# Neural Network Based Modeling of a Large Steam Turbine-Generator Rotor Body Parameters from On-Line Disturbance Data


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**Abstract:** A novel technique to estimate and model rotor-body parameters of a large steam turbine-generator from real time disturbance data is presented. For each set of disturbance data collected at different operating conditions, the rotor body parameters of the generator are estimated using an Output Error Method (OEM). Artificial neural network (ANN) based estimators are later used to model the non-linearities in the estimated parameters based on the generator operating conditions. The developed ANN models are then validated with measurements not used in the training procedure. The performance of estimated parameters is also validated with extensive simulations and compared against the manufacturer values.



**Keywords:** Parameter identification, large utility generators, rotor body parameters, artificial neural networks.


## I. INTRODUCTION

On-line parameter identification for large synchronous generators is a beneficial procedure which does not require any service interruption to perform. Thus, machine parameters, which can deviate substantially from manufacturer values during on-line operation at different loading levels, can be determined without costly testing [1]. These deviations are usually due to magnetic saturation [2-4], internal temperature, machine aging, and the effect of centrifugal forces on winding contacts and incipient faults within the machine. The references [5-7] include investigations into modeling synchronous generator parameters as a function of operating condition. In most of these studies, the independent variables used in modeling non-linear variations of the parameters are primarily the terminal voltage, current or a combination of these quantities including the phase angle. A similar study can be found in reference [7] for a small round rotor synchronous generator.

In this study, disturbance data sets acquired on-line at different loading and excitation levels of a large utility generator are utilized to identify the machine parameters. It is assumed that the machine model order is known (i.e. the number of differential equations). Estimated rotor body parameters for each operating point are then mapped into operating condition dependent machine variables using artificial neural networks. The ANN can easily identify the shape of the non-linear function from training data. Therefore, no apriori knowledge of the shape of the mapping is required. The effects of generator saturation, rotor position and loading are included in the mapping process. Finally, extensive validation studies are conducted to investigate the performance of ANN models and estimated parameters.

## II. MACHINE MODEL DESCRIPTION AND PROBLEM FORMULATION

The structure of the synchronous machine model used in this study is a *model 2.1.* type [1], with one damper in the *d-axis* and one damper in the *q-axis*, given in Fig. 1.

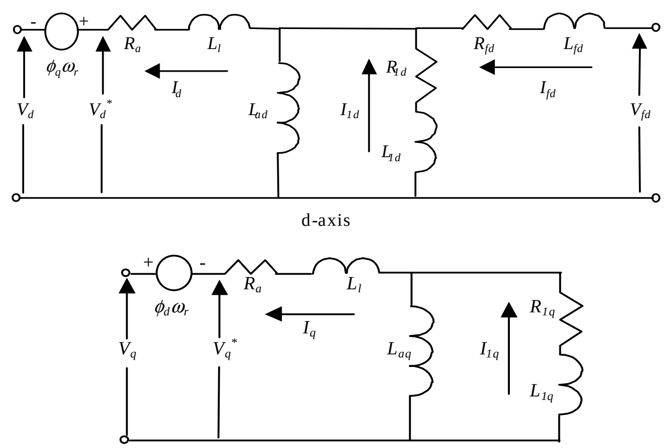



Fig. 1 On-line model structure

For continuous time systems, the state space representation of this model is,

$$dX(t)/dt = A(\theta)\cdot X(t) + B(\theta)\cdot U(t) + w(t)$$
$$Y(t) = C\cdot X(t) + v(t) \qquad (1)$$

where $w(t)$ and $v(t)$ represent the process and measurement noise. Also,

$$X=[i_q\ i_d\ i_{1q}\ i_{1d}\ i_{fd}^*]^T \qquad U=[v_q\ v_d\ v_{fd}^*]^T$$
$$Y=[i_q\ i_d\ i_{fd}^*]^T$$
$$\theta=[R_a\ R_{fd}^*\ R_{1d}\ L_l\ L_{ad}\ L_{fd}\ L_{1d}\ a\ R_{1q}\ L_{aq}\ L_{1q}]^T.$$

All parameters are in actual units. Also, it is assumed that the machine power angle $\delta$ is available for measurement. Variables $v_d$, $v_q$, $i_d$, $i_q$ represent generator *d-* and *q-axis* terminal voltages and currents respectively. The quantities $i_{fd}^*$ and $v_{fd}^*$ represent field current and field voltage respectively as measured on the field side of the generator and $R_{fd}^*$ is the field winding resistance as measured on the field side. Terms $i_{fd}$, $v_{fd}$ and $R_{fd}$ represent corresponding transformed quantities on the stator side through the field to stator turns ratio $a=N_{fd}/N_s$ as follows,

$$i_{fd} = \frac{2}{3} a i_{fd}^* \qquad v_{fd} = \frac{v_{fd}^*}{a} \qquad R_{fd} = \frac{3}{2}\frac{1}{a^2} R_{fd}^* .$$

All other variables and parameters are referred to the stator.

The identification of machine parameters including armature, field and rotor body parameters involve the following five stages:

1) Measurement data is validated.
2) Using small excitation disturbance data, armature circuit parameters including field to stator turns ratio $a$ are estimated and ANN models for saturated mutual inductances are developed.
3) Using the armature circuit parameter estimates from previous step, rotor body parameters are estimated from disturbance data acquired when the machine is operating online under various test conditions.
4) ANN models are developed and validated to map variables representative of generator operating condition to each rotor body parameter.
5) Estimated parameters are validated with extensive simulations in which the machine power angle $\delta$ is calculated.

Stages 1 and 2 are discussed in detail in a recent study by the authors [17]. Stages 3, 4 and 5 comprise the primary objectives of this paper.

In order to validate the established model based on estimated parameters, simulation studies are also performed and the results are compared against the simulation results with manufacturer parameters. In these studies, measured terminal and field voltages are used to excite the machine model to obtain power angle, terminal and field currents. The simulated currents and rotor angle are compared against corresponding actual measurements.

## III. MEASUREMENT CONFIGURATION

The Arizona Public Service Co. (APS) Four Corners Unit 5 power generation system (including the HP and LP units) and its instrumentation is given by Fig. 2. In Fig. 2, PT1, PT2 represent the voltage measurement transformers; CT1, CT2 are current transformers; B1, B2 and B3 are circuit breakers; RCC represents the reactive current compensators; DFR represents digital fault recorder inputs; Ex is the exciter system for both the HP and LP units, rev represents the revolution of the HP unit's shaft; and GSU is a step up transformer (22/500 kV). The large steam turbine-generator used for study purposes was the HP Unit rated at 483 MVA, 22 kV and 3600 rpm. This unit is a participant owned unit which is operated by APS. The LP unit is not included in this study.

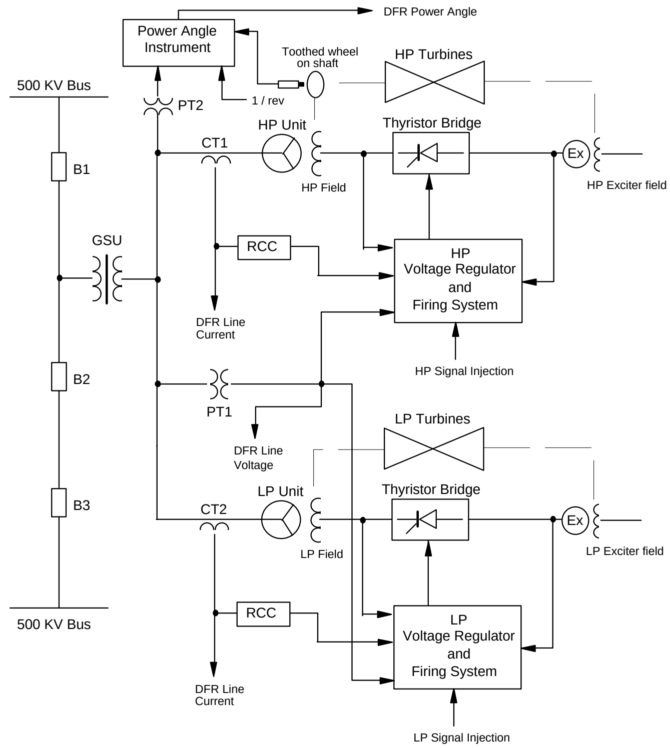



Fig. 2 Measurement setup for 4 Corners Unit 5 system

## VI. ESTIMATION OF ROTOR BODY PARAMETERS

The estimation procedure involves the identification of field winding, $d$- and $q$- axis damper winding parameters from disturbance data. For estimation of rotor body parameters, operating data due to disturbances that will excite adequate amount of damper winding currents are needed. For instance, this can be achieved by perturbing the field excitation voltage in the range of five to ten percent or by capturing line fault events.

The armature circuit parameters obtained in Stage 2 [17] are fixed in this estimation procedure. These parameters include $R_a$ , $L_l$ , $L_{ad}$ , $L_{aq}$ and $a$. Then the parameter vector to be estimated for *d-axis* is $\theta_d = [R_{fd}^* \;\; L_{fd} \;\; R_{1d} \;\; L_{1d}]$ and for *q-axis* is $\theta_q = [R_{1q} \;\; L_{1q}]$. The model for estimation should first be established. Normally, $d$- and $q$-axis models are coupled by the speed voltage terms, $\phi_q\omega_r$ and $\phi_d\omega_r$ , as can be seen in Fig. 1. In order to decouple the model, the voltages $v_d^*$ and $v_q^*$ should be computed as follows. The stator voltages in rotor reference frame are,

$$v_d = -R_a i_d - \phi_q\omega_r + p\phi_d \tag{2}$$

$$v_q = -R_a i_q + \phi_d\omega_r + p\phi_q. \tag{3}$$

From (2) and (3) flux dynamics are established as,

$$p\begin{bmatrix}\phi_d\\ \phi_q\end{bmatrix} = \begin{bmatrix}0 & \omega_r\\ -\omega_r & 0\end{bmatrix}\begin{bmatrix}\phi_d\\ \phi_q\end{bmatrix} + \begin{bmatrix}v_d + R_a i_d\\ v_q + R_a i_q\end{bmatrix} \tag{4}$$

Once the flux terms are computed using (4), the voltages $v_d^*$ and $v_q^*$ can be found as,

$$v_d^* = v_d + \phi_q\omega_r \tag{5}$$

$$v_q^* = v_q - \phi_d\omega_r. \tag{6}$$

Finally, based on $v_d^*$, the decoupled $d$-axis and $q$-axis dynamics are,

$$\begin{bmatrix} v_d^* \\ v_{fd} \\ 0 \end{bmatrix} = \begin{bmatrix} -R_a & 0 & 0 \\ 0 & R_{fd} & 0 \\ 0 & 0 & R_{1d} \end{bmatrix} \begin{bmatrix} i_d \\ i_{fd} \\ i_{1d} \end{bmatrix} + \qquad (7)$$

$$\begin{bmatrix} -(L_l + L_{ad}) & aL_{ad}/1.5 & L_{ad} \\ -aL_{ad} & a^2(L_{fd}+L_{ad})/1.5 & aL_{ad} \\ -L_{ad} & aL_{ad}/1.5 & L_{1d}+L_{ad} \end{bmatrix} p \begin{bmatrix} i_d \\ i_{fd} \\ i_{1d} \end{bmatrix}$$

$$\begin{bmatrix} v_q^* \\ 0 \end{bmatrix} = \begin{bmatrix} -R_a & 0 \\ 0 & R_{1q} \end{bmatrix} \begin{bmatrix} i_q \\ i_{1q} \end{bmatrix} + \qquad (8)$$

$$\begin{bmatrix} -(L_l + L_{aq}) & -L_{aq} \\ -L_{aq} & -(L_l + L_{1q}) \end{bmatrix} p \begin{bmatrix} i_q \\ i_{1q} \end{bmatrix}$$

The model (7-8) is not in the proper form for estimation. To render them amenable for state space representation, they should be rearranged. This is accomplished by taking current vector $i$ as outputs and voltage vector $v$ as inputs of the system, then the state space form for both models is,

$$\dot{i} = -L^{-1} R\, i + L^{-1} v. \qquad (9)$$

In Equations (7) and (8), $i_{1d}$ and $i_{1q}$ represent unmeasurable rotor body currents for both $d$- and $q$-axis. Once the state space estimation models in the form of (7) are obtained, Output-Error-Method (OEM) can be employed for the estimation of $d$- and $q$-axis rotor body parameters. The OEM uses a block of input and output data over a fixed time period and minimizes the cost function proportional to the error between the measured and calculated outputs. In this case, the input data vector is $v$ comprising measured field and stator voltages and the output vector is $i$ comprising measured stator and field currents. The estimation algorithm also requires initial values for the parameters to be estimated. Manufacturer values are utilized for this purpose.

In this study, disturbance data was collected at different operating and loading conditions by perturbing the field excitation of the machine. This was achieved by injecting step inputs into the automatic voltage regulator of the generator. A total of such ten disturbance data records were captured and made available for identification. Nine of these records include proper large transient dynamics required for the estimation of $d$-axis parameters and only six records include proper large transient dynamics required for $q$-axis. Therefore, nine sets of $\theta_d$ and 6 sets of $\theta_q$ are generated through OEM estimation.

## V. NEURAL NETWORK ROTOR BODY MODELS

Using artificial neural networks, the variables representative of generator operating condition are mapped to each rotor body parameter being modeled. Thus, a total of six ANNs are used to model the rotor body parameters $R_{fd}^*$, $L_{fd}$, $R_{1d}$, $L_{1d}$, $R_{1q}$, $L_{1q}$.

The generator testing procedure is generally conducted at rated terminal voltage. Hence the operating region of the generator can be determined by using the field current $i_{fd}^*$ and power angle $\delta$. Due to the fact that the variables $i_{fd}^*$ and $\delta$ are not constant during a disturbance, there is no one unique point that can represent each measurement record to be used to develop ANN models of rotor body parameters. Therefore, some statistical variables that are defined based on $i_{fd}^*$ and $\delta$ are used in this study to represent each operating point defined by a specific disturbance data set. Well-known statistical variables, mean value and standard deviations of $i_{fd}^*$ and $\delta$ (described in the appendix) are used for this purpose. Thus, each rotor body ANN model consists of four inputs, one output and a single hidden layer having arbitrary number of processing elements to be determined by the training procedure. Mathematical formulation of this ANN model is given as,

$$P = [\, E(\boldsymbol{i_{fd}^*})\ \sigma(\boldsymbol{i_{fd}^*})\ E(\boldsymbol{\delta})\ \ \sigma(\boldsymbol{\delta})\,]^T$$
$$\theta_{r,est} = W_2 \cdot \tanh(W_1 \cdot P + B_1) + B_2 \qquad (10)$$

where $P$ is the input vector. Notations $E$ and $\sigma$ refer to mean value and standard deviation respectively. Notations $\boldsymbol{i_{fd}^*}$ and $\boldsymbol{\delta}$ represent field current and power angle arrays given in each measurement record. The output of neural network $\theta_{r,est}$ refers to the rotor body parameter estimated by corresponding ANN model. $E(\boldsymbol{i_{fd}^*})$, $\sigma(\boldsymbol{i_{fd}^*})$ are computed based on per unit field current and $E(\boldsymbol{\delta})$, $\sigma(\boldsymbol{\delta})$ are in units of radian so as to keep each ANN input in the same numeric range. $W_1$, $B_1$, $W_2$ and $B_2$ are the weight and bias matrices to be adjusted to train the network. The description of these matrices can be found in [7]. The structure of this ANN is visualized in Figure 3.

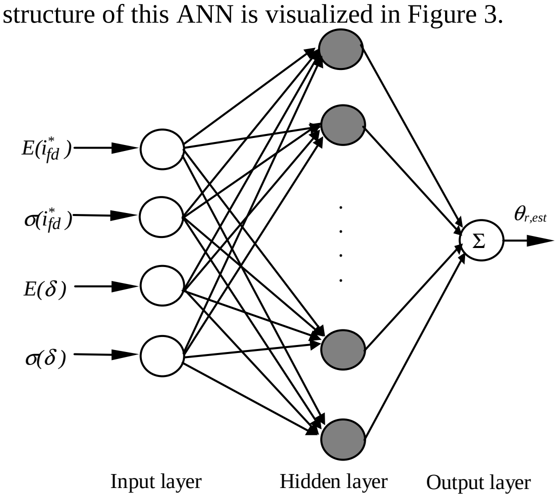



Fig. 3 Rotor body ANN model

It is desirable to visualize the transfer functions of rotor body parameters with respect to all variables of input vector space $P$, however; this can be at most represented in three dimensions. For example, the approximate non-linear mappings between $E(\boldsymbol{i_{fd}^*})$, $E(\boldsymbol{\delta})$ and operating condition dependent rotor body parameters are portrayed in Figures 4-6. These 3-D plots represent the variation manifolds within the bounds of estimated parameter values.

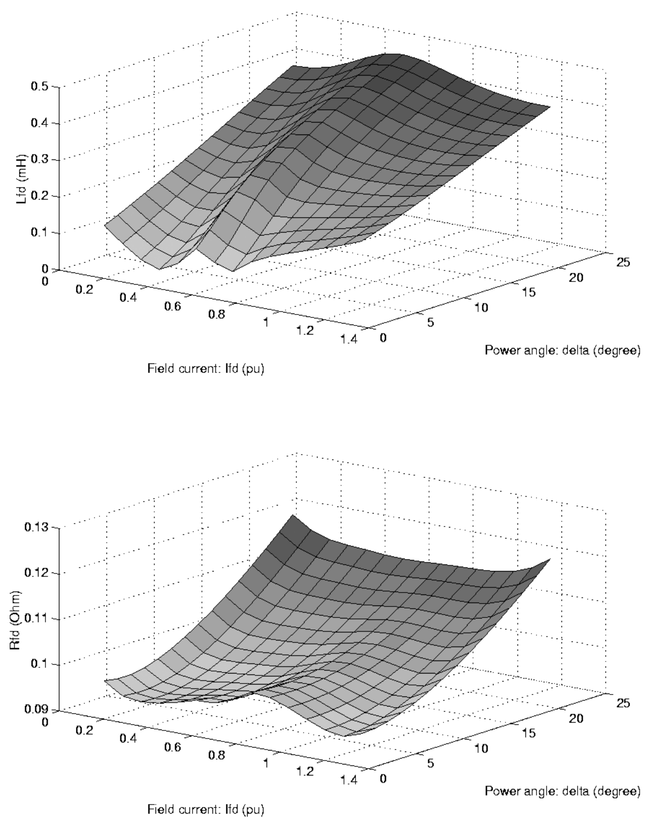


Fig. 4 Transfer functions of $L_{fd}$ and $R_{fd}^*$ w.r.t. the mean values of $i_{fd}^*$ and $\delta$

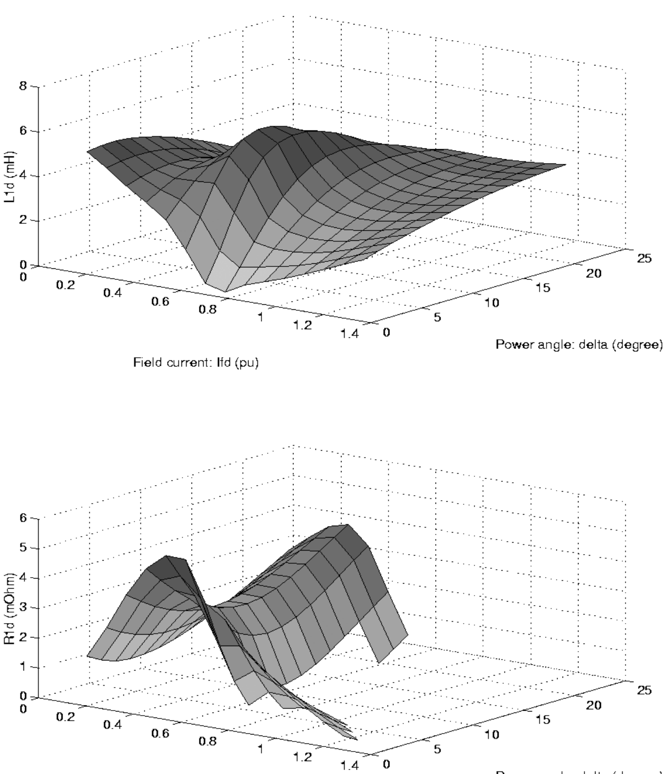


Fig. 5 Transfer functions of $L_{1d}$ and $R_{1d}$ w.r.t. the mean values of $i_{fd}^*$ and $\delta$

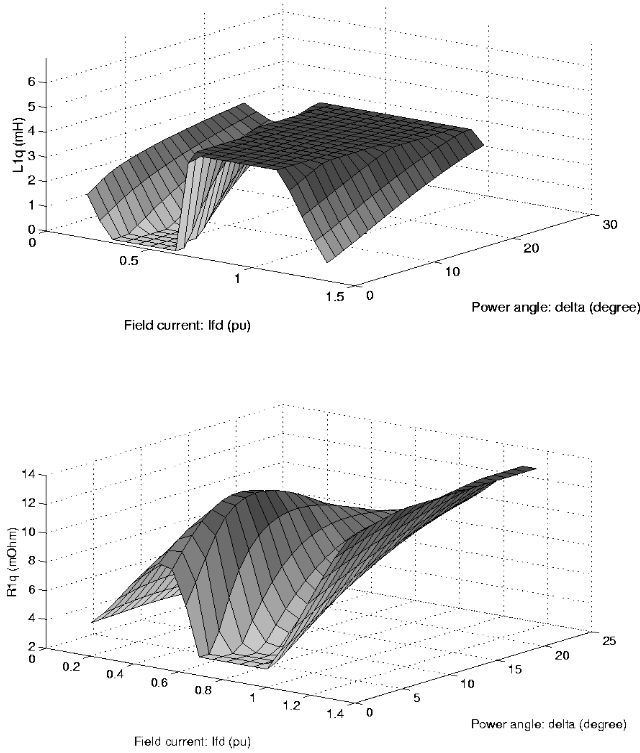


Fig. 6 Transfer functions of $L_{1q}$ and $R_{1q}$ with respect to the mean values of $i_{fd}^*$ and $\delta$

During the weight adjustment procedure a trial error procedure is used to determine the number of hidden layer neurons. A satisfactory convergence criterion has been met with five hidden layer neurons for each ANN estimator. All ANN models are trained using Levenberg-Marquardt algorithm [18]. The results of training procedure for $R_{1d}$ and $L_{1d}$ are given in terms of the weights and biases in the appendix. Due to the space limitations, the weights and biases for the other parameters are not given.

In order to verify that the networks are able to generalize properly, a cross validation data set, which is not included in the training, is used after the training. Table 1 compares ANN estimated and OEM estimated *d*-axis parameters for the data set not used in training. As can be seen, ANN models can correctly interpolate for the patterns not used in training.

Table 1. Comparison of OEM estimated and ANN estimated parameters for the cross validation data set

| | $R_{fd}^*$ (Ω) | $L_{fd}$ (mH) | $R_{1d}$ (mΩ) | $L_{1d}$ (mH) |
|---|---|---|---|---|
| OEM Estimate | .1009 | .1075 | 2.7294 | .5275 |
| ANN Estimate | .0965 | .1038 | 2.8100 | .4544 |
| % Error | 4.36 | 3.44 | 2.87 | 13.8 |

Due to the very limited number of data sets available for *q*-axis rotor body parameter estimates, all estimates are used for ANN model training and not left for validation procedure. It is expected that the more disturbance data sets are provided for this machine, the better estimates will be obtained by the rotor body ANN models for previously unseen data patterns.

## VI. PARAMETER VALIDATIONS

For the purpose of comparatively validating estimated and manufacturer parameters, Four Corners HP unit is simulated for per-unit model in time domain. Eventually, the machine output variables obtained from simulation studies are compared with the measurement records.

The simulation models are developed in Matlab programming environment. First the state space equations have to be established. The machine mathematical model includes both electrical and mechanical dynamics. The electrical dynamics are given by Equation 1 for the identification model. For the manufacturer model, the only difference is that there is one extra damper winding in the $q$-axis model (*model 2.2* [1]). The mechanical dynamics for both models can be given as,

$$\dot{\omega}_r = \frac{1}{2H}(T_{pm} - T_e) + B\omega_r \qquad (11)$$
$$\dot{\delta} = \omega_r - \omega_e$$

where $B$ is the damping constant and $H$ is the inertia constant. $T_{pm}$ represents prime mover torque and $T_e$ represents electromagnetic torque.

For the complete state space model, the system state, input and output vectors respectively, are given as,

$$X = [i_q \ i_d \ i_{1q} \ i_{1d} \ i_{fd}^* \ \omega_r \ \delta]^T$$

$$U = [v_t \ v_{fd}^* \ T_{pm}]^T$$

$$Y = [i_q \ i_d \ i_{fd}^* \ \delta]^T$$

where $v_t$ represents terminal voltage peak value and can be computed in terms of line to line stator voltage measurements. The state vector $X$ also includes $i_{2q}$ for the manufacturer model. Since $T_{pm}$ is not measured, some assumptions have to be made for $T_{pm}$ calculations:

- For disturbances that result in small active power changes, $T_{pm}$ is assumed to be constant and equal to the initial value of $T_e$ .
- For disturbances that result substantial active power changes, $T_{pm}$ is assumed to be equal to $P_{active} / \omega_r$ by neglecting electromechanical power losses.

For the simulations 3rd order Runge-Kutta method is utilized as the differential equation solver. For the first electrical cycle of the disturbance, the mean and variance of the simulation errors are listed in Table 2 for some of the measurement records. Table 3 lists the error statistics for the first 60 cycles of the disturbance.

As can be seen from Table 2 and 3, the simulations, with estimated parameters, perform much better than simulations with manufacturer parameters. Especially for Tests 3 and 4 where the unit is tripped, the simulation errors for $\delta$ are quite substantial for manufacturer parameters. Also for Test 4, the simulated machine variables vs. measurement data records are plotted for entire data set and given by Figs. 7 through 10.

## IX. CONCLUSIONS

An Artificial Neural Network based modeling technique for the rotor body parameters of a large utility generator is developed. Disturbance operating data collected on-line at different levels of excitation and loading conditions are utilized for estimation. The disturbance data is obtained by perturbing the field side of the machine in large amounts. An OEM technique is later employed to estimate the operating point dependent rotor body parameters. Rotor body ANN models are developed by mapping field current $i_{fd}^*$ and power angle $\delta$ to the parameter estimates. Validation studies show that ANN models can correctly interpolate between patterns not used in training.

Table 2. Error Statistics of Simulated Machine Variables for the first cycle of the disturbance

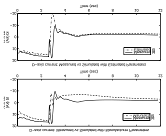
| Simulated machine variable statistics | | | Test 1 | Test 2 | Test 3 | Test 4 |
|---|---|---|---|---|---|---|
| $i_q$ (kA) | *Error mean* | E* | 0.2058 | 0.1926 | 0.4130 | 0.0524 |
| | | M** | 0.3101 | 0.2959 | 0.9458 | 0.1309 |
| | *Error variance* | E | 0.0435 | 0.0381 | 0.2831 | 0.0028 |
| | | M | 0.0989 | 0.0900 | 1.0464 | 0.0176 |
| $i_d$ (kA) | *Error mean* | E. | 0.0050 | 0.0464 | 0.1828 | 2.0715 |
| | | M | 3.5531 | 3.6241 | 3.2867 | 5.5473 |
| | *Error variance* | E | 0.0000 | 0.0022 | 0.0347 | 4.4102 |
| | | M | 12.976 | 13.499 | 11.103 | 31.627 |
| $i_{fd}^*$ (kA) | *Error mean* | E. | 0.0009 | 0.0012 | 0.0215 | 0.3165 |
| | | M | 0.5808 | 0.5724 | 0.5326 | 1.2216 |
| | *Error variance* | E. | 0.0000 | 0.0000 | 0.0005 | 0.1055 |
| | | M | 0.3467 | 0.3367 | 0.2915 | 1.5339 |
| $\delta$ (degree) | *Error mean* | E | 1.3904 | 1.4176 | 0.8356 | 0.1495 |
| | | M | 1.9436 | 1.9847 | 5.7259 | 14.821 |
| | *Error variance* | E | 1.9885 | 2.0683 | 0.7176 | 0.0272 |
| | | M | 3.8839 | 4.0514 | 33.699 | 225.78 |

* Value obtained using estimated parameters,
** Value obtained using manufacturer' parameters,

Table 3. Error Statistics of Simulated Machine Variables for the first 60 cycles of the disturbance

| Simulated machine variable statistics | | | Test 1 | Test 2 | Test 3 | Test 4 |
|---|---|---|---|---|---|---|
| $i_q$ (kA) | *Error mean* | E* | 0.2023 | 0.1972 | 0.4341 | 1.1680 |
| | | M** | 0.3063 | 0.3035 | 0.7016 | 1.5285 |
| | *Error variance* | E | 0.0411 | 0.0390 | 0.3195 | 1.5499 |
| | | M | 0.0941 | 0.0923 | 0.7124 | 2.8439 |
| $i_d$ (kA) | *Error mean* | E. | 0.0372 | 0.0648 | 0.2180 | 1.1350 |
| | | M | 3.6682 | 3.7618 | 3.7421 | 3.2465 |
| | *Error variance* | E | 0.0017 | 0.0045 | 0.0645 | 1.4516 |
| | | M | 13.492 | 14.192 | 14.171 | 11.5084 |
| $i_{fd}^*$ (kA) | *Error mean* | E. | 0.0041 | 0.0078 | 0.0287 | 0.1249 |
| | | M | 0.5935 | 0.5950 | 0.6239 | 0.7126 |
| | *Error variance* | E. | 0.0000 | 0.0001 | 0.0016 | 0.0217 |
| | | M | 0.3531 | 0.3549 | 0.3912 | 0.5340 |
| $\delta$ (degree) | *Error mean* | E | 1.3843 | 1.4305 | 1.6282 | 1.4099 |
| | | M | 1.9490 | 2.0146 | 4.5504 | 18.255 |
| | *Error variance* | E | 1.9213 | 2.0546 | 3.9814 | 3.3327 |
| | | M | 3.8081 | 4.0716 | 21.316 | 335.01 |

* Value obtained using estimated parameters,
** Value obtained using manufacturer' parameters,



It is expected that richer data set collected at different loading and excitation levels would improve the performance of such ANN models. It has also been shown through extensive simulations that the estimated parameters can correctly predict the internal variables of the machine during large transient events. Only field and terminal voltage measurements are utilized during these simulations.

## X. ACKNOWLEDGEMENTS

This work is supported in part by the National Science Foundation, Grant No. ECS9722844. Also, the authors acknowledge the assistance of Mr. John Demcko of APS.

Fig. 7 The simulated $\delta$ vs. measured $\delta$ for both estimated and manufacturer parameters

Fig. 8 The simulated $i_{fd}^*$ vs. measured $i_{fd}^*$ for both estimated and manufacturer parameters

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Fig. 9 The simulated $i_q$ vs. measured $i_q$ for both estimated and manufacturer parameters

Fig. 10 The simulated $i_d$ vs. measured $i_d$ for both estimated and manufacturer parameters

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## Appendix

*The estimated weights and biases for $L_{1d}$ ANN model*

Input to Hidden Layer

*Weights*, $W1$

| | | | |
|---|---|---|---|
| 0.9788 | 3.2250 | 1.5682 | -3.0754 |
| -2.1159 | 4.1708 | -5.1911 | -0.3545 |
| -0.3607 | 2.6550 | -5.3582 | 0.9816 |
| -0.1081 | -6.0435 | -3.2224 | -4.0616 |
| 1.0061 | -3.4998 | 2.1998 | -4.3176 |

*Biases*, $B1^T$

| | | | | |
|---|---|---|---|---|
| -1.5524 | 1.2151 | 2.3107 | 0.1652 | 1.5486 |

Hidden Layer to Output

*Weights*, $W2$

| | | | | |
|---|---|---|---|---|
| 1.7618 | 5.4068 | -0.9097 | -5.4107 | 2.3757 |

*Bias*, $B2$

1.0925

*The estimated weights and biases for $R_{1d}$ ANN model*

Input to Hidden Layer

*Weights*, $W1$

| | | | |
|---|---|---|---|
| 0.5659 | -4.6565 | -3.8250 | 0.7801 |
| -1.7650 | -0.9102 | 4.3498 | -1.6474 |
| -3.3118 | 2.7679 | 1.7180 | -2.3505 |
| -0.2118 | -3.8658 | -0.9416 | -3.2274 |
| 1.2872 | -6.7329 | -2.2611 | -3.4213 |

*Biases*, $B1^T$

| | | | | |
|---|---|---|---|---|
| 0.3642 | 1.4991 | 2.4391 | 2.5116 | -0.3280 |

Hidden Layer to Output

*Weights*, $W2$

| | | | | |
|---|---|---|---|---|
| 1.0870 | 3.8530 | 3.5253 | -3.2647 | 5.5263 |

*Bias*, $B2$

2.1265

## BIOGRAPHIES

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