Improve the Performance of different order plants by using Neuro Fuzzy Based PIDController

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Abstract- **During the past several years, fuzzy control has emerged as one of the most active and fruitful areas for research in the applications of the fuzzy set theory, especially in the field of the industrial processes, which do not lend themselves to control by conventional methods because of a lack of quantitative data regarding the input output relationsi.e., accurate mathematical models. The fuzzy logic controller based on wavelet neural network provides a means of converting a linguistic control strategybased on expert knowledge into an automatic strategy. In this paper, Self Tuning Fuzzy PID controller is developed to improve the performance ofthe plants having 2nd order, 3rd order and 5th order system as a plant transfer function. Through A simulation in MATLAB by selecting appropriate fuzzy rules are designed to tune the parameters.**

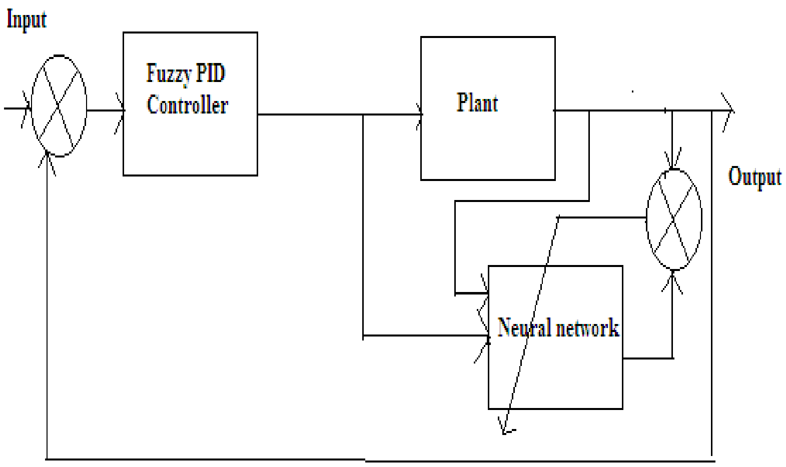
Keywords: k_p; k_i; k_d;*WNN.*

I. INTRODUCTION

Our plan is to use Wavelet Based Neural Network to identify the plant because now days, wavelet becomes most powerful tool for approximation and identification of any signal. For the identification of the plants we will use Wavelet as activation function and off line method.

The Wavelet Neural Network Function consists of a set of rules. Each rule corresponding to a sub-WNN consists of single scaling wavelets. Through the efficient bases selection, the dimension of approximated function does not cause the bottleneck for constructing WNF. By implementing Wavelet based Neural Network using MATLAB M-file command get best approximation of simulated results of Fuzzy PID output.

Figure1 shows the structure of control system plant which is having fuzzy-PID Controller and Neural Network for controlling the plants and identification of plants.



LITERATURE REVIEW

T. Yucelen, O.Kaymakci and S. Kurtulan at.(1) modified PID controller and presented as a dynamic system controller and necessary steps are explained to express the presented PID algorithm is more functional then classical PID controller algorithm. Here Ziegler-Nichols method is clarified to designate self-tuning. An adaptive PI-D controller algorithm is used by self-tuning methods. In this PI-D, proportional and integral parameter are used in control of the adaptive algorithm and derivative parameter take constant which found in Ziegler-Nichols based self-tuning method.

CONVENTIONAL CONTROL SCHEMES

A PID controller is a generic control loop feedback mechanism. A PID controller calculates an "error" value which is the difference between a measured process variable and a desired set point or a desired value. The controller attemptsto minimize the error by making adjustment of the process control inputs. The PID controller can be realizedin two forms

- Series PID
- Parallel PID

PROPOSED RESEARCH WORK

Network for controlling the plants and identification of plants. In this proposed work we shall use off line method to identify the plant by using Wavelet based Neural Network.

There are different types of activation functions are used in neural network such as step, ramp, sigmoid etc. However the most commonly used activation functions are tan-sigmoid, log-sigmoid and linear function. But in this work we will use wavelet as activation function.

1. Manual tuning
2. Ziegler-Nichols method
3. PID tuning software

ADAPTIVE PID CONTROLLER

As shown in figure2 is a block diagram of a fuzzy system, which includes a fuzzification block, a knowledge base, a fuzzy inference engine or decision making logic and a defuzzification block. The functions of the blocks and working principles of the fuzzy system are explained here, by briefly summarizing the basic concepts of fuzzy sets and fuzzy logic.

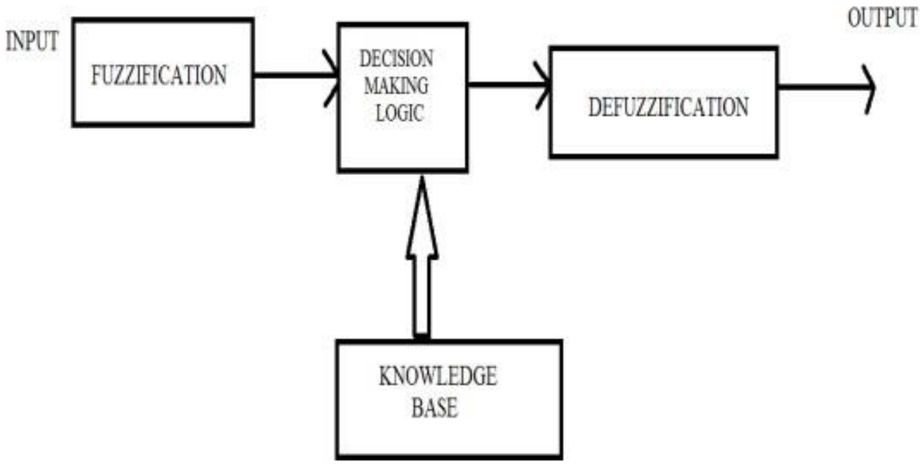


Figure2. Structure of Fuzzy system

A. WAVELET

We can find some orthogonal "wavelets" which are infinitely continuously differentiable [2]. The support of this wavelet is □ □ □ X □ □,Daubechies presented wavelet bases which iscompactly supported but not infinitely supported. Significant points of these wavelets are

- Calculation of wavelet coefficients arerestricted to integration within a closed interval andthus very simple,
- The number of wavelet bases for onescaling parameter is definite, when the range of the variable is definite; and
- We don"t need to consider the error based on cutting out of the wavelet expansion.

All the wavelet bases are allocated over thenormalized range [0,1] on the variable space. Over-complete number of wavelet bases are adopted
here, i.e., the no. of bases should be 1,2,3,□,and
M for scaling factora= a □ 0,a □ 1,a □ 2,□,a □ M,respectively; while that in the orthogonal system should be1,2,4,8,16,□,2^a
respectively.(a+1)□ $_{a,0}$,□ $_{a,1}$,□,□ $_{a,a}$ are assignedfor one scaling parameter a and □ $_{0,0}$ is assigned to be a constant. The shape of the bases a is not equal to 0 is smooth and finitely supported width is as follows:

(A) (B) (C)

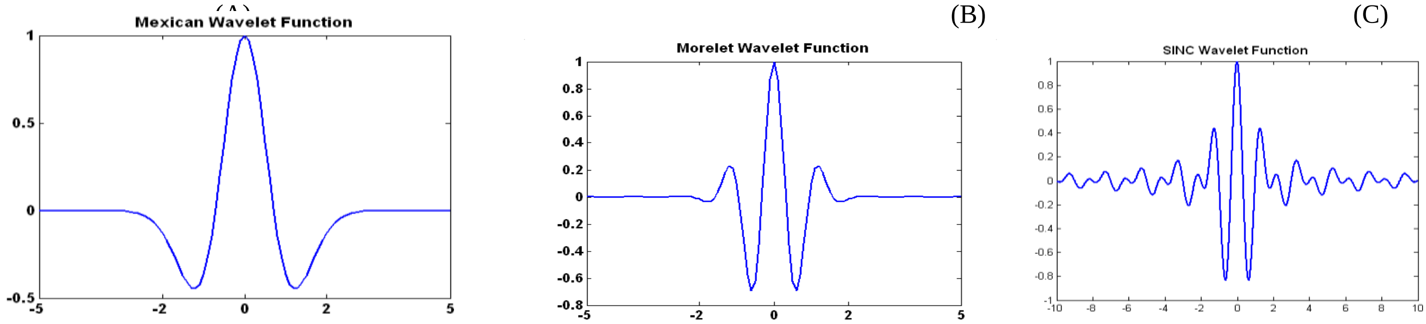


Figure4 Mexican (a), morlet (b) sinc & (c) wavelet function

In the figure4 non-orthogonal and orthogonal wavelets are shown. The mathematical expressions of these wavelet functions with their support width are given below:

- Mexican hat wavelet $\psi(x) = (1 - 2x^2)exp(-x^2)$ (1)
- Morlet wavelet

$$\psi(x) = exp(-x^2)cos(5x) \quad (2)$$

Sinc (Shannon) waveletAA

$$\psi(x) = \varphi(2x) - \varphi(x) \quad (3)$$

Scaling function

$$\psi(x) = sin(\pi x)/(\pi x) \quad (4)$$

Where 'b'is the shifing parameter ,

The maximum value of which is equal to the corresponding scaling parameter. But it does not mean that the value of the maximum shifting is always equal to the value of the scaling parameter; it may be any and depends on the signal that‟s analysis is to be carried out.

B. Wavelet Neuron Models:

A basic McCulloch and Pits neuron model is characterized by weighted sum (linear sum) of inputs and a sigmoid activation function. Two wavelet neuron models are proposed by T.Yamakawa (2)by modifying the basic neuron model. We are using wavelet activation function neuron model in this work, which is shown in the given figure 5.

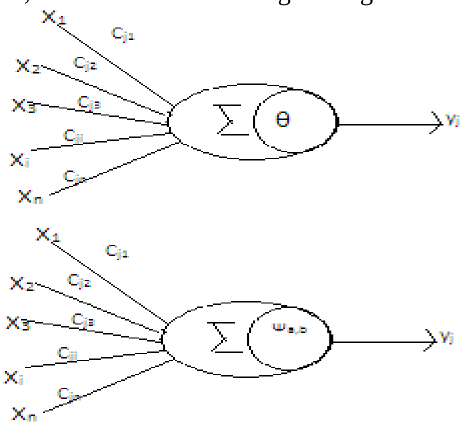


Figure5.Simple neural network models wavelet activation function neuron models

B. Wavelet Neural Network Architecture:

Takeshi Yamakawa, Eiji Uchino and Takeshi Samatsu have proposed four wavelet neural network architecture WNN1, WNN2, WNN3 and WNN4. We have used WNN3, in this paper the architecture of the WNN3 is shown in figure (6). The output equation of the WNN3 is:

(6) $$\hat{Y} = \sum_{a=1}^{M} \sum_{b=0}^{a} W_{a,b} \cdot \psi_{a,b}\left(\sum_{i=1}^{n} C_{a,b}^{i} \cdot X_i\right)$$

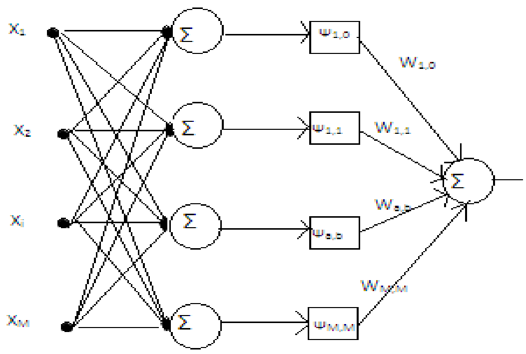


Figure6. Wavelet Neural Network

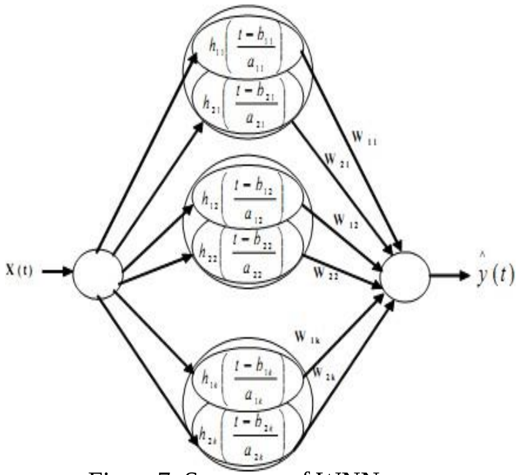


Figure7. Structure of WNN

C. Learning Algorithm:

The learning rules correlate the input and output values of the nodes by adjusting the weights in a neural network. The steepest descent algorithmrequires a selection of user defined parameters. In this work back propagation scheme is used. Expressions for the error gradients described below are for error function defined by theequation (7). All the computations are done in off- line mode. The error gradients for all the patterns are obtained by summing up and averaging the error gradients for the individual patterns.

$$j = \frac{1}{2p}\sum_{p=1}^{p}\left(\hat{Y} - y_p\right)^2 \qquad (7)$$

- *Gradient descent learning of parameters:* In the batch learning scheme employing P- data sets, change in any parameter is governed by the equation:

$$\Delta W(q) = \sum_{p=1}^{p}\Delta_p W(q) + \alpha_p . W(q-1) - \gamma . W(q)$$

and the parametric update equation are:

$$W(q+1) = W(q) + \Delta W(q)$$

(8)

(9)

Where 'q' is q *th* epoch, $\square_p$ is a momentum coefficient in the limits0 $\square$ $\square_p$ $\square$ 1(typically$\square_p$ =0.9), $\square$ is a decay factor *Parameter update formula*: We applythe gradient descent technique to modify the parameters $\square W_{a,b}$,ΔC
j a,b

S.No	Transfer function(Plant)
1.	$F(s) = \frac{1}{(s^2 + 2s + 4)}$
2.	$F(s) = \frac{(s+1)}{(s^3 + 2s^2 + 4s + 16)}$
3.	$F(s) = \frac{(s^3 + 4s^2 + 2s + 4)}{(s^5 + 4s^4 + 5s^3 + 3s^2 + 18s + 16)}$

Table 1. Transfer Function of plant

The parameter update formula for data set are as follows:

$$\Delta W_{a,b} = -\alpha.\frac{\partial J}{\partial W_{a,b}}$$

(10)

(11)

$$\Delta C^j_{a,b} = -\alpha.\frac{\partial j}{\Delta c^j_{a,b}}$$

Applying the chain rule to the above equations, we obtains

$$\Delta W_{a,b} = -\alpha.\frac{\partial J}{\partial \hat{Y}}\frac{\partial Y}{\partial W_{a,b}} \quad (12)$$

$$\Delta C^j_{a,b} = -\alpha.\frac{\partial J}{\partial \hat{Y}}\frac{\partial Y}{\partial C_{a,b}} \quad (13)$$

From the equations 6 and 7, we obtain;

$$\frac{\partial J}{\partial \hat{Y}} = \frac{1}{p}\left(y_p - \hat{Y}\right) \quad (14)$$

$$\frac{\partial \hat{Y}}{\partial W_{a,b}} = \psi_{a,b}\left(\sum_{j=1}^{p} C^j_{a,b}.X_j\right) \quad (15)$$

$$\frac{\partial \hat{Y}}{\partial C^j_{a,b}} = \psi'_{a,b}\left(\sum_{j=1}^{p} C^j_{a,b}.X_j\right).X_j \quad (16)$$

$$W(q+1) = W(q) - \alpha.\frac{1}{p}\left(y_p - \hat{Y}\right).\psi_{a,b}\left(\sum_{j=1}^{p} C^j_{a,b}.X_j\right)$$

(17)

$$C(q+1) = C(q) - \alpha.\frac{1}{p}\left(y_p - \hat{Y}\right).X_j.\psi'_{a,b}\left(\sum_{j=1}^{p} C^j_{a,b}.X_j\right).X_j$$

(18)

By using equation 17 and 18, we learn theabove wavelet neural network.

II. RESULTS AND DISCUSSION

A. Introduction:

The results of the plant with using different type of controllers are shown here. The responses of the plant with several controllers such as PID, Fuzzy Logic Controller are being applied. In this section transfer function are used as a plant and find out the response of the plant i.e2^{nd} order, 3^{rd} order and 5^{th} order respectively by applying the step function as an input. In order to find out the response the following transfer function taken as a plant:

B. PID Controller:

The PID control method is used by adjusting the value of gain K_p, K_i, and K_d in order to get the best response of the system. SIMMULATION model are shown in figure8.

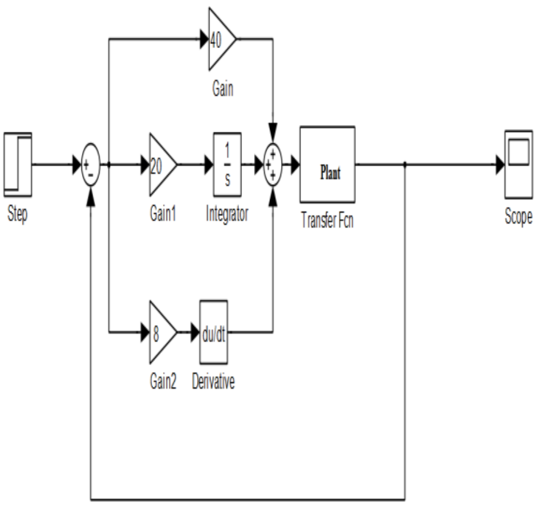
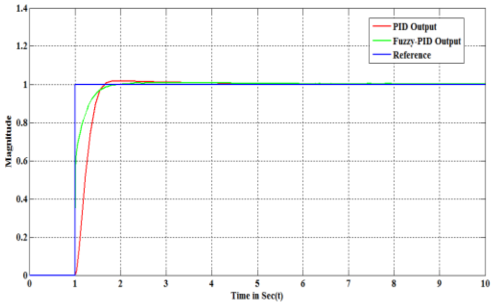
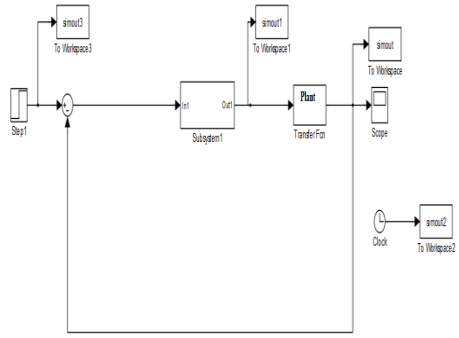


Figure8. Matlab/Simulation model of plant using PID Controller

C. FUZZY LOGIC CONTROL METHOD:

Fuzzy Logic Controller can receive two inputs (Error and derivative of Error) from the system. The output of the Fuzzy Logic Controller were tuned the PID Controller by adjusting the value of gain Kp, Ki, and Kd. Figure 6.3 shows the simulation of Fuzzy Logic Controller.





(b) Comparative result of 3rd order plant

Figure10(a) Simulink model of plant using Fuzzy LogicController

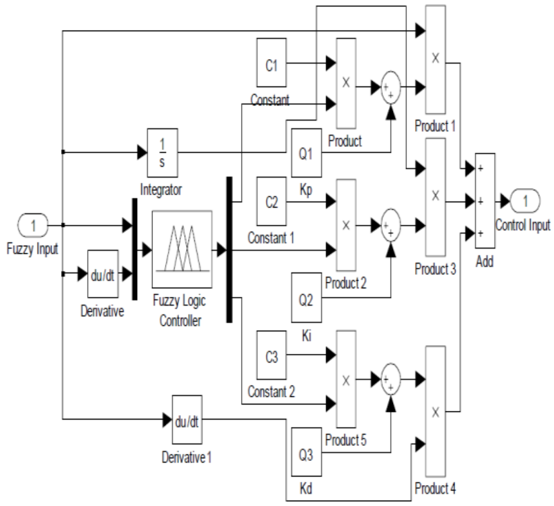


Figure10 (b) Simulink Block of Fuzzy PID regulator

Figure 12(a),(b),(c) shows the comparative results of Adaptive Fuzzy PID controller and PID Controller for different order plants.

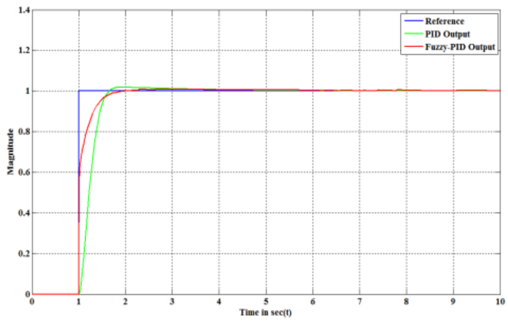
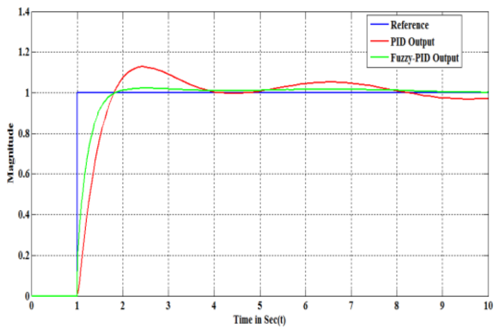


Figure12 (a) Comparative result of 2nd order plant



(c) Comparative result of 5th order plant

D. Neural Network Method:

In this section we have used Neural Network for the identification of the plants used in the previous sections. For the identification of the plants we have used Wavelet as activation function and off line process. The output of adaptive Fuzzy PID Controller and output of the plants as the input to the Wavelet based Neural Network. We have train the Network by using the Steepest Gradient

Descent learning. By implementing Wavelet based Neural Network into MATLAB M-file command, and the results of different order could be seen in figure 13(a),(b),(c).

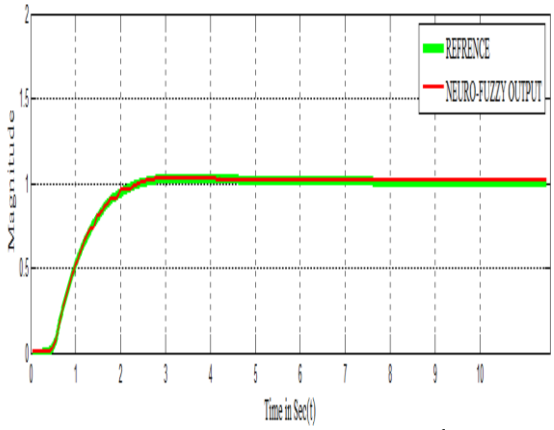
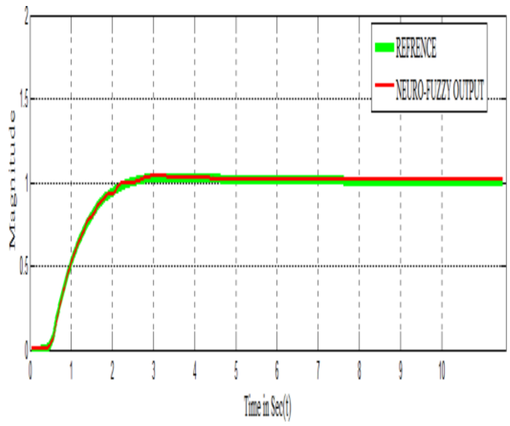
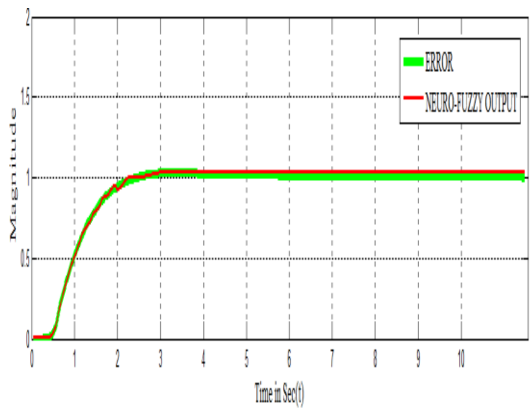


Figure13 (a).Neural Network Output of 2nd order plant



(b) Neural Network Output of 3rd order plant



(c) Neural Network Output of 5th order plant

Above results show that the Wavelet based Neural Network is the best identification for the different order.

III. CONCLUSIONS

Self-tuning fuzzy controller is applied to tune the value of K_p, K_i, and K_d of the PID controller. Through tests on the plant by using step input signals, the response of higher order plants are indicate the performance of the plant is improved and the results are satisfactory as compare to conventional PID controller. Neural Network used for the identification of the plant. Wavelet is used as an activation function In the Neural Network. Simulated results coming from plants show thatwavelet gives best approximation result in offline process. Hence wavelet networks may be used as a better tool for function learning.

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