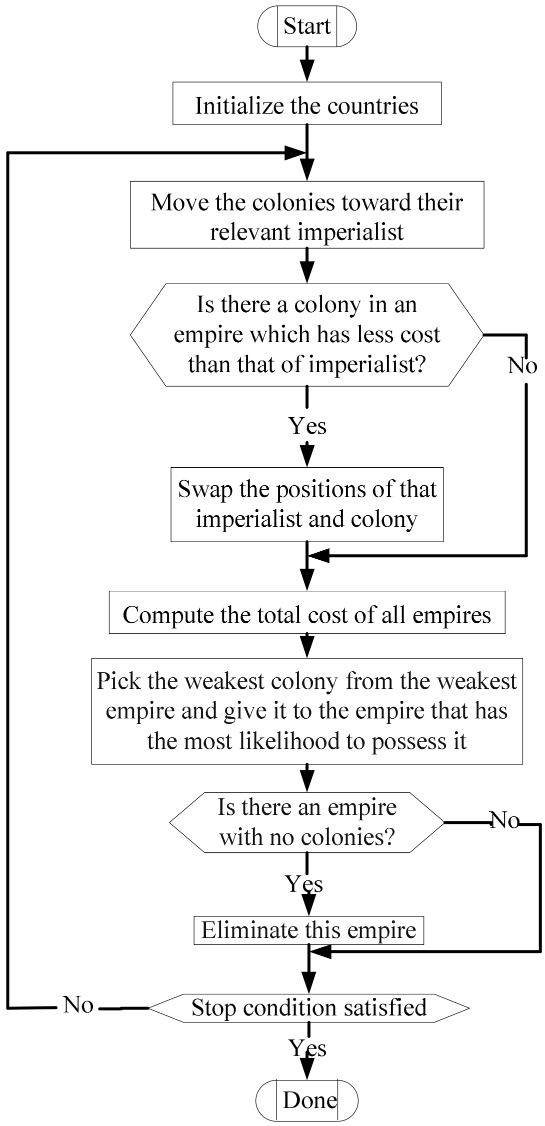

Figure 1. *Flow chart showing the working of ICA.*

3.1.1. Generating Initial Empires

The algorithm-user creates an array of variable values which are desired to be optimized. In the ICA terminology, this array is called a 'country' (equal with '*chromosome*' in GA). It is clearly figured out that when solving a N_{var} dimensional optimization problem, a country is a 1 × N_{var}

array. This country is defined as follow:

$$\text{country} = [P_1, P_2, P_3, ..., P_{N_{\text{var}}}] \tag{16}$$

where P_is are considered as the variables that should be optimized.

The candidate solutions of the problem, called country, include a combination of some socio-political characteristics such as, welfare, culture, religion and language. Figure 2 shows the interpretation of country using some of socio-political characteristics.

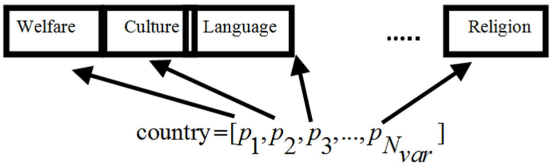

Figure 2. *Interpretation of country using some of socio-political characteristics.*

By evaluating the cost function, *f*, for variables ($p_1, p_2, p_3, ..., p_{N_{\text{var}}}$), the cost of a country will be found (Eq. (17)):

$$\cos t_i = f(\text{country}) = f(P_1, P_2, P_3, ..., P_{N_{\text{var}}}) \tag{17}$$

In the first step of ICA algorithm, initial population of size $N_{country}$ is produced. We select N_{imp} of the strongest population in order to form the empires. The remaining N_{col} of the population will form the colonies which are under control of one of the empires. We give some of these colonies to each imperialist for dividing the early colonies among the imperialist according to their power. To proportionally divide the colonies among imperialists, the normalized cost of an imperialist is explained as follows:

$$C_n = \max_i \{c_i\} - c_n \tag{18}$$

In the above mentioned equation, c_n is defined as the cost of *n*th imperialist and C_n is its normalized cost. When the normalized costs of all imperialists are gathered, the normalized power of each imperialist is evaluated according to the following equation:

$$P_n = \left| \frac{C_n}{\sum_{i=1}^{N_{imp}} C_i} \right| \tag{19}$$

The initial colonies are distributed among empires based on their power. Accordingly, initial number of colonies for *n*th empire will be:

$$N.C._n = round\{P_n . N_{col}\} \tag{20}$$

where $N.C._n$ factor represents the initial number of colonies of the empire and N_{col} is the total number of existing colonies countries in the initial countries crowds.

3.1.2. Absorption Policy Modeling

Actually, the central government attempts to close colony country to its self by applying attraction policy, in different political and social dimensions, with considering showing manner of country in solving optimization problem. Figure 3 illustrates this movement in which a colony moves toward the imperialist by units.

In Figure 3, *d* and *x* variables present distance between imperialist and colony countries is and accidental number with steady distribution, respectively.

Therefore, *x* can be defined as follows:

$$x \sim U(0\ ,\ \beta \times d) \tag{21}$$

where β is a number greater than one and nears to two. A good selection can be β=2. In Figure 3, θ is a parameter with uniform distribution. Then:

$$\theta \sim U(-\gamma\ ,\ +\gamma) \tag{22}$$

where γ (the its value is about π/4 (Rad)) is ideal parameter that it's growth causes increase in searching area around imperialist [21].

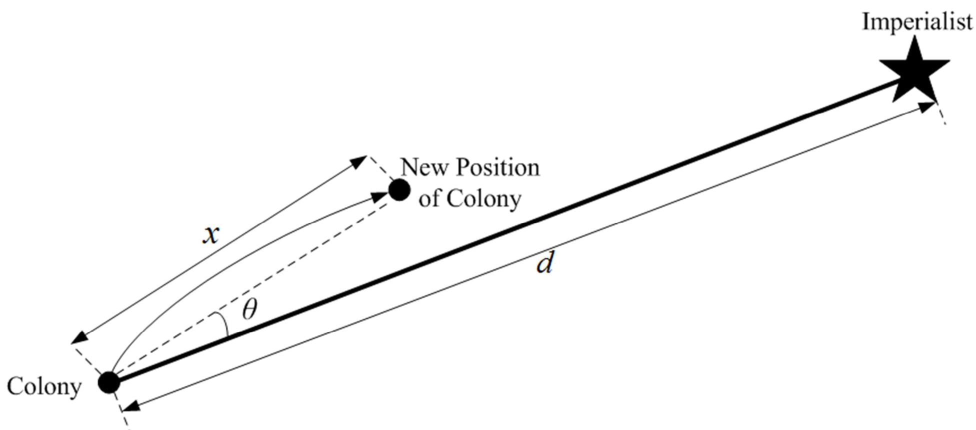

Figure 3. *Giving a move to the colonies toward their corresponding imperialist in an accidental deviated orientation.*

3.1.3. Position Displacement of Colony and Imperialist

If a colony reaches a better point than an imperialist in its movement towards the imperialist country (equal to having more power than the country), it will replace that imperialist country.

3.1.4. Total Power of an Empire

Taking into account the both above mentioned factors affecting the power of the empire, the sum cost of an empire calculates as follow:

$$T.C._n = Cost(\text{imperialist}_n) + \xi \,\text{mean}\{Cost(\text{colonies of empire}_n)\} \tag{23}$$

where $T.C._n$ is defined as the total cost of the nth empire and ξ is a positive number that has value between zero and one and near to zero. The value of 0.15 for ξ has shown good balanced results in most of the implementations.

3.1.5. Imperialistic Competitions

The imperialistic competition in ICA is modeled by the above fact and works by just picking some (usually one) of the weakest colonies of the weakest empire and making a competition among all empires to possess these (this) colonies. These weakest colonies will not definitely be possessed by the most powerful empire.

3.2. The Proposed Modified Algorithm (MICA)

In real geo-political interactions between countries, the imperialist countries themselves will also move towards the most powerful imperialist countries on different economic, political and social axis which they see themselves weak. Even at some points, the affiliated imperialists will overtake the greater imperialist in this axis and its power will be increased as the result. Of course they don't always succeed or will face some resistance. But this interaction will force inevitable changes on geopolitical status of imperialist countries and as a result of that, force changes on absorption of their colonies. On this modification of MICA propose these actions between imperialist countries.

Figure 4 illustrates the whole schematics of this movement, which is similar to the movement of colonies towards their imperialists. But the difference of this movement is that the movement will occur only if the new position gives more power to the imperialist country. Otherwise the imperialist will maintain its previous position. As it's shown in Figure 4, the imperialist which sees itself weaker at some, will move towards the position of the most powerful imperialist by x_{imp} units and take new position with condition of more power. The x_{imp} is a random value with uniform distribution and as it's shown in the Figure 4, the distance between to imperialist is illustrated by d_{imp}. Of course this movement of imperialists doesn't fully comply with the applied policies of the imperialist country and some deviation was observed in the final result which is modelled by adding random angle (θ_{imp}) to the movement course of imperialists. The θ_{imp} angle is also a random value with uniform distributed (although any other appropriate distribution can be used). So we have as follows:

$$x_{imp} \sim U(0\ ,\ \beta_{imp} \times d_{imp}) \tag{24}$$

$$\theta_{imp} \sim U(-\gamma_{imp}\ ,\ +\gamma_{imp}) \tag{25}$$

The act β_{imp} and γ_{imp} like the β and γ.

Figure 5 illustrates the new absorption action, in which first imperialists move towards the most powerful imperialist to increase their power and then, colonies will pull to their imperialists.

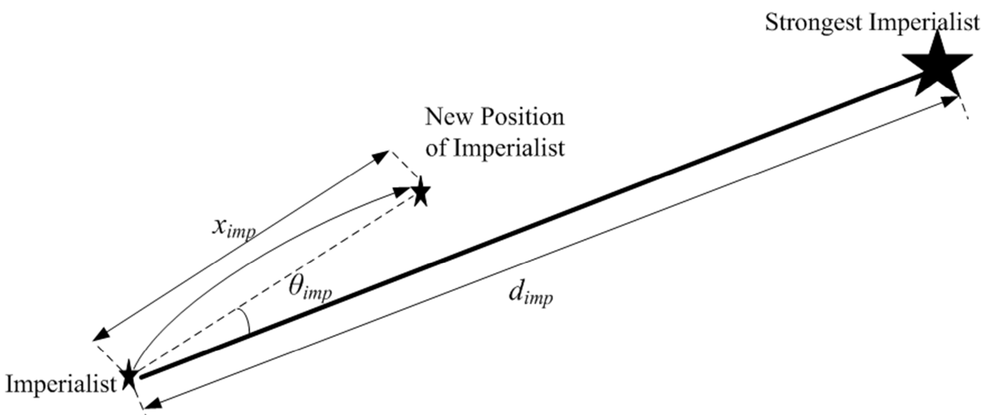

Figure 4. *Giving a move to the imperialist toward the strongest imperialist in an accidental deviated orientation.*

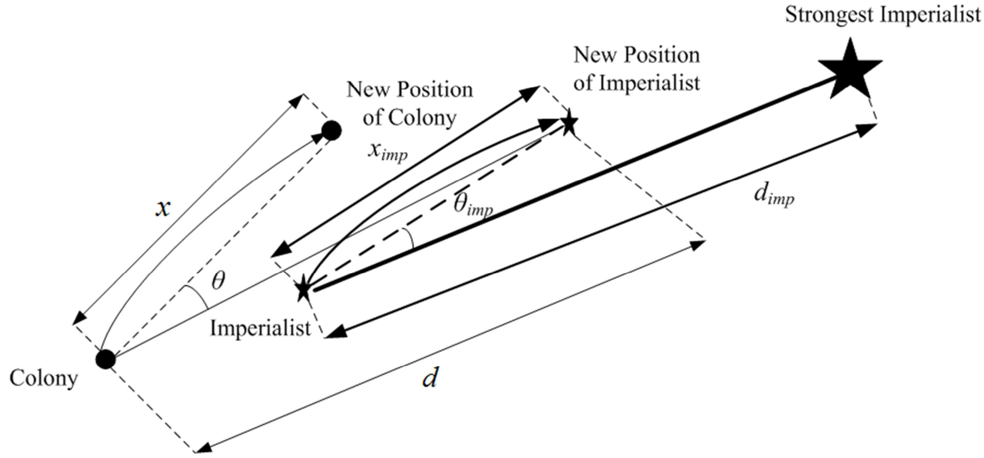

Figure 5. *General model of absorption policy of MICA.*

4. Numerical Results

In order to verify the performance and efficiency of the proposed modified algorithm (MICA) based ORPD approach, MICA is tested on IEEE 30-bus [8], IEEE 57-bus [9] and IEEE 118-bus [9] power systems. The MICA algorithm has been implemented in MATLAB 7.6 and the simulation run on a Pentium IV E5200 PC 2 GB RAM. Iterations for all the test systems are limited to maximum number of 300.

The population size and the number of the imperialists in ICA and MICA are, respectively, set as 70 and 7 for IEEE 30-bus power system; 140 and 12 for IEEE 57-bus power system; 200 and 18 for IEEE 118-bus power system. A good selection can be $\beta = \beta_{imp} = 2$ and $\gamma = \gamma_{imp} = \pi/4$ (Rad). The reactive powers of capacitor banks and the transformer taps are discrete variables with the step size of 0.01 p.u and the penalty factors in (13) are set to 500. The results of ICA and MICA, which follow, are the best solutions over 30 independent trails.

4.1. IEEE 30-bus Test System

In the following section, numerical results extracted from solving ORPD problems by implementation of ICA and MICA in the simulation runs will be presented. In order to evaluate the performance of the ICA and MICA approach based on is tested on standard IEEE 30-bus test system as shown in Figure 6. The IEEE 30-bus system data and initial operating conditions of the system are presented in [8-9]. The minimum and maximum limits for the control variables are given in Table 1.

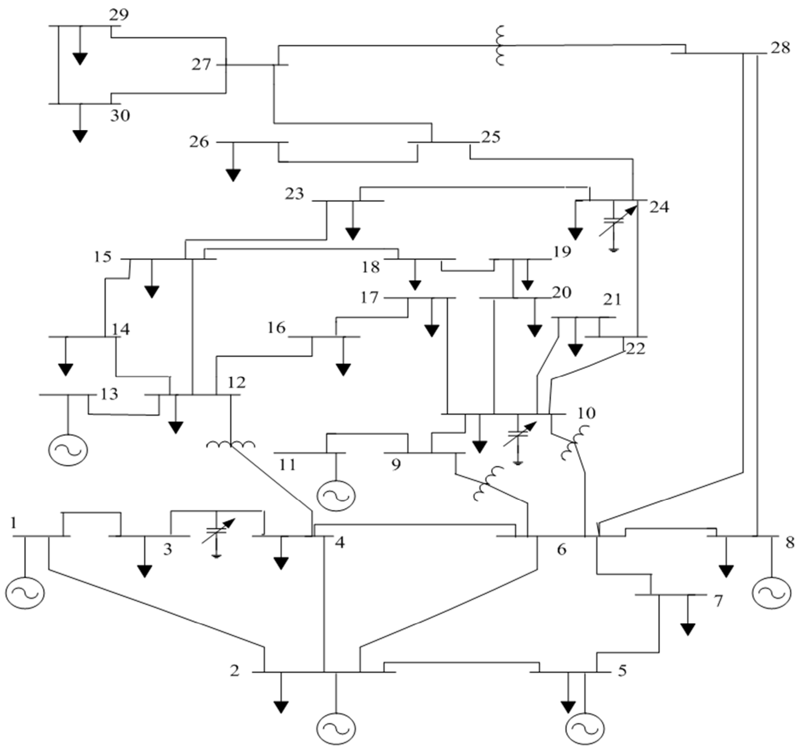

Figure 6. *Single line diagram of IEEE 30-bus test system.*

Table 1. *The limits of the control variables.*

Limits of generation reactive power (p.u.)						
Bus	**1**	**2**	**5**	**8**	**11**	**13**
Q_G^{max}	0.596	0.48	0.6	0.53	0.15	0.155
Q_G^{min}	-0.298	-0.24	-0.3	-0.265	-0.075	-0.078

Limits of voltage and tap-setting (p.u.)					
V_G^{max}	V_G^{min}	V_{PQ}^{max}	V_{PQ}^{min}	T_k^{max}	T_k^{min}
1.1	0.9	1.05	0.95	1.05	0.95

Limits of reactive power sources (p.u.)			
Bus	**3**	**10**	**24**
Q_C^{max}	0.36	0.36	0.36
Q_C^{min}	-0.12	-0.12	-0.12

The IEEE 30-bus test system's components include six generators at the buses 1, 2, 5, 8, 11 and 13 and. In addition, buses 3, 10 and 24 have been chosen as shunt VAR compensation buses [8, 24].

The system loads are given as follows:

P_{load} = 2.834 p.u., Q_{load} = 1.262 p.u.

The initial total generations and power losses are as follows:

$\sum P_G$ = 2.893857 p.u., $\sum Q_G$ = 0.980199 p.u., P_{loss} =0.059879 p.u., Q_{losss} = -0.064327 p.u.

There are three bus voltages outside the limits in the network:

V_{26} = 0.932 p.u., V_{29} = 0.94 p.u., V_{30} =0.928 p.u.

Table 2 illustrates the best ORPD solutions obtained by the methods in the 30 trials. Comparison between Simulation results with various techniques, specifically SGA method, PSO method and multiagent-based particle swarm optimization (MAPSO) approach is given in [8]. The results show that employing MICA results in 0.048595 p.u active power loss which is less than the amount obtained by other algorithms, particularly, 0.048608 p.u active power losses which obtained by the ICA. In the MICA* both penalty factors in (13) equal with 2000 are chosen.

Table 2. *Best control variables settings and active power loss for IEEE 30-bus test system (p.u.).*

Variable	**SGA [8]**	**PSO [8]**	**MAPSO [8]**	**ICA**	**MICA**	**MICA***
V_{G1}	1.0751	1.0725	1.078	1.07863	1.07929	1.07376
V_{G2}	1.0646	1.0633	1.0689	1.06941	1.07016	1.06472
V_{G5}	1.0422	1.041	1.0468	1.04702	1.04802	1.04256
V_{G8}	1.0454	1.041	1.0468	1.04702	1.04831	1.0428
V_{G11}	1.0337	1.0648	1.0728	1.06837	1.03822	1.03716
V_{G13}	1.0548	1.0597	1.0642	1.07118	1.07064	1.06993
T_{6-9}	0.94	1.03	1.04	1.05	1.04	1.05
T_{6-10}	1.04	0.95	0.95	0.96	1.0	0.97
T_{4-12}	1.04	0.99	0.99	1.0	1.0	1.0
T_{28-27}	1.02	0.97	0.97	0.97	0.98	0.97
Q_{C3}	0.0	0.0	0.0	-0.05	-0.06	-0.07
Q_{C10}	0.37	0.16	0.16	0.24	0.36	0.35
Q_{C24}	0.06	0.12	0.12	0.11	0.12	0.12
P_{loss}	0.0498	0.049262	0.048747	0.048608	0.048595	0.049039

When considering convergence characteristics, Fig. 7 shows MICA has faster convergence to a better solution than ICA. Also Figs. 8 - 10 shows the convergence graphs of the optimized control variables by the MICA with respect to the number of generations for the best solution.

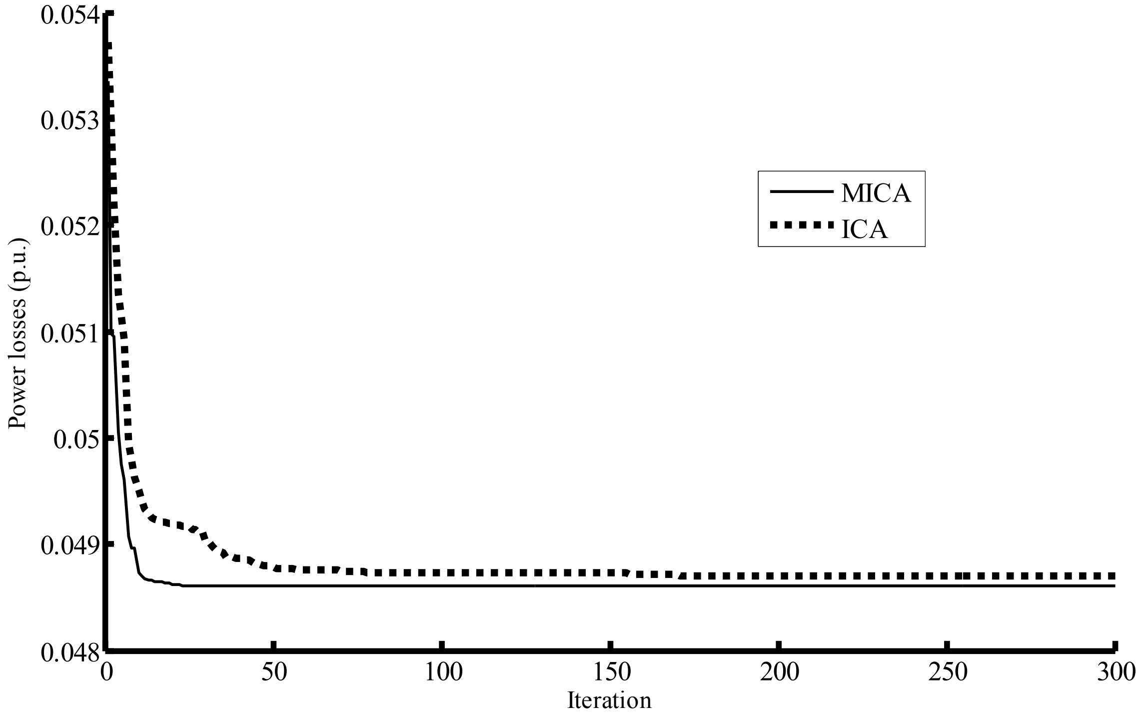

Figure 7. *Performance characteristics for IEEE 30-bus test system.*

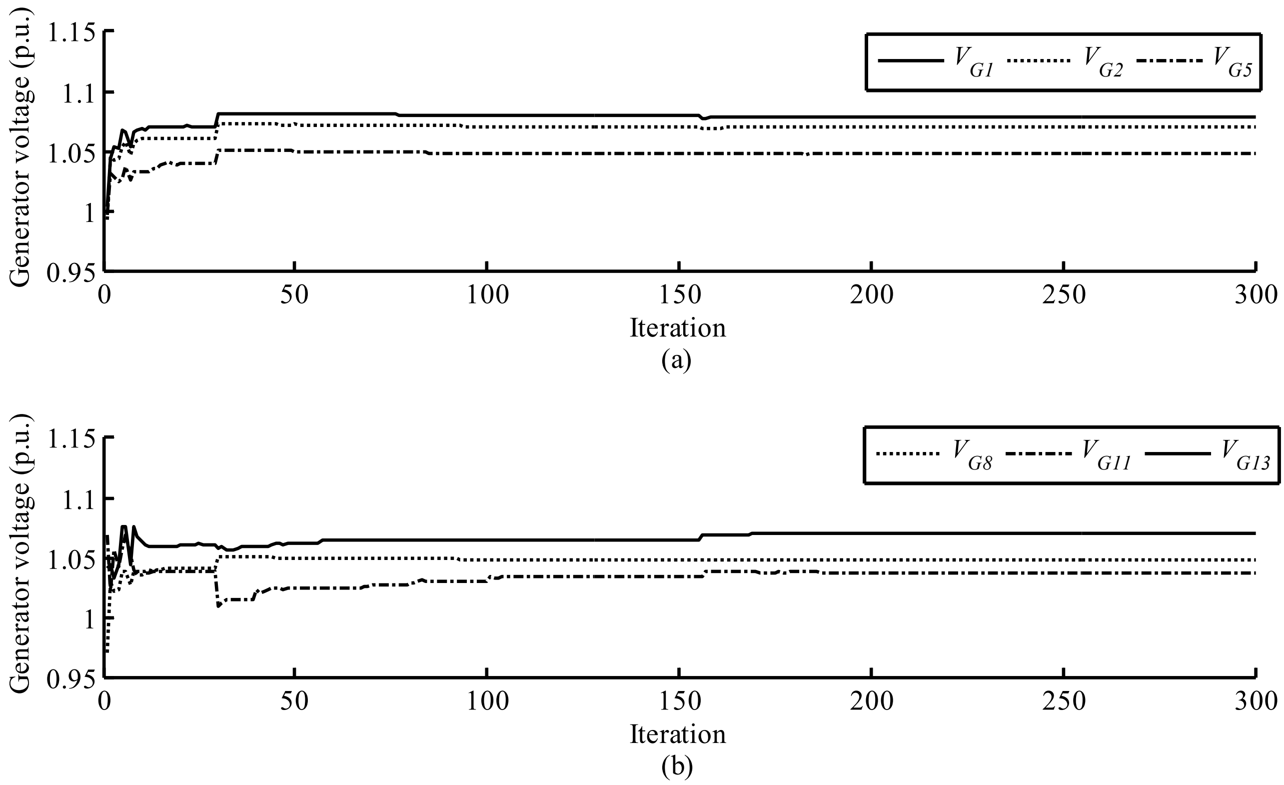

Figure 8. *Convergence of generator voltages V_G for IEEE 30-bus test system.*

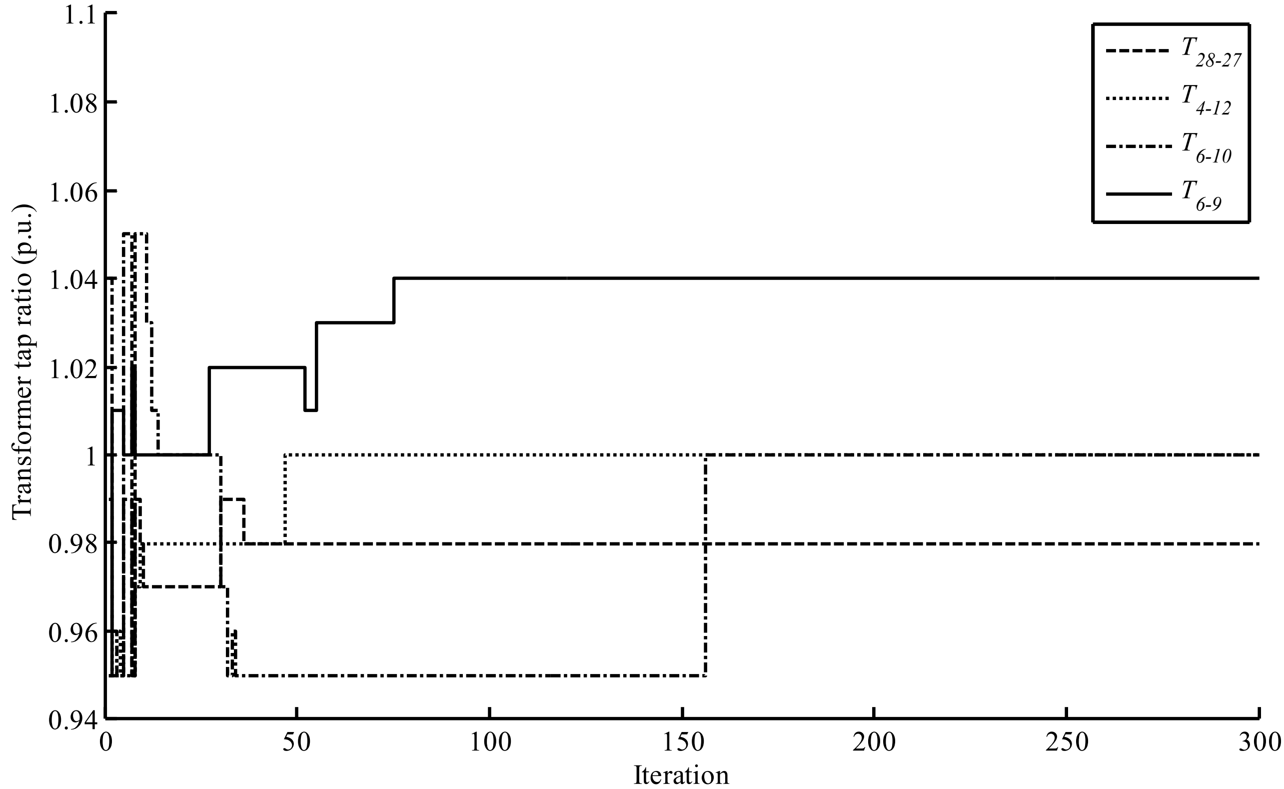

Figure 9. *Convergence of transformer taps T for IEEE 30-bus test system.*

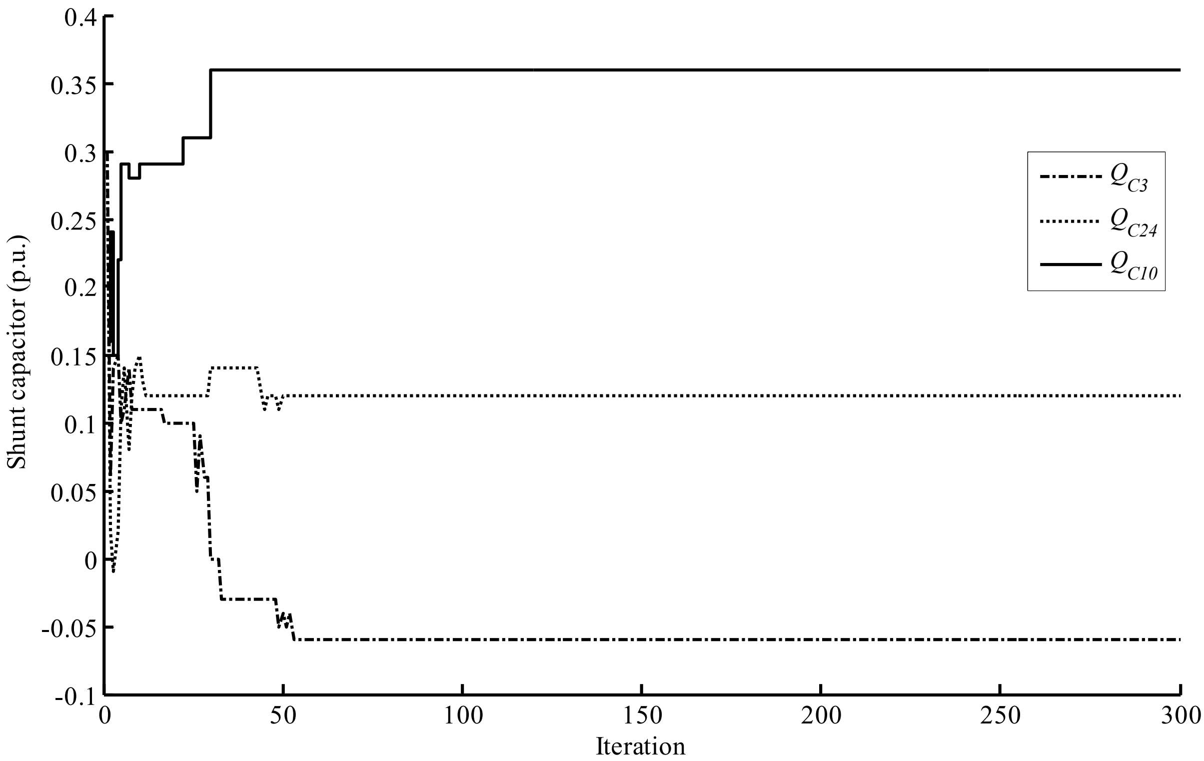

Figure 10. *Convergence of shunt capacitor Q_C for IEEE 30-bus test system.*

The concerned performance indexes including the best active power losses (Best), the worst active power losses (Worst), the standard deviation (Std), the mean active power losses (Mean), and average execution times (sec) for IEEE 30-bus system for 30 independent runs are shown in Table 3. The Table 3 illustrates that an 18.84% decrease in active power loss is achieved by employing the MICA approach, which is the biggest reduction of active power loss compared to that obtained by the other approaches. Judging from the presented results, it turns out that MICA algorithm has better performance and robustness than ICA. Table 3 indicates that MICA algorithm literally has the smallest Best, Mean and Std.

Table 3. *Statistical details for IEEE 30-bus power test system.*

Algorithms	*Best* (p.u.)	*Worst* (p.u.)	*Mean* (p.u.)	*Std.*	%P_{save}	Average times (*sec*)
SGA [5]	0.049408	0.051651	0.050378	-	16.07	-
PSO [5]	0.049239	0.050576	0.04972	-	17.02	-
HSA [5]	0.049059	0.049653	0.04924	-	17.32	-
DMSDE [7]	0.04922	-	0.049242	1.7×10^{-5}	18.3883	143.88
DE [7]	0.049338	-	0.049443	6.6×10^{-5}	18.1918	141.3891
CLPSO [7]	0.049292	-	0.049453	1.14×10^{-4}	18.2689	128.7073
PSO-cf [7]	0.049228	-	0.049378	1.71×10^{-4}	18.3751	144.3448
PSO-w [7]	0.049232	-	0.049516	5.62×10^{-4}	18.3684	143.499
AGA [7]	0.04971	-	0.051067	1.074×10^{-3}	17.5759	147.563
CGA [7]	0.04984	-	0.051429	8.47×10^{-4}	17.3603	165.0224
SGA [8]	0.0498	0.05214	0.05081	-	16.84	156.34
PSO [8]	0.049262	0.050769	0.049973	-	17.62	59.21
MAPSO [8]	0.048747	0.048759	0.048751	-	18.59	41.93
ICA	0.048608	0.050992	0.049367	9.943×10^{-4}	18.82	63.05
MICA	0.048595	0.04861	0.0486	9.7×10^{-6}	18.84	64.62

4.2. IEEE 57-bus Test System

In order to evaluate the effectiveness and performance of proposed method in IEEE 57-bus test system. This system is includes seven generators at the buses 1, 2, 3, 6, 8, 9 and 12, 80 transmission lines and 15 branches under load tap setting transformer branches. The shunt reactive power sources are considered at buses 18, 25 and 53. The bus data, the line and minimum and maximum limits of real power generations are taken from Refs [24-29] and the variable limits are given in Table 4.

Table 4. *The limits of the control variables for IEEE 57-bus test system.*

Limits of generation reactive power (p.u.)							
Bus no.	**1**	**2**	**3**	**6**	**8**	**9**	**12**
$Q_G^{\max}$	1.5	0.5	0.6	0.25	2.0	0.09	1.55
$Q_G^{\min}$	-0.2	-0.17	-0.1	-0.08	-1.4	-0.03	-1.5

Limits of voltage and tap-setting (p.u.)					
$V_G^{\max}$	$V_G^{\min}$	$V_{PQ}^{\max}$	$V_{PQ}^{\min}$	$T_k^{\max}$	$T_k^{\min}$
1.06	0.94	1.06	0.94	1.1	0.9

Limits of reactive power sources (p.u.)			
Bus no.	**18**	**25**	**53**
$Q_C^{\max}$	0.1	0.059	0.063
$Q_C^{\min}$	0.0	0.0	0.0

The system loads (p.u.)			
P_{load}	12.508	Q_{load}	3.364

The initial total generations and power losses (p.u.)			
$\sum P_G$	12.7926	P_{loss}	0.28462
$\sum Q_G$	3.4545	Q_{losss}	−1.2427

Table 5 summarizes the results of the optimal settings as obtained by different methods. In this table we can see that a 14.7752% reduction in power loss is accomplished using the MICA approach, which is more than that obtained by the other approaches. It can be seen that MICA algorithm is more robust than ICA. In order to guarantee a near optimum solution for any random trial, the standard deviation for multiple runs should be very low, which is satisfied better by MICA in comparison with main ICA.

Table 5. *Statistical details for IEEE 57-bus power system.*

Algorithms	*Best* (p.u.)	*Worst* (p.u.)	*Mean* (p.u.)	*Std.*	*%P_{save}*	Average times (*sec*)
SGA [5]	0.2564	0.277651	0.268378	-	-	-
PSO [5]	0.2503	0.270576	0.264742	-	-	-
HSA [5]	0.249059	0.269653	0.25924	-	-	-
DMSDE [7]	0.24266	-	0.24359	1.011×10^{-3}	14.7425	156.11
DE [7]	0.250862	-	0.255509	3.003×10^{-3}	11.8607	152.0557
CLPSO [7]	0.250684	-	0.256381	3.601×10^{-3}	11.9233	104.4016
PSO-cf [7]	0.243449	-	0.263949	2.6513×10^{-2}	14.4653	152.7011
PSO-w [7]	0.2440741	-	0.274727	4.9692×10^{-2}	14.2456	155.4432
AGA [7]	0.244857	-	0.253251	6.635×10^{-3}	13.9706	165.8703
CGA [7]	0.248853	-	0.264826	6.671×10^{-3}	12.5666	176.6708
CGA [12]	0.2524411	0.2750772	0.2629356	6.2951×10^{-3}	11.3059	411.38
AGA [12]	0.2456484	0.2676169	0.2512784	6.0068×10^{-3}	13.6925	449.28
PSO-w [12]	0.2427052	0.2615279	0.2472596	7.0143×10^{-3}	14.7266	408.48
PSO-cf [12]	0.2428022	0.2603275	0.2469805	6.6294×10^{-3}	14.6925	408.19
CLPSO [12]	0.245152	0.2478083	0.2467307	9.3415×10^{-4}	13.8669	426.85
SPSO-07 [12]	0.2443043	0.2545745	0.2475227	2.833×10^{-3}	14.1647	137.35
L-DE [12]	0.2781264	0.4190941	0.3317783	4.7072×10^{-2}	2.2815	431.41
L-SACP-DE [12]	0.2791553	0.3697873	0.310326	3.2232×10^{-2}	1.92	428.98
L-SaDE [12]	0.2426739	0.2439142	0.2431129	4.8156×10^{-4}	14.7376	410.14
SOA [12]	0.2426548	0.2428046	0.2427078	4.2081×10^{-5}	14.7443	391.32
ICA	0.244799	0.2554803	0.2538722	8.0561×10^{-3}	13.9909	44.32
MICA	0.2425668	0.2429263	0.2426758	2.8859×10^{-5}	14.7752	49.28

Table 6 illustrates the best results obtained by ICA and MICA methods. In the 30 trial runs performed, MICA found the best solution. It can be seen that the active power losses obtained by the MICA method is 0.2425668 p.u.. Figure 11 shows the convergence characteristics of real power loss by the number of iterations and as it can obviously be seen, the MICA obtained solution converges to high quality solutions at initial stage. A good optimization results in convergence of all control variables to a steady value. Figure 12 shows the variation of the continuous control variable, V_G, with respect to the number of generations. It is observed that by 120 iterations all generator voltages settle to a steady value. Figs. 13 and 14 show the variation of the discrete control variables – tap position and capacitor bank switching. It can be seen that all discrete control variables also converge to an acceptable state before 120 iterations.

Table 6. *Best control variables settings and active power loss for IEEE 57-bus test system (p.u.).*

Variable	Base case	PSO-w [12]	PSO-cf [12]	L-SaDE [12]	SOA [12]	ICA	MICA
Generator voltage V_G							
V_{G1}	1.04	1.06	1.06	1.06	1.06	1.06	1.06
V_{G2}	1.01	1.0578	1.0586	1.0574	1.058	1.05747	1.05838
V_{G3}	0.985	1.04378	1.0464	1.0438	1.0437	1.04232	1.04556
V_{G6}	0.98	1.0356	1.0415	1.0364	1.0352	1.03504	1.03959
V_{G8}	1.005	1.0546	1.06	1.0537	1.0548	1.05088	1.06
V_{G9}	0.98	1.0369	1.0423	1.0366	1.0369	1.01917	1.02736
V_{G12}	1.015	1.0334	1.0371	1.0323	1.0336	1.02869	1.03498
Transformer tap ratio T							
T_{4-18}	0.97	0.9	0.98	0.94	1.0	0.9	0.98

Variable	Base case	PSO-w [12]	PSO-cf [12]	L-SaDE [12]	SOA [12]	ICA	MICA
T_{4-18}	0.978	1.02	0.98	1.0	0.96	1.01	0.97
T_{21-20}	1.043	1.01	1.01	1.01	1.01	1.0	1.02
T_{24-26}	1.043	1.01	1.01	1.01	1.01	1.01	1.01
T_{7-29}	0.967	0.97	0.98	0.97	0.97	0.97	0.96
T_{34-32}	0.975	0.97	0.97	0.97	0.97	0.98	0.98
T_{11-41}	0.955	0.9	0.9	0.9	0.9	0.9	0.9
T_{15-45}	0.955	0.97	0.97	0.97	0.97	0.96	0.95
T_{14-46}	0.9	0.95	0.96	0.96	0.95	0.94	0.94
T_{10-51}	0.93	0.96	0.97	0.96	0.96	0.95	0.95
T_{13-49}	0.895	0.92	0.93	0.92	0.92	0.92	0.91
T_{11-43}	0.958	0.96	0.97	0.96	0.96	0.95	0.95
T_{40-56}	0.958	1.0	0.99	1.0	1.0	1.0	1.0
T_{39-57}	0.98	0.96	0.96	0.96	0.96	0.96	0.97
T_{9-55}	0.94	0.97	0.98	0.97	0.97	0.96	0.96
Capacitor banks Q_C							
Q_{C18}	0.0	0.05136	0.09984	0.08112	0.09984	0.041	0.1
Q_{C25}	0.0	0.05904	0.05904	0.05808	0.05904	0.059	0.059
Q_{C53}	0.0	0.06288	0.06288	0.06192	0.06288	0.063	0.063
P_{loss}	0.28462	0.2427052	0.2428022	0.2426739	0.2426548	0.244799	0.2425668

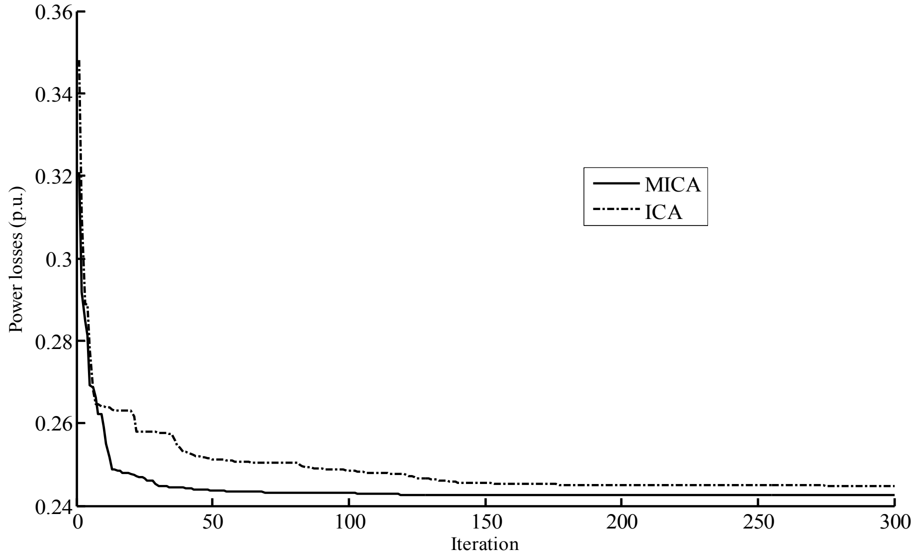

Figure 11. *Performance characteristics for IEEE 57-bus test system.*

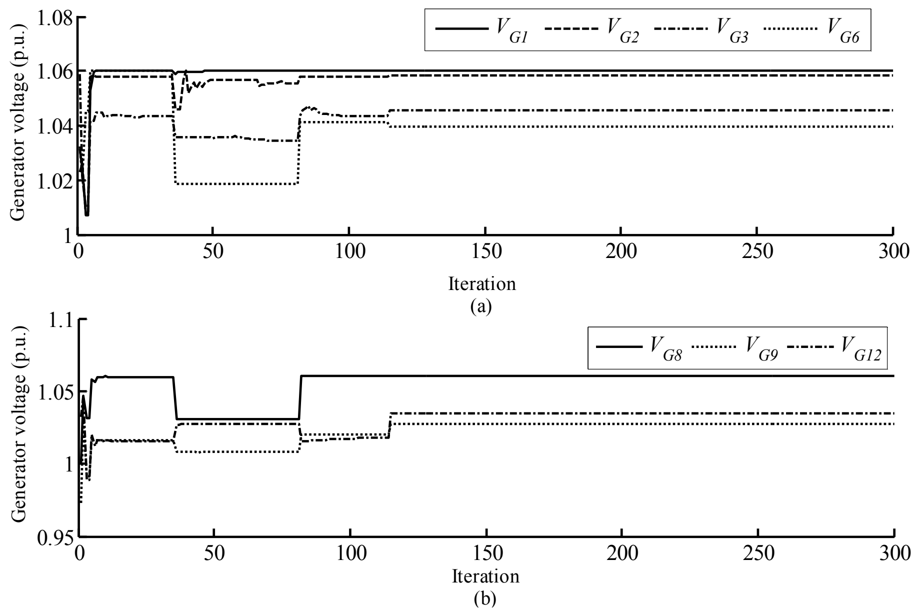

Figure 12. *Convergence of generator voltages V_G for IEEE 57-bus test system.*

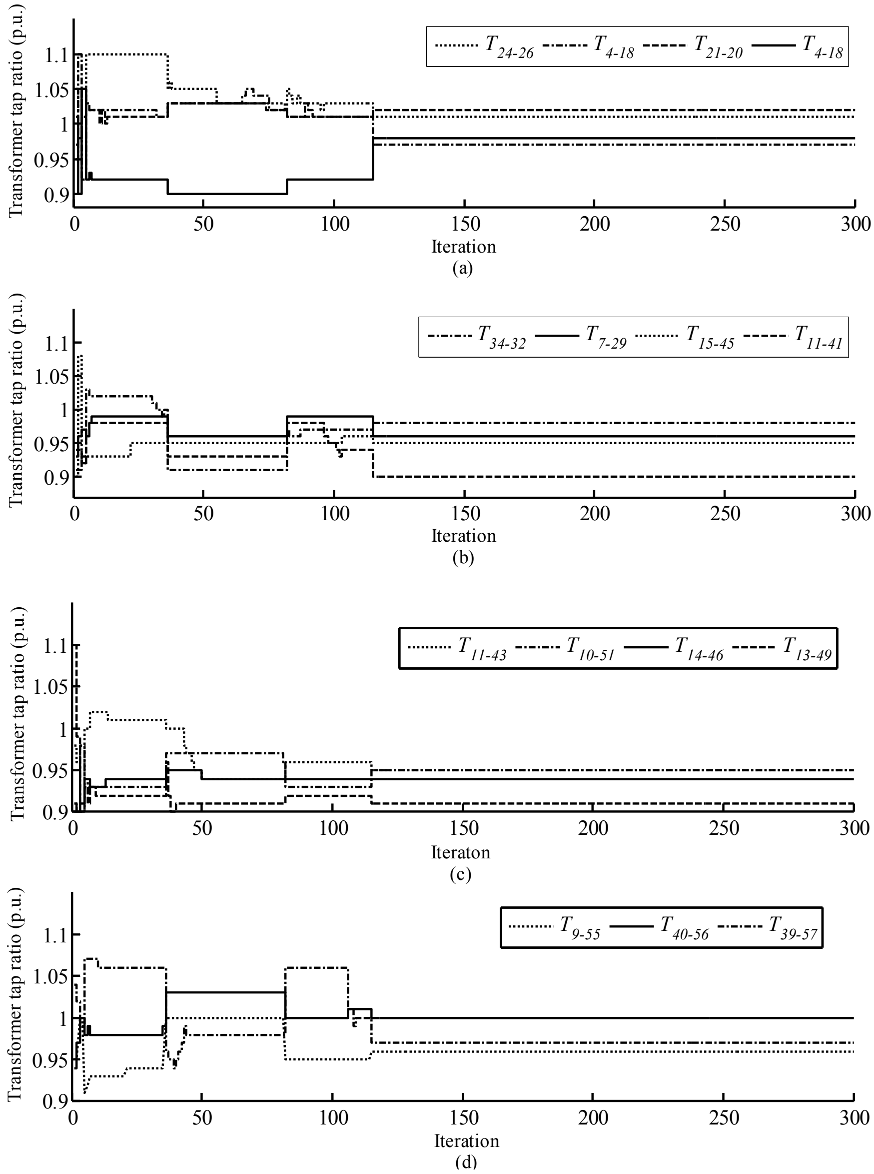

Figure 13. *Convergence of transformer taps T for IEEE 57-bus test system.*

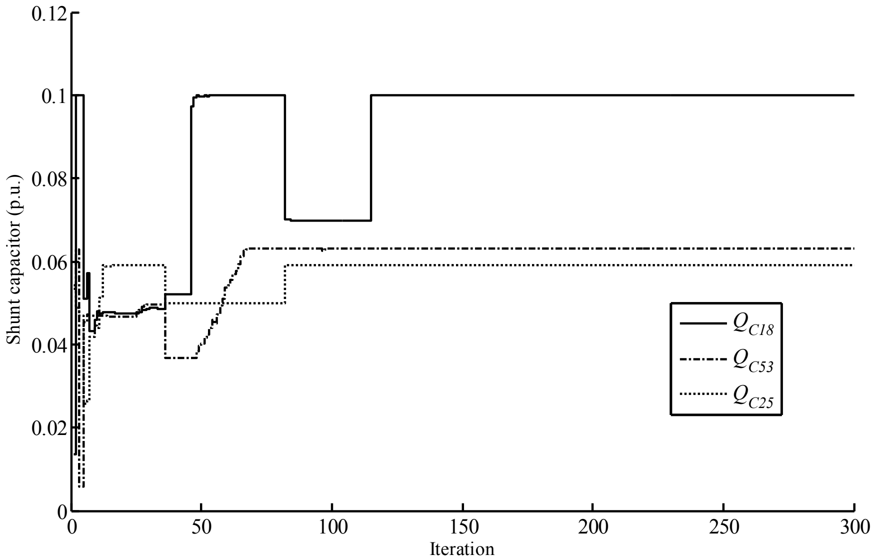

Figure 14. *Convergence of shunt capacitor Q_C for IEEE 57-bus test system.*

4.3. IEEE 118-bus Test System

Further study of effectiveness of the proposed algorithm is done by employing the algorithm on a practical 118-bus system. The IEEE118-bus system data and initial operating conditions of the system are given in [12, 24]. The minimum and maximum limits for the control variables are presented in Table 7.

The IEEE 118-bus test system includes 54 generators, and nine transformers with off-nominal tap ratio, and 14 shunt VAR compensation [12, 24].

Fig. 15 illustrates the convergence characteristics of transmission loss obtained by ICA and MICA. According to this figure, the MICA algorithm has faster convergence to a better solution than the ICA algorithm. The best ORPD solutions in 30 runs for ICA and MICA algorithms and results in the [12] are presented in Table 8. The information of Table 8 demonstrates that a power loss reduction of 14.22% is achieved using the MICA approach, which is biggest reduction of power loss than that obtained by other algorithms. Comparing the results given in Table 8, it is concluded that MICA has the best performance among all rival approaches.

Table 7. *The limits of the control variables for IEEE 118-bus test system.*

Limits of reactive power sources (p.u.)							
Bus	**5**	**34**	**37**	**44**	**45**	**46**	**48**
Q_C^{max}	0.0	0.14	0.0	0.1	0.1	0.1	0.15
Q_C^{min}	-0.4	0.0	-0.25	0.0	0.0	0.0	0.0
Bus	**74**	**79**	**82**	**83**	**105**	**107**	**110**
Q_C^{max}	0.12	0.2	0.2	0.1	0.2	0.06	0.06
Q_C^{min}	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Limits of voltage and tap-setting (p.u.)					
V_G^{max}	V_G^{min}	V_{PQ}^{max}	V_{PQ}^{min}	T_k^{max}	T_k^{min}
1.06	0.94	1.06	0.94	1.1	0.9

The system loads (p.u.)			
P_{load}	42.42	Q_{load}	14.38

The initial total generations and power losses (p.u.)			
$\sum P_G$	43.7536	P_{loss}	1.33357
$\sum Q_G$	8.8192	Q_{losss}	-7.8511

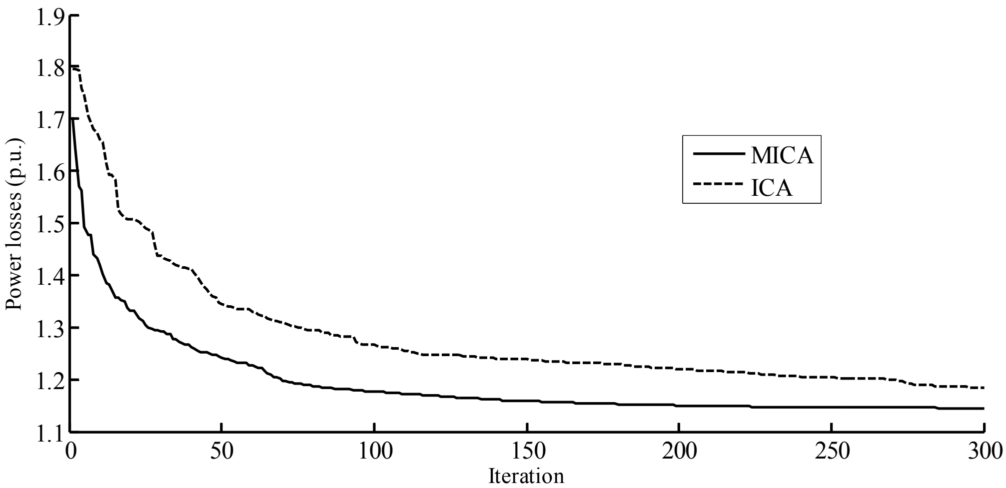

Figure 15. *Convergence of active power losses for IEEE 118-bus test system.*

Table 8. *Statistical details for IEEE 118-bus test system (p.u.).*

Algorithms	*Best*	*Worst*	*Mean*	*Std.*	Average execution times (sec)
ICA	1.1832197	1.2152677	1.1897025	6.4261×10^{-3}	60.14
MICA	1.1439722	1.1556274	1.1488262	1.635×10^{-3}	63.02
CGA [12]	1.3941498	1.4900944	1.4354781	2.6026×10^{-2}	-
AGA [12]	1.2420915	1.3107819	1.2770138	1.836×10^{-2}	-
PSO-w [12]	1.1581511	1.1821422	1.1677096	6.8971×10^{-3}	-
PSO-cf [12]	1.1564182	1.1805839	1.1620185	6.1864×10^{-3}	-
CLPSO [12]	1.2315216	1.2549893	1.2408008	6.4325×10^{-3}	-
SPSO-07 [12]	1.3927522	1.5024378	1.4626565	2.653×10^{-2}	-
L-DE [12]	1.5100861	1.7661426	1.6231526	8.2443×10^{-2}	-
L-SACP-DE [12]	1.4179864	1.7681178	1.606785	1.0643×10^{-1}	-
L-SaDE [12]	1.1690569	1.1886155	1.1759774	5.4041×10^{-3}	-
SOA [12]	1.1495013	1.1634725	1.1567443	3.5908×10^{-3}	-

Table 9 shows the control variable setting and active power losses obtained illustrates the best ORPD solutions found by the methods in 30 runs. Again, the numerical results indicate lower active power loss by MICA when compared to ICA algorithm. The numeric values of power losses obtained by the ICA and MICA methods are 1.1832197 p.u. and 1.1439722 p.u. respectively.

Table 9. *Best control variables settings and active power loss for IEEE 118-bus test system (p.u.).*

Variable	ICA	MICA	Variable	ICA	MICA
V_{G1}	1.00798	1.04138	V_{G89}	1.06	1.06
V_{G4}	1.02957	1.05999	V_{G90}	1.03401	1.04175
V_{G6}	1.01491	1.05238	V_{G91}	1.03739	1.04553
V_{G8}	1.03805	1.06	V_{G92}	1.04699	1.05498
V_{G10}	1.06	1.06	V_{G99}	1.03088	1.04418
V_{G12}	1.01305	1.04848	V_{G100}	1.02566	1.04515
V_{G15}	1.00058	1.04397	V_{G103}	1.01126	1.02709
V_{G18}	0.99874	1.04621	V_{G104}	0.99487	1.013
V_{G19}	1.00357	1.04311	V_{G105}	0.99227	1.00716
V_{G24}	1.03884	1.04979	V_{G107}	0.98004	0.99438
V_{G25}	1.06	1.06	V_{G110}	0.99836	1.00601
V_{G26}	1.06	1.06	V_{G111}	1.00797	1.01421
V_{G27}	1.00929	1.04215	V_{G112}	0.98232	0.9915
V_{G31}	0.99575	1.03762	V_{G113}	0.97864	1.05328
V_{G32}	1.00159	1.04102	V_{G116}	1.04731	1.06
V_{G34}	1.02669	1.05887	T_{5-8}	0.99	1.0
V_{G36}	1.02569	1.05707	T_{25-26}	1.1	1.1
V_{G40}	1.01814	1.0369	T_{17-30}	1.03	0.99
V_{G42}	1.02846	1.03799	T_{37-38}	1.01	0.98
V_{G46}	1.04092	1.04618	T_{59-63}	0.98	0.98
V_{G49}	1.05349	1.05936	T_{61-64}	1.01	1.0
V_{G54}	1.02907	1.03743	T_{65-66}	0.94	0.9
V_{G55}	1.02852	1.0366	T_{68-69}	0.98	0.95
V_{G56}	1.02864	1.03668	T_{80-81}	0.99	0.99
V_{G59}	1.04782	1.05999	Q_{C5}	-0.0732	-0.2991
V_{G61}	1.04059	1.05997	Q_{C34}	0.0477	0.0849
V_{G62}	1.03455	1.05581	Q_{C37}	-0.1268	0.0
V_{G65}	1.05998	1.06	Q_{C44}	0.0	0.0019
V_{G66}	1.06	1.06	Q_{C45}	0.0505	0.0459
V_{G69}	1.06	1.06	Q_{C46}	0.0669	0.0525
V_{G70}	1.03712	1.03489	Q_{C48}	0.0321	0.0093
V_{G72}	1.03898	1.03967	Q_{C74}	0.0	0.0759
V_{G73}	1.04109	1.03327	Q_{C79}	0.0	0.0
V_{G74}	1.02347	1.02471	Q_{C82}	0.0	0.0
V_{G76}	1.01068	1.0217	Q_{C83}	0.026	0.0001
V_{G77}	1.02966	1.04415	Q_{C105}	0.1995	0.0
V_{G80}	1.03889	1.05569	Q_{C107}	0.0235	0.0002
V_{G85}	1.05138	1.06	Q_{C110}	0.0483	0.0277
V_{G87}	1.04167	1.05856			
P_{loss}				1.1832197	1.1439722

5. Conclusions

In this study, an ICA and MICA algorithms has been offered as a novel solution for solving ORPD problem. The proposed ICA and MICA approach has been evaluated on IEEE test power systems and the gathered results are compared with other methods reported. The simulation results confirm the capability of MICA in more efficiently balancing global search ability and convergence speed than other algorithms. So, it is believed that the proposed MICA approach is able of swift and effective solving reactive power dispatch problem as one of the candidates.

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