NEURAL NETWORKS FOR ADAPTIVE CONTROL COORDINATION OF PSSs AND FACTS DEVICES IN MULTIMACHINE POWER SYSTEM

by

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ABSTRACT

The paper develops a new design procedure for online control coordination which leads to adaptive power system stabilisers (PSSs) and/or supplementary damping controllers (SDCs) of FACTS devices for enhancing the stability of the electromechanical modes in a multimachine 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 a neural network synthesised to give in its output layer the optimal controller parameters adaptive to system operating condition and configuration. A novel feature of the neural adaptive controller is that of representing the system configuration by a reduced nodal impedance matrix which is input to the neural network. 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 input to the neural network. For a representative power system, the neural network is trained and tested for a wide range of credible operating conditions and contingencies. Both eigenvalue calculations and time-domain simulations are used in the testing and verification of the dynamic performance of the neural adaptive controller.

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.

It is acknowledged that PSSs and/or FACTS devices with SDCs can enhance or maintain the stability of the electromechanical modes. In this context, there has been extensive research in the application of PSSs and/or SDCs of FACTS devices, particularly their control coordination, for achieving optimal damping of electromechanical modes, including inter-area modes in a power system [1-6]. In [1-6], control coordination design

procedures in off-line environment which lead to fixed-parameter controllers have been reported. However, it is, in general, accepted that there are disadvantages associated with fixed-parameter controllers, even with those obtained by robust design.

If the design is based on one particular power system operating condition and configuration [1], it is possible that the performances of the controllers will deteriorate under other operating conditions or configurations. There have been publications [2-8] reporting research on off-line robust design of damping controllers with fixed parameters, taking into account the variation of power system operating condition and/or configuration. In [4], an LMI (linear matrix inequality) approach to normalised H_∞ loop-shaping was proposed for robust control design of power system damping controllers with fixed parameters to ensure a minimum damping ratio for inter-area modes.

However, there remains a key disadvantage with fixed-parameter controllers. It is, in general, not possible to achieve maximum damping performance for each and every operating condition or contingency when the controller parameters are fixed.

Based on Lyapunov function and modeling approximation [9, 10], robust control laws together with decentralised control structure have been derived for FACTS devices to achieve damping of electromechanical oscillations.

More recently, adaptive control techniques have been applied for power system damping controller design. In [11, 12], neural networks and radial basis function networks were proposed for implementing PSS in a single-machine infinite bus system. Control coordination among different PSSs in multimachine power system and/or SDCs has not been considered. Furthermore, the changes in system configuration due to contingencies, which have a significant impact on electromechanical mode dampings, have not been discussed in the design procedure.

The use of neural networks is extended to SDCs of FACTS devices in [13, 14]. The adaptive thyristor-controlled series capacitor (TCSC) controller was designed for a single-machine infinite bus system in [13]. Transmission line power flows were used as neural network inputs. The design procedure has not taken into account the control coordination and

contingencies arising in a larger system with multimachines. The approach in [14] proposed an 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 approach proposed.

Multiple-model adaptive control strategy was proposed in [15] 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 [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 above review indicates that there remain two key issues that need to be addressed in relation to the design of adaptive PSSs and SDCs:

(i) Optimal control coordination.

It is required to achieve online control coordination of multiple PSSs and/or SDCs in a multimachine power system. The requirement is to maximise the damping ratio for electromechanical modes for each and every credible system operating condition or configuration.

(ii) Representation of power system configuration.

The optimal controller parameters depend importantly 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.

The present paper develops an adaptive control coordination scheme for PSSs and SDCs that addresses the above two issues. The scheme is based on the use of a neural network

which identifies online the optimal controller parameters. The inputs to the neural network include the active- and reactive- power of the synchronous generators which represent the power loading on the system, and 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 neural network in terms of generator powers are available from measurements.

The neural network is trained and tested off-line 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 both eigenvalue calculations and time-domain simulations, which confirm that good dampings of the rotor modes are achieved.

2 Representing system configuration by reduced nodal impedance matrix

2.1 Concept

In addition to active- and reactive-power loading on the power system, the optimal parameters of PSSs and SDCs of FACTS devices depend importantly 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 neural network-based adaptive controller.

2.2 Forming reduced nodal impedance matrix

The steps of forming the reduced nodal impedance matrix are given in Table 1.

Table 1: Forming the reduced nodal impedance matrix

Step Number	Description
1	Forming the power system configuration from circuit-breaker and isolator status data [17]
2	Forming 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.
3	Reducing the system nodal admittance matrix formed in step 2 to the nodal impedance matrix for the power system nodes that have direct connections to generators and SDCs. This is achieved through sparse matrix operations and LU matrix factorisation.
4	- Online modification of the reduced nodal impedance matrix. The LU matrix factorisation in step 3 of the system nodal admittance matrix is performed only once in an off-line mode for the system configuration of the base case (i.e. full system). The results of the factorisation are then stored for subsequent use in the online mode. A scheme based on the compensation technique reported in [18] is adopted to form the reduced nodal impedance matrix for any contingency, using the stored results of the base-case factorisation, and only a minimal amount of computation which does not involve the refactorisation is required. The scheme is suitable for online application of the adaptive controller. - With the present advances in LU factorisation techniques, it is possible that the online full refactorisation can be carried out to form the reduced nodal impedance matrix, without using the compensation method. This also allows load models in the form of admittance to be represented in the system nodal admittance matrix.

3 Power system damping controllers

The power system damping controllers include PSSs and SDCs of FACTS devices which are installed for the primary function of power flow and voltage control. The unified power flow controller (UPFC) [19, 20] can be seen as a general form of FACTS devices. In Table 2 and Fig.1 are shown the structures of the UPFC together with an SDC and PSS.

Table 2: UPFC and PSS structures

Controller Type	Structure Description
UPFC	• Fig.1a shows the general structure of the UPFC [19, 20]. The UPFC combines two voltage source converters linked by a dc bus. • In Figs.1b and 1c are shown the dynamic models for the shunt and series converter controllers respectively [19, 20]. • In addition to the main controllers, there is an SDC the output of which is input to the shunt converter controller as shown by the dashed box in Fig.1b. • The input to the SDC is the active-power flow in the transmission line controlled by the UPFC series converter. However, other forms of input signal such as the phase difference between transmission line terminal voltages can also be used for SDC input. The purpose of this supplementary controller is to improve the damping of electromechanical modes. • It is also possible to use an SDC in conjunction with the series converter controller.
PSS	In Fig.1d is shown the structure for the PSS [21] in which the input is the generator rotor speed and the output is fed to the excitation controller.

4 Development of neural network-based adaptive controller

4.1 General concept of neural network

The relationship among the optimal controller parameters and power system operating condition including system configuration is, in general, a nonlinear one. The present paper draws on the key property of the multilayer feedforward neural network, which is that of nonlinear multi-variable function representation [22]. The neural network is used for the mapping between the power system configurations and/or operating conditions and optimal controller parameters.

In Fig.2a is shown the general structure of the multilayer feedforward neural network adopted in the present work. The structure description is given in Table 3.

Table 3: Neural network structure

Layer Identification	Layer Description
Input Layer	- There are two separate sets of nodes in the input layer in Fig.2a. - The first set has n nodes the inputs to which are obtained from the real and imaginary parts of the reduced nodal impedance matrix as formed in Section 2. These inputs represent power system configuration. If there are $\mathcal{N}_G$ generator nodes and FACTS device nodes, the number of input nodes in the first set is $\mathcal{N}_G^2 + \mathcal{N}_G$, when the symmetry in the nodal impedance matrix is exploited. - The second set of inputs comprises active- and reactive-power of each and every generator. Therefore, if there are $\mathcal{N}_G$ generators in the power system, there will be $2\mathcal{N}_G$ input nodes in the second set. These inputs in the second set represent power system operating condition. - The total number of inputs is $\mathcal{N}_G^2 + \mathcal{N}_G + 2\mathcal{N}_G$.
Hidden Layer	The number of hidden layers, the number of nodes in each hidden layer and the weighting coefficients of the connections between nodes in the structure of Fig.2a are to be determined by neural network training, and verified by testing which will be discussed in Sections 4.3 and 4.4.
Output Layer	- The nodes in the output layer of the neural network structure in Fig.2a give the optimal values of the parameters of PSSs and FACTS device control systems, including the SDCs. - It is possible to exclude the FACTS device main controllers from the adaptive control coordination. However, to achieve maximum benefit in terms of damping, both FACTS device main controller and SDC are included in the adaptive control coordination in the present work. - The structure in Fig.2a assumes that there are M controller parameters to be tuned online. On this basis and with the controllers in Fig.1, the output parameters from the neural network in Fig.2a are described in the following: a) PSS - PSS gain (denoted by K_{PSS}) - Time constants of PSS washout block (denoted by T_{PSS}) - Time constants of PSS lead-lag blocks (denoted by T_{PSS1}, T_{PSS2}, T_{PSS3} and T_{PSS4}) b) SDC - SDC gain (denoted by K_{SDC}) - Time constants of SDC washout block (denoted by T_{SDC}) - Time constants of SDC lead-lag blocks (denoted by T_{SDC1}, T_{SDC2}, T_{SDC3} and T_{SDC4}) c) UPFC Main Controller - Shunt converter controller gains (denoted by K_{sh1} and K_{sh2}) - Shunt converter controller time constants (denoted by T_{sh1} and T_{sh2}) - Series converter controller gains (K_{se1} and K_{se2}) - Series converter controller time constants (T_{se1} and T_{se2})

4.2 Overall structure

In Fig.2b is shown the overall structure of which the neural adaptive controller described in Section 4.1 is a part. For online tuning of the parameters of PSSs and FACTS device main controllers together with SDCs, the inputs required are, as shown in Fig.2b:

- circuit-breaker and isolator status data
- power network branch parameters
- generator active- and reactive-powers.

The output of the trained neural network in response to the changes in the input determined by the changes in circuit-breaker status data and/or generator active- and reactive-powers gives the updated optimal parameters for the PSSs and FACTS device main controllers together with SDCs. The feedback inputs to these controllers are generator speeds and transmission line active-powers, as in the case of fixed-parameter controllers.

4.3 Training procedure for neural adaptive controller

In Table 4 are given the stages required in off-line training procedure for the neural adaptive controller.

4.4 Neural network testing and sizing

In addition to forming the training data set, a separate testing data set is also required. The procedure for testing data generation is similar to that of training where the optimisation-based control coordination method in [6] is used.

The trained neural network in Section 4.3 is then tested with the testing data set. The interaction among the training, testing and sizing the neural network is explained in the flowchart of Fig.3.

Table 4: Neural adaptive controller training procedure

Stage in Training	Task Required
1	Training Set Generation: - The training set is generated using the optimisation-based control coordination method in [6]. A brief description of the method is given in the following. - The method is based on a constrained optimisation in which the objective function formed from the real part of eigenvalues of selected modes is minimised. The method does not require any special eigenvalue/eigenvector calculation software. Eigenvalue-eigenvector equations are represented in terms of equality constraints in the optimisation. Based on the linear independence of eigenvectors, additional equality constraints are derived and included in the optimisation to guarantee distinct modes at the convergence. Inequality constraints related to minimum damping ratios required and controller parameter limits are represented in the control coordination. - For a given power system, a wide range of credible operating conditions and configurations which include those arise from contingencies is considered in the training data generation. For the i^{th} training case, the pair of specified input and output vectors is $\{p_i, t_i\}$. Based on the structure in Fig.2a, the input vector p_i is: $p_i^T = (p_{1i}, p_{2i}, \dots, p_{mi}); i=1, 2, \dots, N$ in which N is the total number of training cases. - The target output vector t_i for the i^{th} training case is the optimal controller parameters vector for the power system with the operating condition and configuration specified by the input vector p_i.
2	Training Error Minimisation: The requirement in the training is to minimise the difference between the target output vector t_i and response of the neural network in Fig.2a. For N training cases, it is proposed to minimise the following mean square error (MSE): $F(x) = \frac{1}{N} \sum_{i=1}^N (t_i - a_i)^T (t_i - a_i)$ where a_i is the neural network response which has the following form, based on the structure in Fig.2a: $a_i^T = (a_{1i}, a_{2i}, \dots, a_{mi}); i=1, 2, \dots, N$ Vector x is the vector of weighting coefficients of the connections in the neural network to be identified. Minimising the error function $F(x)$ with respect to x gives the weighting coefficient vector. In the present work, the Levenberg-Marquardt algorithm which is a second-order method with a powerful convergence property is adopted for minimising $F(x)$.
3	Verifying Convergence in Training: - One of the criteria for the convergence in training is that the error function $F(x)$ has to be less than a specified tolerance. - In addition to the training performance expressed in terms of error function $F(x)$, the controller parameters obtained from the trained neural network are also used for calculating the damping ratios of the rotor modes, which are then compared with the optimal damping ratios obtained at the stage of training data generation. - The convergence in training is confirmed when both the error function $F(x)$ and the damping ratio comparison satisfy the specified tolerances.

5 Simulation results

5.1 Power system structure

The system in the study is based on the two-area 13-bus power system of Fig.4a [23]. Each of the four synchronous generators in the system is represented by a fifth-order dynamical model described in the Appendix. Initial investigations have been carried out for the system. The investigations confirm that the inter-area mode has poor damping. Stabilisation measure based on PSSs and FACTS device controllers with SDCs as discussed in [6] is, therefore, proposed for improving the damping of the inter-area mode in the power system. However, these controllers will also enhance local mode dampings.

Stability analysis of the power system without any PSSs and FACTS devices indicate that, among the four generators in Fig.4a, participation factors of the inter-area mode in generators G1 and G3 are greater than those in the other two generators. On this basis, it is proposed to install PSSs for generators G1 and G3 only. The other two generators (generators G2 and G4) do not have PSSs. The PSSs for generators G1 and G3 have adaptive parameters. The PSSs have the structure described in Section 3 with rotor speed inputs. A FACTS device, i.e. a UPFC with an SDC, is installed at node N13 in line L16. Also, it is proposed to use the line active-power as the input to the SDC which has the structure given in Fig.1b. For this system with 4 generators, there are three swing modes (two local modes and one inter-area mode) of low frequency oscillations. All of these electromechanical modes are represented in the control coordination and the design of the neural adaptive controller described in the next section.

5.2 Design of the proposed neural adaptive controller

5.2.1 Neural network training and test data

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 referred to in Sections 4.3 and 4.4 based on the selection

of the training and testing data sets. 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. 4a for line(s) outages, load and power generation variations are shown in Tables 5 and 6 respectively. Both single-line outages and double-line outages are considered in the postulated contingencies where there is no loss of any generator, and the two areas remain connected. The input and output pairs for neural network training and testing cases are generated from the combinations of these contingencies and operating conditions.

For the system in Fig.4a, the number of neural network inputs, as determined on the basis of Section 4.1, is 38. In this paper, the parameters of both the main controller and SDC of the UPFC are to be tuned online to achieve the maximum benefit in terms of damping. Therefore, 26 linear neurons are needed in the output layer (6 for each PSS controller and 14 for the UPFC controller).

Table 5: Line(s) outages cases

No.	Single-Line Outages	Double-Line Outages					
		No.	Lines	No.	Lines	No.	Lines
1.1	Line L5	1.11	Lines L5 and L9	1.22	Lines L7 and L12	1.33	Lines L11 and L13
1.2	Line L6	1.12	Lines L5 and L10	1.23	Lines L8 and L9	1.34	Lines L12 and L13
1.3	Line L7	1.13	Lines L5 and L11	1.24	Lines L8 and L10	1.35	Lines L5 and L14
1.4	Line L8	1.14	Lines L5 and L12	1.25	Lines L8 and L11	1.36	Lines L6 and L14
1.5	Line L9	1.15	Lines L6 and L9	1.26	Lines L8 and L12	1.37	Lines L7 and L14
1.6	Line L10	1.16	Lines L6 and L10	1.27	Lines L5 and L13	1.38	Lines L8 and L14
1.7	Line L11	1.17	Lines L6 and L11	1.28	Lines L6 and L13	1.39	Lines L9 and L14
1.8	Line L12	1.18	Lines L6 and L12	1.29	Lines L7 and L13	1.40	Lines L10 and L14
1.9	Line L13	1.19	Lines L7 and L9	1.30	Lines L8 and L13	1.41	Lines L11 and L14
1.10	Line L14	1.20	Lines L7 and L10	1.31	Lines L9 and L13	1.42	Lines L12 and L14
		1.21	Lines L7 and L11	1.32	Lines L10 and L13	1.43	Lines L13 and L14

The load demands together with their power factors (PFs) at nodes N9 and N10 are varied in the representative range between minimum and maximum values. Power-flow solutions with the specified load demands give the range of active- and reactive- power at generator nodes as shown in Table 6. It has been taken that the load demands at nodes N9 and

N10 follow similar patterns. However, any different patterns of load demand variations, for example, in areas in different time zones, when they arise, can be included in the data set without difficulty.

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 [6]. These optimal controller parameter values are used as the specified network output data.

Table 6: Variations of load and power generation

No.	Load Demand (pu)				Power Generation (pu)			
	Node N9		Node N10		Slack Bus (node N1)		PV Bus	
	Load	PF	Load	PF	P _{GEN}	Q _{GEN}	P _{GEN}	Q _{GEN}
2.1	8 + j 2	0.97	11 + j 3	0.96	5.4 – 6.8	-1.0 – -0.9	4.5 – 5.0	-2.0 – -1.1
2.2	8 + j 2	0.97	12 + j 3	0.97				
2.3	9 + j 8	0.75	11 + j 9	0.77	5.0 – 6.4	2.1 – 2.2	5.0 – 5.5	1.6 – 3.3
2.4	9 + j 8	0.75	12 + j 9	0.80				
2.5	10 + j 5	0.89	13 + j 6	0.85	6.5 – 7.9	0.9 – 1.0	5.5 – 6.0	0.1 – 1.3
2.6	10 + j 5	0.89	14 + j 6	0.91				
2.7	11 + j 6	0.88	13 + j 7	0.92	6.0 – 7.4	1.3 – 1.4	6.0 – 6.5	0.7 – 2.1
2.8	11 + j 6	0.88	14 + j 7	0.89				
2.9	12 + j 8	0.83	15 + j 9	0.86	7.7 – 9.0	3.0 – 3.1	6.5 – 7.0	2.0 – 4.2
2.10	12 + j 8	0.83	16 + j 9	0.87				
2.11	13 + j 4	0.96	15 + j 5	0.95	7.1 – 8.5	0.7 – 0.8	7.0 – 7.5	-0.2 – 1.1
2.12	13 + j 4	0.96	16 + j 5	0.95				
2.13	14 + j 7	0.89	17 + j 8	0.90	7.5 – 8.8	2.9 – 3.1	8.0 – 8.5	2.0 – 4.0
2.14	14 + j 7	0.89	18 + j 8	0.91				
2.15	15 + j 2	0.99	17 + j 3	0.98	6.9 – 8.2	0.1 – 0.2	8.5 – 9.0	-0.7 – 0.4
2.16	15 + j 2	0.99	18 + j 3	0.99				

pu on 100 MVA

In applying the optimal control coordination [6] for training and test data generation, the sum of the squares of the real parts of all of the eigenvalues of the electromechanical modes is maximised, with the constraints that the minimum damping ratio of the local modes is to be 0.3, and that of the inter-area mode 0.1.

The cases generated from Tables 5 and 6 are sub-divided into the training set and test set. For the training set, line outage cases 1.1 – 1.4, 1.6 – 1.9, 1.11 – 1.20, 1.22 – 1.27, 1.29 –

1.34 and 1.36 – 1.42 together with load demand variations in cases 2.1 – 2.5, 2.7 – 2.10, and 2.12 – 2.16 are selected. The remaining cases of line outages and load demand variations in Tables 5 and 6 are used for the test set.

5.2.2 *Training, testing and sizing the neural network*

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 according to the procedure described in Section 4.4.

The performance goals specified in terms of the error function $\mathcal{E}(x)$ of 0.004 (for training) and 0.006 (for testing) are used. The maximum differences between the optimal damping ratio and the damping ratio calculated using neural network outputs of 0.03 (for training) and 0.05 (for testing) are also used as the performance goals. Maximum number of epoch of 100 is specified for the network training. 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 10 hidden neurons in one hidden layer satisfies the convergence criteria. On this basis, the trained and tested neural network is used in the application mode, and its dynamic performance is evaluated by simulation in the following section.

5.3 *Dynamic performance of the system in the study*

Table 7 shows the comparison of modal response characteristics (electromechanical mode eigenvalues, frequencies and damping ratios) between non-adaptive and adaptive controllers of the system in Fig.4a for a range of contingencies and operating conditions. For non-adaptive controller, the controller parameters derived from the base case design are used for all of the contingency cases and load changes.

The base case (referred to as case 1 in Table 7) is that with the full system in Fig.4a, and load demands at nodes N9 and N10 being $10+j2$ pu and $13+j2.5$ pu respectively. The comparison in Table 7 for case 1 confirms that the damping ratios for the electromechanical

modes achieved by the neural adaptive controller are closely similar to those obtained from the fixed-parameter controllers (i.e. non-adaptive) designed with the system configuration and operating condition specified in the base case. In the off-line training of the neural adaptive controller, the base case has not been included in the training set. The comparison for case 1 can, therefore, be seen as a neural adaptive controller testing.

Table 7: Dynamic performances of controllers

No	Case	Non-Adaptive Controller			Adaptive Controller		
		Eigenvalues	Freq. (Hz)	Damp. Ratio	Eigenvalues	Freq. (Hz)	Damp. Ratio
1	Base Case Load (pu) : Node N9 : 10 + j2.0 Node N10 : 13 + j2.5	$-2.3699 \pm j7.0642^*$	1.12	0.3181	$-2.3089 \pm j7.3413^*$	1.17	0.3000
		$-2.3448 \pm j6.6088^{**}$	1.05	0.3344	$-2.3925 \pm j7.1246^{**}$	1.13	0.3183
		$-0.5329 \pm j3.5437^{***}$	0.56	0.1487	$-0.5036 \pm j3.3037^{***}$	0.53	0.1507
2	Load-Change Case Load (pu) : Node N9 : 15 + j7 Node N10 : 16 + j8	$-1.8169 \pm j7.5759^*$	1.21	0.2332	$-2.3145 \pm j7.2747^*$	1.16	0.3032
		$-1.8685 \pm j7.1286^{**}$	1.13	0.2535	$-2.2683 \pm j7.0094^{**}$	1.12	0.3079
		$-0.3723 \pm j3.1591^{***}$	0.50	0.1170	$-0.5303 \pm j3.1685^{***}$	0.50	0.1651
3	Line L5 Out	$-2.3783 \pm j7.3294^*$	1.17	0.3086	$-2.2690 \pm j6.9820^*$	1.11	0.3091
		$-1.4468 \pm j6.6625^{**}$	1.06	0.2122	$-2.0757 \pm j6.6838^{**}$	1.06	0.2966
		$-0.2630 \pm j3.3211^{***}$	0.53	0.0789	$-0.5093 \pm j3.4126^{***}$	0.54	0.1476
4	Lines L7 & L11 Out	$-1.7872 \pm j6.8207^*$	1.09	0.2535	$-2.0100 \pm j6.6457^*$	1.06	0.2895
		$-1.5108 \pm j6.5671^{**}$	1.05	0.2242	$-2.0145 \pm j6.4854^{**}$	1.03	0.2966
		$-0.3246 \pm j3.2679^{***}$	0.52	0.0988	$-0.4865 \pm j3.2230^{***}$	0.51	0.1493
5	Line L13 Out	$-2.5048 \pm j7.4695^*$	1.19	0.3179	$-2.3543 \pm j7.4433^*$	1.18	0.3016
		$-2.5559 \pm j7.3784^{**}$	1.17	0.3273	$-2.4456 \pm j7.3200^{**}$	1.17	0.3169
		$-0.1622 \pm j3.7914^{***}$	0.60	0.0427	$-0.5619 \pm j3.3340^{***}$	0.53	0.1662
6	Lines L5 & L14 Out	$-2.5297 \pm j7.5291^*$	1.20	0.3185	$-2.4497 \pm j7.3964^*$	1.18	0.3144
		$-1.5138 \pm j6.6691^{**}$	1.06	0.2214	$-1.9943 \pm j6.5613^{**}$	1.04	0.2908
		$-0.1575 \pm j3.5010^{***}$	0.66	0.0449	$-0.4610 \pm j3.0515^{***}$	0.49	0.1494

* local mode associated with generators G1 and G4

** local mode associated with generators G2 and G3

*** inter-area mode

In case 2 of Table 7, the load demands at nodes N9 and N10 increase to 15+j7 pu and 16+j8 pu respectively while the system configuration remains as that of the base case. With non-adaptive controllers, the damping ratios of the electromechanical modes decrease noticeably in comparison with those in the base case. However, with the neural adaptive controller, the damping ratios are maintained at the levels similar to those of the base case.

Further comparisons in cases 3-6 of Table 7 focus on contingencies where one or two transmission circuits are lost. The load demands are those in the base case. In case 3 where there is an outage of transmission line L5 in Fig.4a, there is a substantial reduction in the

inter-area mode damping in comparison with the base case. The decreases in the local mode damping are non-uniform. The local mode associated with generators G2 and G3 is affected severely in terms of damping, given that these generators are electrically close to the outage location. The damping ratio of this mode is reduced to 0.2122, compared to 0.3344 in the base case. The damping of the local mode associated with generators G1 and G4 is hardly affected by this outage. Its damping ratio is now 0.3086 in comparison with 0.3181 of the base case. With the adaptive controller, the damping ratios of all of the electromechanical modes are only marginally affected by the outage, in comparison with those in the base case, as indicated in Table 7.

The response characteristics of the three electromechanical modes in case 4 where there are double outages of transmission lines L7 and L11 are given in Table 7. The modal damping ratios with non-adaptive controllers are now substantially lower than those of the base case. In comparison, the adaptive controllers are able to restore the damping ratios to the levels which are nearly equal to those of the base case, even though the contingency of case 4 has not been included in the off-line training of the adaptive controller.

The outage of transmission line L13 in case 5 of Table 7 affects the damping of the inter-area mode very severely when the non-adaptive controllers are used. The damping ratio of 0.1487 in the base case is now reduced to 0.0427 in the outage case 5. However, the outage does not affect the local mode dampings to any significant extent, relative to those in the base case. This response characteristic is consistent with the topology of the power system in Fig.4a where transmission line L13 has the primary function of interconnecting the two areas. The robustness of the adaptive controller in this outage case is confirmed by the results of Table 7. The controller parameters determined by the trained neural network are able to adapt to the new system configuration for maintaining the modal damping ratios at the levels similar to those in the base case.

Double outages of transmission lines L5 and L14 are then considered in case 6 of Table 7. As expected, the additional outage of transmission line L14 which interconnects the two areas affects mainly the damping of the inter-area mode when non-adaptive controllers

are used. Comparisons among the damping ratios of the inter-area mode achieved by the non-adaptive controllers in cases 1, 3 and 6 confirm the effect of the outage of transmission line L14 on the inter-area mode damping. With adaptive controller parameters, the adverse effects of the outages in case 6 are largely countered, as indicated in the damping ratios results of Table 7. The levels of electromechanical mode dampings are almost the same as those in the base case.

5.4 Time-domain simulations

In order to further validate the performance of the proposed neural-adaptive controller, time-domain simulations are carried out for the selected contingency cases (i.e. line L13 outage and lines L5 and L14 outage). The time-step length of 50 ms is adopted for the simulations. The descriptions of the line(s) outage cases and the disturbances used to initiate the transients for each case are given in Table 8.

Table 8: Descriptions of line(s) outage cases and disturbances

Case	Outage Description	Disturbance Description
A	Line L13 has to be disconnected to clear the fault.	Three-phase fault near node N13 on line L13. The fault is initiated at time $t = 0.1$ s, and the fault clearing time is 0.1 s.
B	Line L5 is initially taken out for maintenance then line L14 has to be disconnected to clear the fault.	Three-phase fault near node N13 on line L14. The fault is initiated at time $t = 0.1$ s, and the fault clearing time is 0.1 s.

In Figs.4b-4e are shown the system transients following the disturbances. As the focus is on the inter-area mode oscillation, relative voltage phase angle transient between nodes N9 and N10 is used in forming the responses in Figs.4b and 4c. From the responses, it can be seen that, with non-adaptive controller, the system oscillation is poorly damped and takes a considerable time to reach a stable condition. With the proposed neural-adaptive controller, the system reaches steady-state condition in 6 – 7 s subsequent to the disturbance for the contingency cases considered (see Figs. 4b and 4c). Further comparison in terms of the transients in the rotor speed of generator G2 relative to that of generator G1 are given in

Figs.4d and 4e. The comparison confirms the noticeable improvement in electromechanical oscillation damping when the adaptive controller is used.

In Figs.5a-5d are also shown the plots of two controller parameters (i.e. PSSs and SDC gains) during the transient period following the disturbance. The plots of PSSs and SDC gains for line L13 outage are shown in Figs.5a and 5c respectively. Whereas, the plots of PSSs and SDC gains for lines L5 and L14 outage are shown in Figs.5b and 5d respectively.

There are rapid changes in the controller gains in the initial transient period following fault and fault clearance, due to the transients in generator powers. To facilitate the adaptation of the controller parameters in the initial transient period typically within the range up to about 6 seconds, the option of keeping the inputs to the neural network representing generator powers at the base-case values, and changing only the inputs derived from the reduced nodal impedance matrix can be used. This option is based on the result of the study given in Table 7 of Section 5.3 which confirms that the overall damping is more substantially affected by system configuration than generator loadings. In Figs.5e and 5f are shown the relative voltage phase angle transient and SDC gain transient for disturbance case B in Table 8 respectively, using the option described in the above. The damping of the transient in Fig. 5e is similar to that in Fig.4c, whilst the transient in the controller parameter in Fig.5f is substantially reduced in comparison with that in Fig.5d, which will facilitate the implementation of the adaptive controller.

In practice, there will be some time delay in the communication channel before the inputs to the neural adaptive controller which represent the power system configuration can be updated, following a disturbance. Studies have been carried out to quantify the performance of the neural adaptive controller when there is the time delay.

In [24], a signal transmission delay of 0.75s has been proposed in the design of H_{∞} damping controllers using remote signals. A time delay up to 2s is, therefore, considered in the presents work for evaluating the effect on the neural adaptive controller performance. With signal transmission delays represented in the inputs to the neural adaptive controller, the

system transient responses for disturbance case B described in Table 8 are re-evaluated and shown in Figs.5e-5h.

Time delays of 1s and 2s in relation to the updating of system topology after fault clearance have been adopted in the study. The comparisons made of the inter-area mode responses of Fig.5e, and the local mode responses of Figs.5g and 5h indicate that the effect of the time delay is to reduce only slightly the electromechanical mode dampings. However, in relation to signal transmission delay and/or communication channel failure, the neural adaptive controller developed in the paper offers a key advantage in comparison with other controller designs using remote signals [7]. When there is a loss of communication channel or substantial time delay, the neural adaptive controller will revert back to the fixed-parameter controller, with sub-optimal damping. In the delay period/loss of communication channel, the PSSs and SDCs still have local input signals (rotor speed/power), and they operate normally to give continuous non-zero outputs which contribute to the system damping. Other controllers which depend totally on remote input signals will not be able to function without the communication channel.

5.5 Possible improvements

Table 9 shows the range of optimal controller parameter variation for different operating conditions and system configurations described in Tables 5 and 6. Results in the table show that the range of variation in the controller gains is wider than that in the controller time constants. This indicates that the controller gains are more sensitive to system changes than the time constants. Therefore, to simplify the adaptive controller and its training, it is possible to adapt only the controller gains to the prevailing system condition, and keep the controller time constants at the constant values determined in the base case.

It is also found out from the investigation that the local modes are more affected by PSSs, whereas, the inter-area mode is more affected by the SDC. In other words, SDCs are more important if only the inter-area modes are to be considered. Therefore, if the damping ratios of the local modes are high in the base case, it is possible to include only the SDCs in

the neural adaptive controller design, and to have fixed-parameter PSSs designed in the base case.

In order to check whether a smaller number of neural network inputs can be used in the adaptive controller, representation of the system configuration with a reduced nodal impedance matrix of a lower dimension is investigated. In the investigation, only power system nodes with direct connections to generators with PSSs and FACTS devices are retained. The neural network with a smaller number of inputs is then trained and tested using the test cases described in Section 5.2.1. Based on the outcome of the investigation, it is found that the neural network with a reduced number of inputs can also provide acceptable results. Further reduction in the number of inputs is also possible by discounting the real parts of the reduced nodal impedance matrix elements, given that the parameters of the transmission circuits are dominated by reactances.

Table 9: Range of optimal controller parameter variation for different operating conditions and system configurations

Controller Type	Parameters		Range
	Symbol	Type	
PSS	K_{PSS}	gain	4 – 20 pu
	T_{PSS}	time constant	0.80 – 1.33 s
	T_{PSS1}	time constant	0.16 – 0.24 s
	T_{PSS2}	time constant	0.05 – 0.13 s
	T_{PSS3}	time constant	0.03 – 0.10 s
	T_{PSS4}	time constant	0.16 – 0.24 s
SDC	K_{SDC}	gain	0.1 – 1.0 pu
	T_{SDC}	time constant	0.16 – 0.24 s
	T_{SDC1}	time constant	0.16 – 0.24 s
	T_{SDC2}	time constant	0.05 – 0.16 s
	T_{SDC3}	time constant	0.03 – 0.08 s
	T_{SDC4}	time constant	0.16 – 0.24 s
UPFC Main Controller	K_{sh1}, K_{sh2}	gain	0.1 – 1.0 pu
	T_{sh1}, T_{sh2}	time constant	0.05 – 0.16 s
	K_{se1}, K_{se2}	gain	0.01 – 0.10 pu
	T_{se1}, T_{se2}	time constant	0.16 – 0.24 s

pu on 100 MVA

By applying the above measures, the size of the neural network and its training can be greatly simplified and kept to be minimal.

5.6 Discussion on large power system application

Drawing on the measures for improvements in Section 5.5 and the development of ultra-large-scale neural network reported in [25], it is feasible to meet the requirements of large power system application in terms of neural network size and response time. For the purpose of illustration, it is taken in the discussion that a large power system has 100 generators and 10 FACTS devices with each generator having a PSS. In Table 10 are shown the comparisons between the adaptive neural controller requirements and the available capability of the ultra-large-scale neural network. The comparisons confirm that the capability exceeds the requirements by a large margin.

Table 10: Comparisons between the adaptive neural controller size and ultra-large-scale neural network capability

Neural adaptive controller size requirements	Ultra-large-scale neural network capability [25]
- The dimension of the reduced nodal impedance matrix is 110×110. Due to the symmetry in the impedance matrix, only 6105 elements are required to represent the power system configuration. The impedance matrix elements are, in general, complex numbers. However, in a transmission system (which is the focus of the present paper), the parameters of transmission circuits are dominated by the reactances. This means that it is possible to discount the real parts of the nodal impedance matrix, for the purpose of representing the system configuration. - In addition to 6105 elements (in real numbers, following the removal of the real parts of the nodal impedance matrix) used for representing the power system configuration, there are 200 input values for representing generator active- and reactive powers. Therefore, in this example of the system having 100 generators each of which has a PSS, and 10 FACTS devices, the total number of input nodes of the neural adaptive controller is about 6300. - Based on the controller output parameters in Table 3, the total number of output nodes of the neural adaptive controller is about 750.	- Multi-processor technology (a cluster of 196 processors). 1.73 million weighting coefficients 9 million training patterns. - Computational speed of 163.3 GFlops/s. - Cost: about 150,000 US dollars (in 2000). It is highly likely that the cost at present is much lower, given that the cost of computer hardware is decreasing while computing capability (in terms of memory and processing speed) is increasing.

6 Conclusions

An adaptive control algorithm and procedure have been derived and developed for online tuning of the PSSs and SDCs of FACTS devices. 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. A particular contribution of the paper is that of representing the power system configuration in terms of a reduced nodal impedance matrix, which is formed using sparse matrix operations. This allows any variation of system configuration to be included and input to the neural adaptive controller.

The neural adaptive controller trained for a representative power system with a UPFC has been comprehensively tested to verify its dynamic performance. Both eigenvalue calculations and time-domain simulations are applied in the testing and verification. Many comparative studies have been carried out to quantify the improved performance of the adaptive controller proposed in comparison with that achieved with fixed-parameter controllers.

The results confirm that the decrease in system dampings arising from the use of fixed-parameter controllers when system operating condition changes will be removed, and maximum or optimal damping is regained by the proposed neural adaptive controller.

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8 References

- 1 Pourbeik, P., and Gibbard, M.J.: 'Simultaneous coordination of power system stabilizers and FACTS device stabilizers in a multimachine power system for enhancing dynamic performance', IEEE Trans. Power Syst., 1998, 13, (2), pp. 473-479
- 2 Sadikovic, R., Korba, P., and Andersson G.: 'Application of FACTS devices for damping of power system oscillations'. IEEE PowerTech 2005, St. Petersburg, Russia, June 2005
- 3 Chaudhuri, B., Korba, P., and Pal, B.C.: 'Damping controller design through simultaneous stabilization technique'. Proceedings of WAC 2004, 2004, 15, pp.13-18
- 4 Majumder, R., Chaudhuri, B., El-Zobaidi, H., Pal, B.C., and Jaimoukha, I.M.: 'LMI approach to normalised H-infinity loop-shaping design of power system damping controllers', IEE Proc. Gener. Transm. Distrib., 2005, 152, (6), pp. 952-960
- 5 Nguyen, T.T., and Gianto, R.: 'Application of optimization method for control co-ordination of PSSs and FACTS devices to enhance small-disturbance stability'. Proceedings of the IEEE PES 2005/2006 Transmission and Distribution Conference & Exposition, Dallas, Texas, May 2006, pp. 1478-1485
- 6 Nguyen, T.T., and Gianto, R.: 'Optimisation-based control co-ordination of PSSs and FACTS devices for optimal oscillations damping in multimachine power system', IET Gener. Transm. Distrib., 2007, 1, (4), pp.564-573
- 7 Chaudhuri, B., and Pal, B.C.: 'Robust damping of multiple swing modes employing global stabilizing signals with a TCSC', IEEE Trans. Power Syst., 2004, 19, (1), pp. 499-506
- 8 Pal, B.C., Coonick, A.H., and Cory, B.J.: 'Robust damping of inter-area oscillations in power systems with superconducting magnetic energy storage devices', IEE Proc. Gener. Transm. Distrib., 1999, 146, (6), pp. 633-639

- 9 Noroozian, M., Ghandhari, M., Andersson, G., Gronquist, J., and Hiskens, I.A.: 'A robust control strategy for shunt and series reactive compensators to damp electromechanical oscillations', IEEE Trans. Power Deliv., 2001, 16, (4), pp. 812-817
- 10 Ghandhari, M., Andersson, G., and Hiskens, I.A.: 'Control Lyapunov Functions for Controllable Series Devices', IEEE Trans. Power Syst., 2001, 16, (4), pp. 689-694
- 11 Segal, R., Kothari, M.L., and Madnani, S.: 'Radial basis function (RBF) network adaptive power system stabilizer', IEEE Trans. Power Syst., 2000, 15, (2), pp. 722-727
- 12 Chaturvedi, D.K., Malik, O.P., and Kalra, P.K.: 'Generalised neuron-based adaptive power system stabiliser', IEE Proc. Gener. Transm. Distrib., 2004, 151, (2), pp. 213-218
- 13 Hsu, Y.Y., and Luor, T.S.: 'Damping of power system oscillations using adaptive thyristor-controlled series compensators tuned by artificial neural networks', IEE Proc. Gener. Transm. Distrib., 1999, 146, (2), pp. 137-142
- 14 Changaroon, B., Srivastava, S.C., Thukaram, D., and Chirarattananon, S.: 'Neural network based power system damping controller for SVC', IEE Proc. Gener. Trans. Distrib., 1999, 146, (4), pp. 370-376
- 15 Chaudhuri, B., Majumder, R., Pal, B.C.: 'Application of multiple-model adaptive control strategy for robust damping of interarea oscillations in power system', IEEE Trans. Contr. Syst. Tech., 2004, 12, (5), pp. 727-736
- 16 Sadikovic, R., Korba, P., and Andersson G.: 'Self-tuning controller for damping of power system oscillations with FACTS devices'. 2006 PES General Meeting, Montreal, Canada, June 2006
- 17 Humpage, W.D., Wong, K.P., and Nguyen, T.T.: 'PROLOG network-graph generation in system surveillance', Electric Power Systems Research, 1985, 9, pp. 37-48
- 18 Alsac, O., Stott, B., and Tinney, W.F.: 'Sparsity-oriented compensation methods for modified network solutions', IEEE Trans. Power Appar. Syst., 1983, 5, (102), pp. 1050-1060

- 19 CIGRE TF 38.01.08: 'Modeling of power electronics equipment (FACTS) in load flow and stability programs: a representation guide for power system planning and analysis', 1999
- 20 Dong, L.Y., Zhang, L., and Crow, M.L.: 'A new control strategy for the unified power flow controller'. IEEE PES Winter Meeting, 2002, 1, pp. 562-566
- 21 Mithulananthan, N., Canizares, C.A., Reeve, J., and Rogers G.J.: 'Comparison of PSS, SVC, and STATCOM controllers for damping power system oscillations', IEEE Trans. Power Syst., 2003, 16, (2), pp. 786-792
- 22 Demuth, H.B., and Beale, M.: 'Neural network toolbox user's guide: for use with MATLAB (version 4)' (The Math Works Inc., 2004)
- 23 Padiyar, K.R.: 'Power system dynamics stability and control' (John Wiley & Sons (Asia) Pte Ltd, Singapore, 1996)
- 24 Chaudhuri, B., Majumder, R., and Pal, B.C.: 'Wide-Area Measurement-Based Stabilizing Control of Power System Considering Signal Transmission Delay', IEEE Trans. Power Syst., 2004, 19, (4), pp. 786-792
- 25 Aberdeen, D., Baxter, J., and Edwards, R.: '924/MFlops/s, ultra-large-scale neural network training on a PIII cluster'. Supercomputing, ACM/IEEE 2000 Conference, Nov. 2000
- 26 Humpage, W.D., Bayne, J.P., and Durrani, K.E.: 'Multinode-power-system dynamic analyses', Proc. IEE, 1972, 119, (8), pp. 1167-1175
- 27 IEEE Std 421.5-2005: 'IEEE recommended practice for excitation system models for power system stability studies', 2005
- 28 IEEE Working Group: 'Dynamic models for fossil fueled steam units in power system studies', IEEE Trans. Power Syst., 1991, 6, (2), pp. 753-761

9 Appendix

Each of the synchronous generators of the system in Fig. 4a is represented by the fifth-order nonlinear model in the d-q axes having the rotor frame of reference [26]:

$$\dot{\Psi}_{rm} = A_m \Psi_{rm} + F_m I_{Sm} + V_{rm} \quad (\text{A.1})$$

$$\dot{\omega}_{rm} = (T_m - T_e)/M \quad (\text{A.2})$$

$$\dot{\delta}_{rm} = \omega_{rm} \quad (\text{A.3})$$

where Ψ_{rm} , ω_{rm} , and δ_{rm} are vector of rotor flux linkages established by the field winding and damper windings, rotor angular frequency and rotor angle respectively; V_{rm} is the rotor voltage vector; T_m and T_e are the mechanical rotor input and electrical torques respectively; M is the machine inertia constant; A_m and F_m are the matrices depending on machine parameters, and I_{Sm} is the stator current vector. For small-disturbance study, a standard linearisation process is applied to (A.1) – (A.3).

List of Captions

FIG.1. BLOCK DIAGRAM OF UPFC AND PSS

- a. UPFC block diagram
- b. UPFC shunt converter control block diagram
- c. UPFC series converter control block diagram
- d. PSS control block diagram

FIG.2. NEURAL NETWORK AND NEURAL ADAPTIVE CONTROLLER

- a. Input and output structure of the neural network
- b. Block diagram of the system with neural adaptive controller

FIG.3. FLOWCHART FOR TRAINING, TESTING AND SIZING OF THE NEURAL NETWORK

FIG.4. TEST SYSTEM AND TRANSIENTS

- a. Two-area 230 kV system
- b. Relative voltage phase angle transients for case A disturbance
- c. Relative voltage phase angle transients for case B disturbance
- d. Relative speed ($G2-G1$) transients for case A disturbance
- e. Relative speed ($G2-G1$) transients for case B disturbance

FIG.5. SYSTEM TRANSIENTS

- a. PSSs gain transients for case A disturbance
- b. PSSs gain transients for case B disturbance
- c. SDC gain transient for case A disturbance
- d. SDC gain transient for case B disturbance
- e. Relative voltage phase angle transients for case B disturbance (Effects of time delay)
- f. SDC gain transients for case B disturbance (Effects of time delay)
- g. Relative speed ($G4-G1$) transients for case B disturbance (Effects of time delay)
- h. Relative speed ($G3-G2$) transients for case B disturbance (Effects of time delay)

FIG.1. BLOCK DIAGRAM OF UPFC AND PSS

- a. UPFC block diagram
- b. UPFC shunt converter control block diagram
- c. UPFC series converter control block diagram
- d. PSS control block diagram

a

b

FIG.2. NEURAL NETWORK AND NEURAL ADAPTIVE CONTROLLER

a. Input and output structure of the neural network

b. Block diagram of the system with neural adaptive controller

$p_1, p_2, \dots, p_n$: Real and imaginary parts of the elements of the reduced nodal impedance matrix

$p_{n+1}, p_{n+2}, \dots, p_m$: Active- and reactive- power of generators

$a_1, a_2, \dots, a_M$: Optimal controller parameters

f : Activation function

FIG.3. FLOWCHART FOR TRAINING, TESTING AND SIZING OF THE NEURAL NETWORK

MSE: Mean Square Error

FIG.4. TEST SYSTEM AND TRANSIENTS

- a. Two-area 230 kV system
- b. Relative voltage phase angle transients for case A disturbance
- c. Relative voltage phase angle transients for case B disturbance
- d. Relative speed (G2-G1) transients for case A disturbance
- e. Relative speed (G2-G1) transients for case B disturbance

In the system of Fig.4a:

Total connected load = 2300 MW

Excitation systems model: based on IEEE Type-ST1 system [27]

Turbine and governor model: adopted from [28]

FIG.5. SYSTEM TRANSIENTS

- a. PSSs gain transients for case A disturbance
- b. PSSs gain transients for case B disturbance
- c. SDC gain transient for case A disturbance
- d. SDC gain transient for case B disturbance
- e. Relative voltage phase angle transients for case B disturbance (Effects of time delay)
- f. SDC gain transients for case B disturbance (Effects of time delay)
- g. Relative speed (G4-G1) transients for case B disturbance (Effects of time delay)
- h. Relative speed (G3-G2) transients for case B disturbance (Effects of time delay)

List of Symbols

m	number of neural network inputs
M	number of neural network outputs
T	vector or matrix transpose
V_{T1}, V_{T2}	ac terminal voltage
I_{sh}, I_{se}	shunt, series current
V_{sh}, V_{se}	shunt, series voltage
I_{shp}, I_{shq}	p, q components of shunt current
I_{sep}, I_{seq}	p, q components of series current
V_{shp}, V_{shq}	p, q components of shunt voltage
V_{sep}, V_{seq}	p, q components of series voltage
k	ratio between ac and dc voltages
m_1, m_2	pulse width modulation ratios for shunt, series converters
Ψ_1, Ψ_2	pulse width modulation phases for shunt, series converters
V_{DC}	dc capacitor voltage
s	Laplace transform operator
V_{SDC}	output signal from supplementary damping controller
P_e	line active-power
V_{REF}	voltage reference
$droop$	slope of the voltage-current characteristic
$V_{DC,REF}$	dc voltage reference
V_{shp0}, V_{shq0}	p, q components of shunt voltage initial value
P_{REF}, Q_{REF}	active-, reactive-power reference
$I_{sep,REF}, I_{seq,REF}$	p, q components of series current reference
V_{sep0}, V_{seq0}	p, q components of series voltage initial value
V_{PSS}	output signal from power system stabiliser
ω_r	input signal to PSS (rotor speed)