Development and Implementation of Neural Network Observers to Estimate the State Vector of a Synchronous Generator from On-line Operating Data

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Abstract: This paper presents a novel technique for developing and implementing artificial neural network (ANN) observers for estimating un-measurable rotor body currents of a synchronous generator from time-domain on-line disturbance data. Data for training the observers are generated through off-line simulations of a 7.5 kVA machine model whose parameters are varied in accordance with previously determined on-line parameter estimates of the generator under consideration. Studies show that observer robustness towards noise can be improved by enhancing the size of the observer input vector. In order to increase observer robustness towards variations in the field-resistance, simulated variations representative of changes in field-resistance were introduced in the training sets. After training, the observers are tested with experimentally obtained on-line measurements to provide estimates of un-measurable rotor body currents. The estimated rotor body currents are then used along with experimental measurements to estimate synchronous generator parameters.

Keywords: Round rotor synchronous generators, artificial neural networks, observers, state estimation.

I. INTRODUCTION

A problem of emerging importance in synchronous machine modeling is the use of on-line response data for accurate parameter estimation [1-6]. Typically, the measured responses are a small subset of the synchronous generator's state vector. In the absence of information pertaining to the generator's un-measurable states (such as currents in the rotor-body circuits), estimation algorithms based on non-linear minimization techniques have to be used to estimate machine model parameters. However, if complete state information is available, recursive algorithms may be used to estimate the machine parameter vector [7].

Observers have often been used to estimate state information by processing available measurements. Investigators have developed various observers for estimating the state vector of a synchronous generator [11-14]. Neural networks, with their parallel processing abilities provide a viable means for re-constructing, in real time, the synchronous generator's state vector from a set of measurements. In the area of electric machine modeling and control, researchers have developed and implemented neural network based observers to re-construct the state vector based on available measurements [15-18].

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In reference [7], we showed how linear neural networks can be trained to estimate un-measurable rotor-body currents by processing sequences of measurements acquired during transient disturbances. The work presented in reference [7] assumed that *nominal* machine model parameters were used to generate simulated measurements for observer development. However, the implementation of a linear neural network in an actual operating environment will result in incorrect estimates of rotor-body currents. This is because machine model parameters estimated on-line can deviate substantially from corresponding nominal estimates obtained off-line. Indeed, references [6, 8] show that on-line machine model parameter estimates are non-linear in nature and influenced by generator operating condition.

In view of the above factors, it is imperative to develop ANN observers which can account for model parameter non-linearities and provide accurate estimates of rotor body currents irrespective of generator operating condition. Instead of using nominal machine parameters, data for training the observers are generated through off-line simulations of a machine model whose parameters are varied according to on-line parameter estimates obtained in reference [8]. During training, all state variables of the machine model are assumed to be known. This corresponds to a stage when simulations are carried out to determine the order and parameters (weights and biases) of the ANN observers. After enhancing observer robustness to simulated parameter variations and noise, the trained ANN observers are tested with experimentally obtained on-line measurements to provide estimates of un-measurable rotor body currents. These estimates are then used along with experimental measurements to estimate machine parameters.

II. PROBLEM FORMULATION

The structure of the machine model used to describe the dynamics of the 7.5 kVA, 240V, 60 Hz. round-rotor generator under study is shown in Figure 1. The procedures used to establish the parameters of this particular machine model from on-line response data are reported in references [8,9].

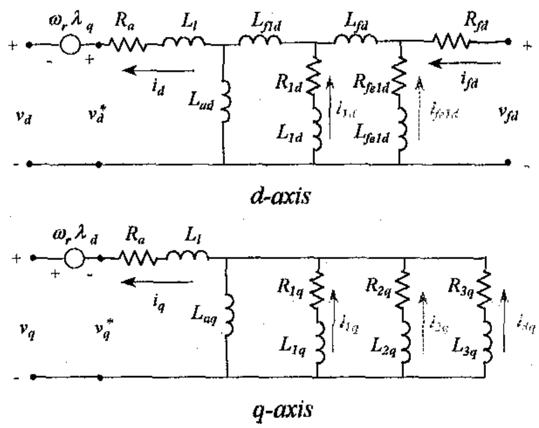


Fig. 1. Model 3'.3: On-line Model Structure

As shown in references [7-9], it is possible to de-couple the state variables appearing in the d- and q-axis equivalent circuits by computing voltages v_d^* and v_q^* from on-line response data. For illustration purposes, the discrete-time state-space representation of the d-axis equivalent circuit is repeated in equation (1). Also, v_{fd}^*, i_{fd}^*, and R_{fd}^* represent the field-voltage in volt, field-current in ampere, and field-resistance in ohm, all measured on the field side of the generator [7]. All quantities appearing in equation (1) are in actual units.

$$\begin{cases} X_d(k+1) = A_d(\theta_d)\cdot X_d(k) + B_d(\theta_d)\cdot U_d(k) \\ Y_d(k) = C_d \cdot X_d(k) \end{cases} \tag{1}$$

where,

$$X_d = [i_{1d} \quad i_{1d} \quad i_{fe1d} \quad i_{fd}^*]^T;\; U_d = [v_d^* \quad v_{fd}^*]^T;\; Y_d = [i_d \quad i_{fd}^*]^T;$$
$$\theta_d = [R_a \quad R_{fd}^* \quad R_{1d} \quad R_{fe1d} \quad L_l \quad L_{ad} \quad L_{1d} \quad L_{fe1d} \quad L_{fd} \quad L_{f1d} \quad a]^T;$$

It must be emphasized that the parameters of the machine models are non-linear and vary as a function of machine operating condition. The observers developed in this study must be able to account for parameter non-linearities and produce accurate estimates of rotor-body currents over the normal operating range of the generator.

III. ANN OBSERVER BASED ESTIMATION OF ROTOR-BODY CURRENTS

We now propose a set of observers which can map sequences of measurable voltages, currents, and stator flux-linkages to un-measurable rotor body currents. It must be noted that the procedures given in references [7-9] can be used to compute stator flux-linkages from records of stator voltages and currents. Due to space limitations, results showing the development and implementation of the d-axis observers will only be described. A similar procedure is adopted to develop the q-axis observers.

In this study, the observers are developed using a two stage procedure. In Stage 1, simulated measurements are generated to train the ANN observers. In Stage 2, the trained observers are tested extensively with simulated as well as experimentally acquired on-line data.

Let vector $\xi(k)$ be a vector comprising of sequences of simulated machine variables. For the d-axis model whose dynamics are represented by equation (1),

$$\xi(k) = [v_d^*(k) \quad v_{fd}^*(k) \quad i_d(k) \quad i_{fd}^*(k) \quad \lambda_d(k) \ldots \\ v_d^*(k-l_1) \quad v_{fd}^*(k-l_2) \quad i_d(k-l_3) \quad i_{fd}^*(k-l_4) \quad \lambda_d(k-l_5)]^T; \tag{2}$$

The lags l_1 through l_5 are established using cross-correlation studies between measurable machine variables and un-measurable rotor body currents.

Let N_{i1d} represent the mapping from $\xi(k)$ to $i_{1d}(k)$, and let N_{ife1d} represent the mapping from to $\xi(k)$ to $i_{fe1d}(k)$. i.e.,

$$\begin{cases} i_{1d}(k) = N_{i1d}(\xi(k)) \\ i_{fe1d}(k) = N_{ife1d}(\xi(k)) \end{cases} \tag{3}$$

All quantities in equations (2) and (3) are given in actual units. N_{i1d} and N_{ife1d} are non-linear in nature. It is desired to establish these mappings by using a pair of multi-layer feed-forward perceptrons (one for each rotor-body current).

Each multi-layer feed-forward perceptron described in this paper consist of n processing elements in the input layer, each processing element corresponding to each element of vector $\xi(k)$. A single processing element is used in the output layer of each network corresponding to the rotor-body current ($i_{1d}(k)$ or $i_{fe1d}(k)$) whose mapping is to be established. The number of hidden layers, and the number of processing elements in the hidden layer of each network are established during observer development. The weights and biases of each network are established by presenting patterns of $\xi(k)$ to the input layer and corresponding desired rotor-body currents to the output layer of each network so as to minimize the following cost functions:

$$\begin{cases} E_{i1d} = \sum_k [i_{1d}(k) - \hat{i}_{1d}(k)]^2 \\ E_{ife1d} = \sum_k [i_{ife1d}(k) - \hat{i}_{ife1d}(k)]^2 \end{cases} \tag{4}$$

In equation (4), E_{i1d} and E_{ife1d} represent the sum-squared-errors (SSE) between actual currents i_{1d}, i_{fe1d} and estimated currents, $\hat{i}_{1d}, \hat{i}_{fe1d}$ produced by each ANN observer respectively. Training is the process of iteratively adjusting the weights of the networks such that the errors E_{i1d} and E_{ife1d} are minimized. Throughout this investigation, the Marquardt back-propagation algorithm [19] is used to train the neural network such that the sum squared errors defined in equation (4) are minimized over all training patterns.

After training, the observers are tested with experimentally obtained on-line measurements to provide estimates of un-measurable rotor body currents. i.e., the elements of vector $\xi(k)$ are obtained experimentally and input to each ANN observer to estimate $\hat{i}_{1d}$, and $\hat{i}_{fe1d}$. These estimated rotor body currents are then incorporated into the d-axis state-vector X_d along with measured currents i_d, and i_{fd}^* as:

Table 1: *d*-axis machine model parameters

Para meter	Case 1 Estimate	Case 2 Estimate	Case 3 Estimate	Case 4 Estimate	Case 5 Estimate	Case 6 Estimate	Case 7 Estimate	Case 8 Estimate	Case 9 Estimate	Case 10 Estimate
R_a	0.4205	0.4205	0.4205	0.4205	0.4205	0.4205	0.4205	0.4205	0.4205	0.4205
R_{1d}	0.5664	0.4921	0.1044	1.0940	2.1049	2.8168	2.6869	1.6736	1.1041	0.6279
R_{fe1d}	184.70	184.70	184.70	184.70	184.70	184.70	184.70	184.70	184.70	184.70
R^*_{fd}	0.5589	0.5589	0.5589	0.5589	0.5589	0.5589	0.5589	0.5589	0.5589	0.5589
L_l	0.0011	0.0011	0.0011	0.0011	0.0011	0.0011	0.0011	0.0011	0.0011	0.0011
L_{ad}	0.0200	0.0329	0.0437	0.0345	0.0367	0.0451	0.0341	0.0314	0.0255	0.0294
L_{1d}	0.0257	0.0151	0.1279	0.0555	0.0062	0.1180	0.0077	0.0436	0.0364	0.0145
L_{fe1d}	2.0568	2.0568	2.0568	2.0568	2.0568	2.0568	2.0568	2.0568	2.0568	2.0568
L_{fd}	0.0200	0.0247	0.0574	0.0533	0.0341	0.0750	0.0352	0.0537	0.0647	0.0605
L_{f1d}	-0.0087	-0.0032	-0.0133	-0.0083	-0.0063	-0.0465	-0.0074	-0.0251	-0.0243	-0.0127
a	1.1971	1.1971	1.1971	1.1971	1.1971	1.1971	1.1971	1.1971	1.1971	1.1971

Resistance (Ω); Inductance (H)

$$X_d = [i_d \ \ \hat{i}_{1d} \ \ \hat{i}_{fe1d} \ \ i^*_{fd}]^T \ ;$$

The vector X_d, along with vector U_d (also obtained from measurement) is processed by the generalized least squares algorithm [10] to yield estimates of the *d*-axis parameter vector θ_d (see equation (1)).

IV. ANN OBSERVER DEVELOPMENT

A. *Generation of Training Data*

In order to generate necessary data for *d*-axis observer development, equation (1) can be simulated to obtain the state vector X_d in response to a pre-specified input vector U_d. In order to ensure richness of the training set, inputs v_d^* and v_{fd}^* are chosen to be random gaussian signals with zero mean and unit variance. To ensure that the magnitudes of all measured state variables are realistic and within the normal operating range of the generator, the field-voltage v_{fd}^* is scaled by a factor of 10. The choice of using random input signals is quite reasonable since the observer is developed using simulated measurements instead of experimentally acquired data. Table 1 lists the *d*-axis machine model parameters used to generate training data for the *d*-axis ANN observer. The parameters listed in Table 1 were estimated experimentally by conducting large excitation disturbance tests on the 7.5 kVA synchronous generator [8].

B. *Cross-correlation Analysis*

Using the simulated states, cross-correlations were calculated between measurable variables (v_d^*, v_{fd}^*, i_d, i_{fd}^*, λ_d) and un-measurable rotor body currents (i_{1d}, i_{fe1d}). Figure 2 shows the cross-correlation between i_{1d} and i_d, i_{fd}^* for data generated by simulating the machine model with parameters listed under Case 1 in Table 1. Due to space considerations, plots showing the cross-correlations between other variables have not been shown.

Studies reveal the presence of peaks in the cross-correlation functions indicating a high degree of correlation between the data separated by the corresponding discrete time-instant. For instance, Figure 2 indicates a high degree of correlation between $i_{1d}(k)$ and $i_d(k)$, and also between $i_{1d}(k)$ and $i_{fd}^*(k)$. Also, the contributions of $i_d(k-l)$ and $i_{fd}^*(k-l)$ on $i_{1d}(k)$ decrease gradually with an increase in the value of lag l ($l = 1, 2, 3\ldots$).

Based on these studies, it is seen that the input vector of the neural network observer can be made sufficiently large to incorporate a large window of delayed measurements. However, if l is made very large, the size of the neural network's input layer will increase proportionally. For instance, if $l = 11$, the number of processing elements in the *d*-axis ANN observer's input layer will be equal to (11+1) x 5 = 60. The issue of sizing the input vector optimally is based on the concept of parsimony. If the performance of the neural network observer does not show significant improvement with an increase in the size of the input vector, then it is favorable to use a fewer number of delays in the measurable inputs.

C. *ANN Observer Training*

Using the simulated currents obtained by perturbing the *d*-axis machine model with v_d^* and v_{fd}^* as described in Section IV A, 10 sets of data were generated corresponding to each case listed in Table 1. Each data set is comprised of data corresponding to 100 different time instants. Thus, a total of 1000 input/output patterns are used for presentation to each of the observers for training.

Using the above data sets, vector $\xi(k)$ is formed at each time instant k. Initially, l_1 through l_5 were set equal to 1. Therefore, each observer has 10 elements in the input layer and 1 element in the output layer. Only one hidden layer is used in each network, with the number of hidden layer elements specified arbitrarily during training. The convergence criterion for each ANN observer is set to 1e-12 amp^2. Also, the number of elements in the hidden layer of each neural network is made equal to 2. The parameters of each observer were initialized randomly to small real numbers. For each observer, 1000 input/output patterns were presented during training. However, it was seen that even by progressively increasing the number of hidden layer elements from 2 to 5, it was not possible to train the networks to satisfy the convergence criterion.

Applying a trial-and-error procedure, it was seen that by gradually increasing the number of lags in the input layer to 5 (i.e., l_1, l_2, l_3, l_4, and $l_5 = 5$), each ANN observer could be trained to satisfy the convergence criterion. The number of processing elements in the hidden layer is chosen arbitrarily during observer development. It was seen that the number of processing elements in the hidden layer of each observer for optimal training is equal to 3. All processing elements in the input and output layers have linear activation functions, where as all elements in the hidden layer have hyperbolic tangent (tanh) activation functions.

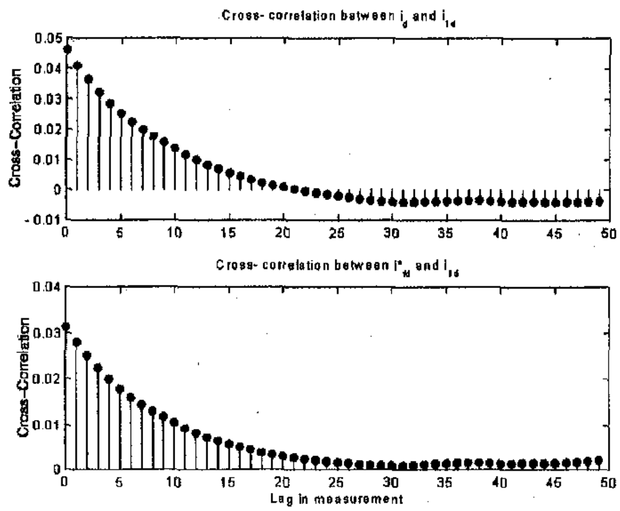


Fig. 2. Cross-correlation function between i_{1d} and i_d , i_{fd}^*

V. ROBUSTNESS CONSIDERATIONS

A. *Robustness to Deviations in L_{ad}*

In order to test the influence of d-axis machine saturation on observer performance, simulated test-data sets were generated with L_{ad} varying in increments from 0.01 H to 0.05 H in steps of 0.01 H. All other parameters of the d-axis machine model are made equivalent to values listed in Table 1, Case 1. The purpose of this evaluation study is to test the effectiveness of the observer in accurately estimating rotor body currents in response to incremental changes in L_{ad}. It must be noted that in reality however, the value of L_{ad} is influenced by machine saturation.

Table 2 lists the sum-squared-errors between the actual and estimated values of i_{1d} and $i_{f e 1d}$ for the data sets under consideration. It must be cautioned that these SSEs are valid only for the 7.5 kVA machine.

Applying the procedure given in Section III, the ANN estimated rotor-body currents are used in the recursive parameter estimation procedure to yield estimates of d-axis machine model parameters. The percentage errors between the actual and the estimated parameter values are computed for each of the eleven d-axis parameters for each test case under consideration. Next, the *average* percentage errors for each parameter are calculated by computing the mean of the percentage error for each parameter obtained over the 5 different test cases listed above. Figure 3 shows a bar chart of the average percentage error for each of the eleven d-axis machine parameters.

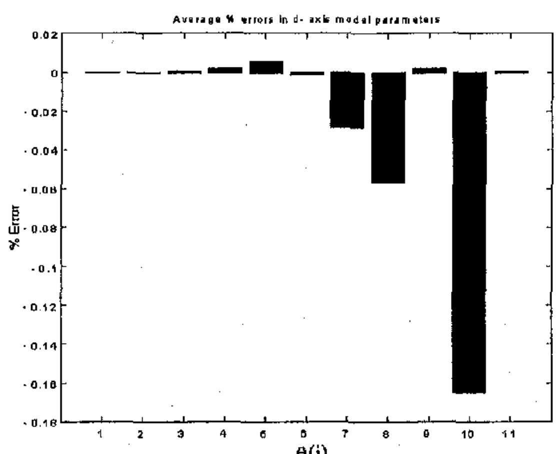
Table 2: Sum-squared errors in i_{1d} and i_{fe1d} for simulated variations in L_{ad}

L_{ad} (H)	SSE in i_{1d} (amp^2)	SSE in i_{fe1d} (amp^2)
0.0100	7.3588e-09	2.3470e-12
0.0200	2.1785e-09	8.5251e-09
0.0300	9.7682e-10	3.6611e-15
0.0400	1.7288e-09	6.3722e-16
0.0500	1.5852e-09	5.9507e-15

B. *Robustness Towards Noise*

In order to investigate the effect of measurement noise on the performance of the trained ANN observers, noise corrupted measurements are generated by adding zero mean independent white gaussian noise to the noise free signals. These noise corrupted signals are then applied to the ANN observers. The equations used to generate the noise corrupted signals are presented in reference [7]. The variance of the noise depends on the signal-to-noise ratio (SNR) under consideration.

Simulated noise corrupted measurements of v_d^*, v_{fd}^*, i_d, i_{fd}^*, and λ_d are then applied (with appropriate lags) to the input layer of the trained ANN observers. The sum-squared-errors between the actual rotor body currents (i_{1d}, i_{fe1d}) and the estimated rotor body currents ($\hat{i}_{1d}, \hat{i}_{fe1d}$) are used to quantify observer performance. In the following studies, the parameters of the machine model used to generate the simulated data are listed in Table1, Case1. As shown in Table 3, with low SNR levels (i.e., large amount of noise), the performance of the ANN observers deteriorate significantly. For the sake of comparison, the SSE for the noise free case is also given.



$\theta = [R_a \;\; R_{fd}^* \;\; R_{1d} \;\; R_{fe1d} \;\; L_l \;\; L_{ad} \;\; L_{1d} \;\; L_{fe1d} \;\; L_{fd} \;\; L_{f1d} \;\; a\;]^T$

Fig.3. Average percentage errors for each d-axis model parameter

Table 3: Sum-squared errors in i_{1d} and i_{fe1d} with different SNR levels in the noise corrupted measurements. No. of elements in ANN input layer = 30.

SNR	SSE in i_{1d} (amp^2)	SSE in i_{fe1d}(amp^2)
No noise	2.1785e-09	8.5251e-09
100,000:1	5.4008e-07	9.7446e-08
50,000:1	2.2042e-06	4.3720e-07
10,000:1	5.2233e-05	1.0652e-05
5,000:1	2.0873e-04	4.2637e-05
1,000:1	5.4183e-03	1.1066e-03
500:1	2.1222e-02	4.3349e-03
100:1	5.2078e-01	1.0632e-01

As explained in reference [7], observer robustness towards noise can be improved by enhancing the size of the ANN input vector by increasing the number of delays used in the input measurements. Table 4 shows the sum-squared-errors between the actual rotor body currents (i_{1d}, i_{fe1d}) and estimated rotor body currents ($\hat{i}_{1d}, \hat{i}_{fe1d}$) by presenting noise corrupted measurements to observers each of which contain 40 elements in their respective input layers (i.e., $l_1 \ldots l_5 = 7$).

It must be remembered that while the number of measurement delays used in the ANN input vector can be made very large, the complexity of training increases because the number of parameters (weights and biases) to be estimated also increases. Therefore, a trade-off has to be made between the size of the neural network and the accuracy of the results desired. Studies indicate that the SSEs in i_{1d} and i_{fe1d} should be no more than 1e-5 amp^2 and 1e-6 amp^2 respectively for reasonably accurate parameter estimation purposes (i.e., for the errors in the parameter estimates to be $\leq$ 3%).

Table 4: Sum-squared errors in i_{1d} and i_{fe1d} with different SNR levels in the noise corrupted measurements. No. of elements in ANN input layer = 40.

SNR	SSE in i_{1d} (amp^2)	SSE in i_{fe1d}(amp^2)
No noise	9.1901e-08	7.1156e-15
100,000:1	1.0222e-08	2.0431e-09
50,000:1	1.3562e-07	8.6402e-09
10,000:1	1.2074e-06	2.2016e-07
5,000:1	4.2082e-06	8.1252e-07
1,000:1	1.0417e-04	2.0559e-05
500:1	4.0772e-04	8.0198e-04
100:1	1.0728e-02	2.1192e-03

C. *Robustness Towards Deviations in Field-resistance R_{fd}^**

In the preceding discussion, the observer was developed to account for variations in L_{ad}, R_{1d}, L_{1d}, L_{fd}, and L_{f1d}. These parameter variations were attributed to changes in machine operating condition. However, the field-resistance, R_{fd}^*, was kept unchanged during the course of observer development. It must be mentioned that in an actual machine, one might anticipate R_{fd}^* to deviate slightly about its average value because of heating in the field-winding. Experimental results indicate that R_{fd}^* varied in the range 0.5573 Ω to 0.5594 Ω, with an average value of 0.5589. Thus the percentage variation in R_{fd}^* is in the range -0.089% to 0.3% about the average value of 0.5589 Ω.

In order to study the effects of variations in R_{fd}^* on observer performance, simulation studies were conducted by incorporating field-resistance variations in the range ± 0.3% in the test set. It was seen that even with a ± 0.1% change in the field resistance, the SSEs in i_{1d} and i_{fe1d} are approximately 0.5 amp^2 and 0.25 amp^2 respectively. Thus, it can be seen that both observers are very sensitive to small changes in R_{fd}^*.

In order to make the observers more robust to deviations in field-resistance, simulated variations in R_{fd}^* are introduced into the *training* sets. For each of the 10 cases listed in Table 1, simulated variations of ± 0.3% in R_{fd}^* are introduced in the machine model to generate the training set. Therefore, a total of 30 cases were generated, each case comprising of 100 input/output patterns. The number of processing elements in the input layer of each ANN observer were set equal to 40. It was seen that to accurately perform the desired mapping, each observer required 8 processing elements in the input layer. After training both observers to account for deviations in field resistance, simulation studies were conducted to investigate observer performance due to deviations in R_{fd}^*. 11 test cases were considered with R_{fd}^* varying in the range -0.5% to +0.5% about the average value of 0.5589 Ω. In addition, two more test cases were considered with R_{fd}^* deviating by ±1%. The results of the study are presented in Figure 4. These results indicate that both observers are accurately able to estimate rotor-body currents even with small deviations in field-resistance.

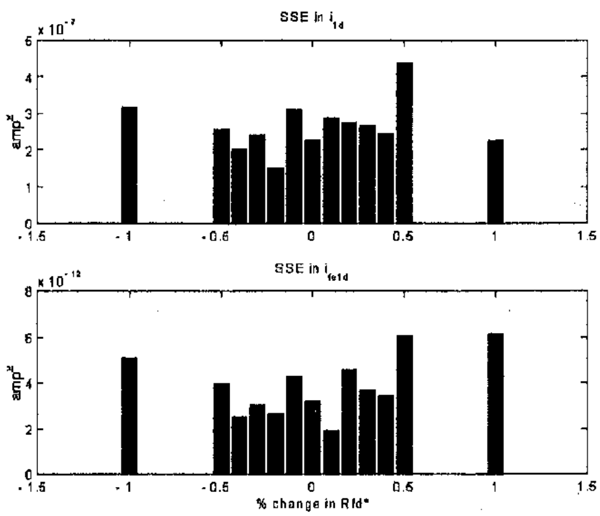


Fig. 4. Sum squared errors in i_{1d} and i_{fe1d} with simulated variations in R_{fd}^*. Both observers were trained by incorporating simulated variations of ± 0.3% in R_{fd}^* in the training set.

VI. EXPERIMENTAL RESULTS

In order to verify the effectiveness of implementing the developed ANN observers in an experimental setting, large excitation disturbance tests are conducted on the actual 7.5 kVA laboratory generator. Fig. 5 shows the filtered orthogonal axis responses obtained by perturbing the generator's excitation reference voltage by 20% with the generator operating over-excited and delivering 500 W of power to the bus. The sampling time for data-acquisition purposes is 500 μsec. All responses are filtered to remove measurement noise.

The experimental measurements are input to the trained observers by constructing the vector ξ for each ANN observer according to equation (2) where $l_1 \ldots l_5 = 7$. Figure 6 shows the observed rotor body currents obtained by presenting 7900 sequential patterns of input vectors to each observer. The estimated rotor body currents are then incorporated into the state vector X_d and used along with input vector U_d (see equation (1)) to recursively estimate model parameters. Table 5 lists the parameter estimates. In order to verify the validity of these estimates, the parameter values listed in Table 5 are incorporated into the machine model. Experimental voltages v^*_d and v^*_{fd} are then applied to the model to obtain simulated currents. These simulated currents are compared with corresponding measured currents and observed rotor-body currents as shown in Figure 7.

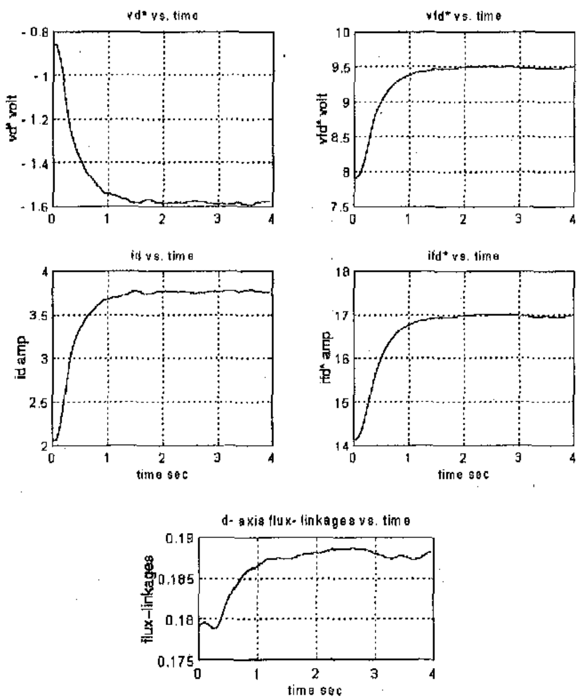


Fig.5. Experimentally measured d-axis responses.

VII. CONCLUSIONS

The observer described in this study is developed to identify machine rotor body currents present during large disturbances in the machine's excitation reference voltage. Such tests are feasible in a laboratory environment and experimental results obtained appear encouraging because accurate trajectories of machine parameters were established by performing tests over the entire operating range of the 7.5 kVA generator. Experimental studies performed on this machine reveal that the estimated rotor body currents are acceptably accurate for use along with on-line responses in estimating model parameters. However, it must be noted that the techniques presented in this paper may not be directly

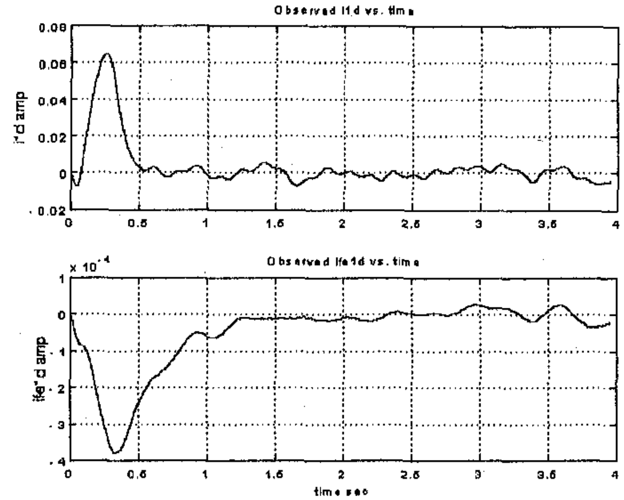


Fig. 6. Rotor body current estimates produced by d-axis ANN observers.

Table 5: Estimated model parameters

Parameter	Estimate
R_a	0.4207
R_{1d}	0.5679
R_{fe1d}	182.21
R^*_{fd}	0.5588
L_l	0.0010
L_{ad}	0.0203
L_{1d}	0.0261
L_{fe1d}	2.0572
L_{fd}	0.0199
L_{f1d}	-0.0073
a	1.1971

Resistance (Ω), Inductance (H)

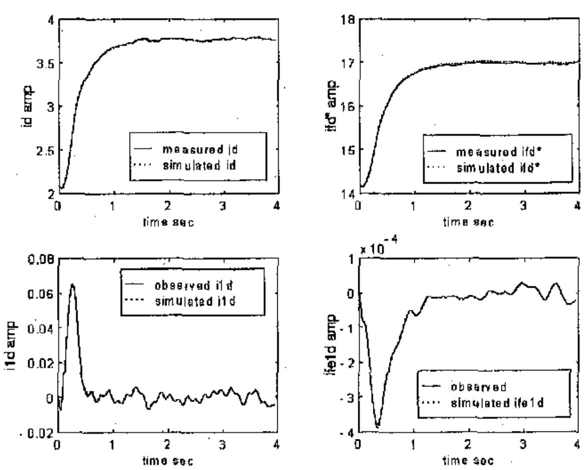


Fig. 7. Comparison of simulated currents against measured currents and observed currents.

applicable for large utility generators owing to system stability considerations. While the results presented in this paper demonstrate the feasibility of implementing neural network observers to estimate un-measurable synchronous rotor body currents from sequences of measurements obtained on-line, further studies are necessary to investigate the methodology for large utility generators.

VIII. ACKNOWLEDGMENTS

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