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Controller Performance Assessment (CPA) of Intelligent Control for Non-linear System

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ABSTRACT

The objective of this paper is to design and undertake comparative analysis of classical and intelligent controllers for nonlinear system. These controllers are compared based on controller performance assessment in which the different parameters as overshoot, steady-state error, rise time, settling time, response of reference change and output variance are analyzed. To achieve these objectives, the water tank control problem as nonlinear system has been built in Simulink and implementations traditionally classical controller and advance intelligent controller as fuzzy logic and neural network are performed. In classical controller, the proposal-integral control law is used as control algorithm. Sugeno model is used for FL controller, while back propagation algorithm is used to train the NARMA-l2 neural network control. Three controllers are designed and their performances are compared.

Keywords: *Controller performance assessment (CPA), classical controller, fuzzy logic controller, NARMA-l2 neural controller, nonlinear system*

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INTRODUCTION

Traditionally, a mathematical model based control strategies have been applied to solve the control problem. Due to nonlinearity and uncertainty, the water level control problem is very complex. The conventional controllers are not convenient to solve the complexities for all operating regimes. The classical controller is very popular and successful for SISO system since the last decade. Fuzzy logic and neural network have become one of the most active and advanced areas of research in the intelligent control application. Now, here the advanced intelligent controller like NARMA-l2 neural network controller and fuzzy logic controller are designed for nonlinear system [1, 2, 14].

The controller performance analysis has been done using control performance assessment (CPA) method [11]. The CPA method is aimed to accomplish the performance assessment of a control system, running online, in real time [5]. It is based on measurement of the reference signal change; the output signal and the error signal in the form of parameters like peak overshoot, rise time, settling time, steady state error and variance in signals. This method is very useful for comparative analysis of various controllers for system user, manager, operator and control engineer. So, the method described in this paper is the comparative analysis of classical, fuzzy and NARMA-l2 neural controllers using CPA.

This paper is organized as follows. In section II, the non-linear system dynamics is discussed. In section III, classical controller has been discussed. In section IV, fuzzy logic controller for the non-linear system is described. In section V is described NARMA-l2 neural network controller. In section VI, the detailed performance assessment of the controller is given. In sections VII and VIII, are described related analysis, the result of experiment and conclusions.

SYSTEM CONFIGURATION

The dynamics of the nonlinear system is described by:

$$\frac{d}{dt}\text{Vol}=A\frac{dH}{dt}=bV-\alpha\sqrt{H}$$

where

Vol	Volume of water in the tank
A	Cross-sectional area of the tank
b	Constant related to the flow rate into the tank
V	Input voltage of pump drive
H	Height of tank water level

The system consists of the servo motor, a pump, and a level transmitter. Water enters the tank from the top and leaves through an orifice in its base. The rate at which water enters is proportional to the voltage, V, applied to the pump. The rate at which water leaves is proportional to the square root of the height of water in the tank. The equation describes the height of water, H, as a function of time, due to the difference between flow rates into and out of the tank.

CLASSICAL CONTROLLER

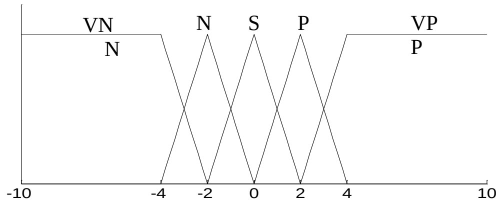
The PID controller based on classical control theory is the most commonly applied algorithms in the industry application [4]. The below algorithm is implemented on a non-linear plan.

$$u(t)=K_p*e(t)+K_i*\int e(t)dt+K_d*\frac{de(t)}{dt}$$

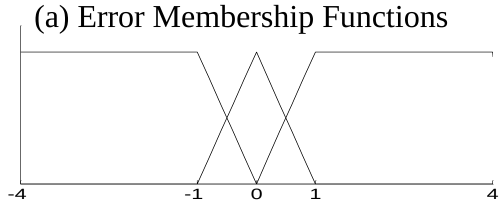
The control strategy is applied on the non-linear system and its performance is analyzed.

FUZZY LOGIC CONTROL

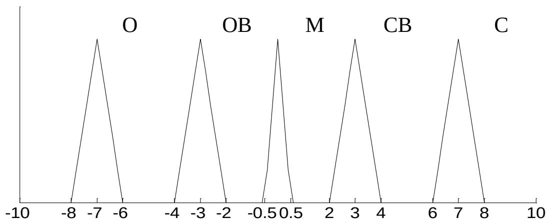
The fuzzy logic controller is designed using two inputs: error (e) and error derivative (ė). The error is calculated by taking the difference between the desired signal and the actual water height. The error derivative is calculated by subtracting a previous error from the current error [1].



(a) Error Membership Functions



(b) Error-Dot



(C) Output Membership Functions

1	If e is HN	Output voltage is O
2	If e is N and ė is NOT P	Output voltage is OM
3	If e is N and ė is P	Output voltage is M
4	If e is S and ė is N	Output voltage is OB
5	If e is S and ė is S	Output voltage is M
6	If e is S and ė is P	Output voltage is CB
7	If e is P and ė is N	Output voltage is M
8	If e is P and ė is NOT N	Output voltage is CB
9	If e is HP	Output voltage is C

(d) Rule base

Fig. 1 Membership Functions and Rule base.

The membership functions for error, error derivative and output voltage error are shown in Figure 1(a–c), respectively. The rule base is given in Figure 1(d). The output voltage of fuzzy logic controller is applied to the motor for water level control. The sugeno model is very popular especially for optimization and adaptive control applications. So, it is selected in this application. This controller is very efficient for dynamic nonlinear systems [2] [3].

NEURAL NETWORK CONTROL

The neural network controller [7] is created directly based on the neural network identifier. Its design is fully incorporated the learning strategy into the trained identifier. The weights of the neural network identifier are constantly verified against the actual plant output. This ensures that the weights allow the neural network identifier to properly predict actual plant output. The neural network identifier is used as means to back propagate the performance error to get the equivalent error at the output of the neural network controller. The accuracy of the plant model is critical in ensuring that the controller is accurate as well. The error between the plant output and the identifier output is also checked for the accuracy level of the identifier. This error is used to back propagate and adjusts the weights of the identifier to provide the most accurate representation of the plant. The neural network for controller is also designed as a three-layer neural network. It has a input layer, a hidden layer, and an output layer as their output values respectively [8]. The neuron numbers in the hidden layers can be chosen also depending on the practical training result.

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A. Identification of the NARMA-L2 Model

The identifier is designed using NARMA-l2 which is identified as the system to be

$$\hat{y}(k+d) = f\cdot[y(k),y(k-1),\ldots,y(k-n+1),u(k-1),\ldots,u(k-m+1)] + g\cdot[y(k),y(k-1),\ldots,y(k-n+1),u(k-1),\ldots,u(k-m+1)]\cdot u(k)$$

controlled. You train a neural network to represent the forward dynamics of the system. The first step is to choose a model structure to use. One standard model that is used to represent general discrete-time nonlinear systems is the nonlinear autoregressive-moving average (NARMA) model [14]. The controller used in this section is based on the NARMA-L2 approximate model (Figure 2).

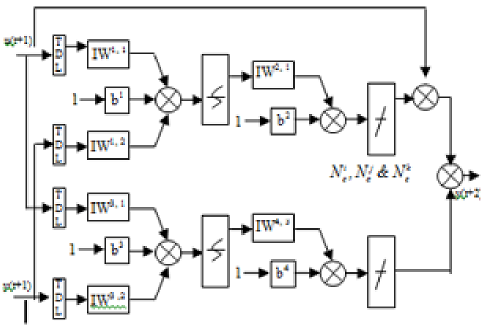


Fig. 2 NARMA Approximation for Identifier.

In training a neural network to learn a forward dynamic model of a plant, the back propagation error signal between the output and the hidden layer [9] is expressed as

$$\delta_k = T_k - N_k^i$$

where Tk is the target pattern and N^ik is the actual output of the identifier, and between the hidden and input layers, it is expressed as

$$\delta_j = f'(net_j)\sum_k \delta_k \cdot |\omega_{kj}$$

Here, $f'(net_j)$ is the derivative of the activation function $f(net_j)$ where

$$f(net_j) = \frac{1}{1+\exp(-net_j)}$$

The weights between the input and hidden layers are updated as

$$\Delta\omega_{ji}(t+1) = \eta\cdot\delta_j\cdot N_i^i + \alpha\cdot\Delta\omega_{ji}(t)$$

and the weights between the hidden and output layer are updated as

$$\Delta\omega_{kj}(t+1) = \eta\cdot\delta_k\cdot N_j^i + \alpha\cdot\Delta\omega_{kj}(t)$$

where and are the outputs of the input and hidden layers, respectively, η is the learning rate, and α is the momentum coefficients.

N_j^i N_j^i

B. NARMA-L2 Controller

Using the NARMA-L2 model [13], the controller can be obtained by:

$$u(k+1) = \frac{y_r(k+d) - f\cdot[y(k),y(k-1),\ldots,y(k-n+1),u(k-1),\ldots,u(k-m+1)]}{g\cdot[y(k),y(k-1),\ldots,y(k-n+1),u(k-1),\ldots,u(k-m+1)]\cdot u(k)}$$

The block diagram of the NARMA-L2 controller [16] is shown in Figure 3. This controller can be implemented with the previously identified NARMA-L2 plant model, as shown in the Figure 4.

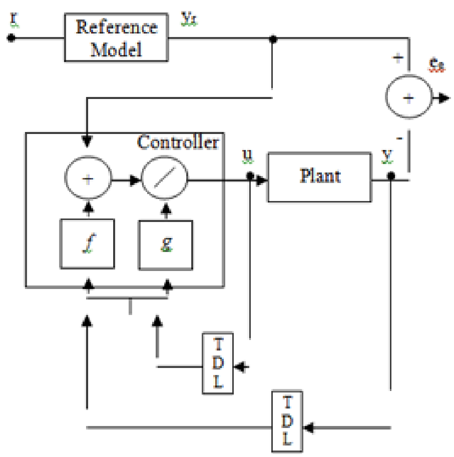
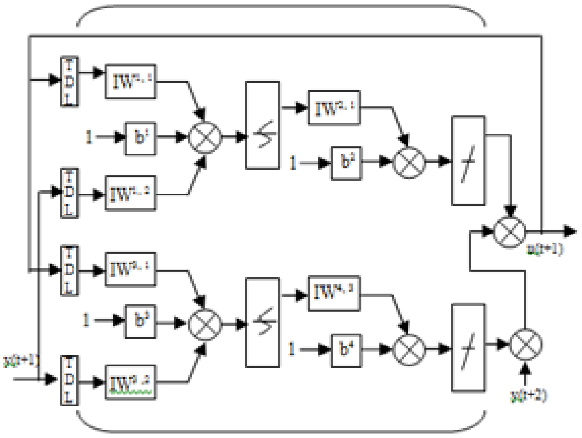


Fig. 3 NARMA-l2 Controller.

Neural Network Approximation of *g* ( )



Neural Network Approximation of f ( )

Fig. 4 NARMA-l2 Controller Implementation Using Neural Network.

The control strategy is applied on the non-linear system and its performance is analyzed.

CONTROLLER PERFORMANCE ASSESSMENT

In the past decades, control performance monitoring has become an active field of research with many potential applications in the industry. These techniques are used to indicate whether the controller performance meets the closed loop requirements [6].

The performance of the controller is characterized through the online measurements of parameters listed below.

A. Overshoot

$$\zeta_y(t) = \frac{y_{\max} - y_\infty}{y_\infty} \times 100$$

where $y_{\max}$ is amplitude maximum value at the output and y_∞ is the steady state value of the output [12].

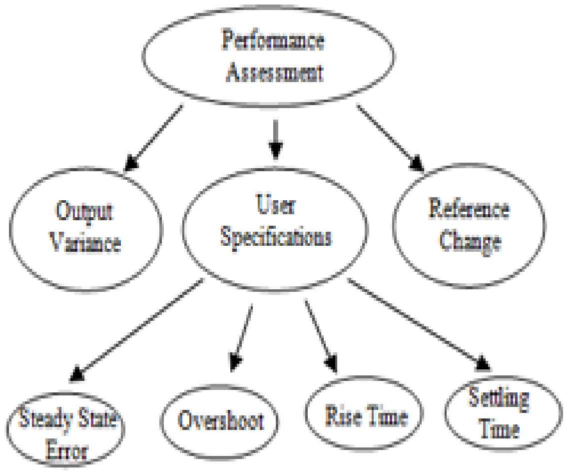


Fig. 5 Controller Performance Assessment Criteria.

B. Steady State Error

$$e_\infty(t) = \lim_{t \to \infty}(w(t) - y(t)) \cong 0$$

where *w(t)* is the desired output and *y(t)* is actual output [11].

C. Rise time

τ_r is the time required to reach the process output from 10% to 90% of *y(t).*

D. Settling Time

τ_y is the time required for a measured process output y(t) to first enter and then remain within a band Δy whose width is computed as ± 5% of the total change in *y(t).*

E. Reference Change

$$\prod_w = w(t) - w(t-1)$$

where *w(t)* is the present state and *w(t*−1*)* is the last state. By comparing the current set-point with the previous one, it will check the state of the reference signal whether it is increasing, decreasing or remaining as it was in the last state[15].

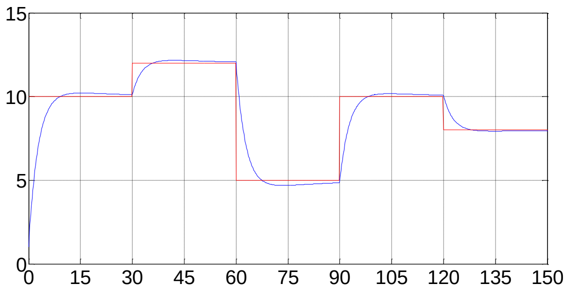
F. Variance

$$V_y(t) = \frac{\sum_{i=1}^{N}(y_i - y_\infty)^2}{N-1}$$

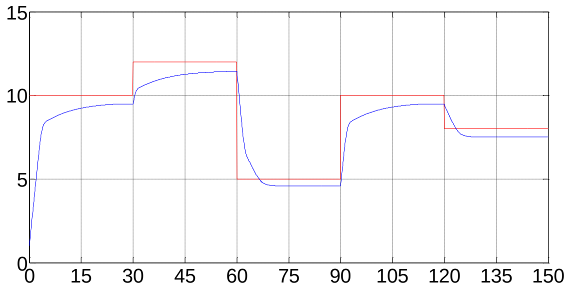
where the variance of sampled population of the output signal *y(t)* is mean squared deviation of the value y_i of *y(t)* from population mean [10] and *N* denotes the size of the sampled population of the output signal.

EXPERIMENTAL RESULTS

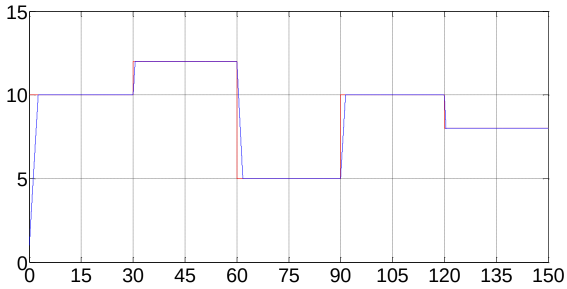
The three controllers are implemented on the plant model. The results with various operating regimes are given in Figure 6 (a) PID Controller, (b) Fuzzy Controller, and (c) NARMA-l2 Neural Network Controller.



(a) PID Controller.



(b) Fuzzy Controller.



(c) NARMA-l2 Neural Network Controller.

Fig.6 Different Controller Response.

Table I shows a summary of comparisons between the three control schemes based on the experimental results of performance parameters

Table I Experimental Result of Performance Parameters.

Controller	**PID**			**Fuzzy**			**NN**		
Desired Value	5	10	12	5	10	12	5	10	12
Overshoot	0	2.68	2.68	0	0	0	0.25	0.11	0.09
Steady State Error	0.04	0.11	0.11	0.35	0.08	0.01	0.04	0.09	0.11
Rise Time	6.05	5.04	5.04	8.2	6.04	12.6	0.89	2.04	2.51
Settling Time	11.1	24.4	24.4	12.5	16.7	17.2	1.09	2.50	3.07
Reference Change	-50	0	20	-50	0	20	-50	0	20
Variance	0.22	1.7	1.7	0.09	0.69	0.03	0.11	0.45	2.38

CONCLUSIONS

This paper proposed three control schemes for the water level control system. From the results of the experimental studies, the following summary can be obtained. For classical controller, performance is satisfactory but tuning of parameter is difficult. For the fuzzy control, in order to ensure the best performance, a number of factors and values need to be determined

online heuristically or by trial and error; for example, the membership functions. For neural network control, the learning parameters and prior well-training is essential for the success of the control. Once trained, the neural network does not require tuning. The controller performance assessment is evaluated based on overshoot, steady state error, rise time, settling time, variance of output signal, and reference change. From these observations of comparative analysis, it is clear that NARMA-l2 Neural Network Controller is a much better option out of these three control strategies. The real time implementation of these three control schemes on non-linear plant and its performance assessment remain in future scope.

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