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PARAMETER ADAPTATION IN A SIMULATION MODEL USING ANFIS

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Key words : *Fussy system, approximation, asynchronous engine model.*

Abstract: *The paper is to demonstrate the development of an ANFIS used in parameter adaptation in a simulation model of an asynchronous machine. The work contains one adaptive model and the ANFIS is used to approximate the function. I have considered non-linearities of the magnetic circuit caused by magnetic saturation. This system is therefore processed as an expert ANFIS.*

1 Introduction

The aim of the paper is to demonstrate the use of Adaptive Neuro-Fuzzy Inference System (ANFIS) for the adaptation of a simulation model parameter that is changed during the simulation. The paper describes the use of an ANFIS for the approximation of point functions. The method is demonstrated during the adaptation of the simulation model parameter in an asynchronous machine.

2 Methods of Fuzzy system and Neural Network combination

There are a number of different combinations of the neural network system and fuzzy system. These combinations are usually divided into two groups:

1. Neural Network (NN) equipped with fuzzy capabilities. The basic structure is Neural Network (NN) and Fuzzy Inference System (FIS) is the second. We can fuzzify a NN by the extension principle so that we can process fuzzy inputs. Or fuzzy techniques are adopted to speed up the learning process. This system is usually called Fuzzy Neural Network (FNN), and its weights are set up by using fuzzy sets at its inputs/outputs.
2. FIS inplanted in neural network. FIS is the basic structure and NN is the second. These can be seen as extensions of FIS by NN, and are usually called Neuro-Fuzzy Systems (NF). One of the Neuro-Fuzzy Systems is called Adaptive Neuro-Fuzzy Inference System (ANFIS).

In this part I will mainly consider the latter case.

3 Neuro-Fuzzy system

Both neural networks and fuzzy system are motivated by imitating human reasoning process. It utilizes human expertise. In fuzzy systems, relationships are represented explicitly in the form of the if-then rules. In neural networks, the relations are not explicitly given, but are encoded in the networks and parameters designed. Neuro-fuzzy systems combine semantic transparency of rule-based fuzzy systems with a learning capability of neural networks. Depending on the structure of the if-then rules, two main types of fuzzy models are distinguished as mamdani (or linguistic) and Takagi-Sugeno models. The mamdani model is typically used in the knowledge-based (expert) systems while the Takagi-Sugeno model is used in data-driven systems.

In this part, we consider only the Takagi-Sugeno model.

4 ANFIS

The Adaptive Neuro-Fuzzy Inference System (ANFIS), first introduced by Jang, is a universal approximator and, as such, it is capable of approximating any real continuous function in to a compact set to any degree of accuracy.

4.1 Architecture of ANFIS

Using a given input/output data set, a Fuzzy Inference System (FIS) is constructed whose membership function parameters are tuned (adjusted) using either backpropagation algorithm alone, or in combination with the least-squares-type method. This allows your fuzzy systems to learn from the data they are modeling.

The ANFIS is a neural-fuzzy system. The system is based on the Takagi-Sugeno fuzzy inference system architecture. The fuzzy rule is determined as

$$\textit{If } x \text{ is } A_i \text{ and } y \text{ is } B_i \textit{ then } f_i = p_i x + q_i y + r_i$$

where i is an index, p, q and r is a parameter set of function f. ANFIS is a multilayer feedforward network which searches for fuzzy decision rules that perform well in any given task. The fuzzy decision rules are implemented as Membership Functions (MFs) and the model learns the best fitting parameters of the MFs. The architecture of ANFIS is shown in Figure 1.

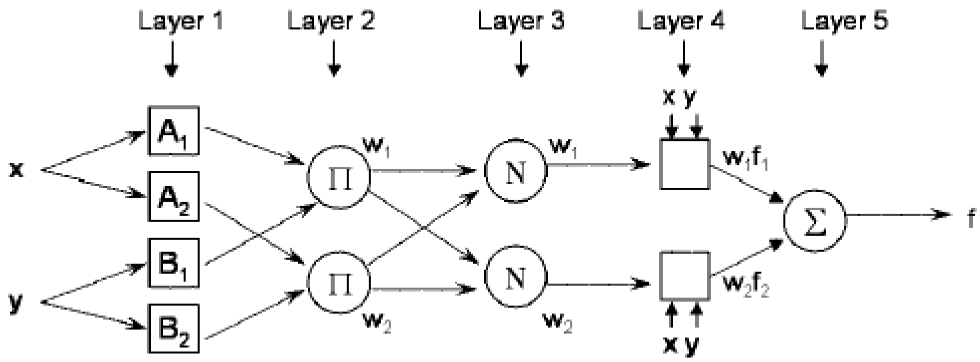

Fig. 1 The general architecture of ANFIS (from Roger Jang, 1993).

ANFIS is a five layer neural network. The detailed function of each layer is as foolows.

Only two of these layers have adjustable weights (here represented by squares). The first layer is composed of *n* MFs, each implementing a fuzzy decision rule. Any type of distributions can be modeled by MFs and the set of parameters to bz minimized is determined accordingly. The second layer computes every possible conjunction of the *n* decision rules. The third layer normalizes the conjunctive MFs in order to rescale the inputs. The fourth layer is a standard Perceptron (Rosenblatt, 1958) and associates every normalized MF with an output (weights are called consequent parameters). Finally, the fifth layer sums the evidences. The output is a real number. The consequent parameters and the MFs parameters are generated and trained using the standard backpropagation method.

4.2 Learning in the ANFIS model

A step in the learning procedure has two parts: In the first part the input patterns are propagated, and the optimal conclusion conseqent parameters are estimated by the iterative least mean square procedure, while the antecedent parameters (membership functions) are assumed to be fixed for the current cycle throughout the training set.

In the second part the patterns are propagated again, and in this epoch back propagation is used to modify the antecedent parameters while the conclusion conseqent parameters remain fixed.

4.3 Training in the ANFIS model

In the ANFIS training algorithm designed by Jang, both antecedent parameters and consequent parameters are optimised. In the forward pass, the consequent parameters are adjusted while the antecedent parameters remain fixed. In the backward pass, the antecedent parameters are tuned while the consequent parameters are kept fixed.

5 Adaptation of simulation model parameter in an asynchronous machine

When compiling an asynchronous machine model, its parameters are usually considered to be fixed. This results in incorrect simulation. The main induction L_h, which is one of the parameters of the machine, depends on magnetic loading of the ferro-magnetic circuit of the machine.

5.1 ANFIS system setup

To set up an ANFIS, the measured and calculated immediate voltage values and the main induction of a non-load asynchronous machine are taken as the range of the input and output variables at supply voltage f = 50 Hz. This training and checking data set you are loaded into the ANFIS editor GUI.

Table 1 Measured and calculated values

u_{1f} [V]	168	135	180	188	202	208	214	218	226	230	237	244	250
l_h [H]	0,22	0,21	0,19	0,18	0,16	0,15	0,14	0,13	0,11	0,11	0,10	0,08	0,08

In a ANFIS setup it is essential to carry out the following steps:

- in this model, an ANFIS is used to follow a trajectory of the non-linear function defined by the equation $l_h=f(u_1)$
- first, we choose the appropriate architecture for the ANFIS, the ANFIS must have inputs u_{1f} and output l_h
- thus, in our data, the ANFIS is defined by rules, and has a structure
- the ANFIS training data include training samples
- validation, using independent data

5.2 Compilation an computation of ANFIS

The Neuro-Fuzzy Systems are generated, trained and checked using the ANFIS editor graphical user interface (GUI) in the Fuzzy Logic Toolbox included in Matlab.

ANFIS Editor GUI display is divided into four main sub windows:

- data loading
- initializing and generating of ANFIS
- training of ANFIS
- testing data against the trained ANFIS.

The results of this process are shown bellow.

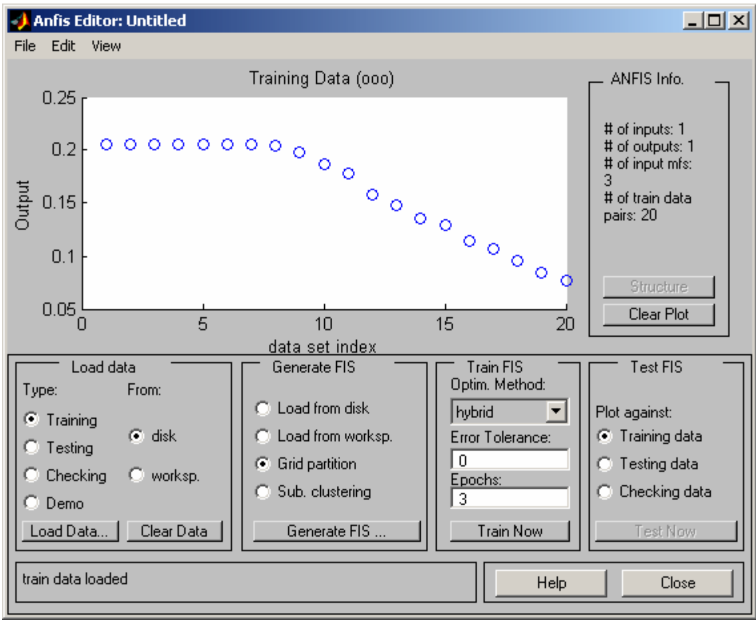

Fig. 2 Training result of data loaded

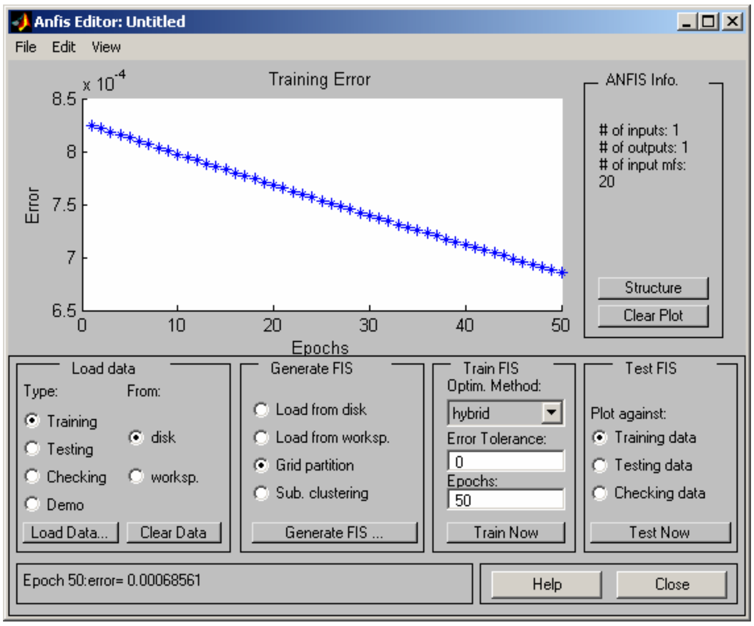

Fig. 3 Training Error

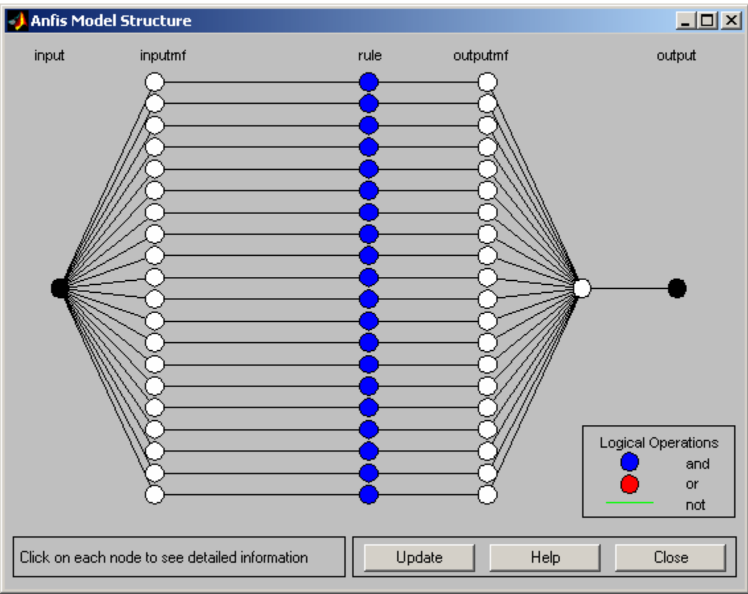

Fig. 4 ANFIS model structure

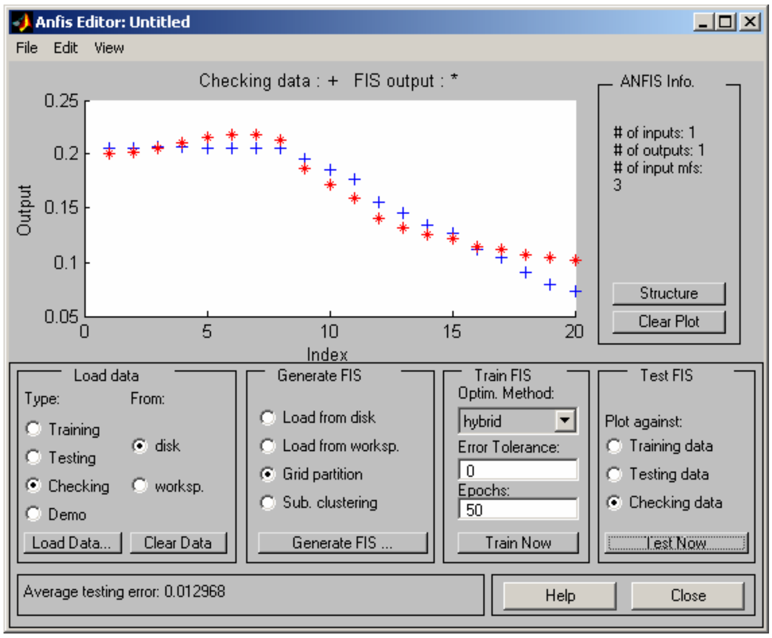

Fig. 5 Testing FIS against the checking data

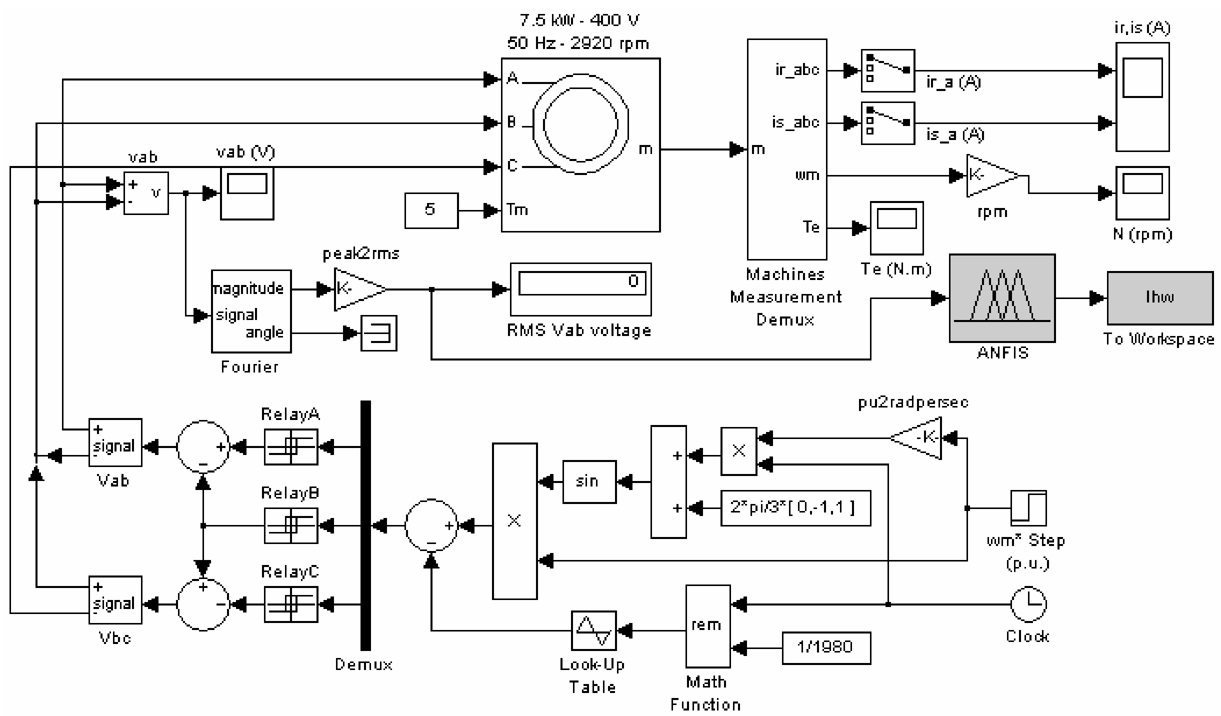

Fig. 6 Testing FIS against the checking data

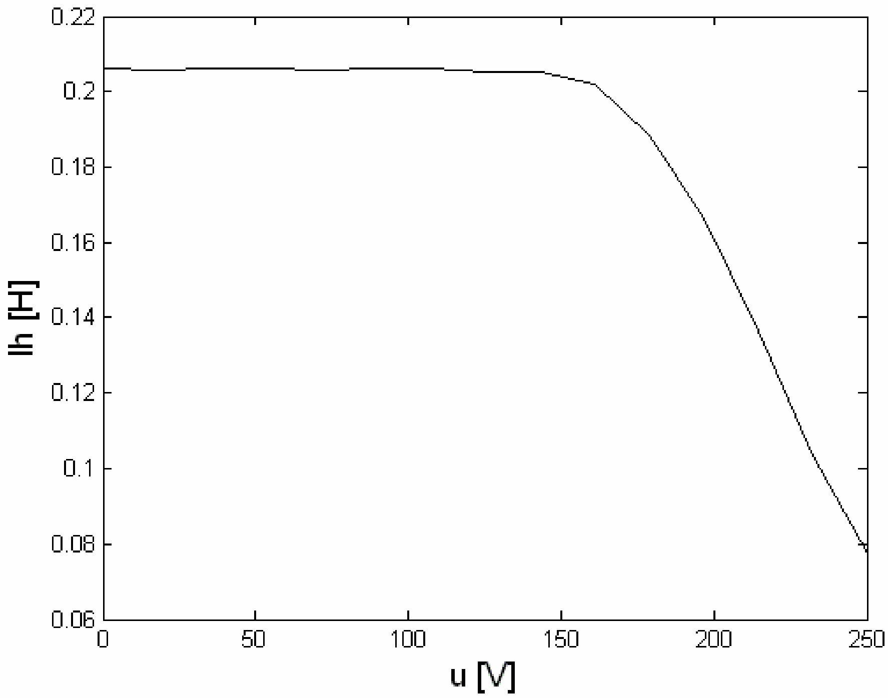

Fig. 7 Dependence of output ANFIS system variable on input variable

6 Conclusions

In conclusion, the use of an ANFIS for the adaptation of the selected simulation model parameter, in an asynchronous machine, results in a more precise simulation. The model is designed in Matlab environment, the Simulink module, where the testing is carried out. The results of the testing have been verified by means of comparison with measured values using a real machine. The presented sample of the simulation model demonstrates that the main induction L_h value changes within the range of between 0.22 and 0.08 H, corresponding to the stator voltage of U_{1f} 168 to 250 V and frequency f 50 Hz .The value of 0.11 H would be chosen if we used a fixed value of the main induction in the simulation model.

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