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Modeling of Greenhouse System Using Adaptive Neuro-fuzzy Inference System (Anfis) Technique

A. Manonmani*, **T. Thyagarajan****, **S. Sutha*****, **G. Guruprasath******

Abstract: The greenhouse system (GHS) is an important and effective measure to get better agricultural productivity. The crop requires a different temperature and humidity for various phases such as multiplication phase, vegetation phase and growth phase. To get proper growth of crops, inside temperature and inside humidity should be maintained at the desired level with respect to climatic condition. The dynamics of complex GHS are very complex due to parameter variation, nonlinearity and disturbances. Hence, it is difficult to develop a mathematical model of the GHS using conventional techniques. Modeling of such complex system can be easily obtained using soft computing technique like Adaptive Neuro-Fuzzy Inference System (ANFIS). In this paper, a cooling model for GHS is developed using ANFIS technique. The advantages of ANFIS model of GHS over conventional model are highlighted.

Keywords: Greenhouse System (GHS), Nonlinear System, Adaptive Neuro-Fuzzy Inference System (ANFIS) and Fuzzy Inference System (FIS).

1. INTRODUCTION

Soft Computing refers to reasoning, thinking and deduction that recognizes and uses the reality of grouping, memberships, and classification of various quantities under study. It is an extension of natural heuristics and capable of dealing with complex systems because it does not require strict mathematical definitions and distinctions for the system components. The modeling of complex system can be easily achieved using soft computing techniques. The main techniques used in soft computing are: evolutionary computing, artificial neural networks, fuzzy logic and ANFIS.

The greenhouse system is a complex system with highly nonlinear interaction and coupling between system variables. ANFIS models can accurately reproduce a system which is highly nonlinear and where there is a problem in framing the relation between input and output that generally cannot be described by a mathematical relationship.

The modeling of complex system can be easily achieved by an input-output data learning using Artificial Neural Network (ANN), [8]. We choose ANN to model a dynamic system and create a fuzzy inference system. There are two ways to train the ANN namely supervised training and unsupervised training. In this paper as the input and desired output of the system are known a supervised training is used.

This paper is organized as follows: Firstly the brief introduction of dynamic system. Section 2 presents the details of mathematical model of a greenhouse system. Section 3 describes the Adaptive Neuro-Fuzzy Inference System (ANFIS) used in formulating the GHS model. Section 4 explains the results and discussion and finally the conclusion of the work are presented in section 5.

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2. GREENHOUSE SYSTEM

The non-linear behavior of the GHS is a combination of a physical interaction between the temperature and humidity. A simple GHS is shown below in the Figure 1.

From the figure 1, the inputs to the GHS are the ventilation rate and water capacity of fog system and the outputs are inside temperature and inside humidity. The disturbances are solar radiation, outside temperature and outside humidity. The method used to determine the dynamic model of GHSisbasedonenergyandmassflows equationsdescribingthe GHS. The GHS consists of heating, cooling and ventilation model. The cooling model is considered here and the mathematical model of greenhouse system for a cooling model is given by equation (2), [2]

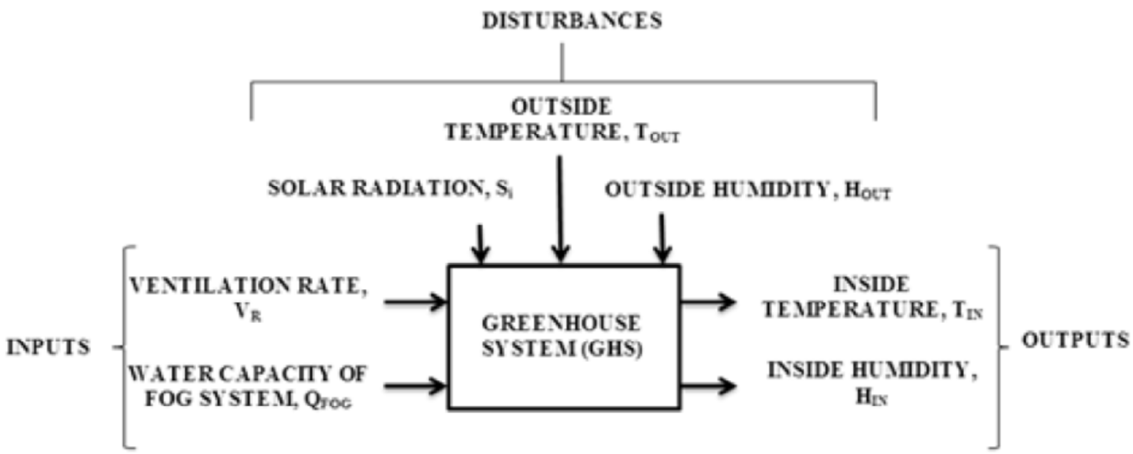

Figure 1: A Simple Greenhouse Systems

$$\left.\begin{aligned} \frac{d}{dt}T_{in}(t) &= \frac{1}{\rho C_p V_T}\left[Qheater(t)+S_i(t)-\lambda Q_{fog}(t)\right]\left(\frac{V_R(t)}{V_T}+\frac{UA}{\rho C_p V_T}\right).\left[T_{in}(t)-T_{out}(t)\right] \\ \frac{d}{dt}H_{in}(t) &= \frac{1}{V_H}Q_{fog}(t)+\frac{1}{V_H}.\left[E(S_i(t),-H_{in}(t))\right]-\frac{V_R(t)}{V_H}\left[H_{in}(t)-H_{out}(t)\right]) \end{aligned}\right\} \quad (2)$$

$$\left[E\left(S_i(t),H_{in}(t)\right)\right]=\alpha\frac{S_i(t)}{\lambda}-\beta_T H_{in}(t)$$

NOMENCLATURE

Parameters	*Values with Units*
Indoor air temperature (T_{in})	25 to 32°C
Outdoor air temperature (T_{out})	35°C
Interior humidity (H_{in})	12 to 21 *g*[H_2O]/kg[dry air]
Exterior humidity (H_{out})	4g[H_2O]/kg[dry air]
Heat transfer coefficient of enclosure(UA)	29.81WK^{-1}
C0	–324.67minW°C^{-1}
T_v	3.41Min
Latent heat of vaporization (λ) and λ′	2257(J/g) and 465W
α′	0.0033gm^{-3}min^{1}W
1/V′	13.3gm^{-3}min^{-1}
Air density(ρ) and Solar radiation (S_i)	1.2 kg/m^3
Specific heat of air C_p	1,006 J/(kg K)

The height and surface area of GHS are 4 m and 1000m^2 respectively.The incident solar radiation energy reduced by the system is about 60%. The ventilation rate is about 20airchangesperhour(22.2 m^3/s) and maximumwatercapacityof the fogsystemis 26 g[H_2O]/m3.

3. FORMULATION OF GHS MODEL USING ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

ANFIS is a kind of artificial neural network that is based on Takagi–Sugeno fuzzy inference system. Its inference system corresponds to a set of fuzzy if-then rules that have learning capability to approximate nonlinear functions. The major steps involved in formulating ANFIS model include:

(i) Generating input/output data

(ii) Identification of architecture

(iii) Network Training

(iv) Validation using trained and test data.

3.1. Generating Input/Output Data

The data that is generated to train the network should contain all the relevant information about the dynamics of the system. The training data is generated by simulation using random values of the inputs namely ventilation rate and water capacity of fog system as shown in Figure 2 and Figure 3 respectively.

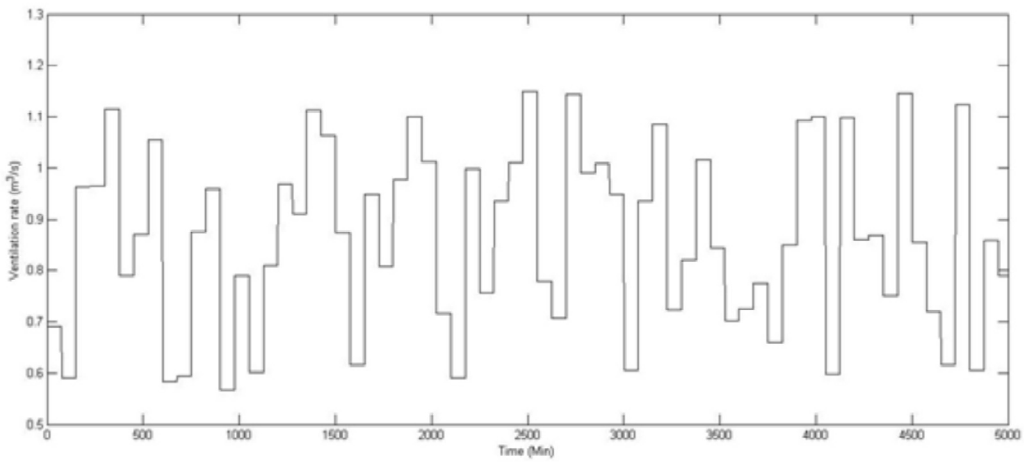

Figure 2 Variation in Ventilation rate of GHS

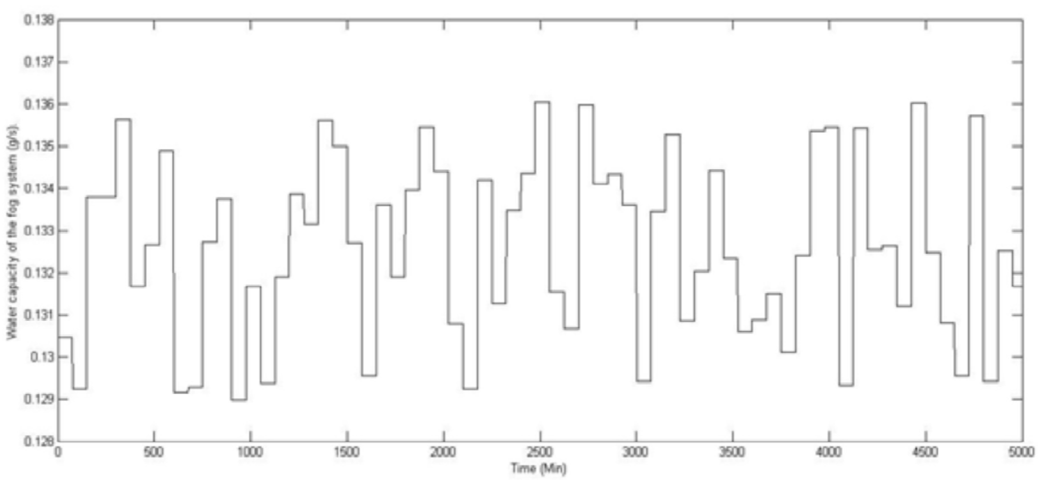

Figure 3 Variation in Water capacity of the fog of GHS

The nonlinearity is evident from the response of temperature and humidity and this is shown in the Figure 4 and Figure 5 respectively.

In this work, 5000 units of data are collected from the conventional model andused to develop the ANFIS model.

3.2. ANFIS Architecture

The ANFIS architecture of the Takagi-Sugeno inference system is shown in Figure 6.

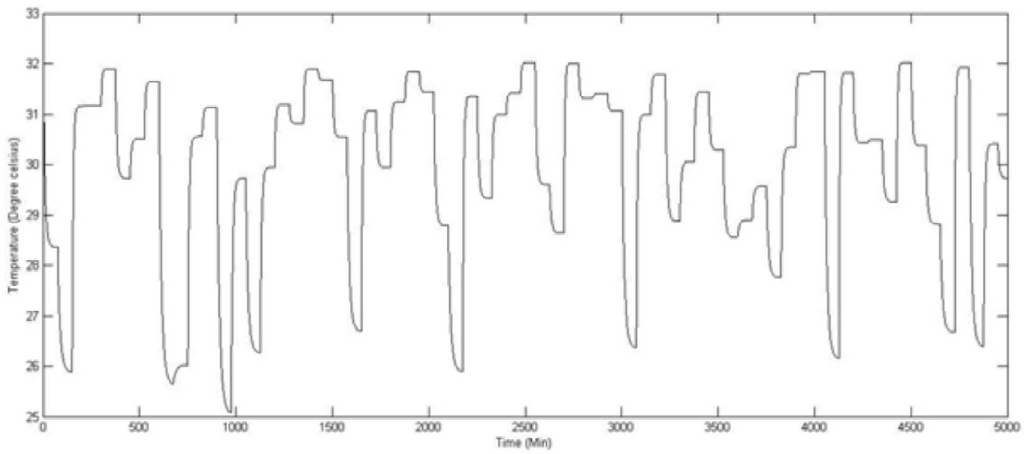

Figure 4 Variation of inside temperature for GHS

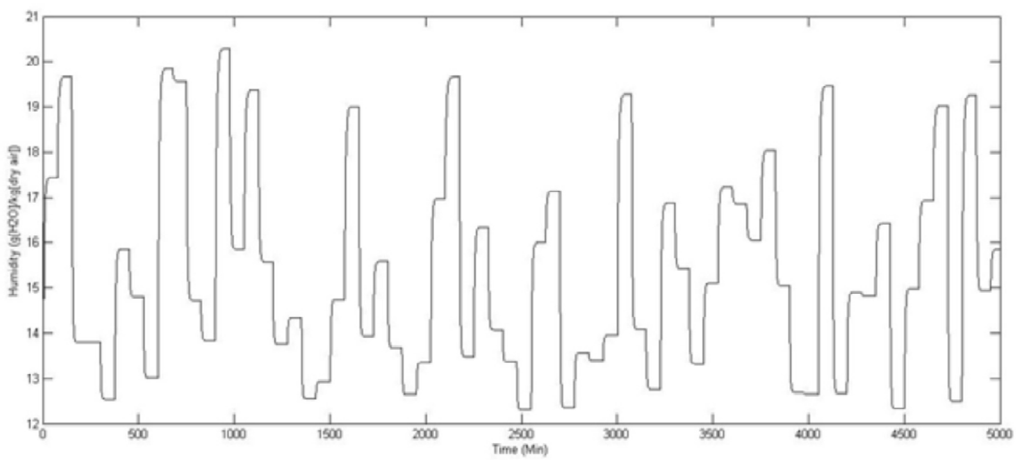

Figure 5 Variation of inside humidity for GHS

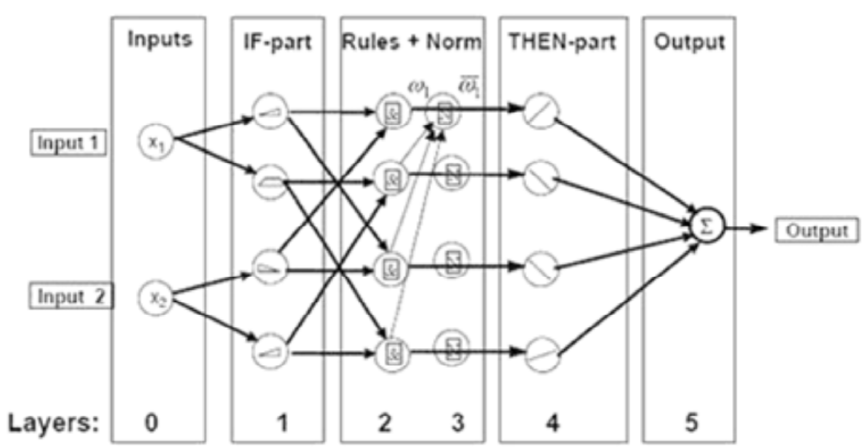

Figure 6: ANFIS Architecture

The entire system consists of five layers and the relationship between the input and output layer is summarized as follows and has been shown in equation (3), [7]

$$\left.\begin{array}{l} 0_1, i = \mu_{A_i}(x) \\ 0_2, i = \mu_{B_{i-2}}(y) \\ 0_2, i = w_i = \mu_A(x) * \mu_{B_i}(y) \\ 0_3, i = \widehat{W}_i = \dfrac{w_i}{w_1 + w_2} \\ 0_4, i = \widehat{W}_i f_i = \widehat{w}_i(p_i x + q_i y + r_{i)} \\ Overall\ output = 0_5 = \sum_i w_i f_i \end{array}\right\} \tag{3}$$

3.3. Training Algorithm

The training algorithms used are back propagation algorithm and hybrid algorithm. ANFIS uses training algorithm to tune the parameters of sugeno type fuzzy inference system. The ANN used here is a Multilayer Perceptron (MLP) network [9].

3.4. Fuzzy Inference System (Fis)

A fuzzy knowledge-based system finds lot of applications, mainly due to its flexibility and simplicity. The functional block of a fuzzy inference system is shown below in the Figure 7.

From the Figure 7 the functional block of fuzzy inference system are: fuzzification, data base, rule base, decision making and defuzzification. The rule base and data base combined known as knowledge base. The basic steps of fuzzy reasoning based on the fuzzy inference system (FIS) as follows:

1. Compare the input variables with the membership functions on the premise part to obtain the membership values (or compatibility measures) of each linguistic label. (This step is often called fuzzification).
2. Combine (through a specific T-norm operator, usually multiplication or min.) the membership values on the premise part to get firing strength (weight) of each rule.
3. Generate the qualified consequent (either fuzzy or crisp) of each rule depending on the firing strength.
4. Aggregate the qualified consequents to produce a crisp output (This step is called de-fuzzification).

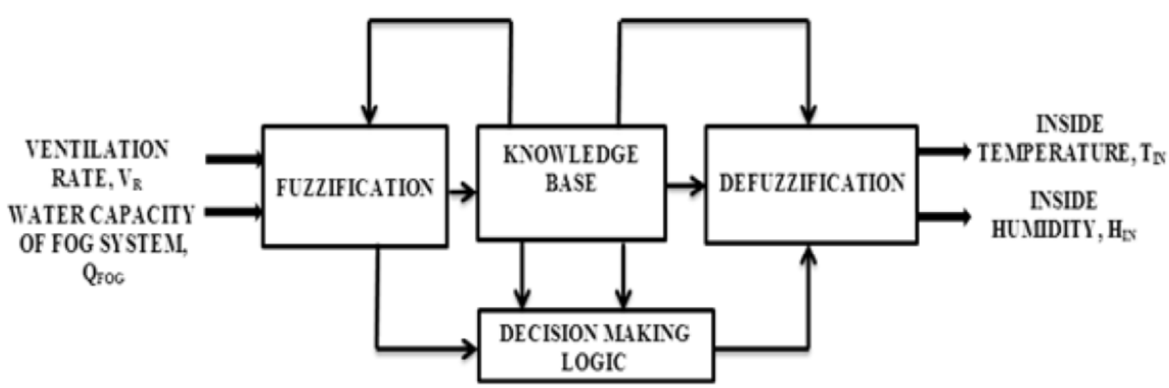

Figure 7: Block of Fuzzy Inference System

The input-output variables of FIS are expressed using linguistic variables and are fuzzified. Takagi-Sugeno-Kang (TSK) inference rule has been applied to the FIS to predict the quality of the system.

3.5. Data Input For Fis

The data set should include data for each process variable, evenly distributed throughout the range for which estimation is desired. The maximum and minimum values of inside temperature and humidity were determined by looking at the operation range of the greenhouse system. Thus, model simulations are performed to obtain the input-output data by using these values. The generated training data is loaded in the FIS using the GUI Editor. Later, design parameters, initial estimator structure are constructed. In this work, 4 FIS structures are used because the interaction between the input and output variables for each FIS will be helpful in modeling the GHS.

3.6. FIS Structure 1

The data from the conventional model loaded through workspace into the ANFIS GUI. In this work 3750 (75%) number of input-output data pairs are used for training the ANN models and 1250 (25%) data pairs are used for validation. Initialize the parameters of FIS and train the model using different training algorithms. The checking data is loaded into ANFIS GUI and validation of training data against test data. The structure of the ANFIS model used for GHS is shown in the Figure 8.

For FIS structure 1, two input membership functions namely: ventilation rate and temperature of previous value and the output is temperature and shown in Figure 9 and Figure 10.

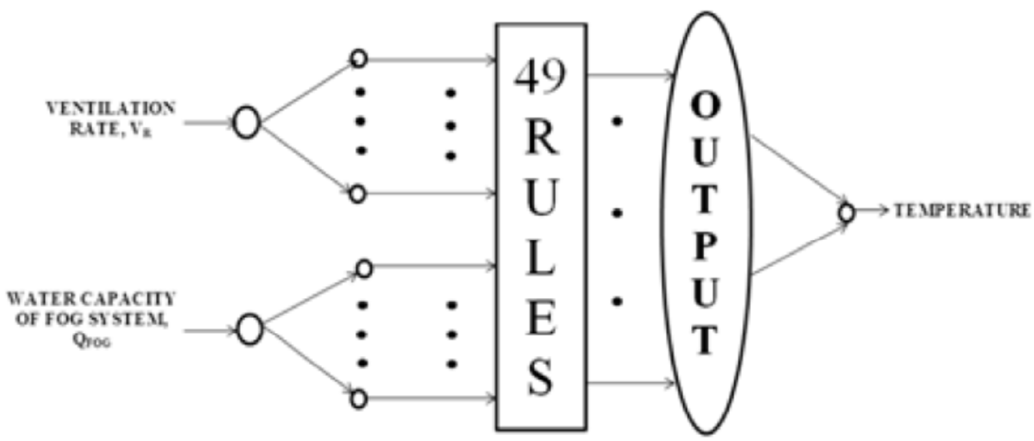

Figure 8: ANFIS Structure 1 used for developing GHS model

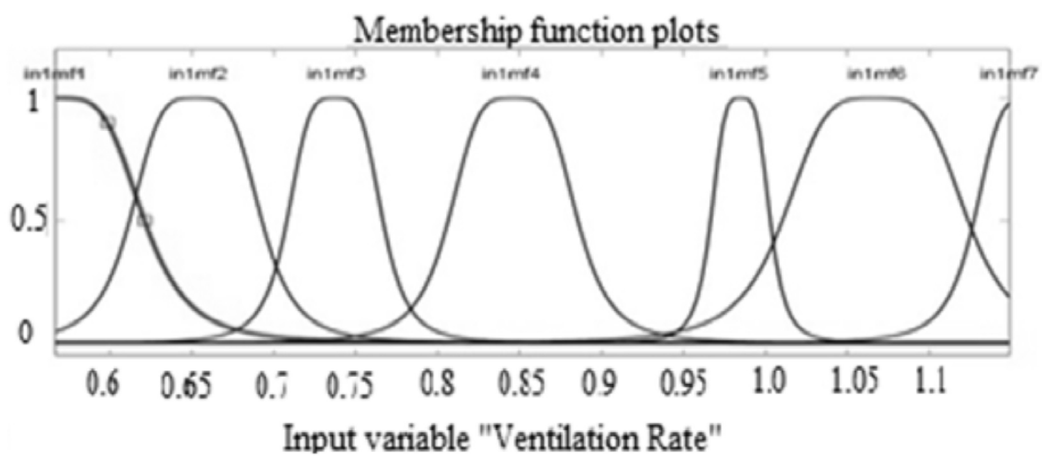

Figure 9: Input1 Membership function plot for ventilation rate

From the Figure 9 and Figure 10, it is inferred that the membership function used here are has seven linguistic levels. Accordingly the 49 rules were formed as shown in the rule base matrix shown in Figure 11.

The ANFIS parameters used for training the model of GHS for ventilation rate and temperature are tabulated in Table 1.

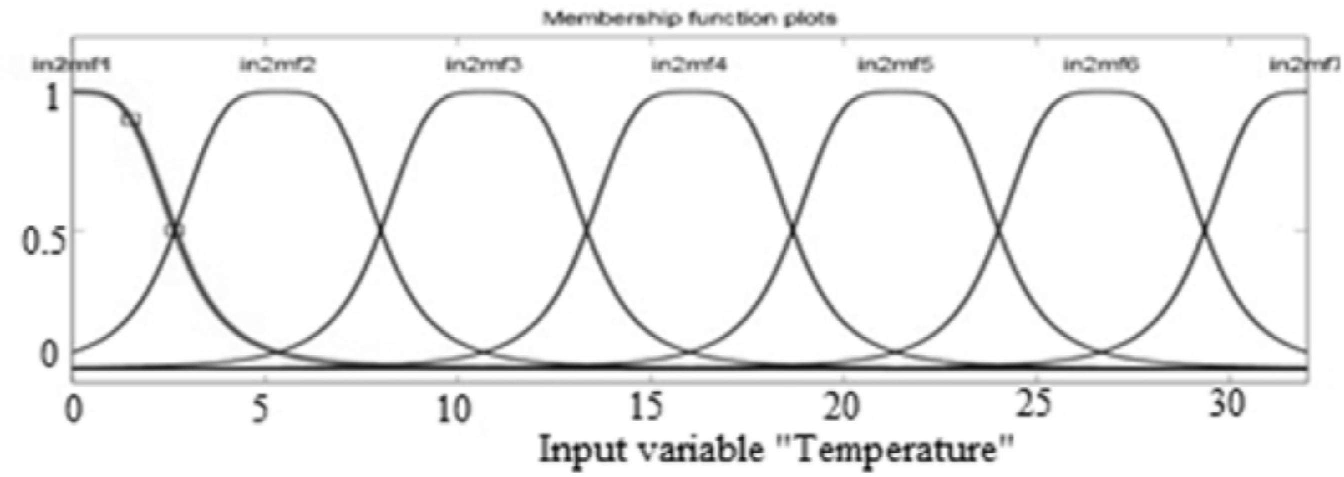

Figure 10: Input Membership function plot for ventilation rate for previous values of temperature

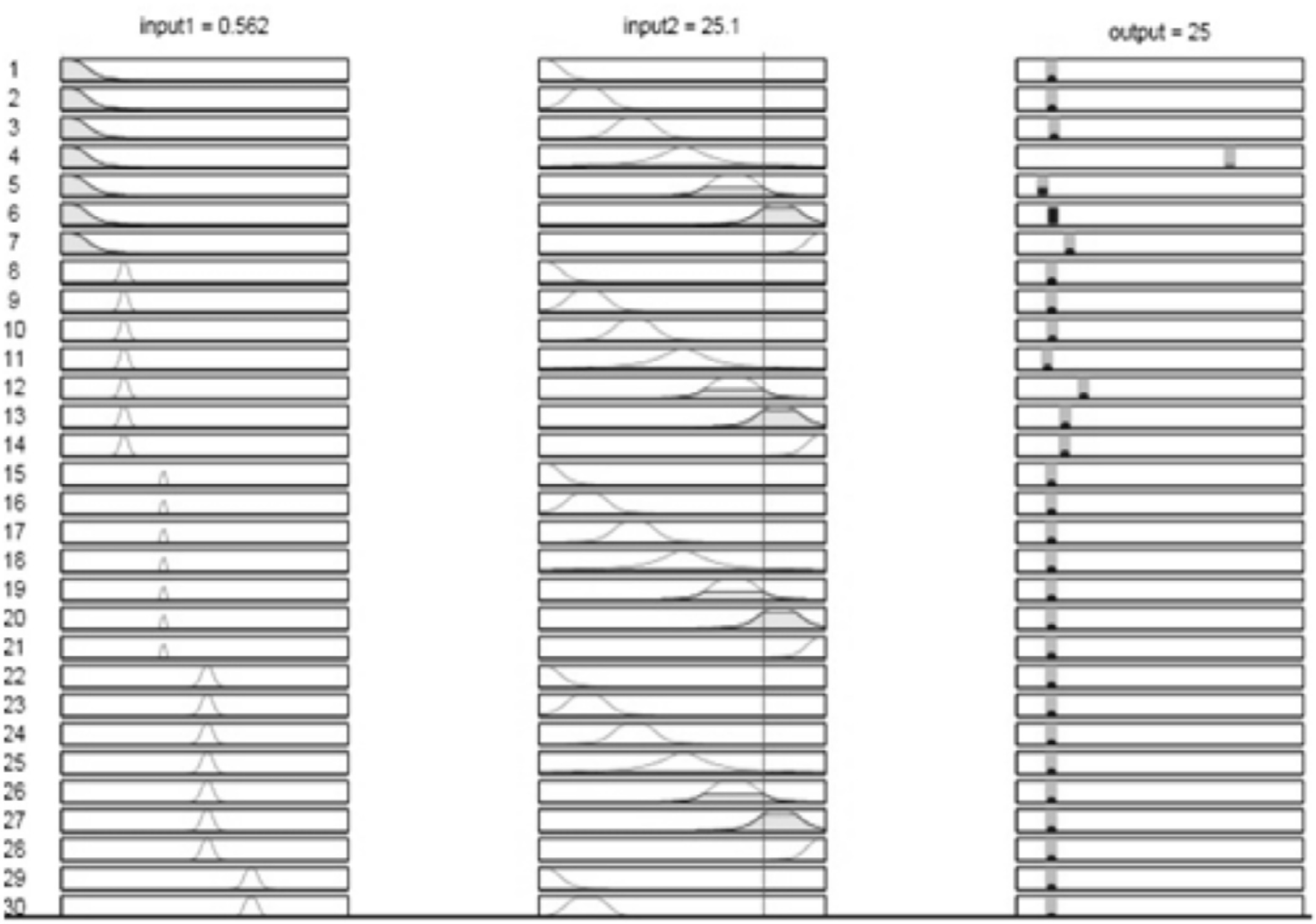

Figure 11: Rule base matrix for ventilation rate and previous values of temperature

Table 1
ANFIS parameters modeling of GHS for Ventilation rate and Temperature

S. No	*Parameter*	*Values*
1	No. of inputs (Ventilation Rate and Temperature past value)	2
2	No. of output (Temperature)	1
3	Model	Takagi-Sugeno model
4	Input space partition	Grid partition
5	Learning algorithm	Hybrid/ Back propagation
6	No. of input MFs	7
7	Input MF type	Gbell
8	Output MF type	Linear
9	Epochs	30

3.7. FIS Structure 2

The data from humidity is taken and loaded into the ANFIS GUI then the data for humidity is checked. The structure of the ANFIS model used for GHS is shown in the Figure 12.

In the FIS structure 2, the input membership is ventilation rate and the output is humidity and shown in Figure 13.

From the Figure 13, it is inferred that the membership function used here are has twenty linguistic levels. Accordingly the 20 rules were formed as shown in the rule base matrix shown in Figure 14.

The ANFIS parameters used for training the model of GHS for ventilation rate and humidity is tabulated in Table 2.

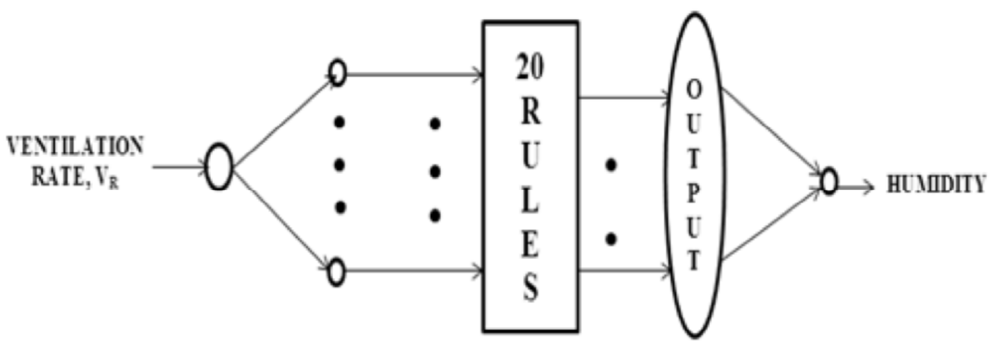

Figure 12: ANFIS Structure 2 used for developing GHS model

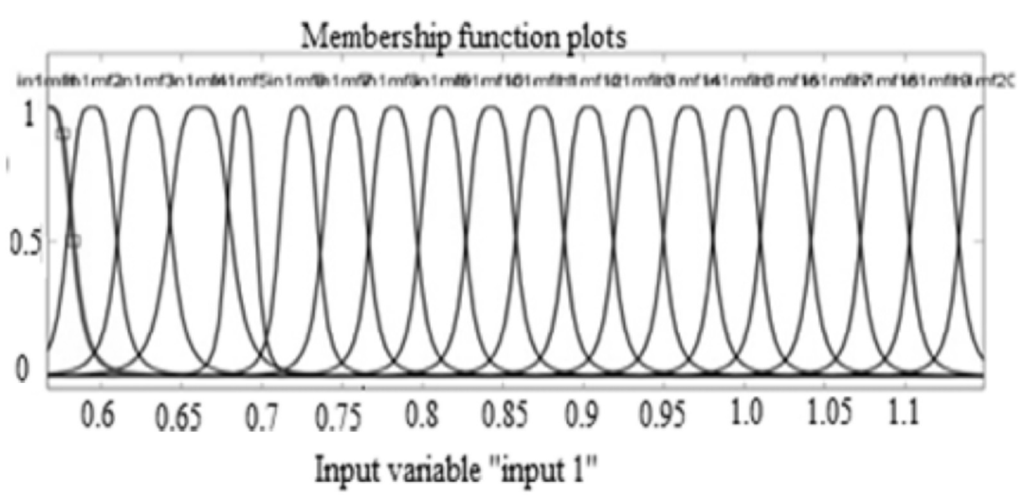

Figure 13: Input: Membership function plot for ventilation rate

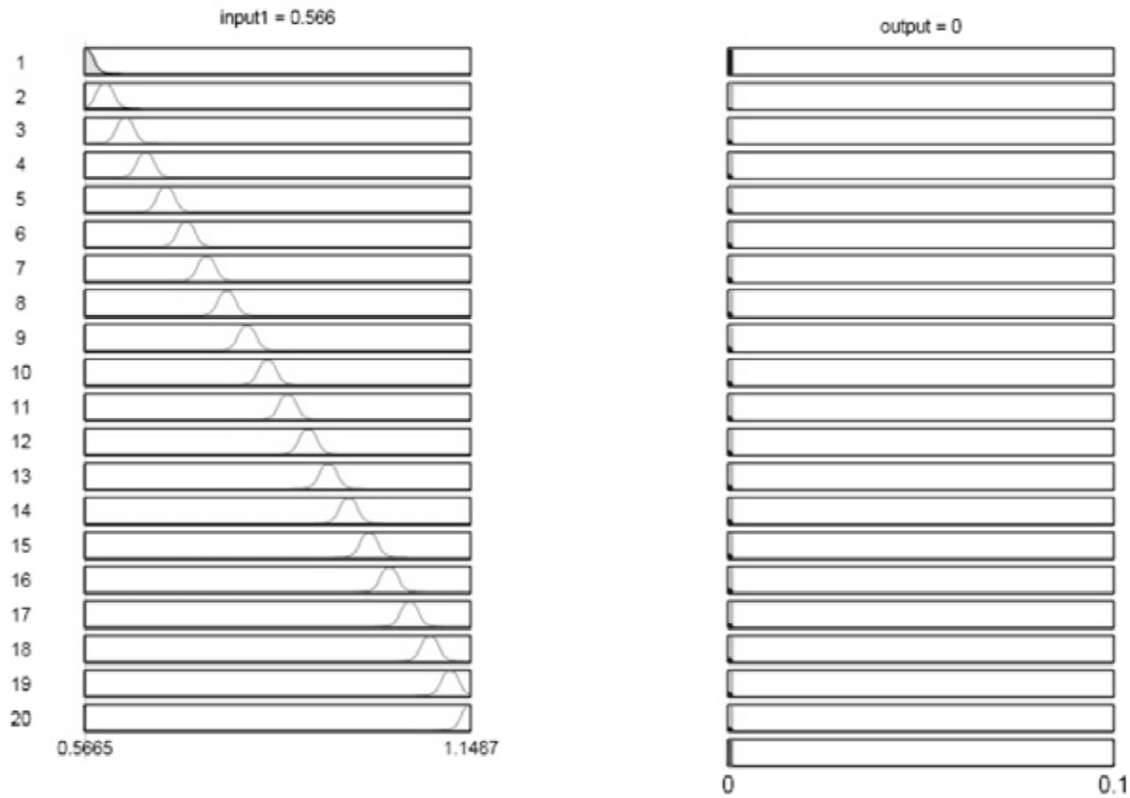

Figure 14: Rule base matrix for ventilation rate and humidity

Table 2
ANFIS parameters modeling of GHS for Ventilation rate and Humidity

S. No	*Parameter*	*Values*
1	No. of inputs (Ventilation rate)	1
2	No. of output (Humidity)	1
3	Model	Takagi-Sugeno model
4	Input space partition	Grid partition
5	Learning algorithm	Hybrid/ Back propagation
6	No. of input MFs	20
7	Input MF type	Gbell
8	Output MF type	Linear
9	Epochs	30

3.8. FIS Structure 3

For FIS structure 3, one input membership water capacity of fog system and temperature is the output. The data from temperature is taken and loaded into the ANFIS GUI and the data for temperature is checked. The structure of the ANFIS model used for GHS is shown in the Figure 15.

The input used is water capacity of fog system and the corresponding membership function is shown in Figure 16.

From the Figure 16 it is inferred that the membership function used here are has thirty linguistic levels. Accordingly the 30 rules were formed as shown in the rule base matrix shown in Figure 17.

The ANFIS parameters used for training the model of GHS for water capacity of fog system and temperature is tabulated in Table 3.

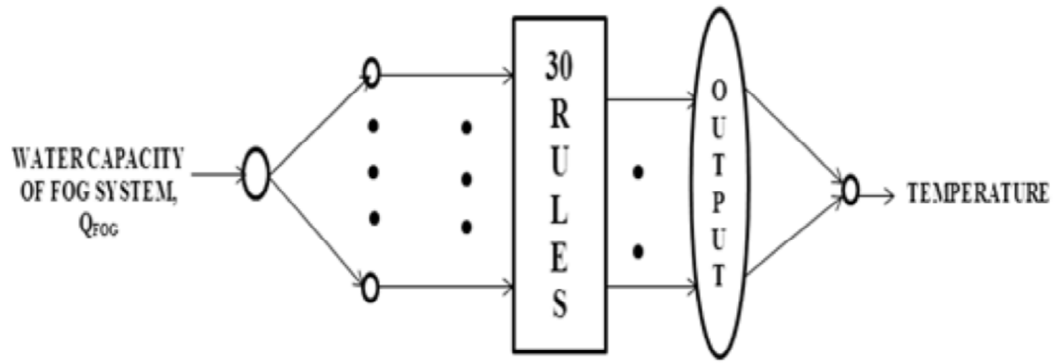

Figure 15: ANFIS Structure used for developing GHS

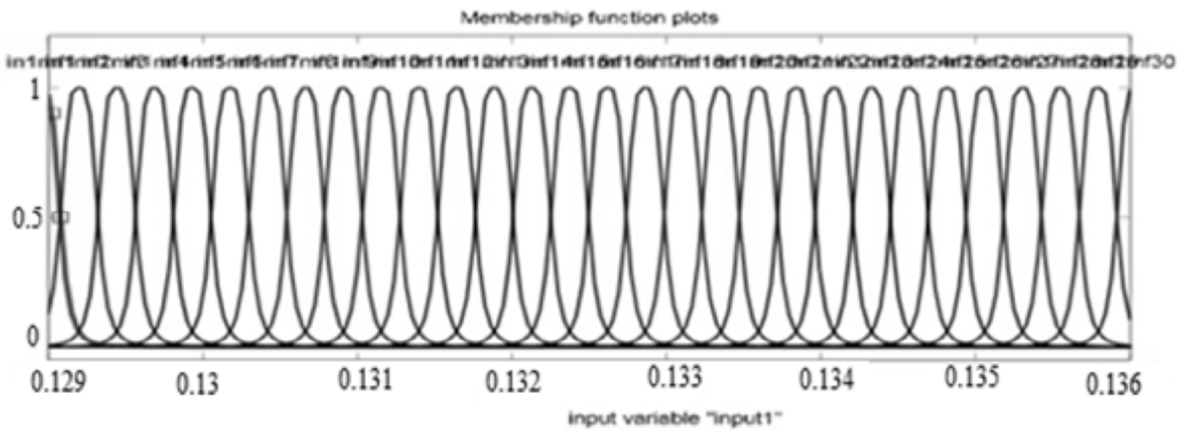

Figure 16: Input: Membership function for water capacity of fog system

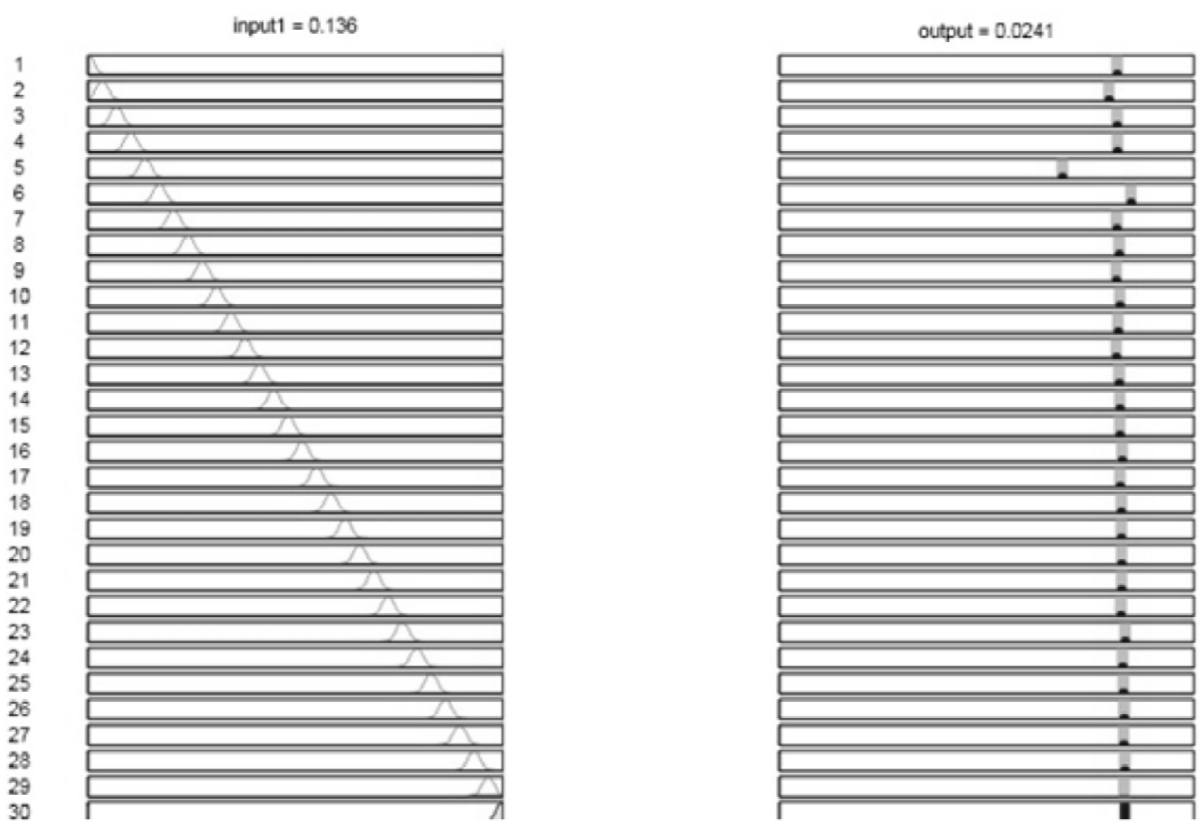

Figure 17: Rule base matrix for water capacity of fog system and temperature

Table 3
ANFIS parameters modeling of GHS for Ventilation rate and Humidity

S. No	*Parameter*	*Values*
1	No. of inputs (Water capacity of fog system)	1
2	No. of output (Temperature)	1
3	Model	Takagi-Sugeno model
4	Input space partition	Grid partition
5	Learning algorithm	Hybrid/ Back propagation
6	No. of input MFs	30
7	Input MF type	Gbell
8	Output MF type	Linear
9	Epochs	30

3.8. FIS Structure 4

In theFISstructure 4 the two inputs namely: water capacity of fog system and the humidity previous value and the output is humidity are considered. The data from the conventional model is loaded through workspace into the ANFIS GUI editor. The data from humidity is taken and loaded into the ANFIS GUI then the data for humidity is checked. The structure of the ANFIS model used for GHS is shown in the Figure 18.

The two input membership function namely water capacity of fog system and humidity previous values are shown in Figure 19 and Figure 20.

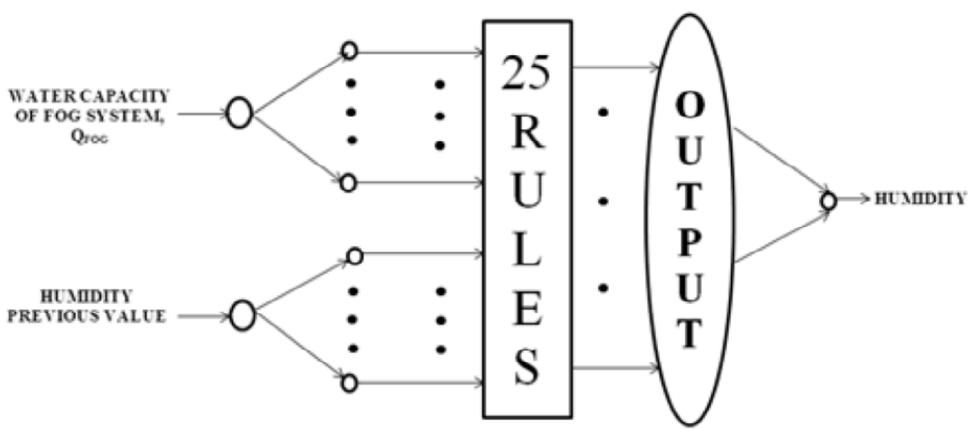

Figure 18: ANFIS Structure 4 used for developing GHS

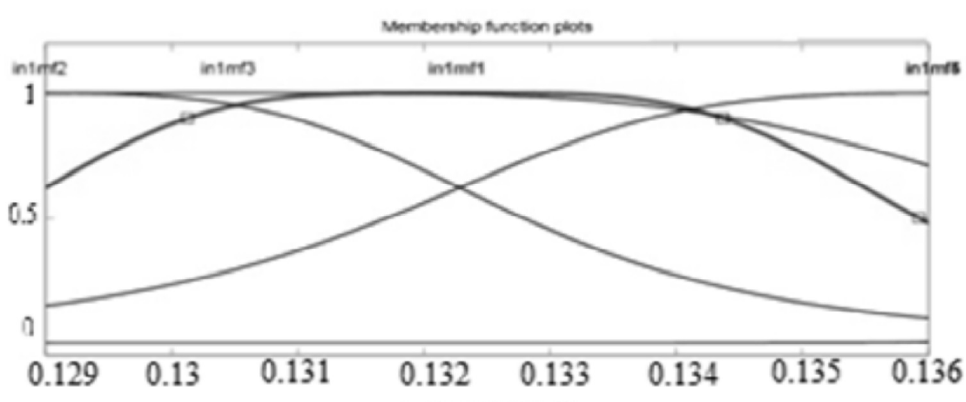

Figure 19: Input 1: Membership function plot for water capacity of fog system

From the Figure 19 and Figure 20, it is inferred that the membership function used here are has five linguistic levels and 25 rules were formed as shown in the rule base matrix shown in Figure 21.

The ANFIS parameters used for training the model of GHS for water capacity of fog system and temperature is tabulated in Table 4.

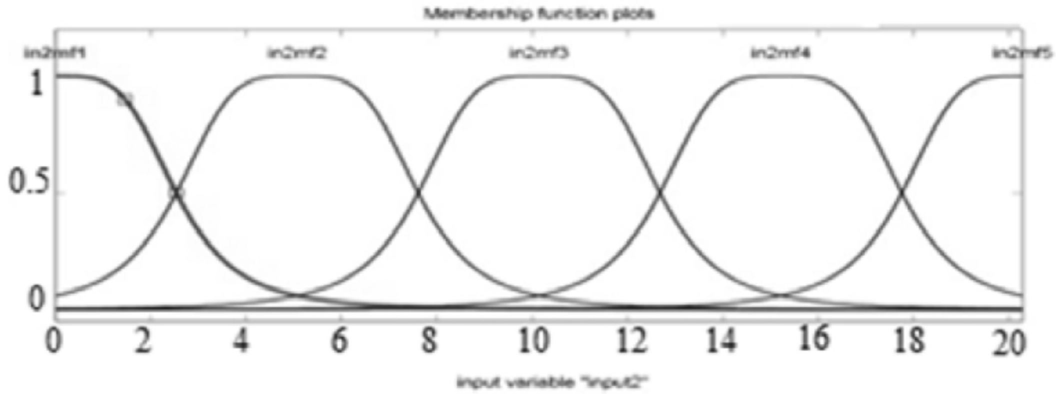

Figure 20: Input 2: Membership function plot for previous values of humidity

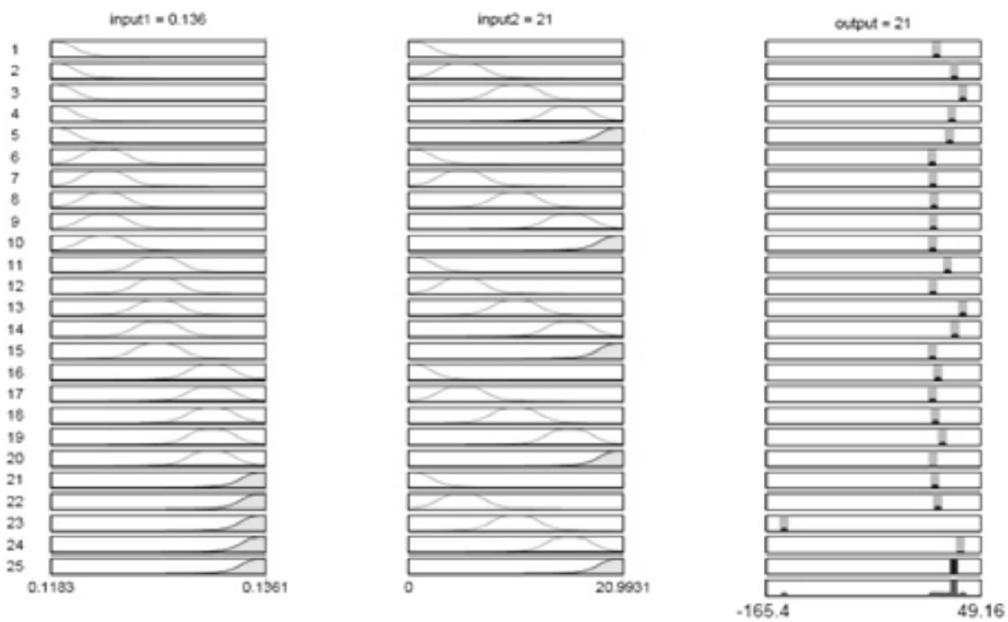

Figure 21: Rule base matrix for water capacity of fog system and previous value of humidity

Table 4
ANFIS parameters modeling of GHS for Water capacity of fog system and Humidity

S. No	*Parameter*	*Values*
1	No. of inputs (Water capacity of fog system and previous value of humidity)	2
2	No. of output (Humidity)	1
3	Model	Takagi-Sugeno model
4	Input space partition	Grid partition
5	Learning algorithm	Hybrid/ Back propagation
6	No. of input MFs	5
7	Input MF type	Gbell
8	Output MF type	Linear
9	Epochs	30

The comparison of different training algorithm error for 30 epochs is tabulated in Table 5.

Table 5
Comparison of different training algorithm for 30 epochs

	Training Algorithm	
	Back propagation	*Hybrid*
Least Square Error	20.5275	0.0316
	23.6481	0.2067
	19.3467	0.0117
	21.7543	0.0586

From the table 5, it is clear that the error of hybrid algorithm which is a combination of least squares and back propagation is much more less when compared to back propagation algorithm. Thus the hybrid algorithm training is used for this model development. The variation in the number of membership function and error is shown in Figure 22.

From the Figure 22 it is inferred that as the membership function increases the error is minimum.

The various steps involved in formulating the ANFIS model are as follows:

1. The input and output data are collected from the conventional model of GHS.
2. Select 75% of generated data from the conventional model of GHS for training data.
3. Select the remaining 25% of generated data as test data.
4. Set initial membership function for input and output parameters.
5. Generate FIS model.
6. Choose FIS model [Hybrid / Back propagation method].
7. Define the number of training epochs.
8. Generate initial fuzzy rules.
9. Train the input training data.
10. Check error for the training data by comparing it with the test data.
11. If the error is minimum, stop the training. Unless, repeat from step 4.

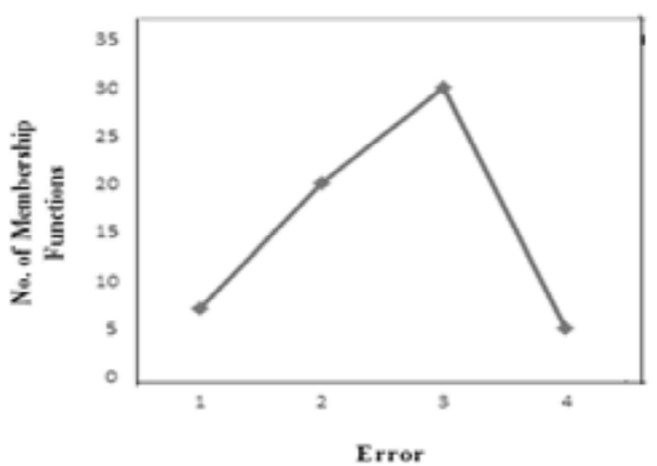

Figure 22: Variation in number of membership function and error

4. RESULTS AND DISCUSSION

Asimulation study ispresentedtoshowthe cooling model of GHS. The open loop ANFIS model using input-output data are designed. The simulation studies are performed in MATLAB R2010a.

4.1. Response of GHS

Figure 23 and Figure 24 shows the dynamic responses of GHS obtained from conventional and ANFIS model for input temperature and humidity respectively.

From the Figure 23 and Figure 24, it is observed that the ANFIS model for the greenhouse system has mapped well with the mathematical model.

6. CONCLUSIONS

In this paper, an ANFIS model representing the nonlinear dynamics of the cooling phase of GHS is formulated. The ANFIS model work satisfactory for GHS by selecting the number of membership function, type of membership function, type of training algorithm and number of epochs to understand easily with the help of knowledge of a system. The error obtained using the mathematical model is about 4% and the maximum fit value is about 96% whereas the error obtained using the ANFIS model is about 8% and has the maximum

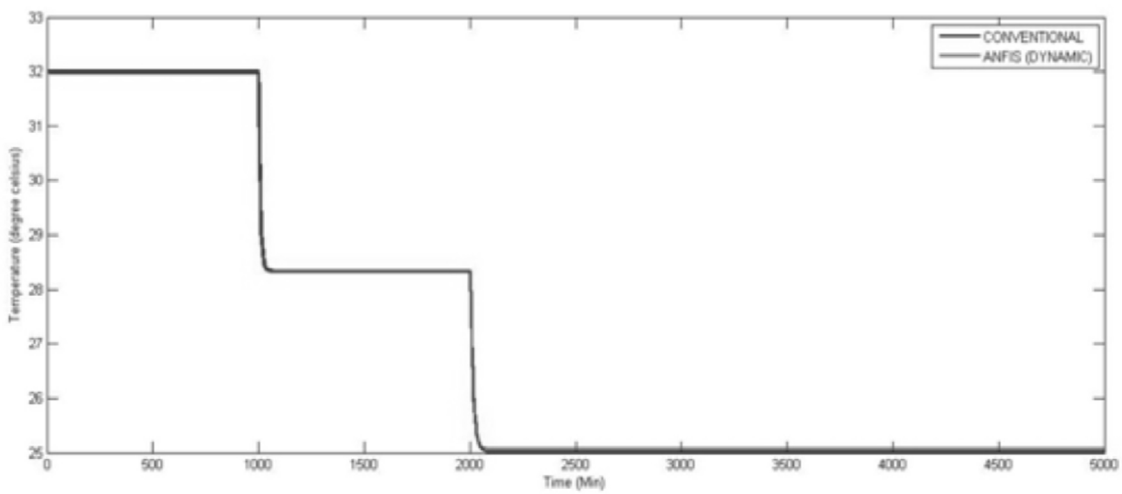

Figure 23: Variation inside temperature for GHS

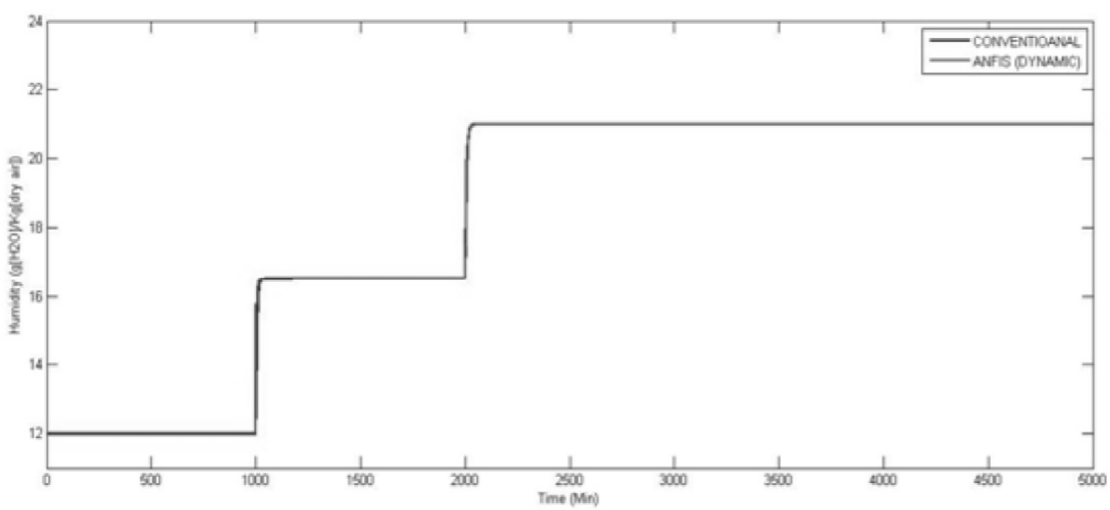

Figure 24: Variation inside humidity for GHS

fit value is about 92%. Sometimes the model error will be there and this can be accepted when a controller is used.

Acknowledgement

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