SOLUTION TO ECONOMIC DISPATCH PROBLEM USING FLOWER POLLINATION ALGORITHM

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Abstract—This paper presents the solution method for economic load dispatch (ELD) problem of thermal plants using Flower Pollination Algorithm (FPA). The proposed optimization strategy can deal with economic load dispatch problems including subject to constraints, for example, transmission power losses, load balance and generation limits. The possibility of the proposed method is implemented for 3 units and 6 units systems, and is compared against Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) techniques as far as the result quality and computational time. Compared with the other existing techniques, the presented solution method has been discovered to perform well in both test cases. Conceiving the superiority of the results obtained, this FPA technique seems to be a promising alternative solution method for resolving the ELD problems in electrical power systems.

Keywords: Flower Pollination Algorithm (FPA), Economic Load Dispatch (ELD), Particle Swarm Optimization (PSO), Genetic Algorithm (GA).

I. INTRODUCTION

In power systems, the optimal operation of power generating units with multiple fuel sources, such as oil, natural gas, and coal, involves the minimization of fuel cost, while continuously respecting the physical constraints of the electricity network. The fuel cost function of units may be segmented according to different piecewise quadratic types. Economic load dispatch (ELD) problem that considers the units constraints is a very significant optimization problem in the power system operation [1,2].

The ELD problem is a nonlinear, nonconvex, and nonsmooth optimization problem because of the characteristics of valve point loading (VPL) effect as a result of the multivalve steam turbine, the network transmission power losses, the ramp rate limits, and the prohibited operating zones (POZ) of power generation units [3-5]. Classical mathematical programming techniques, such as evolutionary programming method [6], the Hopfield artificial neural network method [7], adaptive Hopfield neural network [8], are used to solve the different ELD problems. These methods obtained solutions that are still far from reliable, fast, and optimum solutions. They are not always effective and cannot guarantee the global optimal solution for different nonconvex and nonsmooth objective functions in power systems [9].

Recently, many inspired optimization algorithms have been used to solve the nonsmooth and nonconvex ELD problems, such as genetic algorithm (GA) [10] and its related algorithms. 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. 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 [10]. The particle swarm optimization (PSO) [11] which is applied to various techniques for solving ELD in the literature [12-14], differential evolution algorithms (DEs) [15], Tabu search [16], and evolutionary programming strategies [17]. Some other optimization techniques have been also applied for solving ELD problems. The PSO has attracted many researchers’ sights due to its simplicity and effectiveness. PSO, inspired from bird flocking and fish schooling, is a flexible, robust, population based algorithm that are adopted by many people for solving ELD problems and various power system problems. However, it is slow to converge and the processes of the exploration and exploitation contradict with each other, so the two abilities should be well balanced for achieving good optimization performance. On the other hand, flower pollination algorithm (FPA) has only one key parameter p (switch probability) which makes the algorithm easier to implement and faster to reach optimum solution. Moreover, this transferring switch between local and global pollination can guarantee escaping from local minimum solution [18]. FPA was first developed by Yang in 2012. It is inspired by the pollination process of flowering plants that has its own feasibility and performance capacity to solve different classical and modern optimization problems effectively and efficiently. It is classified as a meta-heuristic algorithm. From the biological evolution point of view the objective of flower pollination is the survival of the fittest and the most optimum reproduction of plants [19]. Yang proved that the Flower Pollination Algorithm is simple, very efficient and can outperform both genetic algorithm and particle swarm optimization. Its convergence rate is essentially exponential.

In this paper, FPA has been proposed for discovering the global solutions of ELD problems in power systems. The capability of the FPA algorithm is carefully looked over in different test systems including benchmark problems and ELD problems, and the results are compared with other inspired algorithms and the obtained results in the literature with the intention of discovering fundamental prominent aspects of the proposed algorithm.

Two cases with three units and six units thermal power system are tested and compared with other approaches and found to be promising. After the introduction, a brief description of the ELD problem associated with its mathematical formulation is presented in Section II, while in Section III explains the FPA. Section IV then details the implementation of proposed FPA to ELD problems. Case studies are presented in Section V. Finally, the conclusion is drawn in Section VI.
II. ECONOMIC LOAD DISPATCH PROBLEMS

Generally, the main purpose of the constrained ELD problem is to reduce the fuel and total operating costs of the thermal generating units. The convex ELD problem assumes quadratic cost function along with system power demand and operational limit constraints. The global ELD mathematical model can be formulated by constrained fuel cost function as [20].

Minimize
\[ F_r = \sum_{i=1}^{n} F_i(P_i) \]  
(1)

Subject to
\[ \sum_{i=1}^{n} P_i = P_{\text{d}} + P_L \]  
(2)

\[ P_i^{\text{min}} \leq P_i \leq P_i^{\text{max}} \]  
(3)

where, \( n \) is the number of units, \( F_i \) is the total fuel cost, \( F_r \) and \( P_i \) are the cost function and the real power output of the \( i^{\text{th}} \) unit respectively, \( P_{\text{d}} \) as the total demand, \( P_L \) is the transmission loss. \( P_i^{\text{min}} \) and \( P_i^{\text{max}} \) are the lower and upper bounds of the \( i^{\text{th}} \) unit respectively. The equality constraint, Eqn. (2) states that the total generated power should be balanced by transmission losses and power consumption while Eqn. (3) denoting unit’s operation constraints.

Traditionally, the fuel cost of a generator is usually defined by a quadratic cost function,
\[ F_i(P_i) = \gamma_i P_i^2 + \beta_i P_i + \alpha_i \]  
(4)

where, \( \alpha_i, \beta_i \) and \( \gamma_i \) are cost coefficients of the \( i^{\text{th}} \) unit.

Conventionally, transmission loss is calculated using B-matrix loss formula [2], i.e.,
\[ P_L = P^T BP + P^T B0 + B00 \]  
(5)

where, \( P \) denotes the real power output of the committed units in vector form, and \( B, B0 \) and \( B00 \) are loss coefficients in matrix, vector and scalar respectively, which are assumed to be constant, and reasonable accuracy can be achieved when the actual operating conditions are close to the base case where the \( B \)-coefficients were derived. In the summary, the objective of economic power dispatch optimization is to minimize \( F_r \) subject to the constraints (2) and (3).

III. FLOWER POLLINATION ALGORITHM

Flower Pollination Algorithm is a new population-based optimization technique that was developed by Xin-She Yang [18]. It mimics the flower pollination behavior. Pollination is a natural physiological process of mating in plants which associated with transfer of pollen by pollinators such as insects etc.

A. Characteristics of Flower Pollination

There are two types of pollination. The first one is Self-pollination which takes place when the pollen from one flower fertilizes the same flower. The other is cross-pollination which occurs when the pollen grains are transferred to a flower from a different plant.

On the other hand, there are various methods that the flowers attempt to spread their pollen. One of them is abiotic pollination where the pollen is transferred by the help of the wind. Another one is biotic pollination which occurs via insects, bats, birds and other animals. Moreover flower constancy has been observed for insect pollinators specially honeybees. These pollinators tend to visit specific flowers species exclusively, ignoring the other species, thus maximizing the reproduction of the same flower species.

From the biological evolution point of view, the goal of flower pollination is the survival of the fittest and the optimum reproduction of plants in terms of numbers as well as the fittest. This may be regarded as an optimizing process of plants species [18]. To develop the FPA, there are four rules should be summarized as follows:

1. Biotic and cross-pollination may be regarded as a global pollination process, and pollen-carrying pollinators can fly a long distance, which obeys Lévy flights (Rule 1).

2. A biotic and self-pollination can be considered as local pollination, (Rule 2).

3. Flower constancy may be regarded as an equivalent to a reproduction probability that is proportionate to the similarity of two flowers involved (Rule3).

4. The switching of local pollination and global pollination is controlled by a switch probability \( p \in [0,1] \) (Rule 4).

Now the rules are converted to the following mathematical equations. For the global pollination step (Rule 1), and flower constancy (Rule 3) can be represented mathematically as [13],
\[ x_i^{t+1} = x_i^t + \lambda U(\lambda)(s, -x_i^t) \]  
(6)

where \( x_i^t \) is the pollen i or the solution vector xi at iteration t and \( g_i \) is the best solution. \( \lambda \) is a scaling factor to control the step size. \( U(\lambda) \) is the Lévy flights-based step size, that corresponds to the strength of the pollination. Insects can fly over a long distance with different distance steps, this is drawn from a Lévy distribution [18].

\[ L \sim \frac{\lambda \Gamma(\lambda) \sin(\frac{2\phi}{\lambda})}{\pi} \frac{1}{s^{1+\lambda}} \]  
(7)

Here \( \Gamma(\lambda) \) is the gamma function, and this distribution is valid for large steps \( s > 0 \).

For the local pollination, both (Rule 2) and flower constancy (Rule 3) can be represented as [13]
\[ x_i^{t+1} = x_i^t + \alpha(x_j^t - x_k^t) \]  
(8)

where \( x_j^t \), \( x_k^t \) are pollen from different flowers of the same plant species. If \( x_j^t \) and \( x_k^t \) come from the same species or are selected from the same population, this equivalently becomes a local random walk if \( s = 0 \) drawn from a uniform distribution in \([0,1] \) [18].

Flower pollination activities can occur at all scales, both local and global. Hence to switch between them, a switch probability (Rule 4) or proximity probability can be effectively used [18].

A Number of runs have been performed before being able to adjust the parameters of the proposed algorithm. It was concluded that a population size \( N = 25 \) is adequate for the ELD problems. The maximum number of iterations is chosen as \( N_{\text{iter}} = 500 \). The probability switch \( P = 0.8 \) is obtained from [19].

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The purpose of this paper is to investigate the capability and effectiveness of FPA when applying to ELD problems that are frequently encountered in power system industry.

IV. IMPLEMENTATION

The candidate solution is encoded in vector form as $x_i = [x_{i1}, x_{i2}, \ldots, x_{in}]^T$, for $i = 1$ to $m$ and $j = 1$ to $n$, where $x_{ij}$ denotes the output power of the $j^{th}$ committed units for the $i^{th}$ candidate solution, $m$ is the number of candidate solutions and $n$ is the number of units. Now, taking FPA as kernel, the developed algorithm for ELD problems are summarized below.

Step 1: Initialize a population of $m$ flowers/pollen gametes with random solutions

Step 2: Find the best solution $g_i$ in the initial population

Step 3: Define a switch probability $p \in [0, 1]$. Define a stopping criterion (either a fixed number of generations/iterations or accuracy). In this application, we assumed stopping criterion as maximum iteration ($t_{\text{max}}$). Set initial iteration count as $t = 1$.

Step 4: For all flowers in the population from 1 to $m$, perform global pollination using (6) and (7) if rand $< p$; or else perform local pollination using (8) and $\in$. 

Step 5: For all flowers, evaluate new solutions using switch probability.

Step 6: If the new solutions are better, update them in the population.

Step 7: Find the current best solution $g_i$ among the flowers in the population.

Step 8: If the convergence criteria are satisfied (t equals $t_{\text{max}}$), output the best solution for ELD problem; otherwise set $t = t + 1$, and repeat the step 4 to 8.

To verify the effectiveness and capability of the proposed method, case studies for two different units are conducted and the results are reported in the next section.

V. EXPERIMENTAL RESULTS

Proposed FPA has been applied to ELD problems in two different thermal unit systems for verifying its feasibility. These are a three units system and a six units system [21-22]. The transmission losses will not take into account in all the case studies here for the sake of comparison with other algorithms presented in existing literatures. The stopping criterion, maximum number of iteration, varies for each case in considering the problem scale. The software has been written in MATLAB language and executed in Pentium ® Dual-Core personal computer with 2GB RAM.

A. Case study 1- Three units system

In this example, a simple system with three thermal units is used to demonstrate how the proposed approach works. The unit characteristics are given in Table 1. In this case, each individual $P_i$ contains three generator power outputs, such as $P_1$, $P_2$, and $P_3$, which are generated randomly. The dimension of the population is equal to 3 X 100. Now, Table 2 provides the statistic results that involved the generation cost, evaluation value, and average CPU time. Figure 1 showed the distribution outline of the best solution for 500 iterations.

<table>
<thead>
<tr>
<th>Unit</th>
<th>$P_{\text{max}}$ MW</th>
<th>$P_{\text{max}}$ MW</th>
<th>$a$</th>
<th>$\beta$ $/$MW</th>
<th>$\gamma$ $/$MW$^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>50</td>
<td>250</td>
<td>328.13</td>
<td>8.663</td>
<td>0.00525</td>
</tr>
</tbody>
</table>

Table 1 Generating unit's capacity and coefficients

In normal operation of the system, the loss coefficients with the 100-MVA base capacity are as follows,

$$B = \begin{bmatrix} 0.000136 & 0.000175 & 0.000184 \\ 0.000175 & 0.000154 & 0.000283 \\ 0.000184 & 0.000283 & 0.00161 \end{bmatrix}$$

Load = 300 MW

Table 2 Best power output for 3-generator system

<table>
<thead>
<tr>
<th>Unit Output</th>
<th>GA [21]</th>
<th>PSO [22]</th>
<th>FPA</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1 (MW)</td>
<td>194.265</td>
<td>209.001</td>
<td>207.6365</td>
</tr>
<tr>
<td>P2 (MW)</td>
<td>50</td>
<td>85.92</td>
<td>87.2839</td>
</tr>
<tr>
<td>P3 (MW)</td>
<td>79.627</td>
<td>15</td>
<td>15.0000</td>
</tr>
<tr>
<td>Total Power Output (MW)</td>
<td>323.892</td>
<td>309.9211</td>
<td>309.9200</td>
</tr>
<tr>
<td>Total Generation Cost ($/h)</td>
<td>3737.16</td>
<td>3621.75</td>
<td>3619.756</td>
</tr>
<tr>
<td>Power Loss (MW)</td>
<td>24.0115</td>
<td>9.9833</td>
<td>9.9204</td>
</tr>
<tr>
<td>Average CPU time (sec)</td>
<td>16</td>
<td>8.7459</td>
<td>4.5595</td>
</tr>
</tbody>
</table>

Figure 1 Convergence characteristic of Three-generator system

B. Case study 2- Six units system

The system contains six thermal units, 26 buses, and 46 transmission lines [10]. The load demand is 1263MW. The characteristics of the six thermal units are given in Tables 3. In this case, each individual $P_i$ contains six generator power outputs, such as $P_1$, $P_2$, $P_3$, $P_4$, $P_5$, and $P_6$, which are generated randomly. The dimension of the population is equal to 6 X 100. Now, Table 4 provides the statistic results that involved the generation cost, evaluation value, and average CPU time. Figure 2 showed the distribution outline of the best solution for 500 iterations.
In normal operation of the system, the loss coefficients with the 100-MVA base capacity are as follows,

\[ B_p = \begin{bmatrix}
0.0017 & 0.0012 & 0.0007 & -0.0001 & -0.0005 & -0.0002 \\
0.0012 & 0.0014 & 0.0009 & 0.0001 & -0.0006 & -0.0001 \\
0.0007 & 0.0009 & 0.0031 & 0 & -0.001 & -0.0006 \\
-0.0001 & 0.0001 & 0 & 0.0024 & -0.0006 & -0.0008 \\
-0.0005 & -0.0006 & -0.001 & -0.0006 & 0.0129 & -0.0002 \\
-0.0002 & -0.0001 & -0.0006 & -0.0008 & -0.0002 & 0.015
\end{bmatrix} \]

\[ B_0 = 10^{-4} \begin{bmatrix}
0.3908 & -0.1297 & 0.7047 & 0.0591 & 0.2161 & -0.6635
\end{bmatrix} \]

\[ B_{00} = 0.056 \]

Table 3 Generating unit's capacity and coefficients

<table>
<thead>
<tr>
<th>Unit</th>
<th>( P_{\text{min}} ) (MW)</th>
<th>( P_{\text{max}} ) (MW)</th>
<th>( \alpha )</th>
<th>( \beta ) ($/MW)</th>
<th>( \gamma ) ($/MW^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>100</td>
<td>500</td>
<td>240</td>
<td>7.0</td>
<td>0.0070</td>
</tr>
<tr>
<td>2</td>
<td>50</td>
<td>200</td>
<td>200</td>
<td>10.0</td>
<td>0.0095</td>
</tr>
<tr>
<td>3</td>
<td>80</td>
<td>300</td>
<td>220</td>
<td>38.5</td>
<td>0.0090</td>
</tr>
<tr>
<td>4</td>
<td>50</td>
<td>150</td>
<td>200</td>
<td>11.0</td>
<td>0.0090</td>
</tr>
<tr>
<td>5</td>
<td>50</td>
<td>200</td>
<td>220</td>
<td>10.5</td>
<td>0.0080</td>
</tr>
<tr>
<td>6</td>
<td>50</td>
<td>120</td>
<td>190</td>
<td>12.0</td>
<td>0.0075</td>
</tr>
</tbody>
</table>

Load = 1263 MW

Table 4 Best power output for 6-generator system

<table>
<thead>
<tr>
<th>Unit Output</th>
<th>GA [21]</th>
<th>PSO [22]</th>
<th>FPA</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1 (MW)</td>
<td>474.8066</td>
<td>447.497</td>
<td>447.4836</td>
</tr>
<tr>
<td>P2 (MW)</td>
<td>178.6363</td>
<td>173.3221</td>
<td>173.3455</td>
</tr>
<tr>
<td>P3 (MW)</td>
<td>262.2089</td>
<td>263.4745</td>
<td>263.4488</td>
</tr>
<tr>
<td>P4 (MW)</td>
<td>134.2826</td>
<td>139.0594</td>
<td>139.0891</td>
</tr>
<tr>
<td>P5 (MW)</td>
<td>151.9039</td>
<td>165.4761</td>
<td>165.4567</td>
</tr>
<tr>
<td>P6 (MW)</td>
<td>74.1812</td>
<td>87.128</td>
<td>87.1339</td>
</tr>
</tbody>
</table>

Total Power Output (MW):

<table>
<thead>
<tr>
<th>Total Generation Cost ($/h)</th>
<th>15,459</th>
<th>15,450</th>
<th>15,449.899</th>
</tr>
</thead>
<tbody>
<tr>
<td>Power Loss (MW)</td>
<td>13.0217</td>
<td>12.9584</td>
<td>12.9576</td>
</tr>
<tr>
<td>Average CPU time (sec)</td>
<td>41.58</td>
<td>14.89</td>
<td>4.6202</td>
</tr>
</tbody>
</table>

VI. CONCLUSION

The proposed FPA has been successfully implemented to solve ELD problems with the generator constraints as linear equality and inequality constraints. The performance of the FPA was tested for three units and six units systems, and compared with the reported cases in other literatures. From the result, it is clear that the proposed algorithm has the ability to find the better quality solution and has better convergence characteristics, computational efficiency and less average CPU time when compared to other methods such as PSO and GA. Thus the proposed FPA method is a promising technique for solving complicated problems in power systems.

REFERENCES


