Abstract—In this paper, a novel Modified Clonal Selection Algorithm (MCSA) has been proposed for optimal design of Conventional Power System Stabilizers (CPSS) to damp low frequency power oscillations in a multi-machine power system. Based on the process of elimination of foreign antigens by the immune cells in any biological system, this paper attempts to optimize three constants each of several Power System Stabilizers (PSS) present in New England 10-machine, 39-bus power system. A multi-objective problem has been formulated to optimize a composite set of objective functions comprising the damping factor, and the damping ratio of the lightly damped electromechanical modes. The eigenvalue analysis and nonlinear simulation results presented under a wide range of operating conditions show the effectiveness and robustness of the proposed MCSA based PSS and its ability to provide efficient damping to low frequency oscillations. Further, all these time domain simulation results have been compared with conventional and clonal selection algorithm based PSS to show the superiority of the proposed design approach.

Index Terms—Damping, Modified clonal selection algorithm, Multi-objective optimization, Power system stabilizer

I. INTRODUCTION

Power systems are highly nonlinear and exhibit low frequency oscillations due to poor damping caused by the high-gain, fast-acting Automatic Voltage Regulators (AVR) employed in the excitation system. Modern power system utilities use Power System Stabilizers (PSS) as auxiliary controllers in the excitation systems of the generators to produce additional damping in the system. These PSSs enhance system damping by providing supplementary stabilizing feedback signal in the excitation system [1, 2].

Despite the potential of modern control techniques with different structures, power system utilities still prefer the conventional lead-lag PSS structure. The reasons behind that is the ease of tuning of conventional stabilizer parameters during commissioning and lack of assurance of the stability related to some adaptive or variable structure techniques. The robustness of these PSSs under changing conditions is a major concern in its operation.

Larsen and Swann systematically explained the concept of PSSs and their tuning procedures in [3]. Kundur et al. [4] has presented a comprehensive analysis of the effect of the different CPSS parameters on the overall dynamic performance of the power system. Impact of single as well as dual input CPSS and GAPSS on the damping performance of low frequency oscillations was investigated on a single machine connected to infinite bus system in [5].

Many approaches have been proposed to tune PSS, such as sensitivity approach [6], pole placement [7], decentralized model control [8] and optimal control [9, 10]...etc. The parameter tuning of PSS in a multi-machine power system has two major methods viz., sequential tuning and simultaneous tuning. In sequential tuning, each PSS is tuned sequentially, taking one electromechanical mode into consideration at a time [11]. The main disadvantage of this method is that the sequential addition of stabilizers will disturb the previously assigned eigenvalues.

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Global optimization technique like genetic algorithm (GA) [12], tabu search [13], simulated annealing (SA) [14], particle swarm optimization [15], bacterial foraging algorithm [16] and harmony search algorithm [17] have been attracting the attention in the field of PSS parameter tuning in the recent times. But when the system has a highly epistatic objective function (i.e., where the parameters being optimized are highly correlated) and number of parameters to be optimized are large, GA has been reported to exhibit degraded efficiency [18]. L.N.de Castro and F. J. Von Zuben have dealt the clonal selection algorithm in [19]. In this paper, Modified Clonal Selection Algorithm has been used for the PSS design to overcome the drawbacks of conventional methods for PSS design. This Modified Clonal Selection Algorithm (MCSA) has several interesting features such as dynamically adjustable population size, exploration of the search space, location of multiple optima, capability of maintaining local optimal solutions and defined stopping criteria and has also appeared as a promising algorithm for solving the constrained optimization problem. It is a population based technique that is not largely affected by the size and nonlinearity of the problem and can converge to the optimal solution in many problems where many analytical methods fail to converge. Considering the strength of this algorithm, it has been employed in the present work for the optimal tuning the parameters of the PSS.

In this paper, attempt has been made to optimize the parameters of all the PSS to obtain a global optimum solution that eliminates the drawback of premature convergence. A multi-objective problem has been formulated to optimize a composite set of two eigenvalue-based objective functions comprising the desired damping factor, and the desired damping ratio of the lightly damped and undamped electromechanical modes. The use of the first objective function will result in PSSs that shift the lightly damped and undamped electromechanical modes to the left-hand side of a vertical line in the complex s-plane, resulting in improvement of damping factor. The use of the second objective function will yield PSSs’ settings that place these modes in a wedge-shape sector in the complex s-plane, thus improving the damping ratio of these modes. Therefore it can be observed that with the use of multi-objective function, both relative stability and time domain specifications have been simultaneously secured.

The proposed design approach has been applied to New England 10-machine, 39-bus power systems. The eigenvalue analysis and the nonlinear simulation results have been carried out to assess the effectiveness of the proposed PSSs under different disturbances, loading conditions, and system configurations. With the proposed scheme, the damping performance for various disturbances has been compared with corresponding performances of CPSS and CSAPSS. It has been found that the proposed technique optimizes the parameters faster besides exhibiting better damping performance with the optimized gains when the system is perturbed.

The remainder of the paper is organized as follows: Section (2) focuses on the statement of the problem. Section (3) emphasizes on the clonal selection algorithm and section (4) focuses on modified clonal selection algorithm. Results and discussions are presented in Section (5) and conclusions are outlined in Section (6).

II. PROBLEM FORMULATION

The complex nonlinear model related to an n machine interconnected power system can be described by a set of differential algebraic equations by assembling the models for each generator, load, and other devices, such as controls in the system, and connecting them appropriately via the network algebraic equations. All machines are represented as fifth-order models and equipped with single time constant fast acting excitors [20]. For a given operating condition, the multi-machine power system is linearized around the operating point.

A. PSS Structure

The PSS considered is a speed-based two-stage fixed-structure lag-lead compensator. Thus, for the ith generator, the PSS is of the form [21]

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

where \( T_w \) is the washout time constant. The PSS structure of Eq. (1) consists of gain \( K_{si} \) 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 \( K_{si} \) and time constants \( T_{1i} \) and \( T_{2i} \) 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 [22]. In the present study, \( T_w \) is set at 10. It was shown in [23] 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.

B. Objective Function

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

\[ J = J_1 + \alpha \cdot J_2 \]  

where,

\[ J_1 = \sum_{i=1}^{NP} \sum_{j} \left[ \sigma_0 - \sigma_{i,j} \right]^2 \]  

\[ J_2 = \sum_{j=1}^{NP} \sum_{i} \left[ \xi_0 - \xi_{i,j} \right]^2 \]  

Here \( \alpha \) is arbitrarily chosen as 10 [24]. 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 only that 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:

\[
\begin{align*}
K_{s1}^{\min} & \leq K_{s1} \leq K_{s1}^{\max} \\
T_{li}^{\min} & \leq T_{li} \leq T_{li}^{\max} \\
T_{2li}^{\min} & \leq T_{2li} \leq T_{2li}^{\max}
\end{align*}
\]

The proposed approach employs MCSA to solve this optimization problem and search for optimal or near optimal set of PSS parameters \{ \( K_{s1}, T_{li}, T_{2li} \); \( i=1,2, \ldots, n \) \}. Typical ranges of the optimized parameters are [0.01 to 50] for \( K_{s1} \) and [0.01 to 1.0] for \( T_{li} \) and \( T_{2li} \).

III. CLONAL SELECTION ALGORITHM

Clonal selection theory is the important content of the biological immune system theory and has been proposed by F. M. Burnet [25]. 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 [26]. 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. 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 are 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 affinity values; i.e., larger the number of clones generated for the antibodies higher the affinity value. The mutation rate is adaptive which is similar to evolutionary programming. Consequently, clones with higher affinity are made liable to undergo mutation to a lesser extent as compared to those with lower affinity. This is repeated till 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 [27].

The flowchart of clonal selection algorithm is shown in Fig.1. 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):

\[
\text{Affinity} = \frac{1}{1 + \text{Objective function value}}
\]

Rank the population by evaluating affinity.
3. Clone: The size of clone is defined by:

\[
\text{Number of clones (} N_i \text{)} = \text{round}\left(\frac{\beta \cdot N}{i}\right)
\]

where \( N \) is a user predefined clone factor (\( N = 30 \)) and \( \beta \) is a parameter that controls the decay of the inverse exponential function (\( \beta = 100 \)).

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 for these two circumstances, a dynamic setting of parameter

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

where \( a \) and \( b \) are lower and upper limits respectively.
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Fig. 1: Flow Chart of Clonal Selection Algorithm

Table 1: Training parameters of CSA and MCSA

<table>
<thead>
<tr>
<th>Parameter</th>
<th>CSA</th>
<th>MCSA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial number of network cells(N)</td>
<td>40</td>
<td>40</td>
</tr>
<tr>
<td>Number of clones generated for each cell (Nc)</td>
<td>10</td>
<td>5</td>
</tr>
<tr>
<td>Scale of the affinity proportional selection (β)</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Maximum number of iterations allowed (Ngen)</td>
<td>200</td>
<td>100</td>
</tr>
</tbody>
</table>
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Fig. 2: New England 10-machine, 39-bus system

Table 2: Tuned Parameters of CPSS, CSAPSS and MCSAPSS

<table>
<thead>
<tr>
<th>Gen#</th>
<th>Parameters of CPSS</th>
<th>Parameters of CSAPSS</th>
<th>Parameters of MCSAPSS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>K_{PSS} T_1 T_2</td>
<td>K_{PSS} T_1 T_2</td>
<td>K_{PSS} T_1 T_2</td>
</tr>
<tr>
<td>G1</td>
<td>10.4818 0.6211 0.1789</td>
<td>14.8299 0.5930 0.3629</td>
<td>35.7382 0.3913 0.0067</td>
</tr>
<tr>
<td>G2</td>
<td>0.6799 0.6185 0.1796</td>
<td>14.6134 0.6969 0.1647</td>
<td>14.8866 0.5671 0.1300</td>
</tr>
<tr>
<td>G3</td>
<td>0.2396 0.5778 0.1923</td>
<td>29.1969 0.6794 0.1180</td>
<td>18.4436 0.5662 0.1272</td>
</tr>
<tr>
<td>G4</td>
<td>1.1531 0.5727 0.1940</td>
<td>15.2680 0.6232 0.3923</td>
<td>6.3088 0.6321 0.0067</td>
</tr>
<tr>
<td>G5</td>
<td>17.0819 0.6143 0.1809</td>
<td>27.5069 0.5389 0.1905</td>
<td>44.2218 0.3913 0.1119</td>
</tr>
<tr>
<td>G6</td>
<td>13.4726 0.6163 0.1822</td>
<td>13.1094 0.6997 0.1309</td>
<td>27.9093 0.3910 0.1119</td>
</tr>
<tr>
<td>G7</td>
<td>4.3773 0.5636 0.1921</td>
<td>12.3118 0.8458 0.1345</td>
<td>4.3799 0.8702 0.0465</td>
</tr>
<tr>
<td>G8</td>
<td>0.5079 0.6099 0.1822</td>
<td>8.8100 0.8679 0.0658</td>
<td>4.9438 0.8857 0.0465</td>
</tr>
<tr>
<td>G9</td>
<td>1.6095 0.5429 0.2046</td>
<td>6.3178 0.7384 0.1815</td>
<td>28.5961 0.4337 0.1449</td>
</tr>
<tr>
<td>G10</td>
<td>19.8488 0.5027 0.2210</td>
<td>18.7814 0.6550 0.0953</td>
<td>19.6299 0.8261 0.2563</td>
</tr>
</tbody>
</table>

Table 3: Comparison of eigenvalues and damping ratios for different cases

<table>
<thead>
<tr>
<th>Case</th>
<th>Without PSS</th>
<th>CPSS</th>
<th>CSAPSS</th>
<th>MCSAPSS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-1.1878 ±10.6655i, 0.1107</td>
<td>-1.5226 ±11.7232i, 0.1288</td>
<td>-2.1541 ±12.2034i, 0.1738</td>
<td>-2.7207±11.9177,0.2225</td>
</tr>
<tr>
<td></td>
<td>-0.3646 ±8.2161, 0.0413</td>
<td>-1.3326 ±11.2726i, 0.1174</td>
<td>-1.5781±11.7177i, 0.1335</td>
<td>-1.5099±11.2052,i.0.1335</td>
</tr>
<tr>
<td></td>
<td>-0.3063 ±8.5938i, 0.0356</td>
<td>-1.9859±11.4999, 0.1753</td>
<td>-1.0795±10.1932i, 0.1053</td>
<td>-2.4765±10.6473i, 0.2265</td>
</tr>
<tr>
<td></td>
<td>-0.2718 ±8.1793i, 0.0332</td>
<td>-0.9837 ±9.35051, 0.1082</td>
<td>-1.9171±10.0117i, 0.1881</td>
<td>-2.248±7.0051i, 0.3056</td>
</tr>
<tr>
<td></td>
<td>-0.0625 ±7.2985i, 0.0066</td>
<td>-0.5380 ±8.5014i, 0.0632</td>
<td>-1.6613±9.5188i, 0.1720</td>
<td>-4.558±5.7011i, 0.6244</td>
</tr>
<tr>
<td></td>
<td>-0.1060 ±6.8725i, 0.0154</td>
<td>-0.1560 ±7.3758i, 0.0213</td>
<td>-3.389±8.3261i, 0.3770</td>
<td>-3.521±4.2379i, 0.6391</td>
</tr>
<tr>
<td></td>
<td>0.2579 ±6.1069i, 0.0422</td>
<td>-1.0658 ±7.2601i, 0.1452</td>
<td>-2.024±3.3567i, 0.5164</td>
<td>-2.926±4.6086i, 0.5361</td>
</tr>
<tr>
<td></td>
<td>0.0620 ±16.1767i, 0.0100</td>
<td>-0.0046 ±6.3800i, 0.0007</td>
<td>-1.380±3.0751i, 0.4096</td>
<td>-1.809±2.7210i, 0.5537</td>
</tr>
<tr>
<td></td>
<td>0.0794 ±3.9665i, 0.0200</td>
<td>-1.2016 ±4.5676i, 0.2544</td>
<td>-1.696±2.6744i, 0.5357</td>
<td>-1.778±2.1468i, 0.6380</td>
</tr>
</tbody>
</table>
4. Affinity Mutation:

\[ a = \frac{1}{\beta} \exp\left( -\text{fitness value} \right) \]  

(9)

5. New population:

\[ C^* = C + \alpha \cdot N(0,1) \]  

(10)

Here \( C^* \) is a mutated cell \( C \) and \( N(0,1) \) a Gaussian random variable of zero mean and unity standard deviation. Mutation is accepted only if the mutated cell \( C^* \) is within its range of domain.

6. 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 calculate the best value from the offspring.

7. Stopping Criterion:

There are various criteria available to stop a stochastic optimization algorithm. Some of them include tolerance, number of times fitness function evaluation and number of iterations. In this paper, maximum number of iterations has been 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 clonal selection algorithm has several interesting features such as dynamically adjustable population size, exploration of the search space, location of multiple optima, and capability of maintaining local optima solutions and defined stopping criteria.

IV. MODIFIED CLONAL SELECTION ALGORITHM

In the Modified Clonal Selection Algorithm (MCSA) the following modifications have been made to the traditional Clonal Selection Algorithm.

1. Best ‘Q’ number of population has been selected from the initial P number of random solutions obtained in step(1) based on the best affinity value.

2. In step(4) affinity mutation has been obtained by modifying the Eq. (9)

\[ a1 = \frac{1}{\beta} \exp\left( -\text{fitness value} \right) \cdot \max K_g \]  

\[ a2 = \frac{1}{\beta} \exp\left( -\text{fitness value} \right) \cdot \max T_1 \]  

(11)

\[ a3 = \frac{1}{\beta} \exp\left( -\text{fitness value} \right) \cdot \max T_2 \]
3. New population is obtained by modifying the Eq.(10)

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

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

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

V. RESULTS AND DISCUSSIONS

The proposed MCSA-based approach has been implemented using MATLAB 7.6 and the simulations have been carried out on 2.27 GHz, 4GB RAM and Intel Core i3 PC. This MCSA has been applied on New England 10-machine, 39-bus system shown in Fig. 2. Details of the system data are given in [28].

A. Eigenvalue Analysis:

To demonstrate the effectiveness and robustness of the proposed MCSA based PSS, eigenvalue analysis of multi-machine system has been carried out under different operating conditions. They can be described as

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

Fig. 3: Speed deviations of 2\textsuperscript{nd} and 3\textsuperscript{rd} generators for Contingency (a)
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Fig. 4: Speed deviations of 4th and 5th generators for Contingency (b)

Fig. 5: Speed deviations of 6th and 7th generators for Contingency (c)
The tuned parameters of the ten PSS using conventional root locus approach, clonal selection algorithm and proposed modified clonal selection algorithm are shown in the Table 2. The electromechanical modes and the damping ratios obtained for all the above cases with the proposed MCSA based PSS, CSAPSS, CPSS and without PSS in the system are given in Table 3. The unstable and poorly damped modes for different operating conditions were found out and highlighted in this Table.

From the eigenvalue analysis between MCSAPSS and CSAPSS, for all the cases, it can be observed that all modes are well shifted in the D-stability region.

For case 1, the minimum damping factor $\zeta_{\min}$ increased from 10.53% to 13.35% and the maximum eigenvalue real part $\sigma_{\max}$ increases from -1.0795 to -1.5099. Similarly for case 2, $\zeta_{\min}$ has increased from 11.26% to 13.51% and $\sigma_{\max}$ from -1.1442 to -1.5319; for case 3, $\zeta_{\min}$ has increased from 11.27% to 13.82% and $\sigma_{\max}$ from -1.1408 to -1.4975; for case 4, $\zeta_{\min}$ has increased from 12.05% to 13.96% and $\sigma_{\max}$ from -1.2135 to -1.4977.

Therefore, it is obvious that the critical mode eigenvalues have been shifted further to the left in s-plane and the system damping has been greatly improved and enhanced with MCSAPSS.

B. Nonlinear Time Domain Simulations:

To demonstrate the effectiveness of the PSS tuned using the proposed MCSA over a wide range of operating conditions and system configurations nonlinear time domain simulations have been carried out on the system under study.

System performance has been demonstrated by using the performance index, which employs Integral of Time multiplied Absolute value of Error (ITAE), given by

$$ITAE = \int_{0}^{10} (|\Delta \omega_1| + |\Delta \omega_2| + \ldots + |\Delta \omega_4|) dt$$  \hspace{1cm} (13)

It is worth mentioning that the lower the value of this index, better is 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, has been simulated. The fault is cleared by tripping the line 4–14. The speed deviation of generators G2 and G3 are shown in Fig. 3.

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 sec. Fig.4 shows the oscillations of G4 and G5 generators.

Contingency (c): Another critical six cycle three-phase fault has been 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 G6 and G7 are shown in Fig. 5.

Contingency (d): A six-cycle three-phase fault, very near to the 14th bus in the line 14–15 with 20% increase in load has also been simulated. The fault is cleared by tripping the line 14–15. The speed deviation of generators G8 and G9 are shown in Fig. 6.

Nonlinear time domain simulation results show that the proposed MCSA based PSS provide improved dynamic performance and faster damping compared with CSAPSS and CPSS. It is also clear that the proposed MCSAPSS provide better damping characteristics to low frequency oscillations to enhance dynamic stability of the power system.
system.

The performance index (\( ITAE \)) obtained for the above contingencies using CPSS, CSAPSS and MCSAPSS are given in the Table 4.

<table>
<thead>
<tr>
<th>Condition</th>
<th>Performance Index (( ITAE ))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Contingency (a)</td>
<td>CPSS 12.6279, CSAPSS 6.0192, MCSAPSS 5.8109</td>
</tr>
<tr>
<td>Contingency (b)</td>
<td>CPSS 12.7930, CSAPSS 5.7570, MCSAPSS 5.7252</td>
</tr>
<tr>
<td>Contingency (c)</td>
<td>CPSS 12.5083, CSAPSS 5.7710, MCSAPSS 5.7069</td>
</tr>
<tr>
<td>Contingency (d)</td>
<td>CPSS 10.4121, CSAPSS 5.6377, MCSAPSS 5.5177</td>
</tr>
</tbody>
</table>

Therefore the system performance characteristic in terms of \( ITAE \) index reveals the solution quality of the proposed MCSAPSS over CSAPSS and CPSS.

VI. CONCLUSION

The use of Modified Clonal Selection Algorithm for the robust design of power system stabilizers in a multi-machine power system operating at various loadings and system configurations has been investigated in this paper. The problem of selecting the PSS parameters, which simultaneously improve the damping at various operating conditions and shift the electromechanical modes to the prescribed D-shape sector, has been converted to an optimization problem with an eigenvalue based objective function which is solved by modified clonal selection algorithm. Eigenvalue analysis under different operating conditions reveals that undamped and lightly damped oscillation modes are optimally placed in the left-half of complex s-plane. Nonlinear simulation results show the superiority of the proposed MCSA based PSS in damping power oscillations over CSAPSS and CPSS.

REFERENCES