Design of Adaptive pH Controller using ANFIS

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ABSTRACT
Conventional control algorithms used in pH control systems give inefficient performance, leading to use of large mixers. To improve the neutralization control process, an ANFIS based advanced controller has been proposed. In this paper, method of design of adaptive controller based on neurofuzzy technique is presented. The method uses ANFIS methodology to automatically generate fuzzy rule base and fuzzy membership functions, which are iteratively adjusted by hybrid learning algorithm that combine the backpropagation gradient descent and least square method to create a fuzzy inference system. In the modeling task, the dynamics of the process is determined by Takagi-Sugeno fuzzy model in order to obtain a suitable structure for the ANFIS based Neurofuzzy controller. ANFIS is used to identify the twelve linear and sixteen nonlinear parameters that describe the behavior of the pH neutralization process. The resulting neurofuzzy controller is simulated by using reference model. Simulation results proved the tracking and adaptive capability of neurofuzzy system applied to pH neutralization process.

Keywords
pH neutralization, Adaptive Neuro Fuzzy Inference System

1. INTRODUCTION
In recent decades, several control strategies have been developed to improve system performance by including a model of the system within the control structure. The combination of learning ability of neural network and fuzzy logic in control systems has recently become a very active research area. Such synergism of integration into a functional system provides a new direction toward the realization of intelligent systems. One of the most modern and new area in system control is Model Predictive Control (MPC) which is widely used in industrial process control practice [1]. The performance of these model-based strategies is influenced by several factors; it is principally dependent on the validity of the model.

Most chemical processes are inherently nonlinear. However, because of their simplicity, linear control algorithms have been used for the control of nonlinear processes. The autoregressive exogenous (ARX)-Model [2] is one of them and has advantage that, one can perform model structure and parameter identification rapidly. However, if a better performance is desired then one has to resort to nonlinear models. The fundamental premise of Model Based Control (MBC) strategies stated that if a system can be modeled well it can be controlled well, and hence for the inherent non-linear behavior of many chemical processes, the case for developing non-linear process models is persuasive [3]. The Takagi Sugeno fuzzy model with a fuzzy-neural implementation is used and incorporated as a predictor in a MBP controller [4]. Various comprehensive real-time identification/control methodologies based on the concept of nonlinear autoregressive exogenous input (NARX) models and adaptive, nonlinear, model-predictive control is applied to a pH neutralization process [5, 6, 7].

A neuro-fuzzy modelling technique, recently presented in the literature [8,9], is used for Nonlinear Model Predictive Control (NMPC) of a pH neutralization process [10]. The structure of the neuro-fuzzy model is physically motivated through linear input/output modelling techniques, as the model consists of a network of a global linear predictor and several local linear predictors. The simplicity of the model can be argued to contribute to making the procedure of tuning the NMPC system more transparent when using the neuro-fuzzy predictor.

2. NEUROFUZZY MODELLING
Process modeling based upon conventional methods is not well suited for dealing with ill-defined, complex and uncertain systems. Fuzzy modeling employing fuzzy if-then rules provides a tool for designing qualitative models without employing precise quantitative analyses. However, there are many situations where expert knowledge, which is usually the basis for designing fuzzy models, is not sufficient, due to incompleteness of the existing knowledge, problems caused by different biases of human experts, difficulties in forming rules, etc. That is why, methods for data-driven fuzzy modeling and identification are of great interest. Among them, the methods based on the combination of artificial neural networks and fuzzy systems take a remarkable place. This combination, in the form of neurofuzzy system, means the enhancement of merits and the reduction of demerits of both contributing techniques in the resultant system. Neurofuzzy systems are able to learn from examples, to generalize from learned knowledge, to explain decisions they make and to synthesize the knowledge – in the form of fuzzy rules – from the data.

The essential part of neurofuzzy system comes from a common framework called adaptive networks, which unifies both neural networks and fuzzy models. The fuzzy model under the framework of adaptive networks is called ANFIS (Adaptive Network based Fuzzy Inference System), which possess certain advantages over neural networks. Different Neurofuzzy models are NEFPROX and ANFIS. Here, ANFIS model is used to design Neurofuzzy pH controller, which is equipped with neural learning capabilities. The aim is to achieve a proper control action. The control action is given as an output of the Neurofuzzy controller whose structure parameters (membership functions and rules) affect the output. Thus, a way to minimize error is to adjust the structure and/or membership function parameters of the NF control network. In this present implementation, the structure of the fuzzy control network is kept constant and only membership function parameters are adjusted.

ANFIS, which can serve as a basis for constructing a set of fuzzy if-then rules with appropriate tuning of membership functions to generate the stipulated input output data pairs. It can achieve a highly nonlinear mapping, therefore it is well suited for predicting nonlinear time series. ANFIS consists of fuzzy rules which are actually local mappings. These local mapping facilitate the minimal disturbance principle which states that the adaptation should not only reduce the output error for the current training pattern but also minimize disturbances to response already learned. This is particularly important in on-line learning. ANFIS uses only differentiable functions hence it is possible to apply standard neural network learning procedures. Here, a mixture of backpropagation (gradient descent) and least squares estimation (LSE) is used. Backpropagation is used to learn the antecedent parameters, and LSE is used to determine the coefficients of the linear combinations in the rule consequents. ANFIS appears to be one of the well-known methods described in detail in [11]. ANFIS requires the antecedent membership functions and fuzzy rules to be defined prior to the training. It is also possible to use fuzzy clustering methods (fuzzy c-means clustering, subtractive clustering), to initialize the neurofuzzy system. In this case, only the number of antecedent membership functions should be specified before training.

The performance of ANFIS system, combined with subtractive clustering show good results [12]. Interpretation of Sugeno rules are, however, complicated and ANFIS can therefore be used successfully only when the performance of the model rather than understanding the nature of the process is important. ANFIS toolbox developed by MATLAB is used to generate the Fuzzy Inference System (FIS) in designing a Fuzzy logic controller. This technique is also used to the heat exchanger analysis; plant identification based on empirical modelling and Fuzzy logic controller simulation using MALTAB [13].

3. pH NEUTRALIZATION PROCESS

pH control is central to many areas of chemical/biotechnological engineering, such as fermentation, precipitation, oxidation, flotation, solvent extraction, wastewater neutralization and the manufacture of fatty acids and soaps. It is important to appreciate the diverse nature of these pH control applications because a small amount of acid or base near the set-point shows drastic change in pH gain and its characteristic. Thus pH control is a challenging control problem in industries, due to its highly nonlinear nature. Numerous schemes [14, 15, 16, 17] have been employed to handle this essentially nonlinear process. This includes the simple PID for regulation, self-tuning adaptive control, linearizing control, Neurofuzzy control and various model-based control. Neurofuzzy modeling can be regarded as a gray box technique [18] on the boundary between neural networks and qualitative fuzzy models.

In this work, a Neurofuzzy hybrid controller is implemented for an industrial pH process. The method uses ANFIS methodology to generate fuzzy rule base and fuzzy membership functions. ANFIS derives its name from adaptive neurofuzzy inference system using a given input–output data set. The function *anfis* construct a fuzzy inference system whose membership function parameters are tuned (adjusted) using either backpropagation algorithm alone or in combination with least square type of method. Fuzzy Modeling and Identification technique have been used to build a Takagi-Sugeno model for controlling the pH dynamics.

A neutralization tank with two influent streams (acid and base) and one effluent stream is depicted in **Fig.1** below. The identification and validation data sets are obtained by performing an experiment for random changes of the influent base stream flow rate $Q(k)$. The influent acid stream is kept constant. The change of pH (pH(k)) of the liquid in the tank is taken as output. Based on prior knowledge about the process, it was decided to include only $Q(k)$ in the antecedent (it is known that the main source of nonlinearity is the titration curve, which is the steady-state characteristic relating base flow rate to pH).

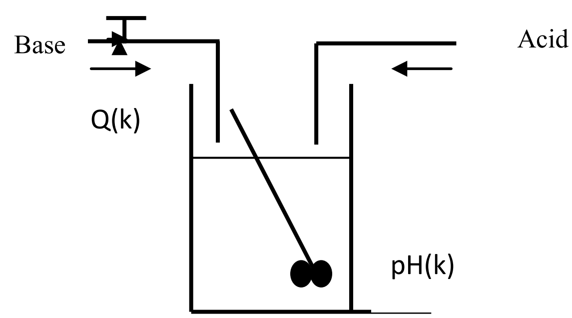

Fig.1 pH neutralization process

The process is approximated as a first-order discrete-time TS model:

$$\mathrm{pH}(k+1) = f(\mathrm{u}(k); Q(k)) \quad \text{(plant)} \quad \ldots \quad (1)$$

$$\mathrm{pH}(k) = \mathrm{g}(\mathrm{pH}(\mathrm{k}); \mathrm{Q}(k)) \quad \text{(controller)} \ \ldots (2)$$

where k denotes the sampling instant, and f is an unknown relationship approximated by TS fuzzy model.

Fig.2 shows the block diagram of a discrete-time ANFIS control system consist of a plant and a controller blocks. The plant block is usually represented by a discrete or difference equation that describes the physical system to be controlled. These equations govern the behavior of the plant. The controller block is a function of $\boldsymbol{g}$(pH(k); Q(k)). The input to the ANFIS controller is (pH(K),Q(k)) that maps into control action u(k) which generates pH(k+1) as an output of plant that is close to pH(k). The control objective here is to design a controller function $\boldsymbol{g(.)}$ such that the plant pH(k+1) can follow a desired reference trajectory as closely as possible.

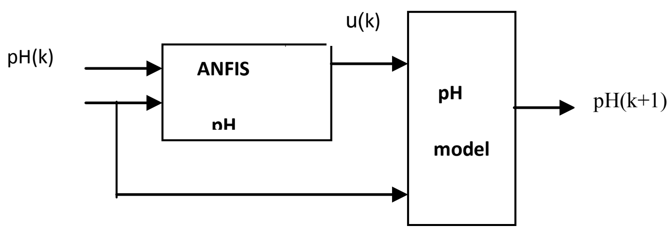

Fig. 2 ANFIS Based pH Controller

4. DESIGN OF ANFIS BASED CONTROLLER

The main problem with fuzzy logic controller is related to the choice of the structure parameters (membership functions and rules), if the system is complex. For this reason, ANFIS methodology is used to adapt the parameters of the fuzzy controller according to real data pertaining to specific problem. ANFIS uses a hybrid-learning algorithm that combines the backpropagation gradient descent and least squares methods to create a fuzzy inference system whose membership functions are iteratively adjusted according to a given input and output data pairs.

The Sugeno fuzzy model for controlling pH dynamics is depicted in **Fig.3** below.

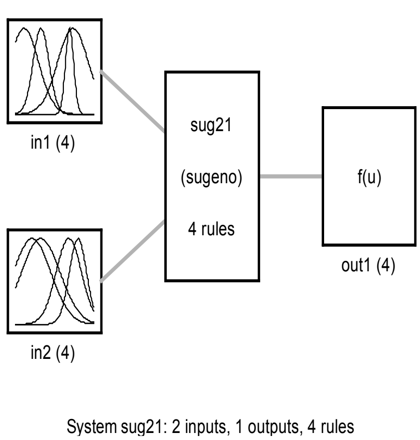

Fig.3 Architecture of Sugeno fuzzy model with ANFIS approach

A fuzzy model of four rules and four membership functions for each linguistic variable has been used. The fuzzy rules generated by the adaptive network are shown in **Fig.4**. These rules are generated automatically with the ANFIS method. The membership functions generated before and after training by ANFIS are shown in **Fig. 5 & 6**. For simulating the ANFIS controller, pH plant model has been obtained by using Fuzzy modeling and identification toolbox (FMID) [24]. This toolbox uses numerical data to build fuzzy model. It employs fuzzy clustering techniques to partition the available data into subsets characterized by a linear behavior. From the obtained fuzzy partitions, a Takagi-Sugeno type model is constructed. The following steps outline development of the TS fuzzy model.

- Collect training and checking data as produced by the pH CSTR process.
- Use FMID toolbox to create a TS fuzzy model that relates base flow rate Q(k) to the pH in the reactor pH(k).
- Validate the new model by giving identical inputs.
- The identification data set, contains N = 499 samples. The identification data set is shown in **Fig.7(a) & Fig.7(b).**

5. SOFTWARE OF ANFIS CONTROLLER

Fig.8 show the flow diagram of ANFIS based neurofuzzy logic controller. In the design of neurofuzzy controller the first and foremost thing is to identify the unknown system from input-output data set, which is obtained from pH neutralization process. Steps involved in designing the software for neurofuzzy pH controller.

- Load data that contains desired input-output data pairs of the target system to be modeled. This data is used to generate initial FIS system.
- Command *genfis2* automatically generate the FIS structure, which uses subtractive clustering to determine number of rules and number of membership functions. This command will go over the data crude way and find a good starting system.
- Choose the number of training epochs and training error tolerance.
- Train the FIS structure using *anfis* command.
- Use command *evalfis* to find the predicted output of the system. It computes the output of fuzzy inference system specified by Fismatrix. In our application the tuned Fismatrix is obtained from *anfis* function.
- Simulate the controller by using reference signal till N=499.

The aim of this controller is to follow the desired reference signal. For simulation, the plant model is identified by using FMID toolbox. **Fig.9** shows the flow chart for simulating the ANFIS controller. The reference signal is a sinusoid $r(k) = 50 \sin(2\pi k / 7) + 45 \sin(2\pi k / 3)$ which is fed to the controller. The control action u(k) from the controller is given to the pH model and this process continue till N=499.

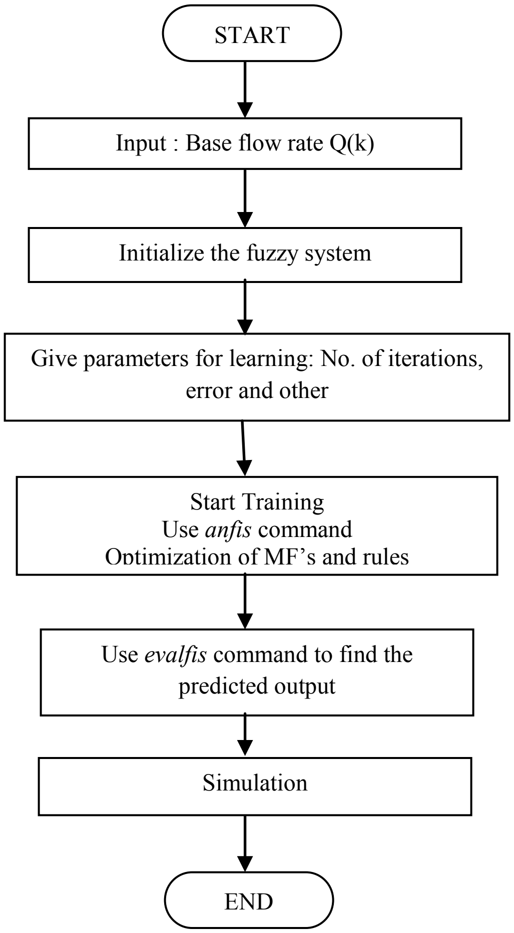

Fig.8 Flow chart of ANFIS based Neurofuzzy pH Controller

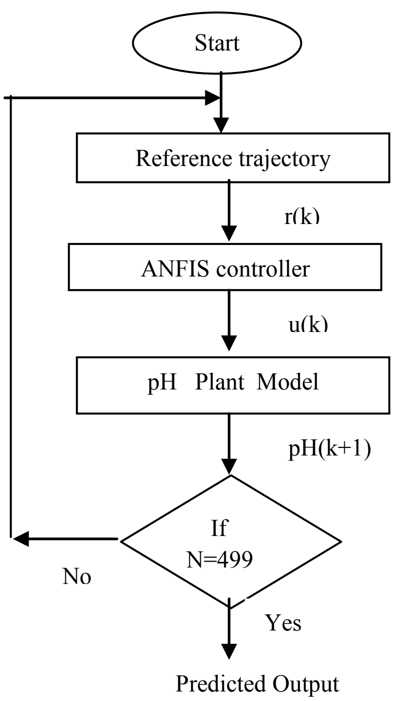

Fig.9 Flow chart for simulation of ANFIS

6. RESULTS AND DISCUSSION

Neurofuzzy Controller can basically learn any static input output characteristics if the training data is available. A Neurofuzzy controller is based on a fuzzy system, which is trained by a learning algorithm, can produce a neurofuzzy controller if the input-ouput data samples from the process is known. This data driven approach is used to model the pH CSTR process. Here, ANFIS is used as a controller to adapt the changing conditions of pH neutralization process. ANFIS controller is trained by using data of the relevant variables pertaining the problem. Designed ANFIS controller is tested by simulating it with the pH plant model, which is obtained from FMID toolbox. The result shows the tracking and adaptive capability of Neurofuzzy controller applied to pH neutralization process. The pH model used for simulation is $pH(k+1)= 0.91\ pH(k) + 0.06\ Q(k) – 0.25$ and the reference signal is given by $r(k) = 50 \sin(2\pi k / 7) + 45 \sin(2\pi k / 3)$. The ANFIS controller used here contains four rule and four membership functions assigned to each input variable and the total number of fitting parameters is 28 which are composed of 12 linear and 16 nonlinear parameters.

In **Fig.10(a)** the predicted values from the neurofuzzy model is plotted against the real values of the system. It can be observed from the figure that the neurofuzzy model is very close to the real values. About 29 hidden nodes and 100 epochs have been used for training. Hybrid learning is implemented using *anfis* function and it is observed that the RMSE value is 0.130348, which is within an acceptable limit for a given system. **Fig.10(b)** show a plot of the difference between the real and the estimated signal by the neurofuzzy controller. The controller tested by giving a reference trajectory to the ANFIS based neurofuzzy controller is shown **Fig.10(c)**. From **Fig.10(d)** it is clear that the output of the plant follows the desired reference signal. Thus, neurofuzzy model is better in tracking and adaptability for the non-linear systems.

Thus, ANFIS based neurofuzzy controller can achieve a highly nonlinear mapping as shown in simulation results, therefore it is superior to common linear methods in reproducing nonlinear system. The ANFIS controller used here has 29 adjustable parameters, which is much less than other controllers. By employing hybrid learning fuzzy if-then rules can be refined. Partitioning the input-space using subtractive clustering generates the rules. Effective partition of the input space can decrease the number of rules and thus increase the speed in both learning and application phase.

7. CONCLUSION AND FUTURE DIRECTIONS

In this paper, the feasibility of Neurofuzzy control for pH neutralization process has been proved and illustrated by simulation. The best parameters for the Neurofuzzy controller were determined by using the ANFIS methodology. Simulation results was used to validate the tracking ability and the sensitivity to plant parameter changes. The Neurofuzzy controller presented very interesting tracking features and was able to respond to different dynamic conditions.

It has been shown that with the aid of ANFIS, a multiple input/ single output fuzzy inference system could be created that accurately characterizes dynamic behavior of a pH system. The result shows that a Neurofuzzy system is able to create an appropriate set of rules easing the difficult process of defining the rule base. The rule base generated through the learning process, although different than the rule base defined by expert man works correctly and the main objective of reaching the desired reference trajectory was achieved with RMSE value of 0.130348. An important practical benefit of the Neurofuzzy model is its speed of execution. The decrease of computational time increases the feasibility of controller.

Following this way, the problem of modeling a process by a set of if-then rules can be made independent from human experience. Future work will include the creation of fuzzy rule-base model based on experimental data. Neurofuzzy modeling should rather be seen an interactive method, facilitating the active participation of the user in a computer-assisted modeling session. Modeling of complex system will always remain an interactive approach.

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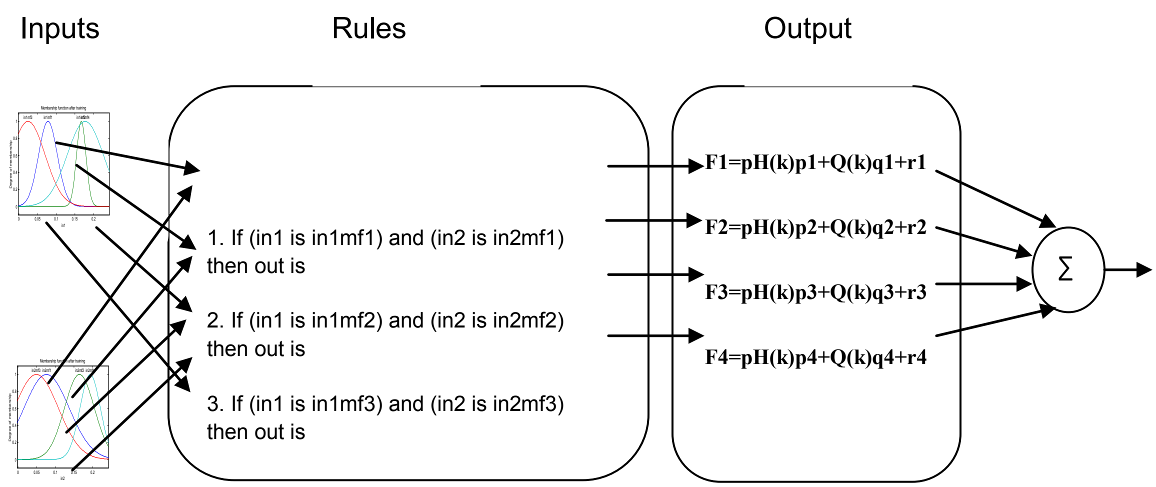


Fig.4 ANFIS architecture showing the inputs and outputs of the system

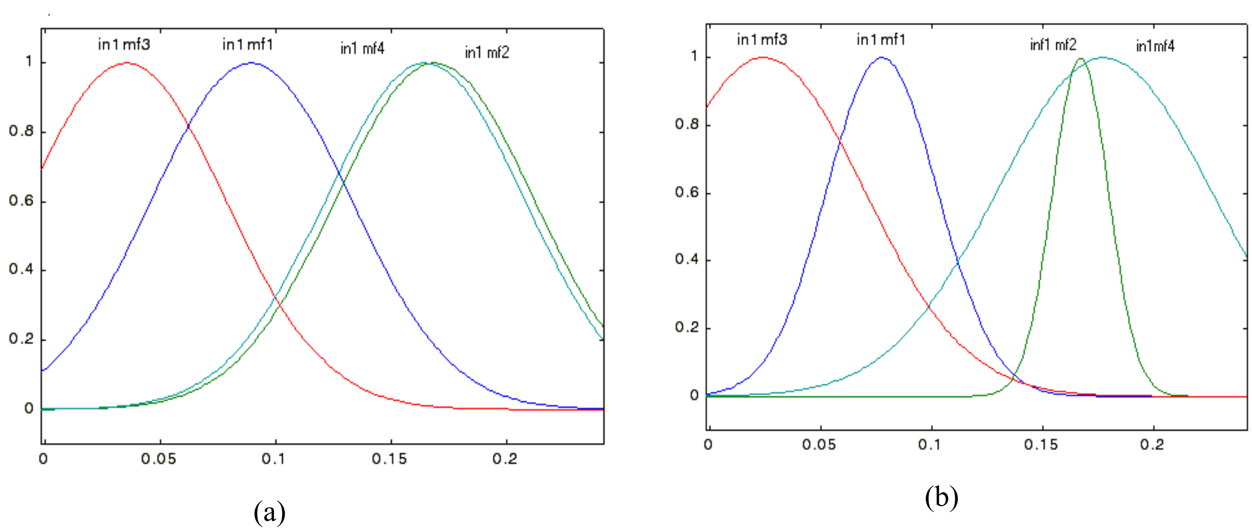
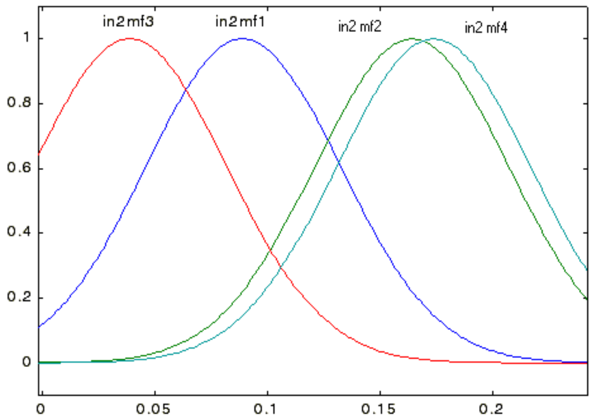
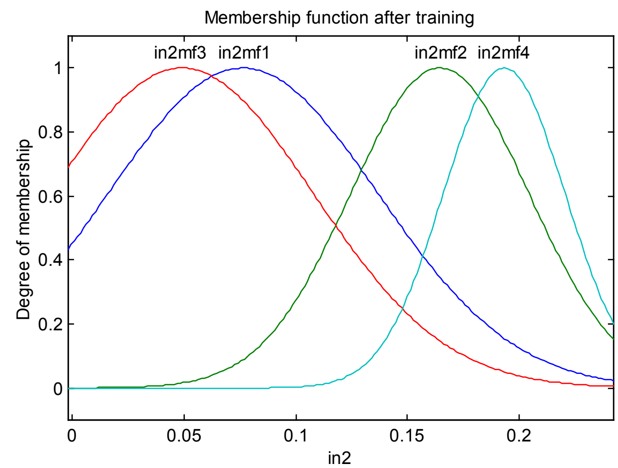


Fig. 5 Membership functions for Input1 (a) Before training; (b) After training

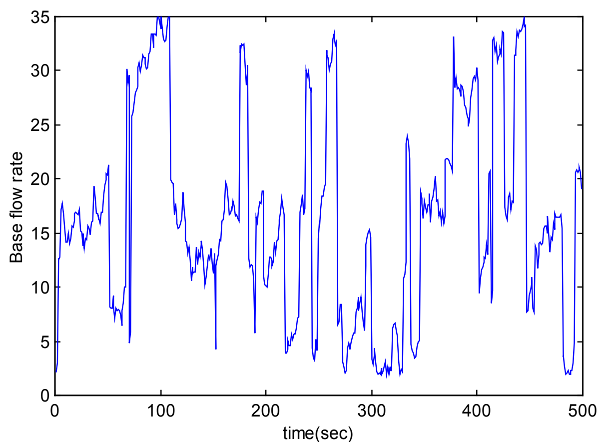


(a)

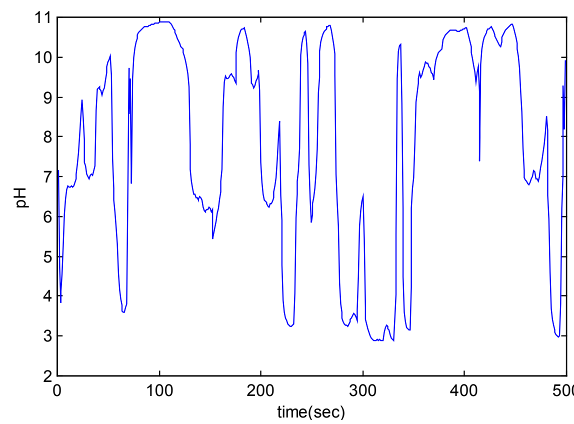


(b)

Fig.6 Membership functions for Input2 (a) Before training; (b)After training



(a)



(b)

Fig.7. Identification data (a) Input : Base flow rate; (b) Output : pH in tank

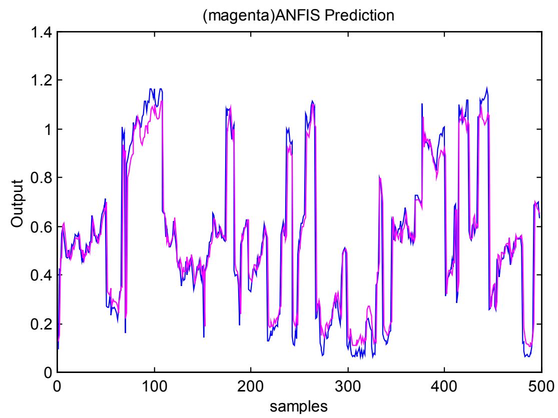


Fig. 10 (a)

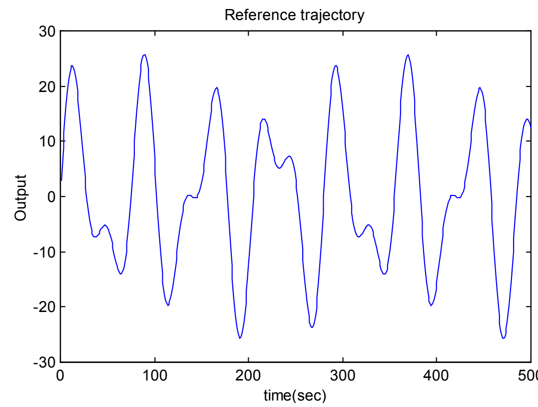


Fig. 10 (c)

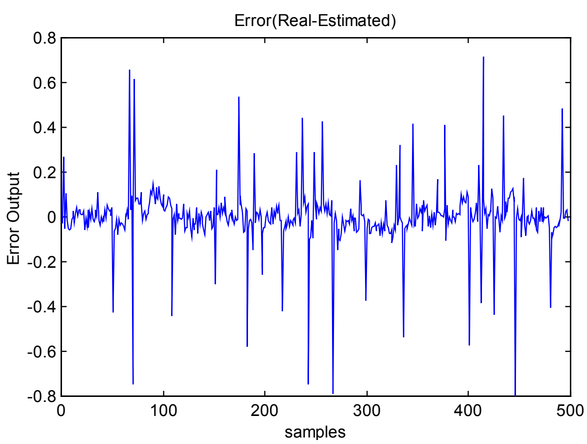


Fig. 10 (b)

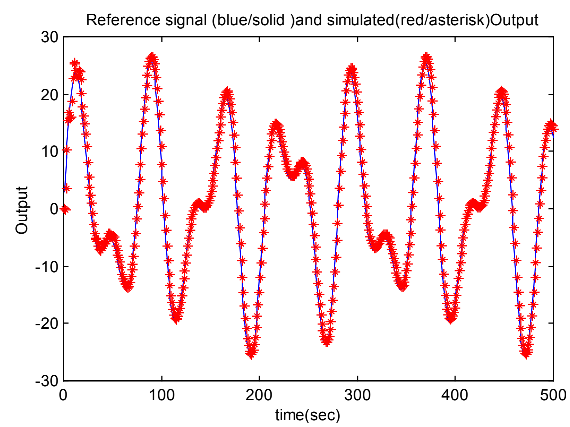


Fig. 10 (d)

Fig.10 (a) Predicted values of neurofuzzy model compared against real values

(b) Difference between the real and estimated values

(c) Reference trajectory

(d) Plant output against reference signal