Neural Network Based Modeling of Round Rotor Synchronous Generator Rotor Body Parameters from Operating Data

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Abstract: It is generally accepted that in order to account for the effect of eddy currents in the solid rotor-iron of a round-rotor synchronous machine, two or more fictitious rotor-circuits are to be used in each axis of the *d*- and *q*-axis equivalent circuit representations of the machine model. This paper presents a novel technique to estimate the parameters of these rotor-circuits (hereinafter referred to as rotor body parameters) from measurements collected on-line at several operating conditions. The effects of generator saturation, rotor position and loading are included in the estimation process. Tests conducted on a round-rotor synchronous generator reveal that certain rotor-body parameters are non-linear functions of generator operating condition. A novel artificial neural network (ANN) based technique is used to map variables representative of generator operating condition to each parameter being modeled. The developed ANN models are validated with measurements not used in the modeling process.

Keywords: Synchronous generators, parameter estimation, feedforward neural networks.

I. INTRODUCTION

In recent years, there has been a considerable interest in the on-line estimation of synchronous generator parameters [1-6]. Online methods are particularly attractive since the machine's service need not be interrupted and parameter estimation is performed by processing measurements obtained during the normal operation of the machine. The need for on-line parameter estimation arises because generator parameters tend to deviate substantially from nominal values obtained from off-line testing. These deviations are usually due to magnetic saturation [7-10], machine aging, internal temperature, the effect of centrifugal forces on winding contacts, and incipient faults within the machine. Investigations into modeling synchronous generator parameters as a function of operating condition have been reported in references [5,6].

In this paper, the rotor-body parameters of a round-rotor synchronous generator are estimated at several operating conditions. The effects of generator saturation, rotor position and loading are included in the estimation process. Studies indicate that certain rotor-body parameters are non-linear functions of generating operating condition. Using a set of training patterns obtained experimentally, neural network models are established to extract the non-linear relationship between variables representative of generator operating condition and rotor-body parameters.

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II. MACHINE MODEL DESCRIPTION AND PROBLEM FORMULATION

The machine considered in this research study is a 240 V, 7.5 kVA, 1800 rpm round rotor synchronous generator whose model structure (Model 3'.3) is shown in reference [19]. The choice of this particular model structure over simpler lower-order model structures is based on the fact that evaluation studies performed on the same machine in reference [19] suggest that Model 3'.3 most accurately describes machine dynamic behavior.

The structure of model 3'.3 is based on the reciprocal per-unit system. For discrete-time systems, the coupled state-space representation of this model can be written as:

$$\begin{aligned} X(k+1) &= A(\theta)\cdot X(k) + B(\theta)\cdot U(k) + w(k) \\ Y(k+1) &= C\cdot X(k+1) + v(k+1) \end{aligned} \tag{1}$$

$w(k)$ and $v(k)$ denote the process and measurement noise, respectively. In addition,

$$\begin{aligned} &X = [i_q \;\; i_d \;\; i_{1q} \;\; i_{2q} \; i_{3q} \;\; i_{1d} \;\; i_{fe1d} \;\; i_{fd}^*]^T; \\ &U = [v_q \; v_d \;\; v_{fd}^*]^T \;; \\ &Y = [i_q \;\; i_d \;\; i_{fd}^*]^T \;; \\ &\theta = [R_a \;\; R_{fd}^* \;\; R_{1d} \;\; R_{fe1d} \;\; L_l \;\; L_{ad} \;\; L_{fd} \;\; L_{1d} \;\; L_{fe1d} \;\; a \\ &\qquad R_{1q} \;\; R_{2q} \;\; R_{3q} \;\; L_{aq} \;\; L_{1q} \;\; L_{2q} \;\; L_{3q}]^T; \end{aligned}$$

The A and B matrices and the parameter vector θ are given in reference [19]. In the above formulation, all parameters are in actual units. Also, it is assumed that the machine power angle, δ, is available for measurement. Also, i_{fd}^* is the field winding current in ampere, v_{fd}^* is the field voltage in volts, both quantities measured on the field side of the generator. R_{fd}^* is the field winding resistance in ohm as measured on the field side. i_{fd}, v_{fd}, and R_{fd} denote corresponding transformed quantities on the stator side of the generator through the field-to-stator turns ratio a. All other variables and parameters are referred to the stator and are in actual units.

In reference [19], the parameters of a 7.5kVA, 240V, 1800 rpm synchronous generator were estimated off-line using standstill time-domain response testing. These estimates are shown in Table 1.

Table 1: SSTR Estimates of Round-Rotor Synchronous Generator

d-axis		q-axis	
Parameter	Estimate	Parameter	Estimate
R_a	0.4205	R_a	0.4205
R_{1d}	0.8792	R_{1q}	0.6434
R_{fe1d}	184.70	R_{2q}	23.579
R^*_{fd}	1.3336	R_{3q}	26.692
L_l	0.0011	L_l	0.0011
L_{ad}	0.0474	L_{aq}	0.0479
L_{1d}	0.0504	L_{1q}	0.0042
L_{fe1d}	2.0568	L_{2q}	0.0007
L_{fd}	0.3412	L_{3q}	0.0231
L_{f1d}	-0.0406	-	-
a	0.5154	-	-

Resistance (Ω), Inductance (H)

In this paper, the same synchronous generator is modeled from on-line measurements collected at various test- and operating-conditions. The machine models are identified in two stages. In Stage 1, the linear model parameters are estimated from on-line small excitation disturbance test responses [4]. Such tests performed over a wide range of operating conditions can be used to model machine saturation [5]. In Stage 2, the rotor body parameters which characterize the generator's large disturbance dynamics are identified. This two stage estimation procedure prevents unwanted biases in the modeling process which may make it impossible to describe the non-linear, large disturbance dynamics of the machine.

The objectives of this paper are:

1) To develop a procedure to estimate rotor body parameters from large disturbance data acquired when the generator is operating on-line under various test conditions. The effects of generator operating condition on rotor body parameter estimates will be investigated.

2) To utilize on-line large disturbance responses and rotor-body parameter estimates obtained above, in the development of rotor body ANN models to map variables representative of generator operating condition to each rotor body parameter being modeled.

3) To validate ANN models with large disturbance data not used in the modeling process.

III. NEURAL NETWORK REVIEW AND DATA ACQUISITION

In this work, we are primarily concerned with developing ANN models which can map variables representative of generator operating condition to each operating condition dependent machine parameter. The type of network used in this study is the multi-layer perceptron shown in Fig.1. It consists of *n* processing elements in the input layer, corresponding to each machine variable that describes the generator operating condition. A single processing element in the output layer corresponds to the machine parameter being modeled. The number of elements in the hidden layer is arbitrarily chosen depending on the complexity of the mapping to be learnt. In order to introduce non-linearity into the network, a hyperbolic-tangent (tanh) transfer function [21] is used in all hidden layer elements. Although any non-linear function could have been used for the purpose, the function should be differentiable and it should be bounded [21]. The tanh function is a convenient choice because its derivative is easy to calculate. Recall, $\tanh(x) = 1-(\tanh(x))^2$. All elements in the input and output layers have linear (1:1) transformations. The back-propagation algorithm [21] is used to train (or adjust the weights of) the neural network such that the sum squared error between actual network outputs and corresponding desired outputs is minimized.

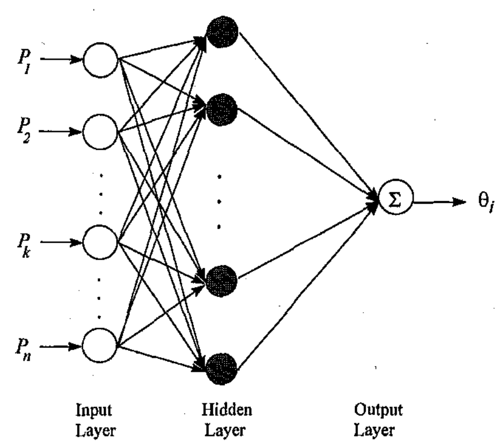

Fig.1: Multilayer feedforward ANN

Once the network has suitably been trained, the network output, θ_i is computed from the $nx1$ input-vector, P, according to the following equation [21]:

$$\theta_i = W_2 \cdot \tanh(W_1 \cdot P + B_1) + B_2 \tag{2}$$

where W_2 denotes the matrix of connecting weights from the hidden layer to the output layer. W_1 is the weight matrix from the input-layer to the hidden-layer. If there are m processing elements in the hidden layer, W_2 is of size $1xm$, and W_1 is of size mxn. Bias terms B_2 and B_1 are used as connection weights from an input with a constant value of one (please see reference [21]). B_2 and B_1 denote the $1x1$ and $mx1$ bias vectors from the bias to the output-layer, and from the bias to the hidden-layer respectively. The task of training is to determine the matrices W_1, W_2, and bias vectors B_1, B_2.

Multi-layer perceptrons can be considered general purpose, flexible, non-linear models that, given enough neurons and enough data, can approximate any function to any desired degree of accuracy [25]. Unlike conventional models where it is possible to relate model parameters to properties of the system being identified, it is not always possible to relate the parameters of the neural network (weights and biases) in the same manner. Thus, the parameters of equation (2) cannot be explained from a physical viewpoint.

The training patterns required to train the neural network models are obtained through an experimental arrangement and on-line data acquisition process described in reference [19]. Data is obtained by staging two types of tests viz., small excitation disturbance tests, and large excitation disturbance tests. For small excitation disturbance tests, the magnitude of the external input ΔV_{ref} is between 2% and 5% of the excitation reference voltage, V_{ref}. For large disturbance testing, ΔV_{ref} is in the range 17% and 25% of V_{ref}. Small excitation disturbance tests do not significantly affect the overall operating status of the system, and they are fairly easy to conduct even on large utility generators. Although it may not be practical to conduct large excitation disturbance tests on utility generators owing to system stability considerations, such tests are feasible in a laboratory environment. For utility generators, large disturbance data may be acquired as and when transient events such as transmission line faults, line switching, outages etc. occur.

IV. ESTIMATION OF LINEAR MODEL PARAMETERS

Table 2 lists the linear model parameters of the synchronous generator which are estimated by conducting small excitation disturbance tests with the machine operating at light load and under-excited conditions. Reference [4] provides an elaborate discussion of the estimation process from test-data.

Table 2: Linear Model Parameters

Parameter	Estimate
R_a (Ω)	0.4205
L_l (H)	0.0011
L_d (H)	0.0559
L_q (H)	0.0464
R_{fd}^* (Ω)	0.5589
a	1.1971

Next, small excitation disturbance tests are conducted over a wide range of operating conditions to estimate the saturated mutual inductances. L_{ads} and L_{aqs} are estimated at various levels of excitation and power generation. A neural network based multi-dimensional non-linear mapping [5] is established to map small-excitation disturbance responses to a set of experimentally obtained saturated mutual inductances. Since the main intent of this paper is to develop a procedure for rotor-body parameter estimation and modeling, the results of generator saturation modeling are not presented here.

V. ESTIMATION OF ROTOR BODY PARAMETERS

It will first be shown that using a record of experimentally measured input-output data (v_d, v_q, i_d, i_q, i_{fd}^*) obtained during a large disturbance transient event, it is possible to estimate stator d- and q-axis flux-linkages, provided an estimate of stator resistance, R_a is known beforehand. An estimate of R_a is obtained from Table 2.

Under large disturbance conditions, the rate of change of stator flux linkages cannot be ignored. In such cases, machine stator voltage equations are arranged in a state-space form to solve for the flux linkages Φ_d and Φ_q using numerical integration.

$$X(k+1) = A \cdot X(k) + B \cdot U(k) \tag{3}$$

where $X = [\Phi_d \quad \Phi_q]^T$. Matrices A, B, U are defined in Appendix A.1. If I_d, I_q, V_d, V_q correspond to the steady-state stator d- and q-axis currents and voltages respectively, the following equations may be used to compute initial flux linkages at steady state (prior to a transient disturbance):

$$\begin{cases} \Phi_d = \dfrac{R_a I_q + V_q}{\omega_r} \\ \Phi_q = -\dfrac{R_a I_d + V_d}{\omega_r} \end{cases} \tag{4}$$

With estimates of stator d- and q-axis flux-linkages, the speed-voltage terms appearing in the d- and q-axis equivalent circuits (see Fig. 1, reference [19]). This would facilitate in de-coupling equation (1) into two subsystems, one for each orthogonal axis:

For the d-axis model,

$$\begin{cases} X_d(k+1) = A_d(\theta_d) \cdot X_d(k) + B_d(\theta_d) \cdot U_d(k) \\ Y_d(k) = C_d \cdot X_d(k) \end{cases} \tag{5}$$

where,

$X_d = [i_d \quad i_{1d} \quad i_{feld} \quad i_{fd}^*]^T$;

$U_d = [v_d^* \quad 0 \quad 0 \quad v_{fd}^*]^T$;

$Y_d = [i_d \quad i_{fd}^*]^T$;

$\theta_d = [R_a \quad R_{fd}^* \quad R_{1d} \quad R_{feld} \quad L_l \quad L_{ad} \quad L_{fd} \quad L_{1d} \quad L_{feld} \quad a]^T$;

For the q-axis model,

$$\begin{cases} X_q(k+1) = A_q(\theta_q) \cdot X_q(k) + B_q(\theta_q) \cdot U_q(k) \\ Y_q(k) = C_q \cdot X_q(k) \end{cases} \tag{6}$$

where,

$X_q = [i_q \quad i_{1q} \quad i_{2q} \quad i_{3q}]^T$;

$U_q = [v_q^* \quad 0 \quad 0 \quad 0]^T$;

$Y_q = [i_q]^T$;

$\theta_q = [R_a \quad R_{1q} \quad R_{2q} \quad R_{3q} \quad L_l \quad L_{aq} \quad L_{1q} \quad L_{2q} \quad L_{3q}]^T$;

Equations (5) and (6) constitute the de-coupled forms of equation (1). De-coupling the d- and q-axis equations facilitates de-coupled estimation of machine parameters. In the above formulation, the parameter matrices A, B are provided in Appendix A.2. The voltages v_d^* and v_q^* are defined as follows:

$$\begin{cases} v_d^* = v_d + \Phi_q \omega_r \\ v_q^* = v_q - \Phi_d \omega_r \end{cases} \qquad (7)$$

For estimation purposes, a batch Output-Error-Method (OEM) is used to estimate the parameter vector using a block of input/output data over a fixed time period. In this case, the input variable is vector U comprising of measured stator- and field-voltages, while the output variable is vector Y comprising of measured stator- and field-currents. See equations (5) and (6). The OEM algorithm is based on the minimization of a cost function proportional to the error between the calculated currents and corresponding experimental currents. The estimation algorithm requires a set of pre-determined initial parameters. The SSTR parameters shown in Table 1 are used to initialize the rotor body parameters. It is not necessary to estimate the armature-circuit parameters (R_a , L_{ad} , L_{aq} , and L_l), field-resistance (R_{fd}^*), and the field-to-stator turns-ratio (a), since accurate estimates were obtained from Stages 1 and 2 of the estimation process. Such a technique helps in preventing unwanted biases in the estimation process which may make it impossible to accurately describe the non-linear effects of the machine.

To estimate the rotor body parameters, large excitation disturbance tests were conducted over a wide range of excitation levels and loading conditions. The purpose of these studies is to investigate possible variations of rotor body parameters as a function of generator operating condition. Estimation results reveal that rotor body parameters R_{1d}, L_{1d}, L_{fd}, L_{f1d}, R_{1q}, and L_{1q} are operating condition dependent. No appreciable differences were noticed between the SSTR and on-line parameter estimates of R_{fe1d}, L_{fe1d}, R_{2q}, L_{2q}, R_{3q} and L_{3q} .

VI. DEVELOPMENT OF ANN ROTOR BODY MODELS

Each non-linear operating-condition dependent rotor-body parameter is modeled by an individual ANN. Thus, a total of 6 ANNs are used to model the rotor body parameters. Each ANN model has 2 inputs, 1 output and a single hidden layer comprising of an arbitrary number of neurons approximated during training. The input pattern to each ANN rotor body model comprises of the real power (in watt) and the power angle (in radian) of the generator. Stator and field voltage/current variables are not included as part of the input pattern because rotor body parameter values are estimated at rated voltage. Hence, the operating condition of the generator at rated voltage is determined uniquely by the real power and the corresponding power angle. The real power is scaled by a factor of 3000 so as to keep each variable of the input pattern in the same numeric range. The output pattern comprising of 1 processing element is the rotor body parameter to be modeled by the ANN. Thus,

$$P = [Power/3000 \quad \delta]^T;$$
$$\theta_{r,est} = W_2 \cdot \tanh(W_1 \cdot P + B_1) + B_2$$

The output of the neural network, $\theta_{r,est}$ refers to the rotor body parameter estimated by the particular ANN model. $\theta_{r,est}$ is in actual units (in ohm or henry) referred to the stator of the synchronous generator.

The non-linear mappings between the ANN input variables and operating condition dependent rotor-body parameters are portrayed in Figures 2-4. During the weight-adjustment procedure, the estimated input and output patterns shown in Figs.2-4 are used as training data. The weights and biases of the ANN models are adjusted to minimize the sum squared error between the actual output of the ANN and the desired output. The sum squared error threshold was fixed at 0.001. All ANN models are trained using the back-propagation algorithm. Table 3 lists the results of the training in terms of network weights and biases for the R_{1d} ANN rotor body model. Due to space limitations, the weights and biases for other ANN rotor body models are not shown.

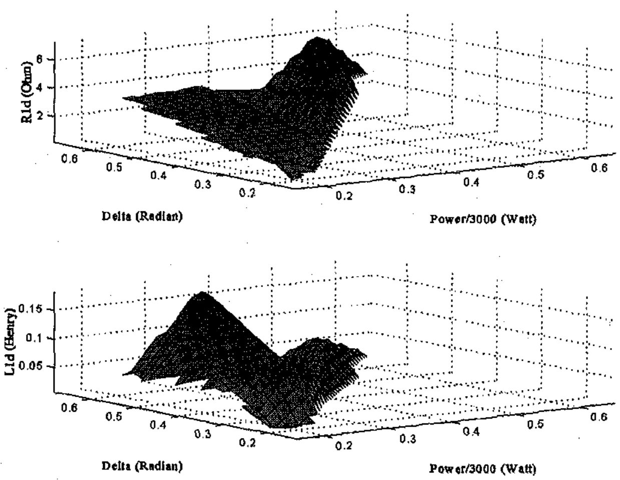

Fig.2: Transfer functions of R_{1d} and L_{1d} ANN models

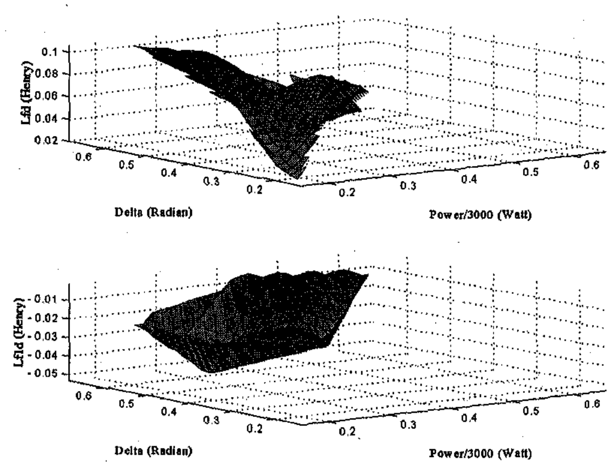

Fig.3: Transfer functions of L_{fd} and L_{f1d} ANN models

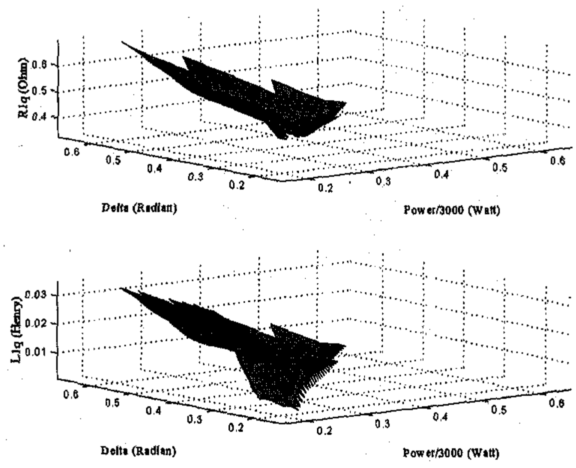

Fig.4: Transfer functions of R_{1q} and L_{1q} ANN models

Table 3: Estimated weights and biases for the R_{1d} ANN model

Input to Hidden Layer:

Weights, W_1

8.5379	-2.3146
17.4480	0.8130
-12.0242	-1.5355
19.4437	13.7912
22.8413	-3.3445
-8.3445	-10.7190
-0.8228	-11.3216

Biases, B_1^T

-1.4828 -4.6537 7.2344 -8.5860 -7.6489 8.3950 7.2317

Hidden Layer to Output:

Weights, W_2

-13.9969 12.7447 6.4885 -5.1555 11.2231 5.3397 -4.6101

Bias, B_2

5.5284

VII. MODEL VALIDATION

In order to verify the accuracy of the established neural network models, two large excitation disturbance tests were conducted. Using measured voltages v_d^*, v_q^* and v_{fd}^*, the currents i_d, i_q and i_{fd}^* are simulated (see equations (5) and (6)) and compared against corresponding measured currents. For simulation purposes, the parameter values used in the machine models are obtained from neural network models developed in the previous sections. In Figures 5 and 6, currents recorded during large excitation disturbances are compared with simulated currents. Fig.5 corresponds to the case when the generator is delivering 1007W of power at rated field current. Fig.6 corresponds to the case when the generator is delivering 760W of power with the field over-excited. Both tests are conducted at rated voltage. While these figures indicate a good match between corresponding simulated and measured currents, it is important to understand the reason for minor discrepancies between the two currents. The machine model used in this study is only an approximation of the actual round-rotor machine which theoretically has an infinite number of rotor body circuits [23]. The parameters estimated in this study represent the best fit of the machine's operating data for the particular machine model under consideration. While even higher-order model structures could have been used in this research, we believe that the amount of effort and expense involved should be justifiable in relation to the dynamics being investigated.

Table 4 compares the operating-condition dependent rotor-body parameters estimated by the output-error algorithm and the established ANN rotor-body models for the two data-sets described above. These results indicate that the ANN models can correctly interpolate between patterns not used in the training process.

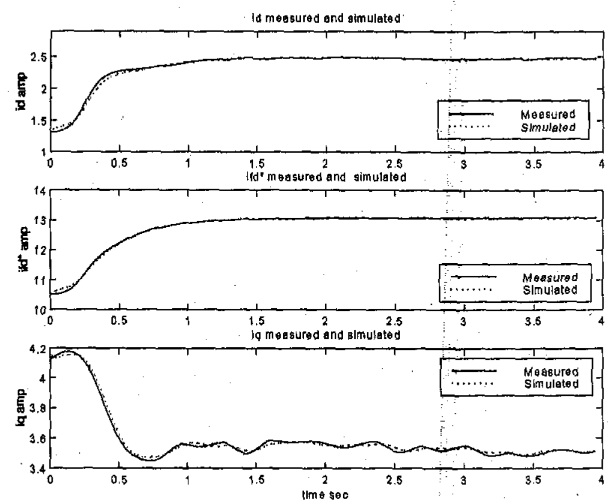

Fig.5: Simulated and measured synchronous generator currents with the generator delivering 1007W of power at rated i_{fd}^*

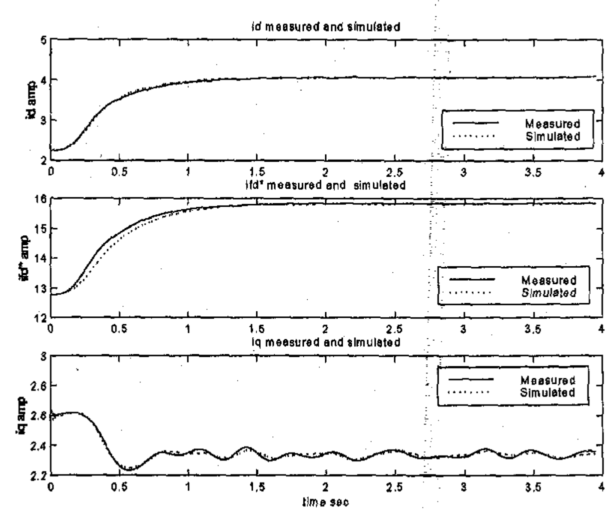

Fig.6: Simulated and measured generator currents with the generator delivering 760W of power at over-excited i_{fd}^*

Table 4: Comparison of Rotor Body Parameters Estimated by OEM Algorithm and ANN Rotor Body Models

	Data Set 1: Real Power = 1007W			Data Set 2: Real Power = 760W		
Parameter	OEM Estimate	ANN Estimate	% Error	OEM Estimate	ANN Estimate	% Error
R_{1d}	2.8168	2.8170	-0.0071	1.0940	1.0944	-0.0365
L_{1d}	0.1298	0.1325	-2.0801	0.0555	0.0543	2.1621
L_{fd}	0.0750	0.0758	-1.0667	0.0533	0.0545	-2.2514
L_{f1d}	-0.0435	-0.0428	1.6091	-0.0083	-0.0086	-3.6144
R_{1q}	0.4221	0.4289	-1.6109	0.4641	0.4700	-1.2713
L_{1q}	0.0119	0.0121	-1.6807	0.0056	0.0053	5.3571

Resistance (Ω), Inductance (H)

VIII. CONCLUSIONS AND REMARKS

A novel estimation procedure is developed to estimate synchronous generator rotor-body parameters from measurements collected when the machine is operating on-line. Data for the estimation procedure is acquired by conducting both small- and large-disturbance tests on a laboratory generator over a wide operating range. Using a batch output-error-estimation algorithm, large disturbance responses are utilized to yield estimates of rotor body parameters. Experimental investigations on a 7.5 kVA laboratory generator reveal that certain rotor body parameters are non-linear with respect to generator operating condition. By developing a training pattern, ANN models are developed to map generator real power and power angle to each operating condition dependent rotor body parameter. Validation studies indicate that the established ANN rotor body models can correctly interpolate between patterns not used in the training process.

The machine described in this paper is a laboratory generator. Although only excitation disturbance data is utilized in this research study, it is believed that additional data sets obtained from load-rejection tests, sudden short-circuit tests etc. may also be utilized in order to yield more accurate rotor-body ANN models. For large utility generators, data acquired from disturbances caused by transient events such as line-switching, transmission line-faults, outages etc. may be included in the training set.

The modeling technique proposed in this paper when applied to large utility generators would facilitate direct implementation of the developed ANN models into synchronous machine dynamic simulation programs for use in transient stability studies with minimal program alteration effort. Furthermore, the proposed technique can be used to estimate a trajectory for each parameter of the machine model, as the machine moves from one operating condition to another. By comparing the latest estimate of a parameter with an earlier trajectory of the same parameter, it may be possible to detect particular types of incipient faults [24]. This is because any deviations in machine model parameters from normal trajectories will have embedded causes in them such as aging, field-winding inter-turn shorts etc. The main intent of our research is to develop a procedure for estimating and modeling rotor body parameters from time-domain operating data. We believe the methodology presented herein appears promising and merits further investigation for accurate modeling of large utility generators.

IX. ACKNOWLEDGMENTS

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Appendix A

A.1. State Space Formulation for Determining Speed Voltages from Measurements

Machine speed ω_r in rad/sec can be computed from the following relationship:

$$\omega_r = \omega_e + \dot{\delta}$$

where ω_e is the synchronous speed in rad/sec, and δ is the measured rotor angle

$$A = \begin{bmatrix} 0 & \omega_r \\ -\omega_r & 0 \end{bmatrix}; \qquad B \cdot U = \begin{bmatrix} v_d + R_a i_d \\ v_q + R_a i_q \end{bmatrix}$$

A.2 De-coupled State Space Representation of Model 3'.3

For the continuous case:

$$A^* = -L^{-1}R; \; B^* = L^{-1}$$

where the L and R matrices for the d- and q-axis models are shown below.

For the d-axis model,

$$R = \text{diag}([-R_a \quad R_{1d} \quad R_{f01d} \quad R^*_{fd}]);$$

$$L = \begin{bmatrix} -(L_{ad}+L_l) & L_{ad} & L_{ad} & \frac{2}{3}aL_{ad} \\ -L_{ad} & L_{f1d}+L_{1d}+L_{ad} & L_{f1d}+L_{ad} & \frac{2}{3}a(L_{f1d}+L_{ad}) \\ -L_{ad} & L_{f1d}+L_{ad} & L_{f01d}+L_{fd}+L_{f1d}+L_{ad} & \frac{2}{3}a(L_{fd}+L_{f1d}+L_{ad}) \\ -aL_{ad} & a(L_{f1d}+L_{ad}) & a(L_{fd}+L_{f1d}+L_{ad}) & \frac{2}{3}a^2(L_{fd}+L_{f1d}+L_{ad}) \end{bmatrix};$$

For the q-axis model,

$$R = \text{diag}([-R_a \quad R_{1q} \quad R_{2q} \quad R_{3q}])$$

$$L = \begin{bmatrix} -(L_{aq}+L_l) & L_{aq} & L_{aq} & L_{aq} \\ -L_{aq} & (L_{1q}+L_{aq}) & L_{aq} & L_{aq} \\ -L_{aq} & L_{aq} & (L_{2q}+L_{aq}) & L_{aq} \\ -L_{aq} & L_{aq} & L_{aq} & (L_{3q}+L_{aq}) \end{bmatrix};$$

The discrete-time matrices parameter matrices A and B can be computed from A^* and B^*

BIOGRAPHIES

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