DECENTRALIZED POWER SYSTEM LOAD-FREQUENCY CONTROL USING A NOVEL COST FUNCTION BASED ON PARTICLE SWARM OPTIMIZATION (PSO)

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Abstract: In this paper, frequency variations are reduced applying an optimal load-frequency controller (LFC) with a new control strategy. The new strategy is based on minimizing the sum of squares of settling time and peak of step response for the load variations utilizing Particle Swarm Optimization (PSO) Algorithm. The proposed controller is designed for two-area power system. The simulations done on such a power system prove the great improvement of system characteristics such as settling time and peak of step response.

1. INTRODUCTION

Load-Frequency Control (LFC) is one of the important issues in electric power system design and operation, because the loading in a power system inevitably changes. The change of load has resulted in the frequency change in power systems. In addition, it is well-known that the operation objectives of the LFC are to maintain reasonably uniform frequency for dividing the load between generators and controlling the tie-line interchange schedules. As a result, it is necessary to design load frequency controller to provide adequate and reliable electric power [1]. Errors in the quantities arise due to unpredictable load variations which cause mismatch between the generator output and load demand. One of the tasks of Automatic Generating Control (AGC) is to minimize the transient deviations and to ensure zero steady state errors of these two variables. Many control strategies have been proposed based on different methods in recent years [2-6]. All these methods try in reducing the frequency variations in dynamic and static conditions. Variable structure control method is one of the applied methods which utilize several algorithms in improving the system response to load changes [7-9]. Another applied method in recent years is utilization of robust controllers. Combination of this controller with other controllers in designing a compensator to guarantee frequency stability with load point variation has been used, recently [10-16]. Fuzzy and Intelligent control methods are also applied for this purpose [17-21]. Application of Genetic Algorithm (GA) is a useful means of optimizing LFC [22]. In a recent paper [22], utilizing GA a cost function defined as:

\[ S_1 = \int_0^\infty e^2(t)dt, \quad S_2 = \int_0^\infty \dot{e}(t)dt \]  

Where \( e(t) \) is the Area Control Error (ACE). In this paper, frequency variations (\( \Delta F \)) is used to reduce the frequency variations instead of ACE. For this purpose, Particle Swarm Optimization (PSO) algorithm is applied in order to minimize the proposed cost function. The PSO algorithm was developed by Eberhart and Kennedy in 1995 and was originated by imitating the behavior of a swarm of bees, a flock of birds or a school of fish during their food-searching activities [23]. This method, finds the optimal solution with the help of particles population. Each particle is an agent and shows a solution for this problem.
This algorithm has great advantages due to its simplicity and high speed in comparison with other resembling methods such as GA.

2. TWO-AREA POWER SYSTEM

A two-area power system model which is linearized for dynamic studies is shown in Fig.1. The system state space equations are:

\[
\begin{align*}
\dot{x} &= Ax + Bu \\
y &= Cx + Du
\end{align*}
\]

where:

\[
A = \begin{bmatrix}
\frac{1}{T_G1} & 0 & \frac{1}{T_G1} R_{Gi} & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & -D_{ij}/M_i & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & -a_{ji} D_{ij}/M_j & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]

\[
B = \begin{bmatrix}
0 & 0 & -1/M_1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & -1/M_2 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]

\[
C = \begin{bmatrix}
\alpha p_{fa} & \alpha F_1 & \alpha F_2 & f_0 & f_0 & f_0 & f_0 & f_0
\end{bmatrix}
\]

\[
x = \begin{bmatrix}
\Delta P_{fa} & \Delta F_1 & \Delta F_2 & \Delta F_2 & \Delta F_2 & \Delta P_{fa}
\end{bmatrix}
\]

\[
y = \begin{bmatrix}
\Delta F_1 & \Delta F_2
\end{bmatrix}, \quad u = \begin{bmatrix}
\Delta P_{fa} & \Delta P_{fa}
\end{bmatrix}
\]

Where:

- \( R_{Gi} \) = speed regulation parameter
- \( T_{Gi} \) = governor time-constant
- \( D_{ij} = 1/K_{pi} \) = load frequency constant
- \( M_i = T_{pi}/K_{pi} \) = inertia constant

Four transfer functions are calculated according to Eq.3 for the 2-input–2-output system.

\[
T(s) = C(sI - A)^{-1} B + D
\]  

Given \( T(s) = \begin{bmatrix} T_{11}(s) & T_{12}(s) \\ T_{21}(s) & T_{22}(s) \end{bmatrix} \), where:

\[
T_{11}(s) = \frac{\Delta F_1}{\Delta P_{fa}}, \quad T_{12}(s) = \frac{\Delta F_1}{\Delta P_{fa}}
\]

\[
T_{21}(s) = \frac{\Delta F_2}{\Delta P_{fa}}, \quad T_{22}(s) = \frac{\Delta F_2}{\Delta P_{fa}}
\]

3. PROPOSED LFC METHOD

A PI controller is designed for dynamic frequency variation reduction (\( \Delta F_1, \Delta F_2 \)) at the load changes in each power system (\( \Delta P_{D1}, \Delta P_{D2} \)). Two parameters of settling time (ST) and response peak (RP) are utilized for comparing the frequency variation reduction optimization which happens for the least values of these two parameters. Therefore in this paper, cost functions are defined as:

\[
f_{11} = \sqrt{(\omega * R_{fa})^2 + ST_{f1}^2}
\]

\[
f_{12} = \sqrt{(\omega * R_{fa})^2 + ST_{f2}^2}
\]

\[
f_{21} = \sqrt{(\omega * R_{fa})^2 + ST_{f1}^2}
\]

\[
f_{22} = \sqrt{(\omega * R_{fa})^2 + ST_{f2}^2}
\]

Where \( R_{fa} \) and \( ST_{fa} \) are the response peak and settling time of frequency variation of area i at load variation in area j, \( \omega \) is the weighting coefficient. The cost function is:

\[
f_T = \gamma_{f1} f_{11} + \gamma_{f2} f_{12} + \gamma_{f2} f_{21} + \gamma_{f2} f_{22}
\]

where \( \gamma_{fj} \) is the weighting coefficient of the corresponding functions. The goal is designing a cost function minimizing Eq.5. In this paper, PSO algorithm is utilized for this purpose.
4. PSO ALGORITHM FOR OPTIMIZING PI CONTROLLER’S PARAMETERS

Fig. 2 shows a swarm of ambivalent bees (designated as agents or particles) flying in a field (a solution space)[24]. The goal of each agent in the swarm is to find a location with the highest flower density. Assume the solution space is N-dimensional and real-valued, each location in the space, \( \bar{x} \), is an N-dimensional real vector and is mapped into a candidate design with \( N \) unknowns. The flower density corresponds to the performance of the design which is represented by a fitness function. In this paper it is set as a default that a better performance leads to a smaller fitness value, and the optimizer is therefore a minimizer. PSO algorithm is defined based on Newton’s second law where each agent is modeled by Newtonian mechanics as two spring-like forces. \( c_1 \) and \( c_2 \) are Hooke’s constants, multiplied by random numbers \( \eta_1 \) and \( \eta_2 \) with uniform distributions in \((0,1)\) to inject the randomness. \( w \) is a time-varying inertial weight.

To inject the randomness into the swarm behavior, Hooke’s constants \( C_1 \) and \( C_2 \) are multiplied by random coefficients \( \eta_1 \) and \( \eta_2 \), respectively. In each dimension, both \( \eta_1 \) and \( \eta_2 \) have a uniform distribution in \((0,1)\), with \( C_1 = 0.3 \) toward the end of the optimization [28]. The velocity update by Equations (9)–(11) has a final form of

\[
\mathbf{v}_{i+1} = \omega \mathbf{v}_i + \mathbf{c}_1 \eta_1 (\bar{p}_i(t) - \mathbf{x}_i) + \mathbf{c}_2 \eta_2 (\bar{g}(t) - \mathbf{x}_i)
\]

in the swarm behavior is that, each agent remembers the location that has the best fitness value on its own trajectory, which is defined as the personal best \( \bar{p}_i = (p_{i1}, p_{i2}, \ldots, p_{iN}) \). The best location found by the entire swarm, called the global best \( \bar{g} = (g_1, g_2, \ldots, g_N) \), is also broadcasted to all agents to adjust their trajectories. Different cognitive and social influences on each agent can be modeled by applying different neighborhood topologies as detailed in [25] and [26]. The influences from each agent’s personal best and global best are modeled by two spring-like attractions, and is expressed by:

\[
\bar{F}(t-1) = C_1 (\bar{p}(t-1) - \bar{x}(t-1)) + C_2 (\bar{g}(t-1) - \bar{x}(t-1))
\]

where \( C_1 \) and \( C_2 \) are Hooke’s constants of two springs (see Fig. 2). Typically equals to in order to balance the cognitive part and the social part.

An important feature underlying in the swarm behavior, Hooke’s constants \( C_1 \) and \( C_2 \) are multiplied by random coefficients \( \eta_1 \) and \( \eta_2 \), respectively. In each dimension, both \( \eta_1 \) and \( \eta_2 \) have a uniform distribution in \((0,1)\), with \( C_1 = 0.3 \) toward the end of the optimization [28]. The velocity update by Equations (9)–(11) has a final form of

\[
v_{id}(t+1) = \omega v_{id}(t) + c_1 \eta_1 (p_{id}(t) - x_{id}(t)) + c_2 \eta_2 (g_{id}(t) - x_{id}(t))
\]

where \( iter \) is the repetition number, \( iter_{max} \) is the maximum repetition number and \( \omega_{max} \) and \( \omega_{min} \) are the maximum and minimum values of \( \omega \). These values are adjusted as \( \omega_{max} = 0.9 \) and
\( \alpha_{\text{min}} = 0.3 \) [28]. The second phrase in Eq.12 is related to personal result and third phrase shows the social mutual effect among the agent. This shows that agent do high attention to their successful results in their neighborhood then their own results. The velocity of agent in any dimension of \( N \)-dimension space is restricted in \( [-v_{\text{min}}, v_{\text{max}}] \) so that there will be less possibility of outgoing of agent from the space. \( v_{\text{max}} \) is usually designed in such a way that \( v_{\text{max}} = k \times x_{\text{max}} \) where \( 0.1 < k < 1 \) and \( x_{\text{max}} \) shows the research length. In Fig.3, the flowchart of PSO algorithm for LFC design is shown.

5. SIMULATION RESULTS

A two-area decentralized power system with the parameters in appendix A as shown in Fig. 1 is utilized [22]. Utilizing the above mentioned algorithm, the improved values for PI controller for \( \gamma_{11} = \gamma_{12} = \gamma_{21} = \gamma_{22} = 1 \) and \( \omega = 0.9 \) are shown in table 1. In addition the results for the proposed methods in this paper and [22] entitled cost function S1 and S2 are compared in table 1. Since the parameters for the two area is the same, therefore is the same PI controllers are designed for the two areas and the values of \( K_{i1}=K_{i2}=K_{r} \) and \( B_{1}=B_{2}=B \) are constant. The step responses \( \Delta T_{i2}, \Delta F_{2}, \Delta F_{1} \) for the load variation in area 1 are compared with two methods of F and S2 in figures 4-6. Also the same responses are shown with two methods F and S1 in figures 7-9. Table 2 shows the settling time and response peak for frequency variation of area 1, area 2 and the variation of transmitted power for step change in load of area 1 (\( \Delta P_{D1} = 1 \text{ pu} \)) utilizing the proposed method in this paper and cost function F application. The same value utilizing S1 and S2 cost functions is shown in table 3. It is proved hat proposed method results in reduction of settling time and response peak for frequency variation in both area and therefore, the dynamic efficiency of the system has improved. But on the other hand, the settling time of transmitted power variations has increased which is due to help of area 2 to area 1 for frequency oscillation reduction. In addition, it took 622 seconds to calculate the PI controller’s parameters using genetic algorithms but this time has reduced to 85 seconds utilizing the proposed method of paper.

Table 1. \( K_{i} \) and P for the three methods with cost functions \( f_{T}, S_{1}, S_{2} \)

<table>
<thead>
<tr>
<th>Cost function</th>
<th>( K_{i} )</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>( f_{T} )</td>
<td>0.1400</td>
<td>1.5677</td>
</tr>
<tr>
<td>( S_{1} )</td>
<td>0.7213</td>
<td>0.2214</td>
</tr>
<tr>
<td>( S_{2} )</td>
<td>0.7019</td>
<td>0.4127</td>
</tr>
</tbody>
</table>

Table 2. Settling time (ST) and response peak (RP) of \( \Delta F_{1}, \Delta F_{2}, \Delta T_{12} \) for 1 pu step load variation utilizing f and PSO

<table>
<thead>
<tr>
<th>( \Delta F_{1} )</th>
<th>( \Delta F_{2} )</th>
<th>( \Delta T_{12} )</th>
<th>ST (sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \Delta F_{1} )</td>
<td>( \Delta F_{2} )</td>
<td>( \Delta T_{12} )</td>
<td>ST (sec)</td>
</tr>
<tr>
<td>2.1</td>
<td>1.5</td>
<td>0.5</td>
<td>8.0</td>
</tr>
<tr>
<td>1.5</td>
<td>2.1</td>
<td>1.8</td>
<td>9.0</td>
</tr>
<tr>
<td>0.5</td>
<td>1.8</td>
<td>0.6</td>
<td>16</td>
</tr>
</tbody>
</table>

Table 3. Settling time (ST) and response peak (RP) of \( \Delta F_{1}, \Delta F_{2}, \Delta T_{12} \) for 1 pu step load variation utilizing S1, S2 and GA

<table>
<thead>
<tr>
<th>( \Delta F_{1} )</th>
<th>( \Delta F_{2} )</th>
<th>( \Delta T_{12} )</th>
<th>ST (sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \Delta F_{1} )</td>
<td>( \Delta F_{2} )</td>
<td>( \Delta T_{12} )</td>
<td>ST (sec)</td>
</tr>
<tr>
<td>2.2</td>
<td>2.2</td>
<td>14.6</td>
<td>11.8</td>
</tr>
<tr>
<td>1.7</td>
<td>1.8</td>
<td>14.6</td>
<td>11.3</td>
</tr>
<tr>
<td>0.6</td>
<td>0.6</td>
<td>10.4</td>
<td>6.7</td>
</tr>
</tbody>
</table>
6. CONCLUSIONS

The proposed new method in this paper for LFC was based on the new cost function on the basis of settling time and peak response and intends to minimize it utilizing PSO algorithm. Comparing the simulation results with the GA based simulations proves the increased dynamic effectiveness, low frequency variation and the greater frequency oscillation reduction. The transmitted power variation between two areas is increased and this proves the help of one area to another area in faster reduction of frequency variation at load changes of the areas. On the other hand, the simulation time with PSO algorithm has obviously decreased in comparison with GA which results in reducing the needed time for calculating PI controller parameters.

APPENDIX

System data.
Area capacity, $P_{R1} = P_{R2} = 2000\text{MW}$
$D_1 = D_2 = 8.33 \times 10^{-3} \text{ p.u.MW/Hz}$
$T_{T1} = T_{T2} = 0.3s,$
$T_{GI} = T_{G2} = 0.08s,$
$T_{p1} = T_{p2} = 20s,$
$R_1 = R_2 = 2.4\text{Hz/p.u.MW},$
$K_{p1} = K_{p2} = 120\text{Hz/p.u.MW},$
$a_{12} = -1, T_{12} = 0.0866 \text{ p.u.MW/radian}$

REFERENCES


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