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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

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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 non-linear 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 $\dot{X} = f(X,U)$, 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.

$$V_{PSS}(s) = K_S \cdot \frac{sT_W}{(1+sT_W)} \cdot \left[\frac{(1+sT_1)(1+sT_3)}{(1+sT_2)(1+sT_4)}\right] \Delta\omega(s) \qquad (1)$$

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 (σ) of an eigenvalue (λ) given in (2), and the corresponding damping factor (ζ), 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:

$$\sigma_{cr} = -2.0, \qquad \zeta_{cr} = 20\%.$$

$$\lambda = \sigma \pm j\omega \qquad (2)$$

$$\zeta = \frac{-\sigma}{\sqrt{\sigma^2+\omega^2}} \qquad (3)$$

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

$$\text{Maximize} \quad f(x) \; ; \; x \in \Re \text{ and}$$

$$x_{i\,\min} \le x_i \le x_{i\,\max} \qquad (4)$$

- $f(x)$ 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 $J1$ and $J2$ where the conditions $\sigma_{i,j} \le \sigma_{cr}$ and $\zeta_{i,j} \le \zeta_{cr}$ are imposed simultaneously. The parameters of the PSS may be selected to minimize the following objective function *J* given by:

$$J = J1 + a.J2 \qquad (5)$$

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$$J1 = \sum_{j=1}^{np} \sum_{\sigma_{i,j} \geq \sigma_{cr}} [\sigma_{cr} - \sigma_{i,j}]^2$$

$$J2 = \sum_{j=1}^{np} \sum_{\zeta_{i,j} \leq \zeta_{cr}} [\zeta_{cr} - \zeta_{i,j}]^2$$

The PSS parameters to be optimized are (K_{si} , T_{1i} and T_{2i}). Here it is assumed that $T_{1i} = T_{3i}$, $T_{2i} = T_{4i}$. Typical ranges of the optimized parameters are [0.01 50] for K_{si}, [0.01 1.0] for T_{1i} and T_{2i}.

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):*

$$Affinity = \frac{1}{1 + Objective\ function\ value} \quad (6)$$

3. Rank the population by fitness.
4. *Clone*: The size of clone is defined as following:

Number of clones (N_c)= $round(\frac{\beta * N}{i})$ (7)

where N is a user predefined clone factor (N=30) and β is user predefined parameter (β =5 to 100)

An ideal value of mutation rate (α) 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

$$\beta = 2a - b + 2 * \frac{(b\text{-}a)}{1 + \exp(iteration\ time)} \quad (8)$$

where a and b are lower and upper limits respectively.

5. *Affinity Mutation:*

$$\alpha = \frac{1}{\beta} * \exp(fitness\ value) \quad (9)$$

6. *New population:*

$$C^* = C + \alpha * N(0,1) \quad (10)$$

$N(0,1)$ 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.

III. Hybrid Clonal Selection Algorithm with Particle Swarm Optimization (HCSAPSO)

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)

$$\alpha 1 = \frac{1}{\beta} * \exp(-fitness\ value) * \max(K_s)$$
$$\alpha 2 = \frac{1}{\beta} * \exp(-fitness\ value) * \max(T_1) \quad (11)$$
$$\alpha 3 = \frac{1}{\beta} * \exp(-fitness\ value) * \max(T_2)$$

3. New population is obtained by modifying the Eq.(10)

$$C^* = C + \alpha * N_r(0,1) \quad (12)$$

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

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

IV. Results And Discussion

The proposed HCSAPSO-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 HCSAPSO 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 HCSAPSOPSSs, 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

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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.

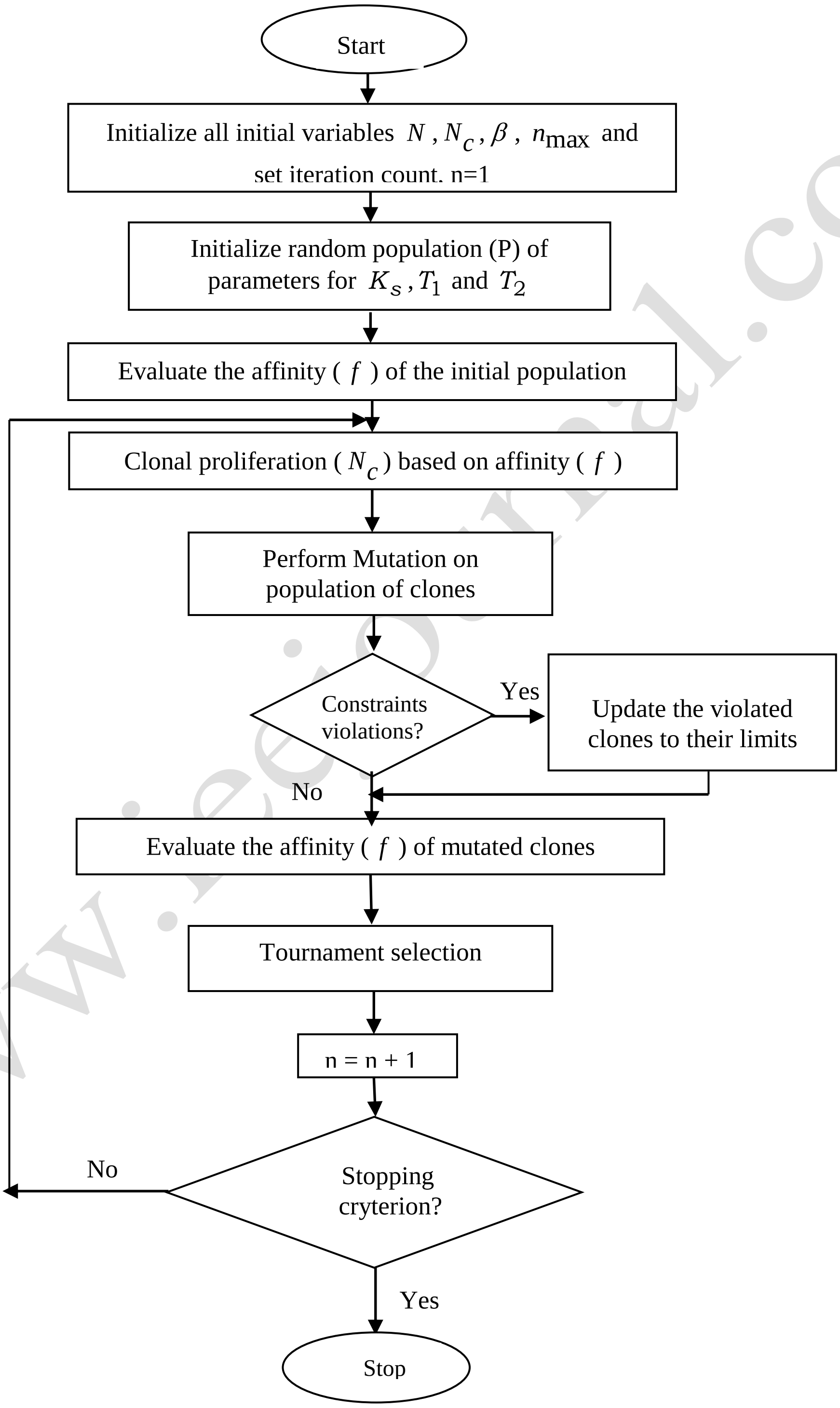

Figure 1: Flow Chart of Clonal Selection Algorithm

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Table 1: Training parameters used for CSA and HCSAPSO

Parameter	**CSA**	**HCSAPSO**
Initial number of network cells(N)	P= 40	Q=40
Number of clones generated for each cell	10	5
Scale of the affinity proportional selection (β)	100	100
Maximum number of iterations allowed	200	100

Table 2: Operating Scenarios

Scenario	**Description**
Scenario 1	All lines in service
Scenario 2	Outage of line connecting bus no. 14 and 15
Scenario 3	Outage of line connecting bus no. 21 and 22
Scenario 4	Increase in generation of G7 by 25% and loads at buses 16 and 21 by 25%, with the outage of line 21–22

Table 3: Tuned Parameters of CPSS, CSAPSS and HCSAPSOPSS

Gen	Parameters of CPSS			Parameters of CSAPSS			Parameters of HCSAPSOPSS		
	K_{PSS}	T_1	T_2	K_{PSS}	T_1	T_2	K_{PSS}	T_1	T_2
G1	10.4818	0.6211	0.1789	14.8299	0.5930	0.3629	29.1401	0.5100	0.3620
G2	0.6799	0.6185	0.1796	14.6134	0.6969	0.1647	12.4885	0.7873	0.1153
G3	0.2396	0.5778	0.1923	29.1969	0.6794	0.1180	3.4503	0.7753	0.1521
G4	1.1531	0.5727	0.1940	15.2680	0.6232	0.3923	7.2830	0.6722	0.1656
G5	17.0819	0.6143	0.1809	27.5064	0.5389	0.1905	23.4427	0.6210	0.1714
G6	13.4726	0.6163	0.1803	13.1094	0.8458	0.1345	11.5024	0.6413	0.0721
G7	4.3773	0.5636	0.1971	12.3118	0.6997	0.1309	22.6447	0.6222	0.1819
G8	0.5709	0.6099	0.1822	8.8100	0.8679	0.0658	9.1202	0.6162	0.0859
G9	1.6059	0.5429	0.2046	6.3178	0.7384	0.1815	11.6975	0.5636	0.1773
G10	19.8488	0.5027	0.2210	18.7814	0.6550	0.0953	16.9927	0.9655	0.2247

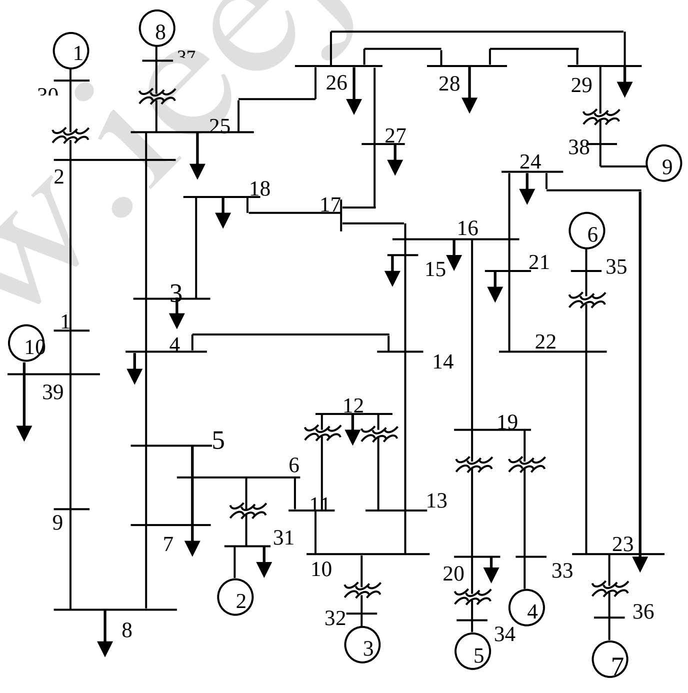

Figure 2: New England 10-machine, 39-bus system

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Table 4: Comparison of eigenvalues and damping ratios for different scenarios

	Without PSS	CPSS	CSAPSS	HCSAPSOPSS
Scenario 1	-1.1878 ±10.6655i, 0.1107	-1.5226 ±11.7232i, 0.1288	-2.1541 ±12.2034i, 0.1738	-2.4162 ±12.0605i, 0.1964
	-0.3646 ± 8.8216i, 0.0413	-1.3326 ±11.2726i, 0.1174	-1.5781 ±11.7177i, 0.1335	-1.9829 ±10.8012i, 0.1806
	-0.3063 ± 8.5938i, 0.0356	-1.9859 ±11.1499i, 0.1753	**-1.0795 ±10.1932i, 0.1053**	-1.7019 ± 9.9476i, **0.1686**
	-0.2718 ± 8.1709i, 0.0332	-0.9837 ± 9.0350i, 0.1082	-1.9171 ±10.0117i, 0.1881	-2.1133 ± 8.0471i, 0.2540
	-0.0625 ± 7.2968i, 0.0086	-0.5380 ± 8.5014i, 0.0632	-1.6613 ± 9.5158i, 0.1720	-2.5967 ± 6.1447i, 0.3893
	-0.1060 ± 6.8725i, 0.0154	-0.1568 ± 7.3758i, 0.0213	-3.3891 ± 8.3261i, 0.3770	-3.2019 ± 5.7563i, 0.4861
	0.2579 ± 6.1069i, -0.0422	-1.0658 ± 7.2601i, 0.1452	-2.0242 ± 3.3567i, 0.5164	-3.0043 ± 5.1421i, 0.5045
	0.0620 ±6.1767i, -0.0100	**-0.0046 ± 6.3800i, 0.0007**	-1.3808 ± 3.0751i, 0.4096	-1.7567 ± 3.0258i, 0.5021
	0.0794 ± 3.9665i, -0.0200	-1.2016 ± 4.5676i, 0.2544	-1.6967 ± 2.6744i, 0.5357	**-1.6782 ± 2.1050i,** 0.6234
Scenario 2	-1.1888 ±10.6603i, 0.1108	-1.5173 ±11.7109i, 0.1285	-2.2153 ±12.1025i, 0.1801	-2.5253 ±12.0542i, 0.2050
	-0.3642 ± 8.8221i, 0.0412	-1.3362 ±11.2695i, 0.1177	-1.5802 ±11.7174i, 0.1336	-1.9901 ±10.8087i, 0.1811
	-0.3087 ± 8.5753i, 0.0360	-1.9880 ±11.1547i, 0.1755	**-1.1442 ±10.1007i, 0.1126**	-1.7102 ± 9.9943i, **0.1687**
	-0.2727 ± 8.1706i, 0.0334	-0.9669 ± 9.0331i, 0.1064	-1.9333 ±10.0018i, 0.1898	-1.9646 ± 7.3887i, 0.2570
	-0.0643 ± 7.2859i, 0.0088	-0.5240 ± 8.4869i, 0.0616	-1.6938 ± 9.5608i, 0.1744	-4.0379 ± 5.8217i, 0.5699
	-0.1000 ± 6.7243i, 0.0149	-0.1593 ± 7.3687i, 0.0216	-3.3884 ± 8.3226i, 0.3771	-2.6472 ± 6.2266i, 0.3912
	0.2997 ± 6.1030i, -0.0490	**-0.0826 ± 6.1146i, 0.0135**	-1.9512 ± 3.2955i, 0.5095	-3.2763 ± 5.7046i, 0.4980
	0.0824 ± 5.7423i , -0.0143	-1.0081 ± 6.0958i, 0.1632	-1.4869 ± 3.0203i, 0.4417	-3.0066 ± 5.1781i, 0.5021
	0.0844 ± 3.8066i, -0.0222	-1.9766 ± 6.0065i, 0.3126	-1.5313 ± 2.6970i, 0.4938	**-1.6607 ± 2.8428i,** 0.5044
Scenario 3	-1.1686 ±10.6268i, 0.1093	-1.3152 ±11.2723i, 0.1159	-2.1375 ±12.2227i, 0.1723	-2.4170 ±11.9233i, 0.1987
	-0.3413 ± 8.7548i, 0.0390	-1.4305 ±11.2210i, 0.1265	-1.6190 ±11.6283i, 0.1379	-2.0174 ±10.7464i, 0.1845
	-0.3013 ± 8.4738i, 0.0355	-2.0125 ±11.0700i, 0.1789	**-1.1408 ±10.0579i, 0.1127**	**-1.6518 ± 9.9336i, 0.1640**
	-0.2575 ± 8.0464i, 0.0320	-0.5674 ± 8.4623i, 0.0669	-2.0117 ± 9.9280i, 0.1986	-1.9970 ± 7.8928i, 0.2453
	-0.0615 ± 7.3143i, 0.0084	-0.7944 ± 8.1979i, 0.0964	-1.4364 ± 9.5652i, 0.1485	-3.9330 ± 5.5921i, 0.5753
	0.1283 ± 6.1862i, -0.0207	-0.1547 ± 7.3961i, 0.0209	-3.3873 ± 8.3309i, 0.3767	-2.3783 ± 6.0489i, 0.3659
	0.0427 ± 6.0556i, -0.0070	**-0.0051 ± 6.3664i, 0.0008**	-2.0905 ± 3.5858i, 0.5037	-3.1392 ± 5.7681i, 0.4780
	0.2018 ± 5.8565i, -0.0344	-0.9179 ± 5.9988i, 0.1513	-1.9863 ± 3.3828i, 0.5063	-3.0050 ± 5.1556i, 0.5036
	0.1659 ± 3.7438i, -0.0443	-0.9712 ± 3.5259i, 0.2656	-1.2815 ± 3.0747i, 0.3847	-1.7401 ± 2.9982i, 0.5020
Scenario 4	-1.1645 ±10.6163i, 0.1090	-1.3405 ±11.3267i, 0.1175	-2.1188 ±12.2578i, 0.1703	-2.4035 ±11.8986i, 0.1980
	-0.3256 ± 8.8902i, 0.0366	-1.3380 ±11.2101i, 0.1185	-1.6418 ±11.5889i, 0.1403	-2.0364 ±10.7212i, 0.1866
	-0.2977 ± 8.4483i, 0.0352	-2.0206 ±11.0315i, 0.1802	-2.0766 ± 9.9063i, 0.2052	**-1.6152 ± 9.9467i, 0.1603**
	-0.2587 ± 8.0346i, 0.0322	-0.5650 ± 8.4482i, 0.0667	**-1.2135 ± 9.9955i, 0.1205**	-1.9381 ± 7.8659i, 0.2392
	-0.0575 ± 7.3333i, 0.0078	-0.7508 ± 8.1182i, 0.0921	-1.2399 ± 9.6233i, 0.1278	-2.3917 ± 6.0340i, 0.3685
	0.1557 ± 6.1630i, -0.0253	-0.1506 ± 7.4154i, 0.0203	-3.3881 ± 8.3301i, 0.3768	-3.1216 ± 5.7626i, 0.4763
	0.0586 ± 6.0959i, -0.0096	**-0.0023 ± 6.3596i, 0.0004**	-2.0472 ± 3.5472i, 0.4999	-3.0032 ± 5.1623i, 0.5029
	0.2089 ± 5.6778i, -0.0368	-0.6910 ± 5.8629i, 0.1171	-1.9578 ± 3.3969i, 0.4993	-1.7228 ± 2.9184i, 0.5084
	0.2352 ± 3.6446i, -0.0644	-0.7668 ± 3.3898i, 0.2206	-1.2181 ± 3.0610i, 0.3697	-1.9297 ± 2.8567i, 0.5598

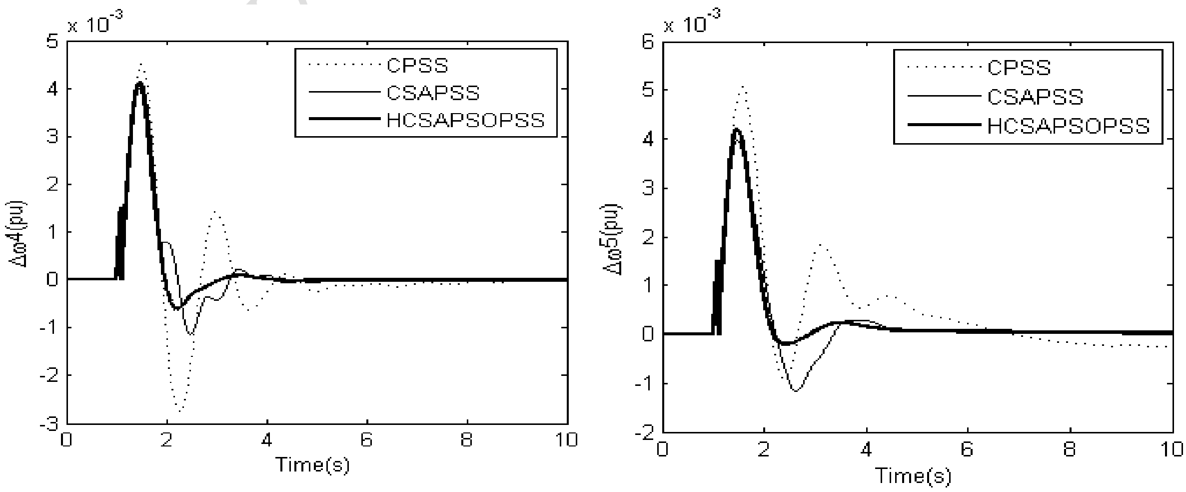

Figure 3: Speed deviations of 4^{th} and 5^{th} generators for Contingency (a)

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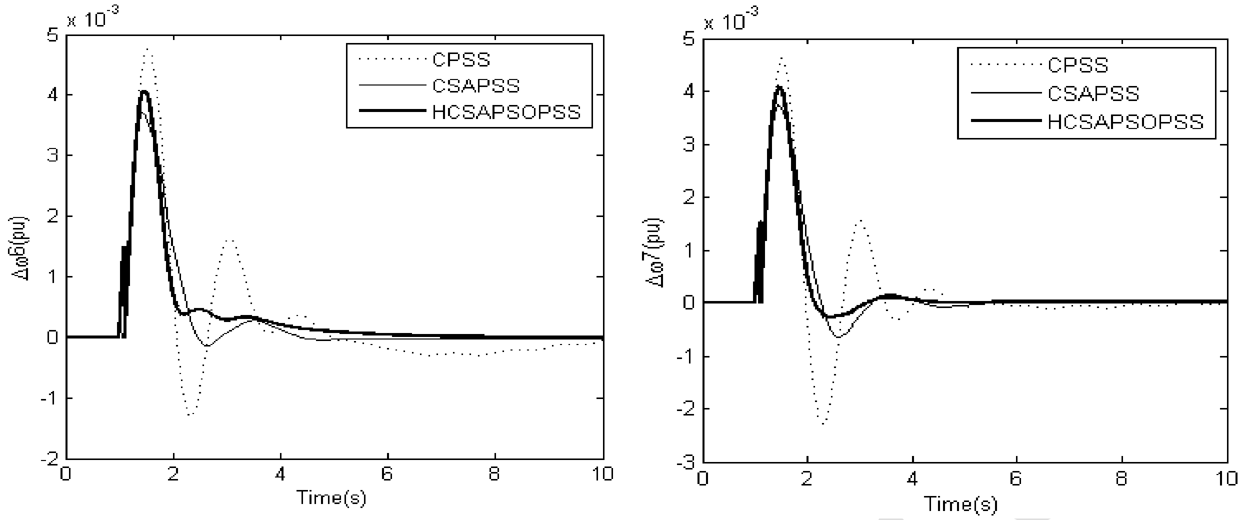

Figure 4: Speed deviations of 6th and 7th generators for Contingency (b)

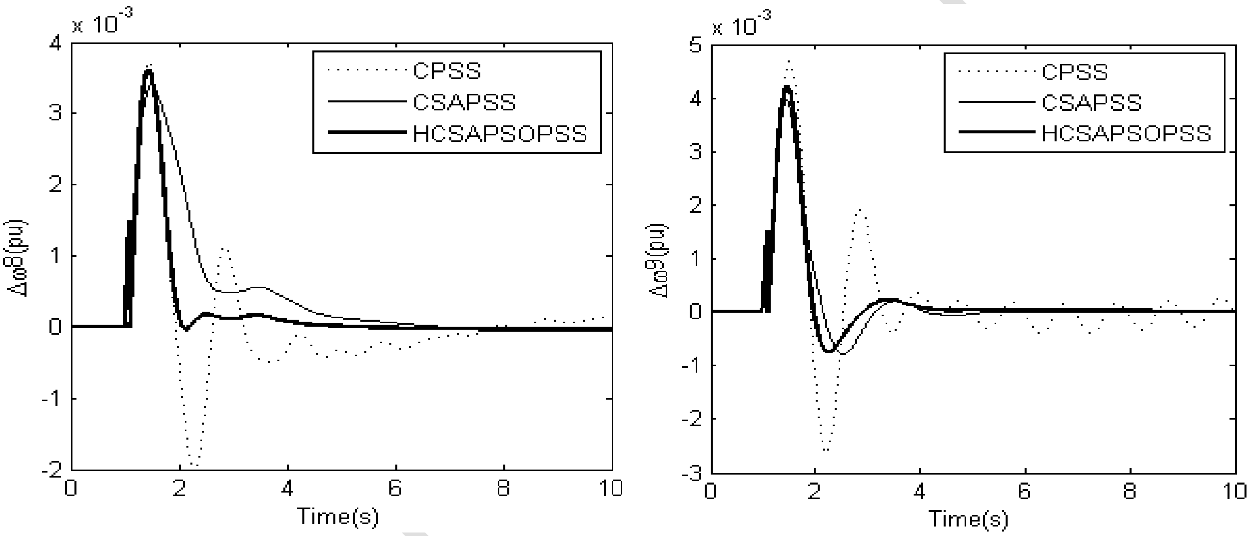

Figure 5: Speed deviations of 8th and 9th generators for Contingency (c)

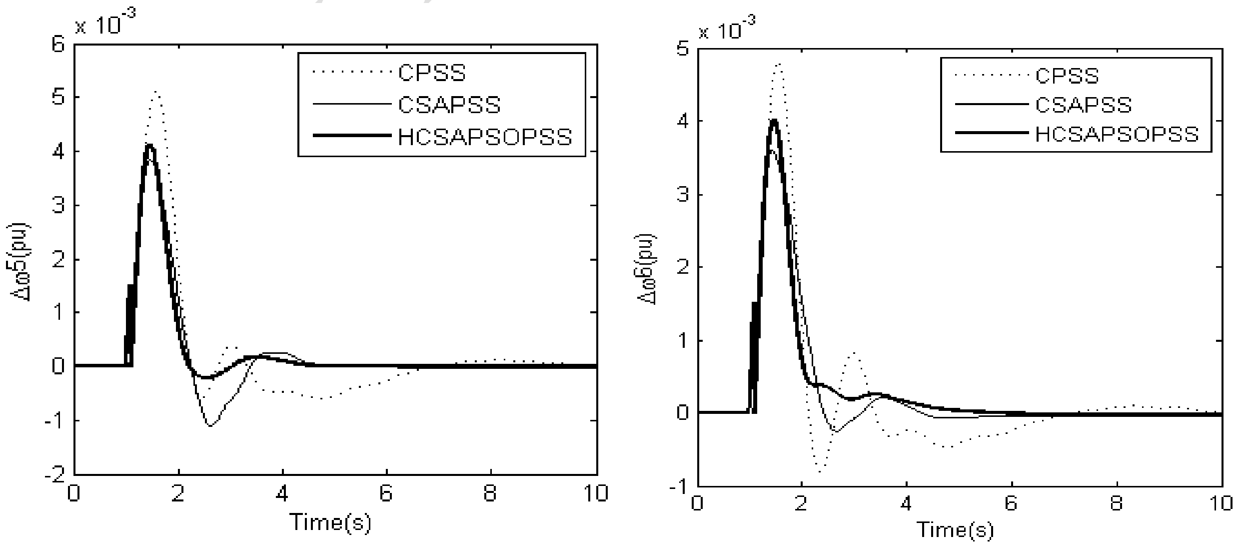

Figure 6: Speed deviations of 5th and 6th generators for Contingency (d)

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Table 5: Values of Performance Index

	ITAE (CPSS)	*ITAE*(CSAPSS)	*ITAE*(HCSAPSOPSS)
Contingency (a)	12.6279	6.0192	4.8679
Contingency (b)	12.7930	5.7570	4.7085
Contingency (c)	12.5083	5.7710	4.7237
Contingency (d)	10.4121	5.6377	4.3179

For scenario 1, the minimum damping factor $\xi_{\min}$ increased from 10.53% to 16.86% and the maximum real part of eigenvalue $\sigma_{\max}$ increases from -1.0795 to -1.6782. Similarly for scenario 2, $\xi_{\min}$ increased from 11.26% to 16.87% and $\sigma_{\max}$ from -1.1442 to -1.6607; for scenario 3, $\xi_{\min}$ increased from 11.27% to 16.4% and $\sigma_{\max}$ from -1.1408 to -1.6518 and for scenario 4, $\xi_{\min}$ increased from 12.05% to 16.03% and $\sigma_{\max}$ from -1.2135 to -1.6152. Therefore, it is obvious that the critical mode eigenvalues have been shifted to the left in *s*-plane and the system damping is greatly improved and enhanced with the proposed HCSAPSOPSSs.

B. Nonlinear Time Domain Simulation:

To demonstrate the effectiveness of the PSSs tuned using the proposed HCSAPSO over a wide range of operating conditions and system configurations, nonlinear time domain simulation is carried out on the system under study. System performance is demonstrated by using the performance index, Integral of Time multiplied Absolute value of Error (*ITAE*), given by

$$ITAE = \int_{0}^{10} t.\left(|\Delta\omega_1| + |\Delta\omega_2| + |\Delta\omega_3| + ... + |\Delta\omega_{10}|\right)dt \qquad (13)$$

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 G4 & G5 are shown in Figure 3. For this case, Clonal Selection Algorithm based PSSs gives $ITAE_{(CSA)}$=6.0192 and Hybrid Clonal Selection Algorithm with Particle Swarm Optimization based PSSs gives $ITAE_{(HCSAPSO)}$=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 $ITAE_{(CSA)}$=5.7570 and Hybrid Clonal Selection Algorithm with Particle Swarm Optimization based PSSs gives $ITAE_{(HCSAPSO)}$=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 by20%, 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 $ITAE_{(CSA)}$=5.7710 and Hybrid Clonal Selection Algorithm with Particle Swarm Optimization based PSSs gives $ITAE_{(HCSAPSO)}$=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 $ITAE_{(CSA)}$=5.6377 and Hybrid Clonal Selection Algorithm with Particle Swarm Optimization based PSSs gives $ITAE_{(HCSAPSO)}$=4.3179.

The system responses to the considered faults with CPSSs, CSAPSSs and with the proposed HCSAPSOPSSs are shown in Figures 3, 4, 5 and 6 respectively. It is clear from the nonlinear time domain simulations that the proposed HCSAPSOPSSs 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 CSAPSSs are well damped and returns to steady state much faster with HCSAPSOPSSs. The performance index (*ITAE)* obtained for the above contingencies using CPSSs, CSAPSSs & HCSAPSOPSSs are given the Table 5. Therefore the system performance characteristic in terms of '*ITAE*' index reveals the solution quality of the proposed HCSAPSOPSSs over CPSSs and CSAPSSs.

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

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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 HCSAPSOPSSs 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 HCSAPSOPSSs over CPSSs and CSAPSSs.

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