Multi-Agent-Based Particle Swarm Optimization Approach for PSS Designing In Multi-Machine Power Systems

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Abstract— In this paper the design of multi-machine Power System Stabilizers (PSSs) by using Multi-Agent Particle Swarm Optimization (MAPSO) is presented. The optimum parameters of PSSs will be obtained by MAPSO and the results will be compared with PSO algorithm which eigenvalue analysis is used for comparison. The aim of the optimization problem is to shift electro-mechanical modes of all machines to the left side of the s-plane as far as possible with considering stability. The proposed method is confirmed by obtained simulation results of a three-machine power system under different operating conditions.

Keywords—Dynamic Stability, Eigenvalue Analysis, Multi-Agent PSO, PSS.

I. INTRODUCTION

With increasing electrical power system demand and need to operate power systems close to their limits, modern power systems can reach stressed conditions more easily than the past. Therefore, un-damped oscillations have been observed more often in today’s power systems. As a result, an adequate tuning of Power System Stabilizers (PSS) had been the topic of many works.

Different optimization and modern control techniques are proposed for obtaining PSS parameters such as:

- Genetic algorithm (GA) [1]
- Tabu search [2]
- Simulated annealing [3]
- Evolutionary programming [4]
- Particle swarm optimization (PSO) [5]
- Rule based bacteria forging [6]
- Neuro-fuzzy algorithm [7]
- Neuro based adaptive control [8]
- Liapanuv PV method [9]

However, in this paper a new modification of particle swarm optimization (PSO), named Multi-Agent PSO (MAPSO), is proposed for optimal design of PSS in multi-machine power systems. The problem is formulated as an optimization problem subject to find the optimal values of the PSS parameters by using MAPSO. The eigenvalue analysis has been carried out to assess the effectiveness of the proposed MAPSO-PSS.

The obtained results ensure robust stability and good performance for the different operating conditions. The simulation results also show that the MAPSO gives better results in compare with PSO.

II. PROBLEM STATEMENT

Consider a multi-machine power system as shown in Fig. 1. The system is composed of three machines connected to a nine-bus system. This system is studied for three different loading conditions i.e., low, nominal and heavy loading.

![Figure 1. Three machine nine-bus power system](image-url)

Each machine consists of a PSS with the typical structure according to (1) where index \(i\) denotes to the \(i^{th}\) machine.

\[
U_i = K_i \frac{ST_W}{1 + ST_W} \left[ \frac{(1 + ST_{1i})(1 + ST_{2i})}{(1 + ST_{2i})(1 + ST_{4i})} \right] \Delta \omega_i (S) \tag{1}
\]

Expression (1) can be shown in Fig. 2 consisting of gain, washout, phase compensation and output limiter blocks. The figure shows that the input is speed difference and the output is damping torque.
Three different objective functions are used in MAPSO to achieve the optimal parameters of PSSs. The first objective function, \( J_1 \), is used for maximize the real part of the electromechanical eigenvalues. The second one, \( J_2 \), minimize the integral of absolute error whereas the third one, \( J_3 \), minimize the integral of square error. \( J_1, J_2 \) and \( J_3 \) improve the settling time and overshoots of the step response of each machine. The optimized parameters are \( K_{pi}, T_{i1}, T_{3i} \) for each machine, the others parameters are not so important in optimum operation of machines, therefore 9 PSS parameters must be obtained for the power system shown in Fig. 1.

**Objective Functions:**

\[
J_1 = \max(\text{real}(\dot{\lambda}_i)) : \lambda_i \in \text{Electromechanical-Modes} \tag{2}
\]
\[
J_2 = \min \left\{ \sum_{r=1}^{i} \sum_{m=1}^{n} IAE_{m,r} = \sum_{r=1}^{i} \sum_{m=1}^{n} \int_{0}^{t} e_{m,r}^1(t) \, dt \right\} \tag{3}
\]
\[
J_3 = \min \left\{ \sum_{r=1}^{i} \sum_{m=1}^{n} ISE_{m,r} = \sum_{r=1}^{i} \sum_{m=1}^{n} \int_{0}^{t} e_{m,r}^2(t) \, dt \right\} \tag{4}
\]

Where:

- \( IAE \): Integral of absolute error
- \( ISE \): Integral of squared error
- \( IAE_{m,r} \): IAE of \( r \)th machine when unit step is applied to \( m \)th machine
- \( ISE_{m,r} \): ISE of \( r \)th machine when unit step is applied to \( m \)th machine.

The optimization problem is defined as:

**Optimized** \( J_1, J_2, J_3 \)

**Subjected to**

\[
K_{i1}^{\min} \leq K_{i1} \leq K_{i1}^{\max} \tag{5}
\]
\[
T_{i1}^{\min} \leq T_{i1} \leq T_{i1}^{\max}
\]
\[
T_{3i}^{\min} \leq T_{3i} \leq T_{3i}^{\max}
\]

Typical ranges of the optimized parameters are [0.01-100] for \( K_i \) and [0.01-1] for \( T_{i1} \) and \( T_{3i} \). The time constants \( T_{i1}, T_{i2} \) and \( T_{3i} \) are set as 10, 0.05 and 0.05, respectively.

In ring topology, each particle is influenced by its immediate neighbors whereas in star topology, each particle is influenced by entire swarm. Both algorithms use the following expressions for updating the velocity, respectively [11].

\[
v_{id}(t+1) = \omega v_{id}(t) + c_1 \text{rand}_1(p_{id}(t) - x_{id}(t))
\]
\[
v_{id}(t+1) = \omega v_{id}(t) + c_2 \text{rand}_2(g_d(t) - x_{id}(t))
\]
\[
v_{id}(t+1) = \omega v_{id}(t) + c_2 \text{rand}_2(n_{id}(t) - x_{id}(t))
\]

Where,

- \( x_{id}(t) \) current position of \( i \)th particle in \( d \)th dimension
- \( p_{id}(t) \) current best position of group in \( d \)th dimension
- \( n_{id}(t) \) current best position of \( i \)th particle’s neighbors in \( d \)th dimension
- \( g_d(t) \) current best position of group \( d \)th dimension
- \( v_{id}(t+1) \) next velocity of particle \( i \) in \( d \)th dimension
\( \omega \) inertial weight  
\( c_1, c_2 \) Hooke’s constants  
\( r_1, r_2 \) random numbers between 0 and 1  

The coefficients \( C_1 \) and \( C_2 \) are equal to 2.05 as suggested by [12]. To accelerate the convergence, a time-varying weight factor, \( \omega \), is set according to the following equation \((\omega_{\text{max}}=0.9, \omega_{\text{min}}=0.1)\):

\[
\omega = \omega_{\text{max}} - \frac{\omega_{\text{max}} - \omega_{\text{min}}}{\text{iter}_{\text{max}}} \text{iter}
\]  

Where  
\( \text{iter} \) current iteration number  
\( \text{iter}_{\text{max}} \) maximum iteration number  

Each particle moves from the current position to the next position by using the following equation \([13]\):

\[
\mathbf{\bar{x}}(t + 1) = \mathbf{x}(t) + \mathbf{\bar{v}}(t + 1)
\]

\[ (9) \]

B. MAPSO Algorithm

The population of the MAPSO algorithm is called swarm. Swarm contains a species set, and each species contains \( n \) particles. i.e., there are totally \( n \times m \) particles in swarm. Swarm and species can be expressed by:

\[ \text{Swarm} = \{ S_1, S_2, \ldots, S_m \} \]

\[ S_i = \{ \mathbf{x}_1^i, \mathbf{x}_2^i, \ldots, \mathbf{x}_n^i \} \]

Two simple topologies are shown in Fig. 4.

\[ (10) \]

\[ (11) \]

![Figure 4. MAPSO topologies of 4 species](image)

(a) The star-star topology  
(b) The ring-ring topology  

The first topology is called star-star and the second one is called ring-ring. In the star-star topology each particle gets information from the other particles in its own species and the other agents, whereas, in the ring-ring topology each particle gets information from its own species and only two neighbors agents. The algorithm updates velocity of \( i^{\text{th}} \) particle in \( l^{\text{th}} \) species for star-star and ring-ring topology based on \((12)\) and \((13)\), consequently.

\[
v_{ld}(t + 1) = \omega v_{ld}(t) + c_1 \text{rand} \mathbf{p}_{ld}(t) - c_2 \text{rand} g_d(t) - x_{ld}(t)
\]  

\[ (12) \]

\[
v_{ad}(t + 1) = \omega v_{ad}(t) + c_1 \text{rand} \mathbf{p}_{ad}(t) - c_2 \text{rand} g_d(t) - x_{ad}(t)
\]  

\[ (13) \]

Where,

\[ x_{ld}(t) \] current position of \( i^{\text{th}} \) particle from \( l^{\text{th}} \) species in \( d^{\text{th}} \) dimension  
\[ p_{ld}(t) \] best position of \( i^{\text{th}} \) particle from \( l^{\text{th}} \) species in \( d^{\text{th}} \) dimension  
\[ g_d(t) \] best position of \( l^{\text{th}} \) species in \( d^{\text{th}} \) dimension  
\[ v_{ld}(t + 1) \] next velocity of \( i^{\text{th}} \) particle from \( l^{\text{th}} \) species in \( d^{\text{th}} \) dimension  
\[ p_{ad}(t) \] position of \( i^{\text{th}} \) agent in \( d^{\text{th}} \) dimension  
\[ v_{ad}(t + 1) \] next velocity of \( i^{\text{th}} \) agent in \( d^{\text{th}} \) dimension  
\[ x_{ad}(t) \] current position of \( i^{\text{th}} \) agent in \( d^{\text{th}} \) dimension  
\[ g_d(t) \] best position of swarm in \( d^{\text{th}} \) dimension

IV. RESULTS AND DISCUSSION

A multi-machine power system shown in Figure 1 is used for case study. Each machine is modeled by the third-order nonlinear model and is equipped with the first order excitation system and a PSS. The detailed machine constants and the network data are given in [14].

The optimal setting of three PSS parameters is determined by the MAPSO, i.e. 9 parameters are to be optimized. The obtained results are shown in Table I in which there are three rows and nine columns. The optimum settings of each PSS are also shown in rows for each generator. As can be seen, the settings are also obtained for J1, J2 and J3 objective functions.

Fig. 5 shows the pole placement of the machine 1. As can be seen, when there is no PSS, all the machine’s poles are near imaginary axes and some of them have positive real part. It means that the machine is unstable. When the proposed method with objective functions is used, the machine’s poles move to the stable region. The results of the pole placement of J1, J2, and J3 are also shown in Fig. 5. The obtained results of the machine 2 and machine 3 are depicted in Fig. 6 and Fig. 7, consequently.

Investigating Fig. 5, 6 and 7 shows that the machines operate stable. To evaluate the performance of the proposed method under disturbances, a disturbance of 0.1 pu is applied to the all machines at time \( t=1 \) second. This study is performed at three different operating conditions according to Table II.
TABLE I. OPTIMAL PSSs PARAMETERS

<table>
<thead>
<tr>
<th>Gen</th>
<th>K</th>
<th>J1</th>
<th>T1</th>
<th>T3</th>
<th>K</th>
<th>J2</th>
<th>T1</th>
<th>T3</th>
<th>K</th>
<th>J3</th>
<th>T1</th>
<th>T3</th>
</tr>
</thead>
<tbody>
<tr>
<td>G1</td>
<td>37.3282</td>
<td>0.1358</td>
<td>0.0897</td>
<td>12.3256</td>
<td>0.6807</td>
<td>0.0826</td>
<td>19.8857</td>
<td>0.6984</td>
<td>0.0576</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>G2</td>
<td>8.4481</td>
<td>0.0163</td>
<td>0.7120</td>
<td>35.4782</td>
<td>0.1086</td>
<td>0.1352</td>
<td>26.5745</td>
<td>0.1266</td>
<td>0.1155</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>G3</td>
<td>38.5067</td>
<td>0.0980</td>
<td>0.0994</td>
<td>21.5287</td>
<td>0.2033</td>
<td>0.2075</td>
<td>26.6679</td>
<td>0.1514</td>
<td>0.1472</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The results are shown in Fig. 8 to Fig. 10, which Fig. 8 shows the speed deviations of G1, G2, and G3 under nominal condition and Fig. 9 and Fig. 10 show the results under heavy and low loading conditions.

It can be concluded that MPSO achieves robust performance and damp the oscillations very well over a wide range of operating conditions. It is clear that the proposed PSS provide good damping characteristics to low-frequency oscillations and greatly enhance the dynamic stability of power system.

TABLE II. LOADING CONDITION

<table>
<thead>
<tr>
<th>Gen</th>
<th>Nominal</th>
<th>Heavy</th>
<th>Light</th>
</tr>
</thead>
<tbody>
<tr>
<td>G1</td>
<td>P</td>
<td>Q</td>
<td>P</td>
</tr>
<tr>
<td>G2</td>
<td>0.72</td>
<td>0.27</td>
<td>2.21</td>
</tr>
<tr>
<td>G3</td>
<td>1.63</td>
<td>0.07</td>
<td>1.92</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Load</th>
<th>P</th>
<th>Q</th>
<th>P</th>
<th>Q</th>
<th>P</th>
<th>Q</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.25</td>
<td>0.5</td>
<td>2.0</td>
<td>0.8</td>
<td>0.65</td>
<td>0.55</td>
</tr>
<tr>
<td>B</td>
<td>0.9</td>
<td>0.3</td>
<td>1.8</td>
<td>0.6</td>
<td>0.45</td>
<td>0.35</td>
</tr>
<tr>
<td>C</td>
<td>1.0</td>
<td>0.35</td>
<td>1.5</td>
<td>0.6</td>
<td>0.5</td>
<td>0.25</td>
</tr>
</tbody>
</table>
The comparison between PSO and MPSO is shown in Fig. 11. This figure sows that the MPSO gives the better results from PSO for different operating conditions. The settling time and oscillation of the generator speed will be decreased if the problem is solved by MPSO.

In addition, the convergence of the proposed method in compare with PSO algorithm is depicted in Fig. 12 and can be seen that MPSO converge faster than PSO. This figure shows the convergence of J2 objective function, because it gives better results than the other objective functions.
V. Conclusion

An optimal design for multi-machine power system stabilizers using MAPSO has been presented. The stabilizers are tuned to shift the electromechanical modes of all plants to left side of the s-plane. The Eigenvalue analysis gave us a satisfactory damping on system modes, especially the low-frequency modes, for systems with the proposed method. Also, time-domain simulations show that the oscillations of synchronous machines can be quickly and effectively damped and the obtained optimum parameter work effectively over a wide range of loading conditions.

References