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Design of ANFIS Controller for Quadruple-Tank Interacting System

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ABSTRACT
This work deals with the design and simulation of an adaptive neuro fuzzy inference system(ANFIS) for controlling the level of the Quadruple Tank interacting system. The advantage of using ANFIS is that it trains the data and computes the membership functions parameters that best allows the associated fuzzy inference system to track the given input/output data. Since Quadruple-Tank is one of the benchmark MIMO system, in this work conventional PI, MPC (Model Predictive Control) and ANFIS controller were carried out. Initially independent PI controller were applied using BLT (Biggest Log – Modulus Tuning) method and module had developed, trained to a membership function. The conventional PI controllers are replaced with ANFIS controller, interaction between different tank is difficult to control it's level. The performance of the control strategy is studied on the control of Quadruple-Tank problem. The results confirmed the control quality improvement with MPC and PI controller.

***Keywords*–**ANFIS,MPC,NeuralModeling,PIcontroller,Quadruple-Tank.

I. INTRODUCTION

The controller always aims to achieve the process variable to the given set point value. This is the main work of the properly designed controller and it should also provide some flexibility in case of change in set point and disturbances. Today there are many methods for designing intelligent controllers, such as model predictive controller, fuzzy logic control, neural network and expert system. Various combinations of these controllers give a number of design possibilities.

Artificial neural networks and fuzzy logic systems are capable of solving highly nonlinear and time varying real world problem. Different types of neuro-fuzzy system are used for different applications of identification, modeling, control, fault detection and expert system purpose. This paper presents a adaptive neuro-fuzzy inference system(ANFIS) controller to control nonlinear multi-input multi-output(MIMO) system. It uses only few rules to provide the control action, instead of the full combination of all possible rules employed [9]. Consequently, the PI controller possesses several advantages over the conventional fuzzy ANFIS controller especially the reduction in execution time, and hence, it is more suitable for real time control.

Fuzzy logic is conceptually easy to understand the mathematical concepts behind fuzzy reasoning are very simple and logic is more intuitive approach without the far-reaching complexity. It has been introduced by Professor Lotfi Zadeh in 1965. There are two types of fuzzy logic which is mamdani and sugeno. In this paper, Takagi-sugeno is used. The main difference is the output membership function are only linear or constant for fuzzy logic sugeno type fuzzy inference. You can create a fuzzy system to match any set of input –output data and this process is made particularly easy by adaptive neuro fuzzy inference system(ANFIS) techniques.

A different training technique in training the ANFIS as a controller for non linear MIMO system and this technique is based on training the ANFIS network by using data which are collected from another working controller. One of the most powerful technique to train a neuro-fuzzy system to act as a feedback controller. Fuzzy inference system is built for achieving a desired i/o mapping.

Learning method used allows the tuning of parameters both of the membership function and consequents in a sugeno-type inference system [1].

This paper is organized as follows. The second section presents basic information of Quadruple-Tank Process. The third section introduces the PI controller. The following two section present classic MPC and ANFIS controller [1, 3]. Simulation and results are presented in the sixth section followed by conclusion in seventh section.

II. QUADRUPLE-TANK PROCESS

In this section we derive a mathematical model for the quadruple-tank process from physical data. The quadruple tank experiment consist of four water tanks and two pumps [2] (see Fig.1. for a system schematic). The aim is to control the water level in the lower tanks (tank 1 and 2) with the two pumps. The inputs of the process to control are the input voltages of the pumps v1 and v2. The output are the corresponding water level in the tanks h1 and h2.The flow from pump j is split up in a part proportional to γj and a part proportional to 1- γj. The flows of the pumps are split up by valves. The flow of pump 1 goes into tanks 1 and 4 whereas pump 2 feeds tanks 2 and 3.

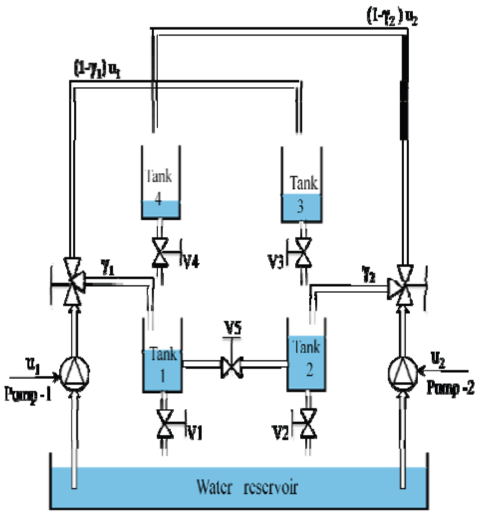

Figure 1 Schematic Diagram of Quadruple Tank Process System

There are two valve section in the setup each consisting of two manually operated valves. Changing the flow ratios of the valve sections makes the system minimum or non- minimum phase. The minimum and non-minimum phase mode can be achieved as

Minimum Phase: **1 < (□1 + □2) < 2**

Non-minimum Phase: **0 < (□1 + □2) < 1**

Mass balance and Bernolli's law yields [2] non-linear plant equation as following

$$\frac{dh_1}{dt} = -\frac{a_1}{A_1}\sqrt{2gh_1} + \frac{a_3}{A_1}\sqrt{2gh_3} + \frac{\gamma_1 k_1}{A_1}v_1$$

$$\frac{dh_2}{dt} = -\frac{a_2}{A_2}\sqrt{2gh_2} + \frac{a_4}{A_2}\sqrt{2gh_4} + \frac{\gamma_2 k_2}{A_2}v_2$$

$$\frac{dh_3}{dt} = -\frac{a_3}{A_3}\sqrt{2gh_3} + \frac{(1-\gamma_2)k_2}{A_3}v_2$$

$$\frac{dh_4}{dt} = -\frac{a_4}{A_4}\sqrt{2gh_4} + \frac{(1-\gamma_1)k_1}{A_4}v_1 \qquad (1)$$

Where

A_i Area of tank i i = 1, 2, 3, 4

a_i Area of the pipe flowing out of tank i

h_i Level of water in tank i

The process transfer function of the quadruple-tank process is given by

$$G_{11}(s) = \frac{2.6}{1+62s} \qquad (2)$$

$$G_{12}(s) = \frac{1.5}{(1+23s)(1+62s)} \qquad (3)$$

$$G_{21}(s) = \frac{1.4}{(1+30s)(1+90s)} \qquad (4)$$

$$G_{22}(s) = \frac{2.8}{(1+90s)} \qquad (5)$$

III. PI CONTROLLER

In control engineering, PI controller (proportional-integral controller) is a feedback controller which drives the plant to be controlled with a weighted sum of the error (difference between the output and desired set-point) and the integral of that value. It is one of the important case of the common PID controller in which the derivative (D) of the error is not used. PI controller, its integral part makes the process variable to move faster to the set point [4]. The PI controller is widely accepted in industries as it does not pose any form of functionality challenge in its application.

$$c = K_p\Delta + K_i \int \Delta dt \qquad (6)$$

K_p = proportional gain

K_I = integral gain

C = Response of system

We were using BLT (Biggest Log – Modulus Tuning) methods for multi-loop PI control systems, Controller Parameter

For Minimum Phase

Kp1 = Kp2 = 15 Ki1 = Ki2 = 5

IV. MODEL PREDICTIVE CONTROL

The wide acceptance of the MPC by many industries is basically for its smart performance in difficult multivariable control condition. It is designed such a way that it inherently ensures the control of process variable as best possible in the absence of a sensor or actuator in the process. The MPC aims at preventing the violations of input and output constraints, as well as preventing the excesses that could arise in the movement of input variable. The model of the process is used in predicting current values of the output variables. When the actual and predicted outputs are compared, their resulting difference is used as a feedback signal to the prediction block and the prediction achieved, were used at each sampling time instant for the calculation of the set point and the control signal calculations [10]. A simple block that illustrates the MPC is Figure 2.

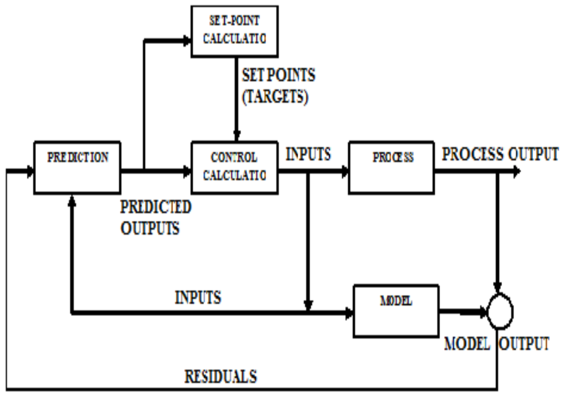

Figure 2 Block Diagram of MPC

Advantage of MPC is able to find most economical set points and operating points. It also ensures reduced maintenance and longer plant life and capable of providing timely warnings, notifications and alarms of the possible future problems in the plant.

The inequality constraints on input and output variables, as the upper and lower limits respectively is included in any of the calculations. According to (Seborg E. Dale and Mellichamp, 2003), the objective of the MPC control calculations is for determining a sequence of the so called control moves (manipulated input changes) such that the predicted response moves to the set point is in an optimal way. In Figure 3, the actual output y(k), the predicted output y(k+i), and the manipulated input u are plotted. Considering the current sampling instant which is denoted as k, the MPC strategy calculates a set of number of input values {u(k + i-1), i = 1, 2, …., M}. The calculated control inputs, consists of the current input u(k) and M-1 future inputs. However, these inputs are calculated such that the set of P predicted outputs {y(k + i), i = 1, 2, …., P} gets to the set point in an optimal way. P is the number of predictions which is referred to as Prediction horizon, and M is the number of control moves also referred to as Control horizon. In the sequence of control moves that is being calculated at each sampling time instant, it is the first move that is practically implemented [5]. Another sequence is also calculated at the next sampling time instant, which is based on the available measurements and only the first control move is implemented as well see Fig 3.

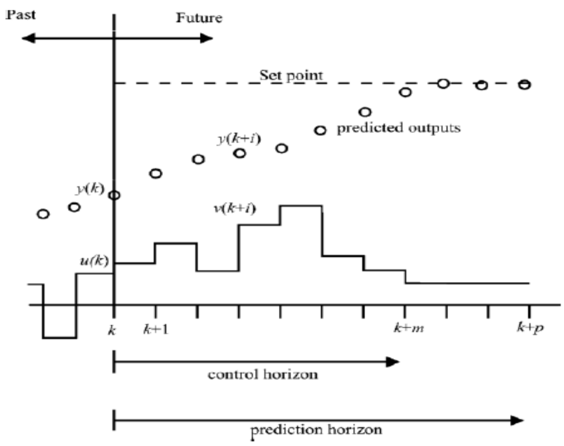

Figure 3 Concepts of Prediction and Control Horizon in MPC

V. ANFIS CONTROLLER

ANFIS stands for Adaptive Neural Fuzzy Inference System. Using a given input/output data set, toolbox function ANFIS constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a back propagation algorithm or in combination with a least squares type of method. This allows your fuzzy system to learn from the data they are modeling. The Takagi-ANFIS architecture is shown below. The circular nodes represent nodes that are fixed whereas the square nodes are nodes that have parameters to be learnt.

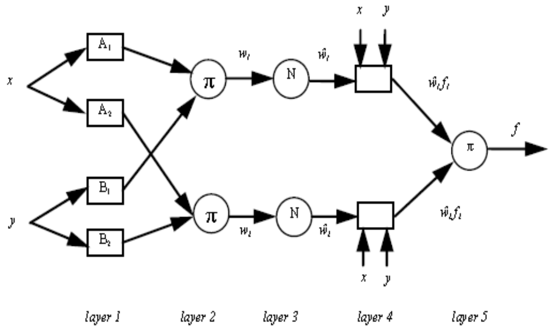

Figure 4 ANFIS Architecture for Takagi-sugeno system

ANFIS has rules of the form:

If x is A_1 and y is B_1 THEN $f_1 = p_1x + q_1y + r_1$
If x is A_2 and y is B_2 THEN $f_2 = p_2x + q_2y + r_2$ (7)

For the two ANFIS parameter optimization method options available for FIS training are hybrid (default, mixed least squares and back propagation) and back propagation. The entire sugeno system consists of five layers and the relationship between the i/o of each layer is summarized as follows:

Layer 1: The output of each node is,

$O_{1,i} = \mu_A(x)$; for i=1,2 (8)

$O_{1,i} = \mu_{B-2}(y)$; for i= 3,4 (9)

So, the $O_{1,i}(x)$ is essentially the membership grade for x and y. Any membership functions can be used but for illustration purposes we will use the bell shaped function given by:

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

where a_i, b_i and c_i are parameters to be learnt.

Layer 2: Every node in this layer is fixed. This is where the t-norm is used to 'AND' the membership grades-for example the product:

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad i = 1,2 \quad (11)$$

Layer 3: It contains fixed nodes which calculates the ratio of the firing strengths of the rules:

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2} \quad (12)$$

Layer 4: Similar to layers two and three, in this layer are adaptive and perform the consequent of the rules:

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

The parameters in this layer (p_i, q_i, r_i) are to be determined and are referred to as the consequent parameters.

Layer 5: A single node in this layer and computes the overall output:

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

The input vector is fed through the network layer by layer. The ANFIS learns the premise and consequent parameters for the membership functions and the rules are then considered.

GENERATION OF TRAINING DATA

If the operating input-output data are outside their Training data range, estimator will not operate accurately. As a result, the training data set should possess sufficient operational range including the maximum and minimum values for input output variables. 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 top and bottom products were determined by looking at the closed-loop responses of the system [3]. Thus, model simulations are done to obtain the input-output data by using these values.

TRAINING OF ANFIS ESTIMATOR

Estimator structure design and training are realized using MATLAB software. First, generated training data is loaded using the GUI Editor. Then, with chosen design parameters, initial estimator structure is constructed. For example, if three triangular MFs are used for each input and constant output MF is chosen, GUI Editor determines the initial parameters of triangular MFs automatically using loaded data and constructs the initial Tri3con (three triangular MFs for each input and constant output MF) ANFIS structure. Trainings of the structures are done by MATLAB. All structures are trained in the same way only by changing the training data.

VI. SIMULATION AND RESULTS

The ANFIS (Adaptive Neuro Fuzzy Inference System) controller is designed using MATLAB software. The error and change of error is used for rule formation in ANFIS controller. The Trapezoidal type input membership function is used for control design. Fig 5, Fig 6 present the ANFIS controller output. The ANFIS(Adaptive Neuro Fuzzy Inference System) controller response is compared with conventional multi loop PI controller and Model Predictive controller (MPC). From the Fig 7, Fig 8 the response of ANFIS controller is Better than the other two controllers. The performance indices (ISE and IAE) of all three controllers are listed in table 1 and table 2.

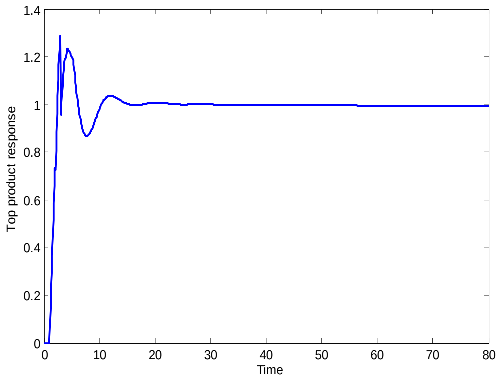

Figure 5 ANFIS controller response for top product

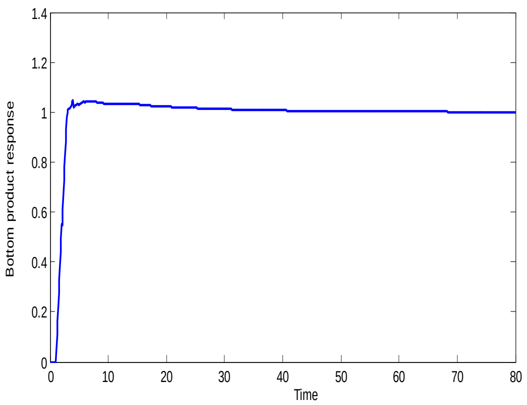

Figure 6 ANFIS controller response for bottom product

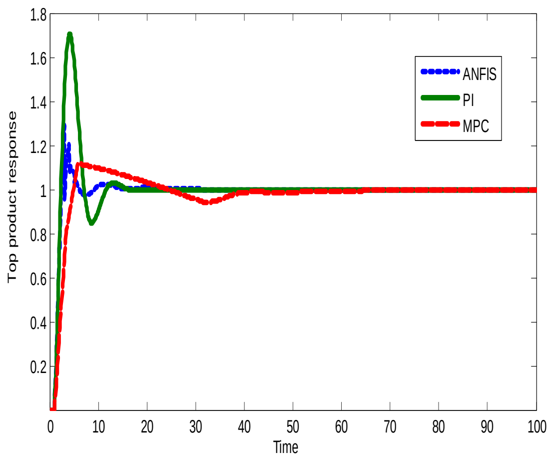

Figure 7 Comparison of PI, MPC and ANFIS controller of top product

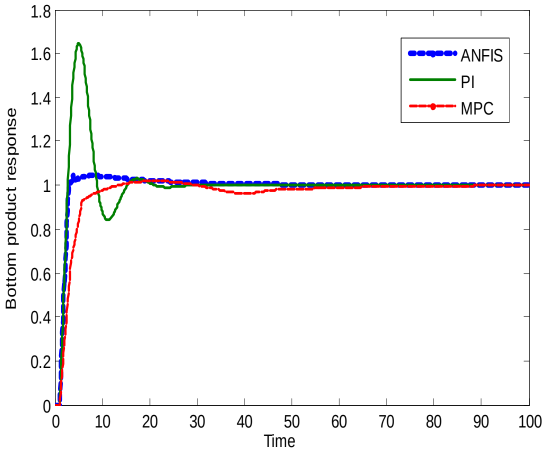

Figure 8 Comparison of PI, MPC and ANFIS controller of bottom product

Table 1 ISE, IAE comparison for top product

PERFORMANCE	PI	MPC	ANFIS
ISE	2.626	2.133	1.608
IAE	4.255	4.717	2.921

Table 2 ISE, IAE comparison for bottom product

PERFORMANCE	PI	MPC	ANFIS
ISE	2.887	2.344	1.648
IAE	5.059	4.373	2.855

VII CONCLUSION

Thus, by comparing the response and their performance of the control strategy of the

Quadruple-tank interacting system obtained using conventional PI controller, MPC and the ANFIS Controller. We can say that the ANFIS (Adaptive Neuro Fuzzy Inference System) controller is better than the other two controller. The quantitative and qualitative analysis of different controller's shows ANFIS controller as better. The peak overshoot is minimized and a smooth response is obtained. This method is simple since the ANFIS itself trains the data and adopts the membership values for better response. In future works consideration of MPC and ANFIS may be applied for the system to enhance controller performance even better.

REFERENCES

[1] R. Sivakumar, K. Balu, ANFIS based Distillation Column Control, *International Journal of Computer Applications Specialissue on Evolutionary Computation, (2),* 2010, 67-73.

[2] Pedram Hjiani, Javad Poshtan,Reconfigurable Controller Design for Actuator Faults in a Four-tank System Benchmark, *International Journal of Instrumentation and Control system(IJICS), (2)*, 2012,
69-76.

[3] R.Sivakumar, C. Sahana, P.A. Savitha, Design of ANFIS based Estimation and Control for MIMO system, *International Journal of Engineering Research and Applications (IJERA)***,** *2(3),* 2012, 2803-2809.

[4] Vanamane V. S, Patel N. V, Modeling and Controller Design for Quadruple Tank System, *Proc. of the intl. conf. on Advances in Computer, Electronics and Electrical Engineering,(1),* 2010, 498-502.

[5] Ademu Victor Okpanachi, *Developing Advanced Control strategies for a 4-Tank Laboratory Process,* Hans-Petter Halvorsen, Telemark University College, Norway, M.sc, 2010.

[6] R. Suja Mani Malar, T. Thyagarajan, Modeling of Quadruple Tank System Using Soft Computing Techniques, *European Journal of Scientific Research,29(2),* 2009, 249-264.

[7] Aidan O'Dwyer, *Handbook of PI & PID Controller Tuning Rules,* Dublin Institute of Technology, Ireland, 2006.

[8] Liuping Wang, *Model Predictive Control System Design and Implementation Using MATLAB,* RMIT University, Melbourne, 2009.

[9] R. Jang, ANFIS: Adaptive Network based Fuzzy Inference System, *IEEE Transaction on System, Man and Cybernetics, 23(3),* 1993, 665-684.

[10] P. Tatjewski, M. L. Czuk, Soft Computing in Model based Predictive Control, *International Journal of Applied Maths and Computer Science, 16(1),* 2006, 7-26.