Neuro-Fuzzy Scheduler for the Control of Real Time Spherical Tank Process

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Abstract- *PID controller is the simplest and best suited controller in process industries to maintain the process at the desired set value. But the linear controller needs adaptation mechanism to cope up with non-linear dynamics of the process. The aim of the proposed work is the real time implementation of the neuro-fuzzy scheduler to contribute the conventional PI control in the entire span of spherical tank process. Neuro-fuzzy integrates the parallel computation and learning abilities of neural network with the human like knowledge representation and explanation abilities of a fuzzy system. The best performance enhancement has been seen in neuro-fuzzy scheduled PI controller than conventional fuzzy scheduled PI control. The real time implementation is done in the laboratory spherical tank setup in MATLAB-SIMULINK environment using V-MAT interface card.*

Keywords — *Neuro fuzzy, scheduler, spherical tank*

I. INTRODUCTION

A Proportional-Integral-Derivative PID controller is a widely used feedback controller in industrial control systems. A PID controller calculates a value called "error" as the difference between a measured process variable and a desired set-point. The controller attempts to minimize the error in outputs by adjusting the process control inputs. The PID values can be interpreted in terms of time as P depends on the present error, I on the accumulation of past errors, and D is a prediction of future errors, based on current rate of change. The weighted sum of these three actions is used to maintain the process variable in the system. By tuning these three parameters in the PID control algorithm, the controller can provide control action designed for specific process requirements. The controller parameters are chosen through a certain optimal method. Since the chosen parameters are fixed, the conventional PID controller cannot always provide satisfying performances and optimal control of the system or stability of the system is not guaranteed.

The simplest solution to this problem is found to be gain scheduling or parameter scheduling. The suitable parameter set is selected depending on a continuous measurable variable that describes the state of the process, typically the control variable itself. If the physical effect, causing the non linearity is known, the corresponding measurement variable should be used for the gain scheduling. The term "parameter scheduling" makes it clear that the "timetable" for adjusting the parameters is specified in advance.

Control of variable area tanks is a challenging cum necessary task in process industries as the variable area contributes the major part of the non - linearity component. Conventional PID controller with fixed PID parameters will not meet out the control demands of such processes. Spherical tank is one such process, needs fixed PI controller parameters to be altered, even for a slight change in operating point of the process. Hence a scheduler is proposed to adjust K_C and T_I values of the PI controller with respect to changes in the operating level ' h' of the tank.

Fuzzy logic is used to convert heuristic control rules stated by a human operator into an automatic control strategy. Lin and Lee [1] proposed a general neural-network model for fuzzy logic control and decision systems. Their connectionist model combined the idea of fuzzy logic controller and neural network structure and learning abilities into an integrated neural-network based fuzzy logic control and decision system called Adaptive Neural Fuzzy Inference System (ANFIS). The proposed work is an attempt to incorporate ANFIS based scheduler to adjust the K_C and T_I values of feedback PI controller in maintaining the desired level of spherical tank process.

In this paper, we proposed neural fuzzy scheduler using subtractive/fcm clustering for control of real time spherical tank process. The remainder of this paper is organized as follows: Section 2 describes the components of the neuro fuzzy system. Section 3 details spherical tank process and modelling procedure. Section 4 introduces the design and implementation of the Neuro fuzzy scheduler to the chosen spherical tank process. Section 5 discusses the results in detail and Section 6 concludes this paper.

II. COMPONENTS OF ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

A specific approach to Neuro fuzzy development is the Adaptive Neuro fuzzy Inference System (ANFIS), which has shown significant results in modelling nonlinear functions [2]. This provides an optimization scheme to find the parameters in the fuzzy system that best fits the data.

A. *Clustering*

Clustering involves the task of dividing data points into homogeneous classes or clusters so that items in the same class are as similar as possible and items in different classes are as dissimilar as possible. Conventional clustering can only discriminate whether an object belongs to a cluster or not. But, such a partition is insufficient to represent many real situations. In fuzzy clustering, the data points can belong to more than one cluster, and associated with each of the points are membership grades, which indicate the degree to which the data points belong to the different clusters. In this contribution, both Fuzzy C-means Clustering and Fuzzy clustering subtractive are presented.

1) Subtractive Fuzzy Clustering:

The subtractive clustering method assumes each data point is a potential cluster center and calculates a measure of the likelihood that each data point would define the cluster center, based on the density of surrounding data points, n Consider m dimensions n data point ($x_1,x_2, \ldots, x_n$) and each data point is the potential cluster center, the density function D_i of data point at x_i is given by

$$D_i = \sum_{i=1}^{n} e\left(\frac{\|x_i - x_j\|^2}{\left(\frac{r_a}{2}\right)^2}\right)$$

Where r_a is a positive number. The data point with the highest potential is surrounded by more data points. A radius defines a neighbour area, then the data points, which exceed r_a, have no influence on the density of data points. After calculating the density function of each data point is possible to select the data point with the highest potential and find the first cluster center. Assuming that x_{c1} is selected and D_{c1} is its density, the density of each data point can be amended by

$$D_i = D_i - D_{c1} e\left(-\frac{\|x_i - x_{c1}\|^2}{\left(\frac{r_b}{2}\right)^2}\right)$$

The density function of data point which is close to the first cluster center is reduced, so these data points cannot become the next cluster center. r_b defines a neighbor area where the density function of data points is reduced. Usually constant $rb>ra$. In order to avoid the overlapping of cluster center near to other(s) is given by

$$r_b = 1.5 r_a$$

Once amending the density function of data points is possible to find the next cluster center. Then repeat this process until find all cluster center. The subtractive clustering is used to determine the number of clusters of the data being proposed, and then generates a fuzzy model [3].

2) Fuzzy C-Means Clustering:

Fuzzy C-means (FCM) is a method of clustering, which permits one point of data to belong to more than one cluster [4]. FCM is an iterative optimization algorithm that minimizes the cost function given by equation.

$$J = \sum_{k=1}^{n} \sum_{i=1}^{c} \mu_{ik}^{m} \|x_k - v_i\|^2$$

where n is the number of data points, c is the number of clusters, x_k is the kth data point, v_i is the i-th cluster center μ_{ik} is the degree of membership of the kth data in the ith cluster, and m is a constant greater than 1 (typically m=2). The degree of membership μ_{ik} is defined by equation.

$$\mu_{ik} = \frac{1}{\sum_{j=1}^{c}\left(\frac{\|x_k - v_i\|}{x_k - v_j}\right)^{2/(m-1)}}$$

Starting with a desired number of cluster c and an initial guess for each cluster center v_i, i = 1,2,3… c, FCM will converge to a solution for vi that represents either a local minimum or a saddle point cost function [5]. The FCM method employs fuzzy partitioning such that each point can belong to several clusters with membership values between 0 and 1. FCM include predefined parameters such as the weighting exponent m and the number of cluster 'c' [6].

B. Training

The most common inference system used in ANFIS is a first order Sugeno-type FIS which is in the form of relation. During the training procedure, rule parameters including antecedent parameters and consequent parameters will be tuned to present more accurate outputs with the minimum error. An ANFIS learns these parameters and tunes membership functions. ANFIS has a similar structure to a multilayer feed forward neural network, but the links in an ANFIS only indicate the flow direction of signals between nodes and no weights is associated with the links. The architecture of ANFIS is shown in Fig.1, and the neuron function in each layer is described below.

Assume that the fuzzy inference system has two inputs x and y and one output z.

- A first-order Sugeno fuzzy model has rules as the following:

Rule1: If x is A1 and y is B1, then $f_1 = p_1x + q_1y + r_1$
Rule2: If x is A2 and y is B2, then $f_2 = p_2x + q_2y + r_2$

Layer 1

Ol,i is the output of the ith node of the layer l.

Every node 'i' in this layer is an adaptive node with a node function

$O_{1,i} = \mu_{Ai}(x)$ for i = 1, 2, or
$O_{1,i} = \mu_{Bi-2}(x)$ for i = 3, 4

x (or y) is the input node i and A_i (or B_{i-2}) is a linguistic label associated with this node

Therefore $O_{1,i}$ is the membership grade of a fuzzy set (A1,A2,B1,B2).

Typical membership function is shown in equation (3)

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

a_i, b_i, c_i is the parameter set and the parameters are referred to as premise parameters.

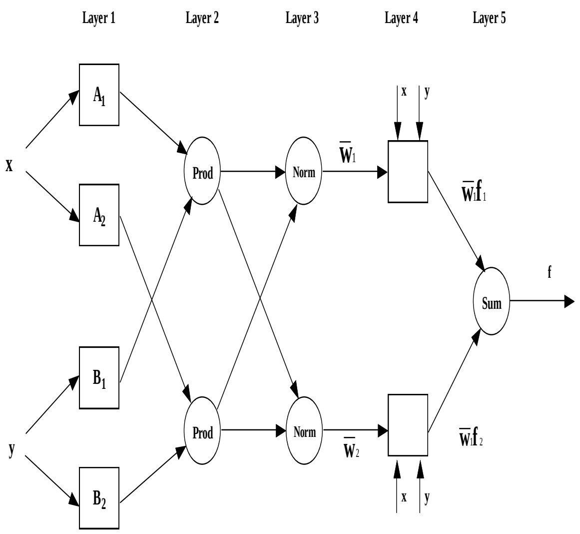

Fig. 1 Architecture of ANFIS

Layer 2:

Every node in this layer is a fixed node labelled Prod. The output is the product of all the incoming signals as in equation (4).

$O_{2,i} = wi = \mu_{Ai}(x) * \mu_{Bi}(y)$, i = 1, 2

Each node represents the fire strength of the rule Any other T-norm operator that perform the AND operator can be used.

Layer 3:

Every node in this layer is a fixed node labelled Norm.

The i^{th} node calculates the ratio of the i^{th} rule's firing strength to the sum of all rule's firing strengths as given in equation.

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2}, i = 1,2$$

Outputs are called normalized firing strengths.

Layer 4:

Every node i in this layer is an adaptive node with a node function mentioned in equation..

$$O_{4,1} = \bar{w}_i f_i = \bar{w}_i (p_x + q_{iy} + r_i)$$

w_i is the normalized firing strength from layer 3.

$\{p_i, q_i, r_i\}$ is the parameter set of this node.

These are referred to as **consequent parameters**.

Layer 5:

The single node in this layer is a fixed node labelled sum, which computes the overall output as the summation of all incoming signals given by equation.

$$\text{Overall output} = O_{5,1} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

The training process changed the parameters of the initial membership functions to optimize their representation of the input and output mappings, thereby changing the shapes of the membership functions.

The basic learning rule of adaptive network is back-propagation algorithm where the model parameters are updated by a gradient descent optimization technique. However, due to the slowness and tendency to become trapped in local minima its application, gradient descent optimization technique, is limited. A hybrid learning algorithm, on the other hand is an enhanced version of the back propagation algorithm [7]. It is applied to adapt the premise and consequent parameters to optimize the network [8]. The hybrid learning rule combines the back-propagation gradient descent method and the least squares estimate (LSE) to update the parameters in the adaptive network. Each epoch of the hybrid learning procedure is composed of a forward pass and a backward pass. The forward pass of the learning algorithm stop at nodes at layer 5 and the consequent parameters are identified by least squares method. After identifying the consequent parameters, the functional signals keep going forward until the error measure is calculated. In the backward pass, the error rate, i.e., the derivative of the error measure with respect to each node output propagates backward from the output end toward the input end, and the premise parameters are updated by the gradient descent method. Heuristic rules are used to guarantee fast convergence. The details of the hybrid rule are given by [9]. The activities in each pass are summarized in Table 1 and flow diagram of ANFIS computations are shown in Fig.2.

Table 1 Summary of Hybrid Learning Process in ANFIS

	Forward pass	Backward pass
Function signals	Node output	Error rates
Premise parameters	Fixed	Gradient
Consequent parameters	Least square estimate	Fixed

C. Model Validation

After running evalfis function which produces output of the ANFIS model for input data set, need to calculate root mean squared error (RMSE) between the net output and the experimental data set of production rate. This statistical criterion is defined as:

Where $xexp$ is the target value, $xsim$ is the output value and n is the number of the experimental data.

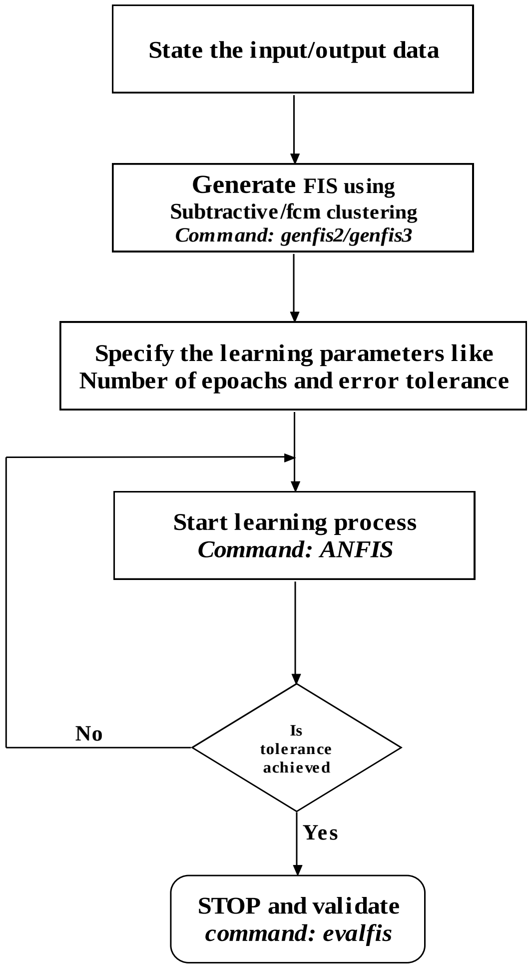

Fig.2 Basic Flow diagram of computations in ANFIS

III. SPHERICAL TANK PROCESS

A real time spherical tank process is utilized to compare the results of various Fuzzy logic based controllers. The experimental setup of spherical tank [10] with detailed specifications [Refer Table.2] is shown in Fig.3.

Fig. 3 Experimental setup for level control of spherical tank process

Table 2 Technical specifications of experimental setup

Part Name	Details
Spherical tank	Material : Stainless Steel Diameter : 50 cm Volume : 102 litres
Storage tank	Material : Stainless Steel Volume : 48 litres
Differential pressure transmitter	Type : Capacitance Range : 2.5-250 mbar Span limit : 0.65-65 kpscal Output : 4-20 mA Make : ABB
Pump	Centrifugal : 0.5 HP
Control valve	Size : 1/4" Air to open Input : 3-15 psi
Rotameter	Range : 0 - 1000 lph
Air regulator I/P converter	Size : 1/4" BSP Range : 0-2.2 bar Input : 4-20 mA Output : 0.2 - 1 bar
Pressure gauge	Range(G_1) : 0-150 psi Range(G_2) : 0-30 psi

A. Black box modelling

The open loop parameters like process gain k, process time constant τ and time delay θ are determined from the response (level) of the process for a sudden step change in flow [11]. The open loop model around 10% operating level is shown in Fig.4. Using the parameters obtained from the open loop response of the process, the PI controller parameters like controller gain K_c and intergral time T_I are calculated [12]. Fig.5 states the controller parameter values against % level variation of the spherical tank.

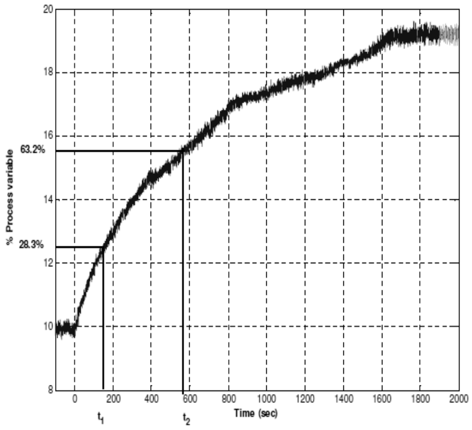

Fig. 4 Open loop response of spherical tank process around 10% operating level

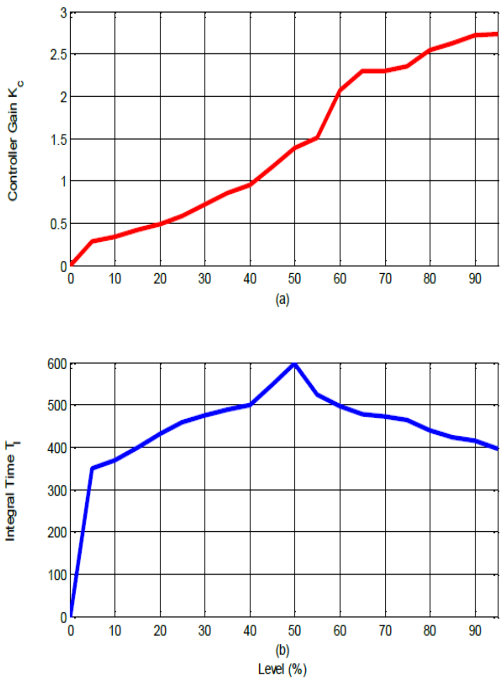

Fig. 5 Level Vs Controller Parameter Variation

IV. ANFIS SCHEDULER

The block diagram of level control in spherical tank process using ANFIS is shown in Fig.6. The adaptive scheduling variable is the height of the liquid in the tank, a measurable parameter which affects the non-linearity of the spherical tank. The relationship between the scheduling variable and the proportional, integral gain of the controller has been found. Based on the relationship, ANFIS is trained. Based on the current level, PI controller variables, namely K_c & T_I are updated at each and every sampling instant as per the control stated in equation (7).

$$u(k) = K_c(h)\left[h(k) - h(k-1) + \frac{T}{T_i(h)}e(k)\right] + u(k-1)$$

A. Rules extraction and Optimization

For the construction of Fuzzy Inference System (FIS) to determine the PI controller parameters, data points $\{x_1, x_2, \ldots, x_n\}$ are collected in the form of vector of h, K_c and T_I at definite step size. Then subtractive clustering or fuzzy c means clustering is applied to group the equivalent and that in turn reduces the number of rules. A hybrid learning algorithm which combines least square estimation and back propagation gradient descent method is used to modify the membership parameters of the clusters obtained by subtractive/fcm clustering to minimize the output error measure. The training process stops whenever the maximum epoch number is reached or the training error goal is achieved.

V. Results and Discussion

The proposed scheduler using subtractive/fcm clustering has been implemented on real time spherical tank process shown in Fig 3. Setpoint tracking and load rejection have been tested with the proposed schedulers in a wide operating range of the process. The results have been compared with conventional fuzzy scheduler. Load rejection has been tested by opening the solenoid valve of the spherical tank for 30s around 20,000s and 40,000s in 40% and 50% level of the tank respectively. The ANFIS scheduler utilizing subtractive clustering shows better tracking and rejection, when compared with schedulers based on ANFIS-fcm clustering and conventional fuzzy. The performance indices are given in Table.3. The ANFIS scheduler (subtractive clustering) gives less settling time, rise time and Integral square error (ISE) value due to optimized rule set.

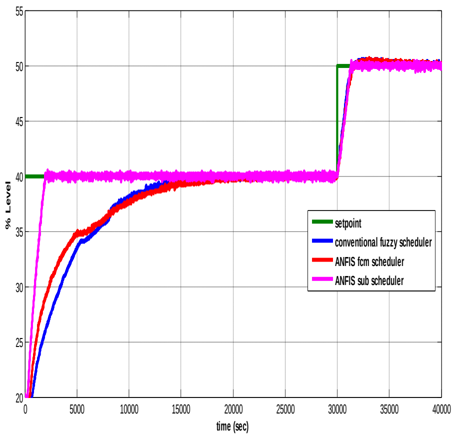

Fig.7 Servo response of spherical tank process

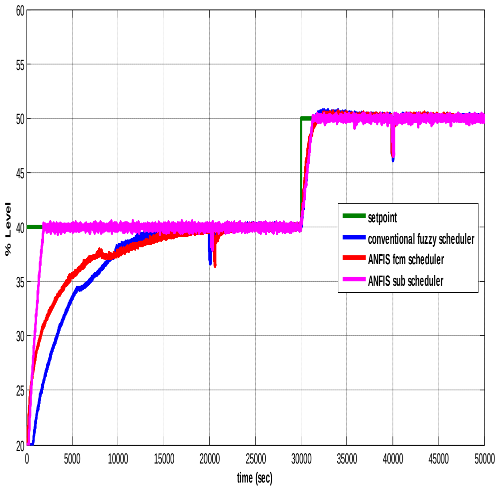

Fig.8 Regulatory response of spherical tank process

Table 3 Performance Indices

Controller type	Rise time (s)	Settling time (s)	ISE	
			Servo	Regulatory
Conventional Fuzzy scheduler	5500	14200	4.3820E+04	4.3697E+04
ANFIS fcm scheduler	4300	13900	3.2252E+04	3.3050E+04
ANFIS sub scheduler	1500	1900	1.3644E+04	1.2893E+04

VI. Conclusions

The presence of scheduler in PI control helps to adapt with inherent non-linear characteristics of spherical tank process due to its shape. Neuro-fuzzy scheduler outperforms conventional fuzzy scheduler in real time control of spherical tank process with less settling time and ISE values, when subjected to servo and servo-regulatory operations. The achievement is because, neural and fuzzy fields contribute mutually towards the disadvantages of each other.

References

[1] C.T. Lin and C.S.G. Lee, "Neural-Network-based Fuzzy Logic Control and Decision System", IEEE Transactions on Computers, Vol. 40(12), pp. 1320-1336, 1993.

[2] Zahedi, "Prediction of Hydrate Formation Temperature by Both Statistical Models and Artificial Neural Network Approaches", Vol 50(8), pp. 2052-2059, 2009.

[3] Ron Ya-Jun, Dou Chun-Xia, Yuan Shi-wen, "A Design of Fuzzy Neural Network Forecast Controller on Superheat Temperature [J]", (Yanshan University, Qinhuangdao 066004, China)

[4] James c. Bezdek, Chris Coray, Robert Gunderson and James Watson, "Detection and Characterization of Cluster Substructure I. Linear Structure: Fuzzy c-Lines", Journal on Applied Mathematics, Vol 40(2), pp. 339-357, 1981.

[5] Z.Y. Wangi , C. Sahay, "Agile monitoring system for turning of difficult – to - cut materials", Computer and Industrial Engineering, 18th International Conference on Computer and Industrial Engineering., Vol. 31(3-4), pp. 537-948, 1996.

[6] Ihsan Erozan, Ozden Ustun, Orhan Torkul, "An Improved Fuzzy C-Means Algorithm for Cell Formation Problems with Alternative Routes", International Journal of Fuzzy System Applications, Vol. 4(4), pp. 15-30, 2015.

[7] J.R. Yang, "ANFIS: Adaptive-Network-Based Fuzzy Inference System", IEEE Transactions on Systems, Man, and Cybernetic, Vol. 23(3), pp. 665-685, 1993.

[8] S.R. Khuntia, K.B. Mohanty, S. Panda, C. Ordeal, "A Comparative Study of P-I, I-P, Fuzzy and Neuro-Fuzzy Controllers for Speed Control of DC Motor Drive", World Academy of Science, Engineering & Technology, Vol. 24(44), pp. 525, 2010.

[9] J.S.R. Jang, C.T. Sun, and E. Mizutani, "Neuro-fuzzy and soft computing; a computational approach to learning and machine intelligence", IEEE Transactions on Automatic Control, Vol. 42(10), 1997.

[10] Boo. Poonguzhali and R. Vinodha, "Implementation of Anti-Reset Windup Scheme in PI Controller for Spherical Tank Process", International Journal of Modelling and Simulation, Vol. 34(4), pp. 1-15, 2014.

[11] K.R. Sundaresan and R.R. Krishnaswamy, "Estimation of Time Delay, Time Constant Parameters in Time, Frequency and Laplace Domains", Canadian Journal of Chemical Engineering, Vol. 56(2), pp. 257-262, 1978.

[12] G. Ziegler and N.B. Nichols, "Optimum Settings for Automatic Controllers", Transcation ASME, Vol. 64(11), pp. 759-768, 1942.