IMPROVED PARTICLE SWARM OPTIMIZATION TO SOLVE THE ECONOMIC LOAD DISPATCH PROBLEMS

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Abstract—The problem of economic dispatch (ED) has been tackled and solved by numerous methods. This paper provides an alternative method to solve the problem. This paper proposes an efficient and simple approach based on particle swarm optimization for solving an economic dispatch problem with considering the generator constraints. The objective is to minimize the total fuel cost of generation and also maintain an acceptable system performance in terms of limits on generator real and reactive power outputs and bus voltages. The proposed approach has been evaluated on an IEEE 30-bus test system. The results obtained with the proposed approach are presented and compared favorably with results of genetic algorithm technique.

Keywords— PSO; IEEE 30 Bus ; GA

1. INTRODUCTION

ECONOMIC dispatch (ED) problem is one of the fundamental issues in power system operation. In essence, it is an optimization problem and its objective is to reduce the total generation cost of units, while satisfying constraints. Previous efforts on solving ED problems have employed various mathematical programming methods and optimization techniques. These conventional methods include the lambda-iteration method, the base point and participation factors method, and the gradient method [1], [2], [18], [19]. In these numerical methods for solution of ED problems, an essential assumption is that the incremental cost curves of the units are monotonicity increasing piecewise-linear functions. Unfortunately, this assumption may render these methods infeasible because of its nonlinear characteristics in practical systems. These nonlinear characteristics of a generator include discontinuous prohibited zones, ramp rate limits, and cost functions which are not smooth or convex. Furthermore, for a large-scale mixed-generating system, the conventional method has oscillatory problem resulting in a longer solution time. A dynamic programming (DP) method for solving the ED problem with valve-point modeling had been presented by [1], [2]. However, the DP method may cause the dimensions of the ED problem to become extremely large, thus requiring enormous computational efforts.

In order to make numerical methods more convenient for solving ED problems, artificial intelligent techniques, such as the Hopfield neural networks, to solve ED problems for units with piecewise quadratic fuel cost functions and prohibited zones constraint [3], [4]. However, an unsuitable sigmoidal function adopted in the Hopfield model may suffer from excessive numerical iterations, resulting in huge calculations.

In the past decade, a global optimization technique known as genetic algorithms (GA) or simulated annealing (SA), which is a form of probabilistic heuristic algorithm, has been successfully used to solve power optimization problems such as feeder reconfiguration and capacitor placement in a distribution system [1], [5]–[7]. The GA method is usually faster than the SA method because the GA has parallel search techniques, which emulate natural genetic operations. Due to its high potential for global optimization, GA has received great attention in solving ED problems. In some GA applications, many constraints including network losses, ramp rate limits, and valve-point zone were considered for the practicability of the proposed method. Among these, Walters and Sheble presented a GA model that employed units’ output as the encoded parameter of chromosome to solve an ED problem for valve-point discontinuities [5]. Chen and Chang presented a GA method that used the system incremented cost as encoded parameter for solving ED problems that can take into account network losses, ramp rate limits, and valve-point zone [8]. Fung et al. presented an integrated parallel GA incorporating simulated annealing (SA) and tabu search (TS) techniques that employed the generator’s output as the encoded parameter [9]. For an efficient GA method, Yalcinoz have used the real-coded representation scheme, arithmetic crossover, mutation, and elitism in the GA to solve more efficiently the ED problem, and it can obtain a high-quality solution with less computation time [10].

Though the GA methods have been employed successfully to solve complex optimization problems, recent research has identified some deficiencies in GA performance. This degradation in efficiency is apparent in applications with highly epistatic objective functions (i.e., where the parameters being optimized are highly correlated) [the crossover and mutation operations cannot ensure better fitness of offspring because chromosomes in the population have similar structures and their average fitness is high.]
toward the end of the evolutionary process) [11],[16]. Moreover, the premature convergence of GA degrades its performance and reduces its search capability that leads to a higher probability toward obtaining a local optimum [11]. Particle swarm optimization (PSO), first introduced by Kennedy and Eberhart, is one of the modern heuristic algorithms. It was developed through simulation of a simplified social system, and has been found to be robust in solving continuous nonlinear optimization problems [13]–[17]. The PSO technique can generate high-quality solutions within shorter calculation time and stable convergence characteristic than other stochastic methods [14]–[17]. Although the PSO seems to be sensitive to the tuning of some weights or parameters, many researches are still in progress for proving its potential in solving complex power system problems [16]. Researchers including Yoshida et al. have presented a PSO for reactive power and voltage control (VVC) considering voltage security assessment. The feasibility of their method is compared with the reactive tabu system (RTS) and enumeration method on practical power system, and has shown promising results [18].Naka et al. have presented the use of a hybrid PSO method for solving efficiently the practical distribution state estimation problem [19]. In this paper, a PSO method for solving the ED problem in power system is proposed. The proposed method considers the nonlinear characteristics of a generator such as ramp rate limits and prohibited operating zone for actual power system operation. The feasibility of the proposed method was demonstrated for three different systems [8], [20], respectively, as compared with the real-coded GA method in the solution quality and computation efficiency.

2. PROBLEM DESCRIPTION

The ED is one sub problem of the unit commitment (UC) problem. It is a nonlinear programming optimization one. Practically, while the scheduled combination units at each specific period of operation are listed, the ED planning must perform the optimal generation dispatch among the operating units to satisfy the system load demand, spinning reserve capacity, and practical operation constraints of generators that include the ramp rate limit and the prohibited operating zone [12].

A. Practical Operation Constraints of Generator

For convenience in solving the ED problem, the unit generation output is usually assumed to be adjusted smoothly and instantaneously. Practically, the operating range of all online units is restricted by their ramp rate limits for forcing the units operation continually between two adjacent specific operation periods [1], [2]. In addition, the prohibited operating zones in the input-output curve of generator are due to steam valve operation or vibration in a shaft bearing. Because it is difficult to determine the prohibited zone by actual performance testing or operating records, the best economy is achieved by avoiding operation in areas that are in actual operation. Hence, the two constraints of generator operation must be taken into account to achieve true economic operation.

1) Ramp Rate Limit: According to [3], [5], and [8], the inequality constraints due to ramp rate limits for unit generation changes are given

\[
P_{i,0} \leq UR_i \quad \text{(1)}
\]

2) as generation decreases

\[
P_{i,0} \geq DR_i \quad \text{(2)}
\]

Where \( Pi \) is the current output power and \( Pi0 \) is the previous output power. \( UR_i \) is the up ramp limit of the \( i \)-th generator (MW/time-period); and \( DR_i \) is the down ramp limit of the \( i \)-th generator (MW/time period).

2) Prohibited Operating Zone: References [2], [3], and [8] have shown the input-output performance curve for a typical thermal unit with many valve points. These valve points generate many prohibited zones. In practical operation, adjusting the generation output \( Pi \) of a unit must avoid unit operation in the prohibited zones. The feasible operating zones of unit can be described as follows:

\[
P_{i,0} \leq UR_i \quad \text{(3)}
\]

\[
P_{i,1} = UR_i \quad \text{(4)}
\]

\[
P_{i,0} \leq UR_i \quad \text{(5)}
\]

\[
P_{i,ni} = UR_i \quad \text{(6)}
\]

\[
P_{i,ni} = UR_i \quad \text{(7)}
\]

Where \( j \) is the number of prohibited zones of unit .

B. Objective function

The objective of ED is to simultaneously minimize the generation cost rate and to meet the load demand of a power system over some appropriate period while satisfying various constraints. To combine the above two constraints into a ED problem, the constrained optimization problem at specific operating interval can be modified as Minimize

\[
F_t = a(P_t^2) + b(P_t)^i + c\quad (6)
\]

Constraints

i) Power balance

\[
\sum (i=1)^k \mathcal{D} P_i = P_{d} + P_{l}(7)
\]

ii) Generator operation constraints

\[
\text{max}(P_{\text{min}}, P_{i0} - DR_i) \leq P_i \leq \text{min}(P_{\text{max}}, P_{i0} + UR_i) \quad \text{(8)}
\]

\[
P_{i,1} - 1 \leq P_i \leq P_{i,j} \quad j = 2, \ldots, n_i \quad \text{(9)}
\]

\[
P_{i,1} - n_i \leq P_i \leq P_{i,1} \quad \text{(10)}
\]

iii) Line flow constraints

\[
P_{L,1} - k \leq L_{\text{max}, f,k} \quad k = 1, \ldots, L \quad \text{(11)}
\]

where the generation cost function \( Fi(P_i) \) is usually expressed as a quadratic polynomial; \( ai, bi, ci \) are the cost coefficients of the \( i \)-th generator; \( D \) is the number of generators committed to the operating system; \( Pi \) is the power output of the \( i \)-th generator; \( PL, f,k \) is the real power flow of line \( j \); \( k \) is the number of transmission lines; and the total transmission network losses is a function of unit power outputs that can be represented using B coefficients

\[
P_i = \sum_{j=1}^{n_i} \sum_{k=1}^{L} P_{L,1} B_{j,k} P_{L,1} + P_{L,1} \quad (12)
\]

Reactive power limit

\[
Q_{i,1} \text{ min} \leq Q_i \leq Q_{i,1} \text{ max} \quad (13)
\]

Voltage limits

\[
V_{i,1} \text{ min} \leq V_i \leq V_{i,1} \text{ max} \quad (14)
\]

3. OVERVIEW OF PARTICLE SWARM OPTIMIZATION

In 1995, Kennedy and Eberhart first introduced the PSO method [13], motivated by social behavior of organisms such as fish schooling and bird flocking. PSO, as an optimization tool, provides a population-based search procedure in which individuals called particles change their
The acceleration constants $C_1$ and $C_2$ are often set to 2.0 according to past experiences. High values result in abrupt movement towards, or past, target regions before being tugged back. On the other hand, low values allow particles to roam far from the target positions.

In many experiences with PSO, $V_{\text{max}}$ was often used. If $V_{\text{min}}$ is too small, particles may not explore sufficiently beyond local solutions. If $V_{\text{max}}$ is too high, particles may fly past good candidate solutions that satisfy the practical operation constraints.

In general, the inertia weight $w$ is set according to the following equation,

$$W = W_{\text{max}} - \frac{(W_{\text{max}} - W_{\text{min}})}{\text{ITER}_{\text{max}} - \text{ITER}}$$

where $W$ -is the inertia weighting factor,
$W_{\text{max}}$ - maximum value of weighting factor
$W_{\text{min}}$ - minimum value of weighting factor
$\text{ITER}_{\text{max}}$ - maximum number of iterations
$\text{ITER}$ - current number of iteration

4. PSO IMPLEMENTATION TO ELD PROBLEM

In this paper, the process to solve a constrained ED problem using a PSO algorithm was developed to obtain efficiently a high-quality solution within practical power system operation. The PSO algorithm was utilized mainly to determine the optimal generation power of each unit that was submitted to operation at the specific period, thus minimizing the total generation cost.

The sequential steps to find the optimum solution are:

- The power of each unit, velocity of particles, is randomly generated which must be in the maximum and minimum limit. These initial individuals must be feasible solutions that satisfy the practical operation constraints.

In every iteration, each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called pbest. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called g-best. When a particle takes part of the population as its topological neighbors, the best value is a local best and is called p-best. After finding the two best values, the particle updates its velocity and position using the following equations:

$$V_{i}(u+1) = w \cdot V_{i}(u) + C_1 \cdot \text{rand}() \cdot (P_{\text{best}_{i}} - P_i(u)) + C_2 \cdot \text{rand}() \cdot (P_{g\text{best}} - P_i(u))$$

Where the term $\text{rand}() \cdot (P_{\text{best}_{i}} - P_i(u))$ is called particle memory influence

The term $\text{rand}() \cdot (P_{g\text{best}} - P_i(u))$ is called swarm influence.

The present velocity $V_i(u)$ which is the velocity of $i$th particle at iteration ‘$u$’ must lie in the range

$$V_{\text{min}} \leq V_i(u) \leq V_{\text{max}}$$

The parameter $V_{\text{max}}$ determines the resolution, or fitness, with which regions are to be searched between the present position and the target position.

If $V_{\text{max}}$ is too high, particles may fly past good solutions. If $V_{\text{min}}$ is too small, particles may not explore sufficiently beyond local solutions.

In many experiences with PSO, $V_{\text{max}}$ was often set at 10-20% of the dynamic range on each dimension.

The constants $C_1$ and $C_2$ pull each particle towards pbest and gbest positions.

Low values allow particles to roam far from the target regions before being tugged back. On the other hand, high values result in abrupt movement towards, or past, target regions.

The acceleration constants $C_1$ and $C_2$ are often set to 2.0 according to past experiences.

Suitable selection of inertia weight ‘$w$’ provides a balance between global and local explorations, thus requiring less iteration on average to find a sufficiently optimal solution.

The cost function of each individual $P_{gi}$, is calculated in the population using the evaluation function $F$. Here $F$ is

$$F = a \cdot (P_{gi})^2 + b \cdot P_{gi} + c$$

where $a$, $b$, $c$ are constants. The present value is set as the best value.

Each pbest values are compared with the other pbest values in the population. The best evaluation value among the pbest is denoted as gbest.

The member velocity $v$ of each individual $P_g$ is updated according to the velocity update equation

$$V_{g}(u+1) = w \cdot V_{g}(u) + C_1 \cdot \text{rand}() \cdot (P_{\text{best}_{g}} - P_{g}(u)) + C_2 \cdot \text{rand}() \cdot (P_{g\text{best}} - P_{g}(u))$$

where $u$ is the number of iteration.

The velocity components constraint occurring in the limits from the following conditions are checked

$$V_{\text{dmin}} = -0.5 \cdot P_{\text{min}}$$
$$V_{\text{dmax}} = 0.5 \cdot P_{\text{max}}$$

The position of each individual $P_g$ is modified according to the position update equation

$$P_{g}(u+1) = P_{g}(u) + V_{g}(u+1)$$

The cost function of each new is calculated. If the evaluation value of each individual is better than previous pbest, the current value is set to be pbest. If the best pbest is better than gbest, the value is set to be gbest.

If the number of iterations reaches the maximum, then go to step 10. Otherwise, go to step 2.
The individual that generates the latest gbest is the optimal generation power of each unit with the minimum total generation cost.

5. IMPROVED SWARM INTELLIGENCE APPROACH TO ELD

Especially, most of the PSO algorithms are aimed at unconstrained problems. For the constrained problems, the approach introduced is just the traditional combination of primitive PSO and the penalty function. It was investigated that the simple penalty function strategy cannot be integrated well with PSO algorithms because it does not utilize the historical memory information, which is an essential of PSO. Besides penalty functions face the difficulty of maintaining a balance between obtaining feasibility even as finding optimality. Thus, in order to solve constrained ELD problem optimization a new constraints handling strategy is used for improvement the optimization mechanism of PSO algorithm. The proposed approach is called preservation of Feasible Solutions Method (FSM). This method for constraint handling with PSO was adapted by Hu and Eberhart in [8]. In the proposed method, fitness function and constraints are handled separately. Fitness function is used to guide search direction. Constraints are used to check the feasibility of particles. When implementing this technique into the global version of PSO, the initialization process involves forcing all particles into the feasible space before any evaluation of the objective function has begun. Upon evaluation of the objective function, only particles which remain in the feasible space are counted for the new PBest and GBest values (or lBest for the local version). Although extra loops are needed to find feasible solutions, the time complexity is not high as expected. A feasible solution has to satisfy all the constraints. Once a constraint is not satisfied, it is not necessary to test other constraints. Thus, the overall time complexity is not proportional to the number of needed loops and the computation time will be much less. The idea here is to accelerate the iterative process of tracking feasible solutions by forcing the search space to contain only solutions that do not violate any constraints. Fig. 2 shows a general flowchart of Improved particle swarm optimization technique.

The process of the modified PSO algorithm for solution of the ELD problem can be summarized as follows:

Step 1: Read the original data including power system data and the PSO parameters.
Step 2: Set the generation counter t = 0. Initialize randomly the particles of the population. Repeat initializing particle until it satisfies all the constraints. Note that it is very important to create a group of individuals satisfying the equality constraint (3) and inequality constraints (4), i.e.: summation of all elements of individual i. P and the created element of individual at random should be located within its boundary. Although, we can create element of individual at random satisfying the inequality constraint by mapping [0, 1] into [Pmax-Pmin], the particles are randomly generated between the maximum and the minimum operating limits of the generators. In the ED problems the number of online generating units is the ‘dimension’ of this problem. For example, if there are N units, the i th particle is represented as follows:

\[ P_i = (P_{i1}, P_{i2}, P_{i3}, \ldots, P_{iN}) \]

Step 3: The particle velocities are generated randomly in the range [-Vjmax, Vjmax]. The maximum velocity limit \( V_{jmax} \) of the jth dimension is computed as follows:

\[ V_{jmax} = \frac{X_j^{max} - X_j^{min}}{R} \] (27)

Where, \( R \) is the chosen number of intervals in the jth dimension. For all the examples tested using the PSO approach, \( V_{max} \) was set at 10–20% of the dynamic range of the variable on each dimension.

Step 4: Calculate the evaluation value of each particle, in the population using the evaluation function (1) as initial fitness and set initial position particles as the initial Pbest value of the particles. The initial best value among the particle swarm is set to initial Gbest.

Step 5: Let \( t = t+1 \).

Step 6: Update velocities and positions for all the dimensions in each particle by Eq. (16) and (17).

Step 7: Calculate the fitness value of the new particles by power flow calculation and object function.

Step 8: Update Pbest by using preserving feasibility strategy. If the new value is better than the previous Pbest and the particle is in the feasible space, then the new value is set to Pbest and then selected the particle with the best Pbest value among all the swarm as the Gbest.

Step 9: The best value among all the Pbest values, Gbest, is identified.

Step 10: Go to step (5) until a termination criterion is met, usually a sufficiently good fitness value or a maximum number of generation is chosen for termination criterion.

6. SIMULATION RESULT

The proposed IPSO algorithm was tested on three representative systems, i.e.: IEEE 3, 6, 30 bus systems in comparison with the PSO based method for solution of the ELD problem. The system line and bus data for 3, 6, 30-buses systems were adopted from [9]. For all problems a population of 20 individuals is used. A time decreasing inertia weight \( w \) which starts from 0.9 and ends at 0.4 was used, according to (6) the default value of acceleration constants \( c_1 \) and \( c_2 \) typically is set to 2 for each problem. 30 independent runs were carried out. The maximum generation was set to 2000 and 2500 for 3, 6, 30-buses power systems. The proposed algorithm was implemented in MATLAB 7.1 and executed on a Pentium 4.2 GHz machine. After several trials, the best obtained result is shown using the predetermined parameters. Table 1 and 2 shows the results for IEEE 3, 6, 30 bus systems that obtained by the IPSO and PSO methods. The convergence characteristics for two test cases with using the PSO methods is shown below. Table I, III, V shows the data of the test system. The best results are obtained from the PSO. The results show that the proposed approaches have high solution quality than others method as depicted. Table II, IV, VI shows the effectiveness in term of the solution quality among 100
trials of proposed methods. The solutions of the proposed methods higher quality than the rest methods in term of minimum cost, average cost, maximum cost, computational time and solution deviation.

The cost coefficients and generation limits of three units system are taken from [2]. Transmission loss for this system is calculated using matrix.

TABLE I
GENERATING UNIT CAPACITY AND COEFFICIENTS: THREE GENERATING UNIT SYSTEM

<table>
<thead>
<tr>
<th>a_i</th>
<th>b_i</th>
<th>c_i</th>
<th>P_{min} (MW)</th>
<th>P_{max} (MW)</th>
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</thead>
<tbody>
<tr>
<td>($/MWh)</td>
<td>($/MWh)</td>
<td>(MW)</td>
<td>(MW)</td>
<td></td>
</tr>
<tr>
<td>0.008</td>
<td>7</td>
<td>200</td>
<td>10</td>
<td>85</td>
</tr>
<tr>
<td>0.009</td>
<td>6.3</td>
<td>180</td>
<td>10</td>
<td>80</td>
</tr>
<tr>
<td>0.007</td>
<td>6.8</td>
<td>140</td>
<td>10</td>
<td>70</td>
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Table II
Result for three bus system

<table>
<thead>
<tr>
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<th>PSO</th>
<th>IPSO</th>
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</thead>
<tbody>
<tr>
<td>P1(MW)</td>
<td>32.8203</td>
<td>34.3249</td>
</tr>
<tr>
<td>P2(MW)</td>
<td>64.5435</td>
<td>64.595</td>
</tr>
<tr>
<td>P3(MW)</td>
<td>54.6427</td>
<td>54.9369</td>
</tr>
<tr>
<td>P4(MW)</td>
<td>2.540060</td>
<td>2.302049</td>
</tr>
<tr>
<td>F($/hr)</td>
<td>1597.72</td>
<td>1597.48</td>
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</table>

TABLE III
SIX GENERATING UNIT SYSTEM

<table>
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<tr>
<th>a_i</th>
<th>b_i</th>
<th>c_i</th>
<th>P_{min} (MW)</th>
<th>P_{max} (MW)</th>
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</thead>
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<tr>
<td>($/MWh)</td>
<td>($/MWh)</td>
<td>(MW)</td>
<td>(MW)</td>
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<td>0.0095</td>
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<td>200</td>
<td>50</td>
<td>200</td>
</tr>
<tr>
<td>0.0090</td>
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<td>80</td>
<td>300</td>
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<tr>
<td>0.0090</td>
<td>11</td>
<td>200</td>
<td>50</td>
<td>150</td>
</tr>
<tr>
<td>0.0080</td>
<td>10.5</td>
<td>220</td>
<td>50</td>
<td>200</td>
</tr>
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</table>

Results of three and six bus generating systems shows that the IPSO has succeeded in finding a global optimal solution.

Table IV
Result for Six bus system

<table>
<thead>
<tr>
<th></th>
<th>PSO</th>
<th>IPSO</th>
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<tbody>
<tr>
<td>P1(MW)</td>
<td>276.2339</td>
<td>323.6373</td>
</tr>
<tr>
<td>P2(MW)</td>
<td>106.1268</td>
<td>76.685</td>
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<td>P3(MW)</td>
<td>143.868</td>
<td>158.435</td>
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<td>P4(MW)</td>
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<td>50.00</td>
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<td>P5(MW)</td>
<td>80.5364</td>
<td>115.976</td>
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<tr>
<td>P6(MW)</td>
<td>50.00</td>
<td>50.00</td>
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<tr>
<td>P7(MW)</td>
<td>11.29094</td>
<td>10.73541</td>
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Table V
Result for IEEE 30 bus system

<table>
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<td>P1(MW)</td>
<td>156.86</td>
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<td>P2(MW)</td>
<td>49.984</td>
<td>46.46</td>
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<td>P3(MW)</td>
<td>21.5873</td>
<td>20.223</td>
</tr>
<tr>
<td>P4(MW)</td>
<td>184.627</td>
<td>182.279</td>
</tr>
<tr>
<td>P5(MW)</td>
<td>190.833</td>
<td>11.054</td>
</tr>
<tr>
<td>P6(MW)</td>
<td>255.44</td>
<td>27.759</td>
</tr>
<tr>
<td>P7(MW)</td>
<td>8.122</td>
<td>8.901</td>
</tr>
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7. CONCLUSION

This paper presents a new approach for solving the nonsmooth ED problems with valve-point and multi-fuel effects based on the improved PSO (IPSO) algorithm. The suggested IPSO includes chaotic sequences for weight parameter, equality and inequality constraints treatment methods, and creation of initial position. The application of chaotic sequences in PSO is a powerful strategy to improve the global searching ability and escape from local minima. Also, the equality and inequality constraints treatment methods have always provided the solutions satisfying the constraints without disturbing the optimum process of the PSO. The proposed IPSO outperforms other state-of-the-art algorithms in solving economic dispatch problems with valve-point and multi-fuel effects.

REFERENCES


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