COMPARATIVE ANALYSIS OF A MODEL-LESS CONTROLLER STRATEGY (FUZZY CONTROLLER) WITH A MODEL PREDICTIVE CONTROLLER

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ABSTRACT

This paper proposes a comparative study of a modeless controller design and a Model Predictive controller strategy (MPC) for a linear process regarding their performance in real time. The system is preferably taken as a level control process with a constant load and both the controllers are developed and implemented in LabVIEW software environment and interfaced to the process using an arduino Mega2560. The defuzzification method chosen for the Fuzzy controller is centre of area. The MPC controller is designed using the approximated first order model from a step response and is verified by finding resistance to the outflow. The controlling of the level is done using a feed pump as actuator. The performance criteria like integral absolute error (IAE), integral square error (ISE), rise time, peak time and percentage overshoot are evaluated for both the control strategies and compared.

KEYWORDS: *MPC, Fuzzy, IAE, ISE, rise time, peak time and percentage overshoot*.

I. INTRODUCTION

In industries as well as in domestic purposes level control is of an utmost necessity and many control strategies have been developed in this regard. The primary work of a controller in a level process is regulation and tracking.[1] One of the classical strategies that is still in the market is PID; which inherently introduces oscillations and overshoot due to lack of proper tuning. PID also requires periodic retuning which is costly and uneconomic.[2]. Henceforth industries are currently employing strategies such as Fuzzy and MPC. A Fuzzy controller does not rely on a model of the process where as an MPC strategy is as good as the estimated process model. MPC or model predictive controller generally refers to a large class of control algorithms that use an explicit process model to predict the behavior of a plant.[3]. An MPC consist of a dynamic model of the plant and an optimizer. [4]. Currently MPC is finding its way to industries like oil and gas, chemicals and refining where as automobile and machinery industries are moving towards Fuzzy. Fuzzy systems can be broadly classified as Mamdani model, Tsukamato and Takagi, Sugeno, and Kang model (TSK model); the main difference between the models is the way of generating crisp output. The mamdani type Fuzzy model uses the technique of defuzzification of a fuzzy output, while Sugeno-type Fuzzy system uses weighted average to compute the crisp output.[5].The Tsukamato model is not used more often due to its lack of transparency to compute crisp output. The defuzzification techniques employed by Mamdani Fuzzy inference system(FIS) can be broadly classified as Centroid of area (COA),Bisector of area (BOA),Mean of maximum (MOM), Smallest of maximum (SOM) and Largest of maximum (LOM). In this paper the defuzzification technique used is COA.[6].

This paper is an effort to compare the performance of an MPC with a Fuzzy controller and from real time data performance of both the controllers is compared regarding error elimination and transient response.

The paper is subdivided into five sections. Methodology as section 2 which discusses about MPC and Fuzzy algorithm with their implementation in LabVIEW environment. Section 2 as Experimental

Result and discussion which presents the result obtained and evaluation. A final conclusion is presented in section 4. Future possible work regarding this work is also presented in section 5.

II. METHODOLOGY

2.1. MPC controller and Fuzzy control strategy

The basic idea behind an MPC is the concept of receding horizon which means at every instant of time the prediction window moves ahead. In MPC a dynamic model of the process is used to determine or predict the behavior of the plant and outputs in future i.e. y(k+i|k) for i = 1,2,..., Hp, for a prediction horizon, Hp and at each instant 'k' based on past and current inputs and outputs measurements up to instant k, and on the future control signal, u(k+i|k)for i = 0,1,…, Hc-1, where Hc is called control horizon. The predicted control signals are calculated in order to optimize the error between reference, r(k+i|k) and the observed trajectories. But only current instant of control u(k|k) is implemented rejecting others, as in the next sampling instant, y(k+1) is known [7],[12]. Figure 1visualizes both the concepts.

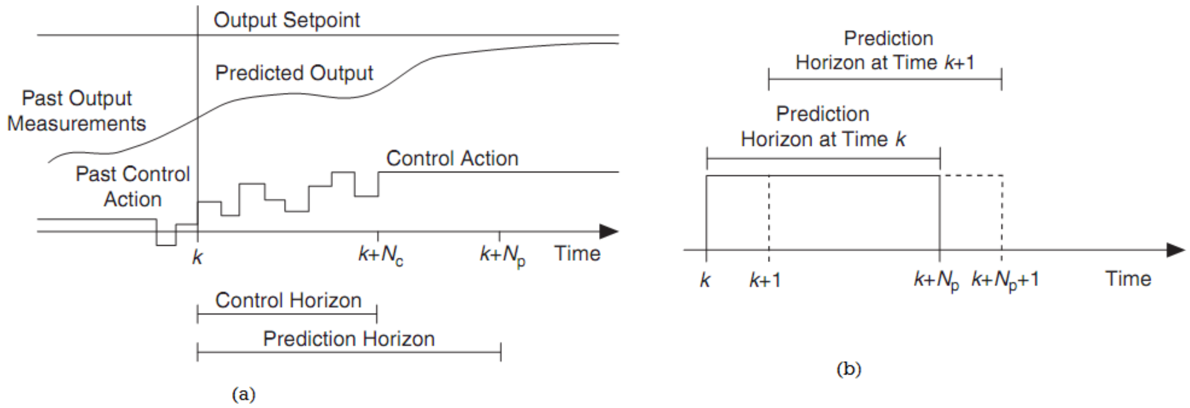


Figure 1.(a) MPC controller prediction horizon and control horizon (b) Concept of receding horizon

The MPC controller in LabVIEW environment tries to minimize the following cost function:

$$
\begin{aligned}
J(k) = &\sum_{i=N_W}^{N_p} [\hat{Y}(k+i\,|\,k) - r(k+i\,|\,k)]^T .Q.[\hat{Y}(k+i\,|\,k) - r(k+i\,|\,k)] + \\
&\sum_{i=0}^{N_c-1} [\Delta u^T (k+i\,|\,k).R.\Delta u(k+i\,|\,k)] + \\
&\sum_{i=N_W}^{N_p} [u(k+i\,|\,k) - s(k+i\,|\,k)]^T .N.[u(k+i\,|\,k) - s(k+i\,|\,k)]
\end{aligned} \tag{1.1}
$$

Where

N_p- No. of samples in the prediction horizon
N_w – Beginning of the receding prediction horizon
N_c - Control horizon
Q - output error weight matrix
R - rate of change in control action weight matrix
N - control action error weight matrix.[8]

A Fuzzy controller imitates the performance of human expert operators by encoding their knowledge in the form of linguistic rules [10]. A fuzzy controller consist of a (i) fuzzification interface or fuzzifier which converts the crisp input into linguistic variables, (ii)a rule base holds the rule and knowledge for output, (iii) an inference engine to determine and evaluate which control rules best fit the relevant input and (iv) a defuzzifier which produce crisp output from the conclusions obtained from inference engine. As discussed earlier a centre of area defuzzification technique can be formulated as

$$COA = \frac{\int_{x_{\min}}^{x_{\max}} f(x).xdx}{\int_{x_{\min}}^{x_{\max}} f(x)dx} \tag{1.2}$$

Where,

CoA- is the center of area,
x -is the value of the linguistic variable,
$x_{\min}$ and $x_{\max}$- represent the range of the linguistic variable.

Figure 2.(a) and (b) shows a block diagram of both the controllers

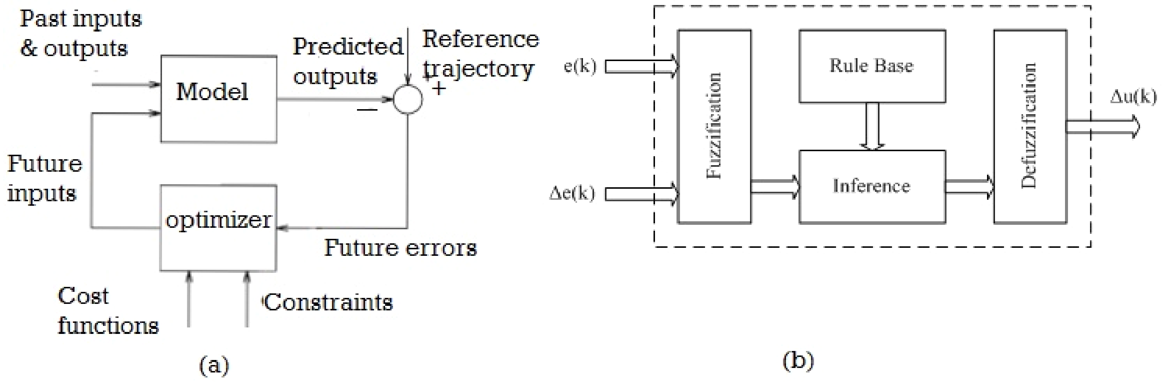


Figure 2.(a) an MPC (b) a Fuzzy controller block diagram

2.2. System identification

System identification is defining a process in terms of a mathematical model or finding the governing equation of a system .There are many open loop time domain system identification methods available of which (i) graphical method i.e. deduction of model directly from process response, (ii) Two -point algorithm and (iii) Area method. [9]. Here the system transfer function is predicted using a step response (process reaction) curve and is approximated as a first order system. The process reaction curve is shown in Figure 3.

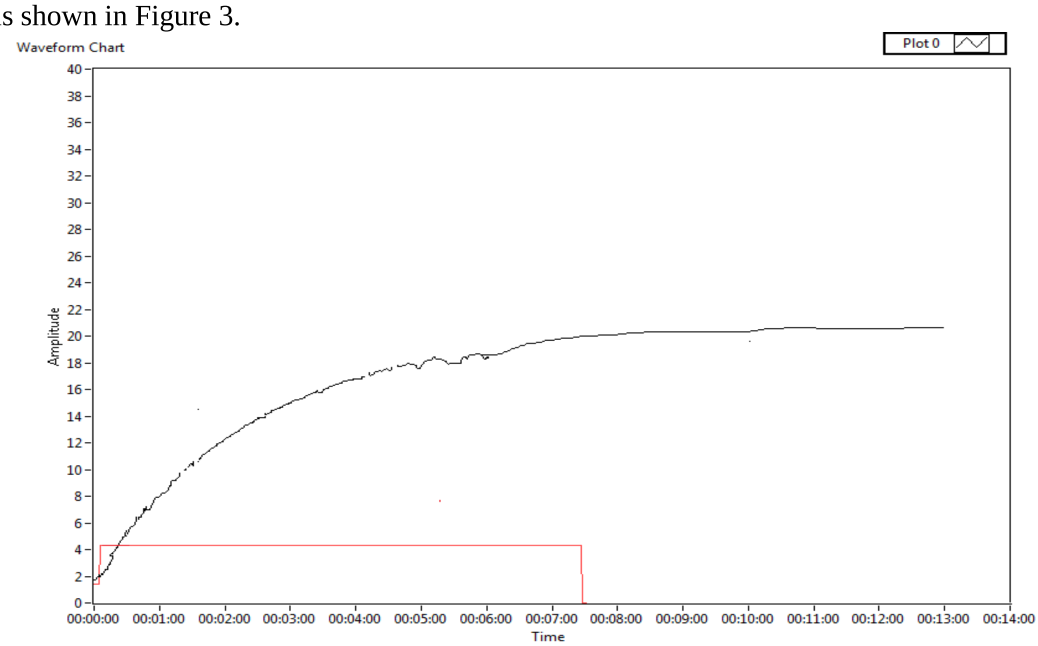


Figure 3. Step response of the process

For a step change from 10% to 30% PWM change the output change is from 2 to18.3cms therefore the system gain is equal to 0.82 i.e.(18.3-2)/(30-10)

The time constant is found out to be 138 sec and since VI loop timing is 1 sec; the actual time constant T is equal to 138 sec (2.3 min)

The system transfer function is predicted as

$$\frac{H(s)}{U(s)} = \frac{0.82}{1+2.3s} e^{-0.01s} \tag{1.3}$$

2.3. Model validation

The system transfer function approximated is validated as a cascade of two transfer function; G1 is the transfer function between the pump outflow to PWM input and G2 is the transfer function of the process between level and the inflow. The cascaded system is shown in Figure 4.

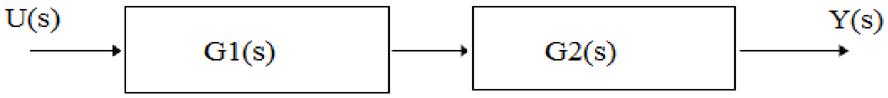


Figure 4. System block diagram with G1(s) and G2(s)

2.3.1. Pump

The pump transfer function is found out from the following data.

Table 1. Gain calculation from flow vs PWM duty cycle

PWM duty cycle change(%age)	Flow rate change(in cm^3/s)	Gain
20 – 10 = 10	75 – 48.33=26.67	2.667
30 – 20 = 10	94.99 – 75=20	2.0
40 – 30 = 10	118.33 – 94.99=23.34	2.334
50 – 40 = 10	140.00 – 118.33=21.67	2.167
60 – 50 = 10	166.67 – 140.00=26.67	2.667
70 – 60 = 10	190 – 166.67=23.33	2.333

The flow vs PWM duty cycle is shown below

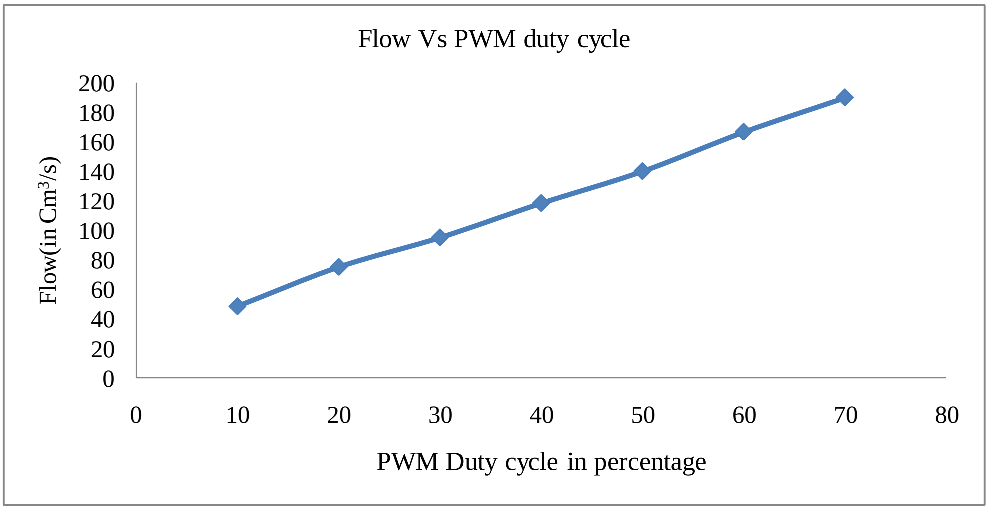


Figure 5. Flow Vs PWM duty cycle

Taking the maximum gain from the table1 the Pump can be approximated as only DC gain; hence

$$G1(s) = \frac{Q(s)}{U(s)} = 2.667 \tag{1.4}$$

2.3.2. Process

The process transfer function model is found out by finding the restriction to flow 'R' and time constant 'T'. The R is found out using table.2.

Table.2. Calculation of 'R' from change in flow vs change in height

Change in height (in cms)	**Change in flow(cm^3/s)**	**Restriction to flow (R)**
23 – 22 = 1	119.07 – 116.16= 2.9	0.34
19.1 – 18.1 = 1	99.1– 95.57 = 3.53	0.28

Taking average restriction, R is equal to 0.31
For finding T,
Area of the tank A is equal to 225cm^2
Since

$$T = AXR \tag{1.5}$$

Hence, T is equal to 70sec or 1.16min
Therefore process transfer function is

$$\frac{H(s)}{Q(s)} = \frac{0.31}{1+1.16s} e^{-0.01s} \tag{1.6}$$

Now the whole system transfer function is a cascade of G1 and G2 and can be found out as

$$G = G1.G2$$
$$G(S) = G1(s)\times G2(s) = \frac{Q(s)}{U(s)} \times \frac{H(s)}{Q(s)} = 2.667 \times \frac{0.31}{1+1.16s} e^{-0.01s} \tag{1.7}$$

i.e.

$$\frac{H(s)}{U(s)} = \frac{0.83}{1+1.16s} e^{-0.01s} \tag{1.8}$$

The discrete state space model deduced from the transfer function obtained with 50mSec sampling time is

$$\begin{aligned} x(k+1) &= [0.98]x(k) + [0.05]u(k) \\ y(k) &= [0.36]x(k) + [0]u(k) \end{aligned} \tag{1.9}$$

2.4. Implementation

2.4.1. MPC controller

The Model Predictive Controller is implemented as follows.

1. The first part of the procedure is to obtain the state space model from the identified transfer function model and converting it into a discrete state space model which is sampled at a sampling time of 50 mili Second.

2. The above procedure is followed by the creation of the MPC with an appropriate prediction horizon, control horizon, Q, R and N matrix for optimization. This achieved using CD-Create MPC controller VI.

The part of the VI that performs the discussed tasks is shown in figure 6.

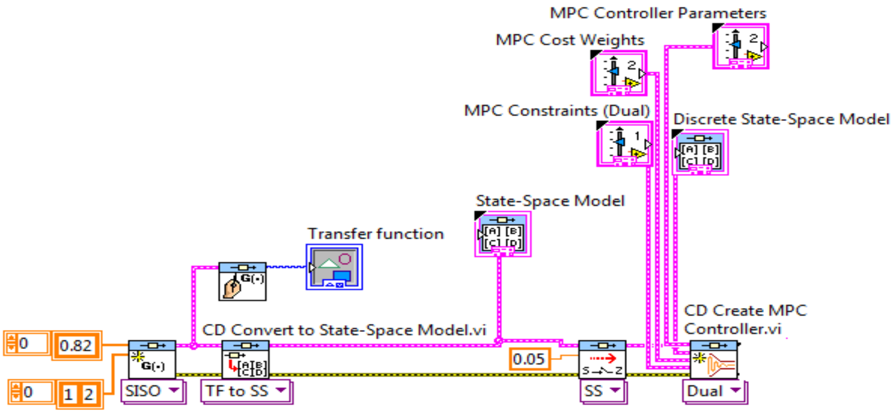


Figure 6. Conversion of Transfer function model to discrete state space model and creation of MPC

3. The deployment of the controller is achieved using CD-implement MPC controller and Set point modification in runtime is done using CD-set MPC controller.
4. The real time measurement of the process variable is carried out by the "Linear sensor" subVI and is feedback to the MPC controller. The controller output which is the PWM duty cycle for the pump is given by "Pump" subVI.

The whole MPC control scheme block diagram is shown in figure7.

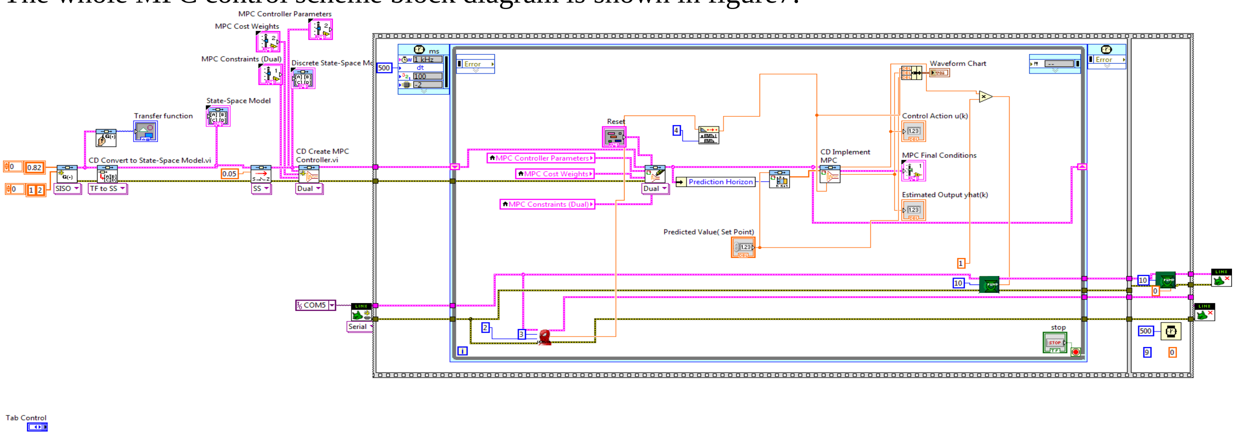


Figure 7. MPC control scheme

The Linear sensor and Pump subVI are shown in figure8.

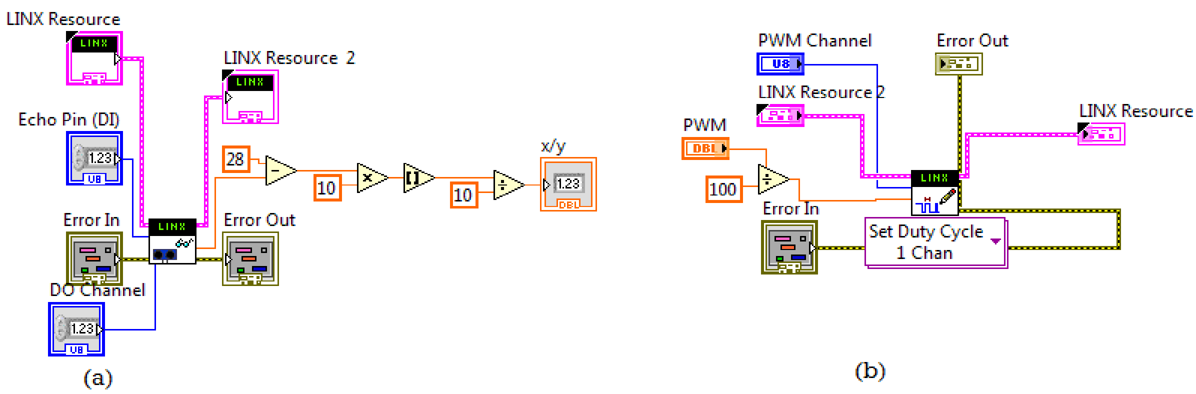


Figure 8. (a) Linear sensor subVI and (b) Pump SubVI.

2.4.2. Fuzzy controller

The Fuzzy controller is basically a Mamdani type FLC designed in LabVIEW using the same subVIs to acquire data and to give controller output. The Fuzzy controller is implemented as follows

1. The fuzzy system is designed using "Fuzzy system designer" in LabVIEW. The fuzzy controller is called into the VI using "FL load Fuzzy system" and the Fuzzy system is implemented using "FL Fuzzy controller VI".
2. The Fuzzy system is designed with two inputs **error**($e(t)$) and **rate of error**($\dot{e}(t)$) and one output PWM duty cycle as a MISO system. The input functions **Error**($e(t)$) is subdivided into five membership function **negative(n), negative zero(nz), zero(z), positive zero(pz), positive(p)**.The **rate of error** ($\dot{e}(t)$) is subdivided into three membership functions namely **negative(n), zero(z), positive(p).**

The membership function of both the inputs is shown in figure 9.

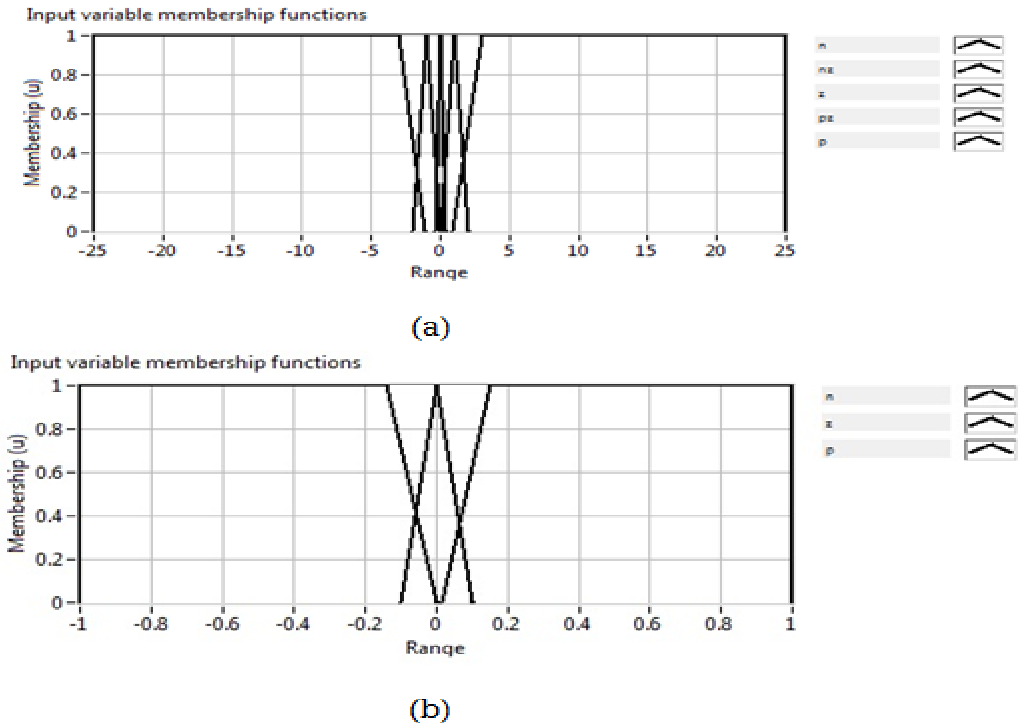


Figure 9. Membership function of (a) Error($e(t)$) and (b) rate of error($\dot{e}(t)$)

3. The defuzzification method employed is '**Centre of Area'** in this regard. The output **PWM** is subdivided into five membership function as **very less, less, medium, high, very high**.

The output membership function is shown in fig.10.

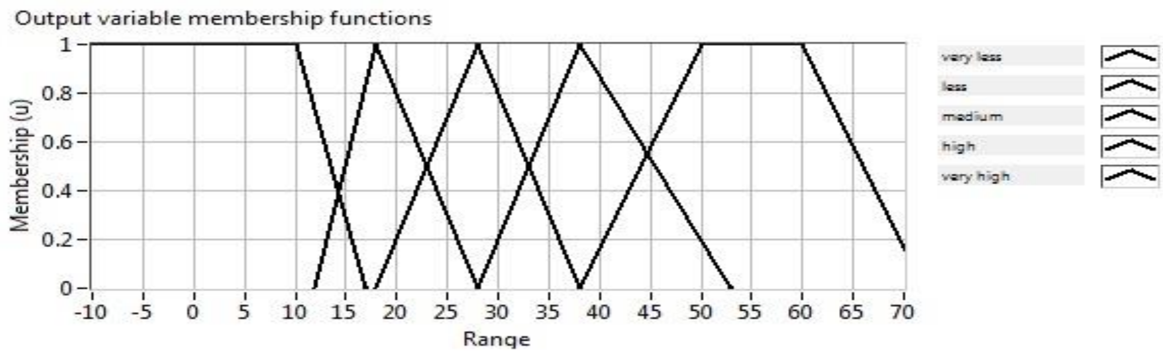


Figure 10. Output variable membership function

The rule base used for inference is tabulated in table 3.

Table.3. Rule base

$\dot{e}(t)$ \ $e(t)$	N	NZ	Z	PZ	P
N	VERY LESS	LESS	MEDIUM	HIGH	VERY HIGH
Z	VERY LESS	LESS	MEDIUM	HIGH	VERY HIGH
P	VERY LESS	VERY LESS	MEDIUM	HIGH	VERY HIGH

The input- output Fuzzy surface and the Fuzzy control scheme block diagram is shown in figure 11 and figure12 respectively.

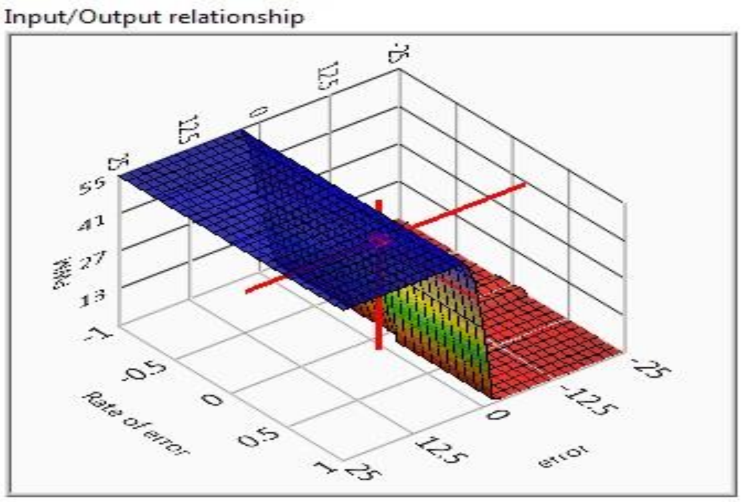


Figure11. Input/Output relationship Fuzzy surface

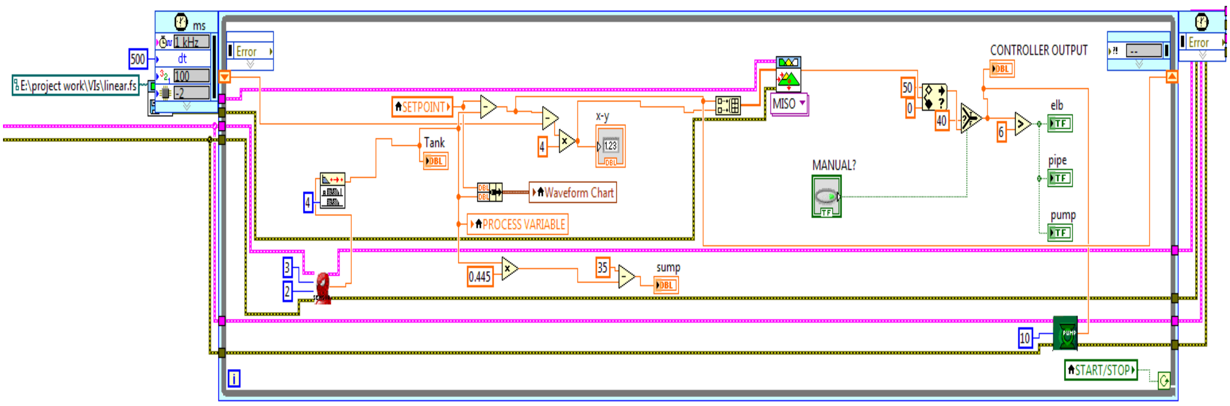


Figure12. Block diagram of the Fuzzy scheme

III. EXPERIMENTAL RESULTS AND DISCUSSION

The experimental setup used here in consisted of a sump, a linear process tank and a dc water pump as actuator. The system is interfaced to LabVIEW using an arduino board. The continuous level monitoring is achieved using an ultrasonic sensor.

The implemented MPC and the Fuzzy controller are subjected to a set point tracking from 10cm to 14cm with 1cm step change for four successive intervals and real time data are acquired. The Integral Absolute Error (IAE) and Integral of Square of Error (ISE) for both the controllers are tabulated in table 4.

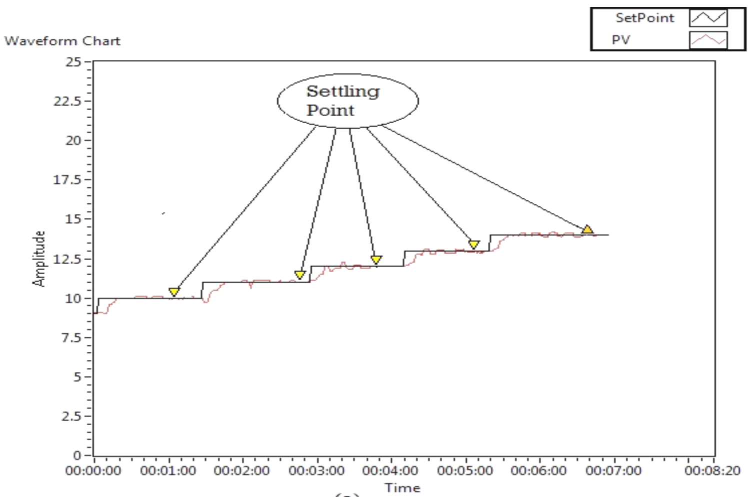
Table 4. IAE and ISE for Fuzzy and MPC controller.

Step change		**FUZZY**	**MPC**
IAE	10-11 cm	7.6	16
	11-12 cm	6.85	14.44
	12-13 cm	10.5	14.84
	13-14 cm	11.55	12.32
ISE	10-11 cm	5.87	10.568
	11-12 cm	3.635	8.412
	12-13 cm	5.25	9.768
	13-14 cm	5.305	7.584

From the above table following can be inferred.

1. A low IAE shows presence of less deviation from set point in Fuzzy as compared to that of MPC.
2. A small ISE in case of Fuzzy characterizes Fuzzy controller a better option in suppressing large errors.

The figure13 shows the above observation



(a)

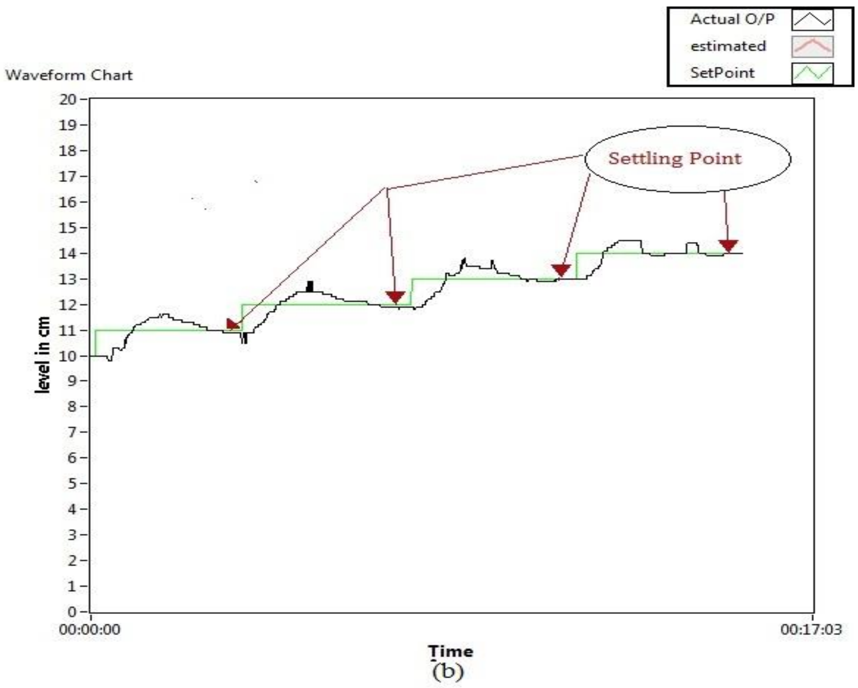


Figure13. Setpoint tracking for (a) Fuzzy controller and (b) MPC

One of the desired criteria of a controller is less maximum overshoot or peak overshoot as defines, "the maximum deviation of the process variable from the desired point." The calculated overshoot values are tabulated in table 5.

Table 5. Peak percentage overshoots

Step size	MPC (in %)	Fuzzy (in %)
10-11 cm	60	10
11-12 cm	70	40
12-13 cm	80	40
13-14 cm	50	20

From table 5 it can be theorize that Fuzzy gives less overshoot as compared to an MPC.

The fastness or speediness of the controllers can be determined from the rise time of the process variable for a change from 10% to 90%.

Table 6. Rise time from 10 – 90%.

Step size	MPC (in seconds)	Fuzzy (in seconds)
10-11 cm	5	6
11-12 cm	6	6
12-13 cm	5	7
13-14 cm	4.4	5

The calculated data regarding rise time is tabulated in table.6 and it can be summarized that both the controllers have a near equal response time; but numerically MPC is faster than Fuzzy controller.

Table 7. Settling time

Step size	MPC (in seconds)	Fuzzy (in seconds)
10-11 cm	36	28
11-12 cm	35.2	24
12-13 cm	31	32.5
13-14 cm	41	38

The tabulated values in table 7 give a clear indication that at constant load condition settling time of the Fuzzy controller increases as the set point becomes higher; whereas MPC gives a near constant settling point even though the settling time is higher than the Fuzzy controller.

IV. CONCLUSIONS

This paper has discussed various performance criteria regarding two most reliable controllers; an MPC with a predictive control strategy which rely on a perfect model of the dynamic of a process and a Fuzzy which rely on human intuition. From real time analysis it is found that in keeping a less error criterion a Fuzzy controller is more preferable and where near optimum solution is only sufficient. But MPC is better in giving a constant settling time. The shortcomings of the MPC may be due to a less accurate model of the process and introduction of non-linearity which is the change in outflow rate with increase in height.

V. FUTURE WORK

A future scope in this regard is the modelling of the process considering all the non linearity aspect of the model for a better response and also implementation of other types of fuzzy model. The work can also be further expanded including completely non linear processes and their response regarding conventional control strategy and a model based approach.

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