International Journal of Engineering Inventions
ISSN: 2278-7461, www.ijeijournal.com
Volume 1, Issue 7 (October2012) PP: 68-75

FUZZY LOGIC AND NEURO FUZZY MODELS FOR DIRECT CURRENT MOTORS

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Abstract:—Fuzzy logic techniques or fuzzy inference systems(FIS) aim at designing systems in which the users create sets of rules. In return, the system transfers these rules to their mathematical counterparts. This technique will make things easier for system designers and computer users, producing results that are more accurate and precise for real world data. Neuro fuzzy inference systems are originally derived from fuzzy logic concepts; these are adaptive techniques. The network takes the data, processes the data, the rules are input by the user, and finally the inference system works out these rules to produce the final output of the system. In this paper both techniques are used to predict the direct current for the motor engines. The two techniques; fuzzy inference system and neuro fuzzy inference system techniques are compared. The neuro inference system outperformed the Fuzzy logic systems.

Keywords:—Direct Current Motor Engine, Fuzzy Logic, Fuzzy Inference System, Neuro Fuzzy Inference System.

I. INTRODUCTION

Direct current motors are the most commonly used in manufacturing and business production today. Direct motors are very popular in high-performance control systems due to the encroachment and innovation they create in power electronics. As a matter of fact, their best traits, such as torque and robot speed control, have made them extensively responsible for their widespread use or application in automation systems [1], [2] and [3]. Direct current motors are applied and used in many sorts of applications such as robotic systems, automation systems, steel manufacturing, and paper processing and mining industries. Direct motors are conventionally modeled linearly in order to aid the application of linear control theory in controller designs. Nevertheless, the majority of the existing linear controllers usually do not lead to good tracking and regulation responses when the controlled system is subjected to a wide range of operating conditions [1], [2] and [3].

Fuzzy logic techniques were pioneered by Lotfi Zadeh when he first proposed the fuzzy set theory technique in 1956 [4], [5], [6], [7], [8], [9], [10]. This technique has been used to solve different applications in the fields of science, control theory and artificial intelligence. Fuzzy logic is considered to be a valued logic or probabilistic logic that is based on reasoning to approximate values rather than constant values. In other words, contrary to conventional logic, fuzzy logic works with changeable values, while binary sets have two-valued logic, true or false. This technique forms variables or features that can have a truth value that varies in degree between 0 and 1. Fuzzy logic techniques have been long-drawn-out to deal with the theory of incomplete truth, and the truth value possibly will vary between a complete true and complete false. In addition, once linguistic variables were applied, these linguistic variables have been represented by some degrees and these degrees are controlled by specific functions [4], [5], [6], [7], [8], [9], [10].

An extended technique called neuro fuzzy is introduced. Basically it is an amalgamation of artificial neural networks and fuzzy logic. The technique is originally invented by J.S. R. Jang [4], [5], [6], [7], [8], [9], [10], and [11]. This amalgamation conveyed a system that is intelligent due to the fuzzy-logic technique which is the human-like reasoning style of fuzzy systems via the use of fuzzy sets and a linguistic model consisting of a set of IF-THEN fuzzy rules, and artificial neural networks, in which the connection weight structures are trained. This sort of integration is commonly understood by the scientific and engineering community as a fuzzy-neural network or neuro fuzzy system [5], [6], [7], [8], [9], [10], [11], [12]. The fuzzy modeling research work of neuro fuzzy is divided into two parts: the first part is the linguistic fuzzy modeling that is focused on interpretability, mainly used the Mamdani model and the second part is the precise fuzzy modeling that is focused on accuracy, mainly the Takagi-Sugeno-Kang model [11]. The main strength of neuro fuzzy systems is that they are universal approximation with the ability to seek interpretable IF-THEN rules. In this paper both fuzzy logic and neuro fuzzy systems are used to predict the direct current of motor engines [5], [6], [7], [8], [9], [10], [11], and [12].

The paper is organised as follow: in section 2, we describe both techniques in detail; in section 3, simulation and results are explained; finally the main conclusions are outlined.

II. FUZZY LOGIC AND NEURO-FUZZY SYSTEMS

A. *Fuzzy logic (Fuzzy Inference System)*

The idea of fuzzy logic was introduced by Professor Lotfi Zadeh at California University at Berkley as method of processing data via allocating partial set membership instead of crisp set membership. Initially the idea was not come as a control methodology. It is worth mentioning that due to the absence of the power of small computers prior to 1970's this idea had not been applied to control systems [5], [6], [7], [8], [9], [10], [11], [12].

Lotfi Zadeh explained that people will not need accurate numerical information input and they are able of well adaptive control. The feedback controllers would be extremely efficient and could be easily implemented if they would allow noisy and inaccurate input. In fact, the European and Japanese embraced this idea very quickly and started to build real products around it; unfortunately, the United States producers did not move as fast to embrace this idea [5], [6], [7], [8], [9], [10], [11], [12], [13], and [14]. The idea of fuzzy logic serves a process that can achieve a distinct conclusion based upon indistinct, uncertain, inaccurate, noisy, or missing input information. The basic approach of fuzzy logic to control problems resembles almost exactly the approach a person would make decisions, only much faster. It is considered to be a problem solving system technique that provides solutions to either hardware and software applications, or a recipe for both. It can be implemented in different systems ranging from small embedded micro controllers to large control systems [14]. The way that fuzzy logic works to solve control problems basically depends on a simple rule: IF <statement 1> then <statement 2> or in other words, IF <premise> THEN <consequent> instead of relying on building a mathematical model for system [14].

The dissimilarity between traditional and fuzzy sets can be expressed by establishing a membership function. Consider a restricted set $X = \{x1, x2, x3,\ldots xn\}$. The subset A of X consisting of the single element x1 can be described by the n-dimensional membership vector $U(A)=(1, 0, 0,...,0)$, where 1 at the i-th position point to a fact that xi belongs to A. The set B consists of the elements x1 and xn is described by the vector $U(B) = (1, 0, 0, 1)$. Any other crisp subset of X can be represented in the same way by an n-dimensional binary vector. If we remove the restriction to crisp values then we can describe the fuzzy set C with the following vector description: $U(C) = (0.6, 0, 0, 0)$ [14].

It is noticeable that in crisp set theory we cannot define a set as such since we have an element that either belongs to a subset or it does not. Nevertheless, we can generalize and define such a set in the theory of fuzzy sets. As it is shown in the description, the element x belongs to the set C only to some degree. This is expressed as the degree of membership that is uttered by a real number in the interval [0, 1], in this case 0.6. The degree of membership is an interpretation which is correlated to the sense that we attribute to such statements as "person x is an expert." As a matter of fact, it would not be possible for us to specify an exact level of expertise which represents the absolute threshold to enter into proficiency. Therefore, in order to become a proficient person takes time, and it is as a continuous process in which the membership of a person to the set of expertise goes gradually from 0 to 1. Fuzzy logic and theory of fuzzy sets attempt to achieve this same idea [14].

B. Neural networks

Artificial neural network is a very popular type of machine learning and it can be considered as another model that is based on modern mathematical concepts. Artificial neural computations are designed to carry out tasks such as pattern recognition, prediction and classification.

The feed-forward artificial neural networks [15] consist of three interconnection layers: one input layer, one or more hidden layers, and one output layer. The feed forward artificial neural networks allow signals to travel one way only--from the input to the hidden layer and then to the output layer. There is no feedback. The output of any layer does not affect that same layer. The feed forward artificial neural networks tend to be straightforward networks that associate inputs with outputs. They are extensively used in pattern recognition.

In fact the key feature of the neural networks is that their structure can learn with training data; the input and output patterns of the particular application. Apparently, the neural network adjusts its internal structure and the weight connections between its artificial layer neurons in the hope to make the process of the mapping between the input/output that represent the behavior of the modeled system with a level of acceptable error for the application [11].

C. Neuro Fuzzy Systems

Fuzzy logic techniques have been widely used and accepted by researchers to deal with real academic and industrial applications; however, designing and developing fuzzy logic systems that can produce a good quality of performance will not be achieved effortlessly [11, 13].

One of the difficulties of fuzzy logic technique is arriving at finding proper membership functions and suitable rules. This process is basically an exhausting process which depends on trial and error. This is where neural networks come hand in hand. Neural networks trained with learning algorithms can be applied to the fuzzy systems. Some efficient learning algorithms to train neural networks were developed to help support the enhancing of tuning fuzzy systems. Jang, Lin and Lee in 1991, Berenji in 1992 and Nauck from 1993 had carried out the first research work on the neuro fuzzy systems; in fact, most of the first applications were in process control. Nevertheless, slowly but surely, its application extended for all the disciplines such as, data analysis, data classification, imperfection detection and support to decision-making [11].

Jang had developed one type of hybrid neuro fuzzy inference expert system that works in Takagi-Sugeno-type fuzzy inference systems [13, 16, 17, 18, and 19]. This is called ANFIS. Both the feed-forward neural network and ANFIS have a similar structure, but the links in an ANFIS only indicate the flow direction of signals between neurons, and no weights are associated with the links. The architecture of the ANFIS consists of five layers. Among those layers, both the first and the fourth layers consist of adaptive neurons, despite the fact that the second, third and fifth layers consist of fixed neurons. The adaptive neurons are related with their respective parameters, and get duly updated with each in subsequent iteration, while the fixed neurons are devoid of any parameters [13, 16, 17, 18, and 19].

Rule 1: *If (x is A1) and (y is B1) then (f1 = p1x +q1y + r1)*
Rule 2: *If (x is A2) and (y is B2) then (f2 = p2x +q2y + r2)*

Where *x* and *y* are the inputs, *Ai* and *Bi* are the fuzzy sets, *fi* are the outputs within the fuzzy region specified by the fuzzy rule, p_i, q_i, r_i is the parameter set of this neuron. These are referred to as consequent parameters. The design parameters are those that are determined during the training process. The architecture of ANFIS is shown in Fig. 1, in which a circle indicates a fixed neuron, whereas a square indicates an adaptive [12, 13].

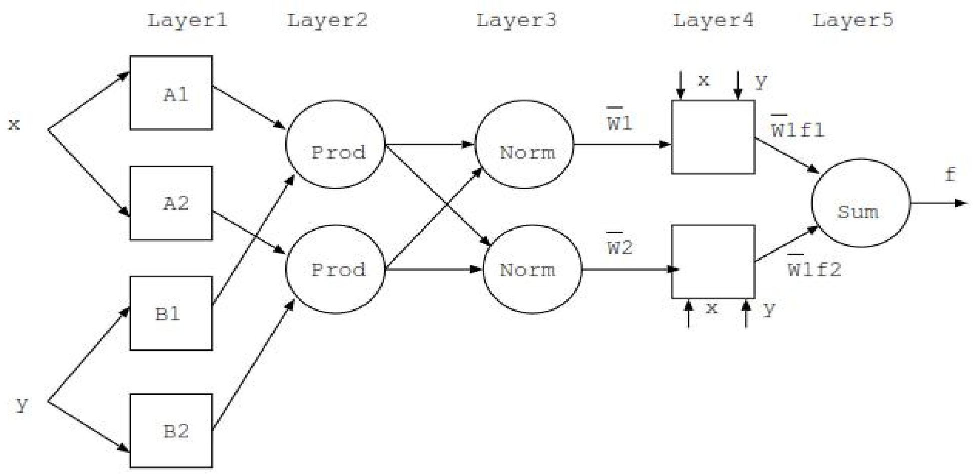

Fig. 1: displays the architecture of neuro fuzzy inference system (ANFIS).

The layers of ANFIS are explained as follows:-

1) Layer 1: this is called the fuzzification layer, in which every ith neuron is adaptive. The outputs of this layer are the fuzzy membership grade of the inputs, they can be expressed as

$$O_{1,i} = «A_i(x)\text{.........} \quad (1) \qquad \textit{for i=1, 2}$$

$$O_{1,i} = «B_{i-2}(y)\text{.........} \quad (2) \qquad \textit{for i=3,4}$$

A_i Or B_{i-2} is the linguistic label associated with *ith* neuron.

$O_{1,i}$ is the membership grade of a fuzzy set (A_1, A_2, B_1, B_2).

Usually we choose $«A_i(x)$ to be bell-shaped with a maximum equal to 1 and a minimum equal to 0, such as:

$$«A_i(x) = \frac{1}{1 + \left\| \frac{x - c_i}{a_i} \right\|^{2bi}} \text{..........} \text{...}(3)$$

Ai, bi and *ci* are the parameters set. Parameters are referred to as premise parameters.

2) Layer 2: this is called a rule layer, a fixed neuron labeled M whose output is the product of all the incoming signals; the outputs of this layer can be represented as:

$$O_{1,i} = w_i = «A_i(x).«B_i(x)........(4)$$

As can be seen from Fig. 1, that every neuron in this layer is fixed and labeled prod .The output is the product of all the incoming signals. Each neuron represents the fire strength of the rule. Any other *T-norm* operator that performs the *AND* operator can be used [12, 13].

3) Layer 3: this is a normalization layer; the neurons in this layer are also fixed and indicated as a circle, and labeled norm. The *ith* neuron computes the ratio of the *ith* rule's firing strength to the sum of all rule's firing strengths. Outputs are called normalized firing strengths. $\overline{w_i}$ is the normalized firing strength from layer 3.

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2}........(5) \quad \textit{for } i = 1, 2$$

4) Layer 4: is called the defuzzification layer; the neurons are adaptive. The output of each neuron in this layer is simply the product of the normalized firing strength and a first order polynomial. The neuron function can be expressed as:

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}\left(p_x + q_i y + r_i\right)........(6)$$

5) Layer 5: this is called a single, summation neuron, and it is fixed and labeled sum which calculates the overall output as the summation of all incoming signals.

$$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}........(7)$$

A hybrid learning algorithm (the back propagation and the least square algorithms are coupled to change and update the membership function parameters of the fuzzy inference system) is used to train the ANFIS model in the hope to adjust all the different parameters above mentioned. The data sets with inputs and outputs are fed to the ANFIS [12, 13].

III. EXPERIMENTAL RESULTS

A relatively large data set is used in this paper. 507 samples are used. The data set is divided into two parts: the training and testing sets; the models are fed with identical inputs and output variables. Three input features are fed into the models, namely: torque, power and speed. We have used two models, namely fuzzy inference system and ANFIS. Both models have only one output to predict which the current of the motor was. Both models used the same range of data sets. Math lab toolbox is used to implement the both fuzzy inference system and ANFIS models. The simulations of models are explained as follows:-

A. *Fuzzy Inference System*

In the experiment, we have used 406 training patterns to train fuzzy inference system model. 100 training samples are used to see the performance of the model. The Mamdani technique is used for this model as shown in Fig 2.

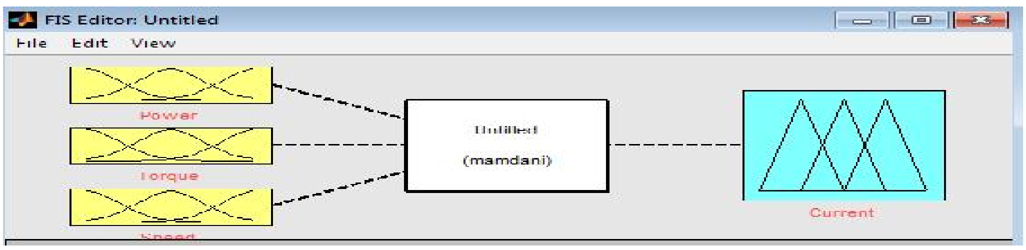

Fig. 2: The Mamdani technique is used for fuzzy inference system.

From the data sets we have specified the range of input variables, the range is set as follows: the power *P* was in between 80- 82, the torque was in between 41-745, the speed *S* was in between 1056-3737, and one output which was the current *I* in between 27 -147 (see Fig 3, 4, 5, 6).

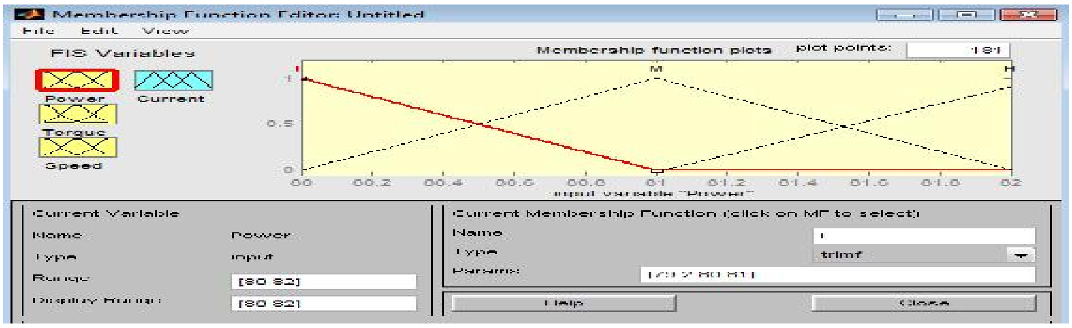

Fig. 3: shows the membership function for the power variable.

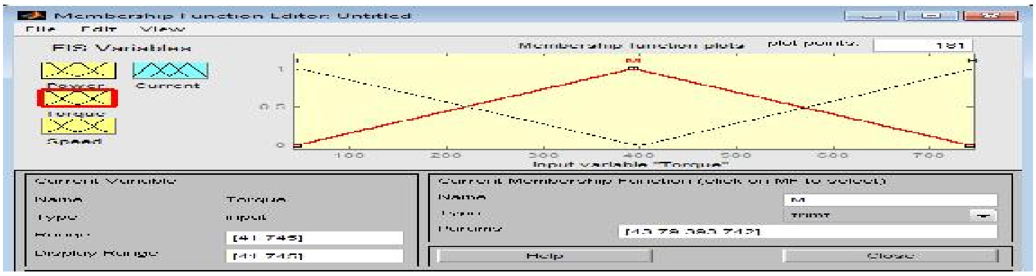

Fig. 4: shows the membership function for the torque variable.

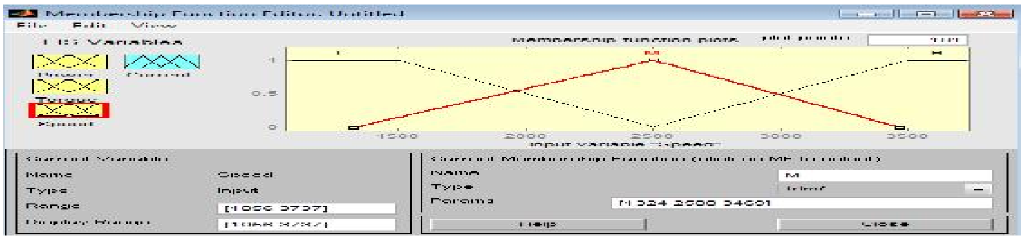

Fig. 5: shows the membership function for the speed variable.

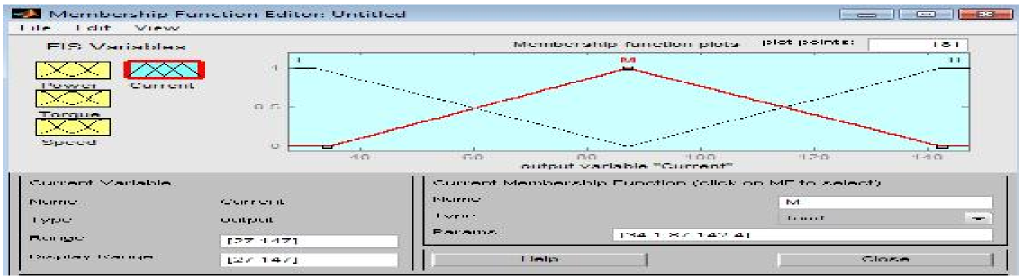

Fig. 6: shows the membership function for the current output.

Under a good visualization to our data set, and the range of the different input variables and the output variable, we come up with some rules. The rules were as follows:

1) If (Torque is L) then (Current is L)
2) If (Torque is M) then (Current is M)
3) If (Torque is H) then (Current is L)
4) If (Torque is L) and (Speed is H) then (Current is L)
5) If (Torque is M) and (Speed is M) then (Current is M)
6) If (Torque is H) and (Speed is L) then (Current is H)
7) If (Power is L) and (Speed is H) then (Current is L)
8) If (Power is H) and (Speed is L) then (Current is H)
9) If (Power is M) and (Speed is M) then (Current is M)

The results are shown in Fig. 7 and 8.

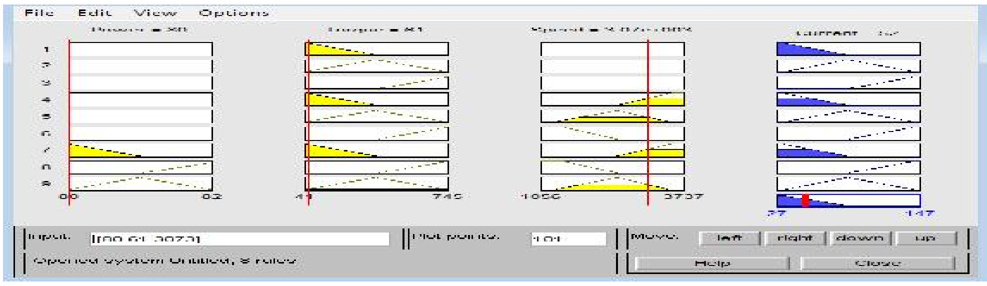

Fig. 7: shows the three variables input power, torque and speed that determine the current value.

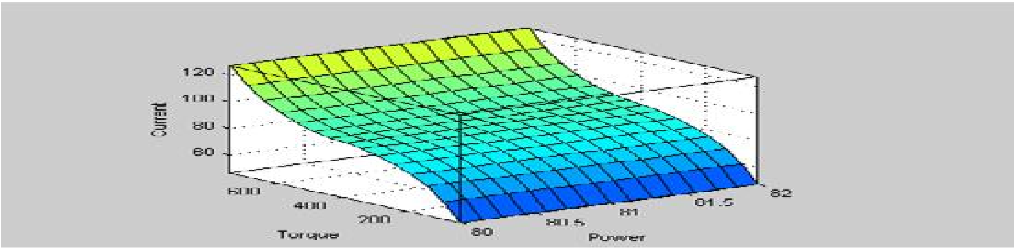

Fig 8: shows the surface of the model.

B. *ANFIS*

In the experiment, the Sungo technique is used as shown in Fig 9.

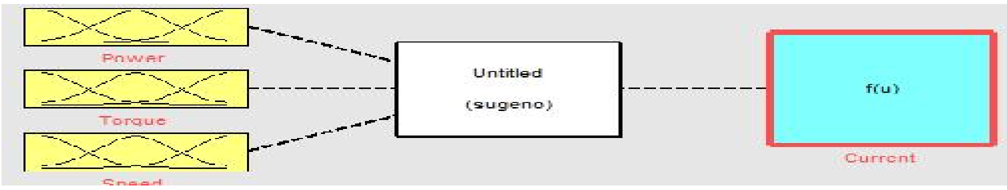

Fig 9: shows the Sungo technique is used for fuzzy inference system.

A trapezoidal-shaped built-in membership function for the three inputs used and a liner function used for the output as shown in Fig 10.

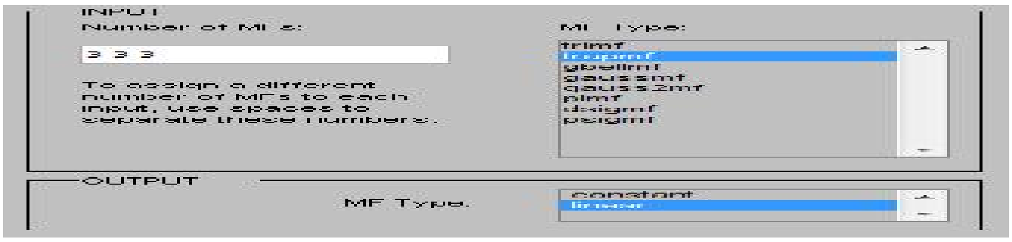

Fig 10: shows how to select the functions for both inputs and output.

The five layers that were explained in section 2 now are drawn for the ANFIS model as shown in Fig 11.

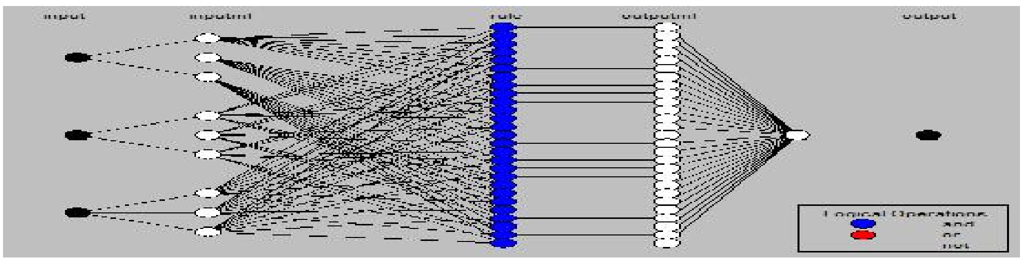

Fig 11: shows the ANFIS model.

The training set was 491 samples; 16 samples are used as a testing set. The two ANFIS parameter optimization method options available for FIS training are hybrid (the default, mixed least squares and backpropagation) and backpropagation. The hybrid is implemented. Error Tolerance is used to create a training stopping criterion, which is related to the error size. The training will stop after the training data error remains within this tolerance. This is best left set to 0 if we were not sure how our training error would behave. The test set is done, and the results were outstanding compared to FIS model, see Fig 12.

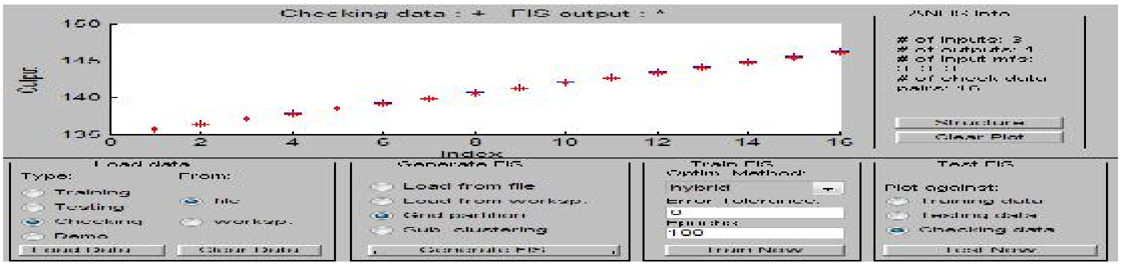

Fig 12: shows the testing session for the FIS model.

Fig 13 and 14 show results that produced by ANIS.

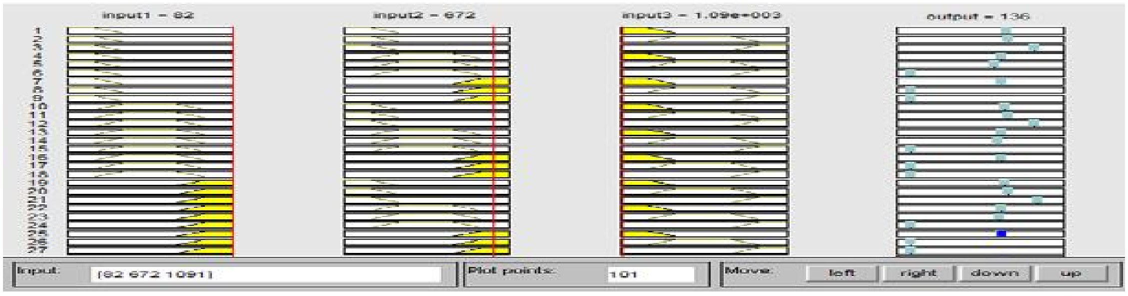

Fig 13: shows the results of the model ANFIS.

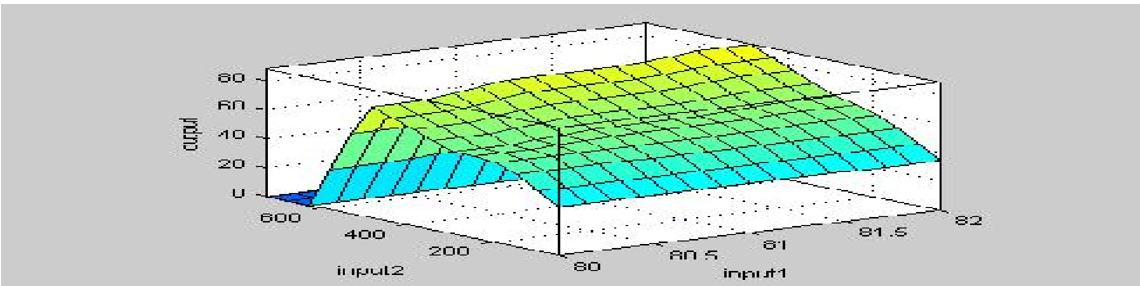

Fig 14: shows the surface view of the model.

IV. CONCLUSION

In this paper both techniques FIS and ANFIS are used to predict the direct current for the motor engines. The two techniques are compared. The ANFIS outperformed the Fuzzy logic systems. Math lab software was used to implement both FIS an ANFIS.

The high-quality features of the fuzzy inference systems are the power to use linguistic variables to represent natural uncertainties of the human knowledge; the creation of relations between the expert of the domain with the designer of the system; producing straightforward analysis of the results, due to the natural rules representation; simple expansion of the base of knowledge via the adding together of new rules. However, the bad things of fuzzy inference systems are: their lack of ability to generalise; difficulty to produce the inference logical rules as their determination depends on the knowledge and the expert; difficulty to find proper membership functions and suitable rules due an exhausting process which depends on trial and error [11, 12, and 13].

Neural networks have important useful features, these are namely: learning competence; generalization power. However, their drawbacks are: impossible interpretation of the functionality; difficulty in determining the number of layers and number of neurons [11, 12, and 13].

Neural networks and fuzzy systems can be combined to join their good things and to restore their drawbacks. Neural networks introduce its computational characteristics of learning in the fuzzy systems and receive from them the interpretation and clarity of systems representation. Thus, the bad things of the fuzzy systems are compensated by the capacities of the neural networks. These techniques are amalgamated to produce a better model [11, 12, and 13].

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