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Relevance of Neural Network in Fault Detection of Single Phase Induction Motor

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ABSTRACT: Electric motors are widely used in industries. These motors are subjective to conditions which depreciate the performance of motor and cause incipient faults. These faults if remains undetected, contribute to dreadful conditions and eventual breakdown of motors .Therefore it is always necessary to monitor motor performance. Monitoring can be done by various traditional methods, but these methods have various drawback like very costly to implement, performed off line, require professional knowledge , unfeasible for small machines, etc.

Neural Networks have been recognized as an alternative to the classical control schemes. This paper attempts to augment the performance of single phase induction motor by using advanced fuzzy logic controller or Neuro fuzzy in AFLFD system .The neural network system not only provide better performance on detecting motor faults, but also allow heuristic understanding of the network fault detection process.

1. INTRODUCTION

Artificial Neural Networks

Artificial Intelligence is basically a name given to software, which tries to intimate some power of human intelligence. ANN is an information-processing hypothesis stimulated by the way the brain processes information. ANNs are collections of mathematical models that follow some of the practical properties of biological nervous systems and represent on the analogies of biological knowledge

An artificial neural **network** is an interconnected group of artificial or biological neurons.

- Biological neural networks, for example the human brain
- Artificial neural networks initially referred to electrical, mechanical or computational simulations of biological neural networks.

- A neural network is the artificial way of trying to simulate the brain electronically. Human brain are made up of about 100 billion tiny units called Neurons. Each neuron is connected to other neurons and communicates with them via electrochemical signals. Signals coming into the neuron are received through junctions called synapses; these in turn are positioned at the end of branches of the neuron cell called Dendrides. The neuron sum up the inputs to itself and if the end result is larger than some threshold value, the neuron fires. It generates a voltage and outputs a signal along something called an Axon**.**

A neuron can have any number of inputs from one to n, where n is the total number of inputs. The inputs may be represented as x_1, x_2, $x_3 \ldots$ x_n. And the corresponding weights for the inputs as w_1, w_2, $w_3 \ldots$ w_n. The summation of the weights multiplied by the inputs we can be written as $x_1w_1 + x_2w_2 + x_3w_3 \ldots + x_nw_n$, is the activation value. So

$$a = x_1w_1+x_2w_2+x_3w_3\ldots +x_nw_n$$

$$\text{or} \qquad a = \sum_{i=0}^{i=n} w_i x_i$$

2. FORMULATION OF CONTROL PROBLEMS AND CONTROL STRATEGY

2.1 Introduction

Different internal motor faults (like short circuit of motor leads, interterm short circuits, ground faults, worn out bearings, broken rotor bars) along with external motor faults (e.g., phase failure, asymmetry of mains supply, mechanical overload, blocked rotor, under load) . These faults are expected to occur in motors. These faults causes unbalanced or increase in line current and excessive heating , which affect the performance of motor by increasing the down time of the motor. To improve the functioning stability and performance of single phase induction motor the advanced or neuro fuzzy logic fault detector system is needed. These include the detector features in software to decrease the machine down time and improve operational stability.

2.2. Intent

The main concern is the control problem. Firstly, the case has considered to detect the incipient faults like, the stator winding faults, bearing faults of single phase induction motor from some other research paper. Then the experimental table from the experiment performed on single phase induction motor is obtained and from this table it is concluded that these faults produce the symptoms of unbalanced/increased line current and excessive heating. Therefore the main objective is to obtain the variation in Temperature corresponding to variation in motor current (I) and Speed (N) of single phase induction motor.

Specifications Single Phase Motor (Taken For Case Study)

1 Phase, 4 poles Induction Motor
Number of turns per pole = 78
Supply Voltage: 220-230 V, 50 Hz
Speed (N)-1420rpm
Ampere-7.6A
Power-750W
Temp-40 $°C$
Cap-100 μf, 275V

Experimental Observation Table

Condition	Current	Speed(N) rpm	Temperature (T) $°C$
1	7.1	1480	41
2	7.3	1465	51
3	7.5	1460	52
4	7.9	1455	54
5	9.6	1430	68

2.3 Advanced Fuzzy Fault Detector System

In the Advanced Fuzzy Logic Fault Detector System, with the collective synergy of fuzzy logic and NN's, a better insightful of the detection process of the system can be achieved. The Advanced Fuzzy Fault detection System is designed to monitor the stator current, rotor speed and temperature. The fault signature is extracted on measuring the above parameters.. The fault detection is carried out by analyzing the fault signature through the advanced fuzzy rules is generated by the expert's knowledge and experimental data. The schematic diagram of Advanced Fuzzy Fault Detector System is shown in figure

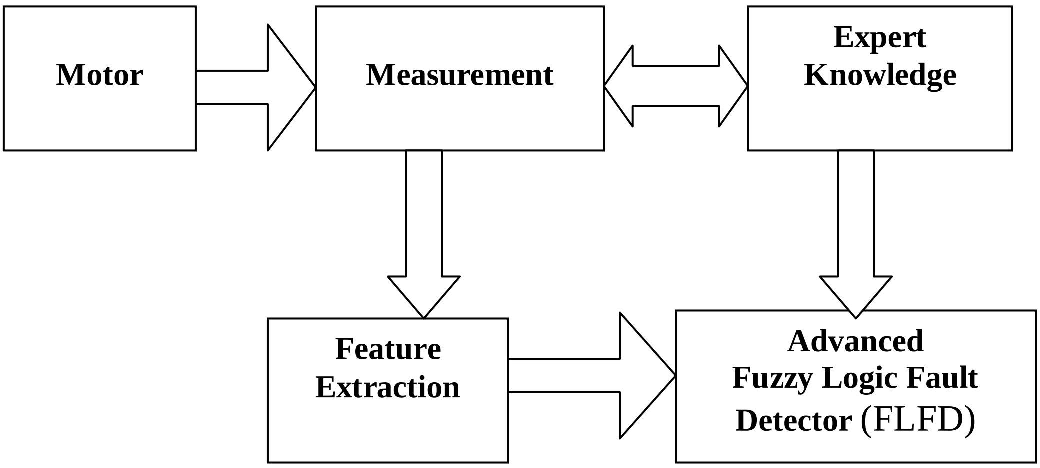

Fig 1 Advanced Fuzzy Logic Fault detection System

2.4 Control Problem Formulation

The control problem formulated on the basis of experimental data obtained after the analysis of single phase induction motor.

2.4.1 Co**ntrol Objective**

Design and Development of advanced Fuzzy logic Fault Detector system

2.4.2 Input Variables

In this case study, the various input variables are

1. Motor current (I)
2. Motor Speed (N)

2.4.3 Output Variables

Temperature (T)

2.4.4 Strategies used to detect the motor incipient faults is:

I. Neuro-Fuzzy logic in AFLFD

2.4.5 Neuro-Fuzzy Logic in AFLFD

The conceptual diagram of fault detector structure in AFLFD as shown in figure Once the neural/fuzzy motor fault detection system has been initialized, it is to be trained for motor bearing faults by actual motor data. Through training, the system modifies the fuzzy membership functions and fuzzy rules based upon the input data and its initial fault detection heuristic knowledge through the neural/fuzzy motor fault detector network weights.

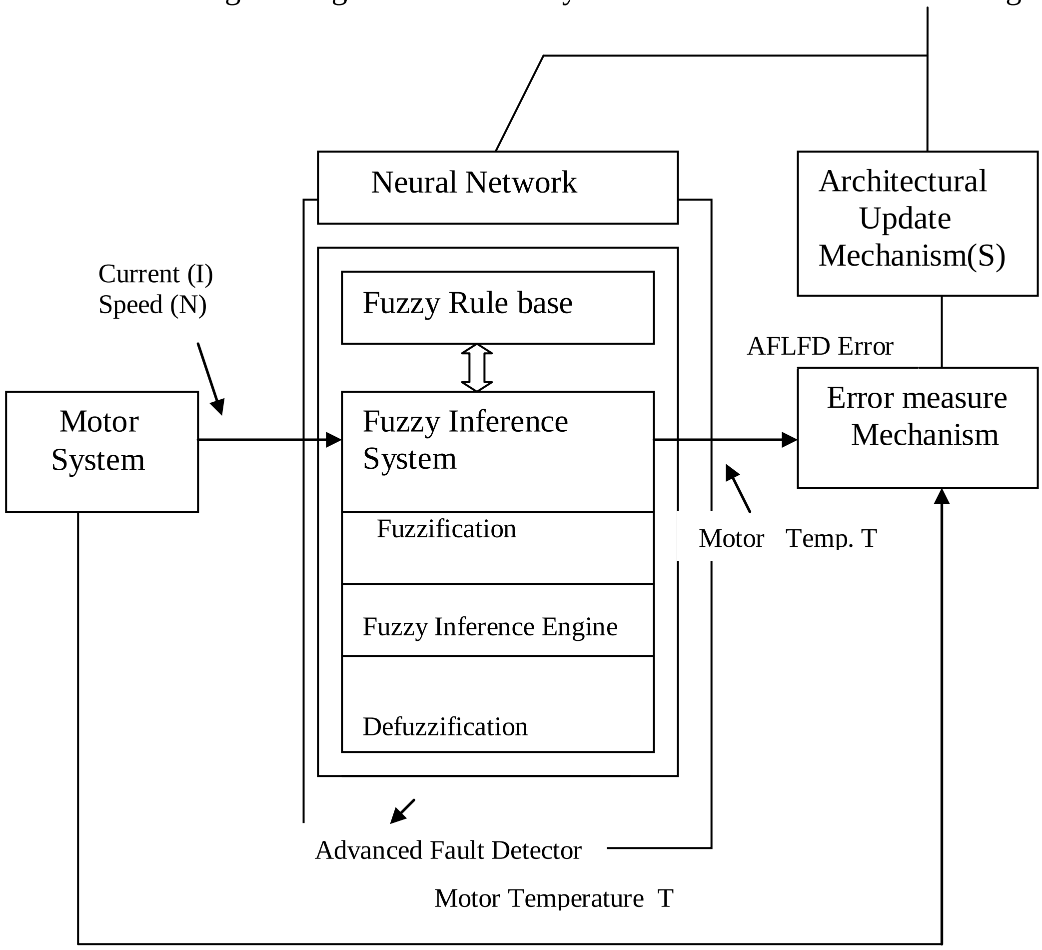

Fig 2 Conceptual Diagram of the Fault Identification System in AFLFD

In a single-phase induction motor, stator currents (I) and rotor angular velocity (N) are measured under different motor temperatures. The magnitude of temperature and load torque affect motor operations, which in turn, affect speed and current measurements.. A single-phase induction motor simulation program is used to provide the experimental data for the motor under different operating conditions to evaluate NN/FZ Motor fault detector. The data consist of single-phase stator currents and rotor angular speed (N) acquired under variable motor temperature values.

2.4.6 Control Structure Used For Motor Fault Detection Neural/Fuzzy System Modification Procedure

The overall motor fault detection neural/fuzzy system approach is shown in Fig3. The bearing motor fault detection procedure is firstly implemented in fuzzy rules and membership functions. Then the neural/fuzzy system is configured based on these preliminary fuzzy rules and membership functions developed in modules. The output of the network provides three decision outputs ε (0, 1) corresponding to GOOD, FAIR, or BAD

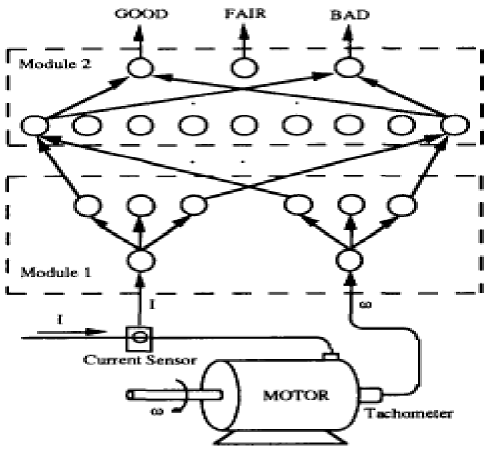

Fig 3

Module 1, the fuzzy membership function module, is comprised of layers 1 and 2 of the neural system. Layer 1 of the module provides the input measurements to the network. Motor current, I, and rotor speed, N measurements are used as inputs for bearing wear fault detection. This is accomplished through the use of an inexpensive current sensor and tachometer. Layer 2 of the module 1 represents output nodes of "sub-networks" that are trained in advance. Each node corresponds to a membership function belonging to the fuzzy set for that input. The sub-networks contain the information for the fuzzy membership functions in their weights. These weights determine the shape of the membership functions of interest. The sub-networks allow representation of very complex membership functions which are more flexible to adaptation for decision classification. Module 1 is trained off-line before being inserted into the neural/fuzzy network. This is done by using vague heuristics of Low, Medium and High to represent each of the input, I and N. These heuristics are constructed into preliminary membership functions which build the universes of discourse X and Y corresponding to the input spaces of I and N respectively. The universes of discourse represent the normalized input data. For example, if the current data ranges in value from 7amps to 10amps, the universe of discourse represents a mapping of the data from the range of 7 to 10 to a range of 0 to 1. These are represented in the standard notation used in

$$X = [\,\mu_{\text{low}}(I\,),\, \mu_{\text{medium}}(I\,)\,,\, \mu_{\text{high}}(I\,)\,]\,,\, I \in X,$$

$$Y = [\,\mu_{\text{low}}(\omega),\, \mu_{\text{medium}}(\omega)\,,\, \mu_{\text{high}}(\omega)\,]\,,\, \omega \in Y,$$

Where μi (A) = the grade of membership of 1 in j = {i ε low, medium, high}, A ε X, Y

The membership functions were chosen based upon heuristics of Low, Medium, and High. Module 2, the fuzzy rule base module, is also comprised of two layers. Layer 1 of the module (layer 3 of the network) provides the fuzzy rules (if-then statements) for the motor fault detection. Each node represents a rule in the fuzzy rule matrix. Each rule node should only have as many connections (weights) to it from the membership function module as there are inputs to the membership function module. These weights will not change since their only function is to pass fuzzy membership function values. Layer 2 of the module (layer 4 of the network) provides the output conditions of GOOD, FAIR, or BAD. The weights between these two layers are obtained by off-line training on a predetermined fuzzy rule base. This provides an initial rule base for the network.

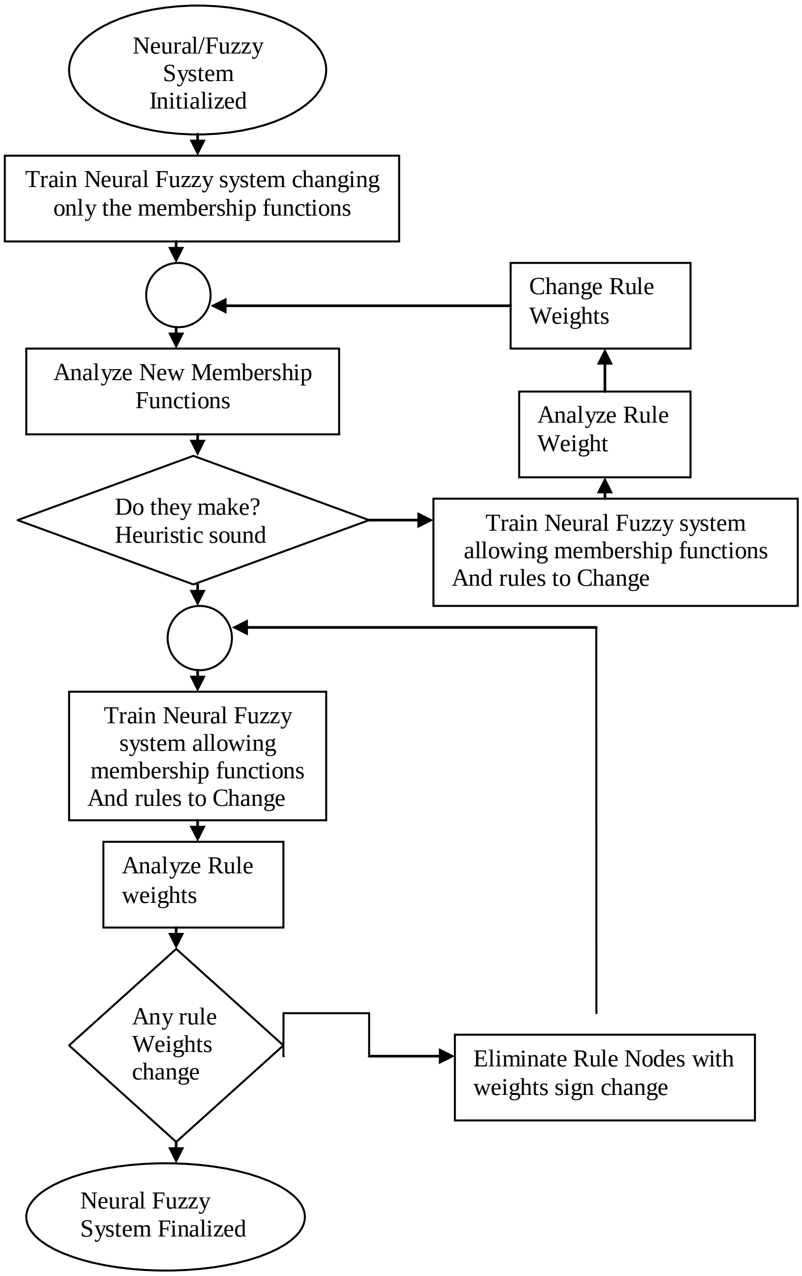

Fig 4 Basic Flow Diagram of Computations in ANFIS.

In Fuzzy Control Toolbox a useful command called Anfis exists. This provides an Optimization scheme to find the parameters in the fuzzy system that best fit the data. Then, in principle, any of the optimization schemes, say those in the MATLAB Optimization Toolbox can be used.Use genfis1 or genfis2 to generate initial FIS system. Use Anfis to generate the best FIS system. Anfis uses the result from genfis1 to start optimization.

The computations in the Anfis system contains following four steps:

- Initialize the fuzzy system .Use genfis1 or genfis 2 commands are used to initialize the fuzzy system

- Give other parameters for learning. Two important parameters are number of iterations (epochs) and tolerance (error)
- Start learning process. Use command ANFIS stop when tolerance is achieved
- Validate with independent data

The computations in the Anfis are shown in the basic flow diagram. This diagram tells the sequence of steps used in computations.

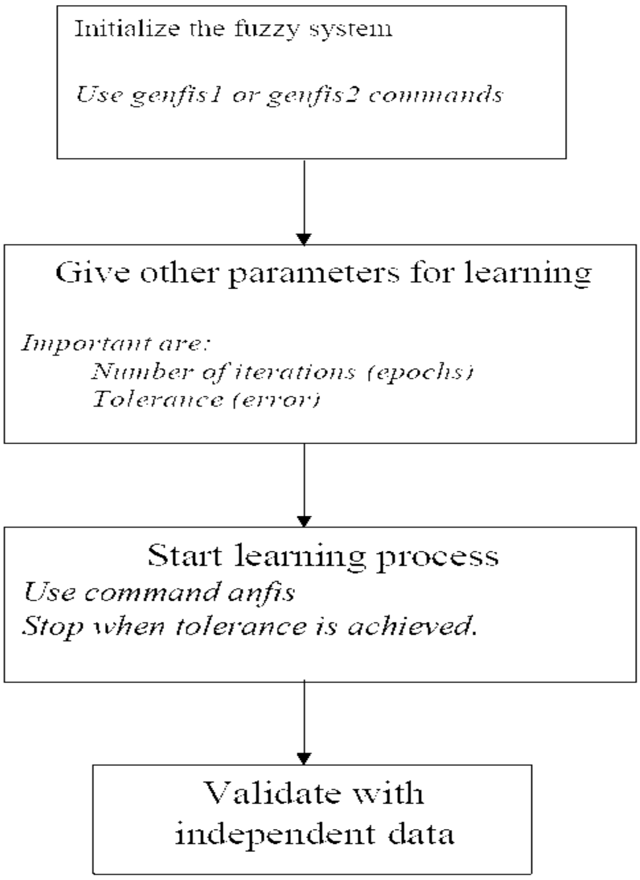

Fig 5 Development of Neuro Fuzzy Controller Used in Advanced Fuzzy Logic Fault Detection System

We use Anfis GUI in the development of Neuro fuzzy controller used in the advanced fuzzy logic fault detector for detecting the incipient motor faults in single phase induction motor. The Anfis Objective is to integrate the best features of Fuzzy Systems and Neural Networks. From Fuzzy Systems the representations of prior knowledge into a set of constraints (network topology) to reduce the optimization search space. From Neural Network the Adaptation of back propagation to structured network to automate FC parametric tuning. The ANFIS application to synthesize the controllers (automated FC tuning) and models (to explain past data and predict future behavior).

Anfis Editor GUI in the Fuzzy Logic Toolbox is divided into four main sub displays:

1. Load data
2. Generate FIS
3. Train FIS
4. Test FIS

3. TESTING AND RESULT

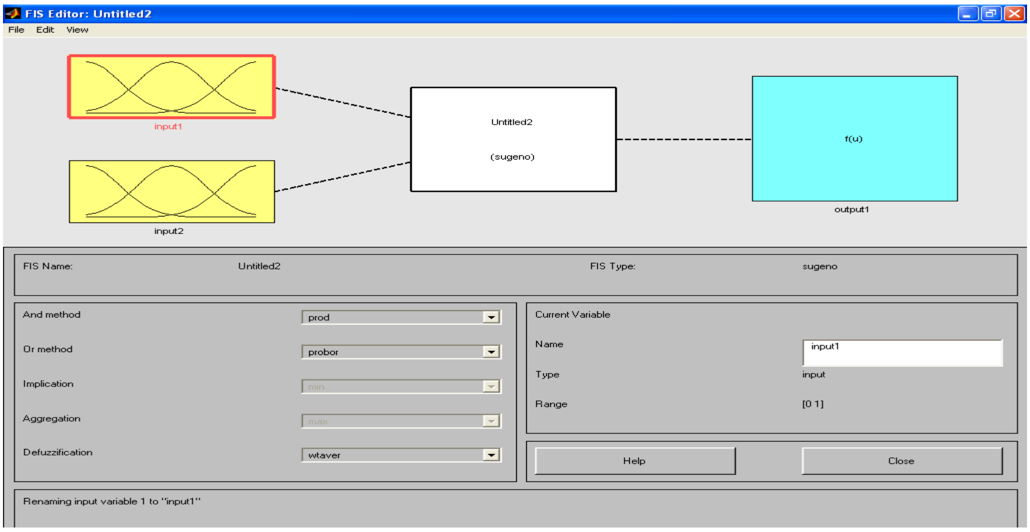

FIG 6 MATLAB windows using fuzzy logic toolbox for AFLFD

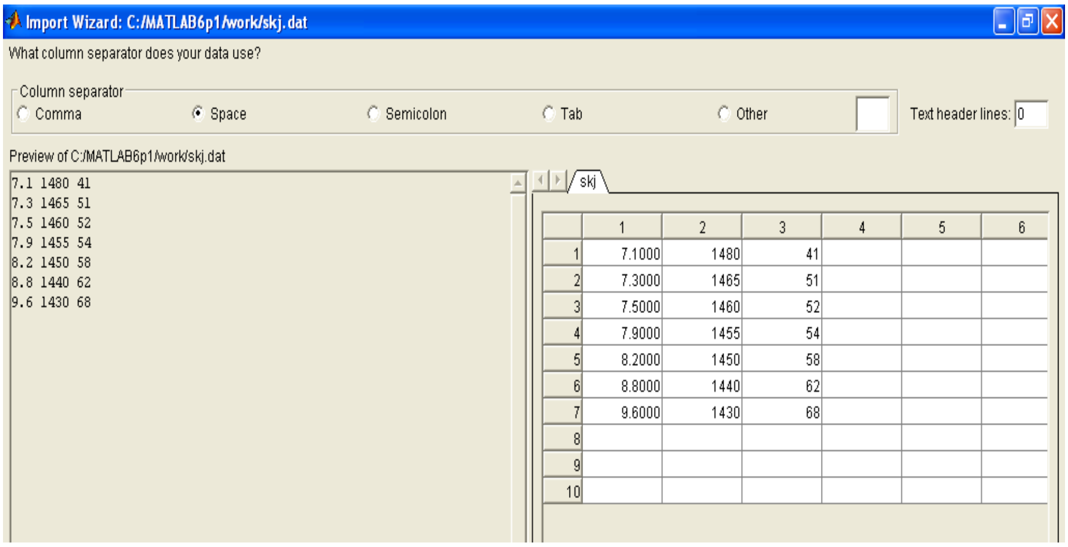

FIG 7 Data Stored in Matrix Form on Workspace

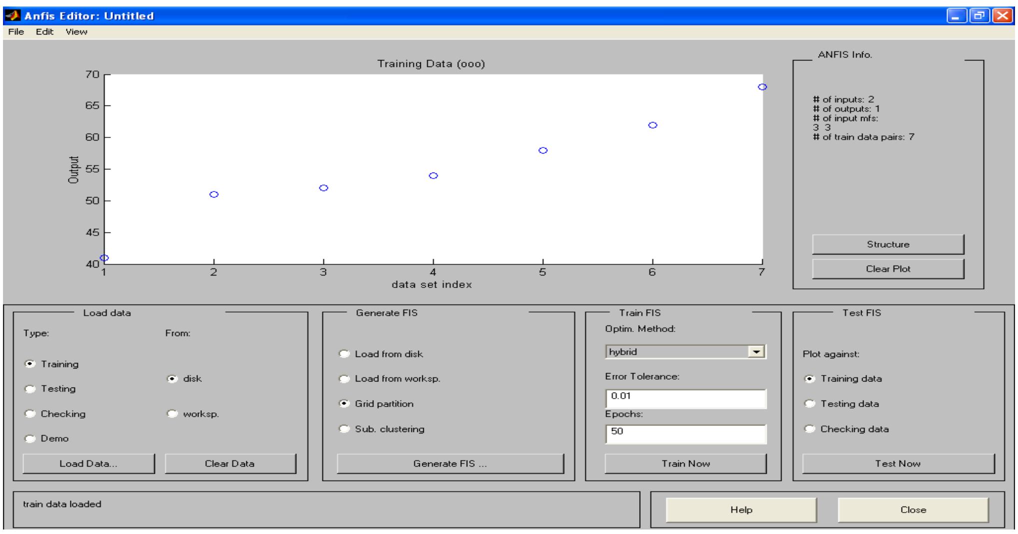

FIG 8 Data Loaded on the ANFIS Editor

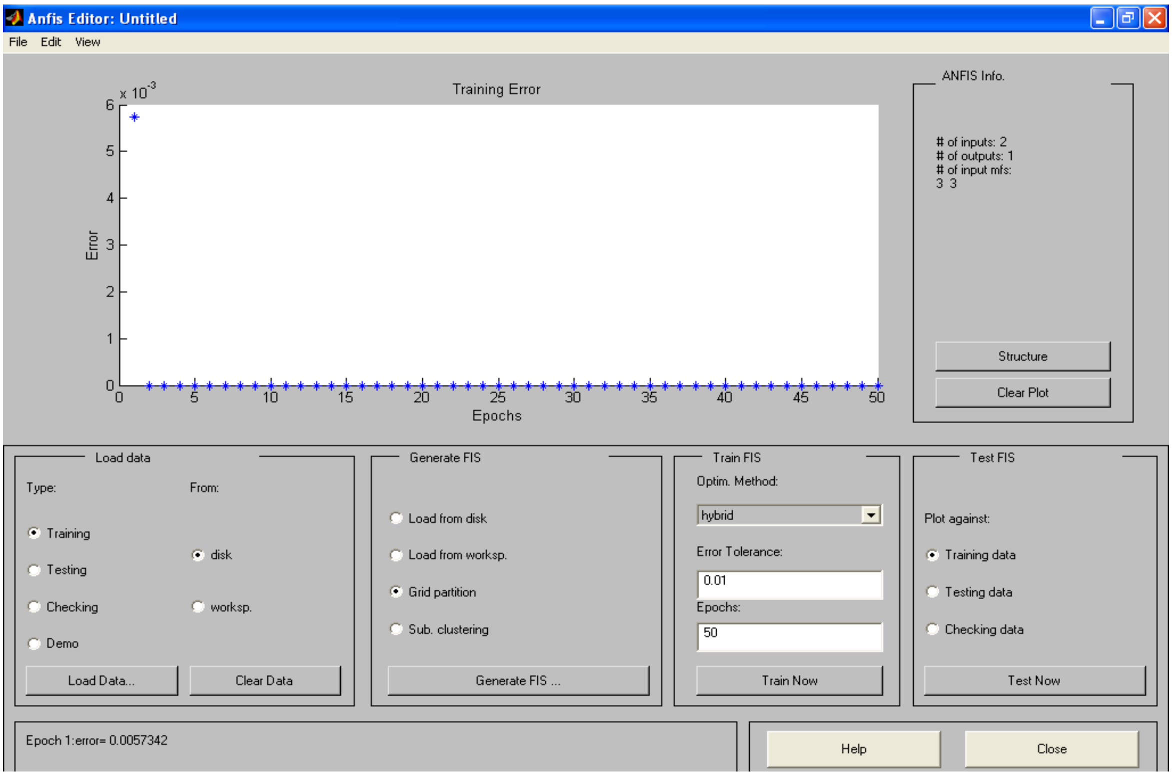

FIG 9ANFIS Editor for After Training Data

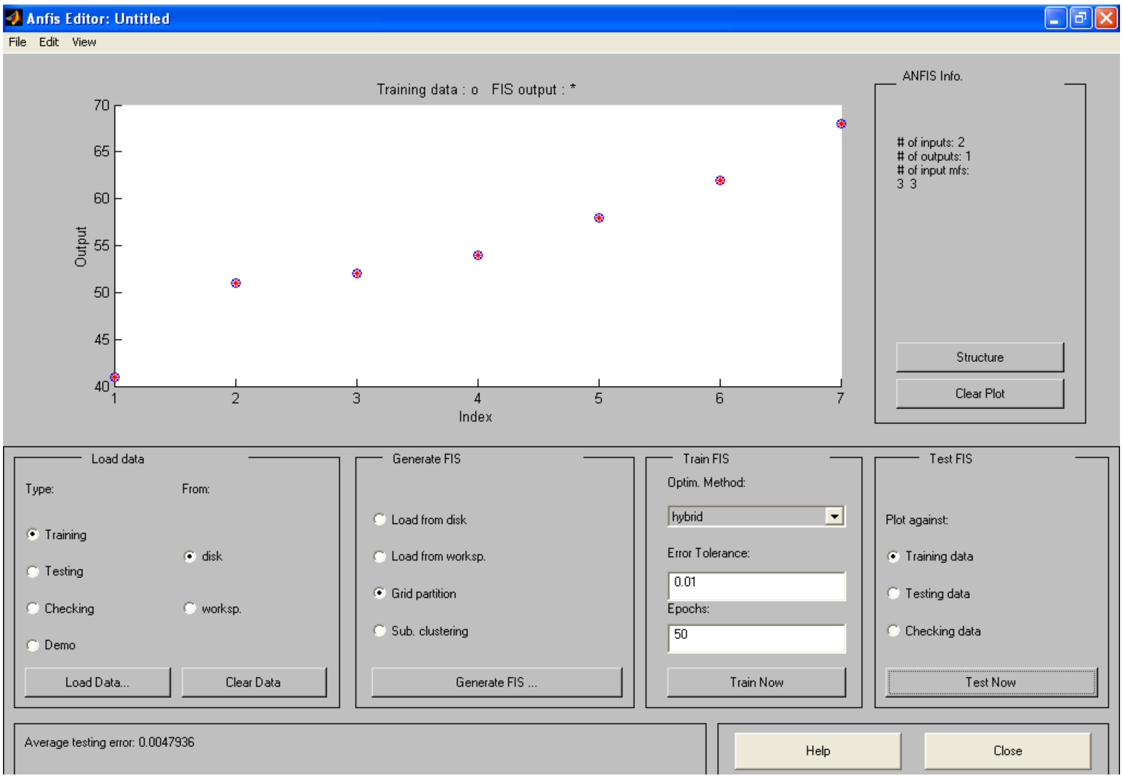

FIG 10 ANFIS Editor after Testing Data

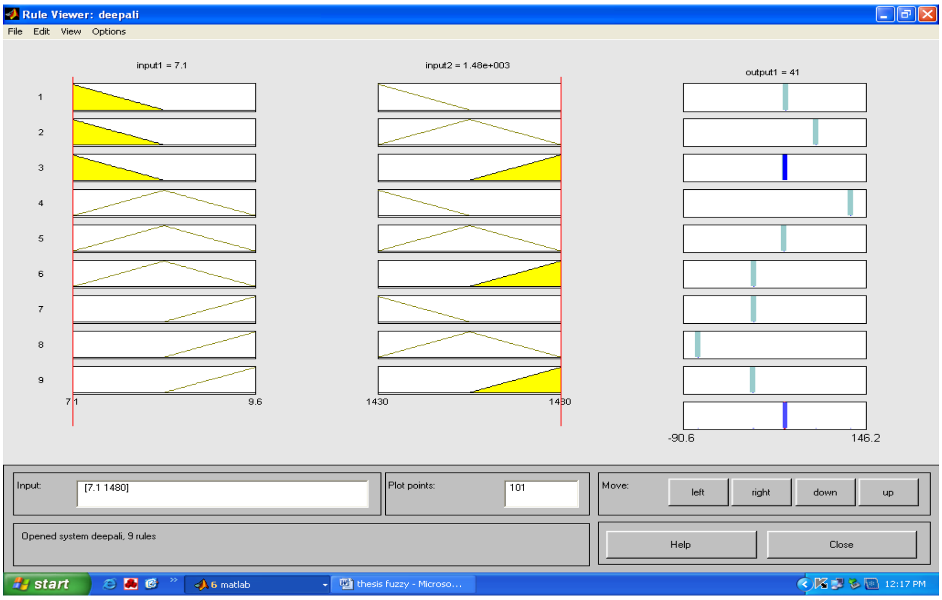

FIG 11 RULE VIEWER

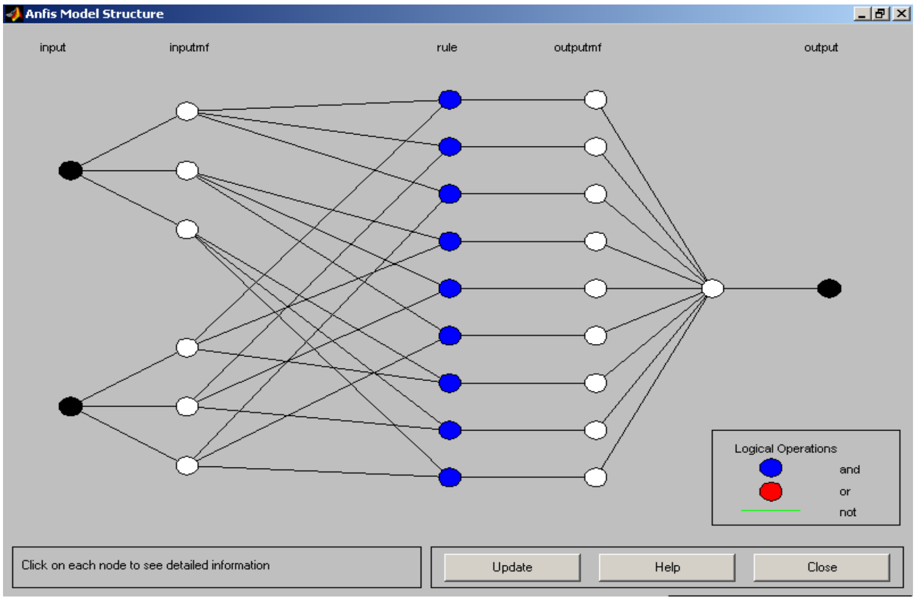

FIG 12 ANFIS Modal Structure for AFLFIS System

Condition	Motor Current(I)	Motor Speed(N)	Temperature °C	Output of FLFD	% Error	Output of AFLFD	% Error
1	7.1	1480	41	40.9	0.24	41	0.0
2	7.3	1465	51	51.1	0.19	51	0.0
3	7.5	1460	52	52.3	0.30	52	0.0
4	7.9	1455	54	54.1	0.18	54	0.0
5	9.6	1430	68	67.9	0.14	68	0.0
Average Error (%)					0.21		0.0

CONCLUSIONS: This work presents the design of a Neuro fuzzy or Advanced Fuzzy controller with simplified architecture that minimizes the processing time used in several stages associated with systems and processes modelling. The basic procedures of Fuzzification and Defuzzification are very simplified, whereas the inference procedures are computed in a direct way. The simplified architecture has allowed a fast and easy configuration of the Neuro fuzzy controller, as consequence, the control rules that define the control actions are obtained automatically.

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