ON-LINE IDENTIFICATION OF SYNCHRONOUS MACHINES USING RADIAL BASIS FUNCTION NEURAL NETWORKS

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Abstract -- **On-line identification of the synchronous machines using Radial Basis Function Neural Network (RBFNN) is presented in this paper. The capability of the proposed identifier to capture the nonlinear operating characteristics of the synchronous machine is illustrated. The results of the proposed identifier performance due to square and uniformly distributed random variations in both mechanical torque and field voltage are compared with that obtained by time-domain simulations. Correlation-based model validity tests using residuals and inputs have been carried out to examine the validity of the proposed identifier. The results of these tests demonstrate the adequacy of the proposed identifier.**

I. INTRODUCTION

In power systems, synchronous machines are widely used and models of such machines play important roles in power system studies such as stability and control analysis. Many synchronous machine models have been developed, for example, the second order model is used to describe a single synchronous machine connected to an infinite bus where the rotor angle and the rotor speed are considered as the state variables [1]. The seventh order current and flux linkage models for a three phase synchronous machine are commonly used models when increased complexity is warranted [2]. More comprehensive studies and more complicated models are being developed to improve the accuracy of the representations. In general, simple machine models are good for analysis purposes but not accurate enough for predicting machine performance for control purposes. On the other hand, the higher order models improve the validity of the results. Unfortunately, the complicated models are too cumbersome for on-line applications. Generally speaking, the synchronous machine is a very complex nonlinear system with dynamics and nonlinearities which cannot be modeled in precise mathematical terms. Consequently, there is a necessity for a non-classical technique which has the ability to accurately model the machine. In this paper, a one-step-ahead identifier based on a radial basis function neural network (RBFNN) is introduced and examined to demonstrate its capability to learn the machine behavior.

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System representation and identification are fundamental problems in engineering where it is often required to approximate a real system with an appropriate model given a set of input-output data. The model structure needs to have sufficient representation ability to enable the underlying characteristics to be approximated with an acceptable accuracy. In many cases, the model also needs to retain simplicity. For linear time-invariant systems, model structure and identification problems have been well studied and the literature abounds with many useful methods and algorithms [3],[4]. Widely used structures are autoregressive moving average (ARMA), autoregressive with exogenous variables (ARX) and autoregressive moving average with exogenous variables (ARMAX) representations. Although the nonlinear autoregressive moving average with exogenous variables (NARMAX) description [5] has been shown to provide a very useful unified representation for a wide class of nonlinear systems, nonlinear system identification is much more complex and difficult. Hence, efficient parameter identification procedures are particularly important with nonlinear systems so that parsimonious model structures can be selected. In general, the problem of identifying a model structure and its associated parameters can be related to the problem of learning a mapping between a known input and output space. A classical framework of this problem can be found in approximation theory.

Recently, it has been shown that feedforward neural networks with one hidden layer can uniformly approximate any continuous function to a chosen degree of accuracy [6],[7],[8]. An introduction to a various neural network models and learning strategies are given in [9]. Feedforward neural networks trained with backpropagation algorithm, referred as backpropagation neural networks (BPNNs), have been applied to identification and control of dynamical systems [10]. BPNNs can be trained to emulate the unknown nonlinear plant dynamics by presenting a suitable set of input-output patterns generated by the plant [10],[11],[12]. In power systems, artificial neural networks (ANNs) are rapidly gaining popularity among power system researchers. The number of ANN applications to electric power system problems has increased dramatically in the last few years. A brief overview of the ANN applications to various power system problems is presented in [13],[14],[15]. Although BPNNs are widely used, there are several problems associated with these networks. First, BPNNs are prone to getting stuck in local minima on the error surface giving a solution that is not optimal [16]. Second, BPNNs have a relatively slow convergence rate, thus causing computation time for training of such networks with large number of parameters to be very long [17]. Finally, it is difficult to determine a minimal but adequate architecture that minimizes training time and optimizes generalization as well. The traditional approach to do so is the trial and error [17].

Similar to BPNN, radial basis function neural network (RBFNN) has the universal approximation ability [17],[18],[19]. Unlike the former, RBFNN has the best approximation property [20]. It has recently been acknowledged that approximation accuracy properties of RBFNN are advantageous as compared to the other methods, including multilayer perceptron networks [17-23]. Even more important for many applications, the RBFNNs provide linear approximation in the network weights. This feature makes powerful tools of the linear system theory applicable to the RBFNN identification of nonlinear systems [24]. The "linear in parameters" of the radial basis functions guarantees the convergence of the parameters to the global minimum. Moreover, the local tunability of the radial basis functions makes only a part of the nodes to be affected by any given input [17],[18], and only a portion of the model parameters may need to be adjusted, thus reducing the training time and computational overhead. Furthermore, RBFNNs are not as sensitive to the architecture as BPNNs [25].

In this paper, a single synchronous machine connected to an infinite bus is on-line identified to obtain one-step-ahead prediction using a radial basis function neural network (RBFNN). The paper is organized as follows. Section II introduces a brief summary of radial basis function neural network applied to model a system. The problem of on-line identification of the synchronous machine is formulated in section III. The correlation-based model validity tests is discussed in section IV. Section V includes the results obtained using the proposed identifier due to square and random variations in the machine inputs. The time-domain simulations are also given in section V for comparison purposes. Finally, some concluding remarks on the performance of the proposed identifier are given in section VI.

II. RADIAL BASIS FUNCTION NETWORK

Recently, there has been an increasing interest in radial basis functions (RBFs) within the neural network community as a traditional and powerful technique for interpolation and function approximation in multidimensional space [26],[27]. The RBF is a function which has in-built distance criterion with respect to a center. Functions like this have been shown to be very effective for interpolation and nonlinear function approximation [27]. A recent application for RBFs is in the area of neural networks where they can be used as replacement for the BPNNs. Like most feedforward networks, RBF networks have three layers, namely, an input layer, a hidden layer and an output layer. The nodes within each layer are fully connected to the previous layer nodes. A schematic diagram of an RBFNN with n inputs and m outputs is given in Fig. 1.

The input variables are each assigned to a node in the input layer and pass directly to the hidden layer without weights. The hidden layer nodes are the RBF units. Each node in this layer contains a parameter vector called a center. The node calculates the euclidean distance between the center and the network input vector, and passes the result through a nonlinear function, $\Phi(.)$, which is analogous to the sigmoid functions commonly used in the BPNN models. The output layer is essentially a set of linear combiners. The overall input-output response of the RBF network is a mapping $f: R^n \to R^m$,that is,

$$y_i = w_{0i} + \sum_{j=1}^{n_h} w_{ji} \Phi\left(\|x - c_j\|, \beta_j\right) \quad (1)$$

where :

$y_i, 1 \le i \le m,$ is the i-th output

$x \in R^n$ is the input vector

w_{0i} is the biasing term

n_h is the number of hidden units

w_{ji} is the weight between the j-th hidden node and the i-th output node

$c_j \in R^n$ is the center of the j-th hidden node

$\|.\|$ is the euclidean norm

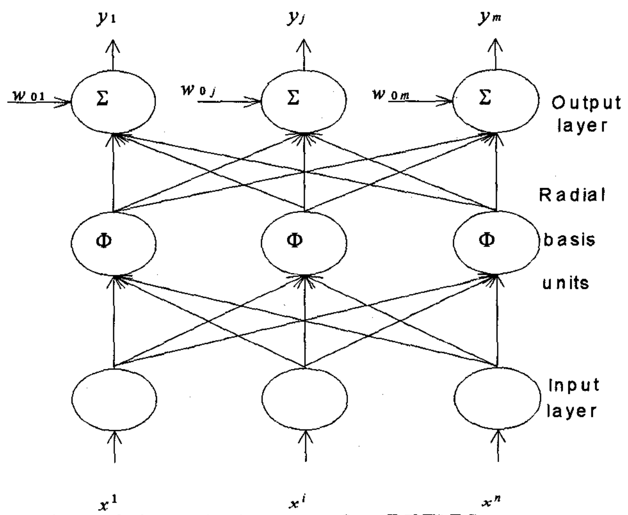


Fig. 1. Schematic diagram of an RBFNN

$\beta_j \in R$ is the j-th hidden unit width

$\Phi(.)$ is the nonlinear function from $R^+ \to R$

Theoretical investigations and practical results suggest that the choice of the nonlinearity $\Phi(.)$ is not crucial to the performance of the RBFNN. Some typical choices of $\Phi(.)$ are given in [18]. In this study, $\Phi(.)$ is chosen to be gaussian activation function, that is,

$$\Phi(z,\beta) = \exp(-z^2 / \beta^2) \tag{2}$$

For on-line identification using RBFNN, a recursive identification algorithm is required to update the network parameters. The centers should suitably sample the network input domain and should be able to track the changing patterns of data. The initial centers are uniformly assigned in the vicinity of the domain of the input space. At each iteration, the centers are updated using k-means algorithm [28]. Since the network response is linear with respect to its weights, the recursive least squares (RLS) method is considered for adjusting the network weights [21]. On the other hand, the width parameter of the i-th hidden unit, β_i, is chosen to be the average distance between the neighboring unit centers [24].

III. PROBLEM FORMULATION

The seventh order flux linkage model [1] of a single synchronous machine connected to an infinite bus through a transformer and two transmission lines as shown in Fig. 2 is used in this study. The state and output equations of the synchronous machine are described by the following nonlinear discrete state space model

$$X(k+1)=F(X(k),U(k)) \tag{3}$$
$$Y(k)=G(x(k)) \tag{4}$$

In the above model, $F(.)$ and $G(.)$ are the nonlinear state and output mapping functions respectively. The input vector, $U(k)$, represents the mechanical torque, T_m, and the field voltage, V_{fd}, that is, $U(k)=[T_m(k),\ V_{fd}(k)]^T$. $X(k)$ is the state vector, that is, $X(k)=[\delta, w, \psi_{fd}, \psi_d, \psi_{kd}, \psi_q, \psi_{kq}]^T$ and $Y(k)$ is the output vector. The rotor angle and the rotor speed are represented by the states δ and w respectively. The states ψ_{fd}, ψ_d and ψ_q are the field, the d-axis and the q-axis flux linkages respectively while ψ_{kd} and ψ_{kq} are the flux linkages in damper windings in the d and q axes respectively. In this study, we observe two quantities: the rotor angle, δ, because it is an important indicator of generator stability, and the flux linkage in the d-axis, ψ_d, because it is a representative of the Q-V transient process. Hence, the output vector $Y(k)=[\delta(k),\ \psi_d(k)]^T$.

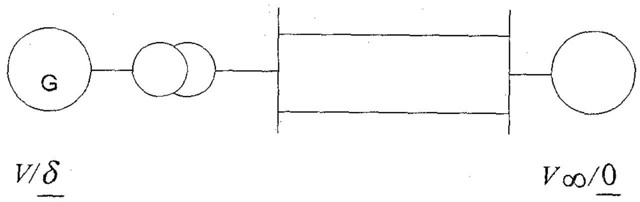


Fig. 2. Synchronous machine connected to an infinite bus

It has been rigorously proved that a wide class of discrete-time nonlinear systems can be represented by the following difference equation model [29]

$$Y(k+1)=F_s[Y(k),Y(k-1),\ldots,Y(k-n_y), U(k),U(k-1),\ldots,U(k-n_u)] \tag{5}$$

where $F_s(.)$ is some nonlinear function and n_y and n_u are the lags of the output and input respectively.

The objective of this study is to use RBFNN to model the synchronous machine as described by (5). Define the input vector of the network at sample k as

$$V(k)=[Y(k),Y(k-1),\ldots,Y(k-n_y), U(k),U(k-1),\ldots,U(k-n_u)]^T \tag{6}$$

Hence the dimension of the input vector and consequently the dimension of the centers of the hidden nodes is given by

$$n_i = m.n_y + n.n_u \tag{7}$$

where m and n are the number of outputs and inputs of the network respectively while n_i is the input vector dimension.

The RBFNN expansion $F_s(V(k))$ is then a one-step-ahead prediction of $Y(k)$. The structure of the RBFNN identification scheme is shown in Fig. 3 where the output of the delay elements block is the delayed values of its input signals and $C(k)$ and $W(k)$ are the updated values of the network centers and weights respectively.

IV. MODEL VALIDATION

The adequacy of the modeling can be tested using the correlation-based model validity tests. Define the residual vector

$$E(k)= Y(k) - Y_{net}(k) \tag{5}$$

It can be shown [30],[31] that if the identified model is operating correctly then the following correlation tests using

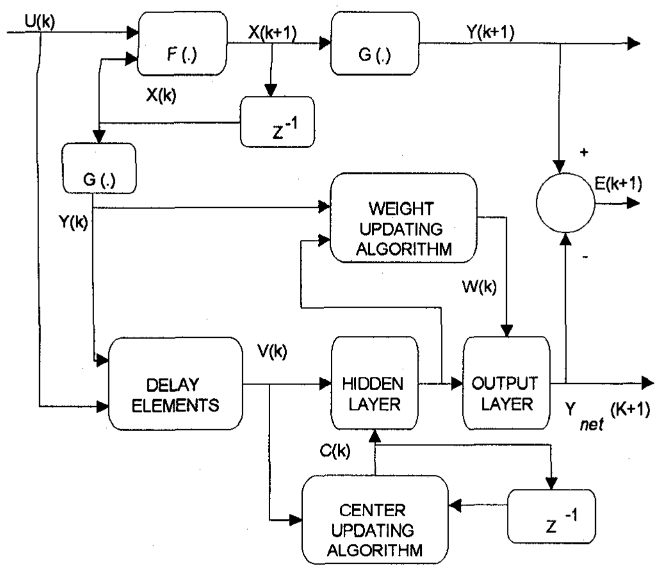


Fig. 3. The structure of the RBFNN identifier

residuals and inputs should be satisfied:

$$\Gamma_{e_ie_i}(\tau)=\Gamma_{e_i^2e_i^2}(\tau)=\delta(t),\forall\tau$$
$$\Gamma_{u_re_i}(\tau)=\Gamma_{u_r^2e_i^2}(\tau)=0,\forall\tau \qquad (6)$$

where e_i is the i-th residual and u_r is the r-th input. Γ_{xx} and Γ_{yx} are the auto-correlation and cross-correlation functions respectively while $\delta(t)$ represents the unit impulse function. In practice, the model will be regarded as adequate if all the tests in (6) fall within the 95% confidence bands at approximately $\pm1.96/\sqrt{N}$ where N is the number of samples. In this study, there are two residuals and two inputs. The residuals are given in (5) and the inputs are the mechanical torque, T_m, and the field voltage, V_{fd}.

V. RESULTS AND DISCUSSION

In order to investigate the performance of the proposed RBFNN identifier, two kinds of disturbances have been applied to the machine inputs, T_m and V_{fd}, to derive the machine and proposed identifier simultaneously. Namely, the first is a square variation in the range of 80-120% of the initial values of the inputs. The second is a random variation signal uniformly distributed in the range of 60-140% of the initial values of the inputs. Initially, the machine was operating at power of 1.0 pu with 0.85 power factor lag and terminal voltage of 1.0 pu. The following studies have been performed and the results of the proposed identifier and time-domain simulations were compared to demonstrate the adequacy of the proposed identifier. Moreover, some correlation-based model validity tests using residuals and inputs have been carried out to show the validity of the proposed identifier. In all cases ten historical values of the inputs and outputs were used to construct the input vector of the network.

A. Variations in the Mechanical Torque (T_m)

The behavior of the proposed identifier due to square variation in the mechanical torque is compared with the time-domain simulations in Figs. 4 and 5. Fig. 4 shows the response of the rotor angle while Fig. 5 shows the response of the d-axis flux linkage. The responses of the rotor angle and d-axis flux linkage due to random variation are shown in Figs. 6 and 7 respectively. It is worth pointing out that it is difficult to discern a difference between the simulated and identified responses confirming the capability of the proposed identifier to capture the nonlinear operating characteristics of the synchronous machine. The results of the model validation tests, as shown in Fig. 8, fall within the 95% confidence bands satisfying the conditions stated in (6) and confirming the adequacy of the proposed identifier. The training error versus time is shown in Fig. 9. It is clear that the training error dramatically decreases converging almost to zero in time less than 0.01 sec. This demonstrate the suitability of the proposed identifier for on-line applications. It is found that only 10 neurons in the hidden layer are adequate for the proposed identifier which makes the structure of the identifier very simple.

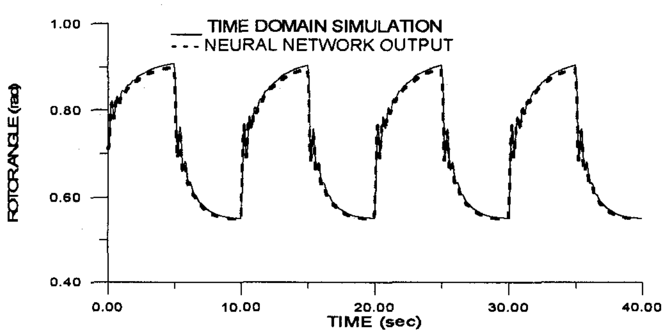


Fig. 4. Rotor angle response due to 80-120% square change in the mechanical torque

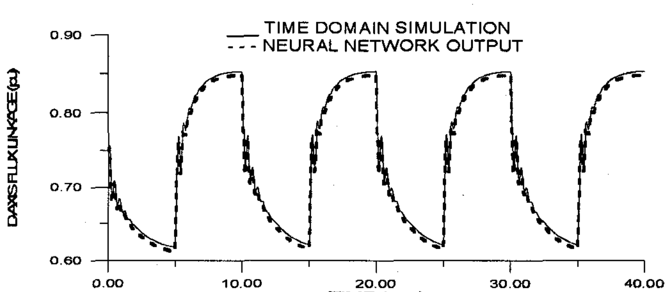


Fig. 5. D-axis flux linkage response due to 80-120% square change in the mechanical torque

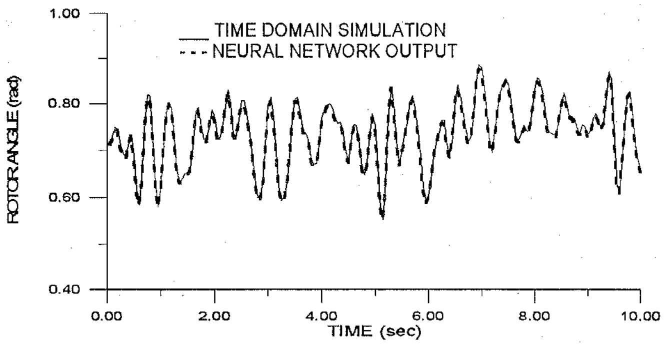


Fig. 6. Rotor angle response due to 60-140% random change in the mechanical torque

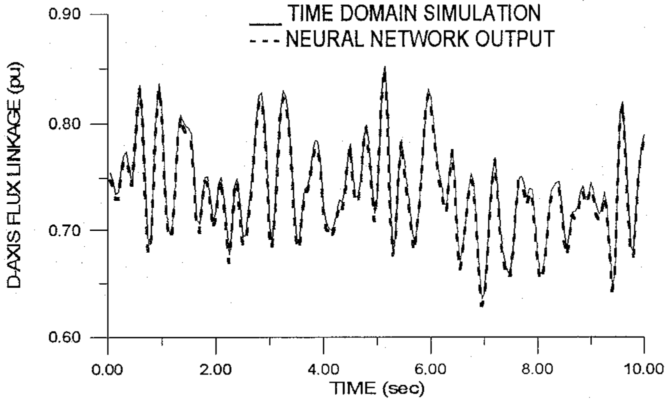
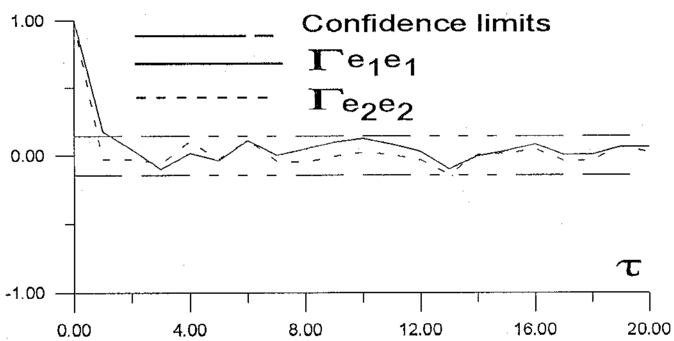
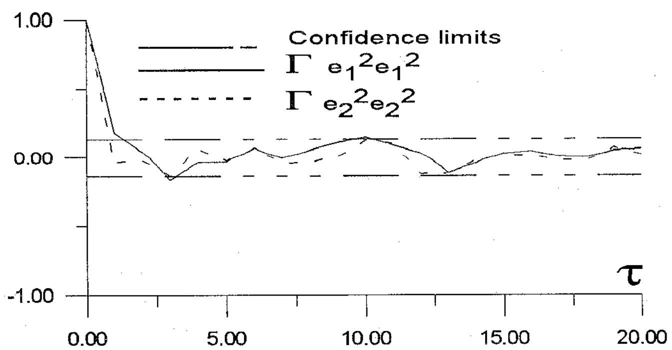


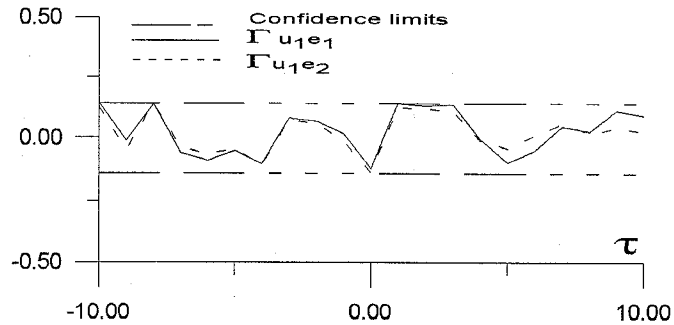
Fig. 7. D-axis flux linkage response due to 60-140% random change in the mechanical torque



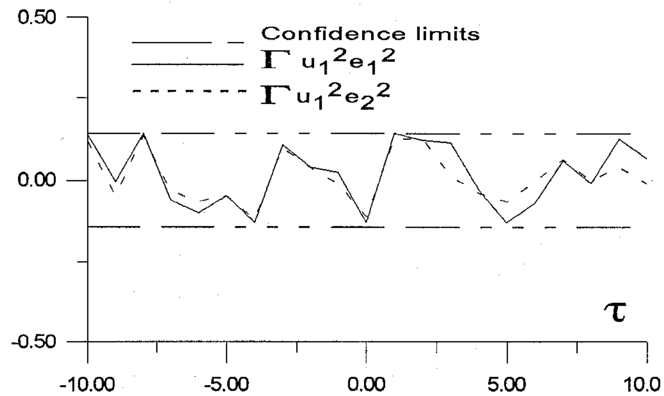
(a)



(b)



(c)



(d)

Fig. 8. Auto-correlation and cross-corelation tests using residuals and T_m

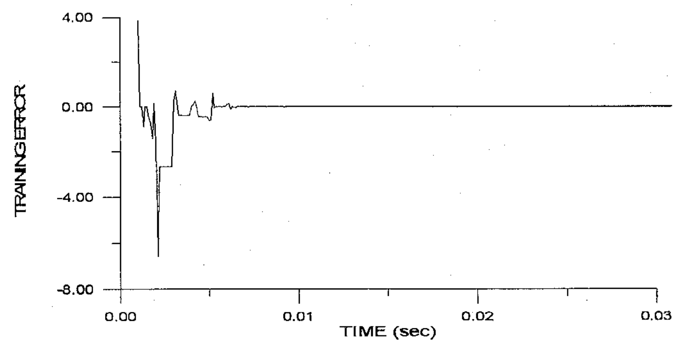


Fig. 9. Training error

B. Variations in the Field Voltage (V_{fd})

The responses of the rotor angle and d-axis flux linkage due to square variation in the field voltage are shown in Figs. 10 and 11 respectively. Figs. 12 and 13 show the responses of the rotor angle and d-axis flux linkage respectively due to random variation. The results demonstrate the capability of the proposed identifier to learn the underlying characteristics of the synchronous machine. In this case, 11 neurons in the hidden layer are found to be adequate.

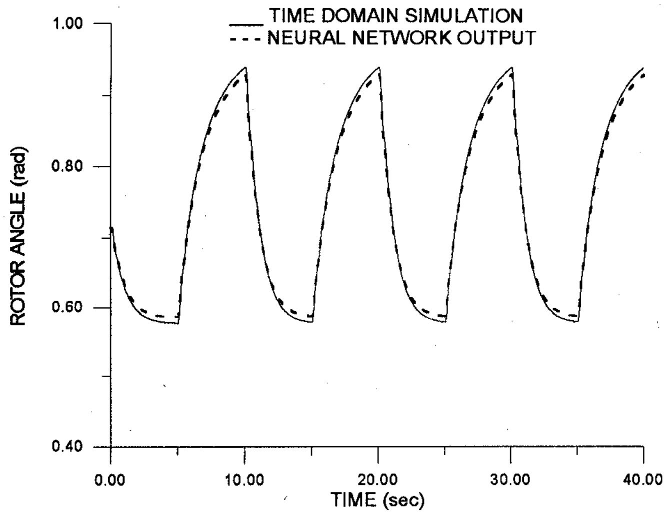


Fig. 10. Rotor angle response due to 80-120% square change in the field voltage

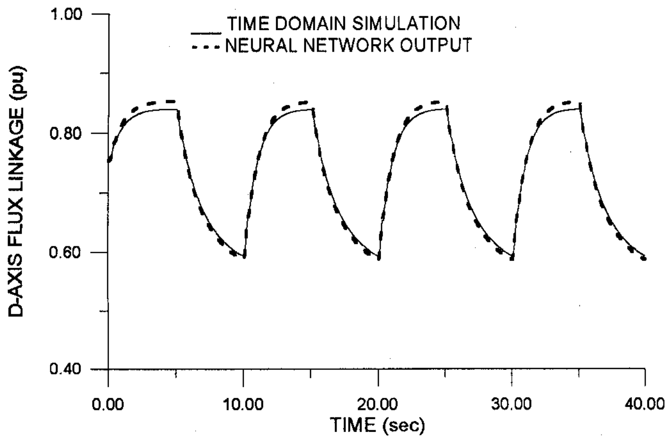


Fig. 11. D-axis flux linkage response due to 80-120% square change in the field voltage

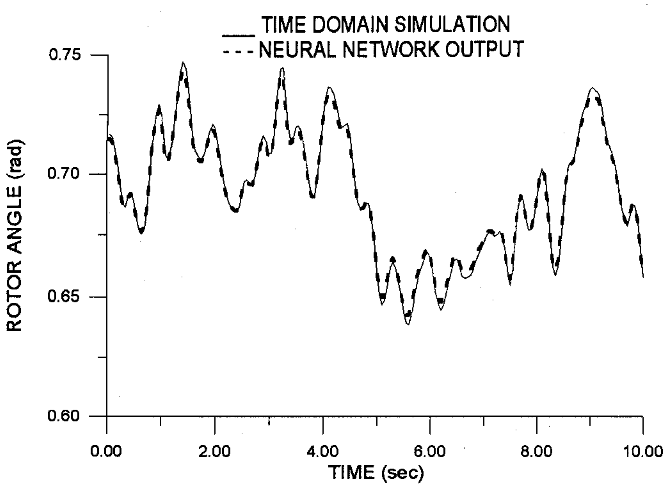


Fig. 12. Rotor angle response due to 60-140% random change in the field voltage

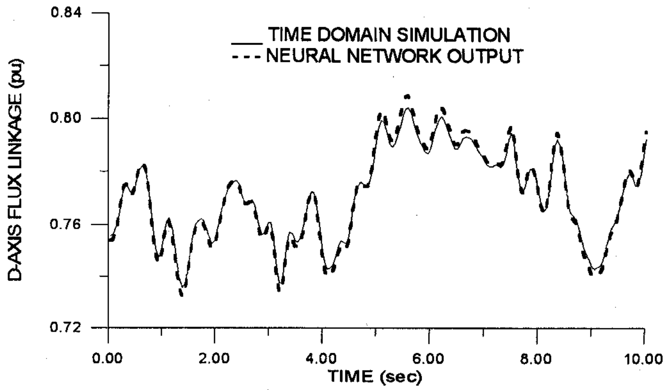


Fig. 13. D-axis flux linkage response due to 60-140% random change in the field voltage

VI. CONCLUSIONS

The synchronous machine has been successfully identified using RBFNN. The results of this paper show that the nonlinear operating characteristics of the synchronous machine have been accurately captured by the proposed RBFNN identifier. The proposed identifier was trained using an adaptive recursive technique that is powerful in on-line applications. The close agreement of the results obtained by simulations and that obtained by the proposed identifier for both the rotor angle and d-axis flux linkage indicates the capability of the proposed identifier for on-line modeling and identification of the synchronous machine. The results of the correlation-based model validity tests using residuals and inputs show that all the tests in (6) fall within the 95% confidence bands confirming the adequacy of the proposed identifier. Finally, the performance results of the proposed identifier with the results of the model validation tests demonstrate the potential of the proposed identifier that exhibits excellent performance with a relatively simple radial basis function neural network architecture.

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