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Identification of a water level system using ANFIS

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***Abstract*—This paper proposes the identification of a water level system using neurofuzzy. Modeling stage is one of the most noteworthy parts in the design of a control system. In this study, a water level system is modeled using ANFIS (Adaptive-Network-Based Fuzzy Inference System), which will be further used to design and apply a proportional integral (PI) control to this system. An input-output data is obtained from the real system and then, this data is employed to create an ANFIS model of the system in the SIMULINK. Both results obtained using real system and ANFIS model are compared. Model consistencies are discussed and effectiveness of ANFIS modelling is noted.**

***Keywords*— Identification, ANFIS, water level system, PI controller, SIMULINK**

I. INTRODUCTION

The design of control systems is currently driven by a large number of requirements posed by increasing competition, environmental requirements, energy and material costs and the demand for robust, fault-tolerant systems. These considerations introduce extra needs for effective process modeling techniques [1]. For obtaining the model, the designer has to follow one of two ways; the first one is using the knowledge of physics, chemistry, biology and the other sciences to describe an equation of motion with Newton's laws, or electric circuits and motors with Ohm's, Kirchhoff's or Lentz's laws depending on the plant of interest. This is generally referred to as mathematical modeling. The second way requires the experimental data obtained by exciting the plant, and measuring its response. This is called system identification and is preferred in the cases where the plant or process involves extremely complex physical phenomena or exhibits strong nonlinearities [2].

Neuro-fuzzy modelling has been recognized as a powerful tool which can facilitate the effective development of models by combining information from different sources, such as empirical models, heuristics and data. Neuro-fuzzy models describe systems by means of fuzzy if–then rules represented in a network structure, to which learning algorithms known from the area of artificial neural networks can be applied [1]. The most popular neurofuzzy system is the ANFIS architecture introduced by Jang. This structure was used in this work to model the water level system and is taken as a black-box in the aim to observe the responses to the introduced inputs [3-6].

The aim of this study is to use the neurofuzzy ANFIS system to identify a real water level system and to compare the model found with real system by applying a proportional integrated controller to the same structures.

The rest of this paper is outlined as follow. Section II gives the description of water level system used in this work. In section III, the ANFIS architecture is presented. Section IV detailed the learning algorithm of ANFIS. The identification of the water level system by using ANFIS and the PI control of both the real system and ANFIS model are presented in section V. Section VI presents conclusions.

II. DESCRIPTION OF WATER LEVEL SYSTEM

The system exploited consists of:

- High tank,
- Low tank (source of water),
- Differential pressure sensor,
- Pump motor to fill the high tank,
- Electronic board of acquisition adapts the sensor voltage output to PIC ADC input.
- Power board formed by a serial chopper which takes the PWM PIC output and supplies the pump motor [7].

The control is ensured by Matlab using a PIC 16F877 board to interface the system with PC.

This water level control system is nonlinear and it is described by the following equation [8]:

$$\frac{\partial H}{\partial t} = \frac{1}{S} Q_e - \frac{s}{S}\sqrt{2gH} \tag{1}$$

With:

H: water level

Qe: input flow

S: tank base surface

s: output water surface

g: heaviness

To control the water level system the PIC 16F877 board takes the measure of level by using the signal given by the electronic board of acquisition and the numerical value of this analogical measure is sending to PC by the RS 232 serial port. The control value is calculated by Matlab and is sent to PIC 16F877 board which converts this control value to a PWM signal in the aim to control the transistor of the serial chopper. The communication between Matlab and real system is done by S-function block created in the SIMULINK of Matlab.

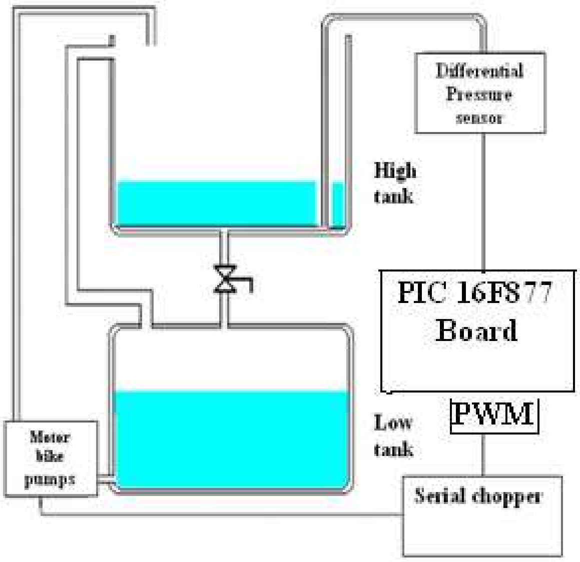

Fig. 1 Water level system

III. ANFIS STRUCTURE

ANFIS is a famous hybrid neuro-fuzzy network for modelling complex systems that was developed by Jang [3]. This system is a useful neural network approach for the solution of nonlinear functions and approximating problems [9].

The proposed neuro-fuzzy model of the ANFIS is a multilayer neural network-based fuzzy system. Both neural network (NN) and fuzzy logic (FL) are used in ANFIS architecture [10]. The system has an adaptive network functionally equivalent to a 1st-order Sugeno fuzzy inference system [3]. The ANFIS uses a hybrid-learning rule, which combines back-propagation, gradient-descent and a least-squares algorithm to identify and optimise the Sugeno system's signals. The fuzzy reasoning is illustrated in Fig. 3(a), and the corresponding ANFIS architecture of a first-order Sugeno fuzzy model with two rules is presented in Fig. 3(b). The square nodes are adaptive nodes, and the circular nodes are fixed nodes whose parameters change during the training process. The system has a total of five layers. In this connected structure, the input and output nodes represent the training and predicted values, respectively. In the hidden layers, there are nodes functioning as the membership functions (MFs) and rules.

For simplicity, it is assumed that the fuzzy inference system has two inputs, x and y, and one output, f. For a first-order Sugeno fuzzy model, a common rule set with two fuzzy if–then rules is defined as follows:

Rule 1: If (x is A_1) and (y is B_1) then ($f_1 = p_1x + q_1y + r_1$)

Rule 2: If (x is A_2) and (y is B_2) then ($f_2 = p_2x + q_2y + r_2$)

where x and y are the inputs, A_i and B_i are the fuzzy sets, f_i is the output within the fuzzy region specified by the fuzzy rule. p_i, q_i and r_i are the design parameters that are determined during the training process. In the first layer, all the nodes are adaptive nodes. The outputs of layer 1 are the fuzzy membership grades of the inputs, which are given by:

$$O_i^1 = \mu_{A_i}(x), \quad i = 3,4 \tag{2}$$

$$O_i^1 = \mu_{B_{i-2}}(y), \quad i = 3,4 \tag{3}$$

where x is the input to node i, and Ai is the linguistic label associated with this node function. Usually μAi(x) and μBi−2(y) are selected to be a Gaussian function given by the expression below.

$$\mu_{A_i}(x) = exp\left[-\left(\frac{x - c_i}{a_i}\right)^2\right] \tag{4}$$

Where a_i and c_i are, respectively, the deviation and center parameters of the membership function.

In the second layer, the nodes are fixed nodes. They are labelled with Π, which indicates that they perform as a simple multiplier. The outputs of this layer can be represented as:

$$O_i^2 = w_1 = \mu_{A_i}(x)\mu_{B_i}(y), \quad i = 1,2 \tag{5}$$

which are called the firing strengths of the rules.

In the third layer, the nodes are also fixed nodes. They are labelled with N, which indicates that they play a normalisation role to the firing strengths from the previous layer. The outputs of this layer can be represented as:

$$O_i^3 = \overline{w}_1 = \frac{w_1}{w_1 + w_2}, \quad i = 1,2 \tag{6}$$

which are called the normalised firing strengths.

In the fourth layer, the nodes are adaptive nodes. The output of each node in this layer is simply the product of the normalised firing strength and a first-order polynomial (for a first-order Sugeno model). Thus, the outputs of this layer are given by:

$$O_i^4 = \overline{w}_1 f_1 = \overline{w}_1(p_1x + q_1y + r_1), \quad i = 1,2 \tag{7}$$

In the fifth layer, there is only one single fixed node labelled with Σ. This node performs the summation of all incoming signals. Therefore, the overall output of the model is given by:

$$O_i^5 = \sum_{i=1}^{2} \overline{w}_1 f_1 = \frac{\sum_{i=1}^{2} w_1 f_1}{w_1 + w_2}, \quad i = 1,2 \tag{8}$$

It can be observed that there are two adaptive layers in this ANFIS architecture, which are the first and the fourth layers. In the first layer, there are two modifiable parameters {ai, ci}, which are related to the input membership functions. These parameters are called premise parameters. In the fourth layer, there are three modifiable parameters {pi, qi, ri}, which pertain to the first-order polynomial. These parameters are called consequent parameters [3][11].

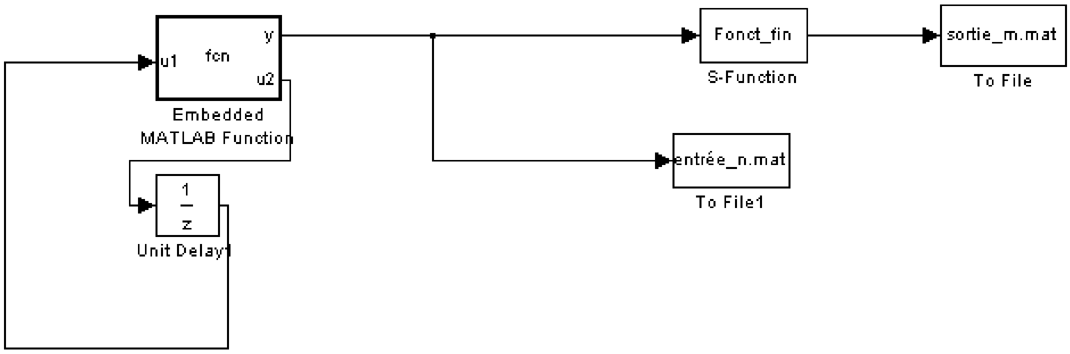

Fig.2. The S-Function block created in SIMULINK

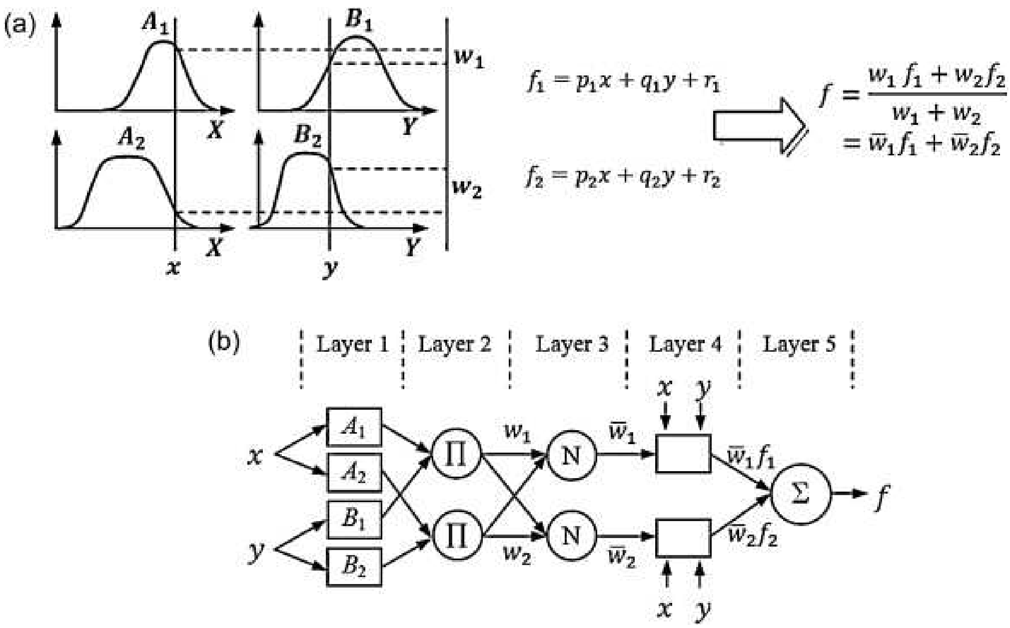

Fig. 3. (a) The reasoning scheme of ANFIS and (b) The ANFIS architecture.

IV. LEARNING ALGORITHM OF ANFIS

The task of the learning algorithm for this architecture is to tune all the modifiable parameters, namely {*ai*, *ci*} and {*pi*, *qi*, *ri*}, to make the ANFIS output match the training data. When the premise parameters a_i and c_i of the membership function are fixed, the output of the ANFIS model can be written as:

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 \tag{9}$$

Substituting Eq. (6) into Eq. (9) yields:

$$f = \bar{w}_1 f_1 + \bar{w}_2 f_2 \tag{10}$$

Substituting the fuzzy if–then rules into Eq. (10), it becomes:

$$f = \bar{w}_1(p_1x + q_1y + r_1) + \bar{w}_2(p_2x + q_2y + r_2) \tag{11}$$

After rearrangement, the output can be expressed as:

$$f = (\bar{w}_1x)p_1 + (\bar{w}_1y)q_1 + (\bar{w}_1)r_1 + (\bar{w}_2x)p_2 + (\bar{w}_2y)q_2 + (\bar{w}_2)r_2 \tag{12}$$

which is a linear combination of the modifiable consequent parameters p_1, q_1, r_1, p_2, q_2 and r_2. The least-squares method can be easily used to identify the optimal values of these parameters. When the premise parameters are not fixed, the search space becomes larger, and the convergence of the training becomes slower. A hybrid algorithm combining the least squares method and the gradient descent method is adopted to solve this problem. The hybrid algorithm is composed of a forward pass and a backward pass. The least squares method (forward pass) is used to optimise the consequent parameters with fixed premise parameters. Once the optimal consequent parameters are found, the backward pass starts immediately. The gradient descent method (backward pass) is used to optimally adjust the premise parameters corresponding to the fuzzy sets in the input domain. The output of the ANFIS is calculated by employing the consequent parameters found in the forward pass. The output error is used to adapt the premise parameters using a standard back-propagation algorithm. It has been demonstrated that this hybrid algorithm is highly efficient in training the ANFIS [3][11].

V. SIMULATIONS

This section presents the simulation results of proposed ANFIS model for the water level system and its control. In order to obtain an input–output data set, an input data set which represents the changes of the control of pump tension for 200 samples is plotted in Fig.4. The maximum tension is 5V and equal to 255 as a numerical value. This input is applied to the system and the corresponding liquid level outputs are obtained and plotted in Fig 5. The maximum water level in the tank is 27 cm converted to 5V by the electronic board of acquisition and 5V is also equal to a numerical value of 255.

The system is modelled as a MISO system having three inputs u(k-1),y(k-1), y(k-2) and one output y(k). u(k) is the input and y(k) is the output.

Each input variable is represented by 2 membership functions. The membership functions for this Takagi-Sugeno fuzzy model are chosen as a Gaussian function. The input-output data is processed by ANFIS and hence the proposed model is obtained. Below in Fig.6, the outputs of real water level system and ANFIS models are plotted for comparison. The two curves are similar to the training input data and the ANFIS model can be used as a model to the real system. The time axes for simulation results are plotted in terms of discrete index number. Fig.7 shows the actual difference between the real water level system and the ANFIS model output at each sample. This error is between -3 and 3 then it is considered very small compared to the maximum value which is 255 and this comparison prove the effectiveness of the model.

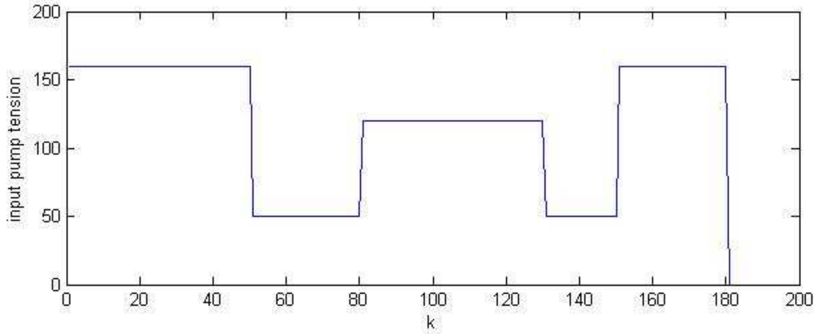

Fig. 4. The input pump tension curve

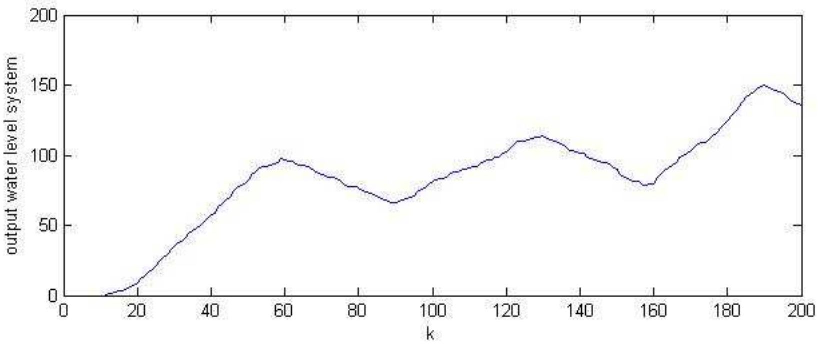

Fig. 5. The output water level system

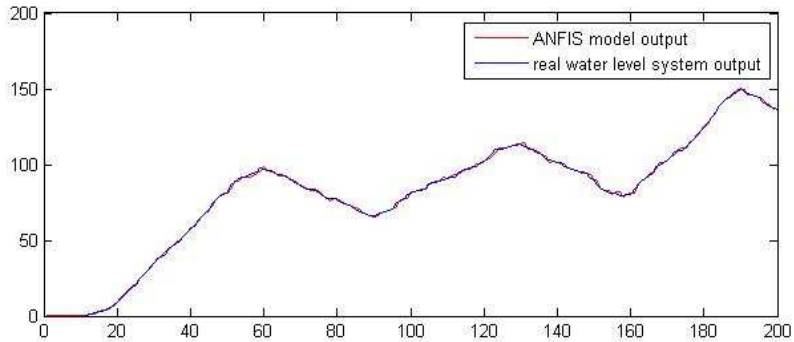

Fig. 6. Responses of the ANFIS model and the real water level system to the training input data

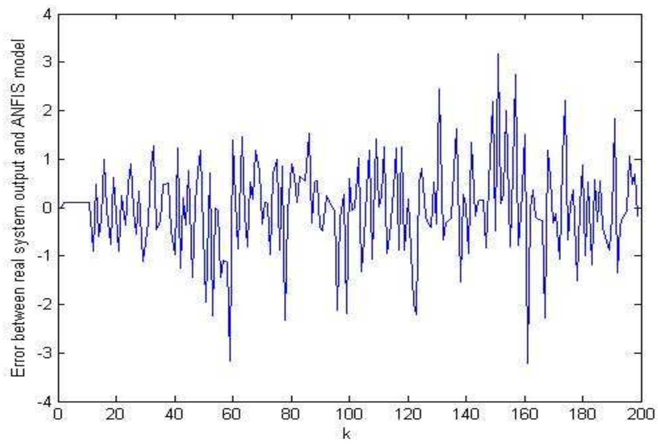

Fig. 7. Error between the real water level system and ANFIS model for the training input

To compare the effectiveness of the model, the parameters of ANFIS model premises and consequences are taken from the Matlab and in SIMULINK a subsystem block is constructed formed the ANFIS model of system and given in the Fig 8.

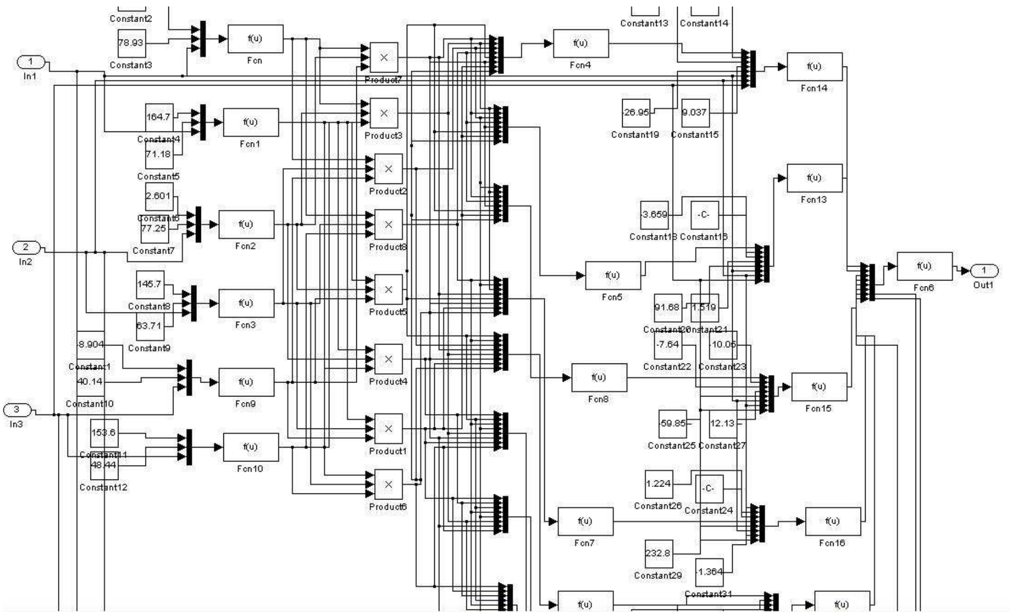

Fig. 8. The internal architecture of the subsystem's ANFIS model created in the SIMULINK

The subsystem bloc described in the Fig 8 is used in the closed loop control given in the Fig 9 replacing the S-function of the real system. A proportional integral controller PI is applied in the same structures to the real system and the ANFIS model. The structure of this controller is given by the Fig 10.

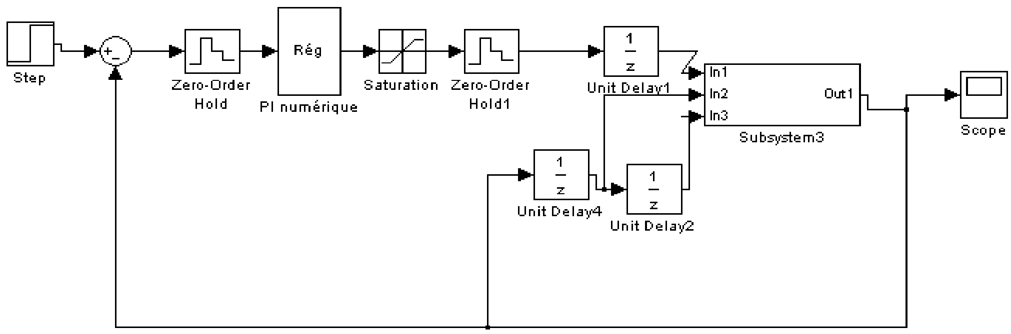

Fig. 9. The closed loop control of The ANFIS model in SIMULINK

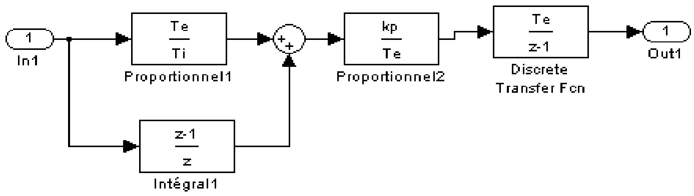

Fig. 10. The structure of PI controller used

The parameters of the PI controller are chosen as:
kp=1.9 , Ti=42 , Te=1s, set-point=120 (represents a level of 13 cm)

The responses of the real water level system and ANFIS model by applied the PI controller is given in the Fig 11 below.

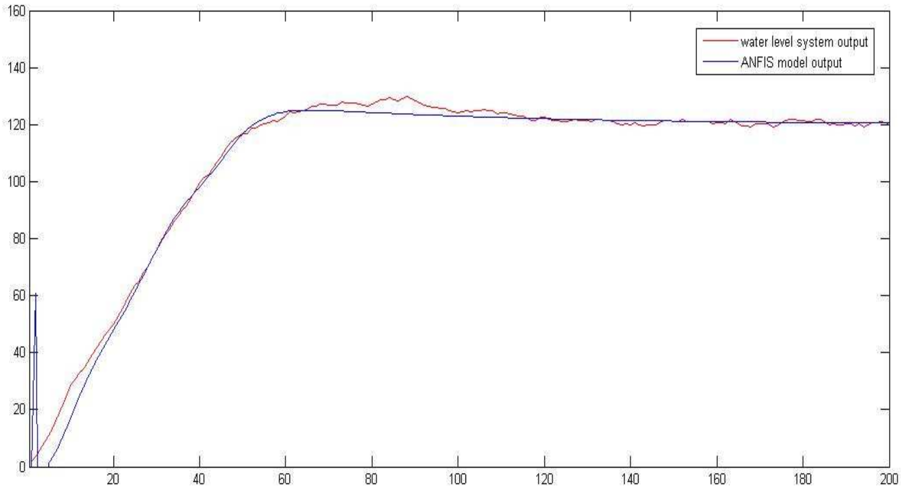

Fig. 11. The responses of real system and ANFIS model of PI controller

Figure 11 shows that the two curves have the same rise time about 50s and the curve of the real system response presents a short overshoot compared to the ANFIS model response. In the steady state the two curves converges to the set point.
In conclusion we can prove the effectiveness of the ANFIS model used to model the water level system.

V. CONCLUSIONS

In this work, a neurofuzzy ANFIS system has been used to the identification of a real water level system. An input-output data of the system is exploited to have the parameters of an ANFIS structure which model the real system. A subsystem bloc representing the ANFIS model is created in SIMULINK and a PI controller is applied to the real system and ANFIS model. The experimental results proves the effectiveness of ANFIS in identification of nonlinear system like the water level system used in this study and gives a similar response in terms of rise time and convergence to the set point compared to the real system response.

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