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Input Maping and Simulation Analysis using Adaptive Network Based Fuzzy Inference System

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Abstract— Fuzzy logic control systems are structured numerical estimators. They combine both the numerical process and human like reasoning. Neural networks are numerical trainable dynamical systems that are able to emulate human brain functions; their connectionist structure can be used to find the proper parameters and structures that resemble human thinking rules for fuzzy logic controllers. Generally fuzzy logic is best applied to non linear, time varying, ill- defined systems, which are too complex for conventional control systems to apply. In this paper a new combinational connectionist structure is proposed which exploits the advantages of both the fuzzy and neural networks avoiding the rule-matching time of the inference engine in the traditional fuzzy logic system. Some examples are presented using MATLAB simulation to illustrate the performance and applicability of the proposed connectionist model.

Keywords— Fuzzifier, membership function, receptive field, hybrid learning, adaptivity, input-output mapping, ANFIS,training, epoch

I. INTRODUCTION

Control system modeling based on conventional control schemes is not suited for the complex, ill – defined and uncertain systems. For such conditions fuzzy plays a major role in controlling a system. During the past decade, fuzzy logic has found a variety of applications in various fields ranging from individual process control to medical diagnosis and securities trading. In contrast to the conventional control schemes, fuzzy logic controllers provide feasible alternatives since they can easily capture the approximate, quantitative aspects of human knowledge and reasoning. However, the performance of them relies on two important factors: the soundness of knowledge acquisition techniques and the availability of domain experts. These two factors substantially restrict the application domain of fuzzy controllers. We can add on learning capability by integrating neural networks to the fuzzy system. Neural networks have a large number of highly connected processing nodes that demonstrate the ability to learn and generalize from training data. They like humans can perform pattern – matching tasks while traditional computers are inefficient at these tasks.

Neural networks like fuzzy logic control system are excellent at developing human made systems that can perform the same type of information processing that our brain performs.

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By combining fuzzy and neural networks, we can integrate the advantages of these two. One such system is Adaptive Network based Fuzzy Inference System (ANFIS). In this connectionist structure, the input and the output nodes represent the input states and the output control/decision signals respectively and in the hidden layers these nodes functioning as membership functions and rules. Therefore, each computing node corresponds to a fuzzy set and its respective field corresponds to the membership function. In this project an ANFIS model is formulated with two inputs and an output which serves as the decision making system to map the inputs. Performance of ANFIS is compared with that of a pure fuzzy or Mamdani system.

II. FUZZY LOGIC SYSTEM

Professor Lofty Zadeh of the University of California at Berkeley put forward the idea of fuzzy logic. The word fuzzy means ' unclear' or 'uncertain'. Hence fuzzy logic can be used to express uncertain conditions. The objective of the fuzzy logic is to make computer ' think' like humans and remove barrier between us and the full utilization of computer capabilities. In classical set theory, an object either belongs to a set or not. Classical set theory was the mathematical background for computer logic, where in fuzzy set theory; degrees of belongings to a set are introduced. Fuzzy set theory is the mathematical background that is needed to capture the way people think. Fuzzy logic systems base their decisions on inputs in the form of linguistic variables derived from membership functions which are formulas used to determine the fuzzy set to which a value belongs and the degree of membership in that set. The most straightforward approach is to define membership functions and the rules subjectively by studying a human operated system or an existing controller and then testing the design for the proper output. The membership functions or the rules should be adjusted if the design fails the test. Although these methods showed promising results they are subjective and somewhat heuristic and the choice of membership functions still depends on trial and error. Hence bringing the learning abilities of neural networks to fuzzy logic systems may provide a more promising approach.

A. BASIC STRUCTURE OF FUZZY LOGIC SYSTEM

Fuzzy logic systems are structured numerical estimators. They start from highly formalized insight about the structure of categories found in real world and then articulate fuzzy IF-THEN rules as a kind of expert knowledge.

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They base their decisions on inputs in the form of linguistic variables derived from membership functions which are formulae to determine the fuzzy set to which a value belongs and the degree of membership in that set. The variables are then matched with the preconditions of linguistic IF-THEN rules and the response of each rule is obtained through fuzzy implication. The response of each rule is weighted according to the confidence or degree of membership of its inputs and the centroid of the response is calculated to generate the appropriate output.

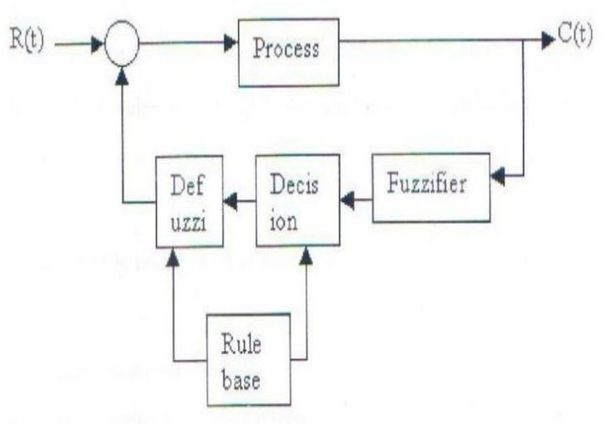

Fig. 1 General model of a Fuzzy Logic System

A fuzzy logic system is generally described by a set of fuzzy rules that constitute the control protocol. The components of the conventional and fuzzy systems are quite alike but differing mainly that the fuzzy system contains fuzzifiers, which convert crisp inputs into their fuzzy representations and defuzzifiers converts the output of the fuzzy process logic into crisp solution variable. The basic fuzzy logic controller contains three parts. They are fuzzifier block, control block and defuzzifier block.

- The fuzzification interface converts the numerical values of the input variables into linguistic variables or fuzzy sets. The conversion requires scale mapping that transforms the range of values of input variables into corresponding universe of discourse.
- The rule based fuzzy control algorithm provides definition of linguistic control rules, which characterize the control policy. Here the block includes the decision making logic, which infers fuzzy control actions employing fuzzy implication and the inference rule mentioned.
- The defuzzification block converts the inferred control action, which interpolates between rules that are fired simultaneously to a continuous signal.

The expert knowledge usually takes the form IF (a set of conditions are satisfied) THEN (a set of consequences can be inferred). The set of conditions belongs to the input domain. The fact that various rules can be fired simultaneously is due to the conversion of values obtained from sensors to linguistic terms, assigning a membership function to each one.

B. FUZZY RULE GENERATION

In most fuzzy problem, the rules are generated based on past experience. Concerning problems that deal with fuzzy control, one should know all the possible input output relationships in fuzzy terms. The operation of a fuzzy logic controller can be broadly classified into two functions, inference and defuzzification. The inference portion of the operation begins with the processing of the production rules. Individual rules are comprised of a condition block (IF block) and a conclusion block(THEN block).

A fuzzy set F in an universe of discourse U is characterized by a membership function $\mu_F : U \rightarrow [0,1]$. Thus a fuzzy set F in U may be represented as a set of ordered pairs. The fuzzy rule base contains a set of fuzzy logic rules R. For MIMO system,

$R = \{ R_{MIMO}^1, R_{MIMO}^2, \ldots\ldots\ldots R_{MIMO}^n \}$

where the i^{th} fuzzy rule is R_{MIMO}^i: IF (x_1 is T_{x1} .....and x_p is T_{xp}) THEN (y_1 is T_{y1} ......and y_q is T_{yq}) where x, y and T represents input linguistic variable, output linguistic variable and term set respectively.

C. DEFUZZIFICATION

In order to set a usable output, a defuzzifier operation is performed to convert the fuzzy logical sum to a fixed, discrete value. The two commonly used methods are:

(i) composite medium

This method produces the output based on the truth produced by a single rule having highest predicate path.

(ii) composite moment or centroid method

The output produced by this method is derived from the centre of gravity of the final fuzzy space. Hence, the output is sensitive to all the rules that have been fixed and so the output moves smoothly over the control surface. So this method is best suited for process control applications.

D. SIGNIFICANCE OF FUZZY

Presently, fuzzy has found a variety of applications in various fields ranging from industrial process control to medical diagnosis. It is a model free estimator and deals with the relationship of the output to the input. To design a conventional control system, one needs a mathematical model for the process and the specifications or the model of the overall system. A mathematical model for the controller can then be produced and implemented. But the fuzzy logic control describes the algorithm for process control as a fuzzy relation between information on the condition of the process to be controlled and the control action. Its systems base their decisions on inputs in the form of linguistic variables derived from the membership functions which are formulae used to determine the fuzzy set to which a value belongs and the degree of membership in that set. The variables are then matched with the preconditions of linguistic fuzzy rules and the responses of each rule are obtained through the fuzzy implication.

III. NEURAL NETWORKS

A learning system can be divided into three groups: 1) statistical pattern recognition 2) machine learning methods in artificial intelligence community 3) neural networks. In the first group, classical method from statistical pattern recognition has been studied far more comprehensively than the other methods. Machine learning methods represent solutions in a form compatible with typical human reasoning.

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The third group of learning system is neural network or connectionist models that are systems that deliberately constructed to make use of some of the organizational principles that resembles the human brain.

A. MODEL OF A NEURON

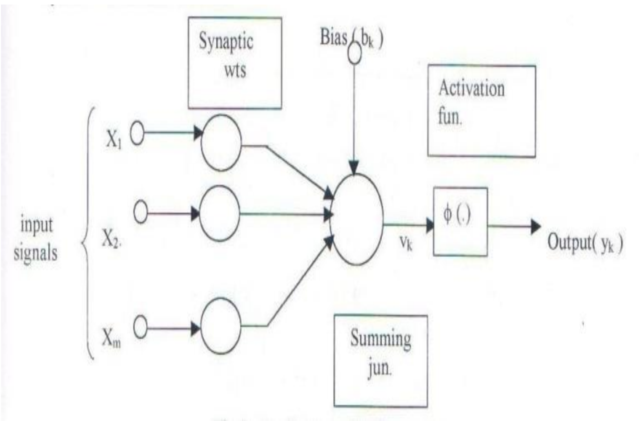

Fig. 2 Non linear model of a neuron

The three basic elements in a neuronal model are: 1) a set of synapses or connecting links each of which is characterized by a weight or strength of its own. 2) an adder for summing the input signals, weighted by the respective synapses of the neuron 3) an activation function or squashing function for limiting the amplitude of the output of the neuron.

In mathematical terms, we may represent a neuron k by writing the following equations:

$$U_k = \sum_{j=1}^{m} w_{kj}\ x_j \qquad (1)$$

$$y_k = \phi(U_k + b_k) \qquad (2)$$

Where x_1, x_2,x_3, …… , x_m are the input signals.w_{k1}, w_{k2}, w_{k3},…., w_{km} are the synaptic weights of neuron k; U_k is the linear combiner output due to the input signals, b_k is the bias; ϕ(.) is the activation function and y_k is the output signal of the neuron.

IV. ADAPTIVE NETWORK BASED FUZZY INFERENCE SYSTEM (ANFIS)

An adaptive network is a feed forward network in which each node performs a particular function on incoming signals using a set of parameters specific to this node. The form of node functions may vary from node to node and the choice of each node function depends on the overall function which the adaptive network is designed to implement.

A. ANFIS BASICS

Functionally there are almost no constraints on the node functions of an adaptive network except piecewise differentiability. Structurally, the only limitations of the network configuration are that it should be of feed forward type. Due to these minimal restrictions, the adaptive network's applications are immediate and immense in various areas. A special configuration of adaptive network is an ANFIS, which are functionally equivalent to fuzzy inference systems. ANFIS is a fuzzy inference system. In this, Takagi Suguno's fuzzy if – then rules are used. The output of each rule is a linear combination of input variables plus a constant term, and the final output is the weighted average of each rule's output. The proposed ANFIS has two inputs x and y, one output z and nine rules. The rules are of the form if x is $A_1$and y is B_1 then f_1=p_1x+q_1y+r_1. The node functions in the same layer are of same function.

B. HYBRID LEARNING ALGORITHM FOR ANFIS

The basic learning rule based on the gradient method is notorious for its slowness and tendency to become trapped in local minima. Hence a better learning rule called hybrid learning rule is proposed for ANFIS. There are two learning paradigms for adaptive networks. They are batch learning and pattern learning. In batch learning (off – line learning) , the update action takes place only after the whole training data set has been presented that is only after each epoch or sweep. On the other hand, if we want the parameters to be updated immediately after each input – output pair has been presented, pattern learning or on-line learning is used.

V. SIMULATION DETAILS

The proposed five layered ANFIS contains two inputs, one output and nine rules. Input membership functions can be varied by adjusting the parameters in the layer one and these parameters are called premise parameters. Output membership functions can be adjusted by the consequent parameters in the layer four. In the hidden layers, rule matching is done. The aim of the project is to map various input signals by making use of ANFIS and compare the results with that of a pure fuzzy system that is a Mamdani system. Mainly a Sugeno system is used for training the ANFIS. The first step for the simulation process is to assign the desired number of inputs and outputs and for that purpose we can use the FIS editor in MATLAB. In this project, an ANFIS having 2 inputs and one output is used.

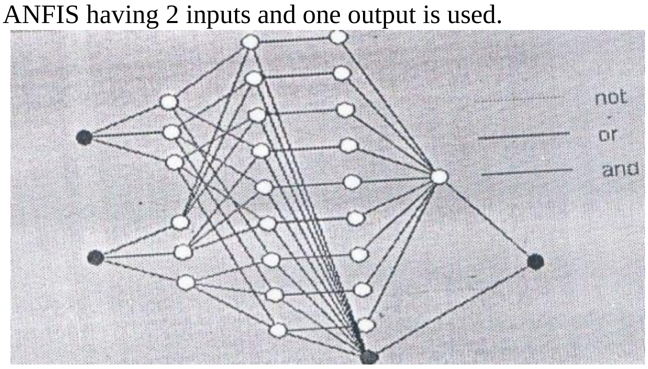

Fig. 3 ANFIS structure

In ANFIS input and output membership functions can be edited in the membership function editor. In the proposed ANFIS structure, there are three membership functions for each input and nine membership functions for the output are assigned. Fuzzy rules can be set and edited by using fuzzy rule editor and it can be trained and tested in ANFIS editor for a designed epoch. The same procedure can be implemented for the simulation of Mamdani system which is purely a fuzzy system but the difference is that it lacks ANFIS editor.

VI. RESULTS AND DISCUSSIONS

Both the ANFIS and Mamdani systems were simulated for different cases of inputs like sine, ramp and sinusoidal signals with the same parameters and the outputs for both the systems were studied and analyzed by plotting the corresponding output waveforms and the error surface.

Root mean square of the error is calculated to analyze the performance of both the systems.

Case 1: With two step inputs:

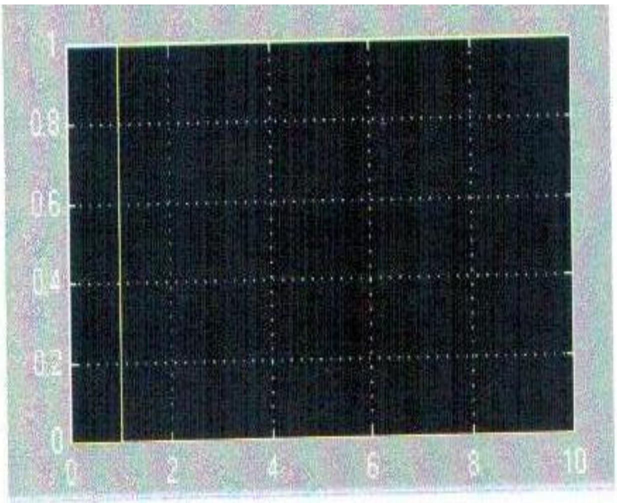

Fig. 4 Step inputs to both ANFIS and Mamdani system.

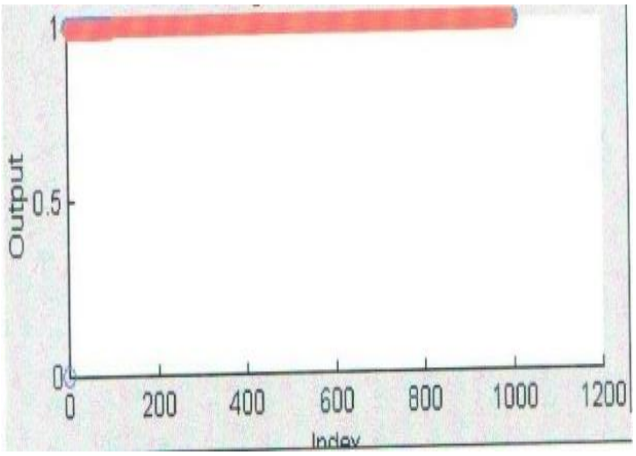

Fig. 5 ANFIS training output

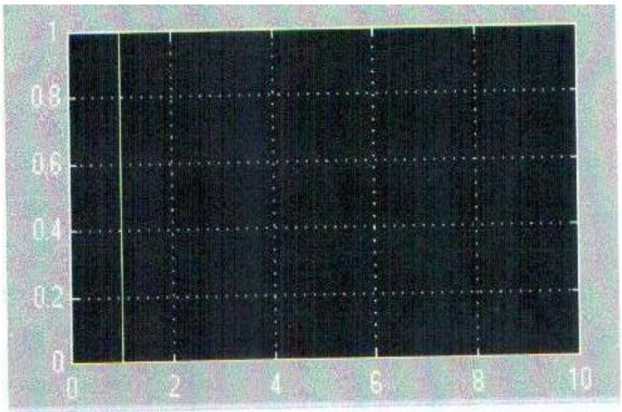

Fig. 6 ANFIS output for two step inputs

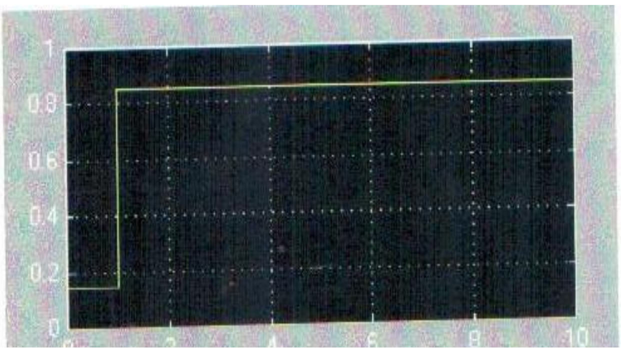

Fig. 7 Mamdani output for two step inputs

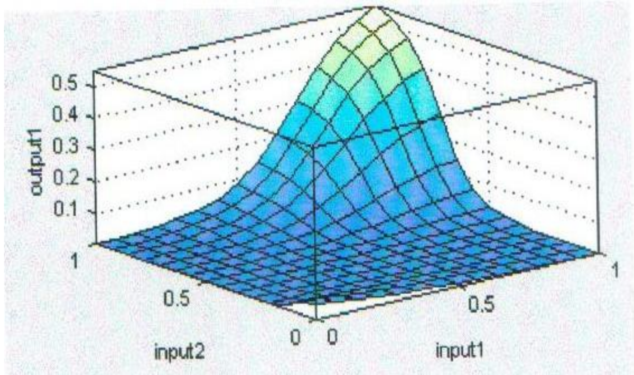

Fig. 8 Error Surface view for ANFIS

Root mean square error for ANFIS: 1.7718×10^{-6}

Root mean square error for Mamdani: 0.0047

Case2: With two sinusoidal inputs

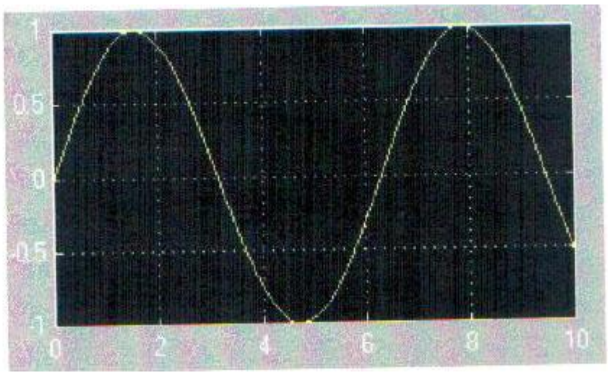

Fig. 9 Sinusoidal inputs to both ANFIS and Mamdani system

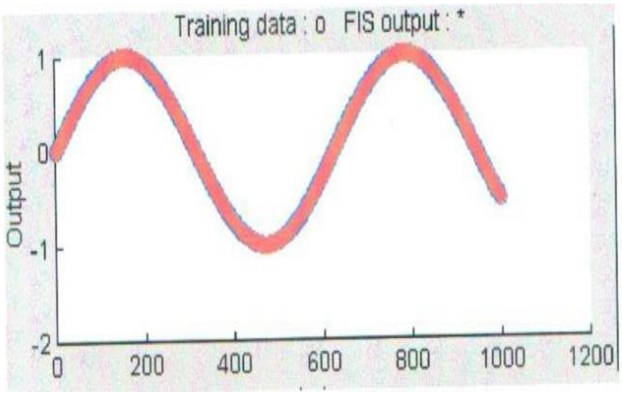

Fig. 10 ANFIS training output

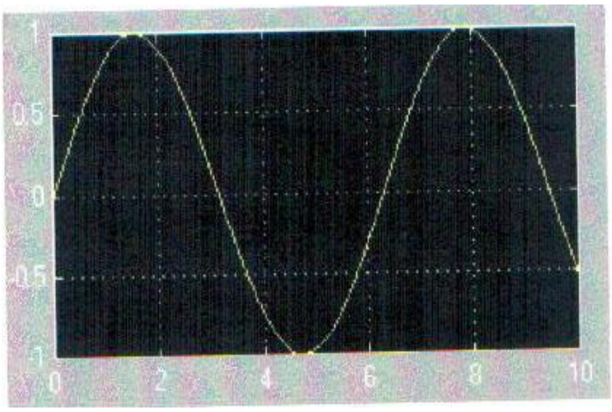

Fig.11 ANFIS output for two sinusoidal inputs

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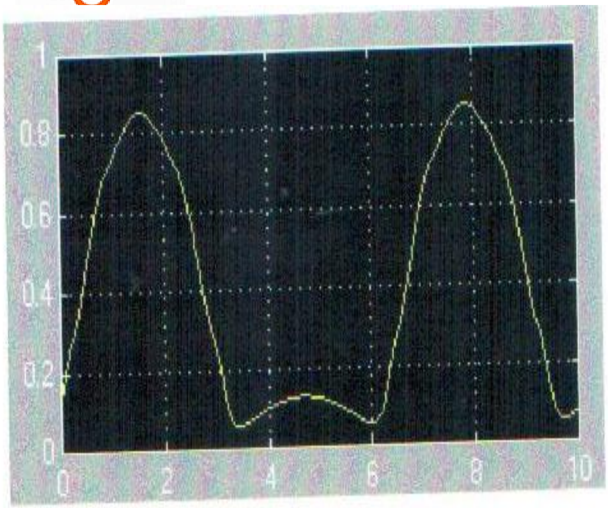

Fig. 12 Mamdani output for two sinusoidal inputs

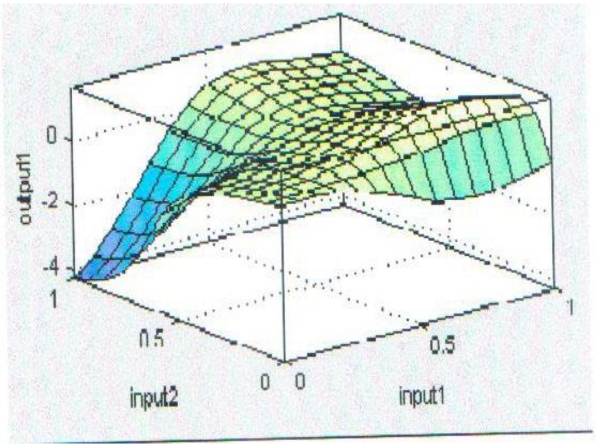

Fig. 13 Error Surface view for ANFIS

Root mean square error for ANFIS: $5.7237\text{x}10^{-5}$
Root mean square error for Mamdani: 0.023
Case3: With one step and ramp inputs

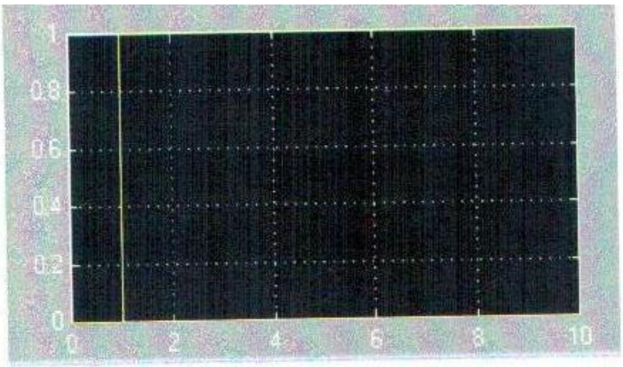

Fig. 14 Step input to both ANFIS and Mamdani system.

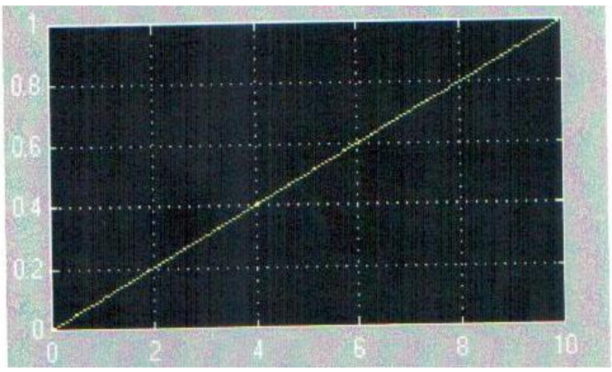

Fig. 15 Ramp input to both ANFIS and Mamdani system.

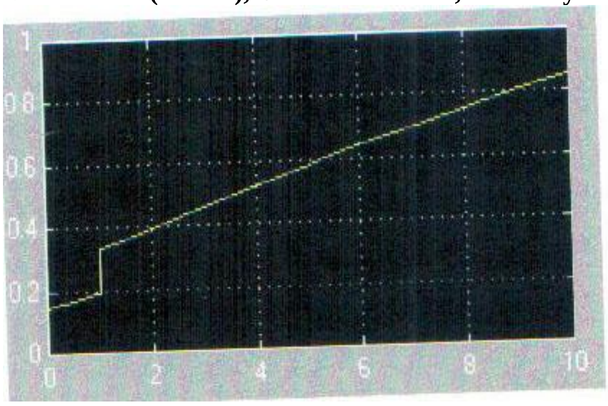

Fig. 16 ANFIS output for step and ramp inputs

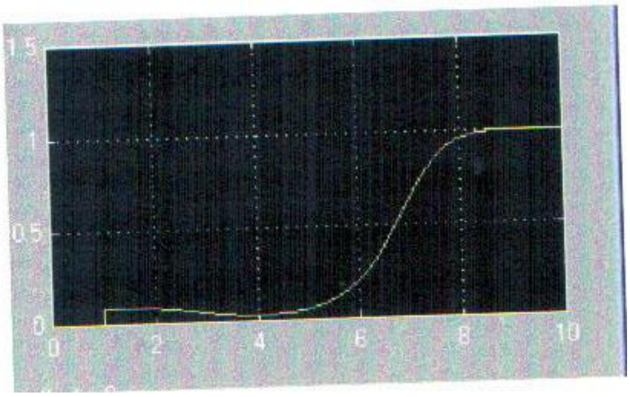

Fig. 17 Mamdani output for step and ramp inputs

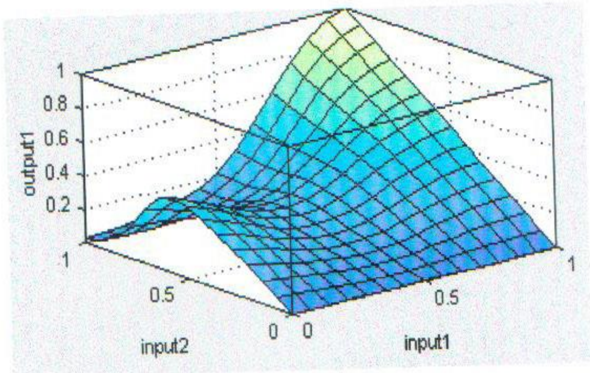

Fig. 18 Error Surface view for ANFIS

Root mean square error for ANFIS: $3.1456\text{x}10^{-5}$
Root mean square error for Mamdani: 0.0324
From the above simulation results it is quite obvious that the output of the Adaptive Network Based Fuzzy Inference System is the exact replica of the input where as in Mamdani model, it failed to map the input correctly. Moreover, the root mean square error of ANFIS is much less compared to Mamdani system.

VII. CONCLUSION

A connectionist model of a fuzzy logic control/ decision system (ANFIS) is made which is much superior to the pure fuzzy logic system (Mamdani). The proposed neuro fuzzy model makes use of hybrid learning algorithm which provides high level human – understandable meaning to the normal connectionist structure. It contains both the fixed and adaptive nodes which provide adaptive capabilities to the network.

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Here, the parameter set of the network is the union of the parameter sets of each node and in order to achieve a desired input – output mapping, these parameters are updated according to the training data. In this project, the ANFIS is made as a decision making system which makes use of sugeno system to map the input signals. The result is compared with a pure fuzzy or Mamdani system and the response of the neuro fuzzy system is found to be much superior with least error to that of a pure fuzzy system.

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