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, turbogenerator, 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 purpose 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 challenging 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 (Z1=Z2=0.025+i0.7559)](image_url)

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
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

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_{dl}$</td>
<td>0.69s</td>
</tr>
<tr>
<td>$T_{dr}$</td>
<td>0.25s</td>
</tr>
<tr>
<td>$X_{d}^*$</td>
<td>0.205pu</td>
</tr>
<tr>
<td>$T_{dl}$</td>
<td>0.66s</td>
</tr>
<tr>
<td>$T_{dr}$</td>
<td>27ms</td>
</tr>
<tr>
<td>$X_{d}^*$</td>
<td>0.164pu</td>
</tr>
<tr>
<td>$T_{dl}$</td>
<td>33ms</td>
</tr>
<tr>
<td>$T_{dr}$</td>
<td>38ms</td>
</tr>
<tr>
<td>$X_{q}^*$</td>
<td>1.98pu</td>
</tr>
<tr>
<td>$T_{dl}$</td>
<td>26.4ms</td>
</tr>
<tr>
<td>$X_{d}^*$</td>
<td>2.09pu</td>
</tr>
<tr>
<td>$X_{q}^*$</td>
<td>0.213pu</td>
</tr>
</tbody>
</table>

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:

$$S_e = 0.6093 \exp(0.2165V_{ref})$$

**Fig. 2 Block diagram of the turbine**

**Fig. 3 Block diagram of the exciter**

### TABLE II: TURBINE AND EXCITER TIME CONSTANTS

<table>
<thead>
<tr>
<th>Time Constant</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Servo time constant, $T_{s1}$</td>
<td>0.15s</td>
</tr>
<tr>
<td>Entrained steam delay, $T_{e2}$</td>
<td>0.594s</td>
</tr>
<tr>
<td>Steam reheat time constant, $T_{e3}$</td>
<td>2.662s</td>
</tr>
<tr>
<td>pu shaft output ahead of re-heater, $F$</td>
<td>0.322pu</td>
</tr>
<tr>
<td>Exciter time constant, $T_e$</td>
<td>0.47s</td>
</tr>
</tbody>
</table>

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, $\Delta \omega$ and $V_T$. 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) $\Delta P_{ref}$ to $P_{ref}$ and $\Delta V_{ref}$ to $V_{ref}$. During second type of training, $S_1$ and $S_2$ are opened. $S_1$ is used to simulate three phase line to ground fault. $S_2$ 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 turbogenerator 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

<table>
<thead>
<tr>
<th>No.</th>
<th>Definition</th>
<th>No.</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$\arctan(k_1\delta\omega(t))$</td>
<td>7</td>
<td>$k_2P_{ref}(t)$</td>
</tr>
<tr>
<td>2</td>
<td>$\arctan(k_1\delta\omega(t-1))$</td>
<td>8</td>
<td>$k_2P_{ref}(t-1)$</td>
</tr>
<tr>
<td>3</td>
<td>$\arctan(k_1\delta\omega(t-2))$</td>
<td>9</td>
<td>$k_2P_{ref}(t-2)$</td>
</tr>
<tr>
<td>4</td>
<td>$k_3V_{ref}(t)$</td>
<td>10</td>
<td>$\tan(k_4\delta\omega(t))$</td>
</tr>
<tr>
<td>5</td>
<td>$k_3V_{ref}(t-1)$</td>
<td>11</td>
<td>$\tan(k_4\delta\omega(t-1))$</td>
</tr>
<tr>
<td>6</td>
<td>$k_3V_{ref}(t-2)$</td>
<td>12</td>
<td>$\tan(k_4\delta\omega(t-2))$</td>
</tr>
</tbody>
</table>

A. Pre-Neuro-Identification Stage

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

$$Y(k+1) = F_2(Y(k), Y(k-1), ..., Y(k-n_y), U(k), U(k-1), ..., U(k-n_u))$$

Where, $F_2(.)$ 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 $(\delta\omega)$ and terminal voltage $(V_T)$ . $n_u$ 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:

$$\delta\omega = \Delta\omega(t) - \Delta\omega(t-1)$$

$$\delta V = V_T(t) - V_T(t-1)$$

To map $\delta\omega$ and $\delta V$ all into similar range, they need to be multiplied by some scaling factor. According to their numerical range, the scaling factors used are $k_1=10^5$, $k_2=1$; $k_3=1$, $k_4=10^7$ respectively. During natural training $\delta\omega$
and \( \delta \) are \( 10^4 \) bigger than that of during the steady state conditions. To avoid severe spikes into the neuro-identifier, \( \delta \) is \( \pi \) bigger than that of during the steady state.

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.

### 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 - \( \dot{\Delta} \delta_{\tilde{V}}(t+1) \). 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:

\[
f(x) = \frac{1-e^{-x}}{1+e^{-x}}
\]  

(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, \( \Delta \delta_{\tilde{V}}(t+1) \) and \( \Delta \delta_{\tilde{P}}(t+1) \). To get the estimations of the plant outputs - \( \Delta \tilde{\omega}(t+1) \) and \( \tilde{V}_f(t+1) \), the output values \( \Delta \tilde{\omega}(t) \) and \( \tilde{V}_f(t) \) at time \( t \) are added to the changes estimated, as shown by (5).

\[
\begin{align*}
\Delta \tilde{\omega}(t+1) &= \Delta \tilde{\omega}(t) + \Delta \delta_{\tilde{\omega}}(t+1) \\
\tilde{V}_f(t+1) &= \tilde{V}_f(t) + \Delta \delta_{\tilde{P}}(t+1)
\end{align*}
\]  

(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. Forced Training

During forced training, pseudorandom binary signals (PRBS), \( \Delta V_{\text{ref}} \) and \( \Delta P_{\text{ref}} \) 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 \( \Delta V_{\text{ref}} \) and \( \Delta P_{\text{ref}} \) 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 $P=0.33$pu and $Q=0.001$pu 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.

The results for operating points change ($P=0.067$pu, $Q=-0.0236$pu to $P=0.4$pu, $Q=0.017$pu). Figs. 13 and 14 show that the neuro-identifier can estimate accurately for different operating points.

After training, the weights of the neuro-identifier are fixed and tested at different operating points ($P=0.2$pu, $Q=-0.0236$pu to $P=0.5$pu, $Q=0.001$pu). The operating points are changed by changing $P_{ref}$ and $V_{ref}$ at 5 and 10 seconds respectively. From the figures it can be 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 ($P=0.2$pu, $Q=-0.0236$pu to $P=0.333$pu, $Q=0.001$pu) 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.
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 $\delta_{\text{dev}}$ and $\delta_{V}$ 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.

**B. Natural training**

After forced training is fulfilled, $\Delta V_{\text{ref}}$ and $\Delta P_{\text{ref}}$ 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
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.

VI. REFERENCE


V. CONCLUSION

VII. BIOGRAPHIES

Wenxin Liu (S’01) was born in Liaoning, P.R. China in 1975. He received the B.S. and M.S. degrees from the Northeastern University, Shenyang, P.R. China in ’86 and ’90 respectively. He joined the applied computational intelligence laboratory of University of Missouri at Rolla as a student in 2001. He is currently a Ph. D. candidate at the University of Missouri-Rolla. His research interests are in power system, nonlinear control, and neural networks.

Ganesh Kumar Venayagamoorthy (S’91-M’97-SM’02) was born in Jaffna, Sri Lanka. He received a BEng (Honors) degree with a First class in Electrical and Electronics Engineering from the Abubakar Tafawa Balewa University, Bauchi, Nigeria, in March 1984. He received his MScEng and PhD degrees in Electrical Engineering from the University of Natal, Durban, South Africa, in April 1999 and February 2002 respectively. He was appointed as a Lecturer with the Durban Institute of Technology, South Africa during the periods of March 1996 to April 2001 and thereafter as a Senior Lecturer from May 2001 to April 2002 where he lectured Control Systems and Signal Processing among other courses. He was a Research Associate at the Texas Tech University, USA in 1999 and at the University of Missouri-Rolla, USA in 2000/2001. He is currently an Assistant Professor at the University of Missouri-Rolla, USA. His research interests are in power systems, control systems, computational intelligence and evolving hardware. He has published over 60 papers in refereed journals and international conferences. Dr. Venayagamoorthy was a 2001 recipient of the IEEE Neural Network Society summer research scholarship and a Member of SAIEE (South Africa) since 1995.

Donald C Wunsch (SM’94) received the Ph.D. EE and the M.S. App. Math from the Univ. of Washington in ’91 and ’87, the B.S. in App. Math from the Univ. of New Mexico in ’84. Since ’99, he is the M.K. Finley Missouri Distinguished Prof. of Computer Engineering in the Dept. of ECE, Univ. of Missouri - Rolla, and heads the Applied Computational Intelligence Laboratory. Previously, he was Associate Prof. at Texas Tech. Prior to joining Tech in ’93, he was Senior Principal Scientist at Boeing, where he invented the first optical ART1 neural network, and other applied research. He also worked for Intl. Laser Systems and Rockwell Intl., and consulted for Sandia Labs, White Sands, and Accurate Automation Corp. Current research includes adaptive critic designs; neural network optimization, forecasting and control; and fuzzy risk assessment for high-consequence systems. He is an Academician in the Intl. Academy of Technological Cybernetics, and is recipient of the Halliburton Award for excellence, and a NSF CAREER Award. He is a member of the Intl. Neural Network Society, ACM, a life member of the AAAI, and previously served as Associate Editor of the IEEE Trans. on Neural Networks and voting member of the IEEE Neural Network Council. He has well over 100 publications in computational intelligence and attracted well over $3 million in competitively awarded sponsored research funding since 1994, and over $1 million since coming to UMR.