Iteration PSO with time varying acceleration coefficients for solving non-convex economic dispatch problems

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A R T I C L E   I N F O

Article history:
Received 29 November 2011
Received in revised form 9 April 2012
Accepted 20 April 2012

Keywords:
Economic dispatch (ED)
Particle swarm optimization (PSO)
Prohibited operation zone (POZ)
Iteration particle swarm optimization with time varying acceleration coefficients (IPSO-TVAC)
Optimization

A B S T R A C T

This paper presents a novel heuristic algorithm for solving economic dispatch (ED) problems, by employing iteration particle swarm optimization with time varying acceleration coefficients (IPSO-TVAC) method. Due to the effect of valve-points and prohibited operation zones (POZs) in the generating units’ cost functions, ED problem is a non-linear and non-convex optimization problem. The problem even may be more complicated if transmission losses are taken into account. The effectiveness of the proposed method is examined and validated by carrying out extensive tests on three different test systems. Valve-point effects, POZs, ramp-rate constraints and transmission losses are modeled. Numerical results show that the IPSO-TVAC method has a good convergence property. Furthermore, the generation costs of the IPSO-TVAC method are lower than other optimization algorithms reported in recent literature.

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1. Introduction

Economic dispatch (ED) problem is one of the important problems in the operation of power systems. The purpose of ED problem is to determine economical combination of generators’ production to satisfy system load and constraints. ED problem is a non-convex and non-linear optimization problem. Due to the high economic benefits of better solutions, many researches have tried to present a proper solution method over the years. A lot of optimization methods including classical and stochastic search approaches have been applied to solve ED problem. Applying conventional methods is always accompanied with some restrictions. The most popular conventional approach to solve ED problem is lambda-iteration method [1] which needs a continuous and monotonically increasing cost function. However, the actual cost function is not continuous due to prohibited operation zones (POZs). In the quadratic programming algorithm [2] and non-linear programming algorithm [3], the objective function should be continuous and differentiable. But, the cost function considering valve-point effects is not differentiable. Using Maclaurin series approximation [4,5] leads to non-optimal solution with great economic loss, but with the advantage of low solution time.

Also, many heuristic search methods were used to solve the ED problem more efficiently. Genetic algorithm (GA) [6,7], improved GA [8,9], atavistic GA [10], hybrid GA [11] and self adaptive real-coded GA [12] have been proposed to solve different types of ED problem.

Hybrid particle swarm optimization (HPSO) has been presented in [13] to solve ED problem considering valve-point effects. A hybrid multi-agent PSO algorithm proposed by [14] to solve ED problem with valve-point constrained. Also, other modifications of PSO method like parallel PSO [15], quantum-behaved PSO [16], fuzzy adaptive hybrid PSO algorithm [17], fuzzy adaptive modified PSO algorithm [18] and anti-predatory PSO [19] have been applied to solve ED problem. Differential evolution (DE) is used in [20] to solve ED problem. Application of modified DE and hybrid DE in ED presented in [21] and [22], respectively. A review of optimal dynamic economic dispatch solution methods is provided in [23]. Application of honey bee mating algorithm (HBMO) in solution of non-convex ED problems is studied in [24].

PSO method has the flexibility to enhance both global and local exploration abilities [25]. It is observed that original PSO suffers from premature convergence, especially for problems with multiple local optima [26,27]. Two stochastic acceleration components (known as cognitive component and social component) guide the particles in the original PSO method to the optimum point. The cognitive component controls local search ability, and
social component wander the particles around the search space and controls the global search ability. Tuning relative values of cognitive and social components plays important role in solution quality of the PSO. Many researches have been done to find the best combination of these components [25,28]. In this paper a novel iteration PSO with time varying acceleration coefficients (IPSO-TVAC) approach is proposed to solve non-convex and non-continuous ED problem. TVAC structure leads to a proper balance between the cognitive and social components in the initial phase and latter iterations [26]. Iteration PSO (IPSO) enriches the solution quality and avoids being trapped into local optimum [29]. The proposed method inherits advantages of both TVAC-PSO and IPSO methods, simultaneously.

The remainder of the paper is organized as follows: Section 2 gives the mathematical formulation of the ED problem considering POZs, ramp-rate limits, valve-point effects and transmission losses. Section 3 describes the proposed IPSO-TVAC algorithm. Implementation of the proposed IPSO-TVAC algorithm to solve ED problem is provided in Section 4. Section 5 presents three application cases and compares corresponding results with most recent applied methods. Conclusions are finally given in Section 6.

2. Formulation of economic dispatch problem

The objective of ED problem is minimizing the total power production cost. The objective function is mathematically stated as follows:

$$\min \sum_{i=1}^{N} F_i(P_i)$$

where \( F_i \) is the \( i \)th unit production cost, \( N \) is the number of power generation units and \( P_i \) is the power output of \( i \)th unit. The production cost of \( i \)th generation unit is defined as:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i$$

Quadratic cost function (2) is used in the most of the literature. In a practical generation units, steam valve admission effects lead to the ripple in the production cost. In order to model this phenomenon more accurately, a sinusoidal term is added to the quadratic cost function. Considering valve-point effects made the problem non-convex and non-differentiable. The unit cost function considering valve-point effects is represented as follows:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i + \varepsilon_i \sin \left( f_i \left( P_i^{\text{min}} - P_i \right) \right)$$

where \( a_i \), \( b_i \), \( c_i \), \( \varepsilon_i \), and \( f_i \) are coefficients of the cost function of unit \( i \).

The power production cost should be minimized subject to following constraints:

- Capacity limits of thermal units
  $$P_i^{\text{min}} \leq P_i \leq P_i^{\text{max}} \quad i = 1, \ldots, N$$

where \( P_i^{\text{min}} \) and \( P_i^{\text{max}} \) are the minimum and the maximum power outputs of \( i \)th unit.

- Ramp-rate limit constraints
  $$P_i - P_i^0 \leq UR_i \quad i = 1, \ldots, N$$
  $$P_i^0 - P_i \leq UR_i \quad i = 1, \ldots, N$$

where \( P_i^0 \) is the previous output power of unit \( i \); \( UR_i \) and \( DR_i \) are up ramp limit and down ramp limit of the \( i \)th generator (MW/h), respectively. By considering ramp-rate limits of generator, generator capacity limit (4) is rewritten as follows:

$$\max \left( P_i^{\text{min}}, P_i - DR_i \right) \leq P_i \leq \min \left( P_i^{\text{max}}, P_i^0 + UR_i \right) \quad i = 1, \ldots, N$$

where \( AZ_i \) is the allowed operation zones of unit \( i \) which is defined in following.

- Prohibited operation zones (POZs)
  Generating units may have certain restricted operation zone due to limitations of machine components or instability concerns. The allowed operation zones of \( i \)th generation unit is defined as:

$$AZ_i = \left\{ \begin{array}{ll}
P_i^{\text{min}} & \leq P_i \leq P_i^{\text{min}} \\
\frac{P_i^{\text{max}m} - P_i^{\text{min}m}}{m - 1} & m = 2, 3, \ldots, M_i, i = 1, \ldots, N
\end{array} \right.$$

where \( P_i^{\text{min}m} \) and \( P_i^{\text{max}m} \) are the lower and upper limits of \( m \)th POZ of unit \( i \), respectively. \( M_i \) is the number of allowed operation zones of unit \( i \).

- Power balance
  Power balance considering system losses is written as:

$$\sum_{i=1}^{N} P_i = P_D + P_{\text{loss}}$$

where \( P_D \) and \( P_{\text{loss}} \) are system total load demand and transmission losses, respectively. Transmission system loss is a function of units’ power production and can be calculated using the \( B \) - matrix coefficients (Kron’s loss formula) as stated in following:

$$P_{\text{loss}} = \sum_{i=1}^{N} \sum_{j=1}^{N} B_{ij} P_i P_j$$

3. Iteration PSO with time varying acceleration coefficients method

3.1. Classic particle swarm optimization

PSO is one of the algorithms based on swarm intelligence and introduced by Kennedy and Eberhart in 1995 for the first time [30]. PSO models the swarm behaviors such as birds flocking and fishes schooling. PSO has been applied to solve many real-world problems after inception in 1995 and many researches have been carried out to improve its performance in recent years. PSO starts with a fixed number of randomly initialized particles (potential solutions) in an \( N \)-dimensional solution space. A particle \( i \) at iteration \( k \) has a position vector \( X_i^k = (x_{i1}^k, x_{i2}^k, \ldots, x_{in}^k) \) and a velocity vector \( V_i^k = (v_{i1}^k, v_{i2}^k, \ldots, v_{in}^k) \). The best solution achieved by \( i \)th particle until the current iteration \( k \) is defined as \( P_{\text{best}i}^k = (P_{\text{best}i1}^k, P_{\text{best}i2}^k, \ldots, P_{\text{bestin}}^k) \). The best \( P_{\text{best}i} \), among the entire particles is denoted as global best (\( g_{\text{best}} \)). A particle approaches to better position (better solution) with randomly weighted acceleration using its current velocity, previous experience, and the experience of other particles. Then, the velocity and position of \( n \)th particle will be updated using following equations:

$$v_{im}^{k+1} = \omega \times v_{im}^k + C_1 \times r_1^k \times \left( P_{\text{best}i}^k - x_{im}^k \right) + C_2 \times r_2^k \times \left( g_{\text{best}} - x_{im}^k \right)$$

$$x_{im}^{k+1} = x_{im}^k + C \times v_{im}^{k+1}$$
where \( \omega \) is inertia weight, \( r_1^k \) and \( r_2^k \) are two independently generated random numbers between 0 and 1. \( C_1 \) and \( C_2 \) are cognitive and social component acceleration coefficients, respectively. \( C \) is the constriction factor and can be calculated using (13) [31]. The inertia weight \( (\omega) \) is linearly decreasing as the iterations proceed and can be calculated using (14) [32].

\[
C = \frac{2}{2 - \phi - \sqrt{\phi^2 - 4\phi}} \tag{13}
\]

\[
\omega = \omega_{\text{max}} - \frac{\omega_{\text{max}} - \omega_{\text{min}}}{K} \times k \tag{14}
\]

where \( \phi \) equals to \( C_1 + C_2 \geq 4 \). \( \omega_{\text{max}} \) and \( \omega_{\text{min}} \) are initial and final weights. \( K \) is the maximum iteration number.

### 3.2. IPSO-TVAC

It has been observed by most researchers that in PSO, problem-based tuning of parameters is a key factor to find the optimum solution accurately and efficiently [33]. With this in view, a novel PSO strategy in which time varying acceleration coefficients are employed is being employed in this paper to solve the ED problem. In order to enrich the searching behavior, solution quality and to avoid being trapped into local optimum, a new index named as iteration best is added to (11). This method is known as Iteration PSO (IPSO) [29]. The velocity updating formula considering iteration best will be as follows:

\[
v_{im}^{k+1} = \omega \times v_{im}^k + C_1 \times r_1^k \times (p_{\text{best}_i}^k - x_{im}^k) + C_2 \times r_2^k \times (p_{\text{best}_j}^k - x_{im}^k)
\times \left( \frac{K}{p_{\text{best}_i}^k - x_{im}} + C_3 \times r_3^k \times \frac{\omega_{\text{best}} - x_{im}}{p_{\text{best}_j}^k - x_{im}} \right) \tag{15}
\]

where \( p_{\text{best}_i}^k \) is the best solution that has been obtained by any particle in iteration \( k \) and \( C_2 \) is the weighting factor of the stochastic acceleration. \( r_2^k \) is a random number in the interval of \([0, 1]\).

In the classic PSO algorithm, the acceleration coefficients are set to a fixed value (conventionally fixed to 2.0). Relatively high value of the social component \( C_2 \) in comparison with cognitive component \( C_1 \) leads particles to a local optimum prematurely and relatively high values of cognitive components results to wander the particles around the search space [30,28]. To improve the solution quality, these coefficients are updated in a way that the cognitive component is reduced and social component is increased as iterations proceed. The acceleration coefficients are updated using the following equations:

\[
C_1 = C_{1i} + C_{1f} - C_{1i} \times k \tag{16}
\]

\[
C_2 = C_{2i} + C_{2f} - C_{2i} \times k \tag{17}
\]

where \( C_{1i}, C_{1f}, C_{2i} \) and \( C_{2f} \) are initial and final values of cognitive and social components acceleration factors, respectively.

At initial iterations, the particles are far away from the optimum point, and hence adding a new term (i.e. iteration best) to the velocity formula, will help the algorithm to converge to a better solutions, due to this fact that \( p_{\text{best}_i}^k \) is the best solution obtained in the current iteration. Due to this, in this paper, \( C_3 \) is updated as follows:

\[
C_3 = C_1 \times (1 - \exp(-C_2 \times k)) \tag{18}
\]

To explain (18), consider a numerical example as follows. By assuming \( C_{1i} = 2.5 \), \( C_{1f} = 0.5 \), \( C_{2i} = 0.5 \) and \( C_{2f} = 2.5 \), and \( K = 100 \). The coefficients \( C_1, C_2 \) and \( C_3 \) are depicted in Fig. 1.

As it is evidentlly observed from Fig. 1, when iterations proceed, \( C_1/C_2 \) decreases/increases monotonically. But, \( C_1 \) is increased swiftly at the initial iterations, and then, decreases slowly. This feature helps us to use benefits of \( i_{\text{best}} \) at the initial iterations, where the algorithm aims to find proper direction for search. But, when the iterations proceed, the algorithm reaches to the near of the solution, and hence due to the high value of the social component \( C_2 \) in comparison with cognitive component \( C_1 \) leads particles to the optimum solution.

### 4. Implementation of IPSO-TVAC for ED problem

The flowchart of proposed IPSO-TVAC algorithm is depicted in Fig. 2. The steps of solution of non-convex ED problem using IPSO-TVAC algorithm are as follows:

**Step 1. Initialization of the particles:** Real power outputs are the decision variables in the ED problem and used to form the swarm. The real power outputs of generators are represented with the positions of particles. Each particle shows a feasible solution of ED problem. Then they should satisfy the problem constraints. The ith particle is represented as \( P_i = [P_{ij}, P_{ij}, \ldots, P_{in}] \). Initial position of the jth unit (generation of jth unit in this paper) of particle i is generated randomly as follows:

\[
P_{ij} = P_{ij}^{\text{min}} + r \times (P_{ij}^{\text{max}} - P_{ij}^{\text{min}}) \tag{19}
\]

where r is a random number between 0 and 1.

**Step 2. Fitness evaluation:** Fitness function is defined to evaluate the quality of each particle. The fitness function should be minimized while satisfying the constraints. The most popular way of constraint handling is adding penalties for violated constraints. Hence, the fitness function \( F_t \) is defined as the summation of the non-convex cost function (3) and penalties as follows:

\[
F_t(P_i) = \sum_{j=1}^{N} F_j(P_{ij}) + \beta_{1} \left[ \sum_{j=1}^{N} (P_{ij} - P_{ij}^0 - P_{ij}^\text{loss}) \right]^2
+ \beta_{2} \sum_{j=1}^{N} \left| P_{ij} - P_{ij}^{\text{min}} \right| + \beta_{3} \sum_{j=1}^{N} \left| P_{ij} - P_{ij}^{\text{pen}} \right| \tag{20}
\]

where \( \beta_{1}, \beta_{2}, \) and \( \beta_{3} \) are penalty parameters and assumed to be 5000 in this paper. The first penalty term handles the load and generation balance constraint, second penalty term handles power generation limits and ramp-rate constraints, and the third penalty term handles the POZ constraints. \( P_{ij}^{\text{pen}} \) and \( P_{ij}^{\text{pen}} \) are constraint violation indicator and defined as follows:
Step 3. Initialization of $P_{best}$ and $g_{best}$: The fitness values calculated using (20) for the initial particles of the swarm are set as the initial $P_{best}$ values of the particles. The best value among all the $P_{best}$ values is identified as $g_{best}$.

Step 4. Velocity update: in the IPSO-TVAC, the velocity of each particle is updated using the following equation:

$$v_{k+1} = \omega \cdot v_k + \left( C_{1i} + C_{2i} - C_{1i} \right) \cdot r_1 \cdot (P_{best} - x_k) + \left( C_{2i} - C_{1i} \right) \cdot r_2 \cdot (g_{best} - x_k)$$

$$v_{k+1} = \frac{p_{max} - p_{min}}{R} \cdot r_3 \cdot \left( p_{best} - x_k \right) + \frac{p_{max} - p_{min}}{R} \cdot r_4 \cdot \left( g_{best} - x_k \right)$$

Step 5. Velocity evaluation: The obtained new velocities should be in the range defined in (24).

$$-\frac{p_{max} - p_{min}}{R} \leq v_k \leq \frac{p_{max} - p_{min}}{R}$$

Step 7. Check stopping criterion: The stopping criterion is selected to be the maximum number of iterations. The algorithm will be terminated if the maximum iteration number reached, otherwise it is continued from Step 4.

5. Case studies and numerical results

In this section, the proposed IPSO-TVAC algorithm is applied on various standard test systems with different number of generating units (6, 13, and 40-units) to solve the constrained ED problem and the results are compared with those obtained by other algorithms. The parameter selection procedure is discussed in Section 5.1.

5.1. IPSO-TVAC parameter selection

The selection of proper values for algorithm control parameters plays a significant role in solution’s quality. In order to obtain the best population size for different test cases, minimum cost was calculated for different set of population sizes and depicted in Figs. 3a, 4a, 5a, and 6a. It can be observed from these figures that proper population size for Case I is 40, for Case II is 100 and for Case III is 350. Similar approach is implemented to evaluate the convergence speed of the algorithm in finding the best solution. It should be noted that the convergence test is performed using the aforementioned size of population for each case. It is evidently observed from Figs. 3b, 4b, 5b, and 6b that the maximum number of iterations needed for cases I, II and III are 60, 150 and 600, respectively. The effect of the initial and final values of cognitive and social components acceleration factors on solution performance are studied by varying their values. Table 8 shows the best, average and worst solutions obtained from 100 runs for test case III. Results of the proposed method are in bold. It should be noted that in Table 8 the population size and maximum iteration number are fixed to 350 and 600, respectively. In all case studies, $x_{\text{max}}, x_{\text{min}}$ and $R$ are fixed to 0.9, 0.4, and 5, respectively. Penalty factors are set to 5000.

5.2. Test system I

The first test system is a 6-unit system. System total demand is 1263 MW. The data for this system is provided in [34]. In this test system, the transmission losses, POZs and ramp-rate constraints are considered.

Table 1 shows the obtained results for this system. Results of the proposed method are in bold. Minimum cost, Mean cost and maximum cost over the 100 trial runs are compared with the results of multiple Tabu search (MTS) algorithm [34], new PSO with local random search (NPSO-LRS) [33], bacterial foraging optimization (BFO)
Table 2
Comparison of simulation results for 13 units (load = 1800 MW).

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Minimum cost

Average cost

Maximum cost

NA denotes that the value was not available in the literature.

Table 3
Comparison of relative frequency of convergence for 13-unit test case (load = 1800 MW).

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<th>18,050–18,100</th>
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NA denotes that the value was not available in the literature.

5.3. Test system II
This test system is a 13-generator system with valve-point loading effect. The coefficients of fuel cost functions are provided in [38]. The ED problem is solved for two different load levels ($P_{D1} = 1800$ MW and $P_{D2} = 2500$ MW). This test system has many local optima and no global solution has been reported yet. The obtained result for load demand equal to 1800 MW is presented in...
Table 2. Results of the proposed method are in bold. The results are compared in terms of minimum cost, mean cost, and maximum cost over 100 runs with the results of hybrid multi-agent based PSO (HMAPSO) [14], modified differential evolution algorithm (MDE) [21], variable DE with the fuzzy adaptive PSO (FAPSO-VDE) [13], Maclaurin series-based Lagrangian (MSL) [5], pattern search method (PSM) [39], hybrid genetic algorithm (HGA) [40], quantum-inspired PSO (QPSO) [25], PSO [14] and PSO with time varying acceleration coefficients (PSO-TVAC) [28]. The results of the aforementioned methods that presented in Table 2, have been directly quoted from their respective references. Convergence characteristic of the IPSO-TVAC for 13-generator test case with load demand of 1800 MW is depicted in Fig. 4. The relative frequency of convergence over the 100 trial runs are compared with the convergence frequency of modified versions of evolutionary programming algorithm (CEP, FEP, MFEP, and IFEP), elite GA (EGA), fuzzy immune algorithm (FIA), and improved PSO (SPSO) [25] in Table 3. It can be observed that the solution obtained from the proposed method is better than other techniques reported in the literature.

Also, simulation is done for power demand of 2520 MW. The obtained results are presented in Table 4 and compared with the results of hybrid genetic algorithm (HGA) [40], differential evolution (DE) [20], FAPSO-VDE [13] and improved coordinated aggregation-based PSO (ICA-PSO) algorithm [41]. The minimum, average and maximum costs presented in Table 4 are obtained over the 100 trial runs. Results of the proposed method are in bold. It can be observed from Table 4 that the proposed technique provided significantly better results in comparison with the previously developed techniques. The convergence behavior of the proposed IPSO-TVAC for power demand of 2520 MW is depicted in Fig. 5.

Table 5
Comparison of simulation results for 40-unit test system (load = 10,500 MW).

<table>
<thead>
<tr>
<th></th>
<th></th>
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<th></th>
<th></th>
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<tbody>
<tr>
<td>1</td>
<td>110.7998</td>
<td>110.8018</td>
<td>111.2</td>
<td>111.136</td>
<td>111.0465</td>
<td>111.3793</td>
<td>110.8</td>
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<td>2</td>
<td>110.7998</td>
<td>110.80003</td>
<td>111.7</td>
<td>111.135</td>
<td>111.5915</td>
<td>110.9278</td>
<td>110.8</td>
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<tr>
<td>3</td>
<td>97.3999</td>
<td>97.39999</td>
<td>97.4</td>
<td>120</td>
<td>97.60077</td>
<td>97.4104</td>
<td>97.4</td>
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<tr>
<td>4</td>
<td>179.7331</td>
<td>179.7331</td>
<td>179.73</td>
<td>177.221</td>
<td>179.7095</td>
<td>179.7331</td>
<td>179.733</td>
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<tr>
<td>5</td>
<td>87.9576</td>
<td>87.9576</td>
<td>90.14</td>
<td>88.699</td>
<td>88.30655</td>
<td>89.2188</td>
<td>87.8</td>
</tr>
<tr>
<td>6</td>
<td>140</td>
<td>140</td>
<td>140</td>
<td>139.9922</td>
<td>140</td>
<td>140</td>
<td>140</td>
</tr>
<tr>
<td>7</td>
<td>259.5997</td>
<td>259.59965</td>
<td>259.6</td>
<td>260.157</td>
<td>259.6313</td>
<td>259.6198</td>
<td>259.6</td>
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<tr>
<td>8</td>
<td>284.5997</td>
<td>284.59966</td>
<td>284.8</td>
<td>284.723</td>
<td>284.7366</td>
<td>284.657</td>
<td>284.6</td>
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<tr>
<td>9</td>
<td>284.5997</td>
<td>284.59965</td>
<td>284.84</td>
<td>283.523</td>
<td>283.7801</td>
<td>283.6588</td>
<td>284.6</td>
</tr>
</tbody>
</table>

| TG   | 10500.0005  | 10498.82519    | 10.500    | 10499.997    | 10499.98069 | 10.500  | 10.500  |
| TCb  | 121420.9    | 121412.56      | 121448.21| 121586.9     | 121426.953 | 121418.27 | 121412.545 |

a Total generation.
b Total cost.

Table 6
Comparison of solution quality for test case III.

<table>
<thead>
<tr>
<th>Method</th>
<th>Maximum cost ($/h)</th>
<th>Average cost ($/h)</th>
<th>Minimum cost ($/h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DE/BBO [43]</td>
<td>121420.8963</td>
<td>121420.8952</td>
<td>121420.8948</td>
</tr>
<tr>
<td>FAPSO-VDE [13]</td>
<td>121421.7800</td>
<td>121421.6100</td>
<td>121421.5800</td>
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<tr>
<td>QPSO [25]</td>
<td>NA</td>
<td>NA</td>
<td>121420.8948</td>
</tr>
<tr>
<td>HMAPSO [14]</td>
<td>121586.9000</td>
<td>121586.9000</td>
<td>121586.9000</td>
</tr>
<tr>
<td>BBO [44]</td>
<td>NA</td>
<td>NA</td>
<td>121426.9530</td>
</tr>
<tr>
<td>HGA [40]</td>
<td>NA</td>
<td>NA</td>
<td>121418.2700</td>
</tr>
<tr>
<td>Proposed</td>
<td>121423.8000</td>
<td>121419.3000</td>
<td>121412.5450</td>
</tr>
</tbody>
</table>

NA: not available.
The relative frequency of convergence are compared with the convergence frequency of modified versions of evolutionary programming algorithm (CEP, FEP, MFEP, and IFEP), Elite GA (EGA), fuzzy immune algorithm (FIA), and improved PSO (SPSO) [25] in Table 7.

<table>
<thead>
<tr>
<th>Method</th>
<th>121,000–121,500</th>
<th>121,500–122,000</th>
<th>122,000–122,500</th>
<th>122,500–123,000</th>
<th>123,500–124,000</th>
<th>124,000–124,500</th>
<th>124,500–125,000</th>
<th>&gt;125,000</th>
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<tr>
<td>CEP [25]</td>
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<td>–</td>
<td>–</td>
<td>2</td>
<td>4</td>
<td>42</td>
<td>22</td>
<td>30</td>
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<tr>
<td>FEP [25]</td>
<td>–</td>
<td>–</td>
<td>6</td>
<td>24</td>
<td>26</td>
<td>20</td>
<td>10</td>
<td>14</td>
</tr>
<tr>
<td>MFEP [25]</td>
<td>–</td>
<td>–</td>
<td>10</td>
<td>50</td>
<td>26</td>
<td>14</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>IEPF [25]</td>
<td>–</td>
<td>–</td>
<td>22</td>
<td>50</td>
<td>18</td>
<td>4</td>
<td>4</td>
<td>2</td>
</tr>
<tr>
<td>EGA [25]</td>
<td>10</td>
<td>31</td>
<td>41</td>
<td>16</td>
<td>2</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>SPSO [25]</td>
<td>4</td>
<td>55</td>
<td>34</td>
<td>5</td>
<td>1</td>
<td>1</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>QPSO [25]</td>
<td>4</td>
<td>40</td>
<td>41</td>
<td>14</td>
<td>1</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Proposed</td>
<td>100</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
</tbody>
</table>

5.4. Test system III

This test case consists of 40 generating units with valve-point effects [42]. Total load demand of the system is 10,500 MW. The obtained results by the proposed IPSO-TVAC algorithm are presented in Table 5. Results of the proposed method are in bold. The obtained results are compared with the results of hybrid DE with biogeography-based optimization (DE/BBO) algorithm [43], variable DE with the fuzzy adaptive PSO (FAPSO-VDE) [13], quantum-inspired PSO (QPSO) [25], multi-agent based hybrid PSO technique (HMPSO) [14], biogeography-based optimization (BBO) algorithm [44] and hybrid GA (HGA) [40]. By studying the results of Table 5, it can be found that the proposed algorithm succeeded in finding better solution for this test system and IPSO-TVAC has shown the superiority to the existing methods. Convergence characteristic of the proposed algorithm for 40-generator test case is presented in Fig. 6. In order to compare the quality of the solution obtained by the proposed algorithm, the performance of the IPSO-TVAC over the 100 trial runs is compared with other methods in terms of average cost, maximum cost and minimum cost as described in Table 6. Results of the proposed method are in bold. The relative frequency of convergence are compared with the convergence frequency of modified versions of evolutionary programming algorithm (CEP, FEP, MFEP, and IFEP), Elite GA (EGA), fuzzy immune algorithm (FIA), and improved PSO (SPSO) [25] in Table 7.

6. Conclusion

This paper introduces a new approach to solve power systems economic dispatch (ED) problem, called time varying acceleration coefficients iteration particle swarm optimization (IPSO-TVAC). Valve-point effect, prohibited operation zones, ramp-rate constraints and transmission losses are modeled and the resulting non-convex optimization problem has been solved by IPSO-TVAC algorithm. The ED constraints are handled using appropriate penalty factors in the fitness function. By selecting the proper penalty factors, it is observed that all constraints are well satisfied. The efficiency of original PSO algorithm is enhanced by combining iteration PSO and TVAC-PSO. The proposed method has been applied on three test cases with 6, 13, and 40 units. Simulation results show that the proposed method is capable to get lower fuel cost compared to previously reported algorithms. The detailed analysis over the 100 trial runs show that IPSO-TVAC has lower variance in results and hence is more reliable. Simulation results validate the applicability of the IPSO-TVAC to solution of constrained ED problems.

References


