

Robust Design of Multi-Machine Power System Stabilizers using Clonal Selection Algorithm

G. Naresh, M. Ramalinga Raju, M. Krishna

Abstract: *Optimal design of multi-machine Power System Stabilizers (PSSs) using Artificial Immune-based optimization technique, Clonal Selection Algorithm (CSA), is presented in this paper. The proposed approach employs CSA to search for optimal parameter settings of a widely used conventional fixed-structure lead-lag PSS (CPSS). The parameters of PSS are tuned using the proposed clonal selection algorithm 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 the damping ratio of lightly damped electromechanical modes. Incorporation of CSA as a derivative-free optimization technique in PSS design significantly reduces the computational burden. The main advantage of the proposed approach is its robustness to the initial parameter settings. In addition, the quality of the optimal solution does not rely on the initial guess. The performance of the proposed CSAPSSs under different loading conditions and system configurations is investigated on New England New York 16-machine 68-bus power system. The eigenvalue analysis and the nonlinear simulation results show the effectiveness of the proposed CSAPSSs over conventional power system stabilizer (CPSS) to damp out the local as well as the inter area modes of oscillations under different operating conditions.*

Index Terms: *Clonal selection algorithm, Damping, Electromechanical oscillations, Power system stabilizer*

I. INTRODUCTION

The low-frequency oscillations in a disturbed power system grow to make the system separate and become unstable, if they are not sufficiently damped out. Modern power system utilities use, conventional power system stabilizers (PSS) as an auxiliary excitation control. PSS enhances system damping by providing supplementary stabilizing feedback signal in the excitation system [1, 2]. Larsen and Swann [3] have systematically explained the application of conventional lead-lag PSS in power systems. The conventional PSS (CPSS) is usually designed with a fixed gain, with an aim to stabilize at the nominal operating condition. However, the inherent non-linearity and multiple operating points of a power system degrade the performance of such a fixed gains CPSS. Adaptive and variable structure

control schemes are also applied [4, 5] for the design of PSS. Looking at the complexity of these designs and also at the fact that these techniques does not assure robust power system stability with varying operating conditions, Kundur et al. [6] have proposed an approach for the design of PSS for a large generating stations, wherein enhancement of overall system stability was the main criterion for the selection of PSS and automatic voltage regulator (AVR) parameters. Using conventional methods, PSS can be designed sequentially taking one electromechanical mode into consideration at a time [7]. However, the limitation of such a design is that the stabilizer designed to damp out one mode may destabilize other modes of the system. In another scheme, a gradient-based optimization method is adopted [8]. Unfortunately, the problem of PSS design is a multi-modal problem and the gradient techniques might fail by getting trapped in one of the local optima.

Recently, global optimization technique like genetic algorithm (GA), and other heuristic techniques like tabu search and simulated annealing have attracted the attention in the field of PSS parameter optimization. Unlike other techniques, GA has the ability to arrive at the global solution point swiftly, as it can handle the search space from different directions simultaneously. Crossover and mutation operators between chromosomes, makes the GA far less sensitive of being trapped in local optima. However, when the system has a highly epistatic objective function (i.e. where parameters being optimized are highly correlated), and number of parameters to be optimized is large, then GA has been reported [9] to exhibit degraded efficiency.

To overcome the drawbacks of conventional and GA based PSS design, a new Artificial Immune-based optimization technique known as Clonal Selection Algorithm is used for the PSS design. In this paper, an eigenvalue based objective function reflecting the combination of damping factor and damping ratio, are optimized for different operating conditions of the power system. It is also seen that some simple adaptive feature incorporated in the main algorithm makes its convergence even faster. It was found that the proposed technique not only optimizes the parameters faster, but also with the optimized gains the CSAPSS shows better damping performance when the system is perturbed.

Results obtained from eigenvalues analysis and nonlinear time domain simulation is compared with results obtained by CPSS. In section (II) statement of the problem and structure of PSS are described. In section (III) Objective function used is presented. In section (IV) an overview of Clonal selection algorithm is presented.

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The simulation and results are presented in section (V) and conclusions are presented in last section.

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 fourth order model and the problem is to design the parameters of the power system stabilizers so as to stabilize a system of 'N' generators simultaneously. The fourth order power system model is represented by a set of non-linear differential equations given for any i th machine,

$$\frac{d\delta_i}{dt} = \omega_i - \omega_s \quad (1)$$

$$\frac{d\omega_i}{dt} = \frac{\omega_s}{2H} (P_{mi} - P_{ei}) \quad (2)$$

$$\frac{dE'_{qi}}{dt} = \frac{1}{T_{d0i}} [-E'_{qi} - I_{di}(X_{di} - X'_{di}) + E_{fdi}] \quad (3)$$

$$\frac{dE'_{di}}{dt} = \frac{1}{T_{q0i}} [-E'_{di} + I_{qi}(X_{qi} - X'_{qi})] \quad (4)$$

$$\frac{dE'_{qi}}{dt} = \frac{1}{T_{d0i}} [-E'_{qi} - I_{di}(X_{di} - X'_{di}) + E_{fdi}] \quad (5)$$

$$T_{ei} = E'_{di}I_{di} + E'_{qi}I_{qi} - (X'_{qi} - X'_{di})I_{di}I_{qi} \quad (6)$$

For a given operating condition, the multi-machine power system is linearized around the operating point. The closed loop eigenvalues 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 any condition.

All generators are represented by fifth order model. The dynamic data of generators, power flow and transmission line can be found in [10].

A. Structure of Power System Stabilizer

The speed based conventional PSS is considered in the study. The PSS considered is a speed-based two-stage fixed-structure lag-lead compensator. Thus, for the i th generator, the PSS is of the form [13]

$$G_{PSS,i}(s) = K_{s,i} \left[\frac{sT_w}{1+sT_w} \right] \left[\frac{(1+sT_{1,i})}{(1+sT_{2,i})} \right]^2 \quad (7)$$

where T_w is the washout time constant. The PSS structure of Eq. (1) consists of gain $K_{s,i}$ a signal washout block with time constant T_w and two stages of lag-lead compensation blocks. In the design of a PSS, washout time constant T_w is usually pre-specified, and PSS gain $K_{s,i}$ and time constants $T_{1,i}$ and $T_{2,i}$ are to be optimized. The required phase lag is

provided by the phase compensation block. The signal washout block serves as a high-pass filter with time constant T_w , high enough to allow signals in the range of 0.2–2.0 Hz associated with rotor oscillations in an input signal to pass unchanged. From the viewpoint of the washout function, the value of T_w is not critical and may be kept constant in the range 1–20 sec [14]. In the present study, T_w is set at 10. It was shown in [15] that the arbitrary setting of the pole locations for the electromechanical oscillation modes may cause new poorly damped or unstable oscillation modes, because of the interactions between the PSSs and other components as well as the interactions among the PSSs. Following a small disturbance, these modes would eventually dominate the dynamic performance of the system.

III. OBJECTIVE FUNCTION

The parameters of PSS are selected so as to minimize the following objective function

$$J = J1 + \alpha \cdot J2 \quad (8)$$

where,

$$J1 = \sum_{j=1}^{NP} \sum_{\sigma_i, j \geq \sigma_0} [\sigma_0 - \sigma_{i,j}]^2 \quad (9)$$

$$J2 = \sum_{j=1}^{NP} \sum_{\xi_i, j \geq \xi_0} [\xi_0 - \xi_{i,j}]^2 \quad (10)$$

Here α is arbitrarily chosen as 10 [16]. Here $\sigma_{i,j}$ is the real part of the i th eigenvalue of the j th operating point and $\xi_{i,j}$ is the damping ratio of the i th eigenvalue of the j th operating point, subject to the constraints that finite bounds are placed on the power system stabilizer parameters.

It is necessary to mention here that only the unstable or lightly damped electromechanical modes of oscillations are relocated. The design problem can be formulated as a constrained optimization problem, where the constraints are the PSS parameter bounds as given below:

Minimize J subject to

$$\begin{aligned} K_{i_{\min}} &\leq K_i \leq K_{i_{\max}} \\ T_{1i_{\min}} &\leq T_{1i} \leq T_{1i_{\max}} \\ T_{2i_{\min}} &\leq T_{2i} \leq T_{2i_{\max}} \end{aligned} \quad (11)$$

The proposed approach employs CSA to solve this optimization problem and search for optimal or near optimal set of PSS parameters $\{K_i, T_{1i}, T_{2i}; i=1,2 \dots n\}$. Typical ranges of the optimized parameters are [0.01 to 50] for K_i and [0.01 to 1.0] for T_{1i} and T_{2i} .

IV. CLONAL SELECTION ALGORITHM

Use either Clonal Selection theory is the important content of the biological immune system theory and is proposed by F. M. Burnet. The main idea of this theory is that the antigens can selectively react to the antibodies,



which are the native production and spread on the cell surface in the form of peptides. The reaction leads to cell proliferating clonally and the colony has the same antibodies. Some clonal cells divide into antibodies that produce cells, and others become immune memory cells to boost the second

immune response [11-12]. The Clonal Selection works on the principle of pattern recognition system. In order to initiate clonal concept in optimization, the affinity concept is transferred to fitness or objective function evaluation and constraint satisfaction.

Table 1: Tuned Parameters of CPSS and CSAPSS

Gen	Parameters of CPSS			Parameters of CSAPSS		
	K _{PSS}	T ₁	T ₂	K _{PSS}	T ₁	T ₂
G1	18.9305	0.8223	0.2758	35.2294	0.4013	0.4570
G2	3.2054	0.5272	0.4301	36.4385	0.5347	0.4926
G3	24.1453	0.6157	0.3683	33.7634	0.5031	0.3668
G4	1.1526	0.5382	0.4213	39.1873	0.4853	0.4646
G5	29.4526	0.5965	0.3802	26.9228	0.2885	0.1509
G6	1.9074	0.5229	0.4336	9.3939	0.5587	0.4866
G7	27.3580	0.5284	0.4291	7.7217	0.6271	0.1704
G8	6.8026	0.5409	0.4193	21.3356	0.4369	0.3326
G9	7.2639	0.5712	0.3970	11.2811	0.9422	0.4130
G10	40.3715	0.5781	0.3923	11.4368	0.6829	0.1920
G11	19.5442	0.4762	0.4762	8.7618	0.3872	0.1729
G12	41.2157	0.5407	0.4194	28.2904	0.4045	0.1377
G13	8.4165	0.5176	0.4381	12.0037	0.5869	0.4829
G14	28.342	0.4762	0.4762	35.3438	0.7966	0.4873
G15	38.4822	0.4947	0.4583	36.2932	0.6341	0.3842
G16	5.4383	0.6176	0.3672	40.000	0.4805	0.2370

Table 2: Comparison of Eigen Values and Damping Ratios for Different Cases

	Without PSS		With CPSS		With CSAPSS	
	Eigenvalues	Damping(ε)	Eigenvalues	Damping(ε)	Eigenvalues	Damping(ε)
Case 1	0.2232 ± 11.5927i	-0.0192	-0.4020 ± 11.8344i	0.0340	-18.4954 ± 10.1150i	0.8774
	-0.6453 ± 10.8838i	0.0592	-1.0373 ± 10.1140i	0.1020	-1.1800 ± 10.9905i	0.1068
	-0.2581 ± 9.5102i	0.0271	-0.5392 ± 8.9798i	0.0599	-2.2633 ± 8.9394i	0.2454
	-0.4378 ± 9.2528i	0.0473	-1.0775 ± 7.8306i	0.1363	-2.7762 ± 4.6850i	0.5098
	0.0524 ± 8.0316i	-0.0065	-0.2333 ± 7.6505i	0.0305	-2.0925 ± 4.1084i	0.4538
	0.1615 ± 8.0203i	-0.0201	-1.2281 ± 5.0348i	0.2370	-2.5934 ± 3.8324i	0.5604
	-0.3616 ± 7.4165i	0.0487	-1.3638 ± 4.5241i	0.2886	-2.3377 ± 3.3594i	0.5712
	0.4825 ± 6.8650i	-0.0701	-0.6353 ± 3.0370i	0.2048	-2.3452 ± 3.2163i	0.5892
	0.1709 ± 7.3108i	-0.0234	-2.4824 ± 2.8069i	0.6625	-1.4130 ± 2.5666i	0.4823
	0.1189 ± 6.8860i	-0.0173	-1.5720 ± 1.7550i	0.6672	-1.8351 ± 2.3110i	0.6218
	-0.0269 ± 4.2593i	0.0063	-1.9504 ± 1.6715i	0.7593	-1.1967 ± 1.8853i	0.5359
	-0.1676 ± 4.9276i	0.0340	-0.7312 ± 1.5280i	0.4317	-2.2889 ± 1.5485i	0.8283
	-0.0047 ± 3.1639i	0.0015	-1.3735 ± 1.5540i	0.6623	-2.2539 ± 1.0568i	0.9054
	-0.0360 ± 1.9272i	0.0187	-1.8711 ± 1.1390i	0.8542	-1.0013 ± 1.2596i	0.6223
	-0.0120 ± 0.4513i	0.0266	-0.4820 ± 0.3520i	0.8076	-2.6139 ± 0.6368i	0.9716
	Case 2	0.2304 ± 11.6149i	-0.0198	-0.3928 ± 11.8278i	0.0332	-18.5405 ± 10.1236i
-0.2581 ± 9.5102i		0.0271	-1.0315 ± 10.1219i	0.1014	-1.1785 ± 10.9712i	0.1068
-0.4378 ± 9.2528i		0.0473	-0.5391 ± 8.9797i	0.0599	-2.2741 ± 8.9220i	0.2470
-0.4336 ± 8.5380i		0.0507	-1.0769 ± 7.8359i	0.1361	-2.8200 ± 4.6615i	0.5176
0.0523 ± 8.0755i		-0.0065	-0.2320 ± 7.6498i	0.0303	-2.0643 ± 4.1053i	0.4492
0.1604 ± 8.0187i		-0.0200	-1.3810 ± 4.5141i	0.2925	-2.5619 ± 3.8043i	0.5586
-0.3617 ± 7.4165i		0.0487	-0.8573 ± 3.9189i	0.2137	-2.3471 ± 3.4204i	0.5658
0.4838 ± 6.8638i		-0.0703	-2.2942 ± 2.8033i	0.6333	-1.3659 ± 2.5391i	0.4737
0.1230 ± 6.8921i		-0.0178	-0.9642 ± 2.1723i	0.4057	-1.4676 ± 2.5600i	0.4974
0.1709 ± 7.3137i		-0.0234	-0.6120 ± 1.6995i	0.3388	-1.8325 ± 2.3059i	0.6222
-0.0292 ± 4.2710i		0.0068	-1.5882 ± 1.7777i	0.6662	-2.3038 ± 1.5178i	0.8351
-0.0618 ± 3.9558i		0.0156	-1.9692 ± 1.6866i	0.7595	-1.1224 ± 1.7119i	0.5483
-0.0425 ± 2.5352i		0.0168	-1.3473 ± 1.5486i	0.6564	-2.2478 ± 1.0471i	0.9065
0.0026 ± 1.8766i		-0.0014	-1.8783 ± 1.1260i	0.8577	-2.6235 ± 0.6303i	0.9723
-0.0026 ± 0.5012i		0.0051	-0.4648 ± 0.4092i	0.7506	-0.8674 ± 1.1719i	0.5949



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Case 3	0.2724 ± 11.6200i	-0.0234	-19.0757 ± 11.4539i	0.8573	-18.4702 ± 9.8166i	0.8830
	-0.2630 ± 9.5123i	0.0276	-0.3582 ± 11.9277i	0.0300	-1.9714 ± 10.5177i	0.1842
	-0.4412 ± 9.2523i	0.0476	-1.0206 ± 10.1357i	0.1002	-2.2132 ± 9.3499i	0.2303
	-0.4290 ± 8.5408i	0.0502	-0.5430 ± 8.9763i	0.0604	-2.8392 ± 4.6702i	0.5195
	0.0601 ± 8.0494i	-0.0075	-1.0815 ± 7.8470i	0.1365	-2.2623 ± 3.8765i	0.5040
	0.1294 ± 8.0450i	-0.0161	-0.3532 ± 7.4357i	0.0475	-2.5595 ± 3.7251i	0.5663
	-0.3627 ± 7.4128i	0.0489	-0.8013 ± 3.9614i	0.1983	-2.1917 ± 3.3725i	0.5449
	0.4951 ± 6.8091i	-0.0725	-1.3154 ± 3.4505i	0.3562	-1.4355 ± 2.4997i	0.4980
	0.2046 ± 7.2443i	-0.0282	-2.5545 ± 3.1475i	0.6302	-1.2727 ± 2.4012i	0.4683
	0.0685 ± 6.6926i	-0.0102	-1.0783 ± 2.1428i	0.4495	-1.7572 ± 2.2846i	0.6097
	-0.0549 ± 4.0100i	0.0137	-1.9381 ± 1.7688i	0.7386	-2.1316 ± 1.6012i	0.7995
	-0.0398 ± 3.4911i	0.0114	-1.5795 ± 1.7775i	0.6643	-1.2245 ± 1.6721i	0.5908
	-0.0262 ± 2.5939i	0.0101	-0.6536 ± 1.6478i	0.3687	-2.2440 ± 1.0457i	0.9064
	-0.0079 ± 1.9186i	0.0041	-1.3399 ± 1.5657i	0.6502	-2.6189 ± 0.6353i	0.9718
	0.0003 - 0.1850i	-0.0014	-1.8532 ± 1.1212i	0.8556	-0.9095 ± 1.1492i	0.6206

Here, antigen represents constraints and antibody-antigen interaction refers to constraints satisfaction, i.e., higher the satisfaction of constraints more is the affinity. The algorithm starts with the random generation of real numbers to check for constraint violation. In case of any constraints violation, random data is generated again and again. This process is repeated iteratively until a deliberate fixed size of population is attained. When the population becomes full then each antibody is evaluated and clones are generated. The number of clones generated per antibody is dependent on the fitness values; i.e. larger the number of clones generated for the antibodies higher the fitness value. The mutation rate is adaptive which is similar to evolutionary programming. Consequently, clones with higher fitness are made liable to undergo mutation to a lesser extent as compared to those with lower fitness. This is repeated until all the clones from the temporary clonal population are endured to mutation. Finally, tournament selection is done to select same number of muted clones as existed in the initial population. This completes one generation of the Clonal Selection Algorithm. The convergence parameter is set when the best solutions of each generation cease to change. Thereby, stopping criteria is taken when either the satisfied convergence level is reached or the maximum number of generations is exhausted [13]

The main steps of Clonal Selection Algorithm are as follows:

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

2. Affinity evaluation (objective function):

$$\text{Affinity} = f = \frac{1}{1 + \text{Objective function value}} \quad (12)$$

3. To rank the population by fitness.

4. Clone: The size of clone is defined as following:

$$\text{Number of clones (NC)} = \text{round}\left(\frac{\beta \times N}{i}\right) \quad (13)$$

where N is a user predefined clone factor (N=20) and β is user predefined parameter ($\beta=5$ to 50).

An ideal value of parameter α (mutation rate) 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 for these two circumstances, a dynamic setting of parameter

$$\beta = 2a - b + \frac{2(b - a)}{1 + \exp(\text{iteration time})} \quad (14)$$

Where a and b are lower and upper limits respectively.

5. Affinity Mutation:

$$\alpha = \frac{1}{\beta} \times \exp(-f) \quad (15)$$

6. New population:

$$C^* = C + \alpha \times N(0,1) \quad (16)$$

$N(0,1)$ is a Gaussian random variable of mean zero and standard deviation $\sigma = 1$.

7. Selection:

In implementation, it was assumed that the highest affinities were sorted in an ascending order. In selection, the offspring produced by mutation process will be sorted and the best value from the offspring will be calculated.

8. Stopping Criterion:

Here are various criteria available to stop a stochastic optimization algorithm. 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.

V. RESULTS AND DISCUSSION

A. Eigenvalue Analysis:

To demonstrate the effectiveness and robustness of the proposed CSAPSS, eigenvalue analysis of multi-machine system is carried out under different operating conditions. They can be described as

- Case 1: Base Case (All lines in service)
- Case 2: Outage of line 1-2.
- Case 3: Outage of line 1-2 and 50% increase in load at bus 41.

The tuned parameters of the sixteen PSS using conventional root locus approach and proposed Clonal Selection Algorithm are shown in the Table 1. The electromechanical modes and the damping ratios obtained for all the above cases with the proposed approach and CPSS in the system are given in Table 2. The unstable and poorly damped modes for different operating conditions were found out and highlighted in this Table.



From the eigenvalue analysis between CPSS and CSAPSS, for all the cases, it can be noticed that all modes are well shifted in the D-stability region. For case 1, the minimum damping factor ξ_{\min} increased from 3.05% to 10.68% and the maximum eigenvalue real part σ_{\max} increases from -0.2333 to -1.0013. Similarly for case 2, ξ_{\min} increased from 3.03% to 10.68% and σ_{\max} from -0.2320 to -0.8674; for case 3, ξ_{\min} increased from 3.00% to 18.42% and σ_{\max} from -0.3532 to -0.9095. Therefore, it is observed 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 CSAPSSs.

B. Non Linear Time Domain Simulation:

To demonstrate the effectiveness of the proposed CSAPSSs over a wide range of operating conditions and system configurations, non-linear time domain simulations are 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

$$ITAE = \int_0^{16} t.(|\Delta\omega_1|+|\Delta\omega_2|+|\Delta\omega_3|+\dots+|\Delta\omega_{16}|)dt \quad (17)$$

It is worth mentioning that the lower the value of this index is, better the system response in terms of time domain characteristics.

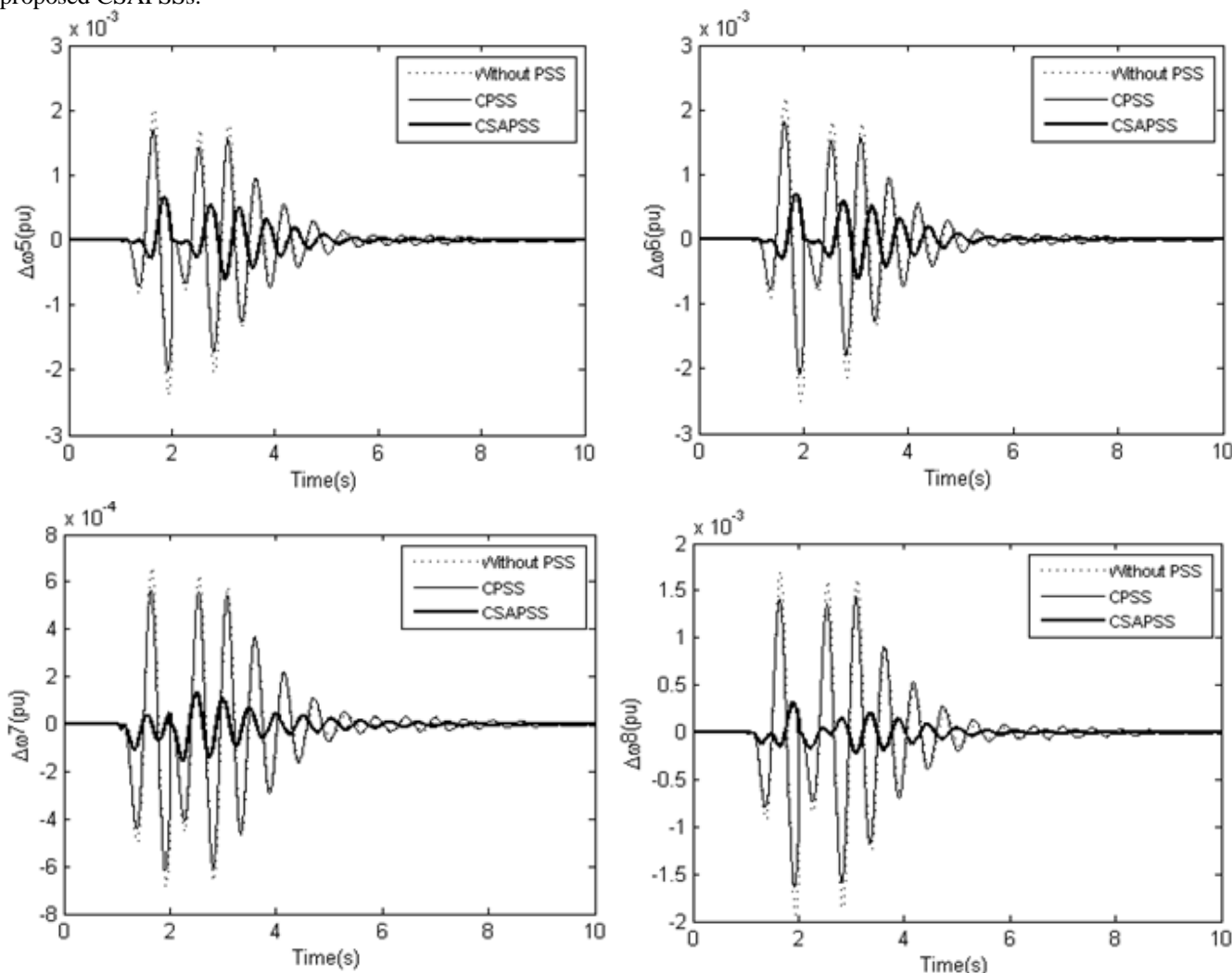


Fig. 6: Speed deviations of 5th and 6th generators for Contingency (a)

Table 3: Values of Performance Index

Contingency	ITAE (CPSS)	ITAE(CSAPSS)
Contingency (a)	24.7153	16.9465
Contingency (b)	24.4962	15.1648

Contingency (a): A 6-cycle fault disturbance at buses 8 and 41 at the ends of lines 8-9 and 41-42, cleared by tripping the lines 8-9 and 41-42 with successful reclosure after 1.0 s
Contingency (b): A 6-cycle fault disturbance at bus 1 at the end of line 1-2 and 50% load increase at bus 41, cleared by tripping the line 1-2 with successful reclosure after 1.0 s

Non-linear time domain simulation results show that the proposed CSPSS provide improved dynamic performance and faster damping compared with CPSS. It is clear from the figures 2 & 3 that the system oscillations are undamped without CPSS. With proposed CSPSS system responses are well damped and returns to steady state much faster compared with CPSS. These simulation results show that the proposed CSPSS provide improved dynamic performance and faster damping compared with CPSS.



It is clear from the figures 2 & 3 that the system oscillations are undamped without CPSS. With proposed CSPSS system responses are well damped and returns to steady state much faster compared with CPSS.

The performance index (*ITAE*) obtained for the above contingencies using CPSS and CSAPSS are given in the Table 3. Therefore the system performance characteristic in terms of '*ITAE*' index reveals the solution quality of the proposed CSAPSSs over CPSSs.

VI. CONCLUSION

The use of Clonal Selection Algorithm to design robust Power System Stabilizers for power systems working at 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 a Clonal Selection Algorithm. An objective function is presented allowing the robust selection of the stabilizer parameters that will optimally place the closed-loop eigenvalues in the left-hand side of a vertical line in the complex plane. The performance and robustness of CSAPSS is then, tested on New England New York 16-machine, 68-bus multi-machine system and compared with CPSS. Simulation results show the effectiveness and robustness of the proposed CSAPSS over CPSS.

APPENDIX

The fifth order power system model is represented by a set of non-linear differential equations given for any i^{th} machine,

$$\frac{d\delta_i}{dt} = \omega_i - \omega_s$$

$$\frac{d\omega_i}{dt} = \frac{\omega_s}{2H} (P_{mi} - P_{ei})$$

$$\frac{dE'_{qi}}{dt} = \frac{1}{T_{d0i}} [-E'_{qi} - I_{di}(X_{di} - X'_{di}) + E_{fdi}]$$

$$\frac{dE'_{di}}{dt} = \frac{1}{T'_{q0i}} [-E'_{di} + I_{qi}(X_{qi} - X'_{qi})]$$

$$\frac{dE_{fdi}}{dt} = \frac{1}{T_{ai}} [-E_{fdi} + K_{ai}(V_{refi} - V_{ti})]$$

$$T_{ei} = E'_{di}I_{di} + E'_{qi}I_{qi} - (X'_{qi} - X'_{di})I_{di}I_{qi}$$

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