Multi-Objective Optimization and Online Adaptation Methods for Robust Tuning of PSS Parameters

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Abstract - **This paper addresses a robust multi-objective optimization approaches for tuning Generator Excitation PSS system parameters of power systems. The objective function which is a composite of different performance indices corresponding to different disturbances and steady-state operating conditions is then posed as a multi-objective nonlinear optimization problem together with parameters from a given set constraint. The nonlinear time solutions for such optimization problem, i.e., the robust parameter set of the Generator Excitation PSS system, are then solved using Sequential Quadratic Programming (SQP) algorithm. Furthermore, an online adaptation of PSS parameters using artificial neural network (ANN) technique in which a pre-calculated optimal parameter sets from the nonlinear optimization solutions corresponding to different loading conditions are then used for training sessions so as to determine the robust parameter sets for the PSS. The proposed approaches have been applied on test system and nonlinear simulation studies have confirmed the robustness of the approaches for all envisaged operating conditions and disturbance scenarios.**

Keywords: M**ulti-objective Nonlinear Optimization, Power System Stabilizer, Robust Control, Artificial Neural Network.**

1. INTRODUCTION

Recently, the electric power systems such as those in Europe and North America have experienced unprecedented changes due to the emergence of deregulation in the sector and the development of competitive electricity market for generations and energy services. These changes have caused a noticeable uncertainty in the load flows, and have also pushed the networks further to their operational and control limits. Besides, the integration of offshore wind generation plants into the existing network is expected to have a significant impact on the load flow of the system as well as the dynamic behaviour of the network. On the other hand, the transmission grids have seen very little expansion due to environmental restrictions. As a result, available transmission and generation facilities are highly utilized with large amounts of power interchanges taking place through tie-lines and geographical regions. It is also expected that this trend will continue in the future and result in more stringent operational requirements to maintain reliable services and adequate system dynamic performances. Critical controls like excitation systems, power system stabilizers, static VAR compensators will play increasingly key roles in maintaining adequate system dynamic performance. Proper design of these control systems and/or optimal tuning of system controller parameters that take into account the continual changes in the structure of the network are imperative to ensure/guarantee robustness over wide operating conditions and/or fault situations in the system.

Moreover, the ever increasing complexity of modern power systems has recently highlighted the need for advanced control techniques for effective controlling and enhancing the dynamic performance of power systems. On the other hand, the dynamic performance of large power systems can often be enhanced by applying those recently developed nonlinear optimization techniques for tuning power system controllers. Some interesting results in this direction have been reported (to cite a few [1] - [7]) where the associated cost function of the optimization problem, which embeds the evolving dynamic state variables of the system as a constraint in the problem, has been used for accessing as well as improving the dynamic behaviour of the system. Moreover, the objective functions for this type optimization problem are chosen to force the system to have a post-disturbance stable operating point as well as a good damping behaviour as quickly as possible. However, due to the nature of the problem, the solutions of the optimization problem are sub-optimal and the system is characterized by showing poor global behaviour and often tends to be unstable to other operating conditions and fault scenarios. Thus, this paper explores the possibilities of a simultaneous multi-objective optimization approach dealing with optimal tuning of Generator Excitation PSS system parameters.

On the other hand, computational intelligence techniques like ANNs, fuzzy logics have proved to be useful tools for complex nonlinear system dynamics control including power systems. ANNs are suitable for multi-variable applications because they can easily represent the nonlinear characteristics between the system inputs and outputs. Their ability to learn and store information about the system allows the ANNs to be used for designing intelligent controllers for power systems [8],

[9], and thus offering alternatives for the traditional linear and nonlinear control techniques. Advantage of ANNs based controllers over the conventional controllers are that they are able to adapt to changes in the system operating conditions automatically unlike the conventional controllers whose performances degrade for such changes in the system. This paper presents how ANNs can be applied to PSS in order to provide robust dynamics performances of the power system under different operating and conditions and/or fault scenarios.

The material in this paper is organized as follows. In Section 2, the necessary background material on multi-objective optimization for tuning PSS system parameters for power systems is presented. The nature of the problem and the associated computation framework are also discussed in this section. Furthermore, an online adaptation of PSS parameters based on ANN technique which improves the robust dynamic performances of power systems for different operating conditions and/or fault scenarios is presented in Section 3. Simulation results of some realistic generalized PSS parametric tuning problems are presented in Section 4. Finally, some topics deserving further attention and concluding remarks are given in Section 5.

2. MULTI-OBJECTIVE OPTIMIZATION USING TIME DOMAIN SIMULATION

Time domain dynamic based simulation analysis and design techniques are widely used in power systems due to their abilities to involve directly the complex nature of nonlinear power systems and dealing with very large power systems. Exploiting these techniques into iterative optimization algorithms failed in the past due to the enormous simulation time which are required for carrying out the associated repeated simulation runs. However, today's modern computers and sophisticated algorithms allow calculating the time response of very large systems in real time. Therefore, the time domain simulation has become a promising and also an alternate approach for multi-objective nonlinear optimization problems arising in power systems.

For a large class of problems, it is sufficient to assume that the cost function derived from the time response is smooth though the underlying dynamic response is non-smooth due to intrinsic interactions between continuous dynamics and discrete events in power systems. Optimization with embedded time domain simulation can be formulated as follows

$$\begin{aligned} &\min \ J(\mathbf{x},\boldsymbol{\theta},t_f) \\ &\text{Subject to} \quad \textit{selected disturbances} \\ &\qquad\qquad \textit{and} \quad \boldsymbol{\theta}_{\min} \le \boldsymbol{\theta} \le \boldsymbol{\theta}_{\max} \end{aligned} \tag{1}$$

where the objective function

$$J(\mathbf{x},\boldsymbol{\theta},t_f) = \int_0^{t_f} \psi(\mathbf{x}(t),\boldsymbol{\theta})dt \tag{2}$$

is the integral of a properly defined function $\psi(\mathbf{x}(t),\boldsymbol{\theta})$ which is estimated by using the time domain simulation. The vector $\boldsymbol{\theta}$ contains the design parameters like gains and time constants of the controllers. During the optimization, the parameters of the controllers are adjusted optimally so as to achieve the desired objectives. Moreover, t_f is the final time and its adjustability is usually problem specific.

The objective of the optimization problem here is to tune the parameters of the controllers so as to force the system to have a post-disturbance stable operating point as well as a better damping behaviour as quickly as possible. For instance, conflicting requirement of improved damping behaviour without voltage degradation for tuning PSS system parameters for the system shown in Fig. 1 can be achieved by minimizing the following performance index function of the form:

$$\begin{aligned} \min_{\boldsymbol{\theta}} \sum_i \{ w_{1i} \int_0^{t_f} (P_{gi} - P_{gi}^0)^2\, dt + w_{2i} \int_0^{t_f} (V_{ti} - V_{ti}^0)^2 dt \\ + w_{3i} \int_0^{t_f} (E_{fdi} - E_{fdi}^0)^2\, dt \} \end{aligned} \tag{3}$$

where w_{1i}, w_{2i} and w_{3i} are weighting factors for the generator real power P_{gi} , the terminal voltage V_{ti} and the exciter field voltage E_{fdi} for the i-th generator, respectively.

The objective functional in the optimization problem (3) that takes into account a certain minimum degree of robustness stability can be further modified as follows

$$\begin{aligned} J = \sum_i e^{2\alpha} \{ w_{1i} \int_0^{t_f} (P_{gi} - P_{gi}^0)^2 dt + w_{2i} \int_0^{t_f} (V_{ti} - V_{ti}^0)^2\, dt \\ + w_{3i} \int_0^{t_f} (E_{fdi} - E_{fdi}^0)^2\, dt \} \end{aligned} \tag{4}$$

for some positive number α.

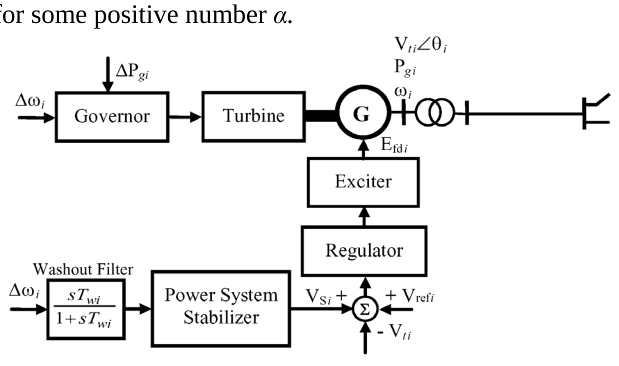

Fig. 1. General structure of the ith-generator together with PSS in a multimachine system.

Though, the above problem formulations in (1) and/or (3) attempt to solve the optimal parameters of the controllers for a particular operating condition and fault scenario. These controllers when implemented in the system do not guarantee the robustness of the overall system to other operating conditions and disturbance scenarios. In the following, a new multi-objective optimization, which considers several operating conditions within the generalized optimization framework of (1) so as to ensure the robustness of the controllers for all the envisage operating conditions and disturbance scenarios, is reformulated using the following composite objective function

$$\begin{aligned} &\min \sum_j w_j J_j(\mathbf{x},\boldsymbol{\theta},t_f) \\ &\text{Subject to} \quad \textit{selected disturbances } j \in D \\ &\qquad\qquad \textit{and} \quad \boldsymbol{\theta}_{\min} \le \boldsymbol{\theta} \le \boldsymbol{\theta}_{\max} \end{aligned} \tag{5}$$

where w_j is the weighting factor for the j-th partial objective function and D defines the set of disturbances and/or operating conditions considered. The weighting factors for the composite objective value are then appropriately selected to reflect the trade-off among the individual objectives corresponding to the respective operating conditions and disturbance scenarios. Moreover, the analysis of these weighting factors allows in selecting the solution that fits best the overall objective goal (i.e., improving damping behaviour of the system as quickly as possible). In contrast to all the other algorithms (see the survey in [10]), the method used in this paper can also provide a sample of solutions representing all possible weighting factors for the objectives used. This further guides how to choose proper weighting factors of the individual objectives that could be used for the composite objective function. The computation structure for solving such optimization problem which primarily embeds the dynamics of the real power system using the Power System Dynamics (PSD) software [11] is shown in Fig.2 and the corresponding generic algorithm is given as follows:

Algorithm I: Multi-objective Optimization Method

1. Run the PSD software with valid network data for jth-operating condition and form the jth-objective function using, e.g., the transient responses of active power, terminal voltage and excitation voltage of the generators (see the objective functional in (4)).
2. Form the composite objective function by using the appropriate weighting values for all operating conditions. This stage relates the multi-models nature of the problem with overall objective function.
3. Embed the above steps, i.e., Step 1 and Step 2, in the Sequential Quadratic Programming (SQP) Optimization Algorithm with parameters from a given finite set.
4. Solve the multi-objective nonlinear optimization problem using SQP Algorithm.

The optimization introduced in this section has been implemented by using the (SQP) Algorithm included into the IMLS library [12] together with the power system dynamic simulator software PSD.

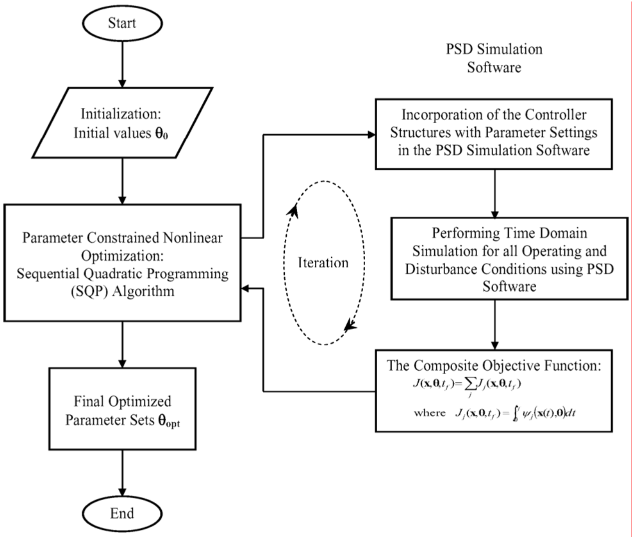

Fig. 2. Flow chart for the multi-objective nonlinear optimization problem.

3. ONLINE NEURAL-NETWORK BASED GENERATOR PSS TUNING

Computational intelligence techniques in particular ANN can be used to design robust PSS controllers for nonlinear power system that will continue to have some desired dynamic response even when system conditions change. A schematic diagram of an ANN based controller is shown in Fig. 3. It basically consists of a general generator/PSS structure extended by an ANN for adapting PSS parameters.

In the training session, the ANNs are trained based on pre-calculated optimal parameter data sets where these data sets corresponding to several hundred operating conditions are calculated using the multi-objective optimization approach discussed in the previous section. The generator active and reactive powers as well as grid voltages at the connection points have been chosen as the input to the ANNs. These variables characterize not only the state of the particular generator but, to some extent, also that of the whole power system. The corresponding outputs of the ANNs are the two time constants T_d, T_v and the gain K of the PSS transfer function. Moreover, the adaptation of these parameters carried out in each integration time step, so that by changing network conditions always optimal PSS parameters are obtained.

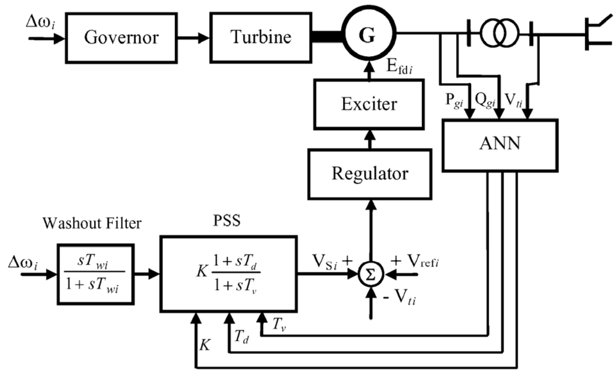

Fig. 3. A schematic diagram of artificial neural network based PSS block for multimachine power system.

A computation structure that deals with ANNs based adaptation that has been developed as an integral part of the PSD software [13] is used to solve such design problem.

4. CASE STUDIES

The approaches for robust tuning of Generator Excitation/PSS system parameters presented in the previous sections of this paper are now applied to a test system. This system, which is shown in Fig. 4, has been specifically designed to study the fundamental behaviour of large interconnected power systems including inter-area oscillations in power systems [14]. The system has four machines and each machine is equipped with IEEE standard exciter and governor controllers. The parameters for the standard exciter and governor controllers used in the simulation were taken from [4]. Moreover, the generators for this simulation are all represented by their fifth-order models with rated terminal voltage of 15.75 kV. The following base loading condition was assumed: at node-1 a load of [P_{L1}=1600 MW, Q_{L1}=150Mvar] and at node-2 a load of [P_{L2} = 2400 MW, Q_{L2}=120 Mvar].

4.1. Case Study - parameters tuning using multi-objective optimization

In the following, the effectiveness of the approach presented in Section 2 is demonstrated on the test system using the PSS block for each generator shown in Fig 5. Using the proposed algorithm in the Section 2, the composite objective functional corresponding to the different operating conditions is calculated for the period of 30 s from the time domain simulations, i.e., from the transient responses of active power, terminal and excitation voltages of the generators to different disturbances at different nodes in the system. This composite objective functional corresponding to the different operating conditions shown in Table 1 defines further a minimum stability degree of α = 0.25 for the overall system (see the objective functional in (4)). Then the optimization algorithm determines the robust optimal PSS system parameter values for the system by using of this composite objective functional. Moreover, the optimal parameter values for the PSSs are given in Table 2. For a short circuit of 150 ms duration at node F in Area-A, the transient responses of generator G2 with and without PSSs in the system are shown in Fig.6. This generator which is the most disturbed generator in the system due to its relative nearness to the fault location has a good damping behaviour.

To further assess the effectiveness of the proposed approach regarding the robustness, the transient performance indices were computed for different loading conditions at node 1 [P_{L1},Q_{L1}] and node 2 [P_{L2},Q_{L2}] while keeping constant total load in the system. The transient performance indices for generator powers P_{qi}, generator terminal voltages V_{ti} and excitation voltages E_{fdi} following a short circuit of 150 ms duration at node F in Area-A are computed using (6a), (6b) and (6c), respectively.

$$I^{P_g} = \sum_{i=1}^{N} \int_0^{t_f} \left| P_{gi}(t) - P_{gi}^0 \right| dt \qquad (6a)$$

$$I^{V_t} = \sum_{i=1}^{N} \int_0^{t_f} \left| V_{ti}(t) - V_{ti}^0 \right| dt \qquad (6b)$$

$$I^{E_{fd}} = \sum_{i=1}^{N} \int_0^{t_f} \left| E_{fdi}(t) - E_{fdi}^0 \right| dt \qquad (6c)$$

These transient performance indices are used as a qualitative measure of system behaviour following any disturbances including controller actions. Moreover, for comparison purpose, these indices are normalized to the base operating condition for which the controllers have been designed:

$$I_N = \frac{I_{DLC}}{I_{BLC}} \qquad (7)$$

Table 1. Operating Conditions in [%] from the total loading condition.

[PL1, QL1]	12.5	25	.0	37.5	50.0	62.5	75	.0	87.5
[PL2, QL2]	87.5	75	.0	62.5	50.0	37.5	25	.0	12.5
Weights w_i, $i=l,2,\ldots, 7$	0.05	0.	1	0.2	0.3	02	0.	1	0.05

Table 2. The robust PSS parameters for each generator.

Gains for the PSS	**Parameter T_{i1}**	**Parameter T_{i2}**
$K1$ = 1.1494	T_n = 0.8441	T_{12} = 0.5347
K_2 = 1.1820	T_{21} = 0.9177	T_{22} = 0.3731
K_3 = 1.2619	$T_3 1$ = 0.8688	T_{32} = 0.5493
$_{K4}$ = 1.1057	T_n = 0.9131	T_{42} = 0.4343

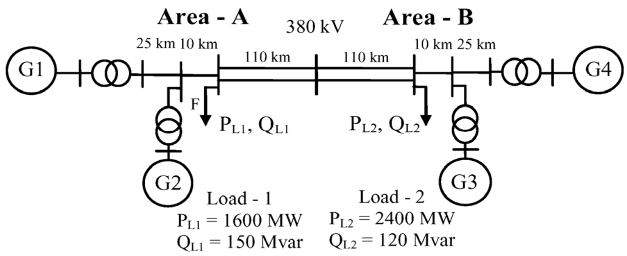

Fig. 4. One-line diagram of four machine two area system.

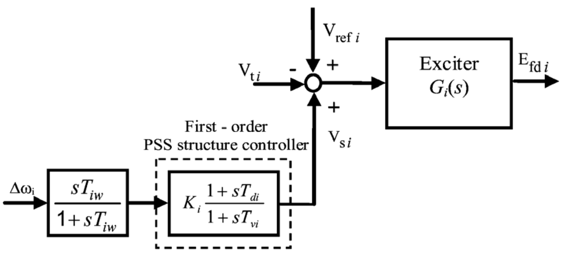

Fig. 5. The PSS block used in both approaches.

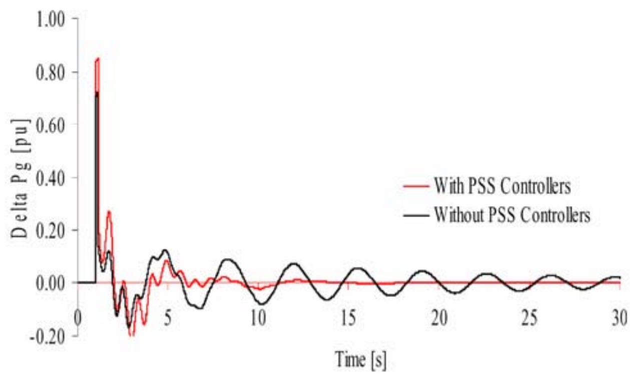

Fig. 6. Transient responses of Generator G2 to a short circuit at node F in Area A for multiobjective optimization.

where I_{DLC} is the transient performance index for different loading condition, I_{BLC} is the transient performance index for base loading condition. A value of $I_N \leq 1.0$ indicates better dynamic performance compared to the base case where as a value of I_N > 1.0 characterizes operating conditions for which the expected behaviour is worse compared to the base case.

The normalized transient performance indices for different loading conditions in the test system are shown in Fig. 7. It can be seen from this figure that the normalized transient performance indices for $I_N(P_g)$, $I_N(V_t)$ and $I_N(E_{fd})$ are either near unity or less than unity for a wide operating conditions. This clearly indicates that the transient responses of the generators for different operating conditions are well damped and the system behaviour exhibits robustness for all loading conditions.

4.2. Case Study - online parameters tuning using ANNs

The effectiveness of the approach that has been presented in Section 3 is further demonstrated on the same test system. The input signals for the training of ANN were selected in such a way that the parameters of the PSS blocks are tuned so as to force the system to have a post-disturbance stable operating point as well as a better damping behaviour for all envisaged operating conditions and fault scenarios. The structure of each ANN used consists of four layers, namely an input layer, first hidden layer with six perceptron, second hidden layer with three-perceptron and an output layer with linear activation functions. The training data for all cases consist of 300 data sets which are related to variations of generator loadings, transformers tap positions and to different load distributions within the grid.

The parameter adaptation mechanism has been further investigated by using two alternative techniques, namely

- Dynamic adaptation in which the optimal parameters are passed to the PSS in every integration step. Thus, the ANN function in this case is evaluated before the PSS response is calculated which also requires more processing time.
- The second option, the parameters are adapted only to the steady-state operating point while they remained fixed during the dynamics.

On the other hand PSS with static parameter sets where the parameters are fixed for all operating conditions and at any times have been included in this simulation studies for the purpose of comparing.

It is observed in many cases simulated in this study that static controllers performed less as compared to those controllers adapted using either the steady-state or dynamic the input signals. Moreover, it is observed that the improvement in performance achieved from controllers adapted continuously is not much as compared to those adapted to the stead-state operating conditions only.

The dynamic responses of generator G1 to a short circuit of 150 ms duration at node F in Area-A are shown in Fig. 8. Moreover, for purpose of comparison, the figure shows the transient responses the generator G1 of the system with PSS parameters adapted using the techniques discussed above and fixed (static) parameter PSS. From this figure it is clear that the steady state adaptation of PSS parameters is sufficient to achieve a good performance in the overall system behaviour. On the other hand, continues dynamic adaptation seems not reasonable considering the time response shown in the figure. This can be further explained from the fact that the post-fault and pre-fault operating conditions are close enough. However, dynamic adaptation which properly tracks the tuning of the parameters is necessary during the transition period if the system moves to a new and less stable operating point for the case when there is a structural change in the system.

For demonstration purpose, the dynamic evolutions of the parameters provided by ANN of the generator G1 during the dynamic process are shown in Fig. 9. It can be seen from this figure that the variation of parameters is small and the parameters tend to the pre-fault steady state values according to the fact that pre- and post-fault stages are identical.

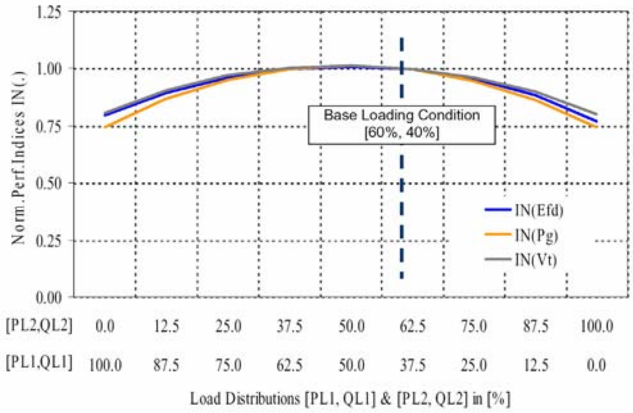

Fig. 7. Plot of the normalized transient performances indices for the multi-objective dynamic embedded optimization approach.

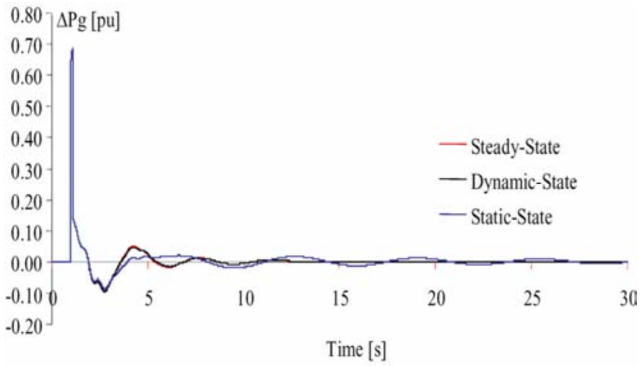

Fig. 8. Transient responses of Generator G1 to a short circuit at node F in Area A for dynamic, steady-state input signals to ANN based PSS and static type PSS.

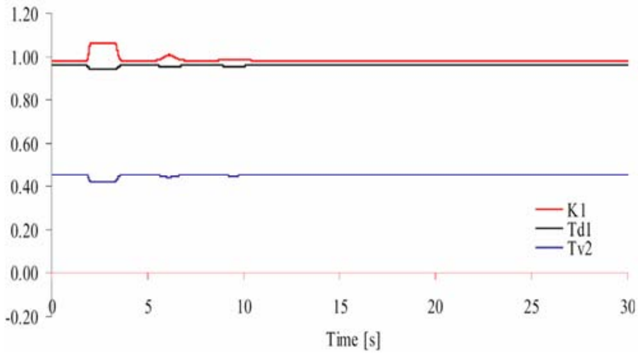

Fig. 9. The dynamic evolutions of the parameters from the output of the ANN of generator G1.

5. CONCLUSION

The central objective of this paper is to present a multi-objective dynamic optimization technique for tuning

Generator Excitation/PSS system parameters based on the time domain dynamic power system simulation. Furthermore, a new online adaptation approach using ANN for PSS parameter tuning is presented. The formulations of the optimisation problem as well as the computation structure for solving are discussed in detail. Besides, the effectiveness of these approaches is demonstrated by tuning realistic power system stabilizes for power system that uses minimum local-feedback information. The followings are summary of the results:

i) In Section 2, a multi-objective optimization approach that deals with optimal tuning of Generator Excitation/PSS system parameters has been formulated. The composite objective functional of the optimization problem that corresponds to different operating scenarios and/or variables in the system is chosen appropriately to reflect an overall appealing system performance. Moreover, the issue of robustness in the approach can be easily considered by carrying out simultaneously the optimization for different operating points. The time domain dynamic simulation which is embedded into the optimization procedure is computational fast even for very large power systems.

ii) In Section 3, computational intelligent techniques in particular ANN has been applied for online tuning of power system stabilizers (PSSs) in order to improve the robust dynamics performances of the power system under different operating and conditions and/or fault scenarios. Their ability to learn and store information about the system nonlinearities allows neural networks based PSS controllers to adapt to changes in the system operating conditions and moreover the system performances well for such changes in the system.

Nonlinear simulation results have confirmed the robustness of the system for all envisaged operating conditions and disturbances by using the proposed approaches. The methods suggested in this paper offer a practical tool for engineers to re-tune PSS parameters for improving the dynamic performance of the overall system.

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