OPTIMAL GENERATOR SCHEDULING BASED ON MODIFIED IMPROVED PARTICLE SWARM OPTIMIZATION

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ABSTRACT

Generator scheduling is one important thing in power system operation. A bad scheduling can affect high cost in operation especially on generation side. The optimal generator scheduling will be obtained by optimizing the combination of the generators used Modified Improved particle swarm optimization (MIPSO) with Constriction Factor Approach (CFA). This method optimize the schedule of generating units to meet the required demand at minimum production cost, satisfying units and system’s operating constraints. The simulation results with the method proposed gives best result and performance compared with lambda iteration method.

Keywords: Power Generation Economics, Generator Scheduling, PSO.

1 INTRODUCTION

Citizen growth causes citizen distribution more vaster affect the need of electricity energy more and more. Power system scheme is show in figure 1. Therefore, preparing the power system sources needed. In power system, generating and distributing process need high cost, that is why the scheduling generator must to optimizing. Coordination between the generators make the scheduling generators meet the required demand at minimum production cost.

One of the latest optimization algorithms based on artificial intelligence technique is the particle swarm optimization (PSO). In PSO, a population of particles called a swarm, interact with each other to move towards a global minimum. PSO has been successfully implemented on many applications in power systems, especially for optimal generation scheduling.

2 MODEL, ANALYSIS, DESIGN, AND IMPLEMENTATION

2.1 Particle Swarm Optimization (PSO)

Particle swarm optimization (PSO) is an evolutionary computation technique developed by Kennedy and Eberhart in 1995. The particle swarm concept originated as a simulation of a simplified social system. The original intent was to graphically simulate the graceful but unpredictable choreography of a bird flock. Initial simulations were modified to incorporate nearest-neighbor velocity matching, eliminate ancillary variables, and incorporate multidimensional search and acceleration by distance (Kennedy and Eberhart 1995). At some point in the evolution of the algorithm, it was realized that the conceptual model was, in fact, an optimizer. Through a process of trial and error, a number of parameters extraneous to optimization were eliminated from the algorithm, resulting in the very simple original implementation (Eberhart, Simpson and Dobbins 1996). PSO is similar to a genetic algorithm (GA) in that the system is initialized with a population of random solutions. It is unlike a GA, however, in that each potential solution is also assigned a randomized velocity, and the potential solutions, called particles, are then “flown” through the problem space. Each particle keeps track of its coordinates in the problem space which are associated with 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
The maximum velocity $V_{\text{max}}$ serves as a constraint to control the global exploration ability of a particle swarm. As stated earlier, a larger $V_{\text{max}}$ facilitates global exploration, while a smaller $V_{\text{max}}$ encourages local exploitation. The concept of an inertia weight was developed to better control exploration and exploitation. The motivation was to be able to eliminate the need for $V_{\text{max}}$. The inclusion of an inertia weight in the particle swarm optimization algorithm was first reported in the literature in 1998. Equations (3) and (4) describe the velocity and position update equations with an inertia weight included. It can be seen that these equations are identical to equations (1) and (2) with the addition of the inertia weight $w$ as a multiplying factor of $V_{\text{ad}}$ in equation (3). The use of the inertia weight $w$ has provided improved performance in a number of applications. As originally developed, $w$ often is decreased linearly from about 0.9 to 0.4 during a run. Suitable selection of the inertia weight provides a balance between global and local exploration and exploitation, and results in fewer iterations on average to find a sufficiently optimal solution.

$$V_{\text{ad}} = V_{\text{ad}} + c_1 \text{rand}_1 x (P_{\text{ad}} - X_{\text{ad}}) + c_2 \text{rand}_2 x (P_{g\text{ad}} - X_{\text{ad}})$$

$$X_{\text{ad}} = X_{\text{ad}} + V_{\text{ad}}$$

After some experience with the inertia weight, it was found that although the maximum velocity factor $V_{\text{max}}$ couldn’t always be eliminated, the particle swarm algorithm works well if $V_{\text{min}}$ is set to the value of the dynamic range of each variable (on each dimension). Thus, the need to think about how to set $V_{\text{max}}$ each time the particle swarm algorithm is used is eliminated. Another approach to using an inertia weight is to adapt it using a fuzzy system. The first paper published reporting this approach used the Rosenbrock function with asymmetric initialization as the benchmark function. The fuzzy system comprised nine rules, with two inputs and one output. Each input and the output had three fuzzy sets defined. One input was the global best fitness for the current generation; the other was the current inertia weight. The output was change in inertia weight. The results reported in the paper showed that by using a fuzzy
adaptive inertia weight the performance of particle swarm optimization can be significantly improved in terms of the mean best fitness achieved in a given number of iterations.

b. Constriction Factor
Because particle swarm optimization originated from efforts to model social systems, a thorough mathematical foundation for the methodology was not developed at the same time as the algorithm. Within the last few years, a few attempts have been made to begin to build this foundation. Recent work done by Clerc indicates that use of a constriction factor may be necessary to insure convergence of the particle swarm algorithm. A simplified method of incorporating it appears in equation (5), where $C$ is a function of $c_1$ and $c_2$ as reflected in equation (6).

$$v(t) = C(v(t-1) + \phi(p - x(t-1)))$$

(5)

$$x(t) = x(t-1) + v(t)$$

(6)

where $\phi = c_1 + c_2$ dan $\phi > 4.0$

$C$ is 0.729. This results in the previous velocity being multiplied by 0.729 and each of the two $(p - x)$ terms being multiplied by 0.729*2.05= 1.49445 (times a random number between 0 and 1).

However, from subsequent experiments and applications it has been concluded that a better approach to use as a “rule of thumb” is to limit $V_{max}$ to $X_{max}$, the dynamic range of each variable on each dimension, while selecting $w$, $c_1$, and $c_2$ according to equations (5) and (6).

2.2 Generating Cost
Operation cost is highest cost in the power system operational. Related with generation optimization cost component are:

1. Fixed Cost
2. Fuel Cost
3. Star-up Cost
4. Production Cost
5. Spinning Reserve Price

To minimization operation cost is the Optimization problems.

a. Generator Input-Output Characteristic
Thermal generator Input-Output Characteristic describe relation of fuel input (liter/hour) and generator output (MW) (Figure 2)

Generally, in Thermal generator Input-Output Characteristic approach with function polynomial:

$$H_i = \alpha_i + \beta_i P_i + \gamma_i P_i^2$$

(7)

with:

- $H_i$ = Input bahan bakar pembangkit termal ke-$i$ (liter/jam)
- $P_i$ = Output pembangkit termal ke-$i$ (MW)
- $\alpha_i, \beta_i, \gamma_i$ = Konstanta input-output pembangkit termal ke-$i$.

If

$$J = \sum_{i=1}^{n} [\alpha + \beta P_i + \gamma P_i^2 - H_i]^2$$

(8)

with:

$$i = 1, 2, 3, ..., n \text{ (jumlah data)}$$

$$J = \sum_{i=1}^{n} [\alpha + \beta P_i + \gamma P_i^2 - H_i]^2$$

(8)

So,

$$\frac{\partial J}{\partial \alpha} = \sum_{i=1}^{n} 2 [\alpha + \beta P_i + \gamma P_i^2 - H_i] = 0$$

$$\frac{\partial J}{\partial \beta} = \sum_{i=1}^{n} 2 P_i [\alpha + \beta P_i + \gamma P_i^2 - H_i] = 0$$

$$\frac{\partial J}{\partial \gamma} = \sum_{i=1}^{n} 2 P_i^2 [\alpha + \beta P_i + \gamma P_i^2 - H_i] = 0$$

(9)

and then

$$(n)\alpha + \left(\sum_{i=1}^{n} P_i\right)\beta + \left(\sum_{i=1}^{n} P_i^2\right)\gamma = \sum_{i=1}^{n} H_i$$

$$\left(\sum_{i=1}^{n} P_i\right)\alpha + \left(\sum_{i=1}^{n} P_i^2\right)\beta + \left(\sum_{i=1}^{n} P_i^3\right)\gamma = \sum_{i=1}^{n} P_i H_i$$

$$\left(\sum_{i=1}^{n} P_i^2\right)\alpha + \left(\sum_{i=1}^{n} P_i^3\right)\beta + \left(\sum_{i=1}^{n} P_i^4\right)\gamma = \sum_{i=1}^{n} P_i^2 H_i$$

(10)
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Matrix equation is

\[
\begin{bmatrix}
\alpha \\
\beta \\
\gamma
\end{bmatrix} =
\begin{bmatrix}
\sum_{i=1}^{n} P_i \\
\sum_{i=1}^{n} P_i^2 \\
\sum_{i=1}^{n} P_i^3 \\
\sum_{i=1}^{n} P_i^4
\end{bmatrix}
\begin{bmatrix}
\alpha \\
\beta \\
\gamma
\end{bmatrix}
\begin{bmatrix}
\sum_{i=1}^{n} P_i H_i \\
\sum_{i=1}^{n} P_i^2 H_i \\
\sum_{i=1}^{n} P_i^3 H_i \\
\sum_{i=1}^{n} P_i^4 H_i
\end{bmatrix}
\]

With inverse the matrix, the Thermal generator Input-Output Characteristic constant is

\[
\begin{bmatrix}
\alpha \\
\beta \\
\gamma
\end{bmatrix} =
\begin{bmatrix}
\sum_{i=1}^{n} P_i \\
\sum_{i=1}^{n} P_i^2 \\
\sum_{i=1}^{n} P_i^3 \\
\sum_{i=1}^{n} P_i^4
\end{bmatrix}^{-1}
\begin{bmatrix}
\sum_{i=1}^{n} P_i H_i \\
\sum_{i=1}^{n} P_i^2 H_i \\
\sum_{i=1}^{n} P_i^3 H_i \\
\sum_{i=1}^{n} P_i^4 H_i
\end{bmatrix}
\]

Hydro generator Input Output characteristic is show in Fig 3.

\[\text{Input} Q \leftrightarrow \text{Output} P(MW)\]

\[\text{Head : 400 ft}\]

\[\text{Figure 3. Hydro Generator Input-Output Characteristic}\]

b. Load limit economic Thermal generator

Generally, the generator has a load limit constraint with economic capacity and restrictiveness of machine components, so in thermal generator load must be carefully with efficiency characteristic and heat characteristic as shown in Fig. 4.

\[\text{Efficiency vs Load (MW)}\]

\[\text{Input Heat (\%)(MW/h/MWh)}\]

\[\text{Figure 4. Load limit generator}\]

2.3 Proposed Algorithm Flowchart

In this paper, we proposed algorithm flowchart shown in Figure 5.

3 RESULT

The proposed methodology has been applied in two example, first example 3.7 page 82 in “Power Generation Operation and Control” by Allen J Wood and second is South Sulawesi Power System.

A. First Example

Exp. 3.7 page 82 in “Power Generation, Operation and Control” by Allen J Wood.

<table>
<thead>
<tr>
<th>Unit</th>
<th>Unit data</th>
<th>Min (MW)</th>
<th>Max (MW)</th>
<th>Fuel Cost ($/MBtu)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>225+8.4P1+0.0025P1^2</td>
<td>45</td>
<td>350</td>
<td>0.8</td>
</tr>
<tr>
<td>2</td>
<td>729+6.3P2+0.0081P2^2</td>
<td>45</td>
<td>350</td>
<td>1.02</td>
</tr>
<tr>
<td>3</td>
<td>400+7.5P3+0.0025P3^2</td>
<td>47.5</td>
<td>350</td>
<td>0.9</td>
</tr>
</tbody>
</table>

Table 2. First Example Result

<table>
<thead>
<tr>
<th>No</th>
<th>Generator</th>
<th>PSO</th>
<th>LI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Load</td>
<td>450</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>Unit 1</td>
<td>206,14</td>
<td>206,0</td>
</tr>
<tr>
<td>2</td>
<td>Unit 2</td>
<td>67,21</td>
<td>67,6</td>
</tr>
<tr>
<td>3</td>
<td>Unit 3</td>
<td>176,63</td>
<td>176,4</td>
</tr>
<tr>
<td>Total cost</td>
<td>4485,6</td>
<td>4485,64</td>
<td></td>
</tr>
</tbody>
</table>

From the first example, with the method proposed gives best result and performance compared with lambda iteration method as shown in Table 2. Also,
accomplish the equality and inequality constraints with total load 450 MW.

B. Second Example

The power system contains five thermal units, the total load is 82 MW, (South Sulawesi Power System). For real system data in South Sulawesi Power System, total cost is Rp.174,924,202.20 per hour.

<table>
<thead>
<tr>
<th>Unit</th>
<th>Load (MW)</th>
<th>Min (29%)</th>
<th>Max (30%)</th>
<th>Fuel Cost (Rp/MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4547.8075 +62.8734 P&lt;sub&gt;1&lt;/sub&gt; + 3.8639 P&lt;sup&gt;2&lt;/sup&gt;</td>
<td>8</td>
<td>30</td>
<td>5411.8</td>
</tr>
<tr>
<td>2</td>
<td>4450.825 + 53.1832 P&lt;sub&gt;1&lt;/sub&gt; + 4.101 P&lt;sup&gt;2&lt;/sup&gt;</td>
<td>8</td>
<td>30</td>
<td>5411.8</td>
</tr>
<tr>
<td>3</td>
<td>345.82 + 82.923 P&lt;sub&gt;1&lt;/sub&gt; + 10.555 P&lt;sup&gt;2&lt;/sup&gt;</td>
<td>6</td>
<td>9</td>
<td>5441.7</td>
</tr>
<tr>
<td>4</td>
<td>760.7825 +39.872 P&lt;sub&gt;1&lt;/sub&gt; + 50.396 P&lt;sup&gt;2&lt;/sup&gt;</td>
<td>6</td>
<td>8</td>
<td>5441.7</td>
</tr>
<tr>
<td>5</td>
<td>322.5 + 156.65 P&lt;sub&gt;1&lt;/sub&gt; + 8.625 P&lt;sup&gt;2&lt;/sup&gt;</td>
<td>6</td>
<td>8</td>
<td>5441.7</td>
</tr>
</tbody>
</table>

Table 3. Second Example data

Table 4. Second Example Result with PSO

<table>
<thead>
<tr>
<th>No</th>
<th>Generator</th>
<th>PSO</th>
<th>L I</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Unit 1</td>
<td>29,1</td>
<td>82</td>
</tr>
<tr>
<td>2</td>
<td>Unit 2</td>
<td>28,1</td>
<td>28,1</td>
</tr>
<tr>
<td>3</td>
<td>Unit 3</td>
<td>9</td>
<td>9</td>
</tr>
<tr>
<td>4</td>
<td>Unit 4</td>
<td>8</td>
<td>8</td>
</tr>
<tr>
<td>5</td>
<td>Unit 5</td>
<td>7,6</td>
<td>7,6</td>
</tr>
<tr>
<td>Total Cost</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PSO</td>
<td>174,857,063,47</td>
<td>L I</td>
<td>174,857,931,11</td>
</tr>
</tbody>
</table>

Figure 6. Simulation curve of second example

For this example, from table 4, three cases have been taken into account.

Case 1: The combination of generator accomplished the equality and inequality constraints with load total 82 MW.

Case 2: With the method proposed gives best result and performance compared with lambda iteration and real system data in South Sulawesi Power System. Total cost with method proposed is Rp.174.857.063,47 per hour, with L I is Rp.174.857.931,11 per hour and in real system Rp.174.924.202,20 per hour. With used method proposed get difference Rp. 67,138,80 per hour if compared real system data in South Sulawesi Power System.

Case 2: With the proposed method, iteration process faster convergent to meet minimum value of total cost as shown in Figure 6.

4 CONCLUSION AND DISCUSSION

In this paper, we propose an approach for the solution of the Optimal Generator Scheduling problem use modified improved particle swarm optimizer algorithm with Constriction Factor Approach (CFA). The proposed approach has been applied to two power systems of the open literature with satisfactory results. Using PSO have better performance than Lambda iteration method.

REFERENCES

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