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Soft Computing Based Controllers for a Humidification Process

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Abstract: The aim of this paper is to implement controllers based on soft computing techniques for a non-linear process. The process taken up for study is to control the humidity in the system. The system identification of this nonlinear process is done and found to be First Order plus Dead Time (FOPDT) model. Then the controller tuning strategy has been applied using IMC tuning method. The soft computing based controller like ANFIS has been implemented and compared with conventional PID tuning method. From the results it is proved that the controllers implemented using soft computing technique out performs the conventional controller.

Keywords: Humidity; FOPDT; IMC; ANFIS.

I. INTRODUCTION

Humidity is defined as the amount of water vapour present in air. Humidification and Dehumidification plays a key role in wide range of applications like textile, paper and wood industries. Many authors stressed the importance of humidity control in their work. Bogaard and Whitmore [1] reported the role of humidity fluctuations in the deterioration of paper. Raj Kumar, Dave, and Srivastava [2] proved that the humidity plays a major role in the soiling behaviour of the textiles. Burton [3] stated that optimal humidity has to be maintained in the atmosphere to increase the productivity with minimal wastage of energy. Moreover the corrosion of main cables on suspension bridges is a major problem on a worldwide basis. Many examples have illustrated that the traditional corrosion protection systems for main cables do not prevent corrosion, but merely slows it down to some extent. Bloomstine and Sorensen [4] developed a dehumidification system in main cables, which truly prevents corrosion. They used silica gel and lithium chloride as a dehumidifying agent to prevent corrosion. Chemical industries also exhibit many challenging problem. Majority of the problems arise due to its non linear nature. The primary task of the controller is to maintain the process under stable condition in spite of the load changes and disturbances. Mouloud [5] designed an ANFIS based modelling and control for knee joint dynamics and demonstrated the utility and effectiveness of soft computing approaches. Omar [6] proposed a genetically trained ANFIS controller for a non linear MIMO system and proved that the controller has remarkable ability in eliminating the external noises or disturbances. Navghare [7] reported that ANFIS configuration is far superior to conventional PID and fuzzy controllers. He also added that ANFIS modelling and control requires additional computational effort in training.

II. EXPERIMENTAL SETUP

Fig.1 shows a schematic diagram of the experimental setup.

The laboratory setup of this system consists of a humidifying chamber, mixing chamber, rotameter, compressor and humidity sensor. Connections of the piping system are designed such that parts can be changed or repaired easily. The air from the compressor is split up into two parts and their flow rates are measured by rotameters placed in their respective paths. One part of the air is humidified to its saturated state by passing through a humidifying chamber while the other part of the air is dried and dehumidified by exposing it to silica gel. The connections are made in such a way that the air in the former and latter paths meets in the mixing chamber. The relative humidity at the mixing chamber is measured using a humidity sensor.

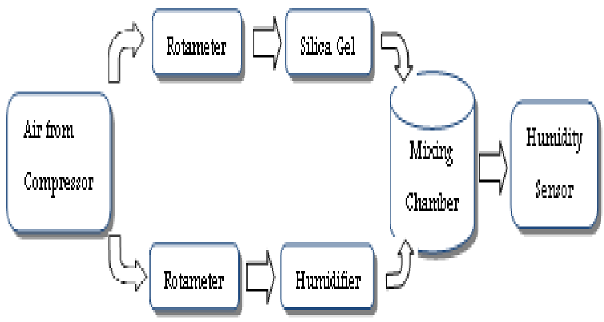

Fig1.Schematic diagram of the proposed system.

The humidifying chamber is introduced to one part of the air whose flow rate is controlled using a float type rotameter. The humidifying chamber is a tank which is partially filled with water at constant height. The inlet to the humidifying chamber is designed to be kept immersed in water at all instants of time irrespective of any disturbances to the system. When air comes in contact with the water in the chamber, bubbles are formed. These bubbles tend to break on reaching the surface of the water. Thus the water molecules are distributed in the air above the water surface. Hence the humidity of the air inside the humidifying chamber increases. It is a well known fact

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that relative humidity (RH) is inversely proportional to density ρ.

$$RH = 1/\rho \quad (1)$$

As humidity increases, the density of the air decreases. Hence the air with higher humidity rises upwards and leaves the chamber through its outlet and enters the mixing chamber. The other part of the air is exposed to a container containing fixed quantity of silica gel. The silica gel crystals perform passive means of dehumidification. It has the tendency to adsorb moisture content from its surrounding atmosphere thus dehumidifying the air that comes in its path. The humidified and dehumidified air is mixed thoroughly inside the mixing chamber. The relative humidity at the mixing chamber is measured using a humidity sensor. The humidity sensor used here is HIH3610 which gives output in terms of voltage (v). The corresponding relative humidity is calculated using the formula,

$$RH = \frac{V-0.958}{0.0307} \quad (2)$$

III. SYSTEM IDENTIFICATION

The change in the flow rate of the dehumidified air causes a pronounced effect in the relative humidity at the mixing chamber. Ziegler and Nichols [8] obtained the time constant and time delay of a FOPDT model by constructing a tangent to the curve obtained from the experimental data. Sundaresan and Krishnaswamy [9] obtained the parameters of a FOPDT transfer function model by allowing the response of the actual system and that of the model to meet at two points which describe the two parameters τ and θ. In this work the proposed times t1 and t2, are estimated from a step response curve. This time corresponds to the 28.3% and 63.2% of the response times. The time constant (τ) and time delay (θ) are given by,

$$\tau = 1.5(t_{63.2\%} - t_{28.3\%} \quad (3)$$
$$\theta = t_{63.2\%} - \tau \quad (4)$$

In the proposed work the flow rate of the dehumidified air is changed from 0 to 0.8 LPM in steps of 0.2. Readings are noted till the process becomes stable in the mixing chamber. The obtained experimental data are approximated to be a FOPDT model and its parameters for change in flow rate of the dehumidified air is given in the following table,

TABLE.1.Parameters of Dehumidified Air

Flow Rate of Dehumidified Air	Gain	Time Constant	Delay Time
0-0.2 LPM	16.3	67.5	9.5
0.2-0.4 LPM	16.25	53	10
0.4-0.6 LPM	8.15	33	2
0.6-0.8LPM	6.5	55.5	9

IV. DESIGN OF PID CONTROLLER

After the derivation of the transfer function model the controller has to be designed in order to maintain the system to the optimal set point. This can be achieved only by properly selecting the tuning parameters K_p, τ_I, τ_D for a PID controller. Consider the standard FOPDT model given by,

$$G(s) = \frac{Ke^{-\theta s}}{\tau s+1} \quad (5)$$

where k and θ are Gain constant and Delay respectively. According to the IMC [10] (Internal Mean Control) the PIDcontroller settings are given by,

$$K_p = \frac{\tau+\frac{\theta}{2}}{K(\tau_c+\frac{\theta}{2})}\ ;\ \tau_I = \tau + \frac{\theta}{2}\ ;\ \tau_D = \frac{\tau\theta}{2\tau+\theta} \quad (6)$$

where $K_{P,}$ $\tau_{I,,}$ τ_D are Gain constant of Proportional, Integeral and Derivative Controllers.

The system was subjected to a uniform random step input signal and the variation in the relative humidity is noted. PID controller is designed using the above formula to track the various set points.

V. OVERVIEW OF ANFIS ARCHITECTURE

ANFIS stands for Artificial Neuro-Fuzzy Inference Systems. It is an algorithm defined by J.-S. Roger Jang [11] in 1992. ANFIS is a class of adaptive networks that are functionally equivalent to that of the fuzzy inference systems. It represents Sugeno e Tsukamoto fuzzy models. ANFIS uses a hybrid learning algorithm. It creates a fuzzy decision tree that classifies the data into one of $2^{\mathbf{n}}$ (or $p^{\mathbf{n}}$) linear regression models in order to minimize the sum of squared errors (SSE) which is given by,

$$SSE = \textstyle\sum_j e_j^2 \quad (7)$$

Where $e_j$is the error between the actual and the desired output, p is the number of fuzzy partitions of each variable and n is the number of input variables.

Layer 1:
It generates the membership values. Every node i in this layer is an adaptive node with a node function given by,

$$O_{1,i} = \mu_{Ai}(x) \text{ for i= 1,2} \quad (8)$$
$$O_{1,i} = \mu_{Bi-2}(y) \text{ for i= 3,4.} \quad (9)$$

Where x/y is the input to the node and A_i /B_{i-2} is the linguistic variable associated with this node such as the generalised bell function given by,

$$\mu_{Ai\,(x)} = \frac{1}{1+\left|\frac{x-c_i}{a_i}\right|2b_i} \quad (10)$$

Where $\{a_i, b_i, c_i\}$ the parameter set is referred to as premise parameters.

Layer 2:
Every node in this layer is a fixed node labelled as Prod. This layer generates the firing strength by multiplying all the incoming signals and gives an output as,

$$O_{2i} = w_i = \mu_{Ai}(x).\mu_{Bi}(y) \text{for i=1,2} \quad (11)$$

Layer 3:
This layer normalises the firing strength.

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$$O_{3i} = \overline{w_i} = \frac{w_i}{w_1+w_2} \text{for i=1,2} \qquad (12)$$

Layer 4:
This layer calculates the outputs based on the consequent parameters $(p_i, q_{i,} r_i)$

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i) \qquad (13)$$

Layer 5 :
This layer computes the overall output as the summation of all the incoming signals.

$$O_{5,i} = \sum_i \overline{w_i}\, f_i = \frac{\sum_i w_i f}{\sum_i w_i} \qquad (14)$$

VI. DESIGN OF ANFIS CONTROLLER

The design of ANFIS controller involves various steps. Initially the training data set for ANFIS controller is selected. The data sets contain the desired input/output data of the system in the form of an array. The input data sets are arranged in first n-1 columns while the output data set is arranged in the n^{th} column. In the current proposed work the error, change in error and the output from the controller obtained while simulating the model are chosen as the parameter for the training data set. This can be well explained with the help of the simulink model given in the following figure.

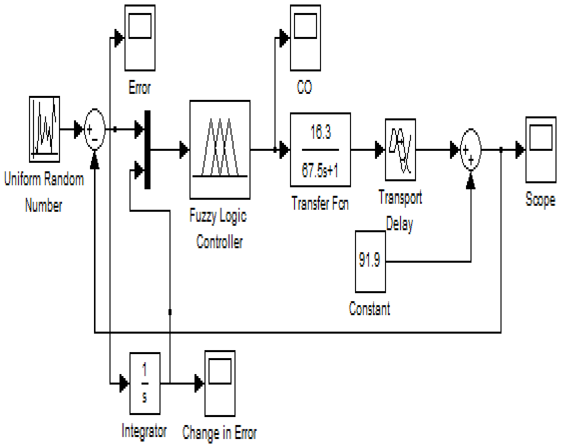

Fig.2. Simulink model for the proposed work.

In general cases however, the data is collected using noisy measurements, and the training data cannot be a successful representative of all the features of the data that will be presented to the model. In such situations, model validation is more helpful. Model validation is the process by which the input vectors from input/output data sets on which the FIS was not trained, are presented to the trained FIS model, to see how well the FIS model predicts the corresponding data set output values. One problem with model validation is selecting a data set that is both representatives of the data the trained model is intended to emulate, yet sufficiently distinct from the training data set so as not to render the validation process trivial. Hence here, all the odd numbered data was considered as the training data whereas the even numbered data was considered as the checking data.

After loading the training and checking data the initial FIS model is generated using the grid partition technique.

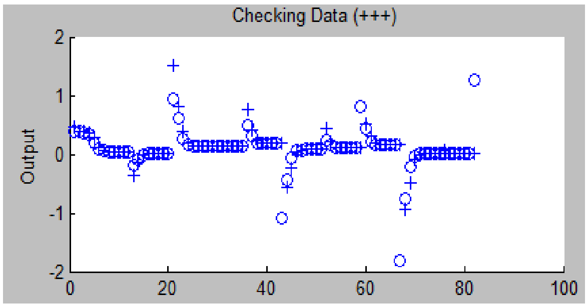

Fig.3. Input data for the ANFIS controller

The number of membership function and the type of membership function for the input and output is assigned here. In the proposed work five input membership function is chosen. Gaussian Bell and Linear type membership function was assigned for input and output data respectively. This method generates a single-output Sugeno-type FIS by using grid partitioning on the data. The generated FIS is trained using hybrid optimisation method. In the forward pass the algorithm uses least-squares method to identify the consequent parameters on the layer 4. In the backward pass the errors are propagated backward and the premise parameters are updated by gradient descent. 40 numbers of epochs are assigned for the training process. The trained FIS is validated using the checking data. It can be observed that the checking error decreases and reaches to its minimum value. Hence there is no model over fitting in the system and thus the trained FIS can be used for controlling purpose.

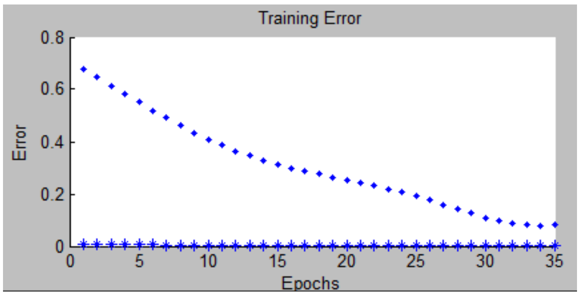

Fig.4. Plot of error against the number of epochs.

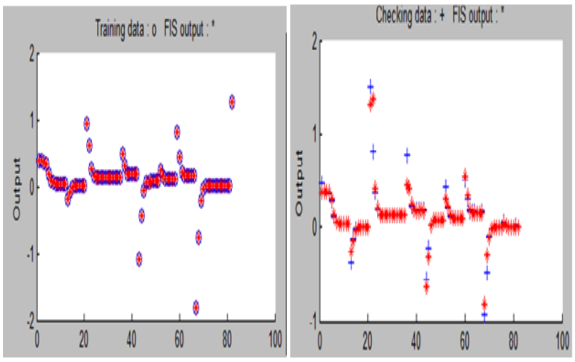

Fig.5. (a) Plot against the trained FIS output and the training data (b) Plot against the trained FIS output and checking data.

Moreover the trained FIS can be tested against the training and checking data to check for the training and testing errors. This self generated trained FIS is imported to a fuzzy logic tool box and the tendency of trained FIS in corporating characteristics of system model is evaluated.

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VII. RESULTS AND DISCUSSIONS

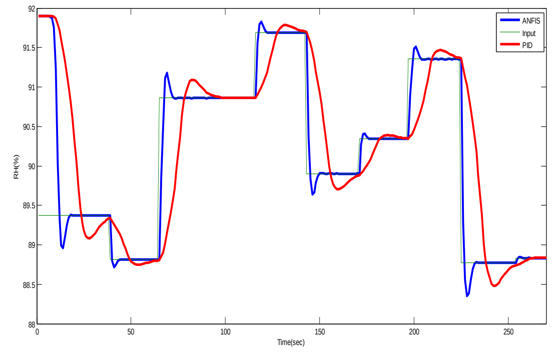

Fig.6. Performance of PID and ANFIS controllers for a step change of 0-0.2 LPM of dehumidified air.

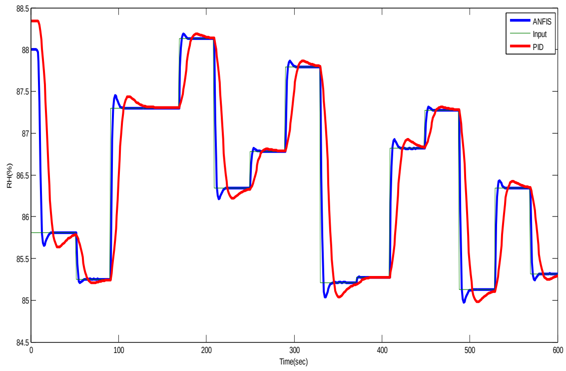

Fig.7. Performance of PID and ANFIS controllers for a step change of 0.2-0.4 LPM of dehumidified air.

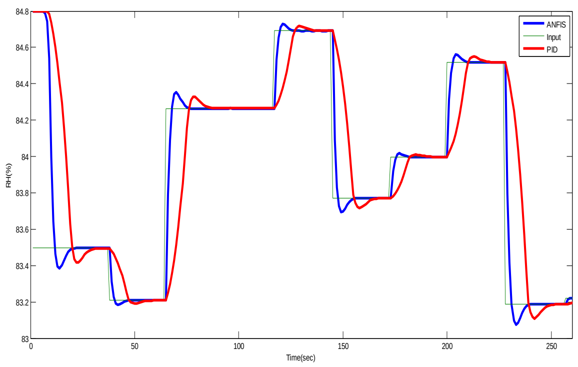

Fig.8. Performance of PID and ANFIS controllers for a step change of 0.4-0.6 LPM of dehumidified air.

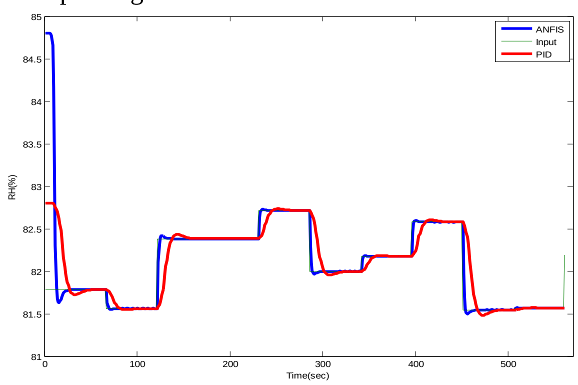

Fig.9. Performance of PID and ANFIS controllers for a step change of 0.6-0.8 LPM of dehumidified air.

A random step input is given to the system and the performance of the soft computing based controller is compared with IMC based PID controller tuning settings. It is observed that in conventional controller it takes much time to reach the set point. From the following graphs it is proved that the soft computing based controller tracks the set point faster with fewer oscillations. Moreover it is clear that the soft computing controllers reach the set point faster and maintains the steady state.

VIII. CONCLUSION

It was found that for a humidity control in the proposed system, for all set point changes, the performance of the soft computing based controller was much superior to that of the conventional control. The response of the soft computing based controller (ANFIS) was proved to be satisfactory when compared with the conventional PID controller. The soft computing based controller was able to keep the process parameters in the optimum range whenever the set point changes occurred. It is concluded that for a nonlinear system the controller's implemented using soft computing technique like ANFIS outperforms the conventional controller.

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