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MULTI–OBJECTIVE NON–DOMINATED SHORTING GENETIC ALGORITHM–II FOR EXCITATION AND TCSC–BASED CONTROLLER DESIGN

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Non-dominated Sorting in Genetic Algorithms-II (NSGA-II) is a popular non-domination based genetic algorithm for solving multi-objective optimization problems. This paper investigates the application of NSGA-II technique for the design of a Thyristor Controlled Series Compensator (TCSC)-based controller and a power system stabilizer. The design objective is to improve both rotor angle stability and system voltage profile. The proposed technique is applied to generate Pareto set of global optimal solutions to the given multi-objective optimization problem. Further, a fuzzy-based membership value assignment method is employed to choose the best compromise solution from the obtained Pareto solution set. Simulation results are presented and compared with a conventionally designed power system stabilizer under various loading conditions and disturbances to show the effectiveness and robustness of the proposed approach.

K e y w o r d s: multi-objective optimization, non-dominated shorting genetic algorithm, pareto solution set, thyristor controlled series compensator, power system stabilizer, power system stability

1 INTRODUCTION

Power system oscillations and system voltage profile are the two important criteria which define the performance of a power system subjected to a disturbance [1]. Power System Stabilizers (PSS) are now routinely used in the industry to damp out power system oscillations. However, during some operating conditions, this device may not produce adequate damping, and other effective alternatives are needed in addition to PSS. Recent development of power electronics introduces the use of Flexible AC Transmission Systems (FACTS) controllers in power systems [2]. Thyristor Controlled Series Compensator (TCSC) is one of the important members of FACTS family that is increasingly applied with long transmission lines by the utilities in modern power systems [3–7].

The problem of PSS and FACTS controllers parameter tuning is a complex exercise as uncoordinated local control of FACTS devices and PSS may cause destabilizing interactions. A number of conventional techniques have been reported in the literature pertaining to design problems of conventional power system stabilizers namely: the eigenvalue assignment, mathematical programming, gradient procedure for optimization and also the modern control theory. Unfortunately, the conventional techniques are time consuming and require heavy computation burden and slow convergence. In addition, the search process is susceptible to be trapped in local minima and the solution obtained may not be optimal. The evolutionary methods constitute an approach to search for the optimum solutions via some form of directed random search process. Recently, Genetic Algorithm (GA) and particle swarm optimization (PSO) appeared as a promising evolutionary technique for handling the optimization problems and have been applied to design the controllers [8, 9].

There has been much research interest in developing new control methodologies for increasing the performance of the power system. The majority of the control methodologies presented in literature concerns improvement of only one type of stability performance; either improving the oscillatory stability performance (reflected in the deviation in generator speed) or the system voltage profile and minimization of a single objective function is employed to get the desired performance. Obviously, the main purpose of design of any controller is to enable it to improve both oscillatory stability and system voltage profile. Design of such a kind of controller is inherently a multi-objective optimization problem.

There are two general approaches to multiple objective optimizations. One approach to solve multi- objective optimization problems is by combining the multiple objectives into a scalar cost function, ultimately making the problem single-objective prior to optimization. However, in practice, it can be very difficult to precisely and accurately select these weights as small perturbations in the weights can lead to very different solutions. Further, if the final solution found cannot be accepted as a good compromise, new runs of the optimizer on modified objective function using different weights may be needed, until a suitable solution is found. These methods also have the disadvantage of requiring new runs of the optimizer every time the preferences or weights of the objectives in the multi-objective function change [10]. The second general approach is to determine an entire Pareto optimal solution set or a representative subset. Pareto optimal solution sets are often preferred to single solutions because they can be practical when considering real-life problems, since the final solution of the decision maker is always a trade-off between crucial parameters [11].

In this paper, the design problem of PSS and TCSC-based controller is formulated as a multi-objective optimization problem. Non-Dominated Sorting in Genetic Algorithms-II (NSGA-II) based multi-objective optimiza-

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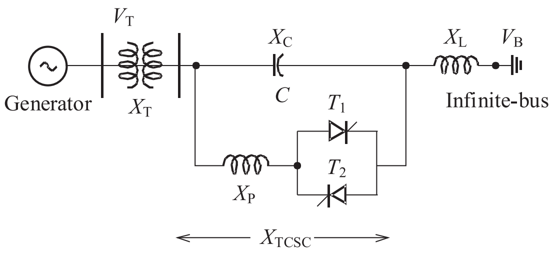

Fig. 1. Single-machine infinite-bus power system with TCSC

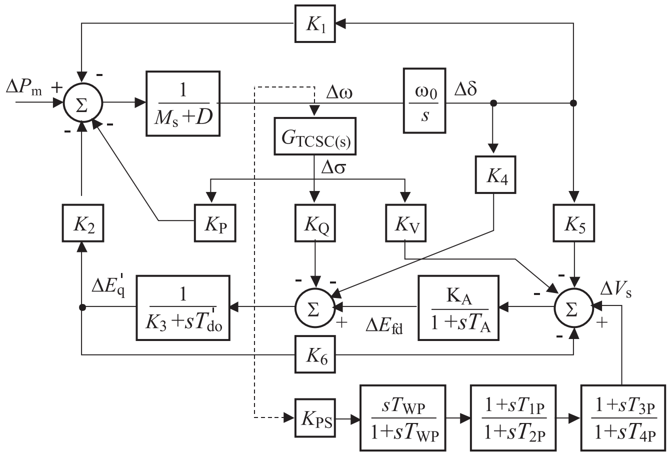

Fig. 2. Modified Phillips-Heffron model of SMIB with TCSC and PSS

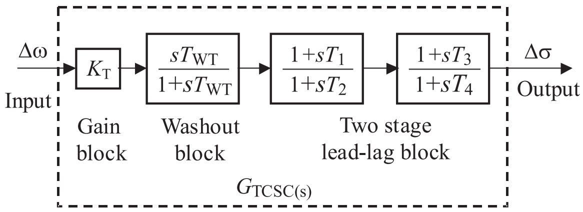

Fig. 3. Structure of TCSC controller

tion method is adapted for generating Pareto solutions in designing the proposed controllers. The design objective is to improve the oscillatory stability and system voltage profile of a power system following a disturbance. Further a fuzzy based membership function value assignment method is employed to choose the best compromise solution from the obtained Pareto set. Simulation results are presented at various loading conditions to show the effectiveness and robustness of the proposed approach.

2 POWER SYSTEM MODELING

The single-machine infinite-bus (SMIB) power system installed with a TCSC, shown in Fig. 1 is considered in this study. In the figure, X_T and X_L represent the reactance of the transformer and the transmission line respectively; V_T and V_B are the generator terminal and infinite bus voltage respectively.

In the design of electromechanical mode damping stabilizer, a linearized incremental model around an operating point is usually employed [1]. The Phillips-Heffron model of the power system with FACTS devices is obtained by linearizing nonlinear equations of the power system around an operating condition.

The linearized expressions are as follows [12]:

$$
\begin{aligned}
\Delta\delta &= \omega_b \Delta\omega\,, \\
\Delta\omega &= \frac{-K_1\Delta\delta - K_2\Delta E'_q - K_P\Delta\sigma - D\Delta\omega}{M}\,, \\
\Delta E'_q &= \frac{-K_3\Delta E'_q - K_4\Delta\delta - K_Q\Delta\sigma + \Delta E_{fd}}{T'_{d0}}\,, \\
\Delta E'_{fd} &= \frac{-K_A(K_5\Delta\delta + K_6\Delta E'_q + K_V\Delta\sigma) - \Delta_{fd}}{T_A}\,.
\end{aligned}
\tag{1}
$$

where,

$$
\begin{aligned}
K_1 &= \frac{\partial P_e}{\partial \delta}\,, & K_2 &= \frac{\partial P_e}{\partial E'_q}\,, & K_3 &= \frac{\partial E_q}{\partial E'_q}\,, \\
K_4 &= \frac{\partial E_q}{\partial \delta}\,, & K_5 &= \frac{\partial V_T}{\partial \delta}\,, & K_6 &= \frac{\partial V_T}{\partial E'_q}\,, \\
K_P &= \frac{\partial P_e}{\partial \sigma}\,, & K_V &= \frac{\partial V_T}{\partial \sigma}\,, & K_Q &= \frac{\partial E_q}{\partial \sigma}\,.
\end{aligned}
$$

The above notation for the variables and parameters described are standard and defined in the nomenclature. For more details, the readers are suggested to refer [1, 12]. The Phillips-Heffron model of the SMIB system with TCSC is obtained using the linearized equations. The corresponding block diagram model is shown in Fig. 2.

3 PROBLEM FORMULATION

3.1 Proposed Controller Structures

The commonly used leadlag structure is chosen in this study as a TCSC controller. The structure of the TCSC controller is shown in Fig. 3. Figure 4 shows the structure of the power system stabilizer used in the present study. Each structure consists of a gain block, a signal washout block and two-stage phase compensation block. The phase compensation block provides the appropriate phase-lead characteristics to compensate for the phase lag between input and the output signals. The signal washout block serves as a high-pass filter, with a time constant high enough to allow signals associated with oscillations in input signal to pass unchanged. Without it steady changes in input would modify the output. From the viewpoint of the washout function, the value of washout time constant is not critical and may be in the range of 1 to 20 seconds [1].

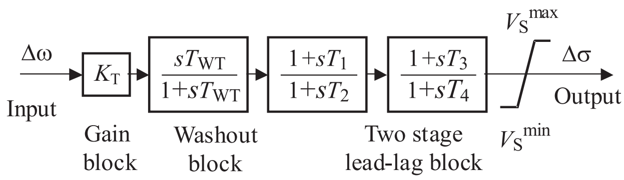

Fig. 4. Structure of the power system stabilizer

3.2 Objective Function

It is worth mentioning that the proposed controllers are designed to damp power system oscillations and improve the system voltage profile after a disturbance. A multi-objective function based on $\Delta\omega$ and ΔV_T is used as an objective function in the present study. The objective can be formulated as the minimisation of function F given by:

$$F = (F_1, F_2) \tag{2}$$

where $F_1 = \int_0^{t_1} |\Delta\omega| t\mathrm{d}t$ and $F_2 = \int_0^{t_1} |\Delta V_T| t\mathrm{d}t$.

In these equations, $|\Delta\omega||$ and $|\Delta V_T|$ denote the absolute values of rotor speed and terminal voltage deviations following a disturbance and t_1 is the time range of the simulation. For the objective function calculation, the time-domain simulation of the power system model is carried out for the simulation period.

4 MULTIOBJECTIVE OPTIMIZATION

A Multi-objective Optimization Problem (MOP) differs from a single-objective optimization problem because it contains several objectives that require optimization. In case of single objective optimization problems, the best single design solution is the goal. But for multi-objective problems, with several and possibly conflicting objectives, there is usually no single optimal solution. Therefore, the decision maker is required to select a solution from a finite set by making compromises. A suitable solution should provide for acceptable performance over all objectives.

A general formulation of a MOP consists of a number of objectives with a number of inequality and equality constraints. Mathematically, the problem can be written as [13]:

$$\begin{aligned}
&\text{minimize/maximize } f_i(x) \\
&\quad \text{for } i = 1, 2, \dots, n\,. \\
&\text{Subject to constraints:} \\
&\quad g_j(x) \le 0\,, \quad j = 1, 2, \dots, J\,, \\
&\quad h_k(x) \le 0\,, \quad k = 1, 2, \dots, K\,.
\end{aligned} \tag{3}$$

where

$f_i(x) = \{f_1(x), \dots, f_n(x)\}$,

$n =$ number of objectives or criteria to be optimised,

$\mathbf{x} = \{x_1, \dots, x_p\}$ is a vector of decision variables,

$p =$ number of decision variables.

There are two approaches to solve the MOP. One approach is the classical weighted-sum approach where the objective function is formulated as a weighted sum of the objectives. But the problem lies in the correct selection of the weights or utility functions to characterise the decision-makers preferences. In order to solve this problem, the second approach called Pareto-optimal solution can be adapted. The MOPs usually have no unique or perfect solution, but a set of non-dominated, alternative solutions, known as the Pareto-optimal set. Assuming a minimisation problem, dominance is defined as follows

A vector $\boldsymbol{u} = (u_1 \dots, u_n)$ is said to dominate $\mathbf{v} = (v_1, \dots, v_n)$ if and only if $\boldsymbol{u}$ is partially less than $\boldsymbol{v}$ ($\boldsymbol{u} p< \boldsymbol{v}$),

$$\forall i \in \{1, \dots, n\}\,,\ u_i \le v_i \wedge\ \exists i \in \{1, \dots n\}\,,\ u_i < v_i\,. \tag{4}$$

A solution $x_u \in U$ is said to be Pareto-optimal if and only if there is no $x_v \in U$ for which $\mathbf{v} = f(x_v) = (v_1, \dots, v_n)$ dominates $\boldsymbol{u} = f(x_u) = (u_1, \dots, u_n)$.

Pareto-optimal solutions are also called efficient, non-dominated, and non-inferior solutions. The corresponding objective vectors are simply called non-dominated. The set of all non-dominated vectors is known as the non-dominated set, or the trade-off surface, of the problem. A Pareto optimal set is a set of solutions that are non-dominated with respect to each other. While moving from one Pareto solution to another, there is always a certain amount of sacrifice in one objective to achieve a certain amount of gain in the other. The elements in the Pareto set has the property that it is impossible to further reduce any of the objective functions, without increasing, at least, one of the other objective functions.

The ability to handle complex problems, involving features such as discontinuities, multimodality, disjoint feasible spaces and noisy function evaluations reinforces the potential effectiveness of GA in optimization problems. Although, the conventional GA is also suited for some kinds of multi-objective optimization problems, it is still difficult to solve those multi-objective optimization problems in which the individual objective functions are in the conflict condition.

Being a population based approach; GA is well suited to solve MOPs. A generic single-objective GA can be easily modified to find a set of multiple non-dominated solutions in a single run. The ability of GA to simultaneously search different regions of a solution space makes it possible to find a diverse set of solutions for difficult problems with non-convex, discontinuous, and multi-modal solutions spaces. The crossover operator of GA exploits structures of good solutions with respect to different objectives to create new non-dominated solutions in unexplored parts of the Pareto front. In addition, most multi-objective approach does not require the user to prioritise, scale, or weigh objectives. Therefore, GA has been the most popular heuristic approach to multi-objective design and optimization problems.

5 NON–DOMINATED SHORTING GENETIC ALGORITHM–II

Pareto-based fitness assignment was first proposed by Goldberg [14], the idea being to assign equal probability of reproduction to all non-dominated individuals in the population. The method consisted of assigning rank 1 to the non-dominated individuals and removing them from contention, then finding a new set of non-dominated individuals, ranked 2, and so forth.

In the present study, after initializing the population the individuals in the populations are sorted based on non-domination into each front. The first front being completely non-dominant set in the current population and the second front being dominated by the individuals in the first front only and the front goes so on. Each individual in the each front are assigned rank (fitness) values or based on front in which they belong to. Individuals in first front are given a fitness value of 1 and individuals in second are assigned fitness value as 2 and so on. In addition to fitness value a new parameter called crowding distance is calculated for each individual. The crowding distance is a measure of how close an individual is to its neighbours. Large average crowding distance will result in better diversity in the population. Parents are selected from the population by using binary tournament selection based on the rank and crowding distance. An individual is selected in the rank is lesser than the other or if crowding distance is greater than the other 1. The selected population generates offsprings from crossover and mutation operators, which will be discussed in detail in a later section. The population with the current population and current offsprings is sorted again based on non-domination and only the best N individuals are selected, where N is the population size. The selection is based on rank and the on crowding distance on the last front.

Implementation of NSGA-II requires the determination of some fundamental issues. In the present paper, after initializing the population the following schemes are employed [15–17]

5.1 Non-Dominated Sort

The initialized population is sorted based on non-domination using the following shorting algorithm.

- For each individual i in the main population MP, find the set of individuals SI, that is dominated by i.
- Find the number of individuals that dominate i, N_i.
- For each individual j in MP, if i dominates j, then add j to set SI. If j dominates i, increment the domination counter N_i for i.
- If no individuals dominate i then i belongs to the first front; Set rank of individual i to one *ie* $i_{\text{rank}} = 1$. Update the first front set by adding i to front one.
- Repeat the above procedure for all the individuals i in main population MP.
- Initialize the front counter $f = 1$. For k^{th} nonempty front F_k, the set S for sorting the individuals for $(k+1)^{\text{th}}$ front is done. For each individual i in F_k, and for each individual j in SI, domination count for individual j is decremented. If $N_j = 0$ then none of the individuals in the subsequent fronts would dominate j. Hence the rank of j is taken as $k+1$ and the set S is updated with individual j.
- Increment the front counter and set S becomes the next front.

5.2 Crowding Distance

The basic scheme behind the crowing distance calculation is the determination of euclidian distance between each individual in a front based on their m objectives in the m dimensional space. All the individuals in the population are assigned a crowding distance value as the individuals are selected based on rank and crowding distance. Crowding distance is assigned front wise as below

For each front F_k , i is the no. of individual

- For all the individuals initialize the distance to be zero. $F_k(d_j) = 0$, where j corresponds to the j^{th} individual in front F_k.
- For each objective function m, sort the individuals in front F_k based on objective m, $I = \text{sort}(f_k, m)$.
- Boundary values for each individual are assigned infinite value, $I(d_1) = \infty$ and $I(d_n) = \infty$.
- For $p = 2$ to $(n-1)$

$$I(d_p) = I(d_p) + \frac{I(p+1)m - I(p-1)m}{f_m^{\max} - f_m^{\min}} . \tag{5}$$

$I(p)m$ is the value of the m^{th} objective function of the p^{th} individual in I.

5.3 Selection

The selection is performed using a crowded comparison operator α_c as below:

- Individuals in front F_k are ranked as $p_{\text{rank}} = i$.
- From the rowding distance $F_k(d_j)$, the ranks are compared using the comparison operator α_c
  ie $p\,\alpha_c\,q$ if $p_{\text{rank}} < q_{\text{rank}}$
  or if p and q belong to the same front F_k then $F_k(d_p) > F_k(d_q)$.

By using tournament selection with crowed comparison operator, the individuals are selected.

5.4 Genetic Operators

Crossover: Simulated binary crossover scheme is employed in the present study which simulates the binary crossover observed in nature given as below:

$$a_{1,k} = \frac{(1-\gamma_k)p_{1,k} + (1+\gamma_k)p_{2,k}}{2} , \tag{6}$$

$$a_{2,k} = \frac{(1+\gamma_k)p_{1,k} + (1-\gamma_k)p_{2,k}}{2} . \tag{7}$$

Where, $a_{i,k}$ is the i^{th} child with k^{th} component, $p_{i,k}$ is the selected parent, $\gamma_k\,$k is the random generated sample (≥ 0) obtained from a uniformly sampled random number u between $(0,1)$ defined by:

$$p(\gamma) = \frac{(\varepsilon_c + 1)\gamma^{\varepsilon_c}}{2} , \qquad \text{if } 0 \leq \gamma \leq 1 , \tag{8}$$

$$p(\gamma) = \frac{(\varepsilon_c + 1)}{2\gamma^{\varepsilon_{c+2}}} , \qquad \text{if } 0 \leq \gamma > 1 , \tag{9}$$

$$\gamma(u) = (2u)^{1/(\varepsilon+1)}, \tag{10}$$

$$\gamma(u) = 1/[2(1-u)]^{1/(\varepsilon+1)} . \tag{11}$$

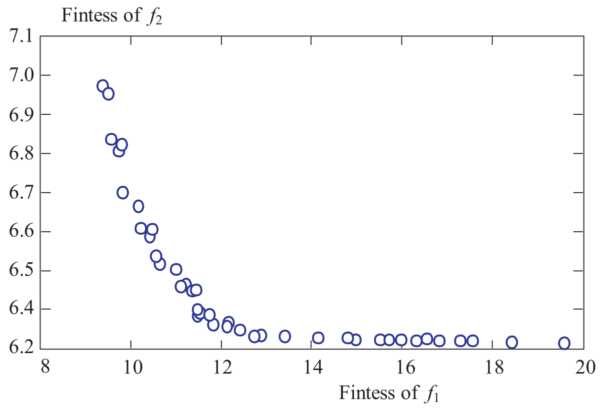

Fig. 5. Pareto optimal solution surface

Table 1. Best compromise solution as PSS and TCSC-based controller parameters

Parameters	PSS	TCSC
K	8.5436	61.4546
T_1	0.1876	0.1842
T_2	0.0972	0.0936
T_3	0.1935	0.1744
T_4	0.1243	0.1256

Where ε_c is distribution index for crossover

Mutation: The polynomial mutation is employed in the presented study defined as:

$$c_k = p_k + \left(p_k^u - p_k^l\right)\Delta_k\,. \tag{12}$$

Where, c_k is the child, p_k is the parent, p_k^u and p_k^l are the upper and lower bounds on the parent components respectively. Δ_k is the small deviation calculated as below:

$$\Delta_k = (2r_n)^{1/(\varepsilon m+1)} - 1\,, \qquad \text{if } r_n < 0.5\,, \tag{13}$$

$$\Delta_k = 1 - [2(1-r_n)]^{1/(\varepsilon m+1)}, \ \text{if } r_n \geq 0.5\,. \tag{14}$$

Where, $r_n \in (0,1)$ is a uniformly sampled random number, εm is mutation distribution factor.

5.6 Recombination and Selection

Selection for individuals for next generation is performed by combining the current generation population and the offspring population. Elitism is ensured as all the previous and current best individuals are added in the population. Based on non-domination, population is sorted and the new generation is completed by each front subsequently until current population size is obtained.

6 RESULTS AND DISCUSSIONS

6.1 Application of NSGA-II to Generate Pareto Solution Set

The objective function given by equation (2) is evaluated by simulating the system dynamic model considering a 10 % step increase in mechanical power input (ΔP_m) at $t = 1.0$ sec. Optimization process is repeated 20 times and the best final Pareto solution surface obtained is shown in Fig. 5 where the Pareto solutions are shown with the marker 'o'.

6.2 Best Compromise Solution

In the present paper, a Fuzzy-based approach is applied to select the best compromise solution from the obtained Pareto set. The j-th objective function of a solution in a Pareto set f_j is represented by a membership function μ_j defined as [18]

$$\mu_j = \begin{cases} 1\,, & f_j \leq f_j^{\min}, \\ \frac{f_j^{\max} - f_j}{f_j^{\max} - f_j^{\min}}\,, & f_j^{\min} < f_j < f_j^{\max}\,, \\ 0\,, & f_j \geq f_j^{\max} \end{cases} \tag{15}$$

where $f_j^{\max}$ and $f_j^{\min}$ are the maximum and minimum values of the j-th objective function, respectively.

For each solution i, the membership function μ^i is calculated as:

$$\mu_i = \frac{\sum_{j=1}^{n} \mu_j^i}{\sum_{i=1}^{m} \sum_{j=1}^{n} \mu_j^i} \tag{16}$$

Table 2. Loading conditions considered

Loading Conditions	P (pu)	Q (pu)	Parameter variation	δ_0 (deg.)
Nominal	0.8	0.3694	No parameter variation	60.39
Light	0.5	0.169	50% increase in line reactance	37.54
Heavy	1.02	0.6479	10% decrease in line reactance and 5% increase in terminal voltage	73.57

Table 3. System electromechanical eigenvalues

Loading Conditions	Without control	With random controller parameters	NSGA-II optimized PSS and TCSC
Nominal	$0.1891 \pm 5.2152i$	$-0.8187 \pm 6.5981i$	$-9.0381 \pm 5.4223i$
Light	$0.0504 \pm 5.5145i$	$-1.0033 \pm 6.63i$	$-9.6788 \pm 3.6388i$
Heavy	$0.4864 \pm 3.9793i$	$-0.7428 \pm 6.586i$	$-8.7501 \pm 6.8753i$

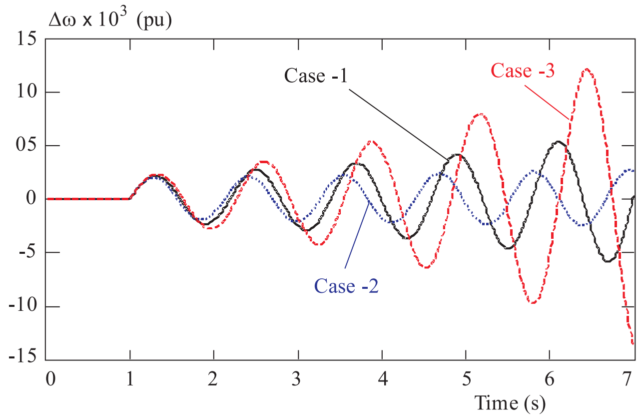

Fig. 6. Speed deviation without PSS and TCSC

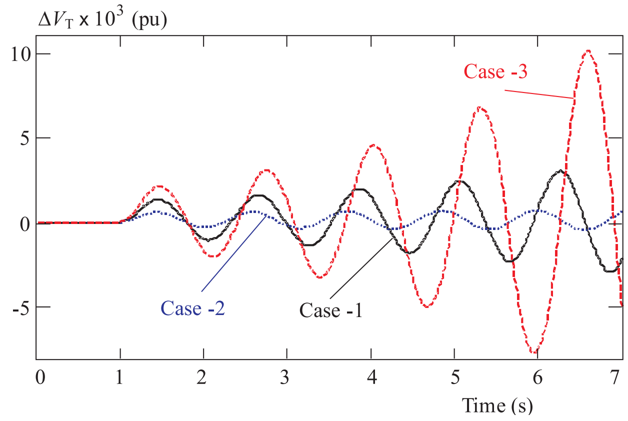

Fig. 7. Terminal voltage deviation response without PSS and TCSC

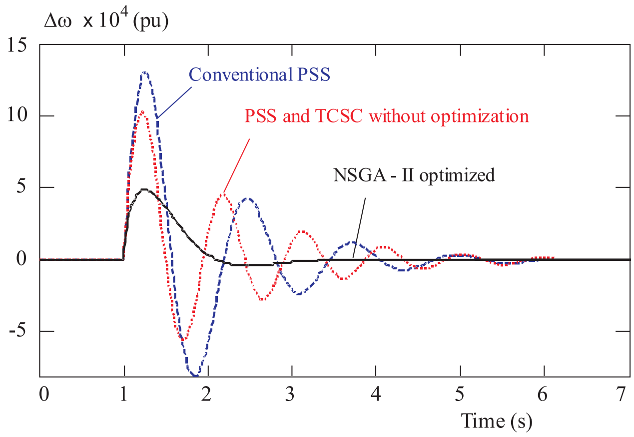

Fig. 8. Speed deviation response at nominal loading

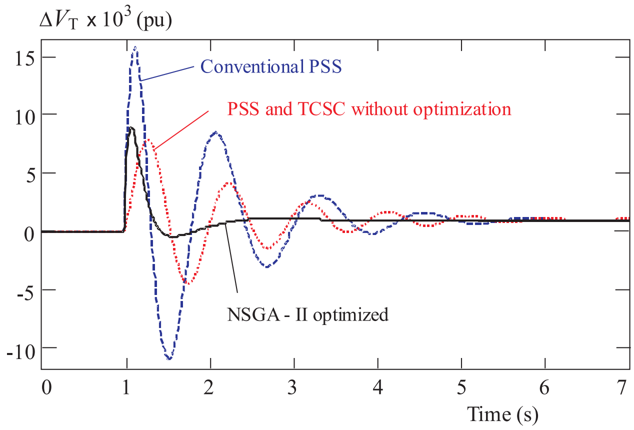

Fig. 9. Terminal voltage response at nominal loading

where, n is the number of objectives functions and m is the number of solutions. The solution having the maximum value of μ^i is the best compromise solution. Table 1 shows the best compromise solution obtained as PSS and TCSC based controller parameters using the above approach.

6.3 Eigenvalue Analysis

To assess the effectiveness and robustness of the proposed stabilizers, three different loading conditions given in Table 2 are considered. The system electromechanical mode eigenvalues without and with the proposed controllers are shown in Table 3. Table 3 also shows the system electromechanical eigenvalues with randomly chosen PSS and TCSC controller parameters (please refer Appendix).

It is clear from Table 3 that the open loop system is unstable at all the loading conditions because of negative damping of electromechanical mode ($s = 0.1891$, 0.0504 and 0.4864 for nominal, light and heavy loading respectively). With randomly chosen PSS and TCSC controller parameters the system stability is maintained as the electromechanical mode eigenvalue shift to the left of the line in s-plane ($s = -0.8187$, -1.0033 and -0.7428 for nominal, light and heavy loading respectively) for all loading conditions. It is also clear that proposed NSGA-II optimized PSS and TCSC controllers shift substantially the electromechanical mode eigenvalue to the left of the line ($s = -9.0381$, -9.6788 and -8.7501 for nominal, light and heavy loading respectively) in the s-plane, which greatly enhances the system stability.

6.4 Simulation Results

In order to verify the effectiveness of the proposed approach, the performance of the NSGA-II optimized PSS and TCSC controller is tested for different loading conditions. The system speed deviation and terminal voltage response for the above contingency at all the loading condition are shown in Figures 6 and 7 respectively. In the Figures the legend Case 1 (shown with solid line) indicates nominal loading condition with no parameter variation, the legend Case 2 (shown with dotted line) indicates light loading condition with 50 % increase in line reactance and the legend Case 3 (shown with dashed line) indicates heavy loading condition with 10 % decrease in line reactance and 5 % increase in terminal voltage. These simulation results confirm the eigenvalue analysis presented in Section 6-B *ie* the system is unstable at all the loading conditions.

The system speed and terminal voltage deviation responses for the above contingency at nominal loading condition are shown in Figures 8 and 9 respectively. For

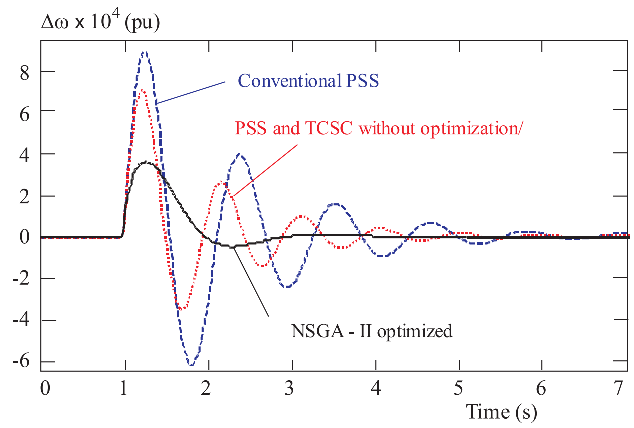

Fig. 10. Speed deviation response at light loading

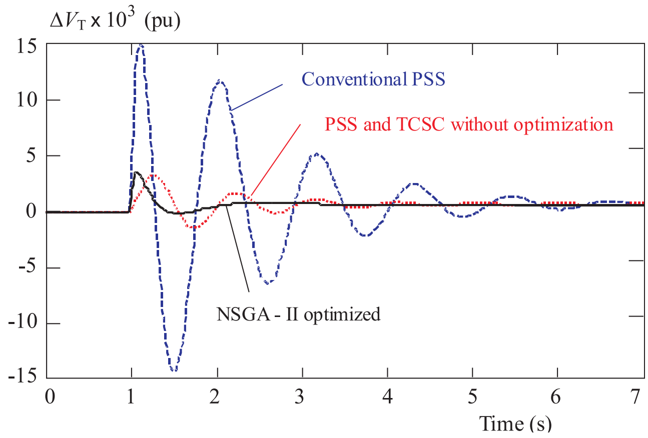

Fig. 11. Terminal voltage response at light loading

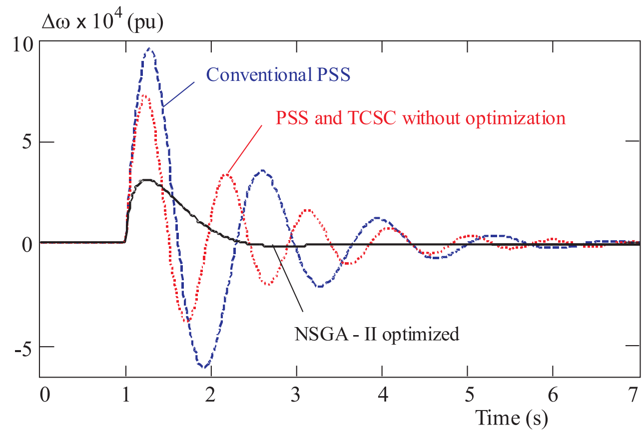

Fig. 12. Speed deviation response at heavy loading

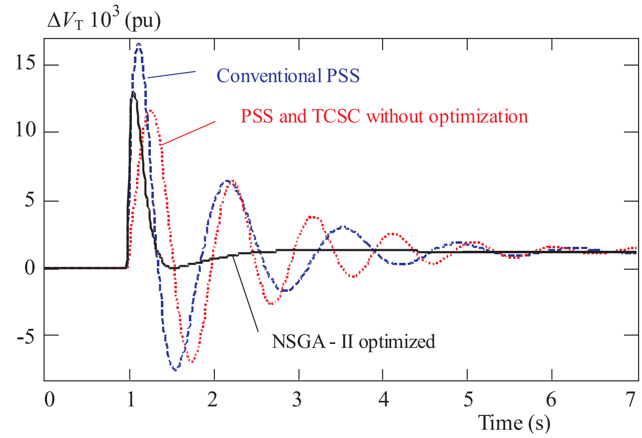

Fig. 13. Terminal voltage at heavy loading

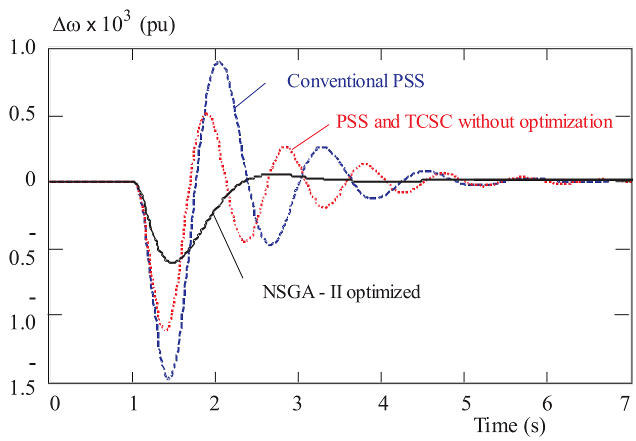

Fig. 14. Speed deviation response under disturbance in reference voltage setting

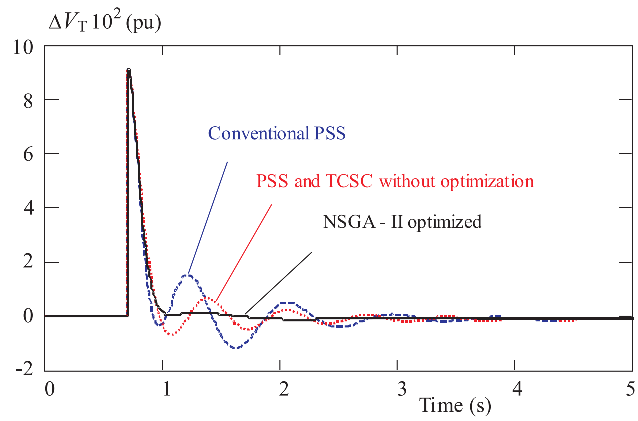

Fig. 15. Terminal voltage deviation response under disturbance in reference voltage setting

comparison the responses with a conventionally designed PSS [19] is shown with dashed lines and the responses with randomly chosen PSS and TCSC controller parameters are shown with dotted lines. It can be observed from Figures 8 and 9 that the responses with proposed NSGA-II optimized PSS and TCSC controller are much faster, with less settling time compared to the case where the controller parameters are not optimized and CPSS.

Figures 10 and 11 show the system response for the above disturbance at light loading conditions with the parameter variation given in Table 2. These simulation results illustrate the effectiveness and robustness of proposed design approach. It is clear that the proposed NSGA-II optimized TCSC controller has good damping characteristics to low frequency oscillations and stabilizes the system quickly at light loading condition with parameter variation.

To illustrate the effectiveness and robustness of proposed design approach, the system response for the same disturbance at heavy loading conditions with the parameter variation (given in Table 2) are shown in Figures 12 and 13. It is clear that the proposed NSGA-II optimized controllers are robust and perform satisfactorily at heavy loading condition with parameter variation.

For completeness, the effectiveness of the proposed controllers is also tested for a disturbance in reference voltage setting. The reference voltage is increased by a step of 10 % at $t = 1.0$ s. Figures 14 and 15 show the system response for the above contingency at nominal loading condition. These positive results of the proposed NSGA-II optimized controllers can be attributed to its faster response compared to that of controllers without optimized parameters. The proposed controllers have good damping characteristics to low frequency oscillations and stabilize the system much faster. This extends the power system stability limit and the power transfer capability.

7 CONCLUSION

In this study, the performance improvement of a power system by optimal design of a TCSC-based controller and a power system stabilizer is presented and discussed. The design objective is to improve both rotor angle stability and system voltage profile. A Non-Dominated Sorting Genetic Algorithm-II based solution technique is applied to generate a Pareto set of global optimal solutions to the given multi-objective optimization problem. Further, a fuzzy-based membership value assignment method is employed to choose the best compromise solution from the obtained Pareto solution set. Eigenvalue analysis and simulation results are presented at various loading conditions to show the effectiveness and robustness of the proposed approach.

Appendix

System data: All data are in per unit (pu) unless specified otherwise. All variables are defined in reference [1].

Generator: $M = 9.26$ s, $D = 0$, $X_d = 0.973$, $X_q = 0.55$, $X'_d = 0.19$, $T'_{do} = 7.76$, $f = 60$, $V_T = 1.05$, $X = 0.997$, $K_A = 50$, $T_A = 0.05$ s. $X_{TCSC0} = 0.2169$, $\alpha_0 = 160°$, $X_C = 0.2X$, $X_P = 0.25X_C$

Random controller parameters:
TCSC: $K_T = 60$, $T_1 = 0.1$, $T_2 = 0.2$, $T_3 = 0.15$, $T_4 = 0.35$,
PSS: $K_{PS} = 10$, $T_{1P} = 0.1$, $T_{2P} = 0.2$, $T_{3P} = 0.15$, $T_{4P} = 0.35$.

References

[1] KUNDUR, P.: Power System Stability and Control, McGraw-Hill, New York, 1994.

[2] HINGORANI, N. G.—GYUGYI, L.: Understanding FACTS: Concepts and Technology of Flexible AC Transmission System, IEEE Press., 2000.

[3] MATTAVELLI, P.—VERGHESE, G. C.—STANKOVITCTT, A. M.: Phasor dynamics of Thyristor-Controlled series capacitor systems, IEEE Trans. Power Systs.,.

[4] LI, B. H.—WU, Q. H.—TURNER, D. R.—WANG, P. Y.—ZHOU, X. X.: Modeling of TCSC dynamics for control and analysis of power system stability, Electrical Power & Energy Systs. **22** (2000), 43–49.

[5] FAN, L.—FELIACHI, A.—SCHODER, K.: Selection and design of A TCSC control signal in damping power system inter-area oscillations for multiple operating conditions, Electrical Power & Energy Systs. **62** (2002), 127–137.

[6] DEL ROSSO, A. D—CANIZARES, C. A.—DONA, V. M.: A study of TCSC controller design for power system stability improvement, IEEE Trans. Power Systs. **18** (2003), 1487–1496.

[7] ABIDO, M. A.: Pole placement technique for PSS and TCSC-based stabilizer design using simulated annealing, Int. J. Elect. Power & Energy Systs. **22** (2000), 543–554.

[8] PANDA, S.—PADHY, N. P.—PATEL, R. N.: Modeling, simulation and optimal tuning of TCSC controller, International Journal of Simulation Modelling. **6** (2007), 37–48.

[9] PANDA, S.—PADHY, N. P.: Comparison of Particle Swarm Optimization and Genetic Algorithm for FACTS-based Controller Design, Applied Soft Computing **8** (2008), 1418–1427.

[10] COELLO, C. A. C.: A comprehensive survey of evolutionary-based multiobjective optimization techniques, Knowledge and Information Systems **1** (1999), 269–308.

[11] CHANKONG, V.—HAIMES, Y.: Multiobjective Decision Making Theory and Methodology, North-Holland, New York, 1983.

[12] WANG, H. F.—SWIFT, F. J.: A unified model for the analysis of FACTS devices in damping power system oscillations part I: single-machine infinite-bus power systems,, IEEE Trans. Power Delivery **12** (1997), 941–946.

[13] RAO, S. S.: Optimization Theory and Application, Wiley Eastern Limited, New Delhi, 1991.

[14] GOLDBERG, D. E.: Genetic Algorithms in Search,Optimization and Machine Learning, Addison-Wesley, 1989.

[15] SRINIVAS, N.—DEB, K.: Multiobjective Optimization Using Nondominated Sorting in Genetic Algorithms, Evolutionary Computation **2** (1994), 221–248.

[16] DEB, K.—PRATAP, A.—AGARWAL, S.—MEYARIVAN, T.: A Fast Elitist Multiobjective Genetic Algorithm: NSGA-II, IEEE Transactions on Evolutionary Computation **6** (2002), 182–197.

[17] RAGHUWANSHI, M. M.—KAKDE, O. G.: Survey on multiobjective evolutionary and real coded genetic algorithms, Proceedings of the 8th Asia Pacific Symposium on Intelligent and Evolutionary Systems, (2004), pp. 150 161..

[18] PANDA, S.: Multiobjective Evolutionary Algorithms for SSSC Based Controller Design, Electric power System Research **79** (2009), 937–944.

[19] YU, Y. N.: Power System Dynamics, Academic press, Inc., London, 1983.

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