POWER SYSTEM STABILIZER DESIGN USING TEACHING LEARNING BASED OPTIMIZATION TECHNIQUE

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Abstract— In this paper, a new technique teaching-learning based optimization technique is use for design power system stabilizer is presented for small signal stability. This algorithm is based on the teaching-learning process and works in the environment as a teacher and learner phase. The performance of PSS tuning with TLBO was verified on a SMIB &three machine nine bus systems. The performance of the proposed controller tested with different loading and fault conditions. The evaluation of the proposed system was compared to the without a controller, with GSA and TLBO through eigenvalues analysis & time-domain simulation. The TLBO tuned PSS parameters are utilized to shift poorly damped electromechanical mode eigenvalue to the left half of the s plane. The TLBOPSSs robustness compares with GSAPSSs through the various operating condition. It is finalized the TLBOPSSs improve the dynamic stability of the system.

Index Terms— Multimachine System; Power System Stabilizer (PSS); Teaching Learning Based Algorithm (TLBO); Eigen-Value Analysis.

I. INTRODUCTION

A quick increment in the unpredictability of present-day non-direct power systems requires the advancement of productive and robust techniques to improve the stability of little signals. The stability of a little sign may be characterized as the capacity of the power framework to keep up synchronism topic to little aggravations. Huge scope interconnected and interconnected power-system creates little recurrence electromechanical oscillation (0.2 to 3.0 Hz) because of abrupt variances in low burden or the event of a flaw [1]. This oscillation can persevere after a mistake and increment consistently, making the framework be detached in case of deficient damping or now and then restricting the power transmission limit. To improve padding and stability, the generators are constrained through the PSS to add an adjustment sign to AVR. It adjusts the generator excitation so the damping torque part of the electric torque is in stage with the speed distinction of the rotor, along these lines lessening low

recurrence oscillation [2].

Most power plant PSSs depend on a linearized generator model through exciter/ AVR close to certain working focuses [3]. Conventional power framework stabilizers (CPSS) with fixed parameters are commonly utilized for power flexibly presentations. In earlier periods, stabilizer alteration depended on strategies got from old-style control [4] [5] and present-day control hypothesis [6]. With these strategies, the choice of the area of the PSS and its ideal coordination is a mind-boggling iterative procedure. A lot of PSS restrictions produce bothersome outcomes under certain working conditions if the working conditions and setups of the power flexibly framework changes radically. To make it versatile, the PSS is intended for all alterations that relate to the distinctive working conditions. They can be acquired gratitude to a variable construction control [7], an ideal regulator [8], a versatile control [9], and robust control techniques [10].To keep up great damping attributes concluded a wide scope of working situations; it is alluring to modify the PSS parameters continuously dependent on online estimations. Thusly, notwithstanding these control hypotheses, AI approaches, for example, ANN [11], the fluffy rationale (FL) [12], and neuro-fluffy [13] were introduced to plan the PSS. The fundamental preferred position of these strategies is that they don't require an exact scientific model of the controller taking care of the framework. In any case, it may not be anything but difficult to get appropriate and precise preparing information for power systems. In this way, no arrangement of rules is accessible in the development of the ANN. FL conquers such confinement. A few meta-heuristic streamlining techniques have likewise been created in ongoing decades. The various calculations dependent on these strategies, for example, the GA [14], tabu research (TS) [15], mimicked toughening [16] and advancement of PSO [17], transformative programming [18] and others have been generally utilized for the structure of multi-machine PSS. These techniques give agreeable outcomes for the improvement of PSS parameters. The uses of these strategies give a specific level of robustness to changes in framework parameters, designs, and different stacking conditions.

This article utilizes the most recent meta-heuristic

TLBO calculation to advance PSS settings with numerous machines. The first strategy for the Teaching-Learning Algorithm (TLA) offers numerous points of interest, for example, less computational exertion, freedom of the underlying estimations of the parameters, and effectiveness contrasted with different calculations [19]. The core of the TLA depends on the connection among instructors and students. From one viewpoint, the instructor is viewed as a profoundly qualified master who attempts to impart his insight to the understudies, then again, students can learn better by interfacing with one another to improve their outcomes or their evaluations. The stabilizer parameters are balanced at the same time so the eigenvalues of the flimsy or inadequately damped electromechanical method of every single working condition are moved to one side portion of the S plane, so the relative stability is improved.

The effectiveness of TLBOPSS is exasperated on a solitary machine, three-machine Infinite transport power framework with PSS under various working conditions and contrasted with GSAPSS [20] by time-space reenactment and investigation of own qualities. The outcomes have demonstrated that TLA can ensure great vibration damping properties of the power framework.

II. POWER SYSTEM MODEL

The complex non-linear power system model can be formulated by a set of nonlinear differential equations.

$$\dot{\mathbf{X}} = \mathbf{f}(\mathbf{X}, \mathbf{U}) \tag{1}$$

X = State variables denominate vector

U = Input Variables denominate vector.

The U is the output-signal of PSSs and linearized incremental representations nearby a stability point are regularly used [19]. So, the state equation of a power system with n machine and m stabilizers can be written as:

$$\Delta \dot{X} = A \Delta X + B U \tag{2}$$

A = 4n × 4nMatrix and equals of
$$\frac{\partial f}{\partial x}$$
 while
B = 4n × m matrix & equal $\frac{\partial f}{\partial U}$. ΔX is 4n×1 state

vector while U is $m \times 1$ input vector [19].

A.PSS Structure

The PSS consists of many components and each components play important role and the controller parameters optimized by TLBO algorithm. The arrangement of PSS may be portrayed as:

$$U_{i} = K_{i} \frac{sT_{wi}}{1 + sT_{wi}} \frac{(1 + sT_{1i})(1 + sT_{3i})}{(1 + sT_{2i})(1 + sT_{4i})} \Delta \omega_{i}$$
(3)

Where, and are the washout time constant, PSS output signal and the speed deviation of i^{th} machine

respectively. , , , , , are gain and time constant.

B.Objective Function

The accompanying target capacity of the PSS parameters can be selected for minimization: The exhibition list depends on the basic of the outright time mistake (ITAE). The target work is characterized as follows.

For equation (3) for the SMIB system and equation (4) for multimachine system

$$j = \int_{0}^{t_{sim}} t \left| \Delta \omega(t) \right| dt$$
(3)

$$\mathbf{j} = \int_{0}^{t_{sim}} t \left\{ \Delta \omega_{12} \right| + \left| \Delta \omega_{23} \right| + \left| \Delta \omega_{13} \right| \right\} dt$$
(4)

Where $\Delta \omega$ the rotor is speed deviation and t_{sim} is the simulation time variety. $\Delta \omega_{12}$, $\Delta \omega_{23} \& \Delta \omega_{13}$ is the speed deviation of the generator. Based on this objective occupation, the difficulty of optimization ϑ can be declared as follows: minimize.

$$K_i^{\min} \le K_i \le K_i^{\max}$$
 (5)

$$T_{1i}^{\min} \le T_{1i} \le T_{1i}^{\max} \tag{6}$$

$$T_{2i}^{\min} \le T_{2i} \le T_{2i}^{\max} \tag{7}$$

$$T_{2i}^{\min} \le T_{2i} \le T_{2i}^{\max} \tag{8}$$

$$\mathbf{T}_{4i}^{\min} \le \mathbf{T}_{4i} \le \mathbf{T}_{4i}^{\max} \tag{9}$$

For the SMIB system we optimize all PSS stricture but 3-machine system we optimize only 3-parameters as Ki, T1i, T3i. The TLBO algorithm usage optimizes supervisor parameters. i=1,2,3... Where m is the quantity of machine.

III. TLBO ALGORITHM

The standard of the TLBO estimation is spurred through the teacher understudy relationship in a learning examination lobby condition, the instructor's effect on understudies or understudies, and the interchanges of understudies and their ramifications for each other. Teachers and understudies are two essential districts of the figuring, called the educator stage and the learning stage independently. The TLBO figuring doesn't require any of these specific parameters. Simply wide parameters, for instance, masses size and the number of ages are required. It is an exciting property which improves the utilization of the computation [21]. The TLBO count is subsequently self-controlled. Figure 1 shows the TLBO affiliation diagram.

A. Teacher Phase: Envision a study hall wherein there are two primary gatherings: an educator who shows the class and a couple of understudies who study. The Page | 02 instructor has to improve the degree of information all in all classes to improve understudy execution in tests. In the instructor stage, the educator attempts to give the information to the students. Along these lines, the educator has an elevated level of information in the study hall and attempts to increase the degree of the class. Assume that there are n students (j = 1, 2, n) in a schoolroom that average mark in an exam is M_i and the top learner who succeeds the best grade $X_{T,i}$ is supposed to be the teacher. The dissimilarity amid the schoolroom average mark (M_i) and the best mark ($X_{T,i}$) can be calculated by [22].

$$\operatorname{Diff}_{i} = r_{i} \left(X_{T,i} - T_{F} M_{i} \right) \tag{10}$$

Where Diff_i = difference between the average grade and the best grade; r_i = random. Number in [0 1] in iteration i; $X_{T,i}$ = grade of the best learner (teacher) in iteration i; T_F = teacher factor which depends on teaching quality and is either 1 or 2; and M_i = average of learners' grades in iteration I. TF is similarly a random quantity which is specified

$$\Gamma_{\rm F} = {\rm round}[1 + {\rm rand}(0,1)\{2-1\}$$
 (11)

Then, by using Diff_i , the new grade of student j in iteration i can be expressed as

$$\mathbf{X}_{j,i}' = \mathbf{X}_{j,i} + \text{Diff}_i \tag{12}$$

Where $X'_{j,i}$ = new grade of student j in iteration i and $X_{j,i}$ = old grade of student j in iteration i. If $X'_{j,i}$ is better than $X_{j,i}$, $X'_{j,i}$ will go through to the learner phase. Otherwise, $X_{j,i}$ will go through to the learner phase.

B. Learner Phase: In class, effective understudies attempt to enable different understudies to improve their degree of information. At the end of the day, understudies help each other somewhat, for example, bunch errands, to get familiar with the course material better than what the instructor educates them. [22] Assume that 2 understudies, students A and B, are picked aimlessly from the students of a class. How they help every other can be communicated as follows:

$$X_{A,i}'' = \begin{cases} X_{A,i}' + r_i(X_{A,i}' - X_{B,i}') & \text{if } X_{A,i}' \ge X_{B,i}' \\ X_{A,i}' + r_i(X_{B,i}' - X_{A,i}') & \text{if } X_{B,i}' \ge X_{B,i}' \end{cases}$$
(13)

If $X''_{A,i}$ is enhanced than $X'_{A,i}$, $X''_{A,i}$ will go over the following iteration. Else $X'_{A,i}$ will go over the next iteration.

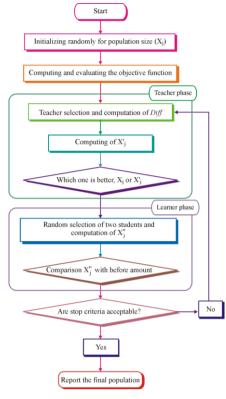


Fig.1 Algorithm Code of TLBO [21]

C. Application of TLBO to PSS Design:

TLBO algorithm has been practical to search for optimum setting of the PSS strictures. The objective function and parameters of PSS are tuned by the TLBO algorithm. The TLBO parameters defined in the appendix. Fig. 2 defines the PSS parameters optimized by TLBO with define objective function. So optimization process of PSS is defined by two examples.

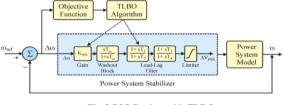


Fig.2 PSS Design with TLBO

IV. EXAMPLE1: SINGLE MACHINE INFINITE BUS SYSTEM

A. Test system and PSS Design

Fig. 3 shows the SMIB system with PSS.Table-1 shows various cases investigated and table-2 and table-3 demonstrations Eigenvalue and damping ratio at various parameters that have been optimized for the PSS controller by different algorithms, and table-4 shows TLBO tuned various parameters. The table-1 is defining the various cases applied in the SMIB test system.

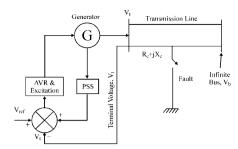


Fig.3 Single Machine Infinite Bus System with PSS

Table-2 is defining the various Eigenvalue presented in different cases. This Eigenvalues define the "stability of the system. When the system is tuned with the TLBO algorithm the Eigenvalues are more shifted to the negative half of s plane.

TABLE 1: FOR VARIOUS CONDITIONS FOR SMIB SYSTEM

Conditions	Description
Scenario-1	Loading conditions (Pe=0.7,Qe=0.2)
Case - 1	5% Increase in Mechanical Torque Input
Case - 2	5% Increase in Reference Voltage Setting
Scenario-2	50% increase in K _A
Case - 1	5% Increase in Mechanical Torque Input
Case - 2	5% Increase in Reference Voltage Setting
Scenario-3	50% Decrease in K _A
Case - 1	5% Increase in Mechanical Torque Input
Case - 2	5% Increase in Reference Voltage Setting

TABLE 2: "EIGENVALUE AND DIFFERENT DAMPING RATIO AT DIFFERENT SCENARIO

Algorithm	Without Controller			With GSAPSS		With TLBOPSS	
Cases	Eigenvalues	Damp. Factor	Freq.	Eigenvalues	Damp. Factor	Eigenvalues	Damp. Factor
Scenario-1	$-0.37 \pm 9.45i$	0.0391	1.5033	$-1.44 \pm 17.12i$	0.0838	-8.29 ±17.27i	0.4327
Scenario-2	-0.03 ±9.20i	0.0036	1.4635	-2.11 ± 17.52i	0.1198	$-10.32 \pm 17.36i$	0.5109
Scenario-3	$\textbf{-0.05} \pm \textbf{9.19i}$	0.0052	1.4624	$\textbf{-1.41} \pm \textbf{16.83i}$	0.0833	$-8.44 \pm 16.78i$	0.4496

Table-3 is defining the various PSS parameters tuned with the TLBO algorithm and their fitness value. The optimized parameters of PSS are applied in the SMIB system and stability of system improved.

TABLE-3: TLBO& GSA TUNED PSS PARAMETERS

Algorithms		Fitness				
, ingoi tuinis	K	T1	T2	Т3	T4	function value
GSA	87.1184	0.5878	0.1075	0.2	0.6894	7.22E-05
TLBO	95 0538	0.9889	3 3164	0 3238	0.0341	6 93E-05

Fig. 4 demonstrations superlative rate v/s iteration graph of TLBO and GSA algorithm.

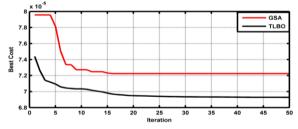
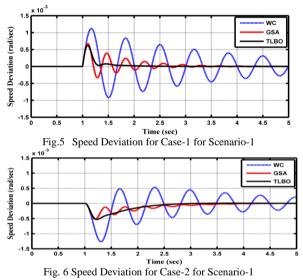


Fig. 4 : Best Cost V/s Iteration of TLBO

B. Simulation Result

(a) Scenario-1: Loading Conditions: Fig. 5 and 6 show the response of the 5% rise in mechanical torque input and reference voltage setting for loading conditions. The without controller system shows high oscillatory response and with TLBO and GSA algorithm oscillation is attenuated very fast.Table-4 is defining various settling time approach of the system. The speed deviation of TLBOPSS is superior to the GSA algorithm.



(b) Scenario-2:50% increase in KA: Fig. 7 to 8 shows parameter variation in K_A . The variation does not affect the system performance and improve stability. The satisfactory result is obtained in the form of eigen value analysis and settling time. All case defines the TLBOPSS controller damping low-frequency oscillation very fast.

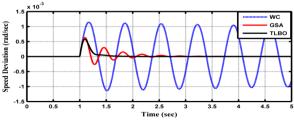
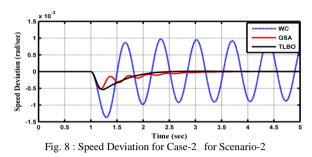


Fig. 7 : Speed Deviation for Case-1 for Scenario-2



Scenario-3:50% Decrease in KA

Fig. 8 to 9 shows the speed deviation curve for a 50% decrease in K_A . The various eigenvalue analysis and settling time represented by the table. So finally conclude that the TLBOPSS system is more stable than GSAPSS. The proposed controller damp out oscillation is very fast.

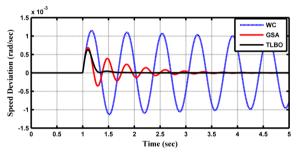


Fig. 9 Speed Deviation for Case-1 for Scenario-3

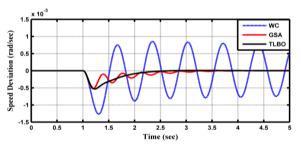


Fig.10 Speed Deviation for Case-2 for Scenario-3

TABLE-8 SETTLING TIME RESPONSE OF DIFFERENT SCENARIO

Fault Cases	(Settl	GSA PSS ling Time) econds	With TLBO PSS (Settling Time) Seconds		
	Speed	Deviation	Speed Deviation		
	Case-1	Case-1 Case-2		Case-2	
Scenario-1	3.7375	4.1943	2.1776	2.9106	
Scenario-2	2.9620	3.4804	1.6845	2.4081	
Scenario-3	3.7698	3.8428	1.6439	2.5118	

V. EXAMPLE 2: WSCC TEST SYSTEM

A. Test System and PSS Design

In these condition three machines, nine bus systems are present in fig. 11. The PSS location and number of PSS define by the participation factor. In this condition, we have required only two PSS on the generator G_2 and G_3 . To performance analysis of the proposed system is tested with many contingencies is presented below.

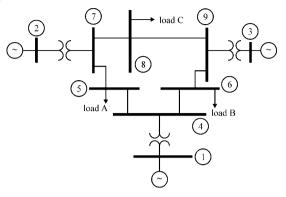


Fig.11 Three Machine Nine Bus System [23]

The various loading and optimized parameters of the system are presented in tables 9 & 10.

TABLE 9-VARIOUS LOADING PARAMETERS OF WSCC TEST SYSTEM [24]

TEST SYSTEM [24]									
Generator	Base	Case	Heavy	Loading	Light I	Loading			
	P(p.u.)	Q(p.u.)	P(p.u.)	Q(p.u.)	P(p.u.)	Q(p.u.)			
G1	0.72	0.27	2.21	1.09	0.36	0.16			
G ₂	1.63	0.07	1.92	0.56	0.8	-0.11			
G3	0.85	-0.11	1.28	0.36	0.45	-0.2			
Load									
Α	1.25	0.5	2	0.8	0.65	0.55			
В	0.9	0.3	1.8	0.6	0.45	0.35			
С	1	0.35	1.5	0.6	0.5	0.25			

TABLE-10 PSSs PARAMETERS FOR WSCC TEST SYSTEM [24]

Method	Gen no.	К	T 1	T ₃	Performance Index
GSA	G ₂	10.4665	0.1019	0.2315	0.0175
	G3	30	0.1	0.1	0.0175
TLBO	G ₂	5.1856	0.1218	0.1281	0.0134
	G3	10	0.1001	0.1	0.0154

Fig.12 show the graph between best cost v/s iteration graph of GSA & TLBO algorithm

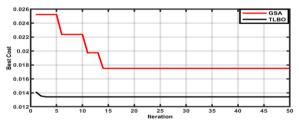


Fig. 12 Best cost v/s iteration graph

B. Eigen Value Analysis

Table-11 is defines Eigen value analysis of the test system. The system tuned with TLBOPSS when the eigenvalue shifted negative half of s plane and the damping ratio is improved. So shifting of eigenvalue show is improving stability of the test system and damp out oscillation very quickly.

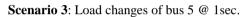
Algorithms	Without PSSs			With GSA		With TLBO		
Loading conditions	Eigenvalues	Damp. Factor	Frequency	Eigenvalues	Damp. Factor	Eigenvalues	Damp. Factor	
Bass Cass	-1.8548±j12.4244	0.1477	1.9774	-4.9037 ±j 8.3694	0.5055	-6.5219 ±j 6.6496	0.7002	
Base Case	-0.7810 ±j 8.1461	0.0954	1.2965	-2.2124 ± j6.8698	0.3065	-3.5255 ± j7.0375	0.4479	
Heavy	-0.4799 ±j13.2295	0.0363	2.1055	-4.7661 ± j8.3428	0.496	-6.3246 ±j 6.3678	0.7047	
Loading	-0.1651 ± j8.4396	0.0196	1.3432	-1.6473 ± j6.5019	0.2456	-2.9447 ±j 5.7150	0.458	
Light	-0.9452 ±j13.1589	0.0716	2.0943	-5.1173 ± j7.8829	0.5445	-6.6393 ± j5.8248	0.7517	
Loading	-0.2475 ±j 8.5563	0.0289	1.3618	-1.9969 ± j6.5673	0.2909	-3.6579 ± j6.0564	0.517	

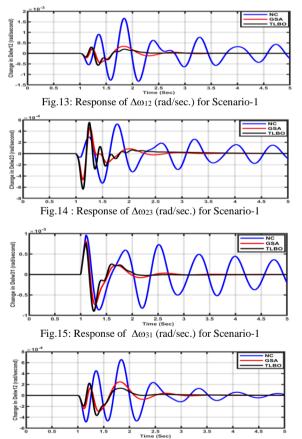
TABLE-11 EIGEN VALUE AND DAMPING RATIO OF WSCC TEST SYSTEM

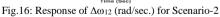
C. Simulation Result

The system is tested with three loadings with three different scenarios define below and various graph of speed deviation is obtain this condition. The various curves define that the proposed controller shows a better response and settles down very fast. Different loading condition at different fault is defined as

Scenario 1: 10% Change in References Voltage Setting, Scenario 2: 10% change in Mechanical Torque Input







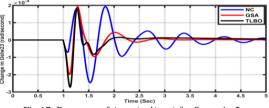
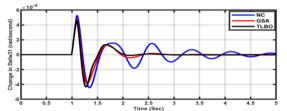
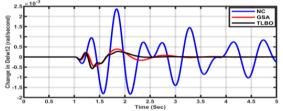
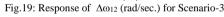


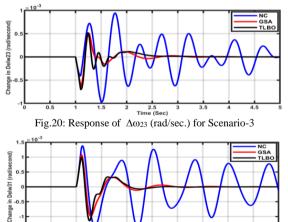
Fig.17: Response of $\Delta \omega_{23}$ (rad/sec.) for Scenario-2











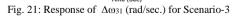


Table-12 Settling time of Different Speed Deviation

-1.5

Loading	Scenario	GSA PSS (Settling Time) (Second)			(S	TLBOPSS ettling Time) (
		W 12	ω23	W 31	W 12	W 23	W 31
Base Case	Scenario 1	3.4003	2.2283	2.3784	3.1553	2.1611	2.2841
	Scenario 2	3.0024	3.1068	2.7989	3.3313	3.4461	2.0342
	Scenario 3	3.7329	3.1031	2.8087	3.5537	3.8141	2.3492
	Scenario 1	3.6383	2.2305	2.3506	3.2160	2.2003	2.3209

Page | 06

Light Loading	Scenario 2	2.9176	3.0727	2.7047	3.4416	3.5440	1.98339
	Scenario 3	2.9418	3.0302	2.7411	4.0098	4.0483	2.6753
	Scenario 1	3.9298	2.2014	2.3786	3.1013	2.1499	2.2658
Heavy Loading	Scenario 2	3.8306	3.0768	2.8398	3.0399	3.0088	2.4870
	Scenario 3	3.8956	3.1275	2.8904	3.1127	3.0981	2.5254

VI. CONCLUSION

In this paper PSS has been utilized as the damping controller which is implemented in the two types test systems i.e. SMIB and 3 machines system displayed. PSS has been designed accordingly and it's parameters are optimized with the use of TLBO as the optimization technique. The dispassionate utility is ITAE based. In the previous section through the different graphical results along with tabulated data for different loading and operating conditions PSS based on TLBO effectiveness has been verified. The two test systems with the proposed controlled is analyzed via eigen value and simulated in time domain which shows it is superior than GSAPSS for the same loading and operating conditions.

APPENDIX

Machine models[2]

• (A.1)
$$\delta_i = \omega_b(\omega_i - 1)$$

•

$$\omega_{i} = \frac{1}{M_{i}} (P_{mi} - P_{ei} - D_{i} (\omega_{i} - 1))$$
(A.2)

$$\mathbf{E}_{qi}^{\bullet} = \frac{1}{T_{doi}^{'}} (\mathbf{E}_{fdi} - (\mathbf{x}_{di} - \mathbf{x}_{di}^{'})\mathbf{i}_{di} - \mathbf{E}_{qi}^{'})$$
(A.3)

•
$$E_{fdi} = \frac{1}{T_{Ai}} (K_{Ai} (\upsilon_{refi} - \upsilon_i + u_i) - E_{fdi})$$
 (A.4)

$$T_{ei} = E'_{qi}i_{qi} - (x_{qi} - x'_{di})i_{di}i_{qi}$$
(A.5)

Where

 δ = rotor angle; ω = rotor speed; P_m and P_e = mechanical and electrical power; υ =terminal voltage;

 T_e =electric torque; T_{do} =excitation circuit time constant

REFERENCES

- P.Kunder, Power System Stability and Control, McGraw-Hill; 1994.
- [2] Sauer, Peter W., and Mangalore Anantha Pai. Power system dynamics and stability. Vol. 101. Upper Saddle River, NJ: Prentice hall, 1998.
- [3] Anderson PM,FouadAA,Power system control and stability, Ames(IA); Iowa State Univ.Press;1977.
- [4] Talaq, Jawad. "Optimal power system stabilizers for multi machine systems." *International Journal of Electrical Power* & *Energy Systems*, pp.793-803,2012.
- [5] Bollinger, K., et al. "Power stabilizer design using root locus methods." *IEEE Transactions on power apparatus and* systems, pp. 1484-1488, 1975.

- [6] Chow, J. H., and J. J. Sanchez-Gasca. "Pole-placement designs of power system stabilizers." *IEEE Transactions on Power Systems*, pp.271-277,1989.
- [7] Rogers, Graham. *Power system oscillations*. Springer Science & Business Media, 2012.
- [8] Youssef, M. Z., P. K. Jain, and E. A. Mohamed. "A robust system stabilizer configuration using artificial neural network based on linear optimal control (student paper competition)." *CCECE 2003-Canadian Conference on Electrical and Computer Engineering. Toward a Caring and Humane Technology*, Vol. 1. IEEE, 2003.
- [9] Ghosh, A., et al. "Power system stabilizer based on adaptive control techniques." *IEEE transactions on power apparatus* and systems, pp.1983-1989,1984.
- [10] Wu, Hongxia, Hui Ni, and Gerald Thomas Heydt. "The impact of time delay on robust control design in power systems." 2002 IEEE Power Engineering Society Winter Meeting. Conference Proceedings, Vol. 2. IEEE, 2002.
- [11] Zhang, Y., et al. "Application of an inverse input/output mapped ANN as a power system stabilizer." *IEEE* transactions on energy conversion, pp. 433-441,1994.
- [12] Sambariya, Dhanesh K., and Rajendra Prasad. "Optimal tuning of fuzzy logic power system stabilizer using harmony search algorithm." *International Journal of Fuzzy Systems*, pp.457-470,2015.
- [13] Segal, Ravi, Avdhesh Sharma, and M. L. Kothari. "A self-tuning power system stabilizer based on artificial neural network." *International journal of electrical power & energy* systems 26.6 (2004): 423-430.
- [14] Panda, Sidhartha, and Narayana Prasad Padhy. "Comparison of particle swarm optimization and genetic algorithm for FACTS-based controller design." *Applied soft computing*, pp.1418-1427,2008.
- [15] Abido, Mohammad Ali, and Youssef Lotfy Abdel-Magid. "Eigenvalue assignments in multimachine power systems using tabu search algorithm." *Computers & Electrical Engineering* 28.6 (2002): 527-545.
- [16] Abido, M. A. "Robust design of multimachine power system stabilizers using simulated annealing." *IEEE transactions on Energy conversion*, pp.297-304,2000.
- [17] Shayeghi, H., et al. "A robust PSSs design using PSO in a multi-machine environment." *Energy Conversion and Management* 51.4 (2010): 696-702.
- [18] Farah, A., et al. "Optimal design of multimachine power system stabilizers using evolutionary algorithms." 2012 First International Conference on Renewable Energies and Vehicular Technology. IEEE, 2012.
- [19] Rao, R. V., and K. C. More. "Optimal design of the heat pipe using TLBO (teaching-learning-based optimization) algorithm." *Energy*,pp.535-544,2015.
- [20] Elazim, SM Abd, and E. S. Ali. "Optimal SSSC design for damping power systems oscillations via Gravitational Search Algorithm." *International Journal of Electrical Power & Energy Systems* 82 (2016): 161-168
- [21] Rao, R. Venkata. "Teaching-learning-based optimization algorithm." *Teaching learning based optimization algorithm*. Springer, Cham, pp.9-39, 2016.
- [22] Rao, R. "Review of applications of TLBO algorithm and a tutorial for beginners to solve the unconstrained and constrained optimization problems." *Decision science letters* , pp.1-30,2016.
- [23] Kamdar, Renuka, Manoj Kumar, and Ganga Agnihotri. "Transient stability analysis and enhancement of ieee-9 bus system." *Electrical & Computer Engineering: An International Journal (ECIJ)*, pp.41-51,2014.