Economic Load Dispatch Using Linearly Decreasing Inertia Weight Particle Swarm Optimization

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Abstract—Economic load dispatch (ELD) is an optimization task in power system. It is the process of allocating generation among the committed units such that the constraints imposed are satisfied and the fuel cost is minimized. Particle swarm optimization (PSO) is a population-based optimization technique that can be applied to a wide range of problems but it lacks global search ability in the last stage of iterations. This paper used a novel PSO with an inertia weight Improved (IWPSO), which enhances the ability of particles to explore the solution spaces more effectively and increases their convergence rates. In this paper the power and usefulness of the NWPSO algorithm is demonstrated through its application for 13 & 15 generator systems with constraints.

Keywords—Economic Load Dispatch (ELD), Particle swarm optimization (PSO), Novel weight improved Particle Swarm Optimization (NWPSO).

I. INTRODUCTION

Electric utility system is interconnected to achieve the benefits of minimum production cost, maximum reliability and better operating conditions. The economic scheduling is the on-line economic load dispatch, wherein it is required to distribute the load among the generating units which are actually paralleled with the system, in such a way as to minimize the total operating cost of generating units while satisfying system equality and inequality constraints. For any specified load condition, ELD determines the power output of each plant (and each generating unit within the plant) which will minimize the overall cost of fuel needed to serve the system load [1]. ELD is used in real-time energy management power system control by most programs to allocate the total generation among the available units. ELD focuses upon coordinating the production cost at all power plants operating on the system.

Conventional as well as modern methods have been used for solving economic load dispatch problem employing different objective functions. Various conventional methods like lambda iteration method, gradient-based method, Bundle method [2], nonlinear programming [3], mixed integer linear programming [4], dynamic programming [8], linear programming [7], quadratic programming [9], Lagrange relaxation method [10], direct search method [12], Newton-based techniques [11], [12] and interior point methods [6], [13] reported in the literature are used to solve such problems.

Conventional methods have many draw back such as nonlinear programming has algorithmic complexity. Linear programming methods are fast and reliable but require linearization of objective function as well as constraints with non-negative variables. Quadratic programming is a special form of nonlinear programming with some disadvantages associated with piecewise quadratic cost approximation. Newton-based method has a drawback of the convergence characteristics that are sensitive to initial conditions. The interior point method is computationally efficient but suffers from bad initial termination and optimality criteria.

Recently, different heuristic approaches have been proved to be effective with promising performance, such as evolutionary programming (EP) [16], [17], simulated annealing (SA) [18], Tabu search (TS) [19], pattern search (PS) [20], Genetic algorithm (GA) [21], [22], Differential evolution (DE) [23], Ant colony optimization [24], Neural network [25] and particle swarm optimization (PSO) [26], [27]. Although the heuristic methods do not always guarantee discovering globally optimal solutions in finite time, they often provide a fast and reasonable solution. EP is rather slow converging to a near optimum for some problems. SA is very time consuming, and cannot be utilized easily to tune the control parameters of the annealing schedule. TS is difficult in defining effective memory structures and strategies which are problem dependent. GA sometimes lacks a strong capacity of producing better offspring and causes slow convergence near global optimum, sometimes may be trapped into local optimum. DE greedy updating principle and intrinsic differential property usually lead the computing process to be trapped at local optima.

Particle-swarm-optimization (PSO) method is a population-based Evolutionary technique first introduced in [26], and it is inspired by the emergent motion of a flock of birds searching for food. In comparison with other EAs such as GAs and evolutionary programming, the PSO has comparable or even superior search performance with faster and more stable convergence rates. Now, the PSO has been extended to power systems, artificial neural network training, fuzzy system control, image processing and so on.

The main objective of this study is to use of PSO with inertia weight improved to solve the power system economic load dispatch to enhance its global search ability.
This new development gives particles more opportunity to explore the solution space than in a standard PSO. The proposed method focuses on solving the economic load dispatch with Generator Ramp Rate Limits constraint. The feasibility of the proposed method was demonstrated for six bus system. The results obtained through the proposed approach and compared with those reported in recent literatures.

II. ECONOMIC LOAD DISPATCH PROBLEM FORMULATION

ELD is one of the most important problems to be solved in the operation and planning of a power system the primary concern of an ED problem is the minimization of its objective function. The total cost generated that meets the demand and satisfies all other constraints associated is selected as the objective function.

The ED problem objective function is formulated mathematically in (1) and (2),

\[ F_T = \text{Min}(F(FC)) \]  
\[ FC = \sum_{i=1}^{n} a_i \times P_i^2 + b_i \times P_i + c_i \]  
\[ D = \sum_{i=1}^{n} P_i - P_D - P_L \]  

Where, \( F_T \) is the main objective function, \( a_i, b_i, \) and \( c_i \) are the cost coefficients, \( e_i, f_i \) are the constant of the valve point effects of the \( i^{th} \) generator, \( D \) is power equilibrium, \( P_D \) and \( P_L \) represent total demand power and the total transmission loss of the transmission lines respectively.

III. CONSTRAINTS

This model is subjected to the following constraints,

1) Real Power Balance Equation

For power balance, an equality constraint should be satisfied. The total generated power should be equal to total load demand plus the total losses,

\[ \sum_{i=1}^{n} P_i = P_{\text{demand}} + P_L \]  
\[ R_L = \sum_{i=1}^{n} \sum_{j=1}^{n} B_{ij} P_i P_j + \sum_{i=1}^{n} B_{i0} P_i + B_{00} \]  

Where, \( P_{\text{demand}} \) is the total system demand and \( P_{\text{Loss}} \) is the total line loss.

\( B_{ij} \) =ith element of loss coefficient symmetric matrix \( B \),

\( B_{i0} \) =ith element of the loss coefficient vector and

\( B_{00} \) =loss coefficient constant.

\( n \) =Number of generator.

2) Unit Operating Limits

There is a limit on the amount of power which a unit can deliver. The power output of any unit should not exceed its rating nor should it be below that necessary for stable operation. Generation output of each unit should lie between maximum and minimum limits.

\[ P_i^{\text{min}} \leq P_i \leq P_i^{\text{max}} \]  

Where, \( P_i \) is the output power of \( i^{th} \) generator,

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

3) Ramp Rate Limit

According to the operating increases and operating decreases of the generators are ramp rate limit constraints described in eq. (7) & (8).

1) As generation increases

\[ P_i(t) + P_i(t - 1) \leq UR_i \]  

2) As generation decreases

\[ P_i(t - 1) - P_i(t) \geq DR_i \]  

When the generator ramp rate limits are considered, the operating limits For each unit, output is limited by time dependent ramp up/down rate at each hour as given below.

\[ P_i^{\text{min}}(t) = \text{max}(P_i^{\text{min}}, P_i(t - 1) - DR_i) \]  

\[ P_i^{\text{max}}(t) = \text{min}(P_i^{\text{max}}, P_i(t - 1) - UR_i) \]  

Where, \( P_i(t) \) =current output power of \( i^{th} \) generating unit,

\( P_i(t - 1) \) =Previous operating point of the \( i^{th} \) generator,

\( DR_i \) =Down ramp rate limit (MW/time period) and

\( UR_i \) =Up ramp rate limit (MW/time period).

IV. OVERVIEW OF SOME PSO STRATEGIES

A number of different PSO strategies are being applied by researchers for solving the economic load dispatch problem and other power system problems. Here, a short review of the significant developments is presented which will serve as a performance measure for the MRPSO technique [26] applied in this paper.

V. STANDARD PARTICLE SWARM OPTIMIZATION (PSO)

Particle swarm optimization was first introduced by Kennedy and Eberhart in the year 1995 [26]. It is an exciting new methodology in evolutionary computation and a population-based optimization tool. PSO is motivated from the simulation of the behavior of social systems such as fish schooling and birds flocking. It is a simple and powerful optimization tool which scatters random particles, i.e., solutions into the problem space. These particles, called swarms collect information from each array constructed by their respective positions. The particles update their positions using the velocity of articles. Position and velocity are both updated in a heuristic manner using guidance from particles’ own experience and the experience of its neighbors.
The position and velocity vectors of the \( i \)th particle of a d-dimensional search space can be represented as \( \mathbf{P}_i = (p_{i1}, p_{i2}, \ldots, p_{id}) \) and \( \mathbf{V}_i = (v_{i1}, v_{i2}, \ldots, v_{id}) \) respectively. On the basis of the value of the evaluation function, the best previous position of a particle is recorded and represented as \( \mathbf{P}_{\text{best}_i} = (p_{i1}, p_{i2}, \ldots, p_{id}) \). If the \( g \)th particle is the best among all particles in the group so far, it is represented as \( \mathbf{P}_{\text{best}_g} = (p_{g1}, p_{g2}, \ldots, p_{gd}) \).

The particle updates its velocity and position using (10) and (11)

\[
\mathbf{V}_{i}^{(k+1)} = \mathbf{W}_{i}^{K} \times c_1 \text{rand}_1() \times (\mathbf{P}_{\text{best}_i} - \mathbf{S}_i^{K}) + c_2 \text{rand}_2() \times (\mathbf{g}_{\text{best}} - \mathbf{S}_i^{K})
\]

(10)

\[
\mathbf{S}_{i}^{(k+1)} = \mathbf{S}_{i}^{K} + \mathbf{V}_{i}^{(k+1)}
\]

Where, \( \mathbf{V}_i^k \) is velocity of individual \( i \) at iteration \( k \), \( k \) is pointer of iteration, \( W \) is the weighing factor, \( c_1, c_2 \) are the acceleration coefficients, \( \text{rand}_1(), \text{rand}_2() \) are the random numbers between 0 & 1, \( \mathbf{S}_i^k \) is the current position of individual \( i \) at iteration \( k \), \( \mathbf{P}_{\text{best}_i} \) is the best position of individual \( i \) and \( \mathbf{g}_{\text{best}} \) is the best position of the group. The coefficients \( c_1 \) and \( c_2 \) pull each particle towards \( \mathbf{p}_{\text{best}} \) and \( \mathbf{g}_{\text{best}} \) positions. Low values of acceleration coefficients 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 the target regions. Hence, the acceleration coefficients \( c_1 \) and \( c_2 \) are often set to be 2 according to past experiences. The term \( c_1 \text{rand}_1() \times (\mathbf{p}_{\text{best}}, -\mathbf{S}_i^{k}) \) is called particle memory influence or cognitive part which represents the private thinking of the particle itself and the term \( c_2 \text{rand}_2() \times (\mathbf{g}_{\text{best}} - \mathbf{S}_i^{k}) \) is called swarm influence or the social part which represents the collaboration among the particles.

In the procedure of the particle swarm paradigm, the value of maximum allowed particle velocity \( \mathbf{V}_{\text{max}} \) determines the resolution, or fitness, with which regions are to be searched between the present position and the target position. If \( \mathbf{V}_{\text{max}} \) is too high, particles may fly past good solutions. If \( \mathbf{V}_{\text{max}} \) is too small, particles may not explore sufficiently beyond local solutions. Thus, the system parameter \( \mathbf{V}_{\text{max}} \) has the beneficial effect of preventing explosion and scales the exploration of the particle search. The choice of a value for \( \mathbf{V}_{\text{max}} \) is often set at 10-20\% of the dynamic range of the variable for each problem.

\( W \) is the inertia weight parameter which provides a balance between global and local explorations, thus requiring less iteration on an average to find a sufficiently optimal solution. Since \( W \) decreases linearly from about 0.9 to 0.4 quite often during a run, the following weighing function is used in (10)

\[
W = W_{\text{max}} - \frac{W_{\text{max}} - W_{\text{min}}}{\text{iter}_{\text{max}}} \times \text{iter}
\]

(12)

Where, \( W_{\text{max}} \) is the initial weight, \( W_{\text{min}} \) is the final weight, \( \text{iter}_{\text{max}} \) is the maximum iteration number and \( \text{iter} \) is the current iteration position.

**Inertia Weight Improved PSO (IWIPSO)**

In this section, for getting the better global solution, the traditional PSO algorithm is improved by adjusting the weight parameter, cognitive and social factors. Based on [15], the velocity of individual \( i \) of IWIPSO algorithm is rewritten as,

\[
\mathbf{V}_{i}^{(k+1)} = w_{\text{new}} \mathbf{V}_i^k + c_1 \text{rand}_1() \times (\mathbf{P}_{\text{best}_i} - \mathbf{S}_i^k) + c_2 \text{rand}_2() \times (\mathbf{g}_{\text{best}} - \mathbf{S}_i^k)
\]

(13)

Where,

\[
w_{\text{new}} = w_{\text{min}} + W \times \text{rand}_3
\]

(14)

\[
W = W_{\text{max}} - \frac{W_{\text{max}} - W_{\text{min}}}{\text{iter}_{\text{max}}} \times \text{iter}
\]

(15)

\[
c_1 = c_{1\text{max}} - c_{1\text{min}} \times \text{iter}_{\text{max}} \times \text{iter}
\]

(16)

\[
c_2 = c_{2\text{max}} - c_{2\text{min}} \times \text{iter}_{\text{max}} \times \text{iter}
\]

(17)

Where, \( w_{\text{min}}, w_{\text{max}} \): initial and final weight,

\( c_{1\text{min}}, c_{1\text{max}}, c_{2\text{min}}, c_{2\text{max}} \): initial and final cognitive factors and social factors.

**VI. ALGORITHM FOR ELD PROBLEM USING IWIPSO**

The algorithm for ELD problem with ramp rate generation limits employing IWIPSO for practical power system operation is given in following steps:-

**Step1:** Initialization of the swarm: For a population size the Particles are randomly generated in the Range 0–1 and located between the maximum and the minimum operating limits of the generators.

**Step2:** Initialize velocity and position for all particles by randomly set to within their legal range.

**Step3:** Set generation counter \( t=1 \).

**Step4:** Evaluate the fitness for each particle according to the objective function.

**Step5:** Compare particles fitness evaluation with its Pbest and gbest.

**Step6:** Update velocity by using (9)

**Step7:** Update position by using (10)

**Step8:** Apply stopping criteria.
VII. CASE STUDY

Test Case -I

The test results are obtained for three-generating unit system in which all units with their fuel cost coefficients. This system supplies a load demand of 150 MW. The data for the individual units are given in Table 1. The best result obtained by NWIPSO for different population size is shown in Table 2 and Table 3.

Table 1
Capacity limits and fuel cost coefficients for thirteen generating units for the demand load of 1800 MW

<table>
<thead>
<tr>
<th>Generating units</th>
<th>Optimal power at different populations (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>10</td>
</tr>
<tr>
<td>P1</td>
<td>502.007</td>
</tr>
<tr>
<td>P2</td>
<td>66.549</td>
</tr>
<tr>
<td>P3</td>
<td>265.761</td>
</tr>
<tr>
<td>P4</td>
<td>118.699</td>
</tr>
<tr>
<td>P5</td>
<td>119.208</td>
</tr>
<tr>
<td>P6</td>
<td>164.909</td>
</tr>
<tr>
<td>P7</td>
<td>86.664</td>
</tr>
<tr>
<td>P8</td>
<td>84.692</td>
</tr>
<tr>
<td>P9</td>
<td>126.113</td>
</tr>
<tr>
<td>P10</td>
<td>79.564</td>
</tr>
<tr>
<td>P11</td>
<td>52.554</td>
</tr>
<tr>
<td>P12</td>
<td>59.851</td>
</tr>
<tr>
<td>P13</td>
<td>72.81</td>
</tr>
</tbody>
</table>

Table 2
Conversation results of 13 thermal generating units using NWIPSO for the different population size of the demand of 1800 MW.

<table>
<thead>
<tr>
<th>Plant No.</th>
<th>Pmin(MW)</th>
<th>Pmax(MW)</th>
<th>ai(M$/h)</th>
<th>bi($/MW)</th>
<th>ci($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
<td>0</td>
<td>680</td>
<td>0.00028</td>
<td>8.1</td>
<td>550</td>
</tr>
<tr>
<td>P2</td>
<td>0</td>
<td>360</td>
<td>0.00056</td>
<td>8.1</td>
<td>309</td>
</tr>
<tr>
<td>P3</td>
<td>0</td>
<td>360</td>
<td>0.00056</td>
<td>8.1</td>
<td>307</td>
</tr>
<tr>
<td>P4</td>
<td>60</td>
<td>180</td>
<td>0.00324</td>
<td>7.74</td>
<td>240</td>
</tr>
<tr>
<td>P5</td>
<td>60</td>
<td>180</td>
<td>0.00324</td>
<td>7.74</td>
<td>240</td>
</tr>
<tr>
<td>P6</td>
<td>60</td>
<td>180</td>
<td>0.00324</td>
<td>7.74</td>
<td>240</td>
</tr>
<tr>
<td>P7</td>
<td>60</td>
<td>180</td>
<td>0.00324</td>
<td>7.74</td>
<td>240</td>
</tr>
<tr>
<td>P8</td>
<td>60</td>
<td>180</td>
<td>0.00324</td>
<td>7.74</td>
<td>240</td>
</tr>
<tr>
<td>P9</td>
<td>60</td>
<td>180</td>
<td>0.00324</td>
<td>7.74</td>
<td>240</td>
</tr>
<tr>
<td>P10</td>
<td>40</td>
<td>120</td>
<td>0.00284</td>
<td>8.6</td>
<td>126</td>
</tr>
<tr>
<td>P11</td>
<td>40</td>
<td>120</td>
<td>0.00284</td>
<td>8.6</td>
<td>126</td>
</tr>
<tr>
<td>P12</td>
<td>55</td>
<td>120</td>
<td>0.00284</td>
<td>8.6</td>
<td>126</td>
</tr>
<tr>
<td>P13</td>
<td>55</td>
<td>120</td>
<td>0.00284</td>
<td>8.6</td>
<td>126</td>
</tr>
</tbody>
</table>

Test Case –II

The test results are obtained for six-generating unit system in which all units with their fuel cost coefficients. This system supplies a load demand of 1263 MW. The data for the individual units are given in Table 4. The best result obtained by IWIPSO for different population size is shown in Table 5 and table 6.

Table 3
Best convergence results of 13 thermal generating units for the demand of 1800 MW.

<table>
<thead>
<tr>
<th>Population sizes</th>
<th>Cost($/h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>15</td>
</tr>
<tr>
<td>Min. cost</td>
<td>18011.24</td>
</tr>
<tr>
<td>Max. cost</td>
<td>18211.63</td>
</tr>
<tr>
<td>Ave. cost</td>
<td>18086.45</td>
</tr>
</tbody>
</table>

Table 4
Capacity limit of generating units and fuel cost coefficients of 15 generating units for the demand of 2650MW.

<table>
<thead>
<tr>
<th>Unit No.</th>
<th>ai(M$/h)</th>
<th>bi($/MW)</th>
<th>ci($)</th>
<th>Pmin(MW)</th>
<th>Pmax(MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
<td>1800299</td>
<td>10.1</td>
<td>671</td>
<td>150</td>
<td>455</td>
</tr>
<tr>
<td>P2</td>
<td>0.000183</td>
<td>10.2</td>
<td>574</td>
<td>150</td>
<td>455</td>
</tr>
<tr>
<td>P3</td>
<td>0.001126</td>
<td>9.2</td>
<td>374</td>
<td>20</td>
<td>130</td>
</tr>
<tr>
<td>P4</td>
<td>0.001126</td>
<td>9.2</td>
<td>374</td>
<td>20</td>
<td>130</td>
</tr>
<tr>
<td>P5</td>
<td>0.000205</td>
<td>10.4</td>
<td>461</td>
<td>150</td>
<td>470</td>
</tr>
<tr>
<td>P6</td>
<td>0.000301</td>
<td>10.1</td>
<td>630</td>
<td>135</td>
<td>460</td>
</tr>
<tr>
<td>P7</td>
<td>0.000364</td>
<td>9.8</td>
<td>548</td>
<td>135</td>
<td>465</td>
</tr>
<tr>
<td>P8</td>
<td>0.000338</td>
<td>11.2</td>
<td>227</td>
<td>60</td>
<td>300</td>
</tr>
<tr>
<td>P9</td>
<td>0.000807</td>
<td>11.2</td>
<td>171</td>
<td>25</td>
<td>162</td>
</tr>
<tr>
<td>P10</td>
<td>0.001203</td>
<td>10.7</td>
<td>175</td>
<td>25</td>
<td>160</td>
</tr>
<tr>
<td>P11</td>
<td>0.003586</td>
<td>10.2</td>
<td>186</td>
<td>20</td>
<td>80</td>
</tr>
<tr>
<td>P12</td>
<td>0.005751</td>
<td>9.9</td>
<td>230</td>
<td>20</td>
<td>80</td>
</tr>
<tr>
<td>P13</td>
<td>0.000371</td>
<td>13.2</td>
<td>225</td>
<td>25</td>
<td>85</td>
</tr>
<tr>
<td>P14</td>
<td>0.001929</td>
<td>12.1</td>
<td>309</td>
<td>15</td>
<td>55</td>
</tr>
<tr>
<td>P15</td>
<td>0.004447</td>
<td>12.4</td>
<td>323</td>
<td>15</td>
<td>55</td>
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</tbody>
</table>
In this paper, the proposed approach is tested for a case study of thermal generation units and thermal scheduling with bilateral traction via bundle method. The analysis results have demonstrated that NWIPSO outperforms the other methods in terms of a better optimal solution. However, the much improved speed of computation allows for additional searches to be made to increase the confidence in the solution. Overall, the NWIPSO algorithms have been shown to be very helpful in studying optimization problems in power systems.

**REFERENCES**


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