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Intelligent control for an experimental greenhouse climate based on ANFIS Technology

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ABSTRACT

This study developed an intelligent control system to improve the climate management under greenhouse. The proposed regulation structure relies on an adaptive neuro-fuzzy inference system (ANFIS) inverse model. At first, the controller was trained with practical database using Matlab tool. Afterwards, it was simulated through a greenhouse model. Finally, it has been validated in real time based on an automated experimental greenhouse. Simulation studies and experimental results proved that the adopted control strategy is able to yield good regulation despite of the greenhouse system complexity and the continuous changes of environmental conditions. Moreover, employing our strategy reduced settling time compared to PID and fuzzy based controllers which are commonly utilized in the control engineering field.

Keywords : Experimental greenhouse, climate, temperature control, ANFIS.

1. INTRODUCTION

Nowadays, the greenhouse cultivation is a sector in full development because needs of agriculture products are increasing due to the demographic growth. In this way, greenhouse producers are looking for efficient productive techniques to meet increased food demand throughout the year. All factors affecting the crop growth could be controlled and maintained at optimum level year-round in the greenhouses [1]. Many previous studies demonstrate that the majority of modern agricultural greenhouses become more sophisticated and computer- assisted. The automation of greenhouses has made the microclimate regulation much easier. This should enhance the production and optimize its quality and also minimize pollution as well as energy consumption [2].

The control of greenhouse climate is a complicated task because it has high nonlinear features, variables strongly correlated and it is largely disturbed by the external weather [3]. Hence, the development of appropriate and advanced strategies is a major priority to establish favorable environmental conditions for the crop's growth. To deal with market globalization, such strategies should not only lead to good efficiency but also to reduce production cost. Some years ago, diverse control techniques were proposed like adaptive control [4]-[5], optimal control [6], robust control [7], predictive control [8]-[9] and sliding mode control [10] … As stated before, greenhouse system presents significant non-linear behaviors. The techniques of artificial intelligence (AI) are recognized as a powerful tool to solve non-linear issues. The AI-based methods are broadly categorized into parts: fuzzy logic systems and neural networks. Fuzzy logic control (FLC) provides many advantages for instance: emulate deductive thinking of human being, good flexibility and it doesn't demand an accurate knowledge of the system mathematical model [11]-[12]. The greenhouse climate regulations using various schemes of FLC were introduced in[13]-[17]. Nevertheless, the based-rules of FLC are formulated by an expert. Thus, the accuracy performances of the FLC depend on the knowledge and experience of users and designers. Furthermore, FLC needs much data which makes the controller more expensive. As for ANN-based algorithms, they have a great capacity to detect and model non-linear [18]as well as complex relationships between different variables. In [19]-[20], ANN controllers for greenhouse climate have been studied. However, this kind of controllers suffers from computational cost because it needs massive training data [21]. In view of the above discussion, the idea to design a new controller has emerged to provide better regulation of greenhouse climate system over the controllers that are already introduced by the scientific community. Temperature is usually the most important variable to control. Indeed, it is the most influential parameter on photosynthesis phenomenon which is responsible for the favorable growth of crops. In this paper, an ANFIS-based temperature controller for the greenhouse system has been implemented. ANFIS consists fundamentally of a fuzzy inference system (FIS) whose rule base is created by neural networks. Thus, the suggested control system incorporates the merits of both neural networks and FLC in a single framework. The input variable to the designed controller is the difference between set points and measured values of internal temperature and the output is the voltage received by fan/heater systems.

2. EXPERIMENTAL SYSTEM OVERVIEW

The experimental greenhouse system under study is a small gable-shaped one. It is designed and implemented at the laboratory of electronics, automatic and biotechnology (LEAB) located in faculty of sciences of Meknes (FSM) in Morocco. The schematic diagram presented in Fig. 1illustrates the experimental greenhouse set-up. A set of measuring and climate control equipment was used. Two similar pairs of sensors (LM35DZ and HIH4000-001) were installed above the roof as well as inside the greenhouse to measure temperature and relative humidity respectively. The measurements of different climatic parameters are stored in a personal microcomputer thanks to a multi-function data acquisition card NI-6024E. The heating process of the internal climate is performed by using an electrical heating system, whereas the ventilation is provided by a variable speed fan [22]-[24].

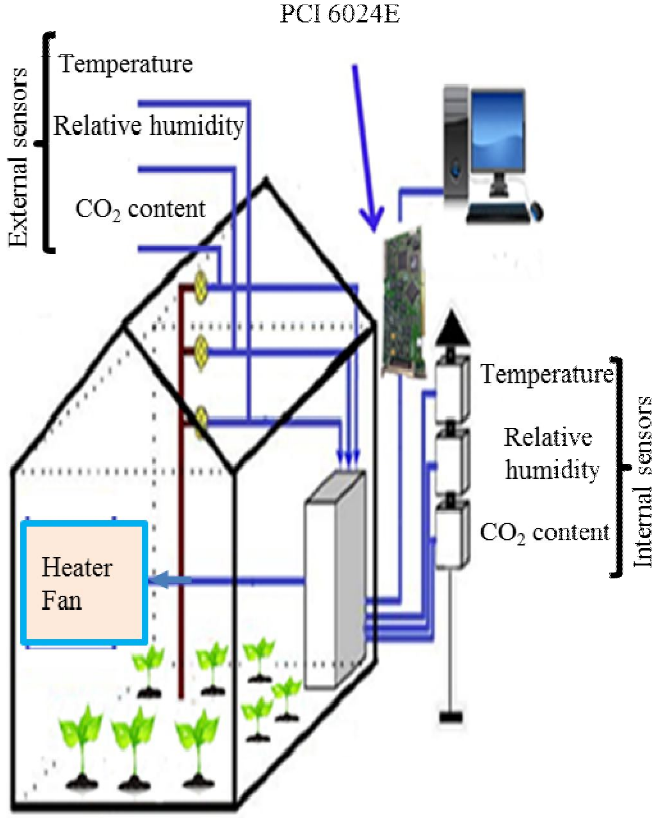

Figure 1: Experimental greenhouse system

3. THEORETICAL ASPECTS OF ANFIS MODEL

ANFIS belongs to neural networks that use the principle of Takagi-Sugeno (T-S) fuzzy system. ANFIS combines neural networks and FIS. So it integrates the learning abilities of neural networks and the explicit knowledge of fuzzy systems [25]. Based on a given dataset, ANFIS utilizes ANN algorithms to generate automatically FIS parameters. ANFIS model is generally trained using hybrid algorithm that merges back propagation algorithms and least squares method [26]. This algorithm has the potential to adapt, adjust and optimize membership functions and FIS rules. ANFIS architecture consists basically of five network layers [27]-[28] as shown in Fig. 2. The corresponding fuzzy rule-based of the T-S model can be written as follows:

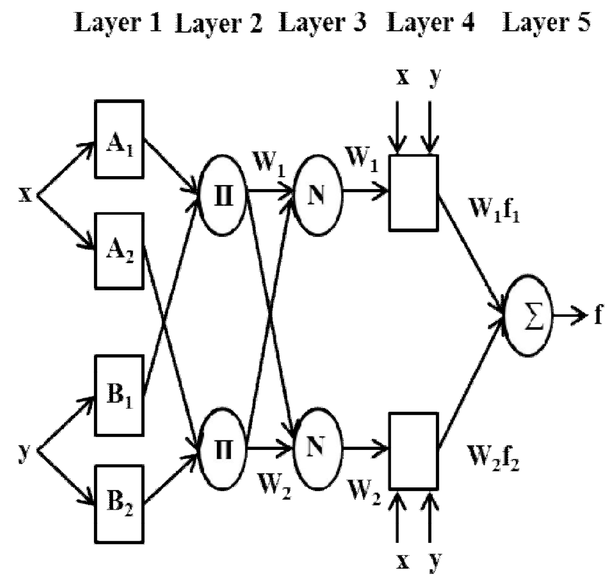

Figure 2: Typical ANFIS structure

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 input variables, A1, A2, B1 and B2 are fuzzy sets, fi are the outputs of all defuzzification neurons and (pi,, qi, ri) is the set of consequent parameters corresponding to the rule. In Fig. 2 square denotes an adaptive node, whereas a circle stands for a fixed node. The purpose of each layer of ANFIS structure is explained below [29].
Layer 1: It is "fuzzification layer" where the crisp values of input are turned into linguistic values. Every node is associated with a node function given as:

$$O_i^1 = \mu_{Ai}(x) \quad for \quad i = 1,2 \tag{1}$$

Where O is membership degree for the inputs x and y, μ is membership function. The subscript i and 1 point out node and layer numbers respectively.
Layer 2: This layer is called as product layer. Each node's output is obtained by multiplying incoming signals to it with each other according to the following equation:

$$O_i^2 = w_i = \mu_{Ai}(x)\mu_{Bi}(y) \quad for \quad i = 1,2 \tag{2}$$

The output of every node represents a rule's firing strength.
Layer 3: It is named "normalization layer". In this layer each node is a fixed one labeled as N. Firing strengths are normalized using the following ratio:

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2} \quad for \quad i = 1,2 \tag{3}$$

Layer 4: It is known as "defuzzification layer". In this layer, the outputs of the nodes are calculated as follows:

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \quad for \quad i = 1,2 \qquad (4)$$

Layer 5: It is considered as output layer and has single node that computes the total number of inputs signals so as to generate the final output:

$$O_i^5 = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad for \quad i = 1,2 \qquad (5)$$

4. CONTROL SYSTEM DESIGN

Since it inherits the properties of ANN systems and inference features of fuzzy logic, ANFIS has the ability to learn based on a sample data. In control system applications, ANFIS could be utilized in various configurations. In this work, ANFIS learned the inverse of the greenhouse climate system, and then the elaborated inverse model can be employed as a controller to regulate the indoor greenhouse temperature. Fig. 3 brings out the training mechanism of ANFIS. Here, u(k) indicates previous voltage value and y(k) points out the previous measured temperature.

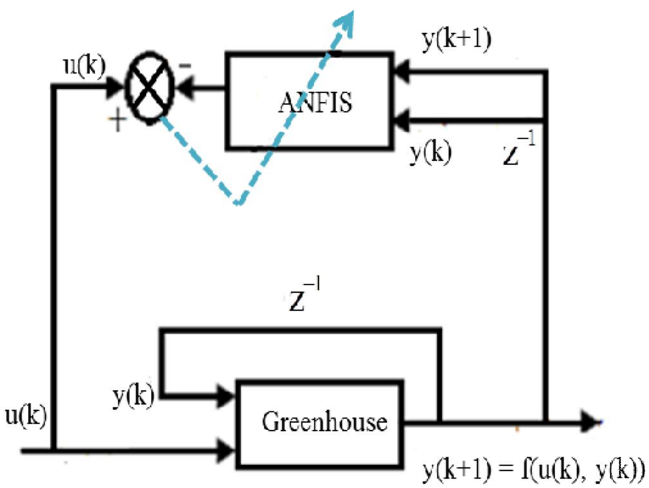

Figure 3: ANFIS learning process

In order to conduct the training process, a sample of input-output pairs was loaded into ANFIS editor. Five Gaussian bell functions have been selected as membership functions to create the ANFIS structure. The ANFIS model was trained based on hybrid optimization algorithm that combines gradient descent and least squares methods. The least squares technique is used to estimate optimal consequent parameters, whereas the gradient descent method optimizes the corresponding premise parameters. Once designed, the proposed ANFIS model was tested with different steps in order to check its functionality.

In this study, the developed intelligent controller was utilized to hold the internal temperature at its set point values by switching on/off the heating and ventilation systems with the appropriate rate at the right time. The rule base of the designed controller applied to the internal temperature is depicted in Fig. 4. Where (dT= $T_s - T_{in}$) denotes the temperature error.

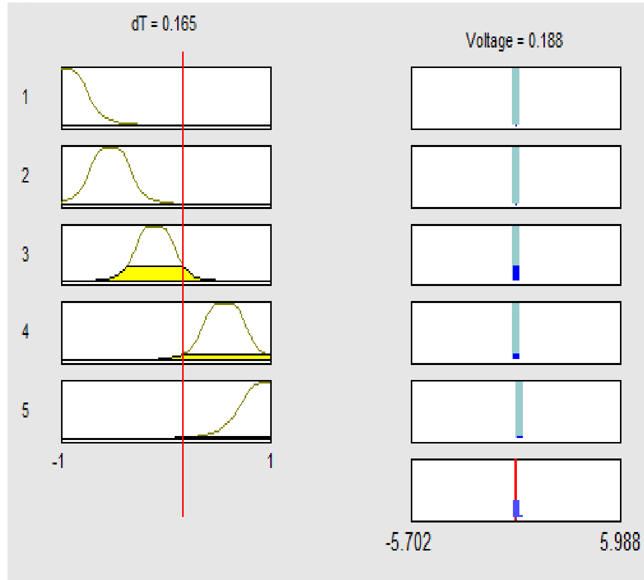

Figure 4: Rule viewer of generated ANFIS controller

5. SIMULATION STUDY AND ANALYSIS:

The internal environment of greenhouse system is assumed to be homogeneous. There are functionally two models available for a greenhouse temperature system such as heating model and ventilation model. In order to elaborate a suitable model for describing temperature behaviors inside our experimental greenhouse, it is necessary to analyze input-output data of the greenhouse system using an identification approach. For simulations purposes, we assimilate the process as a first order pure delayed system. Thus, the representation model of internal temperature behavior whose parameters are calculated using the graphical method of BROÏDA is given by the following transfer function:

$$F(s) = \frac{6.51}{111.52s + 1} e^{-10.5s} \qquad (6)$$

The proposed ANFIS controller was applied to the model expressed by (6). The simulation results were performed in MATLAB/SIMULINK as depicted in Fig. 5.

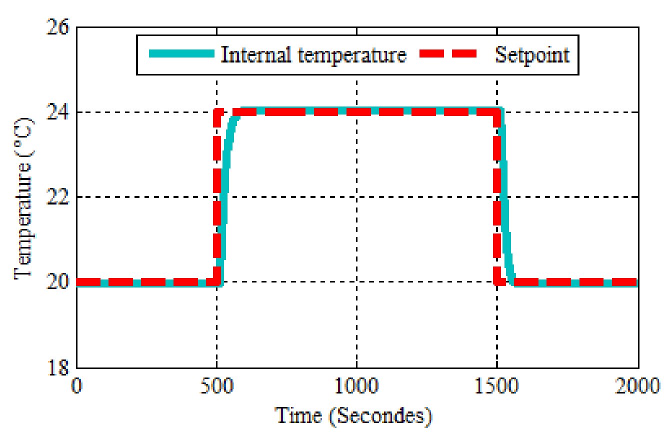

Figure 5: Simulated temperature response of ANFIS

It is clear that the inside temperature tracks exactly the set point temperature. What is more, the simulated internal temperature takes short time to reach the required levels. These results highlight that the adopted control strategy leads to quick response and accurate regulation.
To analyze the performance of the proposed controller, a comparative study was carried out with PID and FLC as presented in Fig. 8.

5.1 PID Controller

PID is largely employed used in industrial control processes because it's easy to design and provides excellent stability. The continuous PID algorithm is generally described by the following formula:

$$u(t) = K_p e(t) + K_i \int e(t)dt + K_d \frac{de(t)}{dt} \quad (7)$$

Where u(t) is the output control signal. K_p, K_i and K_d stand for gains of proportional, integral and derivative terms respectively. e(t) is the tracking error expressed as:

$$e(t) = T_S(t) - T_{In}(t) \quad (8)$$

With $T_s(t)$ and $T_{In}(t)$ denote set point and internal temperature respectively.
The parameters of the PID controller are computed based on the model given by (6):
Kp = 0.9, Ki = 5.99, Kd= 0.07

5.2 Fuzzy Logic Controller

Fuzzy logic systems use human reasoning and linguistic labels to provide the output control. There are mainly three steps involved in FLC systems:fuzzification, fuzzy inference and defuzzification. The fuzzification process converts real input values into fuzzy data. During this stage, suitable membership functions are selected. The fuzzy inference system manipulates membership functions to create the corresponding fuzzy rule base. The defuzzification transfers the fuzzy output to a numerical value.
In the present paper, the inputs to the FLC are error (e(t)) and change in error (de(t)) and the output variable is the voltage received by heater (H) or fan (F). Here, the variables are normalized by scale gains. The linguistic variables consist of three variables for inputs and five variables for output such as N (negative), Z (zero), P (positive), NB (negative big), NS (negative small), PS (positive small) and PB (positive big) as shown in Fig. 6 and 7. The generated if-then rules are provided in Table 1.

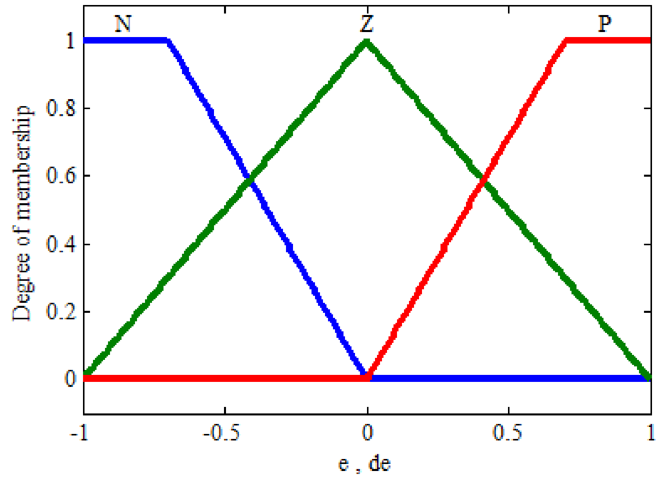

Figure 6: Inputs fuzzification

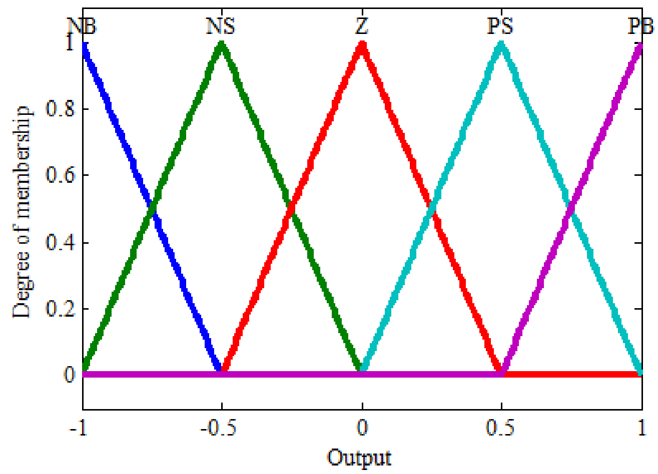

Figure 7: Outputs membership functions

Table1:FLC rule base

e \ de	**N**	**Z**	**P**
N	NB	NS	NS
Z	NS	Z	PS
P	PS	PS	PB

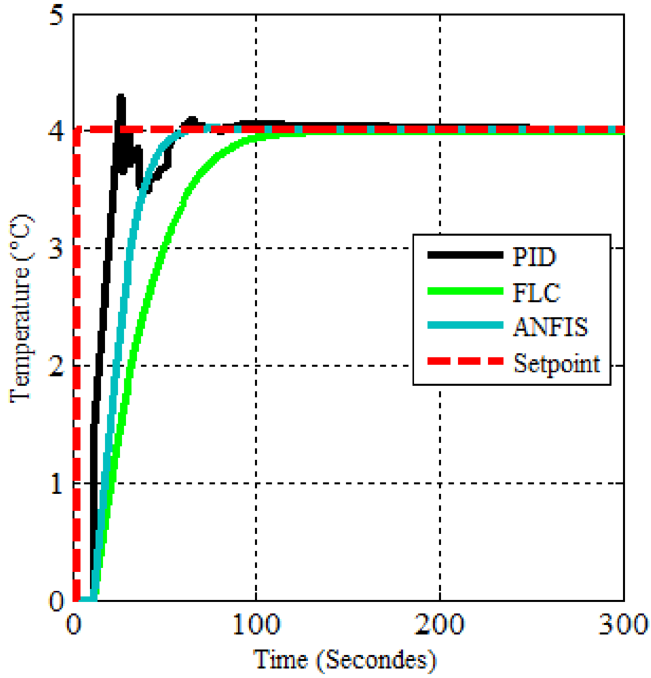

Figure 8: Temperature step response withPID, fuzzy logic and proposed ANFIS controllers

From Fig. 8, it is observed that all controllers are useful to meet the desired temperature under greenhouse. Nevertheless, ANFIS controller is faster than PID and FLC controllers. The performance of PID has large overshoot which can generate the depreciation of the actuators in long time. On the other side, the FLC takes much time to achieve the set value which justifies the design and tuning problems of this kind of controllers.

According to the above simulations, we can summarize the quantitative comparison results as listed in Table 2. From these comparisons, the performance indices seem to be in favor of ANFIS controller. In fact, it allows overcoming the difficulties of both PID and FLC controllers.

Table2: Settling time, overshoot and MSE of controllers

Controller	Settling time (s)	Overshoot (%)	MSE
PID	58.33	6.98	0.20
FLC	93.92	0.21	0.40
ANFIS	55.42	0.50	0.31

6. EXPERIMENTAL RESULTS AND DISCUSSION

The schematic diagram of the implemented control system is shown in Fig. 9. The proposed controller is linked to the experimental greenhouse in real time. The voltage supplied to heater and fan is specified according to the temperature tracking error ($\Delta T = T_s - T_{in}$).

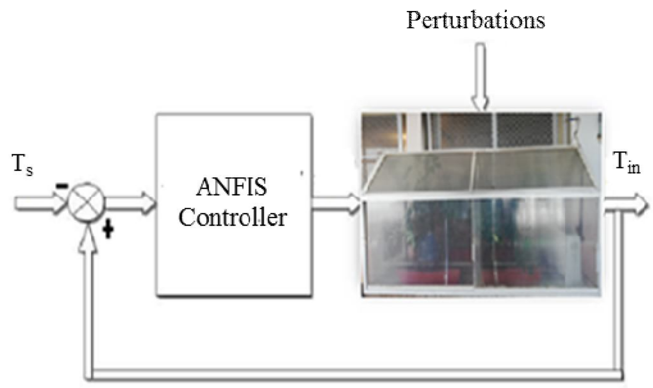

Figure 9: Block diagram of experimental setup

To assess the efficiency of the proposed control technique, a set of experiments have been carried out using the greenhouse prototype presented in Fig. 1. The suggested controller is applied in closed-loop to control greenhouse temperature as illustrated in Fig. 9. In practice, the determination of set points should take into account the requirements of crops. The measurements were recorded in real time to analyze the tracking performance of the implemented controller. Measured results during these tests are displayed in Fig. 8. As it can be seen, the temperature under greenhouse matches closely its reference trajectories without any appreciable overshoot. Furthermore, we can observe that the temperature has converged quickly (less than 5 minutes). Besides, the steady state performance is very good despite the sudden fluctuations of external temperature between 18°C and 20°C. These results confirm the reliability, fastness and robustness of our intelligent control system.

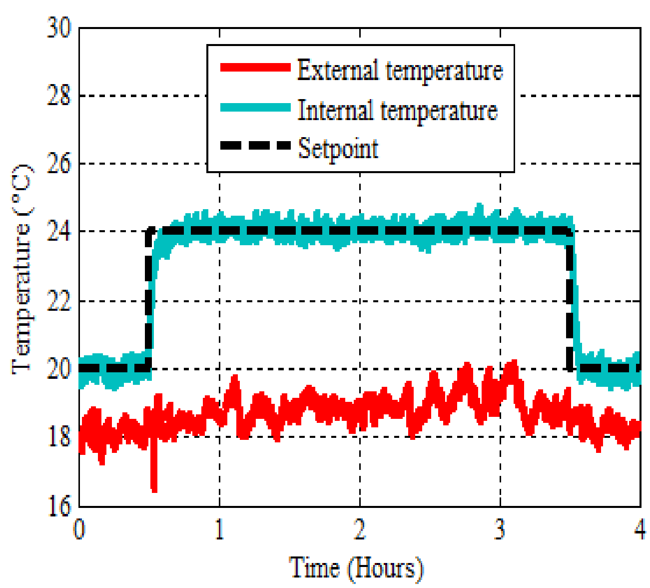

Figure 10: Evolution of regulated temperature using ANFIS

The variations of the control signals, during these experiments, are shown in Fig. 10. We observe that the heating system is turned on to increase the greenhouse indoor temperature when the tracking error is positive. On the other hand, when the temperature error becomes negative the used intelligent controller activates the ventilation system to decrease the internal greenhouse temperature. Furthermore, we can see that the generated voltage rise when the set point value changed. However, it started to decrease gradually within a short period of time. In other words, the command signal was close to zero for a large part of time. That means clearly that the implemented controller is able to regulate the greenhouse indoor temperature with little energy consumption.

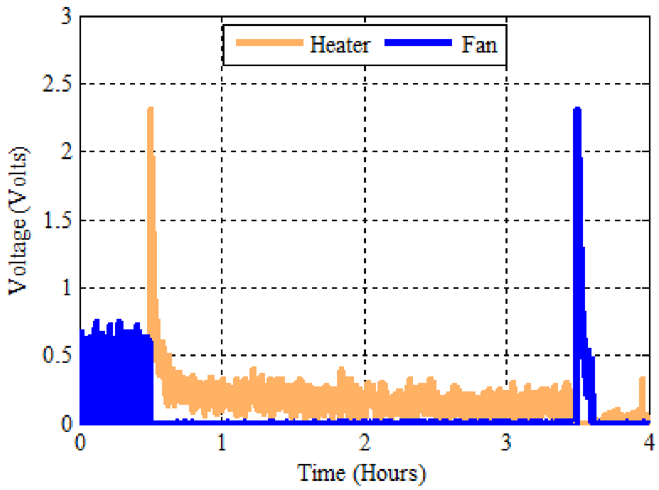

Figure 11: Controlsignals of heater/fan

7. CONCLUSION

This paper presented an investigation of ANFIS algorithm in a greenhouse climate control.It can be concluded that the implemented control strategy represents a feasible and reliable alternative to conventional approaches. The experimental results are satisfactory and proved that ANFIS-based control technique can be used successfully to control the greenhouse indoor temperature because it is efficient, flexible, and robust and it has fast response time. From cost-effectiveness view point; it is possible to make considerable savings on the energy consumed by heater and fan.

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