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Analysis of Adaptive Neuro-Fuzzy Inference System in Different Environmental Conditions*

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Abstract

Regardless of vast advances in field of control systems engineering, PID scheme still remains the most common algorithm in industrial use today. A Fuzzy Logic controllers (FLC) with an efficient understanding and small rule base that can be simply implemented in existing industrial controllers. In an industrial setting FLC is much more capable than the existing temperature controller for flowing water type applications. This includes compensating for thermo mass changes in system, dealing with unknown and variable delays, operating at different temperature setpoint without retuning etc. Also predicting the results by simulation would hide actual disturbances coming into picture during implementation. Hence this paper makes a differential study on various weather conditions and ANFIS designed controller analysis is presented with the help of identical industrial lab model. Once designed ANFIS controller is found to be suitable for concern weather condition (season) as compared to other. The graphical representation and mean error values depicts the uncertainties of ANFIS controller over wide span of time.

Keywords: ANFIS, FLC, ANN, FIS.

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1. Introduction

During the last decade, there have been significant developments in methods for model-based-control. Model-based control schemes require the existence of suitable process models. For nonlinear systems, lack of good nonlinear process models is a bottleneck for using model-based controllers. Among different approaches for modeling nonlinear systems, artificial neural networks (ANN), fuzzy logic (FL) and neuro-fuzzy system (NFS) are widely used. Having enough data neuro-fuzzy networks are suitable structures for modeling nonlinear systems [6].

There has been growing interest in using Fuzzy and Neural systems for control [1, 7]. Fuzzy controllers, in general are suitable for non-traditionally modelled industrial processes and also for the systems that cannot be precisely described by mathematical formulation. One of the motivations in this research is the success of the fuzzy controller developed, where it has been demonstrated that, it is better than the conventional one for nonlinear systems [3]. Fuzzy controllers often produce superior results to those of classical controllers.

The design of fuzzy control system involves many design parameters such as scaling factors, membership functions, and control rules. The generation of membership functions for fuzzy systems is a challenging problem. The performance of fuzzy controller is highly dependent on the membership functions. Various methods have been proposed over the years for the optimization of fuzzy membership functions. Control engineer has the difficulty in accessing the fuzzy controller because of the following limitations:-

- The design of the fuzzy controller is not straight forward due to heuristics involved with control rules and membership functions.
- The tuning of the parameters of fuzzy logic controllers is very complex.

This paper addresses an application that involves temperature control system. It presents a fuzzy controller that uses an Adaptive Neuro-Fuzzy Inference System (ANFIS). Artificial Neural Network (ANN) learns from scratch by adjusting the interconnections between layers. Fuzzy Inference system (FIS) is a popular computing framework based on the concept of fuzzy set theory, fuzzy ‘if-then’ rules, and fuzzy reasoning. A neuro-fuzzy system is simply a fuzzy inference system trained by a neural network learning algorithm. The learning mechanism tunes the underlying fuzzy inference system. Fuzzy system faces difficulties like lack of completeness of the rule base, lack of definite criteria for selection of the shape of membership functions, their degree of overlapping and level of data quantization. Some of these problems can be solved if neural technique is used for fuzzy reasoning.

2. Outline of ANFIS

The most common structure of neuro-fuzzy network, ANFIS, is considered. Figure 1 shows the scheme of linear Sugeno type fuzzy inference system (FIS). In this structure, “antecedent” of rules contains fuzzy sets and “consequent” is a crisp function. The structure shown in figure 1 can be transformed to neuro-fuzzy network shown in figure 2. Assume a fuzzy inference system with two inputs x and y and one output z. Suppose that the rule base contains two fuzzy ‘if-then’ rules of Takagi and Sugeno's type [2]:

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 $f2 = p2x + q2y + r2$,

then the fuzzy reasoning is illustrated in Figure 2.

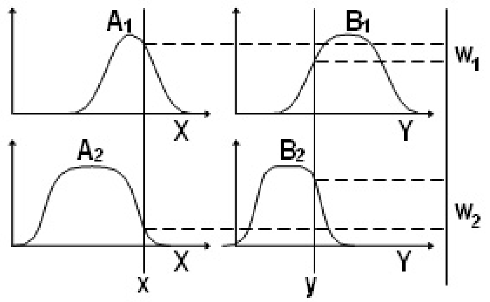

Figure 1: Firing of rules for different membership functions

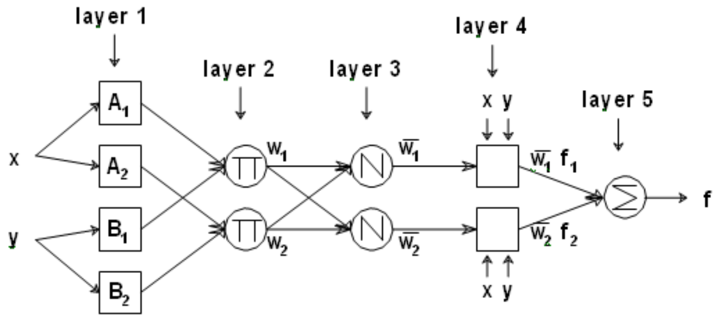

Figure 2: ANFIS structure for two input variables and five layers.

The structure of temperature control system is shown in Figure 3. The concise details of different parts of the system are the water chamber, the sensor module, the input-output interface, the computer system and the actuator.

The lab model of temperature controller can be divided in above mentioned five parts. The system is modeled using a chamber having capacity of 0.5 litres. Chamber consists of a heater coil at the mouth of water inlet. Temperature sensor is inserted in chamber near the outlet. Signal conditioner is used to transfer sensed signal to the computer. Here PCL-207 is used to interact between analog and digital signal.

The water at room temperature enters the chamber at a constant flow rate through inlet. The controlled water at constant temperature is available at outlet. To analyze and control, the ANFIS based software is developed. The control signal is available in the range of 0v to 5v. The actuator requires its control signal to be 4mA to 20mA. Here analog signal is therefore converted into said range using Voltage to Current (V-I) converter. Actuator circuitry generates A.C. signal to drive the heater.

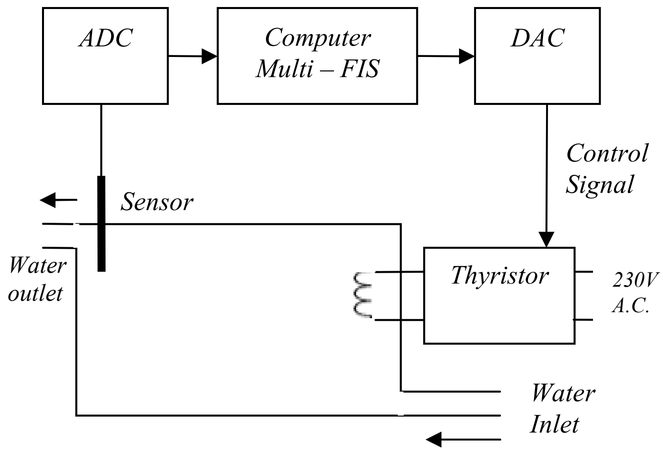

Figure 3: Block diagram of system

4. Outlet – Temperature analysis:

The aim is to control outlet water temperature at desired set point. System uses PT-100 sensor to sense temperature of inlet and outlet flowing water from chamber. A database is collected for day wise and month wise of water temperature reading taken in a tank. The general observation of this data indicates that water temperature varies from day to day and month too. Also in the keen observation of database it can be found that there is enough variations in readings taken during day time and night time. The temperature measured in middle of December at Maharashtra (India) is around 16^{o}C – 17^{o}C and same measured in month of February is around 20^{o}C. Furthermore at daytime and night-time it shows a difference of 3^{o}C – 4^{o}C

In this paper different case studies are taken assuming different weather conditions to analyze Fuzzy controller tuned with the help of Adaptive Neuro-Fuzzy Inference System (ANFIS).

Case I: (Controller designed, tuned & tested in summer season)

Generally in summer season normal water temperature is near about 25^{o}C which is feed to system (chamber). For current and all subsequent cases the output temperature of system is set to be 40^{o}C & 45^{o}C. Fuzzy Inference System (FIS) is designed considering above summer conditions. The FIS is tuned with the help of ANFIS tool available in MATLAB. Here different ANFIS arguments may be set to tune FIS. The FIS contains two input parameters error and change in error, and one output which is applied to heater via DAC. ANFIS tuned FIS is tested on real time lab model of constant flowing temperature controller. In this investigation the task of FIS is to provide outlet water at desire set point temperature with minimum or no overshoot. It is necessary to write a set of fuzzy control statements based on error signal measured in between set point & current value of temperature at water outlet for first iteration. Thereafter it is possible to calculate change in error, where FIS is formed having inputs error and change in error.

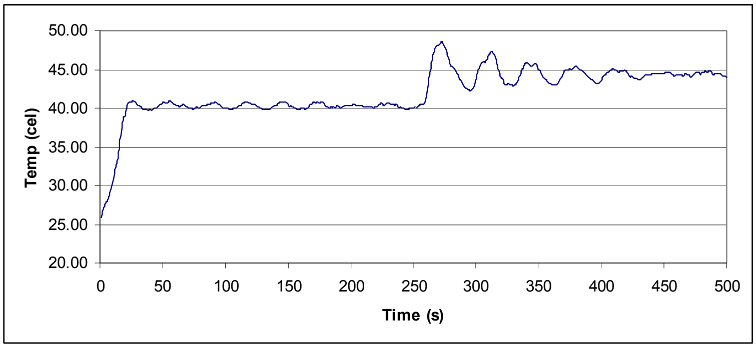

Figure 4: Controller response in case – I

As per graphical representation of controller output, it has faster response & rise time as well as settling time. At initial iteration the outlet temperature is near about 25^{o}C, which attendances set point in few seconds. Also there are on major overshoots observed after first crossover point of outlet water with set point. The error mean value is calculated based on readings available after first crossover point.

Case II: (Controller designed, tuned in summer & tested in monsoon season)

The ANFIS controller is designed for weather conditions in summer, where inlet water temperature is around 25^{o}C. Whereas in monsoon the inlet water temperature is found to be dropped down at around 21^{o}C – 22^{o}C. It shows 3^{o}C – 4^{o}C dropdown as compared to summer inlet water temperature. With this dropped temperature the ANFIS controller is tested. The readings are taken in number of turns so that the best one can be compared.

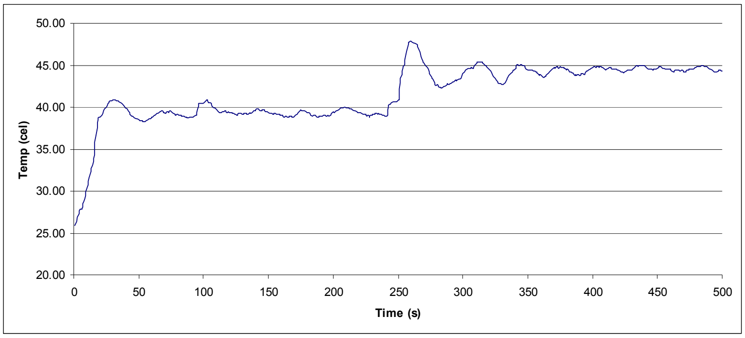

Figure 5: Controller response in case – II

The outlet water temperature at initial stage is 21°C, which gradually increases towards set point. Rise time and response of controller tends to be same as that for case I. The system is unable to archive set point and also doesn't maintain it constantly. Output temperature of water remains at lower end, creating an average difference of 1.5°C. Oscillations are seen in the outlet water temperature giving rise to increase in error mean value.

Case III: (Controller designed, tuned in summer & tested in winter season)

Consider the same circumstances as that in case II, the ANFIS controller is tested for weather conditions in winter. Here inlet water temperature drops to 17°C – 18°C, forming a dropdown difference of 8°C – 7°C as that of case I. The similar type of rise time is observed, but outlet water temperature is not stable at set point. It is clear that outlet water temperature creates a difference of 2°C – 3°C with respect to set point. The major effect is seen on mean error value.

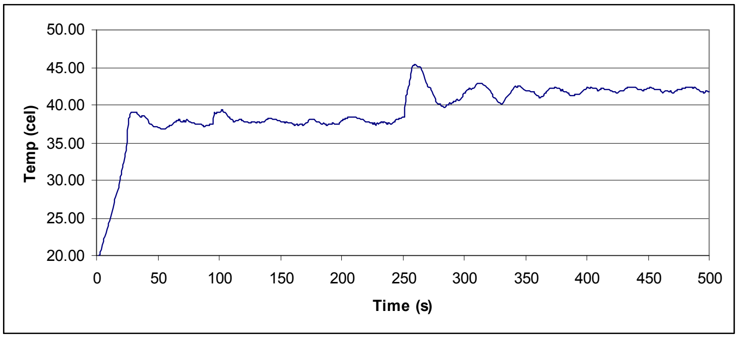

Figure 6: Controller response in case – III

5. Result & Discussion

This paper demonstrates an application of artificial intelligent techniques in control of flowing water temperature. An effectiveness of ANFIS controller for wider range of practical conditions is been tested. Different case studies are proposed, to give apparent performance during actual application implementation.

Table – 1: Mean of error for different set points and FIS controller system.

Weather (season)	Mean 40°C	Mean 45°C
Summer	-0.270	0.429
Monsoon	0.588	0.642

Winter	2.157	3.129

To demonstrate the performance of ANFIS controller, it is tested practically on a lab based model of flowing temperature. The mean error value is calculated for initial set point (40°C) and change in set point (45°C). Both set points mean error values are further compared with different weather conditions as illustrated in table – 1. It is clear that the performance of controller crumble as it moves from summer towards winter. The mean error difference between summer and winter for 40°C is 0.415 and that for 45°C is 0.544. Hence the disintegration of controller is tangential for both set points. Also, the similar graphical response is observed as seen previously in figure 4, 5 and 6, apart from drop of signal by few °C for different weather conditions.

6. Conclusion

A differential study on various weather conditions and ANFIS designed controller analysis is presented here with the help of identical industrial lab model. The ANFIS controller is designed at start of summer and tested over the span of whole year. The graphical and analytical analysis is presented to study the performance of controller. It can be worth concluded that, ANFIS controller is well suited for conditions to which it is designed. The ANFIS have to be retuned or designed for each disturbance that is possible in practical implementation.

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