ANN based Adaptive Control Coordination of PSSs and FACTS Devices in Multi-machine Power Systems

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Abstract—This paper proposes a new procedure for the coordination of the control of PSSs and supplementary damping controller of TCSC for enhancing the stability of the electromechanical modes in a multi-machine power system. The controller parameters are adaptive to the changes in system operating condition and/or configuration. Central to the design is the use of an ANN synthesized to give in its output layer the optimal controller parameters adaptive to system operating condition and configuration. In this approach the system configuration is represented by a reduced nodal impedance matrix which is given as the input to the ANN. Only power network nodes with direct connections to generators and FACTS devices are retained in the reduced nodal impedance matrix. The system operating condition is represented in terms of the measured generator power loadings, which are also taken as input to the ANN. For a representative power system, the ANN is trained and tested for a wide range of credible operating conditions and contingencies. Time–domain simulations are used for the testing and verification of the dynamic performance of the neural-adaptive controller.

Key words: control co-ordination, optimization, Facts, power system stabilizer, small signal stability, TCSC

1 INTRODUCTION

Following the restructuring of the power supply industry and increased trend of interconnecting power systems, the damping of electromechanical modes of oscillations among the interconnected synchronous generators, including the inter-area modes, is a growing concern, and constitutes one of the essential criteria for secure system operation.The power system stabilizers (PSSs) and/or Flexible AC transmission system(FACTS) devices with supplementary damping controllers (SDCs) can enhance the stability of the electromechanical modes. In Ref. [1–6], the control coordination design procedures in offline environment which lead to fixed-parameter controllers have been reported. In Ref. [1] the design is based on one particular power system operating condition and configuration, so, it is possible that the performances of the controllers will deteriorate under other operating conditions or configurations. Ref. [2-8] reports offline robust design of damping controllers with fixed parameters, taking into account the variation of power system operating condition and/or configuration. In Ref. [4], a linear matrix inequality (LMI) approach to normalized H∞ loop shaping has been proposed for robust control design of power system damping controllers with fixed parameters to ensure a minimum damping ratio for inter-area modes. However, with fixed-parameter controllers, it is, not possible to achieve maximum damping performance for each and every operating condition or contingency when the controller parameters are fixed. In Ref. [9-10] a method based on the Lyapunov function and modeling approximation, robust control laws together with decentralized control structure have been derived for FACTS devices to achieve damping of electromechanical oscillations. In Ref. [11, 12], artificial neural networks have been proposed for implementing PSS in a single-machine infinite bus system. However Control coordination among different PSSs in multi-machine power system and/or SDCs has not been considered. Furthermore, the changes in system configuration because of contingencies, which have a significant impact on electromechanical mode dampings, have not been discussed in the design procedure. In Ref. [13], the adaptive thyristor controlled series capacitor (TCSC) controller has been designed for a single-machine infinite bus system. Transmission line power flows were used as artificial neural network inputs. The design procedure has not taken into account the control coordination and contingencies arising in a larger multi-machine system. The approach in Ref. [14] proposed a static var compensator (SVC) damping controller based on a neuro-identifier and neuro-controller to be trained online. The disadvantages include the application of trial-and-error technique for forming the cost function in the neuro-controller training, the possibility of convergence difficulty encountered in training, and how to choose the order of the neuro-identifier. The levels of electromechanical mode dampings required cannot be specified in the proposed approach. In Ref. [15], Multiple-model adaptive control strategy was proposed for robust damping of inter-area oscillations. The plant models need to be simplified and linearised with reduced order for controller design and tuning. There is another issue related to the choice of the appropriate number of plant models, particularly for large systems with a wide range of disturbances and responses. A self-tuning controller for one TCSC is proposed in Ref.

[16]. It is based on a linear model with time-varying coefficients identified online to represent the power system. A procedure remains to be developed for determining an appropriate model order, given that the number of electromechanical modes with low or negative dampings depends on system operating condition and/or configuration.

The literature review indicates that there remains two key issues that need to be addressed in relation to the design of adaptive PSSs and SDCs are Optimal control coordination and Representation of power system configuration. It is required to achieve online control coordination of multiple PSSs and/or SDCs in a multi-machine power system. The requirement is to maximise the damping ratio for electromechanical modes for each and every credible system operating condition or configuration. The optimal controller parameters depend mainly on power system configuration. There is a need to represent directly and systematically the change in system configuration in online tuning and coordination of multiple controllers. This paper develops an adaptive control coordination scheme for PSSs and SDCs that addresses these two issues. The scheme is based on the use of an artificial neural network(ANN) which identifies online the optimal controller parameters. The inputs to the ANN include the active and reactive powers of the synchronous generators and the elements of the reduced nodal impedance matrix for representing the power system configuration. It is therefore not required to form and store a range of system models for subsequent online use.The use of the reduced nodal impedance matrix is a novel feature in the scheme proposed by which any power system configuration can be represented very directly and systematically. The matrix is formed for only power network nodes that have direct connections to synchronous generators and FACTS devices. The reduced nodal impedance matrix is derived very efficiently from the power system nodal admittance matrix and sparse matrix operations. The remaining inputs to the ANN in terms of generator powers are available from measurements.The ANN is trained and tested offline with a wide range of credible power system operating conditions and configurations. For all of the tests considered, the controller parameters obtained from the trained neural network are verified by time–domain simulation.

2 Representing system configuration by reduced nodal impedance matrix

In addition to active- and reactive-power loadings on the power system, the optimal parameters of PSSs and SDCs of FACTS devices depend mainly on system configuration. In designing adaptive controllers, it is required to represent power system configuration which is variable. One option is to use a set of discrete variables to describe the power system topology. However, this option is not a practical one as it will lead to a very large number of combinations, particularly for a large power system. The present paper proposes to use the nodal impedance matrix confined to the controller locations to represent the effects of system configuration on controller parameters. The matrix elements are input to the ANN-based adaptive controller.

The sequence of main steps to be followed for forming the reduced nodal impedance matrix are as follows

i. Form the power system configuration from circuit-breaker and isolator status data

ii. Form system nodal admittance matrix. The system configuration determined in step 1 is used in conjunction with the network branch parameters stored in the power system database to form the system nodal admittance matrix

iii. Reduce the system nodal admittance matrix formed in step (ii) to the nodal impedance matrix for the power system nodes that have direct connections to generators and Supplementary damping controllers (SDC).

3 small-disturbance model of multi-machine power system

The state-space equation of a power system installed with PSSs and FACTS devices linearized about a selected operating point can be compactly written as follows:

$$\begin{pmatrix} p\Delta x \\ 0 \end{pmatrix} = \begin{pmatrix} J_1 & J_2 \\ J_3 & J_4 \end{pmatrix} \begin{pmatrix} \Delta x \\ \Delta w \end{pmatrix} \quad (1)$$

where x is the vector of state variables; w is the vector of non state variables; J_1, J_2, J_3 and J_4 are Jacobian sub matrices obtained by linearizing system equations, and p is time derivative operator. Eliminating the non-state variables leads to:

$$p\Delta x = A\Delta x \quad (2)$$

In Eqn(2), $A = J_1 - J_2 \; J_4^{-1} J_3$ is the system state matrix based on which small-disturbance stability investigation and control co-ordination design of power system controllers is carried out.

3.1 PSS model interface

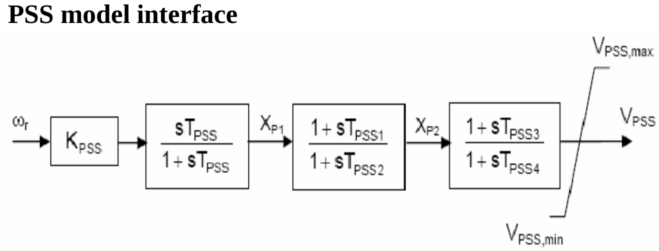

Fig.1 PSS block diagram

The linearised equation of PSS can be arranged as follows:

$$\Delta \dot{X}_p = A_p \Delta X_p + C_p \Delta \dot{\omega}_r \quad (3)$$

X_p: vector of state variables of PSS

A_p,C_p: matrices the elements of which depend on the gains and time constants of PSS

3.2 TCSC Model interface

Thyristor Controlled Series Capacitor (TCSC) is a FACTS device that can provide fast and continuous changes of transmission line impedance, and can regulate power flow on the line. The possibility of controlling the transmittable power implies the potential application of this device for the improvement of power oscillations damping.

The control system of a TCSC is shown in Fig.2, X_C is the reactance of TCSC. The TCSC control block diagram contains Proportional-Integral (PI) controller block, SDC block and the block that represents the TCSC thyristor firing delays.

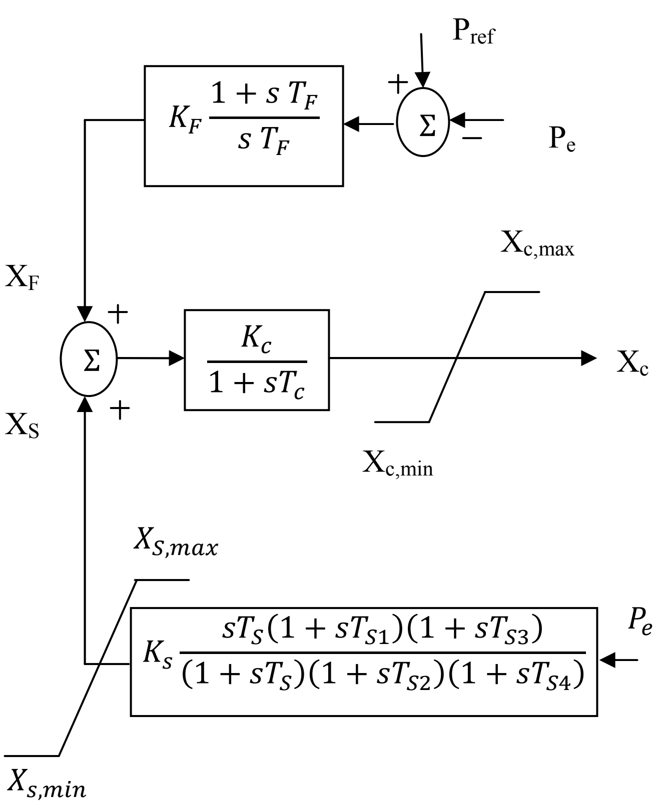

Fig.2 Block diagram of TCSC with SDC

The power flow control is usually implemented with a slow controller which is typical for a PI controller with a large time constant. The SDC block provides a modulation for power oscillation damping or small-disturbance stability improvement control. The SDC block contains a washout, lead-lag blocks and a limiter. The washout block is used to make the controller inactive to the input signal dc offset. The lead-lag blocks are needed to obtain the necessary phase-lead characteristics. Transmission line power flow is taken as an input signal to the SDC.

It can be shown that the equations system for the TCSC main control system in Fig.1 can be arranged as follows:

$$p\Delta x_{TCSC} = A_{TCSC}\Delta x_{TCSC} + B_{TCSC}\Delta x_{SDC} + C_{TCSC}\Delta P_e + D_{TCSC} p\Delta P_e \qquad (4)$$

where:
x_{TCSC}: vector of state variables of TCSC
x_{SDC} : vector of state variables of SDC
A_{TCSC}, B_{TCSC}, C_{TCSC}, D_{TCSC}: matrices which depend on the gains and time constants of the controllers.
P_e : input active-power to the controller

Equation (4) is derived by examining the transfer functions of the PI controller block and the block that represents the TCSC thyristor firing delays. It can also be shown that the equations system for the supplementary damping controller can be written as follows:

$$p\Delta x_{SDC} = A_{SDC}\Delta x_{SDC} + C_{SDC} p\Delta P_e \qquad (5)$$

where:
A_{SDC}, C_{SDC} : matrices which depend on the gain and time constants of the controllers.

4. Control Co-ordination Design

In the present work, the design problem is transformed into a constrained optimization problem to search for the optimal settings of controller parameters. The design is based on the minimization of the real parts of any number of eigen values. Therefore, the objective function to be minimized with respect to controller parameters in the control co-ordination design is

$$\text{min. } f(K) = -\sum_{i=1}^{m}[Re(\lambda_i)]^2 \qquad (6)$$

where:
K: vector of controller parameters to be optimized
λ_i: the i^{th} eigen value to be placed
m: number of eigen values

In the proposed method, only the parameter constraints of, which prevent optimized parameters from reaching unacceptable values, are used.

The above-mentioned objective is a general parameter-constrained nonlinear optimization problem and can be solved successfully. In this paper, the optimization-based simultaneous coordinated tuning algorithm the flow chart of which is shown in Fig. 3 is used.

The optimization starts with the pre-selected initial values of the controllers: K_0. Then the nonlinear algorithm is employed to adjust the parameters iteratively, until the objective function (4) is minimized. The parameters so determined are the optimal settings of the TCSC main controller, SDC and PSS controllers.

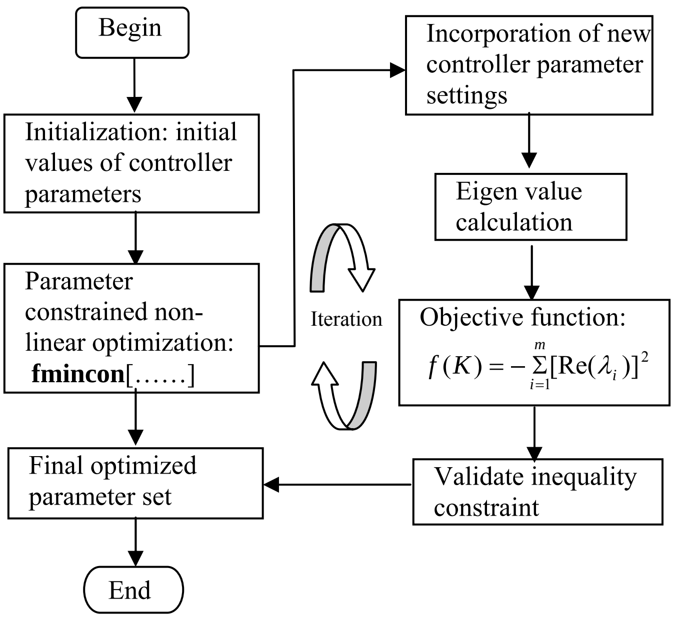

Fig.3 flow chart of optimization based coordinated tuning.

5 Design of the ANN controller

The relationship among the optimal controller parameters and power system operating condition including system configuration is, in general, a nonlinear one. The paper draws on the key property of the multilayer feed forward ANN, which is that of the nonlinear multi-variable function representation. The ANN is used for the mapping between the power system configurations and/or operating conditions and optimal controller parameters. Levenberg-marquardt error back propagation algorithm is used in the training process. Fig. 4 shows the general structure of the multilayer feed forward ANN topology for the proposed controller.

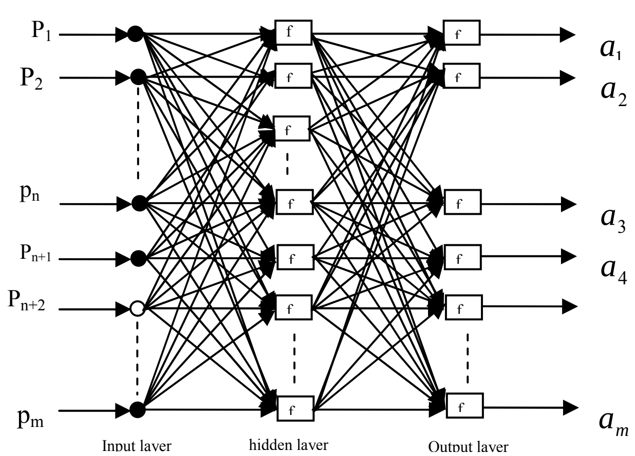

Fig.4 Input and output structure of the neural network

In this figure,
P1, P2. . . Pn are the real and imaginary parts of the elements of the reduced nodal impedance matrix
P_{n+1}, P_{n+2}. . . Pm are the active- and reactive- power output of generators
a1, a2. . . am are the optimal controller parameters
f is the activation function

Training, Testing and Sizing of Proposed ANN Controller

The key requirement is to design a neural controller that has the capability of generalising with high accuracy from the training cases. This requirement is achieved through the neural network training, testing and sizing. The neural network training set should be representative of the cases described by credible system contingencies and changes in system operating conditions. The possible contingencies of the system in Fig. 4 for line(s) outages are shown in Table1.

Table 1 line outage cases

S.No	Outage description
1	Line L_1
2	Line L_6
3	Line L_9
4	Line L_1 and Line L_6
5	Line L_6 and Line L_9
6	Line L_1 and Line L_9
7	Line L_1,Line L_6 and Line L_9

In addition to the outages described in Table 1 various operating conditions were considered in training the ANN. In Table 1 case 7 is used for testing the ANN.
For each contingency, the procedure described in Section 2 and power-flow studies are used for forming the neural network input data in the training case. The optimal controller parameters are also determined for each case using the method described in section 4. These optimal controller parameter values are used as the specified network output data.

The total number of inputs for the ANN controller is identified as 58 among them 8 inputs are from the generators active and reactive powers and the remaining are the real and imaginary parts of the elements of the reduced impedance matrix. In this paper, the parameters of both the main controller and SDC of the TCSC are to be tuned. Therefore 22 linear neurons are needed in the output layer, which are the gains and time constants of PSS and TCSC main and supplementary damping controllers in the system. The training algorithm used is Levenberg-Marquardt back propagation. In the present work, the neural network is initially assumed to have one hidden layer and the number of hidden nodes is taken to be 5. The size of the neural network is then adjusted accordingly. The performance goals specified is 1e-7. Maximum number of epoch of 200 is specified for the network training.

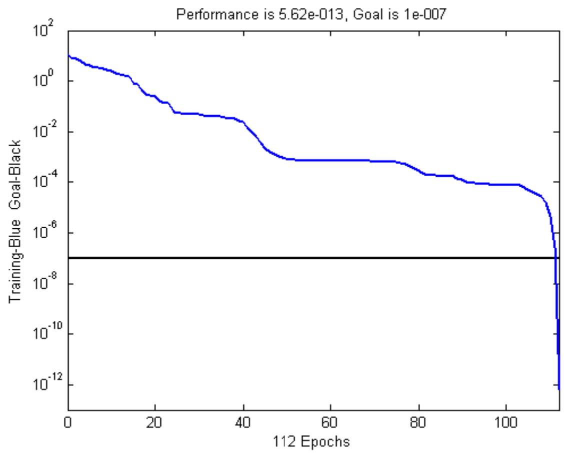

Fig 5 ANN performance goal Vs number of epochs

Several network sizes (i.e. number of hidden neurons) are investigated to achieve the performance goals. Based on the investigation, it is found that the network with seven hidden neurons in one hidden layer satisfies the convergence criteria. Fig 5 shows the performance of the proposed ANN controller.

6. Test System and Simulation Results

To verify the performance of the proposed method, the algorithm is tested on a two-area power system with 4 generators, 12 and having a total connected load of 2734 MW. The two areas are connected by two AC tie lines. A TCSC is connected in one of the lines between two areas.

The synchronous generators in the system are represented by the fifth-order model. IEEE Type-ST1 model [18] is used to represent the excitation system and the governor model [18] is used for the representation of the governor together with turbine model are used in the test system.

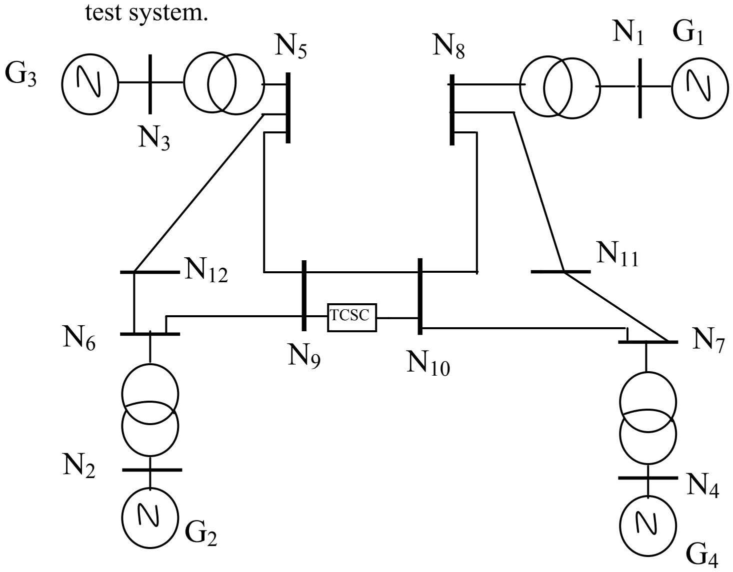

Fig.6 Test System

In the initial investigation, PSSs and FACTS devices are not included. The variations of the relative rotor angles of generators 2, 3 and 4 with respect to generator1 are obtained for 1% change in field voltage of generator1. From fig 6(a) to 6(c), it is observed that the system is going unstable without the presence of controllers in the system. So a stabilization measure is therefore to stabilize the system.

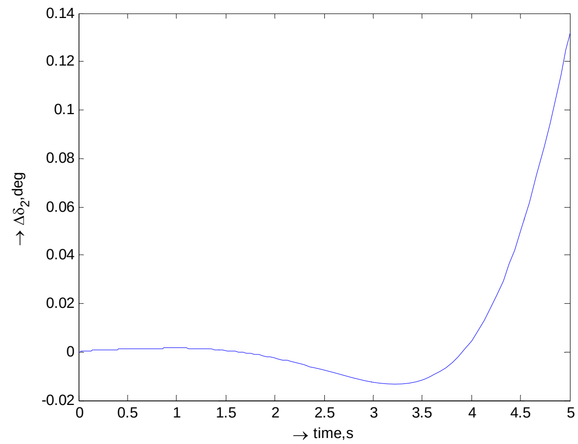

Fig.6 (a): Relative variation of rotor angle of Gen2

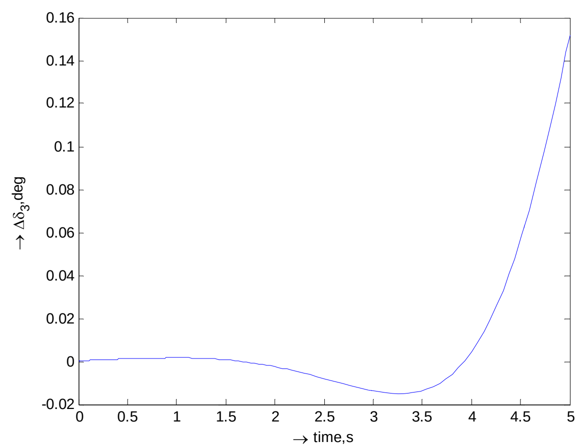

Fig.6 (b): Relative variation of rotor angle of Gen3

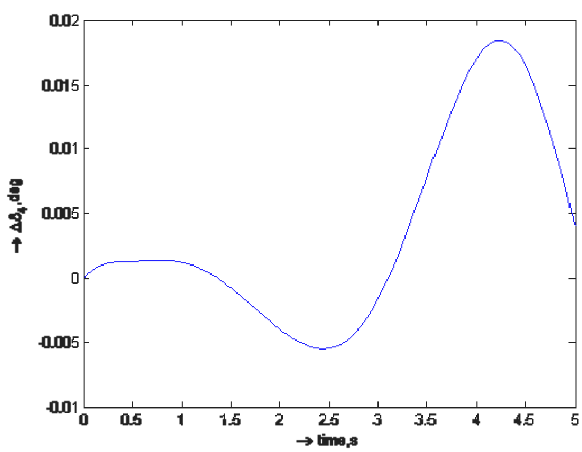

Fig.6(c): Relative variation of rotor angle of Gen4

The PSSs are installed at generator1 in area1 and generator2 in area2. The co-ordination procedure described in section 4 is applied to the test system of Fig.6. After applying stabilizers the relative variations of rotor angles are as shown in figures 7(a), 7(b) and 7(c) which are obtained by solving the system of differential algebraic equations including the equations of PSSs by using the trapezoidal rule of numerical integration method. From the figures it is observed that the system damping is improved when the system installed with PSSs. However, the improvements in dampings offered by PSSs are minimal.

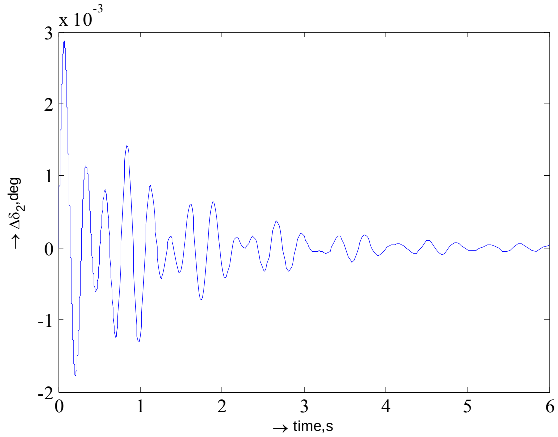

Fig.7 (a): Relative variation of rotor angle of Gen2

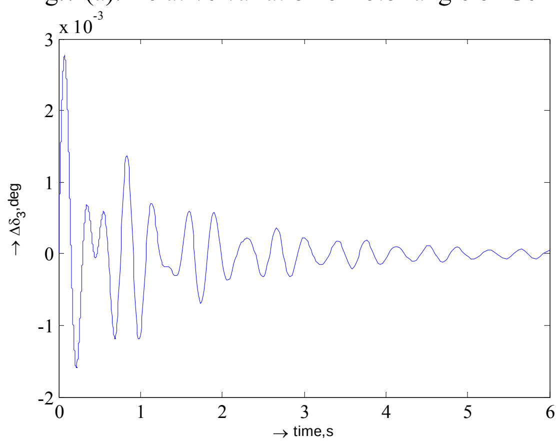

Fig.7 (b): Relative variation of rotor angle of Gen3

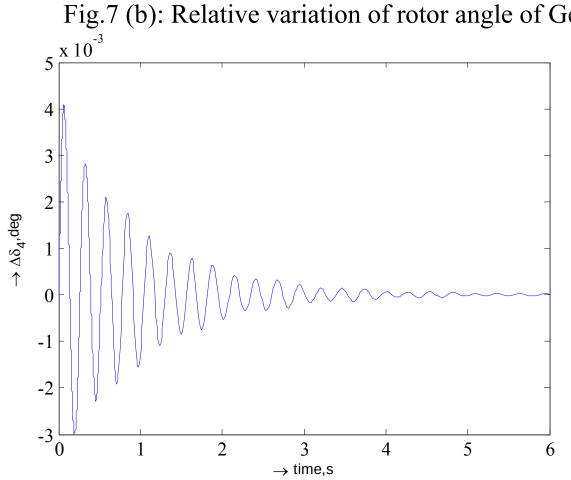

Fig.7 (c): Relative variation of rotor angle of Gen4

In addition, for the primary purpose of power flow controls in the system, a FACTS device, i.e. a TCSC, is installed in the long transmission line between nodes N9 and N10. An opportunity is then taken to equip the TCSC installed with an SDC to provide a secondary function for damping improvement of the low-frequency electromechanical mode to ensure faster settling time. The relative variation of rotor angles of the generators 2, 3 and 4 which are obtained from the time-domain simulation are shown in figures 8(a),8(b) and 8(c).

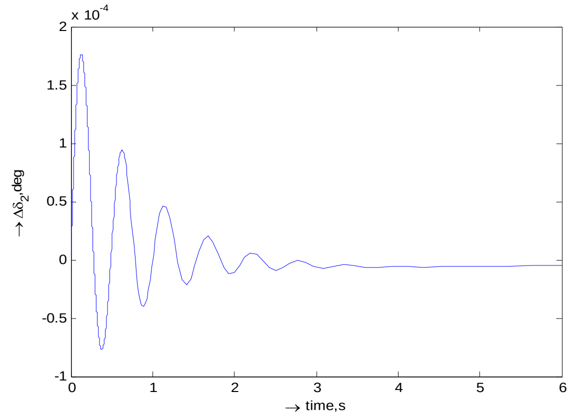

Fig.8 (a): Relative variation of rotor angle of Gen2

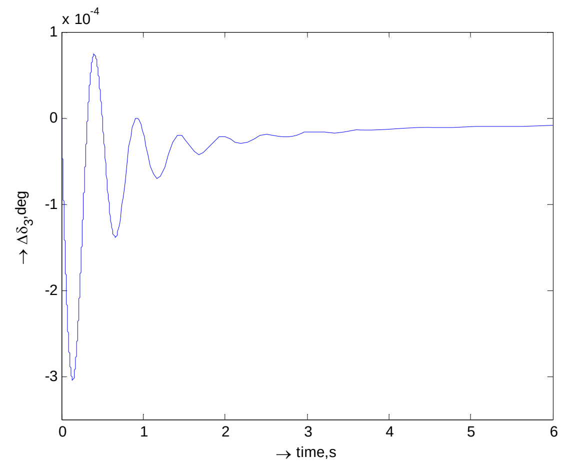

Fig.8 (b): Relative variation of rotor angle of Gen3

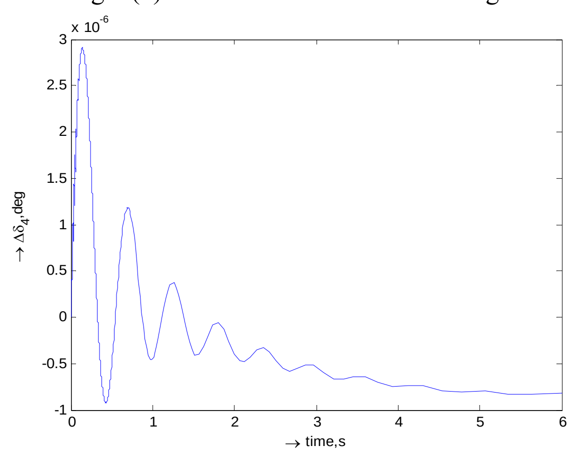

Fig.8 (c): Relative variation of rotor angle of Gen4

With the PSSs and TCSC with an SDC installed, the oscillation is damped more quickly and settled down after about 4 – 5 seconds (see figs (8(a), 8(b), 8(c)).

7. Conclusion

This paper has proposed a procedure for optimal control co-ordination design of PSSs and FACTS devices in a multi-machine power system. The control co-ordination problem is solved through the application of constrained optimization method. The procedure is based on the use of a neural network which adjusts the parameters of the controllers to achieve system stability and maintain optimal dampings as the system operating condition and/or configuration change. The ANN controller is trained for a representative power system with a TCSC has been comprehensively tested to verify its dynamic performance.

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