Online Identification of Turbogenerator's Dynamics Using a Neuro-Identifier

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Abstract - **The increasing complexity of modern power systems highlights the need for effective system identification techniques for the successful control of power system. This paper proposes a robust continually online trained neuro-identifier to predict the outputs of turbogenerator - terminal voltage and speed deviation. The inputs to the neuro-identifier are the changes of the plant's outputs and plant's inputs. It overcomes the drawback of calculating deviation signals from reference signals for different operating points in previous work. Simulation results show that the neuro-identifier can provide accurate identification under different operating conditions. Furthermore, the neuro-identifier can learn the dynamics of the system in a short period of time, which makes it suitable for use with an online adaptive controller for the control of turbogenerators.**

Index Terms—**Neural networks, online identification, turbo-generator, and power system.**

I. Introduction

POWER systems are complex combination of multiple electrical and mechanical devices. These devices are nonlinear and their parameters vary with operating conditions, load changes, and unpredictable random disturbances. In power systems, turbogenerators are widely used and models of these machines play important roles in power system dynamic and transient studies.

Many synchronous machine models have been developed for different propose such as [1]-[3]. These models are good for analysis purposes but are not sufficient for design of nonlinear controllers. Firstly, the detailed high order models are too expensive to build and too computationally intensive to be used online [4]. Secondly, there are still lots of dynamics and nonlinearities that cannot be modeled in precise mathematical terms. Consequently, there are needs for effective identification technique that can accurately model the generators [5].

Artificial Neural networks (ANN) have excellent nonlinear mapping ability. They can adaptively model a dynamic nonlinear multi-input multi-output system on-line even when the system dynamics are changing. In recent years, lots of works have been done on the identification of power system using neural networks. According to the difference in network structures, these neuro-identifiers can be classified as feedforward types (multilayer perceptron - MLP, such as [6]-[10] and radial basis function network - RBF [5], [11]) and recurrent types, such as [12]-[13]. But effective identification technique that is suitable for online identification and can provide accurate prediction over a wide range of operating conditions is still a changeling work.

In this paper, a new neuro-identifier that can accurately estimate the outputs of the turbo-generator one time step ahead is proposed. In previous work ([6], [14]), the inputs to the neural network identifier are deviation signals. To compute these deviation signals, knowledge of their reference values ahead of time is required which is impossible in practice especially when random disturbances occur. In this paper, the inputs to the neuro-identifier are the changes between two consecutive plant outputs, so knowledge of the reference values ahead of time is not required. Simulation results show that the neuro-identifier is fast to learn and can provide accurate estimation over a wide range of operating conditions.

The power system model is described in section II. The design of the neuro-identifier is described in section III. Simulation results for training and testing are presented in section IV. Finally, the conclusions in section V.

II. Power System Configuration

The single machine infinite bus power system model used in this paper is shown in Fig. 1.

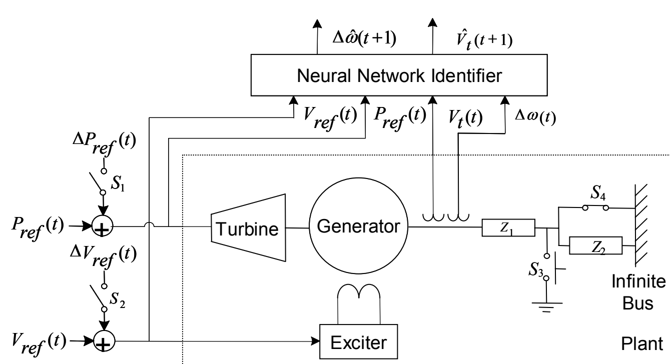

Fig. 1. Plant model used for on-line identification
(Z_1=Z_2=0.025+i0.7559)

The plant to be identified consists of a generator, a turbine, an exciter and a transmission line connected to an infinite bus. The generator is described by a seventh order d-q axis set of equations with the machine current, speed and

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rotor angle as the state variables [1, 3]. The parameters of the 3kW, 220V, 3-phase synchronous generator is given in Table 1 [6].

TABLE I: SYNCHRONOUS GENERATOR PARAMETERS

$T_{d0}'=6.69s$	$T_{q0}''=0.25s$	$X_d'=0.205pu$
$T_d'=0.66s$	$T_q''=27ms$	$X_d''=0.164pu$
$T_{d0}''=33ms$	$T_{kd}=38ms$	$X_q=1.98pu$
$T_d''=26.4ms$	$X_d=2.09pu$	$X_q''=0.213pu$

The transfer function block diagrams of the turbine and the exciter are shown in Figs. 2 and 3 respectively. The time constants of the turbine and exciter are given in Table II. The exciter's saturation factor S_e is given by:

$$S_e=0.6093exp(0.2165V_{fd}) \quad (1)$$

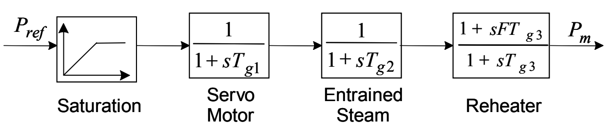

Fig. 2 Block diagram of the turbine

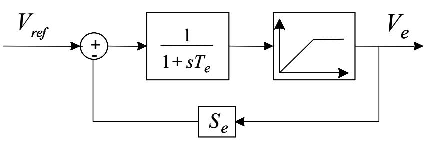

Fig 3 Block diagram of the exciter

TABLE II: TURBINE AND EXCITER TIME CONSTANTS

Servo time constant, T_{g1}	$0.15s$
Entrained steam delay, T_{g2}	$0.594s$
Steam reheat time constant, T_{g3}	$2.662s$
pu shaft output ahead of re-heater, F	$0.322pu$
Exciter time constant, T_e	$0.47s$

In these models, P_{ref} represents the turbine input power, V_{ref} represents the exciter input voltage, $\Delta\omega$ represents the speed deviation and V_T represents the terminal voltage. The neuro-identifier is used to estimate the outputs of the turbogenerator, $\Delta\hat{\omega}$ and $\hat{V}_T$. Two types of training are conducted and are discussed in section IV. During first type of training the switches S_1 and S_2 in Fig. 1 are closed in order to add pseudorandom binary signals (PRBS) ΔP_{ref} to P_{ref} and ΔV_{ref} to V_{ref}. During second type of training, S_1 and S_2 are opened. S_3 is used to simulate three phase line to ground fault. S_4 is used to simulate a transmission line impedance change. In this paper the plant refers to the combination of generator, exciter, turbine transmission line and infinite bus.

III. THE NEURO-IDENTIFIER DESIGN

During large operating condition changes, the turbo-generator outputs $\Delta\omega$ and V_t change a lot. But when the plant operates around its stable operating conditions, the changes are very small. If the plant outputs are directly fed into the neuro-identifier, the identifier can either learn severe or small changes. So some kind of transformation is needed to learn both small and large changes simultaneously.

In previous papers ([6], [14]), the inputs to the neuro-identifier are combination of deviation and actual signals. These means that the real values of the plant outputs are subtracted from their reference values in order to compute the deviation signals. In reality, since the changes in the operating conditions are random, it becomes impossible to compute the correct deviation signals for all instances.

In this paper, the plant outputs' changes over two consecutive time steps are calculated and mapped to limit range before they are fed into the neuro-identifier. The definitions of the twelve input nodes are shown in Table III. The three stages in the design of the neuro-identifier are described below.

TABLE III: DEFINITION OF INPUT NODES OF NEURAL NETWORK

NO.	DEFINITION	NO.	DEFINITION
1	$arctan(k_1\delta_{\Delta\omega}(t))$	7	$k_3P_{ref}(t)$
2	$arctan(k_1\delta_{\Delta\omega}(t-1))$	8	$k_3P_{ref}(t-1)$
3	$arctan(k_1\delta_{\Delta\omega}(t-2))$	9	$k_3P_{ref}(t-2)$
4	$k_2V_{ref}(t)$	10	$tan(k_4\delta_V(t))$
5	$k_2V_{ref}(t-1)$	11	$tan(k_4\delta_V(t-1))$
6	$k_2V_{ref}(t-2)$	12	$tan(k_4\delta_V(t-2))$

A. *Pre-Neuro-Identification Stage*

It has been shown that discrete-time nonlinear systems can be represented by the following difference equation [15]:

$$Y(k+1)=F_s[Y(k),Y(k-1),\ldots Y(k-n_y),U(k),U(k-1),\ldots,U(k-n_u)] \quad (2)$$

Where, $F_S(.)$ is nonlinear function; U and Y are plant's input and output respectively; n_u and n_y are delay values of the input and output respectively. The neuro-identifier proposed in this paper is similar to this and the model IV proposed in [16]. Here, Y denotes the estimated outputs of plant, speed deviation $(\Delta\hat{\omega})$ and terminal voltage $(\hat{V}_T)$. n_u and n_y are both selected to have three time delays. The definition of U is described in the following paragraphs.

Since V_{ref} and P_{ref} are per-unit values and between 0 and 1, they can be fed into the neuro-identifier directly. The changes in speed deviation and terminal voltage can be expressed as:

$$\delta_{\Delta\omega}=\Delta\omega(t) - \Delta\omega(t-1)$$
$$\delta_V=V_t(t) - V_t(t-1) \quad (3)$$

To map $\delta_{\Delta\omega}$, P_{ref}, V_{ref} and δ_V all into similar range, they need to be multiplied by some scaling factor. According to their numerical range, the scaling factors used are $k_1=10^5$, $k_2=1$; $k_3=1$, $k_4=10^3$ respectively. During natural training $\delta_{\Delta\omega}$

and δ_V are 10^4 bigger than that of during the steady state conditions. To avoid severe spikes into the neuro-identifier, arctangent functions are used to transform them to $(-\pi/2, \pi/2)$.

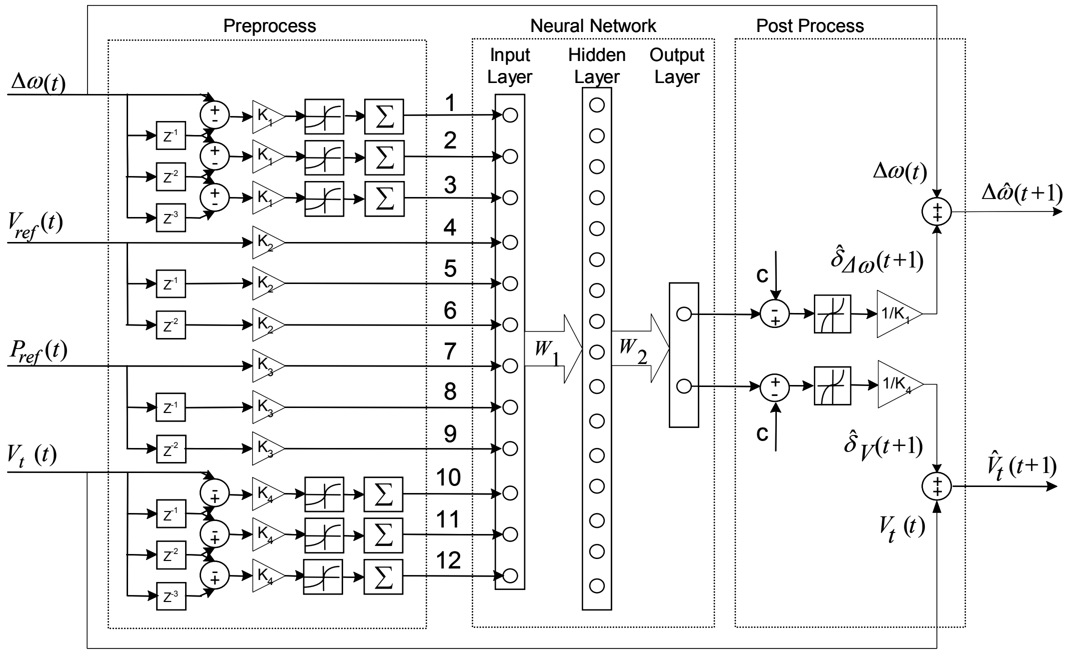

Fig. 4. Structure of the neural network identifier

B. Neuro-Identification Stage

Simulation results using recurrent neural networks for online identification of turbogenerator show that recurrent networks cannot improve the performance apparently and they need more computation for training. So feedforward network structures seem to be more preferable for online application. It is well known that Multi-Layer Perceptron (MLP) trained with Back-Propagation algorithm (BP) sometimes have problems with convergence. However, global convergence is not as important for online training as it is for offline training. Furthermore, the performance of MLP can be further improved by some modified kind of BP.

The neuro-identifier is a MLP with three layers, input, hidden and output layers. There are 12 neurons in the input layer (decided by the dimension of input vector). The outputs of the neuro-identifier are the estimated changes of the plant outputs at next sample time $-\hat{\delta}_{\Delta\omega}(t+1), \hat{\delta}_V(t+1)$. The number of neurons in the hidden layer is 14, which is found by trial and error. The sigmoid function used in the hidden layer is defined as:

$$f(x)=(1-e^x)/(1+e^x) \tag{4}$$

Since it maps the input to the range of [-1, 1], there is no need to use biases in the hidden layer. Simulation results show that small learning rate (0.04) using BP is better for the identifier to learn the dynamics of the plant gradually.

Another important issue is when to stop the training process for each training sample. There are two conflict criteria to be considered; one is the desired training error, the other is the maximum time for training (decided by the control sample time, can be defined as maximum training steps). Based on observations on convergence speed of the training process, the number of training steps for each training sample is set to 5.

C. Post Neuro-Identification Stage

The outputs of the neuro-identifier are the estimations of the changes in the plant outputs, $\Delta\hat{\delta}_{\Delta\omega}(t+1)$ and $\Delta\hat{\delta}_V(t+1)$. To get the estimations of the plant outputs - $\Delta\hat{\omega}(t+1)$ and $\hat{V}_t(t+1)$, the output values $\Delta\omega(t)$ and $V_t(t)$ at time t are added to the changes estimated, as shown by (5).

$$\begin{aligned} \Delta\hat{\omega}(t+1) &= \Delta\omega(t) + \hat{\delta}_{\Delta\omega}(t+1) \\ \hat{V}_t(t+1) &= V_t(t) + \hat{\delta}_V(t+1) \end{aligned} \tag{5}$$

IV. SIMULATION RESULTS

Two kinds of training are carried out to train the neuro-identifier, one is called the *forced training* and the other is called the *natural training*.

A. A. Forced Training

During forced training, pseudorandom binary signals (PRBS), ΔV_{ref} and ΔP_{ref} are added to the input of exciter and turbine respectively to excite all possible dynamics of the plant being identified by closing the switches S_1 and S_2 in Fig. 1. The magnitudes of the PRBS signal ΔV_{ref} and ΔP_{ref} are set to be 0.1 times of the magnitude of V_{ref} and P_{ref} respectively. Examples of the PRBS inputs applied to the turbine and the exciter at P=0.33pu and Q=0.001pu are shown in Figs. 5 and 6 respectively. The initial weights of the neuro-identifier are set to random value between -0.1 and 0.1. The learning rate for each training cycle is set to 0.04. The sampling frequency is set to 50 Hz.

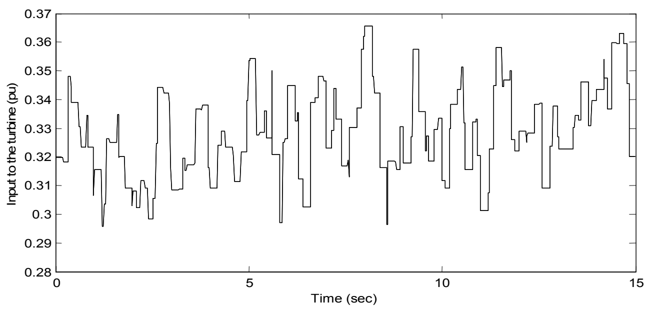

Fig. 5 Training signal P_{ref} applied to the turbine
(P = 0.333pu, Q = 0.001pu)

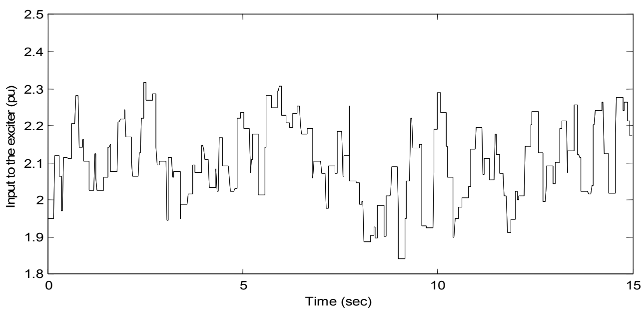

Fig. 6 Training signal V_{ref} applied to the exciter
(P = 0.333pu, Q = 0.001pu)

Fig. 7 shows the actual and estimated values $\delta_{\Delta\omega}$ and $\hat{\delta}_{\Delta\omega}$ of the changes in the speed deviation respectively. From the figures, it can be seen that the neuro-identifier needs very little time to learn the dynamics of the plant. Since the input and output signals to the neuro-identifier are both the changes in the speed deviation and these are much smaller compared with the actual value of the speed deviation, even if there are some errors between the actual and estimated speed deviation change, the estimated speed deviation is accurate therefore the separate curves are not visible in Fig. 8. Figures 9 and 10 are about the comparison of terminal voltage change $\hat{V}_t$ and terminal voltage V_t respectively. After training, the weights of the neuro-identifier are fixed and tested under the same and different operating points. The results are similar to that of training. This means the identifier have learnt the dynamics of the plant around the operating point very well. This is very important for online identification since it can save time needed to update the weights of the identifier.

The results for operating points change (P = 0.067pu, Q= - 0.0236pu to P = 0.333pu, Q = 0.001pu to P = 0.5pu, Q=0.048pu) are shown in Figs. 11 and 12. The operating points are changed by changing P_{ref} and V_{ref} at 5 and 10 seconds respectively. From the figures it can seen that the neuro-identifier can estimate the output of the plant very well. After training, the weights of the neuro-identifier are fixed and tested at different operating points (P = 0.2pu, Q = -0.02pu to P = 0.4pu, Q = 0.017pu). Figs. 13 and 14 show that the neuro-identifier can estimate accurately for different operating points.

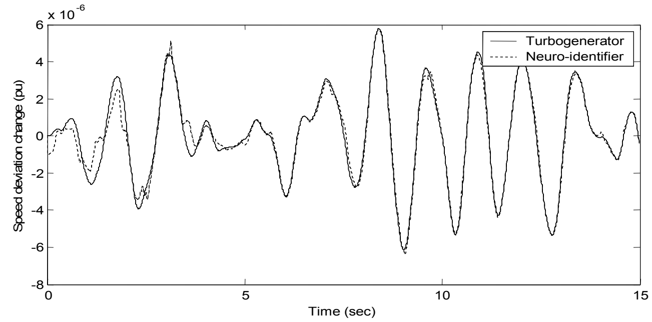

Fig. 7 Actual and estimated speed deviation change with forced training
(P = 0.333pu, Q = 0.001pu)

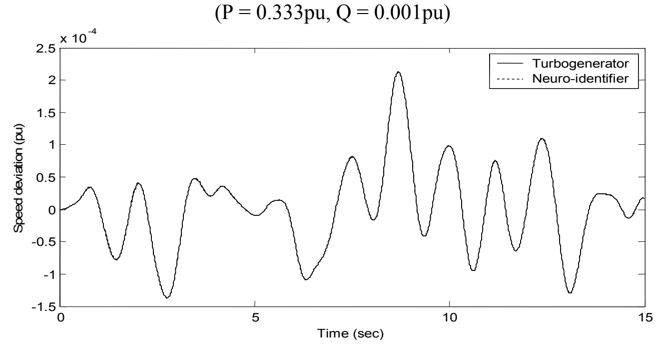

Fig. 8 Actual and estimated speed deviation with forced training
(P = 0.333pu, Q = 0.001pu)

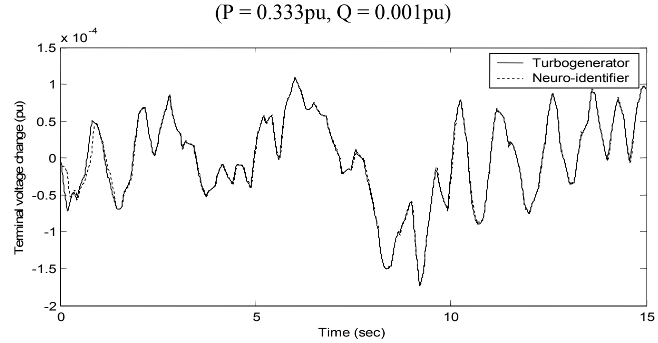

Fig. 9 Actual and estimated terminal voltage change with forced training
(P = 0.333pu, Q = 0.001pu)

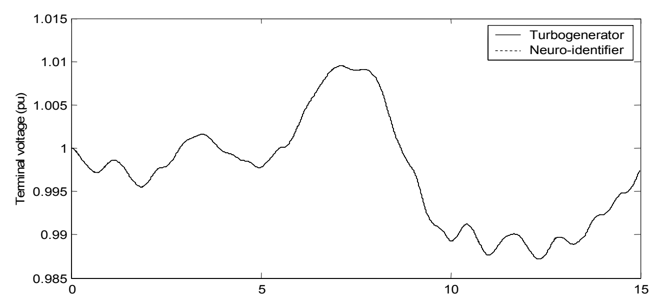

Fig. 10 Actual and estimated terminal voltage with forced training
(P = 0.333pu, Q = 0.001pu)

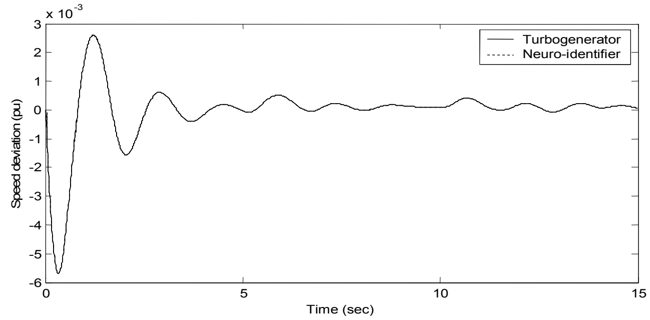

Fig. 11 Actual and estimated speed deviation with forced training (P = 0.067pu, Q= - 0.0236pu (0 - 5sec) to P = 0.333pu, Q = 0.001pu (5 - 10sec) to P = 0.5pu, Q=0.048pu (10-15 sec))

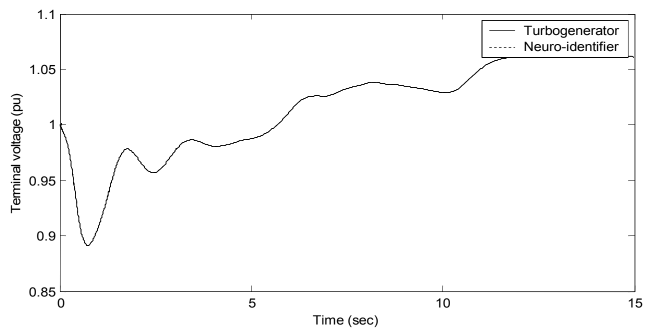

Fig. 12 Actual and estimated speed deviation with testing (P = 0.067pu, Q= - 0.0236pu (0 - 5sec) to P = 0.333pu, Q = 0.001pu (5 - 10sec) to P = 0.5pu, Q=0.048pu (10-15 sec))

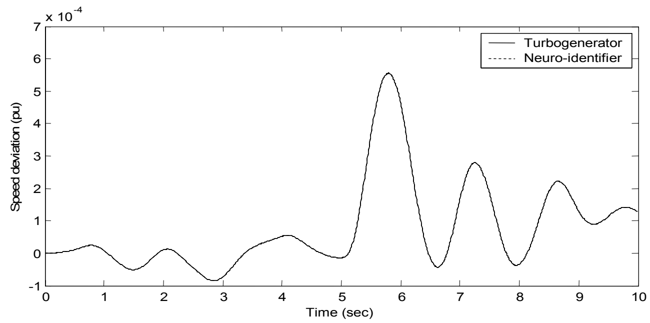

Fig. 13 Actual and estimated speed deviation with testing (P = 0.2pu, Q = - 0.02pu (0-5sec) to P = 0.4pu, Q = 0.017pu (5-10sec))

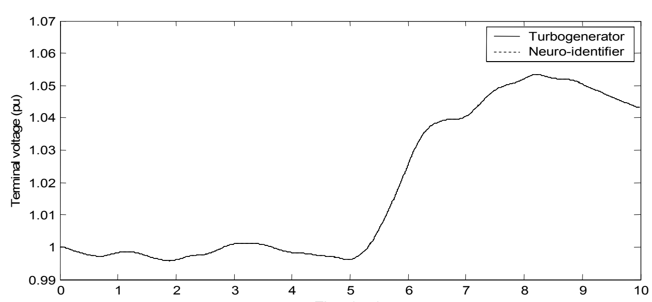

Fig. 14 Actual and estimated terminal voltage with testing (P = 0.2pu, Q = - 0.02pu (0-5sec) to P = 0.4pu, Q = 0.017pu (5-10sec))

B. B. Natural training

After forced training is fulfilled, ΔV_{ref} and ΔP_{ref} are set to zero and the operating conditions or the configurations of the system are changed at some time to do the so-called natural training. Two sets of natural training are conducted to simulate the changes in the configuration of the system, which are change in transmission line impedance and three phase short circuit fault. Switch S_3 is used to simulate the three phase short circuit fault and switch S_4 is used to simulate the transmission line impedance change.

Figs. 15 and 16 show the performance of the neuro-identifier when transmission line impedance changes at t = 2 second. Figs. 17 and 18 show the performance of the neuro-identifier when three phase short circuit occurs for the interval of [0.5 sec, 0.55 sec]. Limited by the length of the paper, the figures for $\delta_{\Delta\omega}$ and δ_V are not shown.

From Figs. 15-18, it is clear to see that the neuro-identifier performs very well for these two sets of system configuration change. Since the plant outputs change severely at the beginning of these changes in system configuration, the neuro-identifier needs time to learn this type of change.

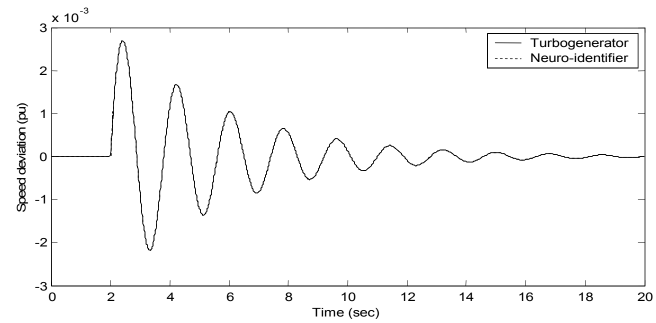

Fig. 15 Actual and estimated speed deviation with natural training (P = 0.333pu, Q = 0.001pu, switch 4 opened at 2sec)

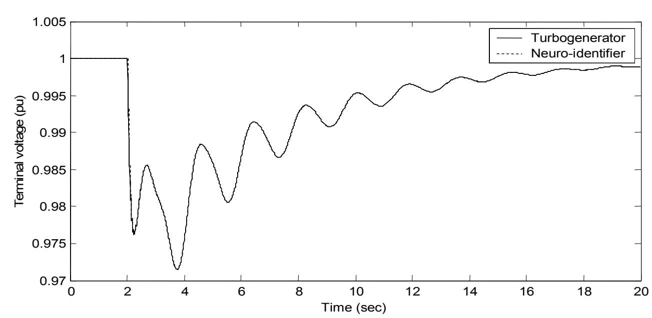

Fig. 16 Actual and estimated terminal voltage with natural training (P = 0.333pu, Q = 0.001pu, switch 4 opened at 2sec)

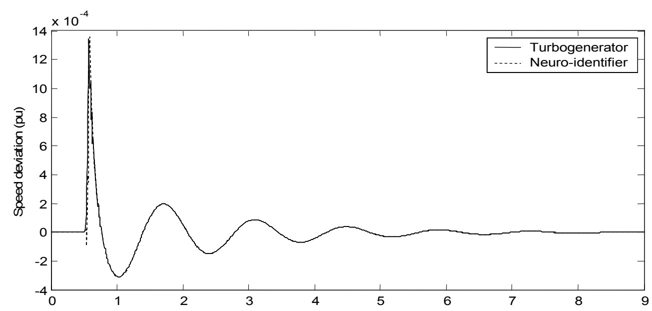

Fig. 17 Actual and estimated speed deviation with natural training (P = 0.333pu, Q = 0.001pu, 3-phase short circuit happens between 0.5 and 0.55sec)

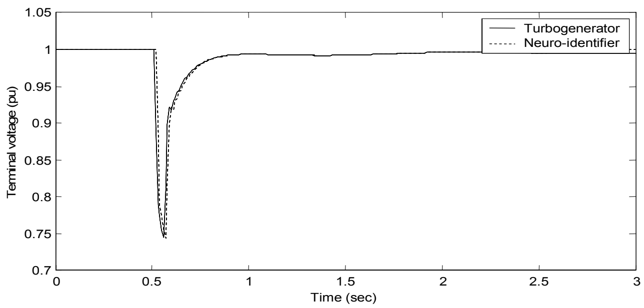

Fig. 18 Actual and estimated terminal voltage with natural training (P = 0.333pu, Q = 0.001pu, 3-phase short circuit happens between 0.5 and 0.55sec)

V. Conclusion

Identification of the dynamics of a turbogenerator connected to a power system is important for the effective control of a turbogenerator. In this paper, a robust neuro-identifier that can estimate the outputs of the turbogenerator one step ahead accurately is proposed. The method proposed shows that inputs and outputs signals of the turbogenerator can be used as inputs to the neuro-identifier without having to know any reference signal values therefore, a more practical technique for real time power system implementations. Simulation results of the forced and natural training show that the neuro-identifier can estimate the outputs of turbogenerator accurately for a wide range of operating range and conditions. Furthermore, the neuro-identifier learns the dynamics of the plant very fast, which is very important for real time implementations, not only for power system applications but any nonlinear large scale system.

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VII. Biographies

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