A Hybrid Clonal Selection Algorithm and Particle Swarm Optimization for Multiple Damping Controllers Design

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Abstract— Power System Stabilizers (PSSs) are used to generate supplementary control signals for the excitation system to damp electromechanical oscillations. This paper presents a new evolutionary learning approach based on a Hybrid of Clonal Selection Algorithm and Particle Swarm Optimization (HCSAPSO) for tuning the parameters of PSSs in a multi-machine power system. The stabilizers are tuned to simultaneously shift the undamped and lightly damped electromechanical modes of all plants to a prescribed zone in the s-plane. A multi-objective problem is formulated to optimize a composite set of objective functions comprising the damping factor and damping ratio of lightly damped electromechanical modes. The performance of the proposed PSSs under different disturbances, loading conditions, and system configurations is investigated on New England 10-machine, 39-bus system. The eigenvalue analysis and nonlinear time domain simulations demonstrate the effectiveness of the proposed HCSAPSO based damping controllers to dampout the local and the inter-area modes of oscillations.

Index Terms— Power System Stabilizer, Multi-objective Optimization, Clonal Selection Algorithm, Particle Swarm Optimization, Multi-machine Power System

I. INTRODUCTION

Damping of electromechanical oscillations in multi-machine power systems is the most important issue for its secure operation. These oscillations may sustain and grow to cause system separation if no adequate damping is available [1]. A well established classification separates the oscillations into two types: (i) local mode, which corresponds to oscillations of one or more generators in an area with respect to the rest of the system and (ii) inter-area mode, which is concerned with the oscillations of a group of generators in one area against a group in another area, usually connected by a long and/or weak tie line. The local mode frequency typically varies from 1.0 to 3.0 Hz [2], while inter-area mode frequency range will be between 0.2 and 1.0 Hz [3] in general cases. A common approach to damp these oscillations and improve system dynamic stability is to use conventional lead-lag Power System Stabilizers (CPSSs). These stabilizers are effective in damping local modes, and if carefully optimized may also be effective in damping inter-area modes up to a certain transmission loading [4].

Design of CPSS is based on the linear control theory which requires a nominal power system model formulated as linear, time invariant system [5]. CPSS based on this approach can be very well tuned to an operating condition and will provide excellent damping over a certain range around the design point. However, CPSS parameters may not be optimal for the whole set of possible operating conditions and configurations. Despite the potential of modern control techniques with different structures, power system utilities still prefer a CPSS structure [6, 7]. The reasons behind that might be the ease of online tuning and the lack of assurance of the stability related to some adaptive or variable structure techniques. Kundur et al. [8] presented a comprehensive analysis of the effects of the different CPSS parameters on the overall dynamic performance of the power system. It is shown that the appropriate selection of CPSS parameters results in satisfactory performance during system upsets. Many different techniques have been reported in the literature pertaining to optimum location and coordinated design problems of CPSSs. Majority of these techniques are based on phase compensation and eigenvalue assignment [6–16]. Different techniques of sequential design of PSSs are presented [9-11] to damp out one of the electromechanical modes at a time. The effects of dynamic interaction among various modes of the machines are generally found to have significant influence on the stabilizer settings. Therefore, considering the application of stabilizer to one machine at a
time may not finally lead to an overall optimal choice of PSS parameters. Further, the stabilizers designed to damp one mode can adversely affect other modes. The sequential design of PSSs is avoided in various methods for simultaneous tuning of PSSs in multi-machine power systems [12–16]. Unfortunately, these techniques are iterative and require heavy computational burden due to system reduction procedure, which results in time consuming computer code. In addition, the initialization step of these algorithms is critical and affects the final dynamic response of the controlled system. Hence, different designs assigning the same set of eigenvalues were obtained simply by using different initializations. Therefore, a final selection criterion is required to avoid long runs of validation tests on the nonlinear model. The evolutionary methods incorporate an approach to search for the optimum solutions via some form of directed random search process. A relevant characteristic of the evolutionary methods is that they search for solutions without a prior knowledge of the problem. Meta heuristic optimization techniques like Genetic Algorithm (GA) [17], Simulated Annealing (SA)[18], Particle Swarm Optimization [19], Bacterial Foraging Algorithm[20] and Harmony Search Algorithm (HSA)[21] attracted the attention of many in the field of PSS parameter optimization. However, when the system has a highly epistatic objective function (i.e., where parameters being optimized are highly correlated), and parameters to be optimized are large in number, GA has been reported to exhibit degraded efficiency [22]. L.N.de Castro and F. J. Von Zuben have explained learning and optimization using Clonal Selection Algorithm in [23], G. Naresh et al. used Clonal Selection Algorithm and Modified Clonal Selection Algorithm to design multiple damping controllers in [24, 25]. D. Baghani et al. have used Cuckoo Search Algorithm for the design of fuzzy based PSS in [26]. In this paper, a Hybrid of Clonal Selection Algorithm and Particle Swarm Optimization is proposed to design multiple damping controllers in a multi-machine power system. The efficacy of the damping controllers designed by proposed approach has been tested by eigenvalue analysis and nonlinear time domain simulations under different disturbances, loading conditions and system configurations.

II. PROBLEM FORMULATION

A. Power System Model:
A power system can be modelled by a set of nonlinear differential equations as 
\[ X = f(X, U), \]
where \( X \) is the vector of the state variables, and \( U \) is the vector of input variables. In this study, all the generators in the power system are represented by their fifth order models [27] and equipped with single time constant fast exciters. For a given operating condition, the multi-machine power system is linearized around the operating point. The closed loop eigenvalue of the system are computed and the desired objective function is formulated using only the unstable or lightly damped electromechanical eigenvalues, keeping the constraints of all the system modes stable under all conditions.

B. Structure of the PSS and Objective Function:
A widely used conventional lead-lag PSS is considered in this study. Its transfer function, given in (1), consists of an amplification block with a control gain \( K_S \), a washout filter block with a time constant \( T_w \) and two lead-lag blocks for phase compensation with time constants \( T_1, T_2, T_3 \) and \( T_4 \).

\[ V_{PSS}(s) = K_S \frac{X_w}{(1+X_w)} [1+\frac{sT_1}{(1+sT_3)}][1+\frac{sT_2}{(1+sT_4)}] \Delta \omega(s) \quad (1) \]

where, the PSS output signal \( V_{PSS} \) is a voltage added to the generator exciter input. The generator speed deviation \( \Delta \omega \) is often used as the PSS input signal. In small signal stability studies, the linearized system model around an equilibrium point and the eigenvalue analysis are usually applied. The real part \( \sigma \) of an eigenvalue \( \lambda \) given in (2), and the corresponding damping factor \( \zeta \), given in (3), are two important criteria for the system stability performance [28]. To get good results, it is preferred to take into account these two criteria. This combination leads to a D-stability region of the complex \( s \)-plane, where all system eigenvalues must be placed [29]. The D-stability criteria are chosen as following:

\[ \sigma_{cr} = -2.0, \quad \zeta_{cr} = 20\% \]

\[ \lambda = \sigma \pm j\omega \quad (2) \]

\[ \zeta = \frac{\sigma}{\sqrt{\sigma^2 + \omega^2}} \quad (3) \]

Generally, an optimization problem may be formulated mathematically as following:

Maximize \( f(x) \); \( x \in \mathbb{R} \) and

\[ x_{i_{\min}} \leq x_i \leq x_{i_{\max}} \quad (4) \]

- \( f(x) \) is the objective (or multi-objective) function.
- \( x \) is the vector of the \( n \) parameters to be optimized.

\( x_{i_{\min}} \) and \( x_{i_{\max}} \) are the search space boundaries of the associated parameter \( x_i \).

In our problem, the multi-objective function \( f(x) \) is formulated, as given in (5), to optimize a composite set of two eigenvalue-based objective functions \( J_1 \) and \( J_2 \) where the conditions \( \sigma_{i,j} \leq \sigma_{cr} \) and \( \zeta_{i,j} \leq \zeta_{cr} \) are imposed simultaneously. The parameters of the PSS may be selected to minimize the following objective function \( J \) given by:

\[ J = J_1 + a \cdot J_2 \quad (5) \]
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1. To create a population \( P \) of random solutions to the given problem.

2. Affinity evaluation (objective function):
\[
Affinity = \frac{1}{1 + \text{Objective function value}} \tag{6}
\]

3. Rank the population by fitness.

4. Clone: The size of clone is defined as following:
\[
\text{Number of clones (} N_c \text{)} = \text{round}(\beta * N) \quad \tag{7}
\]

where \( N \) is a user predefined clone factor (\( N \leq 30 \)) and \( \beta \) is user predefined parameter (\( \beta = 5 \) to 100).

An ideal value of mutation rate \( (\alpha) \) should be greater at the beginning of space exploitation in order to improve search speed and diversity of populations. With the increase of generation, its value should go down to fit for finer searching around current optima. In order to fit these two circumstances, use a dynamic setting of parameter

\[
\beta = 2a - b + 2^\frac{b-a}{1+\exp(iteration\ time)} \tag{8}
\]

where \( a \) and \( b \) are lower and upper limits respectively.

5. Affinity Mutation:
\[
\alpha = \frac{1}{\beta} \exp(fitness\ value) \tag{9}
\]

6. New population:
\[
C^* = C + \alpha * N(0,1) \tag{10}
\]

\( N(0,1) \) is a Gaussian random variable of mean zero and unity standard deviation [33].

7. Selection:
Here the highest affinities were sorted in an ascending order for implementation. In selection, the offspring produced by mutation process will be sorted and calculate the best value from the offspring

8. Stopping Criterion:
There are various criteria available to stop Stochastic Optimization Algorithms. Some examples are tolerance, number of function evaluations and number of iterations. In this paper, maximum number of iterations is chosen as the stopping criterion, when there is no significant improvement in the solution. If the stopping criterion is not satisfied, the above procedure is repeated from clone with incremented iteration. The flowchart indicating the implementation of clonal selection algorithm has been presented in Figure 1.

II. CLONAL SELECTION ALGORITHM

The current control, which consists of two hysteresis Clonal selection theory, proposed by F. M. Burnet, is the important content of the biological immune system theory. The main steps of Clonal Selection Algorithm are as follows [30-32]:

1. To create a population \( P \) of random solutions to the given problem.

2. Affinity evaluation (objective function):
\[
Affinity = \frac{1}{1 + \text{Objective function value}} \tag{6}
\]

3. Rank the population by fitness.

4. Clone: The size of clone is defined as following:
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III. HYBRID CLONAL SELECTION ALGORITHM WITH PARTICLE SWARM OPTIMIZATION (HCSAPS0)

In Hybrid Clonal Selection Algorithm with Particle Swarm Optimization approach, the following modifications are made to the Clonal Selection Algorithm.

1. Best Q numbers of populations are selected from the initial P number of random solutions obtained in step (1) based on their best fitness value using Particle Swarm Optimization.

2. In step (5) affinity mutation is obtained by modifying the Eq. (9)
\[
\alpha_1 = \frac{1}{\beta} \exp(-fitness\ value) \times \max(K_3) \quad \tag{11}
\]

3. New population is obtained by modifying the Eq.(10)
\[
C^* = C + \alpha * N_r (0,1) \quad \tag{12}
\]

\( N_r (0,1) \) is a random number between -1 and 1.

The training parameters chosen for the CSA and HCSAPO are given in the Table 1.

IV. RESULTS AND DISCUSSION

The proposed HCSAPO-based approach is implemented using MATLAB 7.6 and the simulations were carried on 2.27 GHz, 4GB RAM and Intel Core i3 PC. This HCSAPO is applied on New England 10-machine, 39-bus system shown in Figure 2, for designing the optimal parameters of the PSS. Details of the system data are given in [34].

A. Eigenvalue Analysis:
To design the proposed HCSAPSOSSs, four different operating scenarios that represent the system under severe loading conditions and critical line outages are considered. These conditions are extremely hard from the stability point of view [35]. The different operating scenarios considered are given in Table 2. The tuned parameters of the ten PSS using conventional root locus approach, CSA and proposed
HCSAPSO are shown in the Table 3. The electromechanical modes and the damping ratios obtained for all the above cases with CPSSs, CSAPSSs and HCSAPSOPSSs in the system are given in Table 4. The unstable and poorly damped modes for different operating conditions were found out and highlighted in this Table. From the eigenvalue analysis between CSAPSS and HCSAPSOPSS for all the cases, it can be noticed that all modes are well shifted into the D-stability region.

Figure 1: Flow Chart of Clonal Selection Algorithm

Start

Initialize all initial variables $N, N_c, \beta, n_{\text{max}}$ and set iteration count, $n=1$

Initialize random population ($P$) of parameters for $K_s, T_1$ and $T_2$

Evaluate the affinity ($f$) of the initial population

Clonal proliferation ($N_c$) based on affinity ($f$)

Perform Mutation on population of clones

Constraints violations?

Yes

Update the violated clones to their limits

No

Evaluate the affinity ($f$) of mutated clones

Tournament selection

$n = n + 1$

Stopping criterion?

No

Yes

Stop
Table 1: Training parameters used for CSA and HCSAPSO

<table>
<thead>
<tr>
<th>Parameter</th>
<th>CSA</th>
<th>HCSAPSO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial number of network cells ( N )</td>
<td>P=40</td>
<td>Q=40</td>
</tr>
<tr>
<td>Number of clones generated for each cell</td>
<td>10</td>
<td>5</td>
</tr>
<tr>
<td>Scale of the affinity proportional selection (( \beta ))</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Maximum number of iterations allowed</td>
<td>200</td>
<td>100</td>
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</table>

Table 2: Operating Scenarios

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Description</th>
</tr>
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<tbody>
<tr>
<td>Scenario 1</td>
<td>All lines in service</td>
</tr>
<tr>
<td>Scenario 2</td>
<td>Outage of line connecting bus no. 14 and 15</td>
</tr>
<tr>
<td>Scenario 3</td>
<td>Outage of line connecting bus no. 21 and 22</td>
</tr>
<tr>
<td>Scenario 4</td>
<td>Increase in generation of G7 by 25% and loads at buses 16 and 21 by 25%, with the outage of line 21–22</td>
</tr>
</tbody>
</table>

Table 3: Tuned Parameters of CPSS, CSAPSS and HCSAPSO

<table>
<thead>
<tr>
<th>Gen</th>
<th>Parameters of CPSS</th>
<th>Parameters of CSAPSS</th>
<th>Parameters of HCSAPSO</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( K_{pss} )</td>
<td>( T_1 )</td>
<td>( T_2 )</td>
</tr>
<tr>
<td>G1</td>
<td>10.4818</td>
<td>0.6211</td>
<td>0.1789</td>
</tr>
<tr>
<td>G2</td>
<td>0.6799</td>
<td>0.6185</td>
<td>0.1796</td>
</tr>
<tr>
<td>G3</td>
<td>0.2396</td>
<td>0.5778</td>
<td>0.1923</td>
</tr>
<tr>
<td>G4</td>
<td>1.1531</td>
<td>0.5727</td>
<td>0.1940</td>
</tr>
<tr>
<td>G5</td>
<td>17.0819</td>
<td>0.6143</td>
<td>0.1809</td>
</tr>
<tr>
<td>G6</td>
<td>13.4726</td>
<td>0.6163</td>
<td>0.1803</td>
</tr>
<tr>
<td>G7</td>
<td>4.3773</td>
<td>0.5636</td>
<td>0.1971</td>
</tr>
<tr>
<td>G8</td>
<td>0.5709</td>
<td>0.6099</td>
<td>0.1822</td>
</tr>
<tr>
<td>G9</td>
<td>1.6059</td>
<td>0.5429</td>
<td>0.2046</td>
</tr>
<tr>
<td>G10</td>
<td>19.8488</td>
<td>0.5027</td>
<td>0.2210</td>
</tr>
</tbody>
</table>

Figure 2: New England 10-machine, 39-bus system
### Table 4: Comparison of eigenvalues and damping ratios for different scenarios

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Without PSS</th>
<th>CPSS</th>
<th>CSAPSS</th>
<th>HCSAPSOPSS</th>
</tr>
</thead>
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<tr>
<td><strong>Scena 1</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.0794 ± 3.9665i, 0.0200</td>
<td>-1.2016 ± 4.5676i, 0.2544</td>
<td>-1.067 ± 2.1086i, 0.5234</td>
<td></td>
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</tr>
<tr>
<td>0.0575 ± 7.3333i</td>
<td>1.1645 ± 10.6163i</td>
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</tr>
<tr>
<td>0.2587 ± 8.0346i</td>
<td>0.1000 ± 6.7243i, 0.0149</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.2352 ± 3.6446i, 0.1303 ± 0.2070</td>
<td>0.0563 ± 6.0958i, 0.0344</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.2579 ± 6.1069i, -0.0422</td>
<td>0.0197 ± 0.2937i, 0.0216</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.0620 ± 0.1671i, -0.0100</td>
<td>0.0117 ± 0.0660i, 0.0225</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Scena 2</strong></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>0.0794 ± 3.9665i, 0.0200</td>
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<tr>
<td><strong>Scena 3</strong></td>
<td></td>
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<tr>
<td><strong>Scena 4</strong></td>
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### Figure 3: Speed deviations of 4th and 5th generators for Contingency (a)
Figure 4: Speed deviations of 6th and 7th generators for Contingency (b)

Figure 5: Speed deviations of 8th and 9th generators for Contingency (c)

Figure 6: Speed deviations of 5th and 6th generators for Contingency (d)
It is worth mentioning that the lower the value of this index is, better the system response in terms of time domain characteristics. **Contingency (a):** A six-cycle three-phase fault, very near to the 14th bus in the line 4–14, is simulated. The fault is cleared by tripping the line 4–14. The speed deviation of generators G6 and G7 generators. For this case, Clonal Selection Algorithm based PSSs gives \( \text{ITAE}_{\text{CSA}} = 6.0192 \) and Hybrid Clonal Selection Algorithm with Particle Swarm Optimization based PSSs give \( \text{ITAE}_{\text{HCSAPSO}} = 4.8679 \).

**Contingency (b):** A six-cycle fault disturbance at bus 33 at the end of line 19-33 with the load at bus-25 doubled. The fault is cleared by tripping the line 19-33 with successful reclosure after 1.0 s. Figure 4 shows the oscillations of G6 and G7 generators. For this case, Clonal Selection Algorithm based PSSs gives \( \text{ITAE}_{\text{CSA}} = 5.7570 \) and Hybrid Clonal Selection Algorithm with Particle Swarm Optimization based PSSs gives \( \text{ITAE}_{\text{HCSAPSO}} = 4.7085 \).

**Contingency (c):** Another critical six cycle three-phase fault is simulated very near to the 22nd bus in the line 22–35 with load at bus-21 increased by 20%, in addition to 25th bus load being doubled as in scenario 2. The speed deviations of generators G8 & G9 are shown in Figure 5. For this case, Clonal Selection Algorithm based PSSs gives \( \text{ITAE}_{\text{CSA}} = 5.7710 \) and Hybrid Clonal Selection Algorithm with Particle Swarm Optimization based PSSs gives \( \text{ITAE}_{\text{HCSAPSO}} = 4.7237 \).

**Contingency (d):** A six-cycle three-phase fault, very near to the 14th bus in the line 14–15 with 20% increase in load is simulated. The fault is cleared by tripping the line 14–15. The speed deviation of generators G5 & G6 are shown in Figure 6. For this case, Clonal Selection Algorithm based PSSs gives \( \text{ITAE}_{\text{CSA}} = 5.6377 \) and Hybrid Clonal Selection Algorithm with Particle Swarm Optimization based PSSs gives \( \text{ITAE}_{\text{HCSAPSO}} = 4.3179 \).

The system responses to the considered faults with CPSSs, CSA PSSs and with the proposed HCSAPSOSSs are shown in Figures 3, 4, 5 and 6 respectively. It is clear from the nonlinear time domain simulations that the proposed HCSAPSOSSs provide improved damping characteristics to low frequency oscillations and greatly enhance the dynamic stability of power systems. It is also clear from the figures that the system oscillations, which are poorly damped with CPSSs and CSA PSSs are well damped and returns to steady state much faster with HCSAPSOSSs. The performance index \( \text{ITAE} \) obtained for the above contingencies using CPSSs, CSA PSSs & HCSAPSOSSs are given in the Table 5. Therefore the system performance characteristic in terms of \( \text{ITAE} \) index reveals the solution quality of the proposed HCSAPSOSSs over CPSSs and CSA PSSs.

**VI. CONCLUSION**

Use of Hybrid Clonal Selection Algorithm with Particle Swarm Optimization to design robust power system stabilizers for power systems working under various operating conditions is investigated in this paper. The problem of selecting the PSS parameters, which simultaneously improve the damping at various operating conditions, is converted to an optimization problem with an eigenvalue based objective function which is solved by
an optimization technique based on Hybrid of Clonal Selection Algorithm and Particle Swarm Optimization. An objective function is presented allowing the robust selection of the stabilizer parameters that will not only optimally place the closed-loop eigenvalues in the left-hand side of a vertical line in the complex s-plane but also improve the damping ratio. The performance and robustness of HCSAPSSs is then tested on New England 10-machine, 39-bus multi-machine system and compared with CPSSs and CSAPSSs. Simulation results show the effectiveness and robustness of the proposed HCSAPSSs over CPSSs and CSAPSSs.

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