

ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM IDENTIFICATION OF AN INDUCTION MOTOR

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ABSTRACT

Modeling and simulation of the squirrel-cage induction motor (SCIM) is very complex and cannot represent the physical system exactly because the system is characterized by highly non-linear, complex and time-varying dynamics and inaccessibility of some of the states and outputs for measurements are depend on a lot of excited input parameters. This work demonstrated experimentally that ANFIS can be effectively used for identification of the system with highly accurate results. The accuracy of the identification results is demonstrated through validation tests including training, testing and validating data.

Keywords: Induction motor, Identification, Neuro-Fuzzy systems, ANFIS, Hybrid Learning, LABVIEW.

INTRODUCTION

AC motors, particularly the Squirrel-Cage Induction Motor (SCIM), enjoy several inherent advantages like simplicity, reliability, low cost and virtually maintenance-free electrical drives. However, they exhibit significant non-linearities and their modeling is highly complicated (Slemon, 1989, P.1126). The need to solve the identification and control problems of highly nonlinear AC motors motivated the use of the promising tools from the field of soft computing such as neural networks, Fuzzy Logic (FL) and Genetic Algorithms (GA) (Salvini *et al*, 2002, p. 873).

The ANFIS structure is considered for dynamic modeling of (SCIM), the objective is mapping relation between the input and output data through hybrid learning (it combines gradient descent and the least-squares method) to determine the optimal distribution of membership functions, to obtain a model of the induction motor without any prior system knowledge pertaining to the exact mathematical model structure permits open-loop system identification (Roger Jang *et al*, 1995, p. 378).

The aim of this paper is to develop an optimal and accurate identification model for Induction motor using ANFIS.

METHODOLOGY ADAPTIVE NEURO-FUZZY INFERENCE

An Adaptive Neuro-Fuzzy Inference System (ANFIS) is a cross between an artificial neural network and a Fuzzy Inference System (FIS). An artificial neural network is designed to

mimic the characteristics of the human brain and consists of a collection of artificial neurons. An adaptive network is a multi-layer feed-forward network in which each node (neuron) performs a particular function on incoming signals. The form of the node functions may vary from node to node. In an adaptive network, there are two types of nodes: adaptive and fixed. The function and the grouping of the neurons are dependent on the overall function of the network. Based on the ability of an ANFIS to learn from training data, it is possible to create an ANFIS structure from an extremely limited mathematical representation of the system. In sequel, the ANFIS architecture can identify the near-optimal membership functions of FLC for achieving desired input-output mapping. Obtaining ANFIS model for the induction motor is complex and time consuming as it often requires some steps to develop the model (Roger Jang *et al*, 1996).

The network applies a combination of the least squares method and the back propagation gradient descent method for training FIS membership function parameters to emulate a given training data set. The system converges when the training and checking errors are within an acceptable bound. The ANFIS system generated by the fuzzy toolbox available in MATLAB (The Math Works Inc. 1997) allows for the generation of a standard Sugeno style fuzzy inference system or a fuzzy inference system based on sub-clustering of the data Figure (1) shows a simple two-input ANFIS architecture (Roger Jang, 1993, p. 665).

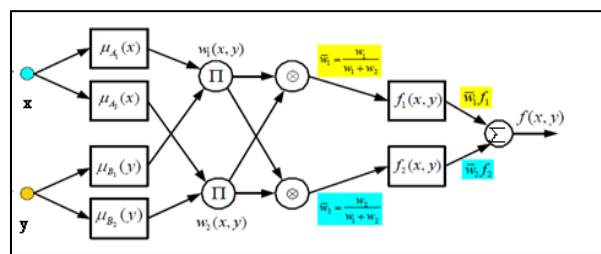


Figure (1) ANFIS architecture for Takagi-Sugeno system with two inputs, one output

The above ANFIS architecture is based on a Sugeno fuzzy inference System. The ANFIS network is composed of five layers. The ANFIS is a fuzzy Sugeno model put in the framework of adaptive systems to facilitate learning and adaptation (Jang, 1992, 1993). Such framework makes the ANFIS modeling more systematic and less reliant on expert knowledge. To present the ANFIS architecture, two fuzzy if-then rules based on a first order Sugeno model are considered:

$$\text{Rule 1: If } (x \text{ is } A_1) \text{ and } (y \text{ is } B_1) \text{ then } (f_1 = p_1x + q_1y + r_1) \quad (1)$$

$$\text{Rule 2: If } (x \text{ is } A_2) \text{ and } (y \text{ is } B_2) \text{ then } (f_2 = p_2x + q_2y + r_2) \quad (2)$$

Where x and y are the inputs, A_i and B_i are the fuzzy sets, f_i are the outputs within the fuzzy region specified by the fuzzy rule p_i , q_i and r_i are the design parameters that are determined during the training process.

In the **first layer (membership functions)**, all the nodes are adaptive nodes. The outputs of layer 1 are the fuzzy membership grade of the inputs, no computation needed in this layer; each node directly transmits input signals to the next layer, which are given by:

$$O_{1,i} = \mu_{A_i}(x), \quad i = 1, 2 \quad (3)$$

$$O_{1,i} = \mu_{B_{i-2}}(y), \quad i = 3, 4 \quad (4)$$

$\mu_{A_i}(x)$, $\mu_{B_{i-2}}(y)$ adopt any fuzzy membership function. For example, if the generalized bell shaped membership function is employed, $\mu_{A_i}(x)$ is given by:

$$\mu_A(x) = \frac{1}{1 + \left| \frac{x-c_i}{a_i} \right|^{2b_i}} \quad (5)$$

where c_i , and a_i , $b_i (> 1)$ are the center (mean) and width (variance) (parameters of the membership function of the i^{th} in layer 2) respectively, n_{i2} the input value of the i^{th} in layer 2, governing the Generalized bell shaped functions accordingly.

In the **second layer (membership layer)**, the nodes are fixed nodes. Each node called MF node. The fuzzification is done in this layer. The membership value of a fuzzy set is calculated in this layer at range [0, 1]. The outputs of this layer can be represented as:

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad i = 1,2 \quad (6)$$

Which are the so-called firing strengths of the rules.

In the **third layer (AND layer)**, the nodes are also fixed nodes labeled by N, each node represent one fuzzy rule (IF-part) to indicate that they play a normalization role to the firing strengths from the previous layer. The output of this layer determined by fuzzy AND – operation (min- operation), one of the operator of fuzzy intersection, and can be represented as:

$$O_{3,i} = \bar{w} = \frac{w_i}{w_1+w_2} \quad i = 1,2 \quad (7)$$

Which are the so-called normalized firing strengths.

In the **fourth layer (OR layer)**, the nodes are adaptive, represent the consequent part (THEN-part) of the fuzzy rules. The output of each node in this layer is determined by fuzzy OR-operation (max- operation), one of the operator of fuzzy union, the output of each node in this layer is simply the product of the normalized firing strength and a first order polynomial (for a first order Sugeno model). Thus, the output of this layer is given by:

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i) \quad i = 1,2 \quad (8)$$

In the **fifth layer (defuzzification layer)**, there is only one single fixed node labeled with Σ . This node performs the summation of all incoming signals. Hence, the overall output of the (neuro-fuzzy) model is given as linguistic variable by:

$$O_{5,i} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (9)$$

It can be observed that there are two adaptive layers in this ANFIS architecture, namely the first and the fourth layers. In the first layer, there are three modifiable parameters, which are related to the input membership functions. These parameters are the so-called premise parameters. In the fourth layer, there are also three modifiable parameters $\{p_i, q_i, r_i\}$,

pertaining to the first order polynomial. These parameters are the so-called consequent parameters (Roger Jang, 1993, p. 665).

THE PROPOSED METHOD

The ANFIS Identification of an Induction Motor is obtained by exciting the plant by firing pulses and observing its input and output over an interval of time. Methodology used in Experimental study is as follows: obtaining a data set (input-output data pairs), finding the initial premise parameters for the membership functions, determining a threshold value for the error between the actual and desired output, finding the consequent parameters by using the least-squares method, calculating an error for each data pair, the process is terminated when the error becomes less than the threshold value, then the checking data set is used to compare the model with actual system.

RESULTS AND ANALYSIS

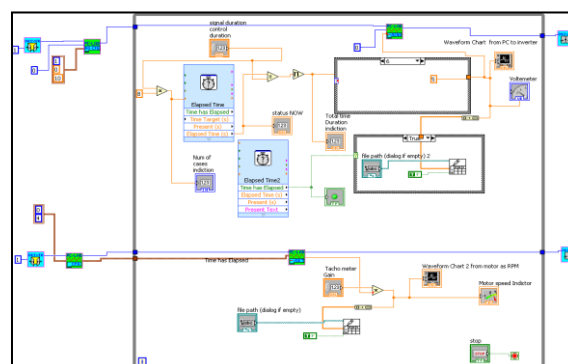
Figure (2) shows the experimental setup which consists of Squirrel Cage Induction Motor (SCIM), and Load (Tachometer), Power module (variable frequency inverter), Data Acquisition Card 4704 for

AdvanTECH company, Host PC, USB cable as Hardware. MATLAB and LABVIEW Programs (*website <http://ni.com/reference/>*) is used here as a Software.



Figure (2) Machine Test-Bench

Figures of the front panel and the block diagram of the LABVIEW used for a Real Time data collection are shown in Figure (3) and Figure (4) respectively.



Model	Description	Training error	Checking error
ANFIS model 1	$y(k-1)$	0.0241	0.0245
ANFIS model 2	$y(k-2)$	0.0209	0.0300
ANFIS model 3	$y(k-3)$	0.0277	0.0277
ANFIS model 4	$y(k-4)$	0.0262	0.0336
ANFIS model 5	$u(k-1)$	0.0945	0.0981
ANFIS model 6	$u(k-2)$	0.0938	0.0918
ANFIS model 7	$u(k-3)$	0.0866	0.0911
ANFIS model 8	$u(k-4)$	0.0866	0.0844
ANFIS model 9	$u(k-5)$	0.0795	0.0838
ANFIS model 10	$u(k-6)$	0.0788	0.0766
ANFIS model 11	$y(k-2)y(k-1)$	0.0177	0.0272
ANFIS model 12	$y(k-2)y(k-3)$	0.0194	0.0288
ANFIS model 13	$y(k-2)y(k-4)$	0.0198	0.0302
ANFIS model 14	$y(k-2)u(k-1)$	0.0181	0.0263
ANFIS model 15	$y(k-2)u(k-2)$	0.0180	0.0262
ANFIS model 16	$y(k-2)u(k-3)$	0.0178	0.0261
ANFIS model 17	$y(k-2)u(k-4)$	0.0795	0.0260
ANFIS model 18	$y(k-2)u(k-5)$	0.0177	0.0259
ANFIS model 19	$y(k-2)u(k-6)$	0.0176	0.0258
ANFIS model 20	$y(k-2)u(k-6)y(k-1)$	0.0154	0.0243
ANFIS model 21	$y(k-2)u(k-6)y(k-3)$	0.0158	0.0255
ANFIS model 22	$y(k-2)u(k-6)y(k-4)$	0.0156	0.0340
ANFIS model 23	$y(k-2)u(k-6)u(k-1)$	0.0168	0.0251
ANFIS model 24	$y(k-2)u(k-6)u(k-2)$	0.0168	0.0251
ANFIS model 25	$y(k-2)u(k-6)u(k-3)$	0.0168	0.0251
ANFIS model 26	$y(k-2)u(k-6)u(k-4)$	0.0168	0.0251
ANFIS model 27	$y(k-2)u(k-6)u(k-5)$	0.0168	0.0260

In the generated FIS matrix the number of fitting parameters is 135, including 27 non-linear parameters and 108 linear parameters. Obviously most of the fitting is done by the linear parameters while the non-linear parameters are mostly for fine-tuning for further improvement. The error curves for both checking and training data are shown in Figure (6); the optimal ANFIS parameters were obtained at the time when the test error reached the minimum indicated by small circle.

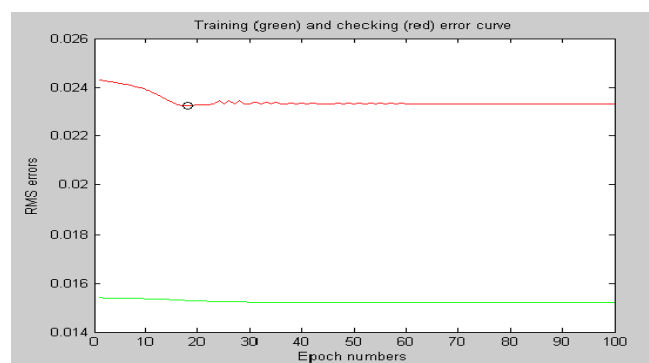


Figure (6) Training and Checking error curves

Actual induction motor speed curve and the ANFIS model output are shown in Figure (7). It is obvious that the two outputs can hardly be distinguished.

Figure (8) shows the output of the induction motor compared with the ANFIS; it demonstrates that the training and test data cover the same region.

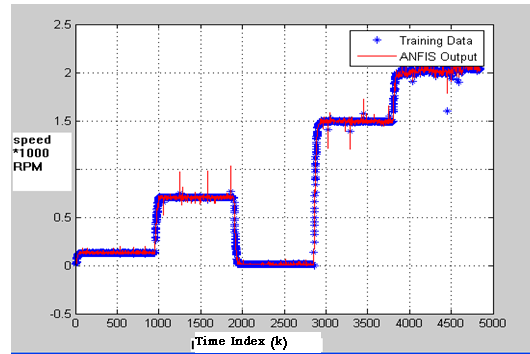


Figure (7) Desired curve and ANFIS prediction

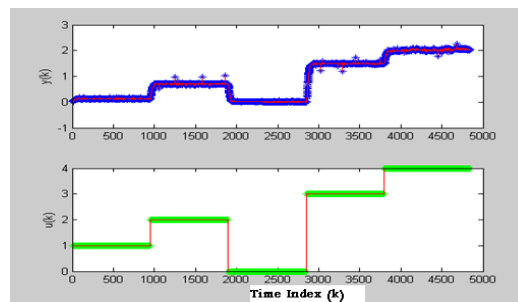


Figure (8) Data Distribution; Training and Test Data

The computing time for selecting the good model is 21.5510 s and resulted in a good prediction with RMSE 0.023 .for training and checking data for 100 epochs, the training error was 0.0154 but the checking one is 0.0243 is straightforward and provides satisfactory results for ANFIS identification induction motor system.

CONCLUSIONS

This work present successful development implemented and tested an ANFIS Identification of Induction Motor. It is clear that the system output closely approximates the required output. Experimental results revealed that ANFIS model was capable of closely reproducing the optimal performance and indicate that the technique is workable with high accuracy. This technique is fast in execution, efficient in identification and easy in implementation for the structure and the parameter of Induction Motor Model. The proposed model is an alternative and less complicated approach in determining the Identification of Induction Motor with good accuracy.

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