MODELING AND SIMULATION OF SYNCHRONOUS MACHINES USING ADAPTIVE NETWORK BASED FUZZY INFERENCE SYSTEMS

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Key words: Adaptive network based fuzzy inference systems, modeling, synchronous machines

ABSTRACT

In this article, the modeling and simulation of the synchronous machines are presented by using Adaptive-Network-based Fuzzy Inference Systems (ANFIS). The capability of the model to approximate the non-linear operating characteristics of the synchronous machine is illustrated. At the beginning, the results of the ANFIS model are compared with that obtained by time-domain simulations of the machine. Finally, correlation-based model validity tests are performed. The all results demonstrate the adequacy of the ANFIS model.

I. INTRODUCTION

The models of synchronous machines widely employed in various areas play important roles in many studies such as stability and control analysis. Different synchronous machine models have been developed [1-3]. Simple machine models are good for analysis studies but not accurate enough for predicting machine performance for control studies. However, the higher order models improve the validity of the results.

Generally, the synchronous machine is a very complex non-linear system with dynamics and non-linearities that cannot be modeled in precise mathematical terms. In order to accurately model the machine, non-classical techniques are needed. Fuzzy logic modeling and neural network modeling have proposed as viable alternatives [4-7]. These two innovative modeling approaches share some common characteristics: they assume parallel operations; they are well known for their fault tolerance capabilities; and they are often called model-free modeling approaches. Despite these similarities, they stem from very different origins. Fuzzy logic modeling is primarily based on fuzzy sets and fuzzy if-then, which are closely related to psychology and cognitive science. On the other hand, neural network modeling is based on artificial neural networks (ANN) that are motivated by biological neural systems. Because of very origins, the respective philosophies and methodologies underlying their problem-solving approaches are quite different and, in general, complementary. As a result, many researchers are trying to integrate these two schemes to generate hybrid models that can take advantage of the strong points of both. This is also the motivation for our research, which aims at providing an integrate framework capable of subsuming both neural networks and fuzzy inference systems [8-10]. In this study, a model based a hybrid architecture, ANFIS (Adaptive-Network-based Fuzzy Inference System), that can encode a priori knowledge (which can assume various forms of fuzzy if-then rules) into their structures and utilize a fast hybrid learning rule to update their parameters based on a desired input-output data set is introduced and researched to demonstrate its capability to learn the machine behavior.

In this article, three-phase synchronous machine having an equivalent circuit with unequal stator and rotor mutual inductances and coupling inductances between d-axis rotor circuits is modeled by using the ANFIS. The remaining of the article is organized as follows. Section II introduces a brief summary of ANFIS applied to model a system. The problem formulation and the model description of the synchronous machine are given in the section III. Section IV includes correlation-based model validity tests. Section V illustrates the results obtained using the ANFIS model because of variations in the machine inputs. Section V presents the time-domain simulations obtained in MATLAB/SIMULINK for comparison purposes. Finally, Section VI contains conclusions

II.ADAPTIVE NETWORK BASED FUZZY INFERENCE SYSTEMS (ANFIS)

ANFIS are one of the best transitions between fuzzy and neural systems. This system makes use of a hybrid-learning rule to optimize the fuzzy system parameters of a first order Sugeno system [8]. ANFIS architecture with two inputs, two rules and one output is graphically represented in Figure 1 for a typical fuzzy rule set as follows:

IF x is A_1 and y is B_1 THEN $f_1=p_1x+q_1y+r_1$
IF x is A_2 and y is B_2 THEN $f_2=p_2x+q_2y+r_2$

The layers for ANFIS in this architecture are defined as:
Layer 1: Every node 'i' in this layer is an adaptive node with a node output defined by

$$O_{1,i} = \mu_{A_i}(x), \quad \text{for } i = 1,2 \text{ or}$$
$$O_{1,i} = \mu_{B_{i-2}}(y), \quad \text{for } i = 3,4 \tag{1}$$

where x (or y) is the input relating to the node, A_j (or B_j) is a fuzzy set associated with this node, $\mu_{A_i}(x)$ is the membership function (MF for short) of x in A. In this study, the gaussian MF's characterized by Eq. (2) are used.

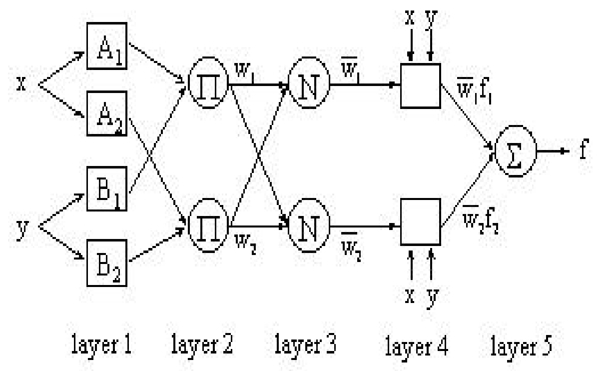

Figure 1. ANFIS architecture for the two-input two-rule Sugeno fuzzy model

$$\mu_{A_j}(x) = e^{-\left(\frac{x-c_j}{\sigma_j}\right)^2} \tag{2}$$

where $\{c_j, \sigma_j\}$ is the nonlinear premise parameter set in this layer.
Layer 2: Every node 'i' in this layer is two fixed node, which multiplies the incoming signals and outputs the product, as defined in the Eq. (3).

$$O_{2,i} = w_i = \mu_{A_j}(x) * \mu_{B_j}(y), \quad i = 1,2; \quad j = 1,2 \tag{3}$$

Each node output represents the firing strength of rule.
Layer 3: Every node 'i' in this layer is a fixed node. The i-th node calculates normalized firing strength:

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1,2 \tag{4}$$

Layer 4: Every node 'i' in this layer is an adaptive node with a node function

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \tag{5}$$

where $\{p_i, q_i, r_i\}$ is the linear consequent parameter set in this layer.
Layer 5: The single node in this layer is a fixed node, which computes the overall output as the summation of all incoming signals:

$$O_{5,l} = \text{overall output} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{6}$$

Hybrid learning algorithm of ANFIS adjusts the consequent parameters in a forward pass and the premise parameters in a backward pass. In the forward pass, node outputs go forward until layer 4 and the consequent parameters are identified by the least-squares method. In the backward pass, the error signals propagate backward and the premise parameters are updated by gradient descent.

Here, the rules and the numbers of MF' s are generated by using subtractive clustering algorithm. The subtractive clustering is based on a measure of the density of data points [10]. The aim is to find regions with high densities of data points. The data point with the highest potential is selected as the center for a cluster. The data points within a prespecified fuzzy radius are removed (subtracted), and algorithm looks for a new point with the highest number of neighbors. This process continues until all data points have been tested. A election of K data points are specified by m-dimensional vectors and normalized. Since each data point is a candidate for a cluster center, a density measure at data point u_k is defined as

$$D_k = \sum_{j=1}^{K} \exp\left(-\frac{\|u_k - u_j\|}{(r_a/2)^2}\right), \tag{7}$$

where k=1,2,3,..,K and r_a is a positive constant. After calculating the density measure for each data point, the point with the highest density is selected as the first cluster center. Let u_{c1} be the point selected and D_{c1} its density measure. Next, the density measure for each data point u_k is revised by the formula

$$D'_k = D_k - D_{c1}\exp\left(-\frac{\|u_k - u_{c1}\|}{(r_b/2)^2}\right), \tag{8}$$

where r_b is larger than r_a to prevent closely space cluster centers. Therefore, the data points near the first cluster center U_{c1} will have significantly reduced density measures, thereby making the points unlikely to be selected as the next cluster center. After the density measure for each point is revised, the next cluster center U_{c2} is selected and all the density measures are revised again.

The process is repeated until a sufficient number of cluster centers are generated. When applying subtractive clustering to a set of input-output data, each of the cluster centers represents a rule. To generate rules, the cluster centers are used as the centers for gaussian MF' s in clustering algorithm.

III. MACHINE MODEL DESCRIPTION AND PROBLEM FORMULATION

The test machine considered in this research study is a 722.222MVA, 60-Hz, two-pole synchronous generator whose model structure is shown in Figure 2. This machine model is only an approximation of the actual round-rotor machine that theoretically has an infinite number of rotor body circuits. We used the model parameters that obtained from a standstill frequency response test by M. Canay in this study [1].

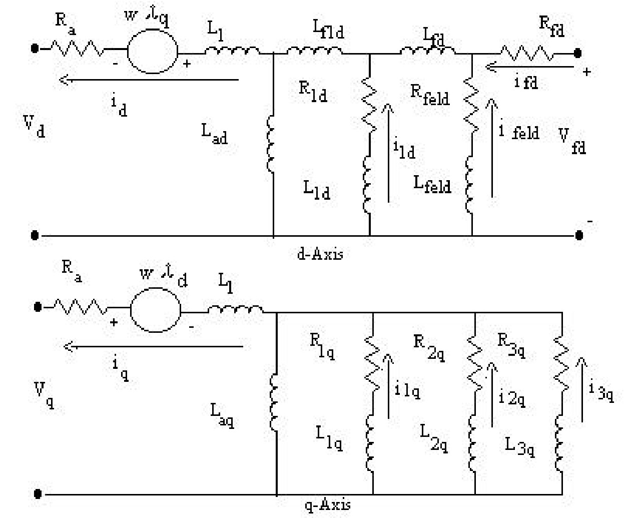

Figure 2. The model with leakage coupling between d-axis circuits

For discrete-time systems, the coupled state space representation of the models shown in Figure 2 can be written as:

$$\begin{aligned} X(k+1) &= F(X(k) + U(k)) + w(k) \\ Y(k+1) &= G(X(k+1)) + v(k+1) \end{aligned} \tag{9}$$

where F(.) and G(.) are the non-linear state and output mapping functions, respectively. w(k) and v(k) also denote the process and measurement noise, respectively. In addition,

$$X = [i_q \ \ i_d \ i_{1q} \ i_{2q} \ i_{3q} \ i_{1d} \ i_{feld} \ i_{fd}]^T; \tag{10}$$

$$U = [v_q \ v_d \ v_{fd}]^T; \tag{11}$$

$$Y = [i_q \ i_d \ i_{fd}]^T \tag{12}$$

where fd, d and q denote the indices of quantities to the d-axis and the q-axis, respectively. i and v also denote the current and voltage, respectively.

The currents and the parameters of rotor body of this model have been modeled and estimated by using ANN' s in reference [4,5]. As different in this study, in order to generate the model which approximates the non-linear operating characteristics of the synchronous generator, we applied the mechanical torque disturbance, T_m, and the field voltage disturbance, V_{fd}, to the machine inputs and modeled the flux linkage in the d-axis, $ø_d$, and rotor angle, $\boldsymbol{d}$, by the ANFIS. We observe only two quantities: $\boldsymbol{d}$, because it is an important indicator of generator stability, and $ø_d$, because it is a representative of the Q-V transient process. Because of our chose, the network input vector and output vector can be written as following, respectively:

$$U1(k) = [T_m(k) \, V_{fd}(k)]^T \tag{13}$$

$$Y1(k) = [ä, ø_d \ ]^T \tag{14}$$

The network outputs are some nonlinear mapping of a vector that consists of the lags of the outputs and inputs with the inputs.

IV. MODEL VALIDATION

The correlation-based model validity tests exhibit the adequacy of the modeling. The residual vector can be defined as

$$E(k) = Y1(k) - Y1_{ANFIS}(k) \tag{15}$$

If the correlation tests in Eq. (16) are satisfied using residual and inputs, then the model should be operated correctly [11].

$$\begin{aligned} \tilde{A}_{e_i e_i}(\hat{o}) &= \tilde{A}_{e_i{}^2 e_i{}^2}(\hat{o}) = ä(t), \forall \hat{o} \\ \tilde{A}_{u_r e_i}(\hat{o}) &= \tilde{A}_{u_r{}^2 e_i{}^2}(\hat{o}) = 0, \forall \hat{o} \end{aligned} \tag{16}$$

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 $ä(t)$ represents the unit impulse functions.

V. SIMULATION RESULTS

In order to examine the performance of the ANFIS model, two kinds of disturbances have been applied to the machine inputs, T_m and V_{fd}, to derive the machine. Initially, the machine was operating rated power at unity power factor into the external bus of one per unit voltage magnitude. In this study, the results of the ANFIS model and time-domain simulations obtained by MATLAB/SIMULINK were compared to demonstrate the adequacy of the ANFIS model. In addition, some correlation-based model validity tests using residuals and inputs have been accomplished to show the validity of the ANFIS identifier. In all cases nine historical values of the inputs and outputs were used to construct the input vector of ANFIS model.

Figure 4, 9 show the response of the rotor angle because of the variations in the mechanical torque shown in Figure 3, and the field voltage shown in Figure 8, respectively. Figure 5, 10 also show the response of d-axis flux linkage because of the variations in the mechanical torque shown in Figure 3, and the field voltage shown in Figure 8, respectively. The results of the model validation tests shown in Figure 6 satisfy the conditions stated in Eq. (16) and fall within the 95% confidence bands. The training error versus time is shown in Figure 7. The all results demonstrate the capability of the ANFIS model to learn the underlying characteristics of the synchronous machine.

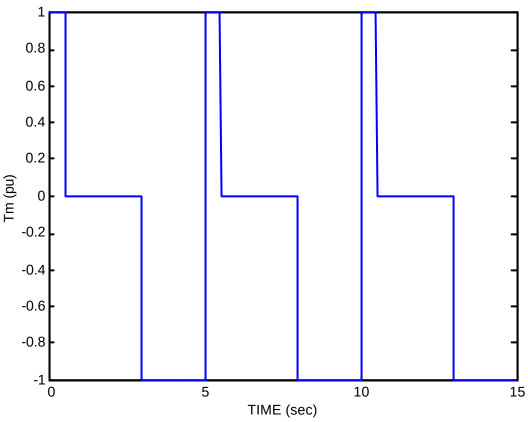

Figure 3. The disturbance mechanical torque applied synchronous machine

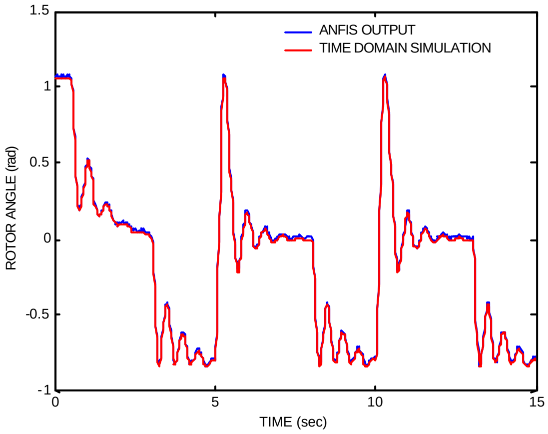

Figure 4. Rotor angle response because of variation in the mechanical torque shown in Figure 3

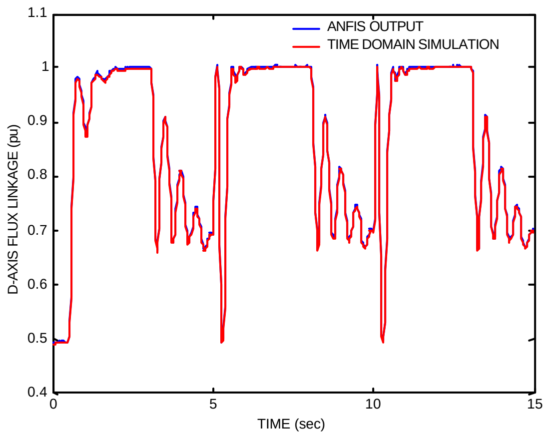

Figure 5. D-axis flux linkage response because of variation in the mechanical torque shown in Figure 3

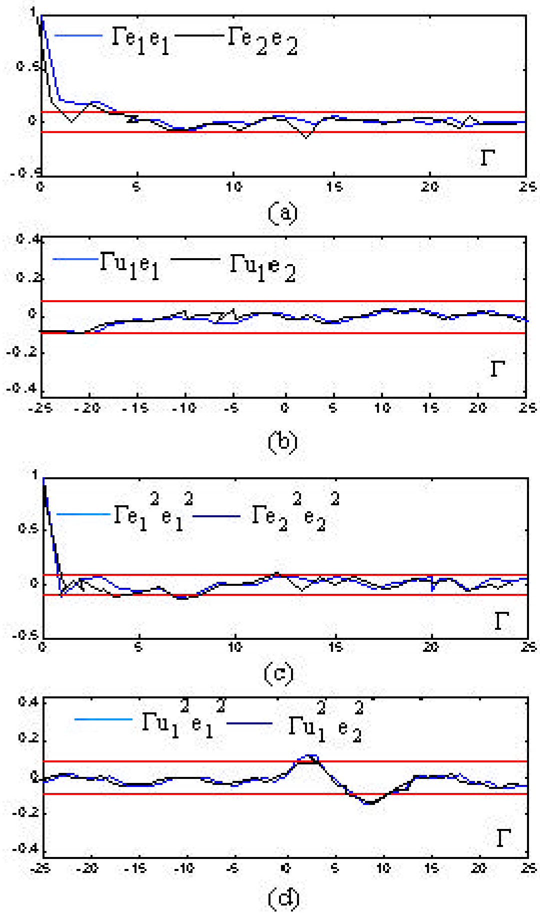

Figure 6. Auto-correlation and cross-correlation tests using residuals and T_m

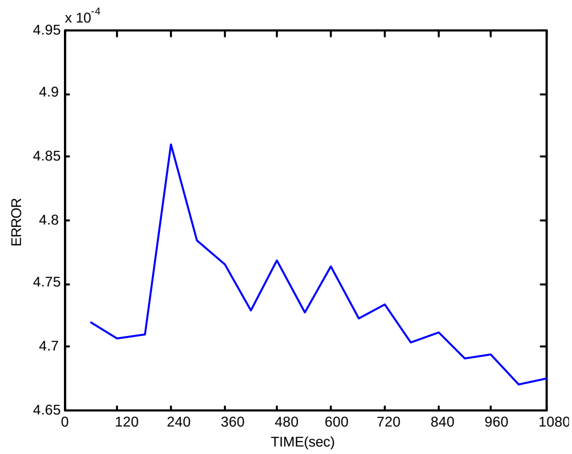

Figure 7. Training error

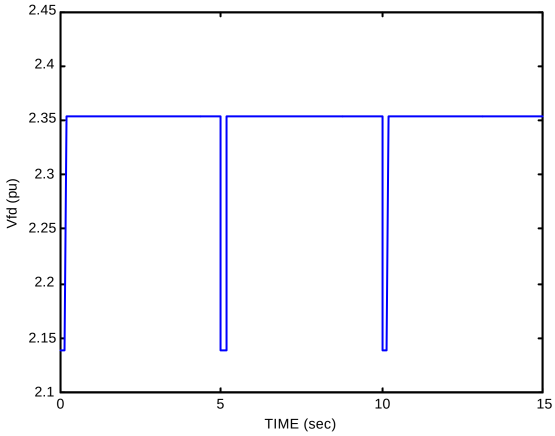

Figure 8. The disturbance field voltage applied synchronous machine

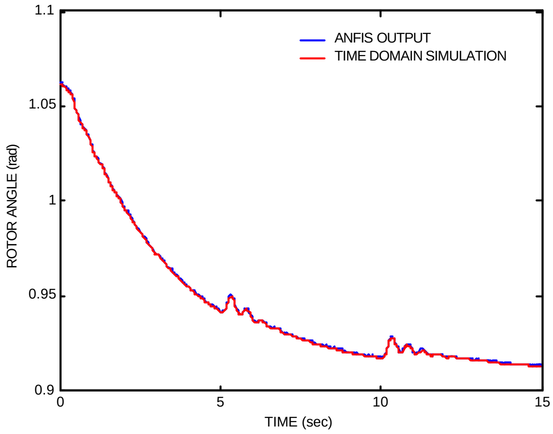

Figure 9. Rotor angle response because of variation in the field voltage shown in Figure 8

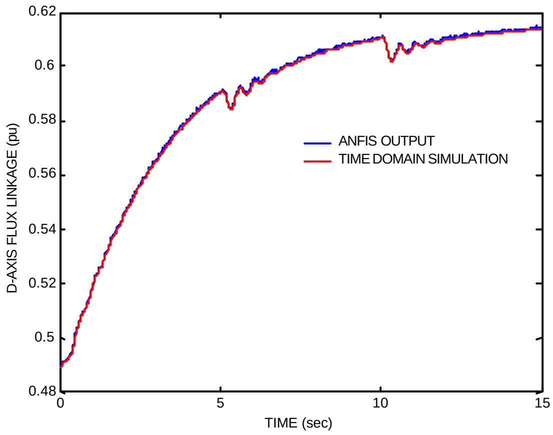

Figure 10. D-axis flux linkage response because of variation in the field voltage shown in Figure 8

VI. CONCLUSION

In this study, the modeling of the synchronous machine successfully made by using the ANFIS. From the obtained results, it was demonstrated that the ANFIS model was approximated the non-linear operating characteristics of the synchronous machine. The ANFIS model was trained by using the hybrid-learning algorithm that combined the backpropagation algorithm with the least-squares algorithm. The results of the ANFIS model and time-domain simulations because of variations in both mechanical torque and field voltage almost coincide with each other. Moreover, the adequacy of the ANFIS model confirm because the results of the correlation-based model validity tests fall within the 95% confidence bands. Consequently, the all results demonstrate the potential of the ANFIS model having a high performance in applications.

REFERENCES

1. C. Ong, Dynamic Simulation of Electric Machinery, Prentice Hall, 1997.
2. W. Jazdzynski, Poland, A method of Searching for the Best Model of Synchronous Machine, Allowing for Unequal Mutual Inductances, International Conference on Electrical Machines, Vol. 1/3, No.1, pp. 54-58, 1998.
3. .L. Xu, Z. Zhao, J. Jiang, On-line Estimation of Variable Parameters of Synchronous Machines Using a Novel Adaptive Algorithm–Estimation and Experimental Verification, IEEE Trans. on Energy Conversion, Vol. 12, No.3, pp. 200-210, 1997.
4. S. Pillutla, A. Keyhani, Neural Network Based Modeling of Round Rotor Synchronous Generator Rotor Body Parameters fom Operating Data, IEEE Trans on Energy Conversion, Vol. 14, No. 3, pp. 321-327, 1999.
5. S. Pillutla, A. Keyhani, I. Kamwa, Neural Network Observers for On-line Tracking of Synchronus Generator Parameters, IEEE Trans on Energy Conversion, Vol. 14, No. 1, pp. 23-30, 1999.
6. W. A. Farag, V. G. Quintana, Lambert-Tarres, An Optimized Fuzzy Controller for a Synchronous Generator in a Multi-Machine Environment, Fuzzy Sets and Systems 102, pp: 71-84, 1998.
7. M. A. Abido, Y. Abdel-Magid, On-line Identification of Synchronous Machines Using Radial Basis Function Neural Networks, , IEEE Trans on Power Systems, Vol. 12, No. 4, pp. 1500-1505, 1997.
8. J. R. Jang, S. Chuen-Tsai, Neuro-Fuzzy Modeling and Control, Proceedings of the IEEE, Vol. 83, No. 3, pp. 378-406, 1995.
9. M. O. Efe, O. Kaynak, Comparative Study of Neural Network Structures in Identification of Nonlinear Systems, Mechatronics, Vol. 9, No. 3, pp: 287-300, 1999.
10. J. Jantzen, Neurofuzzy Modelling, Technical Report 98-H-874, Department of Automation Technical University of Denmark, 1998.
11. I. Petrovic, M. Baotic, N. Peric, Regularization And Validation of Neural Network Models of Nonlinear Systems, Elektrotechnik & Informationtechnik, 1/2000, pp. 24-31, Springer-Verlag, Vienna, Austria.