An Optimal Design of Coordinated PI based PSS with TCSC Controller using Modified Teaching Learning Based Optimization

Bagepalli Sreenivas Theja, Anguluri Rajasekhar
Department of Electrical Engineering
National Institute of Technology-Warangal, India
Email: sreenivastheja11972@gmail.com
rajasekhar.anguluri@ieee.org

Ajith Abraham[1,2]
[1]IT4Innovations, VSB-Technical University of Ostrava, Czech Republic
[2]Machine Intelligence Research Labs (MIR Labs), WA, USA
Email: ajith.abraham@ieee.org

Abstract—**This paper deals with an interesting application of recently evolved Teaching Learning based Optimization (TLBO) algorithm in designing coordinated Proportional-Integral (PI) controller based Power System Stabilizer (PSS) for single machine infinite bus power system equipped with Thyristor Controlled Series Compensator (TCSC). As the design is for coordinated system, traditional TLBO results in suboptimal solution and hence we propose a modified TLBO method based on the concept of opposition based learning for designing coordinated controllers. Computer simulations of the proposed approach on various loading conditions reveal the superiority of modified TLBO in designing coordinated controller for enhancing the dynamic stability of power system.**

Keywords: PSS, TCSC, TLOBA, small signal stability, SMIB.

I. INTRODUCTION

Owing to the growing complexity of modern day power systems, they are often interconnected with weak tie lines. Fast acting, high gain Automatic Voltage Regulator's (AVR) are being employed to the synchronous generators to maintain the distantly located, inter connected power systems at constant operating voltage [1]. Though AVRs can enhance the overall transient stability, they are responsible for low frequency generator rotor angle oscillations (0.1-3 Hz). They may further grow in magnitude affecting the small signal stability, which is the ability of the power system to remain in synchronism when the small disturbances due to variations in generation and loads occur [2].

In order to produce positive damping on these small frequency oscillations, Power System Stabilizers (PSS) are employed. The purpose of PSS is to introduce supplementary signals (derived from speed deviation signal $\Delta\omega$) in the feedback loop of voltage regulator. Design of effective PSS is very difficult when the frequency of oscillations begun to vary over a wide range. Also PSS causes variations in voltage profiles and their operation is relatively slow [3].

The recent advancements in the high power semiconductor technology lead to the development of Flexible AC Transmission devices (FACTS), which can enhance the power system stability and power transfer capability. They are economical, fast acting and can improve the efficiency and security of power system [4]. Thyristor Controlled Series Compensator is one of the first generation FACTS devices. It is economical and effective means of enhancing dynamic stability of power system by quick and flexible means of adjusting line reactance. It assures better control over power flow, improvement of transient stability limits and fault current limitation [5-9]. For the small signal stability studies of Single Machine Infinite Bus system (SMIB) linear model of Philip-Heffron is considered. To avoid the destabilizing interactions the tuning of TCSC controller is coordinated with PSS. To further enhance the dynamic stability, PI controllers are incorporated along with TCSC and PSS controllers.

As the coordinated controllers consist of more parameters to be selected judiciously for better performance of the power system, this calls for real parameter optimization in *n*-dimensional hyperspace. To carry out this optimization task we chose Teaching Learning Based Optimization (TLBO) algorithm, a newly evolved optimization algorithm. TLBO draws its inspiration from knowledge sharing phenomenon between students and teacher in a classroom. To further enhance the performance of TLBO method in designing the coordinated controllers we propose a new variant TLBO method based on the concept of Opposition. It is referred as TLOBA i.e., teaching learning opposition-based algorithm.

The rest of paper is organized as follows. Section II deals with mathematical modeling of power system considered. In Section III a brief outline of problem is discussed. Section IV summarizes the proposed approach followed by design perspectives in Section V. In section VI we elucidated the performance of modified TLBO over various loading conditions and at the end we provide some conclusions and future scope in Section VII.

II. POWER SYSTEM MODELING

The Single Machine connected to Infinite Bus through transmission line with TCSC controller shown in Figure 1 is being considered for small signal stability studies

A. Generator Modeling

The 3rd order model consisting of the swing equation and the generator internal voltage equation describes the generator. IEEE–ST1type excitation system is considered.

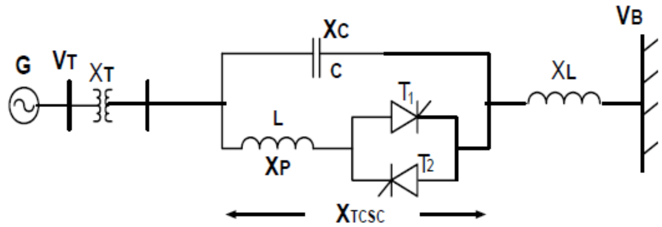


Figure 1: Single machine infinite bus power system with TCSC [6]

The nonlinear model of SMIB system with TCSC is given as below

$$\dot{\delta} = \omega_0(\omega - 1) \;; \qquad (1)$$

$$\dot{\omega} = (P_m - P_e)/M \;; \qquad (2)$$

$$\dot{E}'_q = (-E'_q - (x_d - x'_d)i_d + E_{fd})/T'_{do} \;; \qquad (3)$$

$$\dot{E}_{fd} = (-E_{fd} + K_A(V_R - V_T + V_s))/T_A \;; \qquad (4)$$

$$P_e = \frac{E'_q\, V_B}{X_{d\Sigma 1}}\sin\delta - \frac{V_B^2(X_q - X'_d)}{2X_{d\Sigma 1}X_{q\Sigma 1}}\sin 2\delta \;; \qquad (5)$$

$$E_q = \frac{E'_q\, X_{d\Sigma}}{X_{d\Sigma 1}} - \frac{V_B(X_q - X'_d)}{X_{d\Sigma 1}}\cos\delta \;; \qquad (6)$$

$$V_{Td} = \frac{X_q\, V_B}{X_{q\Sigma 1}}\sin\delta \qquad (7)$$

$$V_{Td} = \frac{X_{Eff}\, E'_q}{X_{d\Sigma 1}} + \frac{V_B X'_d}{X_{d\Sigma 1}}\cos\delta \;; \qquad (8)$$

$$V_T = \sqrt{(V_{Td}^2 + V_{Tq}^2)} \;; \qquad (9)$$

$$X_{Eff} = X_T + X_L - X_{CF} - X_{TCSC}(\alpha)\,;\; X_{q\Sigma 1} = X_q + X_{Eff}$$

$$X_{d\Sigma 1} = X'_d + X_{Eff}\;;\; X_{d\Sigma} = X_d + X_{Eff}$$

To obtain the Philip-Heffron's model of Single Machine Infinite Bus with TCSC controller, the system equations are to be linearized around an operating condition of Power system.

$$\Delta\dot{\delta} = \omega_0\Delta\omega \qquad (10)$$

$$\Delta\dot{\omega} = [-K_1\Delta\delta - K_2\Delta E'_q - K_p\Delta\sigma - D\Delta\omega]/M \qquad (11)$$

$$\Delta\dot{E}'_q = [-K_4\Delta\delta - K_3\Delta E'_q - K_q\Delta\sigma + \Delta E_{fd}]/T'_{do} \qquad (12)$$

$$\Delta\dot{E}_{fd} = [-K_A(K_5\Delta\delta + K_6\Delta E'_q + K_v\Delta\sigma) - \Delta E_{fd}]/T_A \qquad (13)$$

$$K_1 = \partial P_e/\partial\delta,\;\; K_2 = \partial P_e/\partial E'_q,\;\; K_p = \partial P_e/\partial\sigma$$

$$K_4 = \partial E_q/\partial\delta,\;\; K_3 = \partial E_q/\partial E'_q,\;\; K_q = \partial E_q/\partial\sigma$$

$$K_5 = \partial V_T/\partial\delta,\;\; K_6 = \partial V_T/\partial E_q{}',\;\; K_v = \partial V_T/\partial\sigma$$

B. PSS and Excitation system

The conventional two-stage lead-lag Power System Stabilizer is considered in this study. IEEE Type-ST1A Excitation system is considered. The inputs to excitation system are terminal voltage (V_T), supplementary signal (V_s) from PSS and reference voltage (V_{ref}). K_A and T_A are the gain and time constant of excitation system respectively.

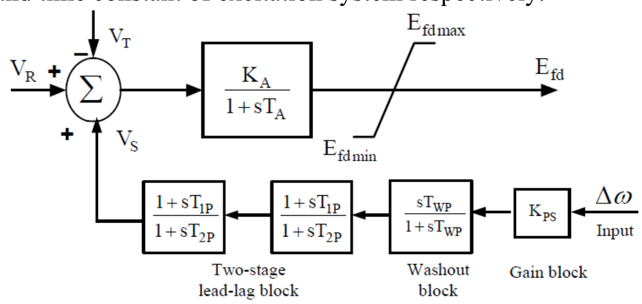


Figure2: PSS and IEEE Type-ST1A Excitation system [6]

The input signal to the PSS is ($\Delta\omega$) and output of PSS is a supplementary control signal (ΔV_S) to excitation system. It comprises a wash out block acting as high pass filter, with time constant (T_W) high enough to allow signals associated with oscillations in input signal to pass unchanged. The lead-lag compensation blocks produce a component of electrical torque in the direction of speed deviation ($\Delta\omega$). The gain (K_p) determines the damping level.

C. Thyristor Controlled Series Compensator (TCSC)

TCSC consists of three main components: capacitor bank C, bypass inductor L and bidirectional thyristor T_1 and T_2. The firing angles of the thyristors are controlled to adjust the TCSC reactance.

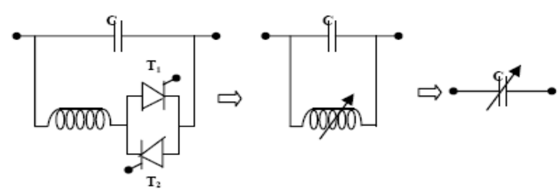


Figure 3: TCSC configuration [6]

The equivalent capacitive reactance provided by TCSC controller as function of firing angle is given as.

$$X_{TCSC}(\alpha) = X_C - \frac{X_C^2}{X_C - X_P}\frac{\sigma + \sin\sigma}{\pi} + \frac{4X_C^2}{(X_C - X_P)}\frac{\cos^2(\sigma/2)}{(k^2-1)}\frac{(k\tan(k\sigma/2) - \tan(\sigma/2))}{\pi} \qquad (14)$$

X_C = Nominal reactance of the fixed capacitor C.

X_P = Inductive reactance of inductor L connected in parallel with C.

$\sigma = 2(\pi - \alpha)$ = Conduction angle of TCSC controller.

$k = \sqrt{\dfrac{X_C}{X_P}}$ = Compensation ratio

III. Problem Formulation

A. *TCSC Controller*

In this study the conventional lead–lag structure has been chosen as a TCSC controller. The TCSC controller block representation is shown in Figure 4. It consists of a gain block, signal wash out block and a two stage lead-lag phase compensation blocks. These blocks serve the same purpose as in PSS. 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. Damping level can be adjusted by modulating K_T.

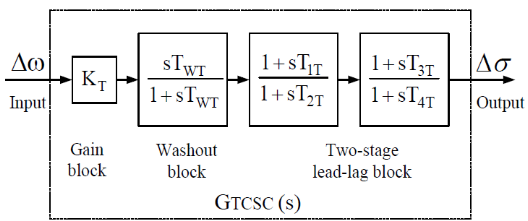


Figure 4: Structure of TCSC controller [6]

The damping torque contributed by TCSC can be considered to be in two parts. The first part K_P referred as direct damping torque and is directly applied to electro mechanical oscillation loop of the generator. The second part comprises of both K_q and K_V referred as indirect damping torque, applied through the field channel of generator. The damping torque contributed by TCSC controller to the electromechanical oscillation loop of the generator is:

$$\Delta T_D = T_D \omega_0 \Delta\omega \cong K_P K_T K_D \Delta\omega \tag{15}$$

The transfer functions of the PSS and the TCSC controller are (8) and (9) respectively:

$$u_{PSS} = K_P \left(\frac{sT_{WP}}{1+sT_{WP}} \right) \left(\frac{1+sT_{1P}}{1+sT_{2P}} \right) \left(\frac{1+sT_{3P}}{1+sT_{4P}} \right) \tag{16}$$

$$u_{TCSC} = K_T \left(\frac{sT_{WT}}{1+sT_{WT}} \right) \left(\frac{1+sT_{1T}}{1+sT_{2T}} \right) \left(\frac{1+sT_{3T}}{1+sT_{4T}} \right) \tag{17}$$

In this structure, the washout time constants T_{WT} and T_{WP} are usually pre-specified, $T_{WT}= T_{WP}=5s$. The controller gains K_T & K_P and the time constants T_{1T} , T_{2T}, T_{3T}, T_{4T}, T_{1P} , T_{2P}, T_{3P} , T_{4P} are to be determined.

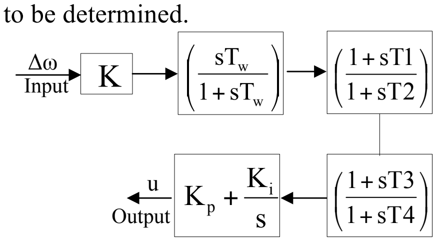


Figure 5: Structure of TCSC controller and PSS with PI controller

The proportional gain K_p provides a control action proportional to the error and reduces the rise time. The integral gain K_i reduces the steady state error by performing an integral control action and eliminates the steady state error. For TCSC controller $u=\Delta\sigma$ and for PSS $u=\Delta V_s$.

Transfer functions of PSS and TCSC controllers with PI controllers are

$$u_{PSS} = K_P \left(\frac{sT_{WP}}{1+sT_{WP}} \right) \left(\frac{1+sT_{1P}}{1+sT_{2P}} \right) \left(\frac{1+sT_{3P}}{1+sT_{4P}} \right) G(s) \tag{18}$$

$$u_{TCSC} = K_T \left(\frac{sT_{WT}}{1+sT_{WT}} \right) \left(\frac{1+sT_{1T}}{1+sT_{2T}} \right) \left(\frac{1+sT_{3T}}{1+sT_{4T}} \right) G(s) \tag{19}$$

where $G(s) = K_p + \frac{K_i}{s}$

The input signal of the TCSC stabilizer is the speed deviation $\Delta\omega$ and the output is change in conduction angle $\Delta\sigma$. During steady state conditions $X_{Eff}= X_T + X_L - X_{TCSC}(\alpha_\circ)$ and $\Delta\sigma = 0$. During dynamic conditions the series compensation is modulated for effective damping of system oscillations. The effective reactance in dynamic conditions is: $X_{Eff}= X_T + X_L - X_{TCSC}(\alpha)$, where $\sigma=\sigma_\circ+\Delta\sigma$ & $\sigma=2(\pi-\alpha)$, $\alpha_\circ$ and $\sigma_\circ$ being initial value of firing & conduction angle respectively.

B. *Objective Function*

The design of coordinated controller is done based on minimizing the objective function considered such that power system oscillations after a disturbance are effectively damped out so as to improve the stability. In this approach the objective function is formulated in such way rotor speed deviation $\Delta\omega$ is minimized and mathematically formulated as follows

$$J = \sum \int_0^{t_1} t\left[\Delta\omega(t, X)\right]^2 dt \tag{20}$$

In the above equations, $\Delta\omega(t, X)$ denotes the rotor speed deviation for a set of controller parameters X. Here X represents the parameters to be optimized. The optimization is carried in two phases, initially the 10 parameters corresponding to both TCSC and PSS controller are been tuned coordinately and in second phase by fixing the obtained parameters of TCSC and PSS controllers, the PI parameters K_p and K_i of both TCSC and PSS are tuned coordinately to obtain optimum system response.

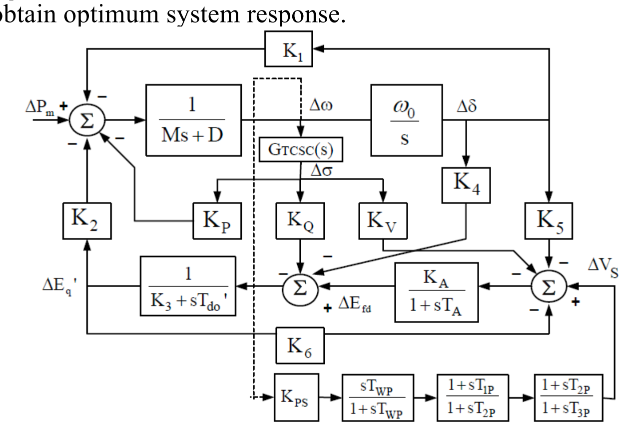


Figure 6: Phillips-Heffron model of SMIB with TCSC and PSS [6]

IV. TEACHING LEARNING OPPOSITION BASED OPTIMIZATION ALGORITHM

A. Teaching Learning Based Optimization

Teaching Learning Based Optimization or simply TLBO is a new meta-heuristic [13-19] optimization algorithm proposed by Rao et al [10]. TLBO can briefly classified into two phases i.e., (i) Teacher Phase and (ii) Learner Phase

i. **Teacher Phase**

In this his phase a teacher tries to ameliorate the mean result of class in the subject taught by him/her based on level of knowledge and skill he/she had in that particular subject. For any i_{th} iteration, let us consider there are m number of subjects (design variables), n number of learners (population size, k=1, 2,..,n) and $T_{j,i}$ be the mean result of the learners in j_{th} subject (where j=1,2,…m). However the best overall result $X_{total\text{-}k\text{-}best,i}$ (considering all the subjects together) in a class of learners can be considered as result of best leaner *k-best* and the best learner identified is replaced by the teacher. As the teacher $X_{total\text{-}k\text{-}best,i}$ will try to move mean T_i towards its own level, an adaptive heuristic is used to update the solution and is done according to the difference between the existing mean result of each subject and the corresponding result of the teacher for each subject is given by.

$$\text{Difference\_mean}_{j,k,i} = \text{rand}_i\left(X_{j,k-best,i} - T_F T_{j,i}\right) \tag{21}$$

where T_F is termed as teaching factor, which decides whether the value of mean is to be changed or not. The value of T_F can be either 1 or 2, which is decided randomly with equal probability and $rand_i$ is a random number in the range [0, 1]. $X_{j,k\text{-}best,i}$ is the result of the teacher in subject j. $Difference\_Mean_{j,k,i}$, defined in Eqn (21) is used in updating the existing solution according to the following expression.

$$X^{new}_{j,k,l} = X_{j,k,l} + \text{Difference\_Mean}_{j,k,i} \tag{22}$$

where $X^{new}_{j,k,i}$ and $X_{j,k,i}$ are the new and existing values corresponding to j_{th} subject of k_{th} learner of i_{th} iteration. A greedy mechanism is performed between $X^{new}_{j,k,i}$ and $X_{j,k,i}$, the learner with better function value is retained.

ii. **Learner Phase**

In the course of time a learner may interact randomly with other learners with the help of communications, discussions, etc. If a leaner interacts with other learner who has more knowledge than him or her, he/she tries to learn new things and tries to increase his/her knowledge. For a class of n learners the learning phenomenon of this phase is expressed with following pseudo code.

Pseudo code of Learner Phase

For k = 1 to n

Randomly select another learner Q, such that $X^{new}_{total-k,i} \neq X^{new}_{total-Q,i}$

IF $X^{new}_{total-k,i} < X^{new}_{total-Q,i}$

$$\mathbf{X}^{new}_{j,k,i} = X^{new}_{j,k,i} + \text{rand}_i\left(X^{new}_{j,k,i} - X^{new}_{j,Q,i}\right)$$

ELSE

$$\mathbf{X}^{new}_{j,k,i} = X^{new}_{j,k,i} + \text{rand}_i\left(X^{new}_{j,Q,i} - X^{new}_{j,k,i}\right)$$

End IF

End FOR

Accept $\mathbf{X}^{new}_{j,k,i}$ if it gives a better function value.

B. Teaching Learning Opposition Based Optimization

i. **Opposition-Based Learning**

Most of the evolutionary optimization methods start with some initial solutions and usually start with random guesses. The computational time depends upon the distance between initial guess and optimal solution. Hence if the guess is not in the vicinity of optimal solution computation time may increase. The chance of improving our convergence can be done by starting with a fitter solution by simultaneously checking the *opposite solution* [11]. If x is a obtained solution of given function then the opposite solution x' can be calculated as follows

$$x' = a + b - x \tag{23}$$

where $x \in R$ within an interval of [a,b]

ii. **Opposition-based Optimization**

Let $P = \{x_1, x_2, ..., x_D\}$ be a point in D-dimensional space, where $x_1, x_2, ..., x_D \in R$ and $x_i \in [a_i, b_i]$ $\forall i \in \{1,2,...,D\}$ Now the opposite point $P' = \{x'_1, x'_2, ..., x'_D\}$ is defined as

$$x'_i = a_i + b_i - x_i \tag{24}$$

Now, with above definition of opposite point the opposition based optimization can be formulated as follows. Assuming $f(\cdot)$ is fitness function via which candidate fitness is measured and according to the above given definitions of P and P', if $f(P') \geq f(P)$ then the point P can be replaced with P'; hence, the point and its opposite point are evaluated simultaneously in order to go with the fitter one.

iii. **Proposed Algorithm**

Opposition scheme discussed above is applied two times for the proposed TLOBO method at starting of teaching phase and learning phase respectively. Once the algorithm has started with random initial population simultaneously opposite population are also calculated and then best n values are picked up (based on the fitness value) and then passed in to the teacher phase. Similarly before entering in to the learning phase opposite population is evaluated and the best n values are passed in to the learning phase and the rest is same as that of TLBO. This is continued till the termination criterion is reached.

Instead of using predefined interval boundaries $[a_i, b_i]$ here we used the minimum and maximum values ($[a_j^{min}, b_j^{max}]$) of each dimension in current population to calculate the opposite population. This type of opposition helps the learners to get good information and it is computed as:

$$OP_{i,j} = a_j^{min} + b_j^{max} - P_{i,j} \tag{25}$$

where $P_{i,j}$ is the j_{th} vector of the i_{th} learner in the population. $OP_{i,j}$ is the opposite position of $P_{i,j}$; a_j^{min} and b_j^{max} are the minimum and maximum values of the j_{th} dimension in current population respectively.

V. DESIGN OF COORDINATED PI CONTROLLER BASED PSS WITH TCSC CONTROLLER

A. *Parameters of power system considered*

For the small signal stability analysis of single machine infinite bus the design of the system and system data is taken from [6]. As the optimization is to be carried out in a bounded search we had used the following ranges for different parameters in our design and they are recorded in Table I. The parameters being considered for tuning were K_T, K_P, T_{1T}, T_{2T}, T_{3T}, T_{4T}, T_{1P}, T_{2P}, T_{3P}, T_{4P} and PI controller parameters (K_p, K_i) of both TCSC and PSS controllers. (the parameters with subscript T indicates they belong to TCSC controller and that of P indicates they belong to PSS Control. The ranges over which these parameters tuned as per standards are $30 < K_P, K_T < 80$ & $0.1 < T_{1T}, T_{3T}, T_{1P}, T_{3P} < 0.6$ & $0.02 < T_{2T}, T_{4T}, T_{2P}, T_{4P} < 0.4$ & $0 < K_p < 50$, $0 < K_i < 10$.

B. *Parameters of TLOBA Algorithm*

The objective function considered consists of total 14-D i.e., 10-D for PSS-TCSC followed by 4-D optimization of two PI controllers. Hence termination criteria of 200 Functional Evaluations (NFEs) are considered to get optimum design. The population has been judiciously chosen to be 10.

VI. SIMULATIONS AND RESULTS

In this context we considered three different loading conditions and they are as follows:

i. Nominal Loading: P_e=1.0, Q_e=0.303.
ii. Light Loading: P_e=0.3, Q_e=0.015 and system inertia reduces by 25%.
iii. Heavy Loading: P_e=1.01, Q_e=0.1 and total line reactance increases by 30%.

For a step change of 5% in input (Pm), in Figures 7-9 the responses obtained for nominal, heavy and light loaded systems are depicted in terms of speed deviation and rotor angle deviations. Figure 8 shows the convergence characteristics of TLOBA progressing towards optimum values without and with PI controllers. Table 3 shows the time domain indices values for different loading conditions in terms of peak value and settling time.

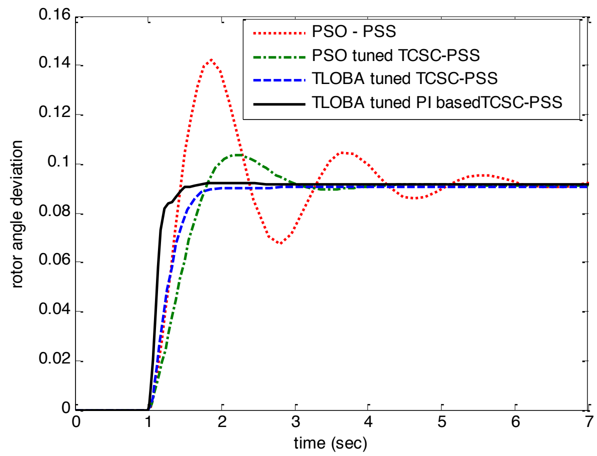


Figure 7(a): Rotor Angle Deviation: Heavy loaded

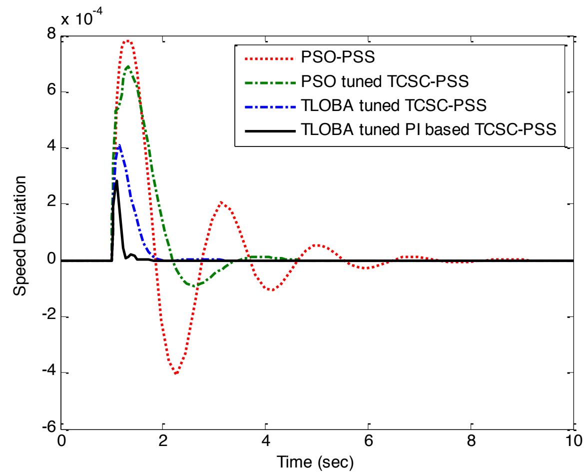


Figure 7(b): Speed Deviation: Heavy loaded

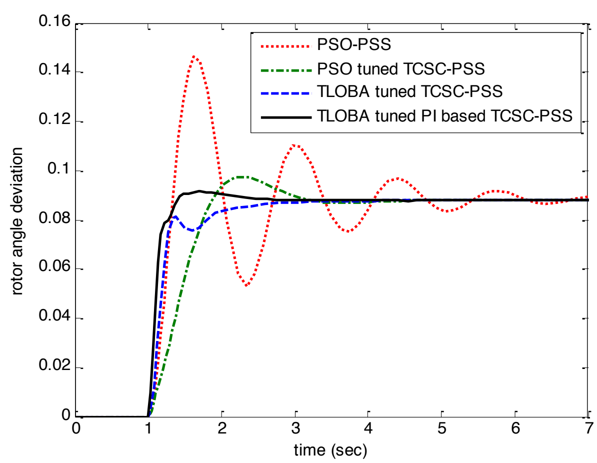


Figure 8(a): Rotor Angle Deviation: Light loaded

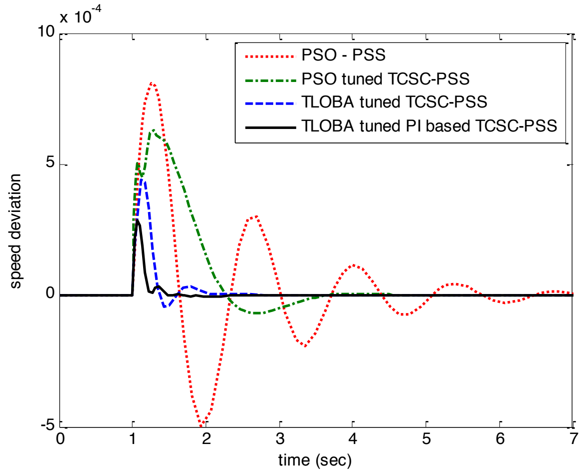


Figure 8(b): Rotor Angle Deviation: Light loaded

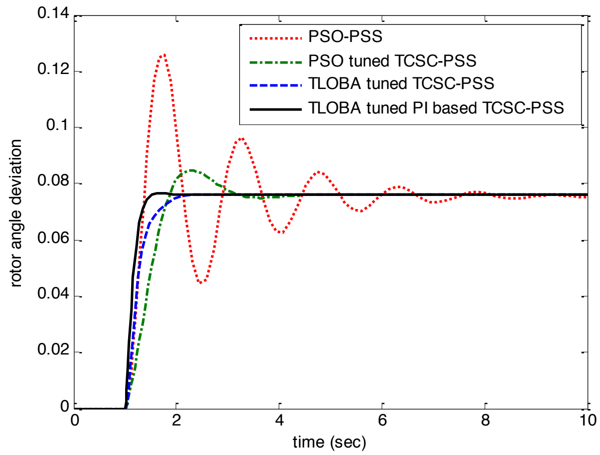


Figure 9(a): Rotor Angle Deviation: Nominal loaded

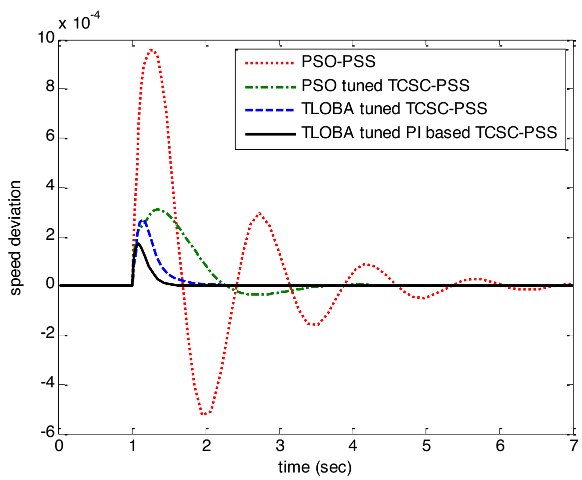
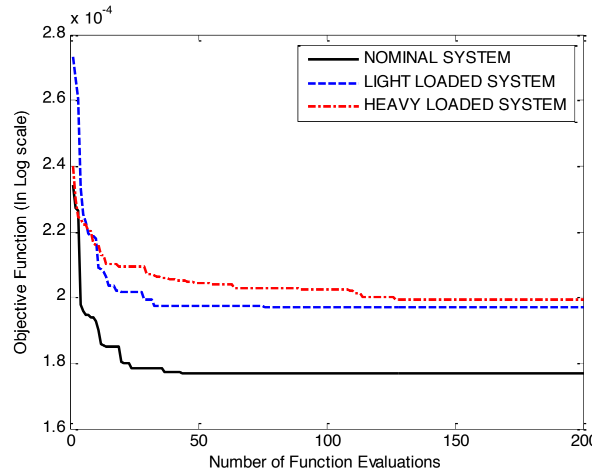


Figure 9(b): Speed Deviation: Nominal loaded

Figures 7(a) and 7(b) show the rotor angle deviation and the speed deviation responses respectively for the heavy loaded system. From Figures 7(a-b) and the time domain indices recorded in Table 3 it is clear that proposed PI controller based TCSC-PSS has produced less peak over shoot and low settling time of speed deviation response. However the peak over shoot value for the rotor angle deviation response with proposed controller is a bit high when compared to case without coordinated tuned PI controllers for TCSC and PSS controllers.

Similarly Figures 8(a) and 8 (b) shows the speed deviation and rotor angle deviation responses for lightly loaded system. As expected proposed PI based TLOBA tuned coordinated TCSC-PSS controller has shown less settling times for both speed and rotor angle deviation responses. Unlike heavy loaded system, this system enriched with coordinated controllers gave less the less peak over shoots for both rotor angle and speed deviation responses. Figures 9(a) and 9(b) depicts the speed deviation and rotor angle deviations for the nominal loaded system. PI based TCSC-PSS controller tuned with TLOBA algorithm has shown relatively less settling times and less peak over shoot values for both speed and rotor angle deviation responses.



Figures 10(a): Convergence of TLOBA towards minimum: without PI Controller

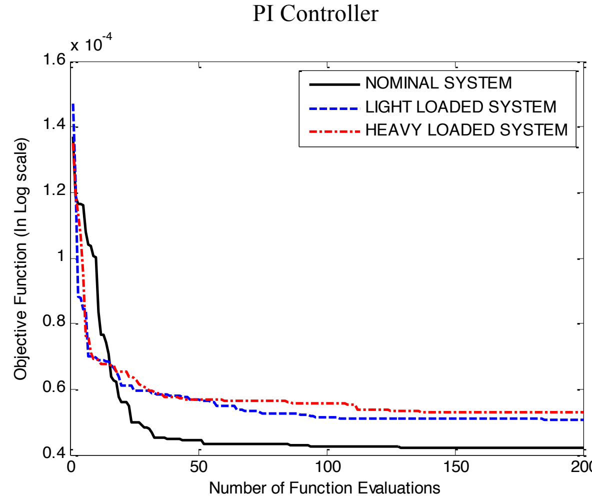


Figure 10(b): Convergence of TLOBA towards minimum: without PI Controller

Table 1: Parametric Values Obtained for coordinated TCSC- PSS Using TLOBA and obj func. Minimization values

Parameter	Nominal Loading	Heavy Loading	Light Loading
K_{TCSC}	30.0000	30.0000	30.0000
T_{1T}	0.4226	0.4185	0.1000
T_{2T}	0.2778	0.2394	0.1912
T_{3T}	0.3428	0.1000	0.2532
T_{4T}	0.3940	0.2067	0.2568
K_{PSS}	30.0000	30.0000	30.0000
T_{1P}	0.3076	0.2198	0.2482
T_{2P}	0.1960	0.3138	0.2733
T_{3P}	0.1021	0.2163	0.1811
T_{4P}	0.3921	0.3353	0.1678
Obj Fun without PI mean(std)	1.7684e-04 (1.300e-07)	1.9699e-04 (4.394e-07)	1.9932-03 (1.125e-08)

Table 2: Parametric Values Obtainedof coordinated PI controller TCSC- PSS Using TLOBA and obj func. Minimization values

Parameter	**Nominal System**	**Heavy loaded System**	**Light Loaded System**
K_{P_TCSC}	4.3709	5.2020	2.6232
K_{i_TCSC}	10.0000	10.0000	10.0000
K_{P_PSS}	0.6785	3.6136	4.8863
K_{i_PSS}	10.0000	10.0000	10.0000
Obj Fun with mean (standard deviation)	**4.2233e-05 (1.136e-07)**	**5.0702e-05 (2.4243e-07)**	**5.29012e-05 (9.71640e-09)**

Table 3. Settling times and peak values for various loading conditions

Loading condition	**Response**	**Settling time T_s(sec)**				**Peak value**			
		PSO-PSS	**PSO-TCSC-PSS**	**TLOBA-TCSC-PSS**	**TLOBA-PI-TCSC-PSS**	**PSO-PSS**	**PSO-TCSC-PSS**	**TLOBA-TCSC-PSS**	**TLOBA-PI-TCSC-PSS**
Nominal system	**Speed deviation**	8.234	5.65	3.65	**2.67**	9.58e-04	3.095e-04	2.725e-04	**1.717e-04**
	Rotor angle deviation	9.452	6.212	4.215	**3.172**	0.1256	0.0848	0.0767	**0.0765**
Heavy loaded system	**Speed deviation**	8.23	6.16	3.31	**2.68**	7.816e-04	6.87e-04	4.09e-04	**2.814e-04**
	Rotor angle deviation	8.76	7.59	5.66	**4.07**	0.1422	0.1035	**0.0909**	0.0922
Light loaded system	**Speed deviation**	7.76	4.56	3.92	**3.16**	8.07e-04	6.258e-04	4.41e-04	**2.84e-04**
	Rotor angle deviation	8.17	5.45	5.17	**2.83**	0.146	0.0975	-	0.0916

Finally Figures 10(a) and 10 (b) shows the convergence characteristics of TLOBA algorithm towards optimum values without and with PI controllers respectively. The parameters obtained via optimal tuning are recorded in Tables 1 and 2. From both the Tables it is further evident that objective function value is less for the PI controller case.

VII. CONCLUSIONS

In this paper, a new intelligent method of designing the coordinated PI controller based TCSC-PSS, tuned with TLOBA algorithm using Philip-Heffron's model for SMIB has been proposed. To show the efficacy of proposed approach we also compared our method with PSO, and also systems not involving PI controller.

Various simulations for different loading conditions have been explored, and results validates the superior performance of the proposed system when tuned optimally.

Our future research will be focusing on implementing fractional order controllers via a multi-objective frame work for multi-machine systems.

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