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Real Time Implementation of Self Tuning Fuzzy PI Controller for a Spherical Tank System

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Abstract: Self Tuning Fuzzy PI Controller (STFPIC) is an efficient technique for the control of non linear process. In this paper, a STFPIC for a level control of spherical tank processhas been designed and implemented in real time. The proposed STFPIC controller is a combination of twoinput two output Fuzzy logic controller and a conventional PI controller. The input to the fuzzy controller is error and change inerror and its outputs are K_P and K_I. The PI controller's parameters are estimated on-line based on error and change in error. Thereal time implementation and control of the process plant is done in MATLAB using VMAT-01 Data Acquisition Module.The performance ofSTFPIC is compared with Gain scheduling Controller in real time. The results clearly indicate that the incorporation of STFPIC in the control loop for spherical tank system provides a good tracking performance than the Gain scheduling controller.

Key words: STFPIC · Spherical tank system · Gain scheduling · Fuzzy controller

INTRODUCTION

Most of the process industries are having lot of control issue because of the dynamic nonlinear behavior of the plant. Many industries such as concrete mixing industry and waste water treatment industry are in need of efficient control techniques because of the inherent nonlinearity. Process industries are in need of the efficient controller for controlling the parameters such as settling time and rise time. Spherical tanks are widely used in process industries such as gas plants, food process industries and waste water treatment industries. The nonlinearity of the system will increase according to the area in the spherical tank. PID controllers are designed for linear systems and they provide a preferable cost/benefit ratio [1]. However, the presence of nonlinear effects limits their performances. Fuzzy controllers are successfully applied to non-linear system because of their knowledge based nonlinear structural characteristics [2]. Nowadays Artificial Intelligence techniques such as neural networks, fuzzy logic and genetic algorithms are gaining increased interest. A lot of techniques have been proposed to tune the gains of PI controller based on artificial intelligence techniques: Self tuning fuzzy logic technique is one of these methods proposed for the online adaptive tuning of PI controller [3]. In such application, the controller gains are online tuned with the variation of system conditions. The advantage of these techniques is that they are model free strategies because they use the human experience for the generation of the tuning law.

A fuzzy system can be shown to be a non-linear, which is useful for designing the controller for a nonlinear process [4]. After the industrial application of the first fuzzy controller by Mamdani (1974) fuzzy systems have obtained a major role in engineering systems and consumer products in the 1980s and 1990s. Recently, fuzzy logic and conventional control design methods have been combined to design a Proportional-Integral Fuzzy Logic Controller (PI-FLC) [5]. Hybriding the fuzzy and PI are to have a better control of non-linear process.

Fuzzy Logic controllers can generally be divided in two types, Mamdani type controllers and Sugeno type controllers. The rule base of Fuzzy controllers consists of rules of the form If x is A then Y is B where x is an input variable, Y is the output variable and A & B are fuzzy sets for the input variable and output variable respectively. In Mamdani type fuzzy controllers both antecedent and consequent of the rules (A&B) are Fuzzy sets. In the case of Sugeno type fuzzy controllers, the antecedent parts of the rules (A) are Fuzzy while the consequent portions (B) are crisp. The present study deals with development of Mamdani type Fuzzy Controllers.

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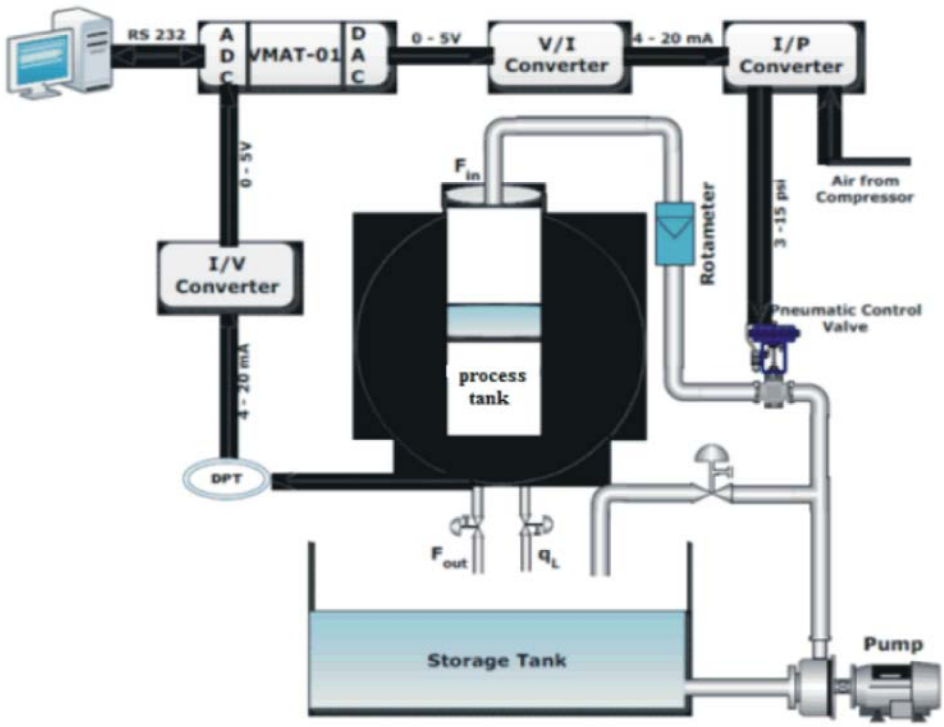

Fig. 1: Experimental setup for liquid level control of a

This work presents a brief description of the mathematical model of Spherical tank system, Self-tuning fuzzy PI controllerand Gain scheduling PI controller, explanation in available in this paper.

Experimental Setup: A real time experimental setup for highly nonlinear spherical tank is constructed. The process is is interfaced using VMAT-01 module to the Personal Computer (PC). The laboratory set up for this system is shown in Figure 1, it consists of a spherical tank, a water reservoir, pump, rotameter, a differential pressure transmitter, I/P converter, a pneumatic control valve, an interfacing VMAT-01Data Acquisition module and a Personal Computer. The differential pressure transmitter output is interfaced with computer using VMAT-01 module in the RS-232 port of the PC.

Spherical Tank: VMAT - 01 module supports 1 analog input and 1 analog output channels with the voltage range of ±5 volt and two Pulse Width Modulation (PWM). The sampling rate of the module is 0.1 sec and baud rate is 38400 bytes per sec with 8-bit resolution. The model is developed using Simulink blockset in MATLAB software and is then linked via this VMAT-01module with the sampling time of 0.1 second. Figure 2 shows the experimental setup of a spherical tank. The pneumatic control valve is air to close, adjusts the flow of the water pumped to the spherical tank from the water reservoir. The level of the water in the tank is measured by means of the differential pressure transmitter and is transmitted in the form of (4-20) mA via I/V (0-5)V converter to the interfacing VMAT-01 module to the Personal Computer (PC). After computing the control algorithm in the PC, control signal is transmitted via V/I converter to the I/P converter in the form of current signal (4-20) mA, which passes the air signal to the pneumatic control valve. The pneumatic control valve is actuated by this signal to produce the required flow of water in and out of the tank. There is a continuous flow of water in and out of the tank. Table 1 shows the various technical specifications of experimental setup. Figure 3 shows the system interfacedwith process. Figure 4 shows VMAT-01 interface card.

Modeling of Spherical Tank Process: The spherical tank system is highly nonlinear system. In order to control this, the most basic and pervasive control algorithm used in the feedback control is the Proportional Integral and Derivative (PID) control algorithm. PID control is a widely used control strategy to control most of the industrial automation. The system identification problem deals with the determination of a mathematical model for a system or

Fig. 2: Experimental set up for a spherical tank

Fig. 3: Real Time Laboratory setup for Spherical Tank Process

Fig. 4: Real Time MATLAB Interface Card

a process by observing the input output data. Historically, system identification has been needed in designing a suitable control process for an unknown system (black box problem). In most practical systems, such as industrial processes, the actual parameter values within a known model structure are unknown. This types of problem are more accurately called as system parameter identification problems. The need for more accurate knowledge of system parameters has increased with recent advances in adaptive and optimal control.

Table 1: Technical Specifications of experimental setup

Part Name	Details
Spherical Tank	Material: Stainless Steel
	Diameter: 50 cm
	Volume: 102 Liters
Storage Tank	Material: Stainless Steel
	Volume: 48 Liters
Differential Pressure Transmitter	Type: Capacitance
	Range: (2.5-250)mbar
	Output: (4-20) mA
Pump	Centrifugal 0.5HP
Control Valve	Size: ¼''Pneumatic Activate
	Type: Air To Close
	Input: (3-15) Psi
Rotameter	Range: (0-18) lpm
Air Regulator	Size: ¼'' BSP
	Range: (0-2.2) Bar
I/P Convertor	Input: (4-20) mA
	Output: (0.2-1) Bar
Pressure Gauge	Range: (0-30) Psi
	Range: (0-100) Psi

Mathematical Modeling: The Spherical tank liquid level system shown in Fig. 5 is essentially a system with nonlinear dynamics. Thespherical tank setup has a maximum, height of H (cm) Maximum radius of r (m). The level in the tank at any instant is obtained by making mass balance as indicated below:

Let,

q_1 – Inlet flow rate to the tank (m3 /min)
q_2 – Outlet flow rate to the tank (m3 /min)
q_L – Load applied to the tank (m3 /min)
H – Height of the Spherical tank (m)
h - Height of the liquid level in the tank at any time't'(m)
R - Top radius of the Spherical tank (m)
r – Radius of the spherical vessels at a particular level of height h (m)

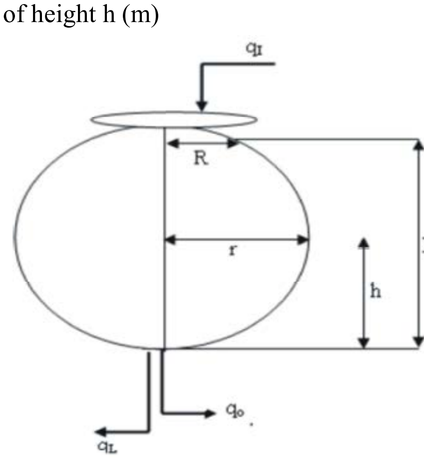

Fig. 5: Spherical Tank Liquid Level System

Let,

Rate of accumulation of mass in the tank=Rate of Mass flow in-rate of mass flow out

Its nonlinear dynamics described by the first – order differential equation.

$$\frac{dv}{dt} = q_1 - q_2 \tag{1}$$

where v is the Volume of the tank, q_1 is the inlet flow rate and q_2 is the outlet flow rate.

$$v = \frac{4}{3}\pi h^3 \tag{2}$$

where h is theliquid level of tank in cm. Applying the steady state values and solving the equations,

$$\frac{H(s)}{Q_1(s)} = \frac{R_t}{\tau_p{}^s + 1} \tag{3}$$

where, $\tau_p = 4\pi R_t h_s$

$$R_t = \frac{2h_s}{Q_2(s)} \tag{4}$$

The dynamic model of the spherical tank is given by;

$$\frac{\partial}{\partial_t}[\int_0^{x_1} A(x)\partial x] = f_{in}(t) - a\sqrt{2g(x - x_0)} \tag{5}$$

where A(x) is the area of the cross section of tank (i.e.) $A(x) = \pi(2rx - x^2)$ 'a' is the cross sectional area of the pipe i.e.

$$a = \pi\left(\frac{d_0}{2}\right)^2$$

'd_o' is the diameter of drain pipe,

Rewrite the equation 5 at time, $t + \partial t$

$$A(x)\partial x = f_{in}\partial t - a\sqrt{2g(x - x_0)}\partial_t \tag{6}$$

Combine equation (5) and (6)

$$\frac{\partial x}{\partial t} = \frac{f_{in}\partial t - \frac{\pi d_0^2}{4}\sqrt{2g(x - x_0)}}{\pi(2rx - x^2)} \tag{7}$$

By applying $\lim_{d\to 0}$ in equation (7) we have, $\frac{\partial x}{\partial t} = \frac{dx}{dt}$

Therefore,

$$\frac{dx}{dt} = \frac{f_{in}\partial t \frac{\pi d_0^2}{4}\sqrt{2g(x-x_0)}}{\pi(2rx-x^2)} \tag{8}$$

$\frac{dx}{dt}$ Represents the dynamic model of the spherical tank level process.

Black Box Modeling: Consider the First Order Process with Time Delay represented by the following transfer function.

$$y(s) = \frac{k_p e^{-tds}}{\tau_p s+1}u(s) \tag{9}$$

In the above equation, y(s) the measured output is in variable form. The process parameters τ_p, k_p, t_d can be estimated by performing a single step test on process input [6]. The process gain is found as simply the long term change in process output divided by the change in process input. There are several ways to estimate time constant for this model. Two point method for estimating the process parameters are shown in Figure 6.

System identification for the spherical tank system is done using black box modeling in real time. For fixed input flow rate and output flow rate, the Spherical tank is allowed to fill with water from (0-50) cm height. At each sample time, the data from differential pressure transmitter i.e. between (4-20) mA is being collected and fed to the system through the serial port RS - 232 using VMAT-01 interfacing module, thereby the data is scaled up in terms of level, the output response for the system is recorded.

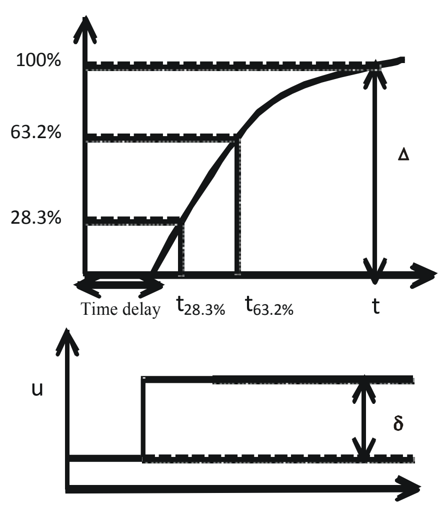

Fig. 6: Two point method for estimating process parameters

Two Point Method for Estimating Time Constant and Time Delay: The parameters of FOPTD transfer function model by letting the response of actual system and that of the model to meet at two points which describes the two parameters τ_p and t_d are obtained. Here the time required for the process output to make 28.3% and 63.2% of steady state value is noted. The time constant and time delay can be estimated from thefollowing equations.

$$K_p = \frac{\Delta}{\delta} = \frac{\text{Change in process output}}{\text{Change in process input}} \tag{10}$$

$$\tau_p = 1.5(t_{63.2\%} - t_{28.3\%}) \tag{11}$$

$$t_d = t_{63.2\%} - \tau_p \tag{12}$$

The proposed work is to find the three different models at various operating ranges. The obtained parameters are reported in Table 2.

Zeigler-Nicholas Method Controller Tuning: Once mathematical model of the plant is obtained then it is possible to apply different design techniques to define controller parameters [7]. On the other hand if the system is complicated and getting the mathematical model is difficult, then experimental approaches used to tune the PID parameters. Zeigler and Nicholas developed the rule based on the transient responsecharacteristics of the system and determined the value of PID controller. Zeigler and Nicholas presents tuning rules based on process models that have been obtained through the open loop step test. Zeigler and Nicholas proposed tuning parameters for a process that have been identified as first order with dead time based on open loop step response. The recommended tuning parameters are shown in Table 3.

Self Tunning Fuzzy Pi Controller: The block diagram of the proposed self-tuning fuzzy logic PI controller is shown in Fig. 7. The main objectives of the proposed self-tuning fuzzy logic PI controller are to reduce the control scheme complexity and therefore to improve the static and the dynamic performances [8], especially for systems whose modeling are complicated or whose parameters are inaccessible. In this case, the self-tuning fuzzy controller is designed to adjust PI parameters K_P and K_I in order to meet the appropriate required characteristics such that maximum overshoot, rise time, settling time and steady state error [9]. Therefore, fuzzy based PI controller is designed, so that it generates its control signal according to the error and change in error.

Table 2: Process gain, Time constant, Time delay at different operating regions

Operating region	K_p	τ_p(sec)	t_d(sec)	Transfer function
30%	11.8	9562.5	52.5	$\frac{11.8e^{-52.5s}}{9562.5s+1}$
46%	7.4	8100	150	$\frac{7.4e^{-150s}}{8100s+1}$
61%	13.48	12225	175	$\frac{13.48e^{-175s}}{12225s+1}$

Table 3: Proportional gain and Integral gain at different operating region

Operating point	K_P	K_I
30%(1st region)	13.89	0.0794
46%(2nd region)	6.567	0.0131
61%(3rd region)	4.667	0.008

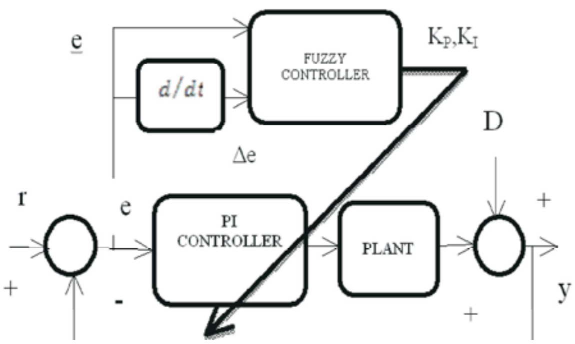

Fig. 7: Self-tuning fuzzy PI controller

The procedures of the Self Tuning Fuzzy PI[2]Control system are as follows:

- Identifying the different combinations of the error e and the change in error Δe.
- Thefuzzy controller adjusts the PI parameters on-line through fuzzy inference.

Design of Self Tuning Fuzzy Pi Controller: Mostly PI controller can give good performance only when the controlled system operates with in the operating region (the region where the controller is designed). The PI controller is often not properly tuned (e.g., due to plant parameter variations, operating condition changes or uncertainties), so there is a significant need to develop methods for the automatic tuning ofPI controller parameters [11]. Fuzzy control theory is used in this work to tune the parameters of PI controller. The basic formula for the PI controller is:

$$u(t) = K_p e(t) + K_I \int e(t)\, d(t) \quad (13)$$

where,
K_P is the proportional gain,
K_I is the integral gain.

The error (e(nT) = r(nT) - y(nT)),

Change in error (Δe(nT) = [e(nT) – e(nT-T)) are considered as inputs to the fuzzy controller. ΔK_P and ΔK_I are chosen as outputs of fuzzy controller.the fuzzy subsets are (PB, PS, Z, NS, NB). Where PB and PS are the abbreviation for positive big, and positive small; Z is the abbreviation for zero; NS and NB are the abbreviation for negative small, and negative big; [10]. The corresponding membership functionsare shown in Fig. (8.1, 8.2, 8.3) and in Fig. (9.1, 9.2, 9.3)

Membership Diagrams

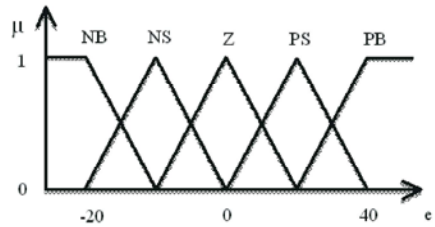

Fig. 8.1: Membership Diagram for Error (e)

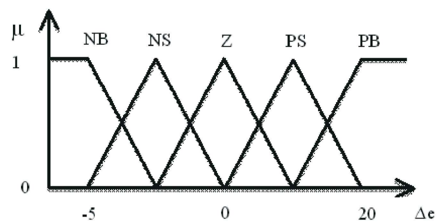

Fig. 8.2: Membership Diagram for change in Error (Δe)

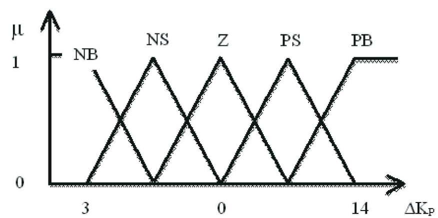

Fig. 8.3: Membership Diagram for change incontroller output (Δkp)

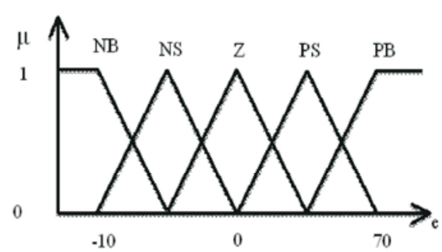

Fig. 9.1: Membership Diagram for Error (e)

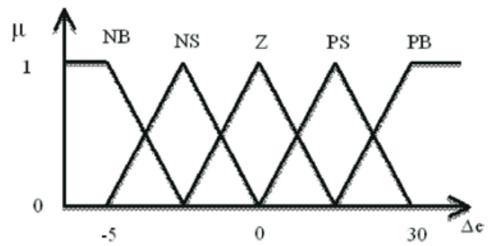

Fig. 9.2: Membership Diagram for change in Error (Δe)

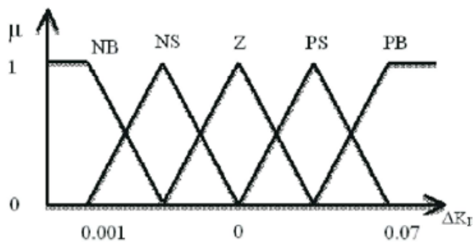

Fig. 9.3: Membership Diagram for change incontroller output (ΔK_I)

Table 4: Fuzzy rule table (with error and change in erroras input)

(i)Table for K_P					
e/ce	NB	NS	Z	PS	PB
NB	NB	NB	NS	NS	Z
NS	NB	NS	NS	Z	PS
Z	NS	NS	Z	PS	PS
PS	NS	Z	PS	PS	PB
PB	Z	PS	PS	PB	PB
(ii)Table for K_I					
e/ce	NB	NS	Z	PS	PB
NB	NB	NB	NS	NS	Z
NS	NB	NS	NS	Z	PS
Z	NS	NS	Z	PS	PS
PS	NS	Z	PS	PS	PB
PB	Z	PS	PS	PB	PB

NB: Negative Big; NS: Negative Small; Z: Zero;
PS: Positive Small; PB: Positive Big.

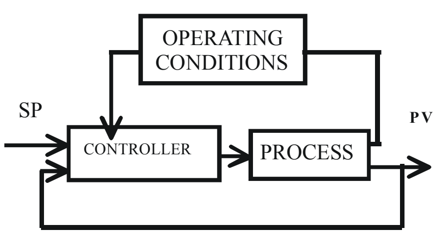

Fig. 10: Schematic diagram of gain scheduling controller

Gain Scheduling Controller: In many situations it is known that the dynamics of a process change with the operating conditions of the process. One source for the change in dynamics will be the known nonlinearities. It is then possible to change the parameters of the controller by monitoring the operating conditions of the process. This idea is called gain scheduling, since the scheme was originally used to accommodate changes in process gain only [12]. Gain scheduling based on measurements of operations of the process is a good way to compensate for variations in process parameters or known nonlinearities of the process [13]. If we use the informal definition of adaptive controller, Gain scheduling is a very useful technique for reducing the effects of parameter variations. There are also many commercial process control systems in which gain scheduling can be used to compensate for static and dynamic nonlinearities. Gain scheduling can thus be viewed as a feedback control system in which the feedback gains are adjusted by using feed forward compensation [14].

When scheduling variables are determined, the controller parameters are calculated at a number of operating conditions by using some suitable design method [15]. The controller is thus tuned or calibrated for each operating condition.

RESULTS AND DISCUSSION

In this section, the realtimeresults for level control of Spherical tank level system are presented to illustrate the performance of the Self tuning Fuzzy PI Controller& Gain scheduling controller. Here, the results are analyzed in three cases. Initially, the spherical tank is maintained the level at 30 %, 46% & 61% is applied to the process with Self tuning Fuzzy PI Controller and the responses are recorded in Figure 11. Similarly, a same procedure is applied to gain scheduling controller for the comparative analysis. The performance indices in terms of rise time, settling time and % overshoot are calculated and summarized in the Table 5.

Realtime Results

Self Tuning Fuzzy Pi Controller

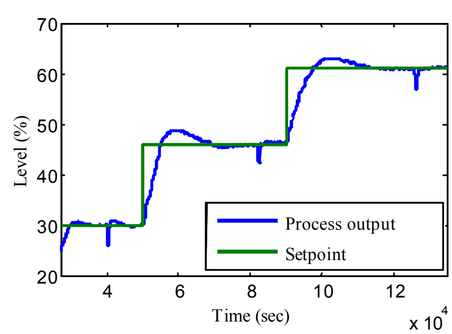

Fig. 11: Servo and Regulatory responses with Self-tuning fuzzy PI controller

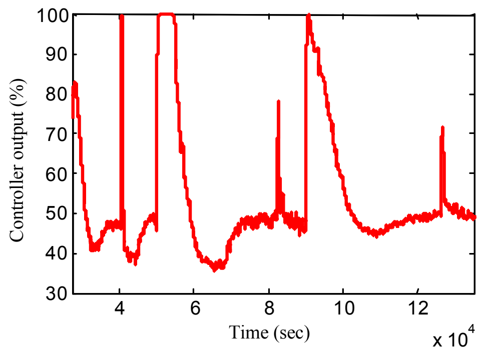

Fig. 12: Self-tuning fuzzy PI controller output

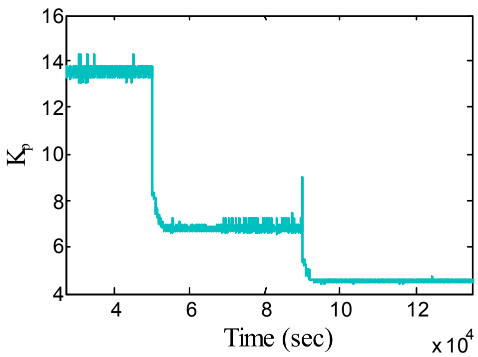

Fig. 13: K_p tuned signal

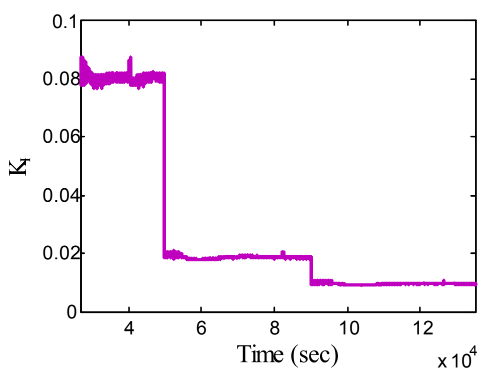

Fig. 14: K_I tuned signal

The realtime Servo and Regulatory responses with Self tuning fuzzy PI controller are shown in Figure 11. The Figure 12 shows the output of Self Tuning Fuzzy PI controller for 3 different operating regions. The Figure13 is Kp tuned signal and Figure 14 is K_I tuned signal. Here the controller gain signal is tuned based on the operating region.

Gain Scheduling Controller: The real time Servo and Regulatory responses with Gain Scheduling controller are shown in Fig. 14. The Fig. 15 shows the output of Gain Scheduling controller for 3 different operating regions.

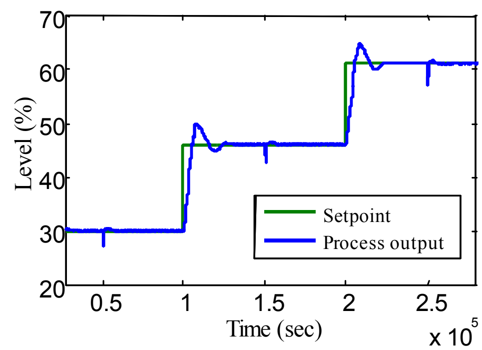

Fig. 14: Servo and Regulatory responses with Gain Scheduling controller

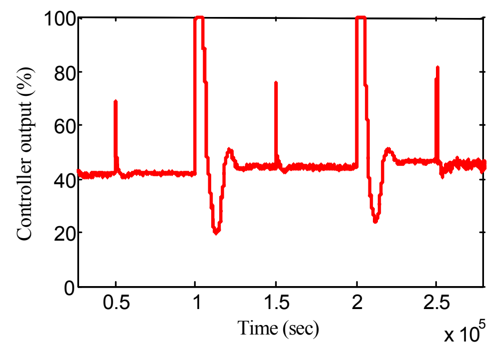

Fig. 15: Gain scheduling controller output

Table 5: Performance indices between GSPIC and STFPIC in real time

Level (%)	Controllers	30%	46%	61%
Rise Time (sec)	STFPIC	2317	254	283
	GSC	2816	275	290
Settling Time (sec)	STFPIC	3422	2478	2159
	GSC	3615	3200	3120
% overshoot	STFPIC	37.22	6.065	3.311
	GSC	15.833	8.582	6.478

CONCLUSION

This paper proposes design of Self tuning Fuzzy PI controller and it is implemented through MATLAB Simulink software using VMAT-01 module for highly non-linear liquid level spherical tank process. By comparing the results the Self tuning Fuzzy PI Controllerbased tuning provides the better results for the nonlinear process than Gain scheduling PI controller. From the real time results, the response of the Self tuning Fuzzy PI Controllerwas proved satisfactory in terms of rise time, percentage overshoot & settling time when compared with gain scheduling PI controller. It is observed that the performance of Self tuning Fuzzy PI Controlleris better for the control of nonlinear spherical tank process.

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