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Model Identification and Predictive Controller Design for a Nonlinear Process

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ABSTRACT
The objective of the study is to develop level controller for conical tank system using Model Predictive Control (MPC) and compare its performance with conventional Discrete Time Proportional Integral Derivative control (DTPID). The nonlinear property of the conical tank is divided into different operating zones and process model is obtained for each zone. The overall process is divided into 6 operating zones and different control schemes such as DTPID and discrete time MPC were simulated in MATLAB environment. Among these two control schemes MPC resulted with better transient performance in all the six operating zones.

Key words: Conical tank, system identification, model predictive control, non linear system

INTRODUCTION
Automation had played a vital role in the different process industries, by implementing advanced controllers with the aid of software algorithms. One among those control algorithms is Model Predictive Control (MPC). For an automatic controller we can have a range of operating conditions. In process industries level control is important. The fluid have to be transferred between the tanks during chemical or mixing treatment but the level have to be maintained. Industries where level control is used are pulp industries, petrochemical industries, water treatment industries, etc. Problems arise if the liquid level is not maintained properly. In processes like evaporators, distillation columns, reboilers the liquid level is of great importance. Higher the level may cause damage to the plant by upsetting the equilibrium of the reaction, which results in spillage of hazardous material and also wastage of valuables. Lower level affects the sequential operations. Conical tanks are mainly utilized in food processing and metallurgical industries, water treatment and food industries. The conical shape helps in better disposal of solids while mixing, at the same time in the case of viscous liquids it provides complete drainage.

Most of the industries use conventional controllers since implementation is easier. But practically, the real time systems are non linear in nature. The real time non linear systems are linearized around a nominal operating region. Lot of conventional controllers are addressed in the literature which have the limitations of offline tuning and fixed controller parameters. For the non linear processes with multiple inputs and outputs, conventional PID controllers will not produce satisfactory results. So, it is essential for the industries to go for highly sophisticated controllers which give better performance than the existing conventional controllers. The predictive controller is an advanced control strategy which attracts most of the industries (Srinivasagupta *et al*., 2004). The process model is used to predict the future output and the control moves are calculated. MPC use a process model to predict the behaviour of a plant. Compared to other controllers MPC have long range prediction concept.

Zhang *et al*. (2013) maintained relative humidity in repining process while investigating the proteolysis of a semi-hard cheese induced by a strain of Mucor spp. Guangul *et al*. (2013) maintain the relative humidity to 80% in the investigation of hygroscopic nature of oil palm fronds. Cai *et al*. (2014) explained the effect of humidity in earthworm treatment.

PI controller for conical tank using Wiener model is developed in real time which resulted better performance than conventional PI controller (Bhaba *et al*., 2007). Nithya *et al*. (2008) implemented artificial intelligence based controllers for a conical tank process and compared their performances. Warier and Venkatesh (2012) have designed model predictive controller for a conical tank for a single operating region. Bhuvaneswari *et al*. (2009) proposed time optimal controller for the non linear conical process in which the neural network was used to adapt the process parameter variations. The proposed controller resulted with better performance than the conventional controllers. Shridhar and Cooper (1997, 1998) explained a tuning strategy for unconstrained multivariable MPC. They also studied a Novel Tuning for multivariable MPC. The move suppression co efficient was computed and different adjustable parameters were demonstrated.

Mohanty (2009) proposed artificial neural network based system identification and model predictive control of a flotation column. The paper describes the design of controllers for the flotation column using neural network based MPC. The designed controller was found to perform efficiently both for liquid gas and liquid gas solid system. GiriRajkumar *et al*. (2010) explained real time interfacing of a transducer with a non-linear process using simulated annealing. They have addressed the PID tuning implementation for conical tank process. Huang and Riggs (2002) presented a paper which compares PI and MPC controllers for a gas recovery unit, where 3 distillation columns are operated in series. Camacho *et al*. (2003) explained the detailed description for the design of MPC (Srinivasagupta *et al*., 2004) proposed a new algorithm for MPC with variable time delays.

Ansarpanahi *et al*. (2008) studied the stability of the system when MPC is implemented under the influence of undesirable factors. Al-Gallaf (2002) designed a non linear model predictive controller based on artificial neural network which showed better performance than the linear model predictive control. Zeng (2013) analyzed the predictive controller based on wavelet transform. Du *et al*. (2013) designed generalized predictive control for a waste water biological treatment plant.

In this study, model predictive controller is developed for the conical tank process which is non linear in nature. This study is organized as follows. The next section addresses details of the experimental set up used in this study followed by modelling and design of controllers. In the next section discusses the result obtained in this study followed by conclusion in the final section.

Experimental set up constructed for this study: The real time process system which is shown in Fig. 1 consist of a conical tank, reservoir, water pump, current to pressure converter, control valve, rotameter, compressor, differential Pressure Transmitter (DPT), ADAM module and a Personal Computer which acts as a controller forms a closed loop system. The inflow rate of the conical tank is adjusted using the stem position change of the pneumatic valve by passing control

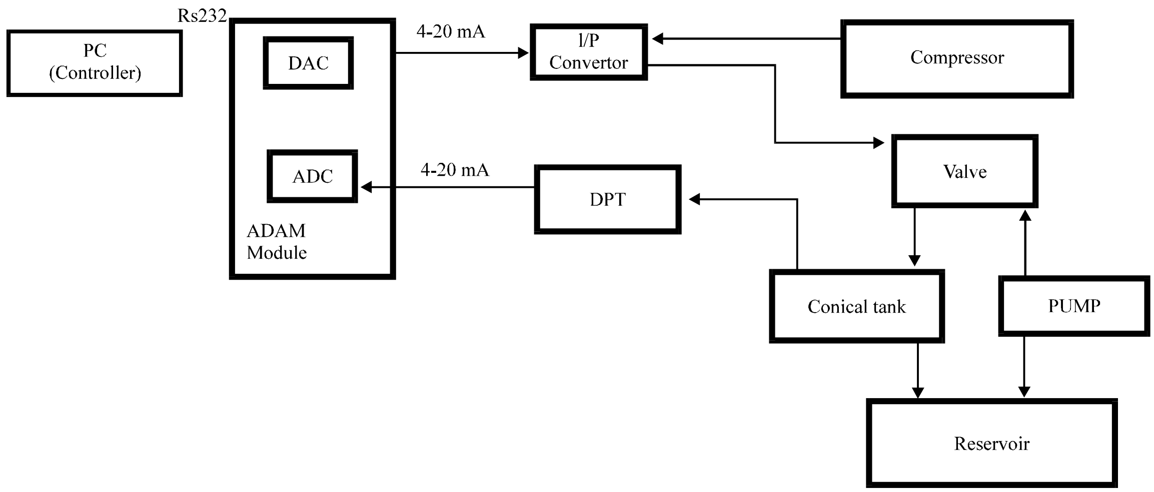

Fig. 1: Block diagram of the conical tank set up

signal from personal computer to the I/P converter through Digital to Analog Converter (DAC) of ADAM module. The ADAM module is used for interfacing the personal computer with the conical tank system. We can also use MATLAB software for interfacing the ADAM module with the computer. The current range for adjusting the valve position is 4-20 mA, which is converted to 3-15 psi. The water level inside the conical tank is measured with the Differential Pressure Transmitter (DPT) which is calibrated for 0-40 cm and is converted to an output current range of 4-20 mA. This output current from DPT is converted to 1-5V range, which is given to the controller through Analog to Digital Converter (ADC) of ADAM module.

The ADAM module has 4 slots for four converter cards. In our process, 2 slots are used, one containing ADC card and the other containing the DAC card. The ADC card has 8 analog input channels with a range of 4-20 mA and DAC has 4 analog output channels. The ADAM module can be operated manually through console software and also with programming software like LABVIEW, MATLAB etc., If using MATLAB software then MATLAB based script files are used for interfacing the controller with the real time system.

Modeling and controller design: This section is addressing the model identification and controller design for the system under study. Since the model under consideration is non linear in nature, the process had been divided into six different operation regions so called zones and black box method was adopted for identifying the process. The models for different zones were approximated to first order plus dead time. For the identified model, different controllers such as DTPID and MPC were designed and implemented.

System identification: The conical tank process exhibits non linear property. It is considered for the real time analysis. The dynamics of the process are analyzed in six different operating regions so as to obtain effective models for the operating ranges. We are defining 6 operating zones here. The first zone is between 12 to 20 cm, second zone is between 21 to 22, third zone is between 22 to 27, fourth zone is between 27 to 32, fifth zone is between 31 to 35 and the final zone i.e., the sixth zone is set between 34 to 38 cm. The inlet valve and outlet valve is set to a particular restriction.

Table 1: Different models obtained using SK method

Operating zones	Identified models
Zone 1	$G(s)\,\frac{12.87e^{-0.13}}{46.9s+1}$
Zone 2	$G(s)\,\frac{1.16e^{-10.93}}{36.85s+1}$
Zone 3	$G(s)\,\frac{10.08e^{-4.683}}{294.8s+1}$
Zone 4	$G(s)\,\frac{9.36^{-3.23}}{274.7s+1}$
Zone 5	$G(s)\,\frac{5.22^{-1.37s}}{341.7s+1}$
Zone 6	$G(s)\,\frac{7.2^{-2s}}{415.4s+1}$

The data obtained from ADAM module are in terms of time and voltage, so it is converted in terms of time and height (level). The height (level) thus obtained is experimental. The calculated height (level) is obtained using Process Reaction Curve method (PRC) and Sundareshan Krishnaswamy(SK) method. For a step change in flow rate, the response in the level is recorded. From the step response curve, dead time (τ_d) and time constant are found. In SK method the time taken for the response to reach 35.3 and 85.3% of the final value are computed and named as t_1 and t_2 respectively. The time delay and time constant can be obtained from the following equations:

- $\tau = 0.67(t_2\text{-}t_1)$,
- $\tau_d = 1.3\ t_1\text{-}0.29\ t_2$

After system identification using PRC and SK method, the ISE values are calculated and it is found that SK method provide minimum ISE value. The transfer functions are obtained using SK method and it is shown in the Table 1.

Design of DTPID: From the data obtained the tuning parameters K, τ, τ_d were found for all the 6 operating regions and discrete PID controller is implemented. The different tuning methods like Zeigler and Nichols, Cohen and coon can be used. Figure 2 shows the block diagram of the Simulink model used for DTPID design. The general format for transfer function is:

$$G(s) = \frac{K_e - \theta_s}{t_s + 1}$$

Design of model predictive control: A mathematical model of the plant is required for the design of model predictive control systems. In the control system design a state space model is used in Eq. 8. The SISO system considered is:

$$x_m(k+1) = A_m x_m(k) + B_m u(k) \tag{1}$$

$$y(k) = C_m x_m(k) \tag{2}$$

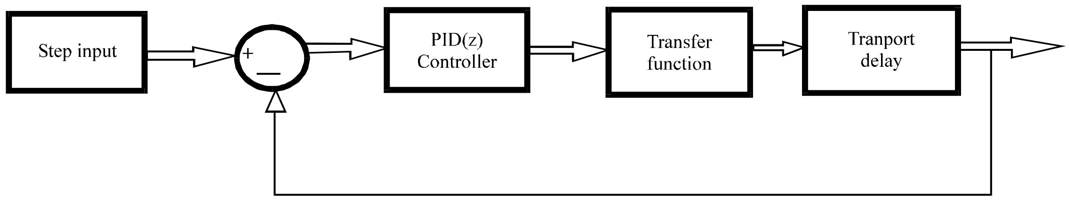

Fig. 2: Block diagram of DTPID simulink model

The state space model obtained is:

$$\begin{bmatrix} \Delta x_m(k+1) \\ y(k+1) \end{bmatrix} = \begin{bmatrix} A_m & O_m^T \\ C_m A_m & 1 \end{bmatrix} \begin{bmatrix} \Delta x_m(k) \\ y(k) \end{bmatrix} + \begin{bmatrix} B_m \\ C_m B_m \end{bmatrix} \Delta u(k)$$

$$y(k) = \begin{bmatrix} O_m & 1 \end{bmatrix} \begin{bmatrix} \Delta x_m(k) \\ y(k) \end{bmatrix} \tag{3}$$

$$A = \begin{bmatrix} A_m & O_m^T \\ C_m A_m & 1 \end{bmatrix}, B = \begin{bmatrix} B_m \\ C_m B_m \end{bmatrix}, C = [O_m \quad 1]$$

where, the input variable is u, the process output is y, the state variable is indicated as x_m, u(k) is the input, o_m is a null matrix of order n1 and the matrices A,B,C is the augmented model. For the design of MPC this augmented model will be used. The future control trajectory is as follows:

$$\Delta u(k_i), \Delta u(k_i+1), \ldots \Delta u(ki+N_c-1) \tag{4}$$

the control horizon is indicated as N_c. The future state variables is:

$$x(k_i+1 \mid k_i), x(k_i+2 \mid k_i), \ldots x(k_i+m \mid k_i), \ldots \ldots \ldots x(k_i+N_p \mid k_i) \tag{5}$$

where, $x(k_i+m \mid ki)$ is the predicted state variable at k_i+m instant with given current plant information x(ki). The predicted output is as follows (Rossiter, 2003):

$$Y = [y(ki+1 \mid ki) y(ki+2) \mid ki \; y(ki+3) \mid ki) \ldots y(ki+Np \mid ki)^T$$

$$\Delta U = [\Delta u(ki) \Delta u(ki+1) \Delta u(ki+2) .. \Delta u(ki+Nc-1)^T$$

$$Y = Fx(k_i) + \varnothing \Delta U \tag{6}$$

$$F = \begin{bmatrix} CA \\ \vdots \\ C_A{}^{Np} \end{bmatrix} \phi = \begin{bmatrix} CB & 0 \cdots & \cdots 0 \\ \vdots & \vdots & \vdots \\ CA^{Np-1}B & \ldots \ldots & CA^{Np-Nc}B \end{bmatrix}$$

The cost function J is defined as:

$$J = (R_s - Y)^T (R_s - Y) + \Delta U^T \bar{R} \Delta U \tag{7}$$

where, the first term is to minimize the error between the set-point signal and the predicted output, the second term deals with the size of ΔU. The necessary condition to obtain the minimum J is:

$$\frac{\partial J}{\partial \Delta u} = 0$$

Therefore, the control signal's optimal solution is:

$$\Delta U = (\varnothing^T \varnothing + R)^{-1} \varnothing^T (Rs\text{-}Fx(k_i)) \tag{8}$$

The minimum of the cost function is obtained as, (Brosilow and Joseph, 2002).

$$J_{min} = (R_s\text{-}Fx(k_i))^T (R_s\text{-}Fx)(k_i)) - (R_s\text{-}Fx(k_i))^T \varnothing (\varnothing^T \varnothing + \bar{R})^{-1} \varnothing^T (Rs\text{-}Fx(k_i)) \tag{9}$$

The transfer functions obtained are discretized and augmented state model is found. The cost function obtained is optimised using the constraints and the receding horizon control is implemented for all the 6 regions.

RESULTS AND DISCUSSIONS

For the conical tank, system identification was carried by conducting step test. The model was identified for six different operating regions taking different flow rates. Figure 3a-f shows the

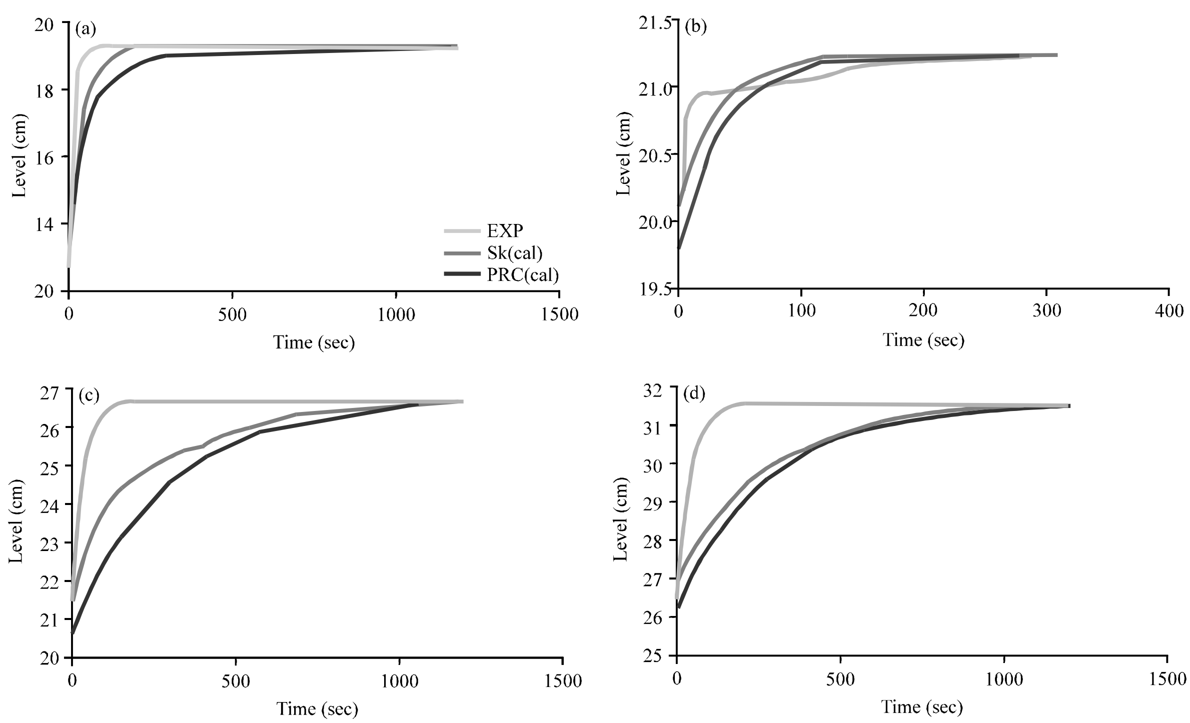

Fig. 3(a-f): Countinue

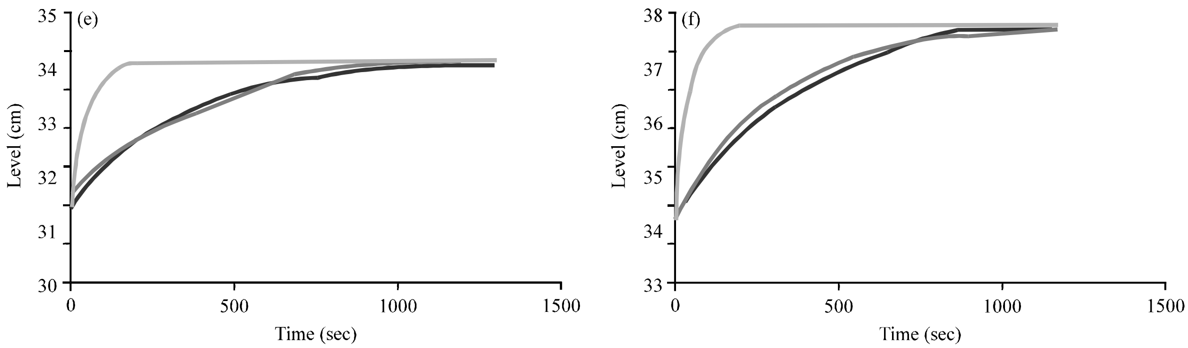

Fig. 3(a-f): Process reaction curve for experimental and calculated data of the process (a) 1 (b) 2 (c) 3, (d) 4, (e) 5 and (f) zone 6

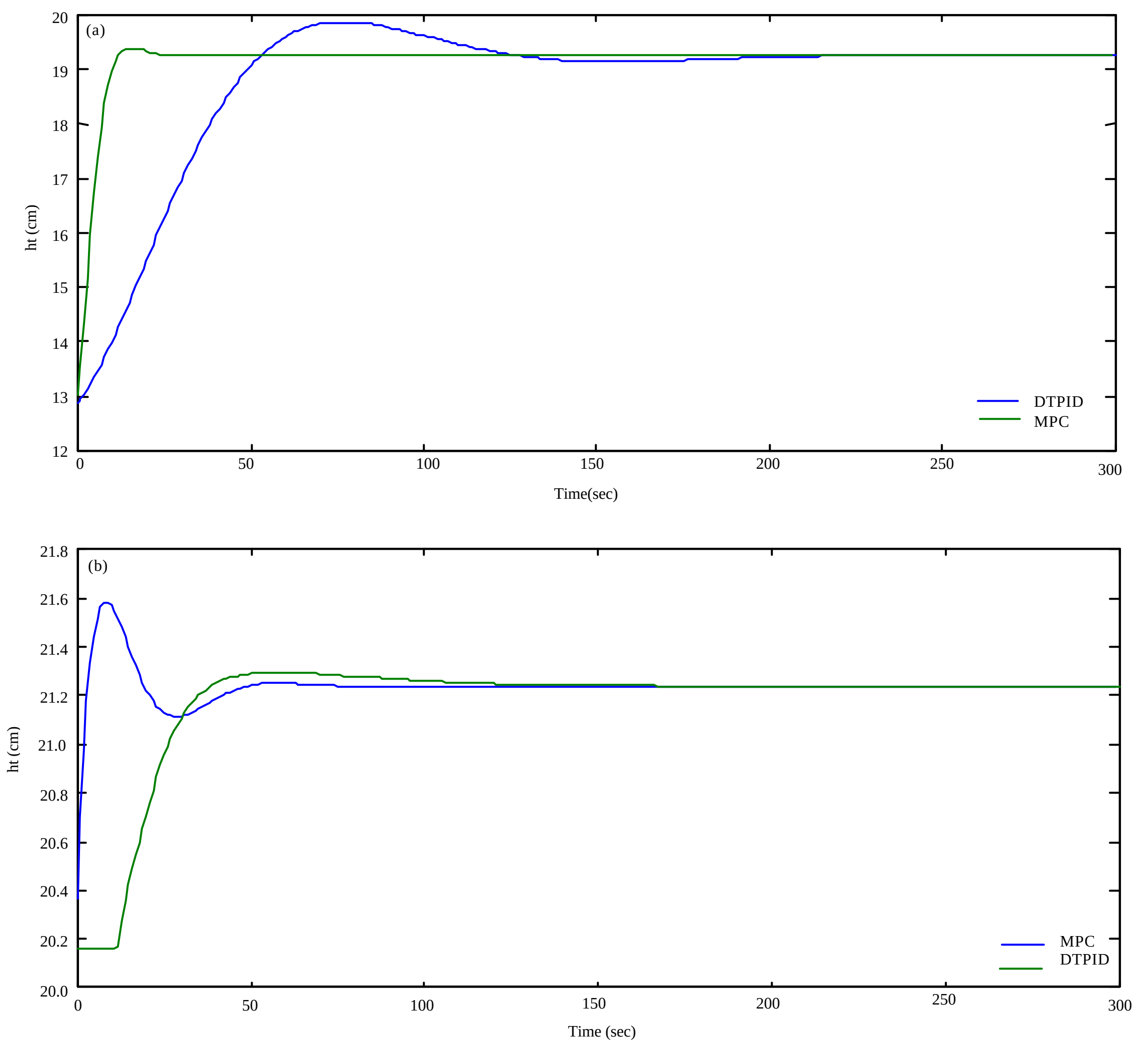

Fig. 4(a-f): Countinue

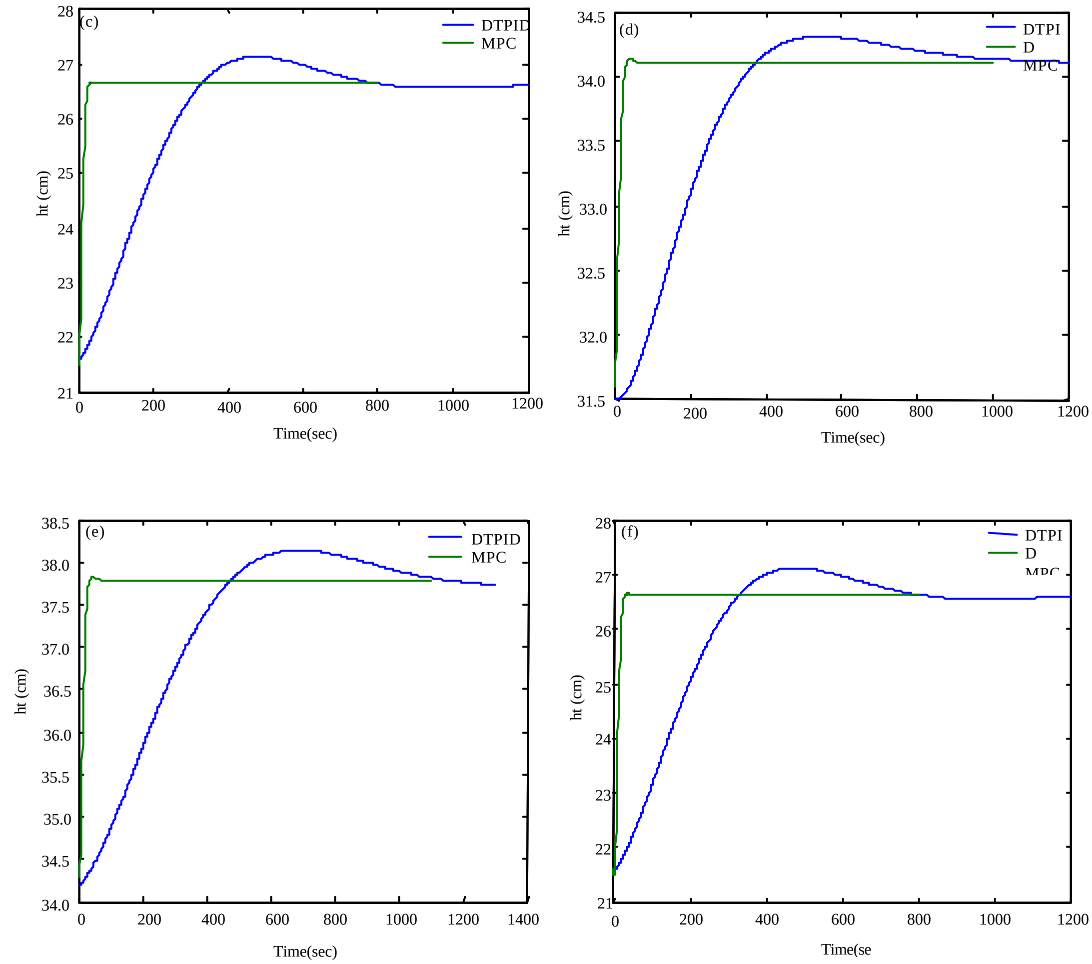

Fig. 4(a-f): Step responses of the process with different controllers inplemented for different operating regions (a) 1 (b) 2 (c) 3 (d) 4 (e) 5 and (f) Zone 6

step response graph showing experimental (blue in color) and calculated data of both SK method (red color) and PRC method (green color). From the graph it is evident that system identification with SK method is closer to experimental data. Table 1 shows the model of the process identified for six different operating regions using SK method.

Figures 4a-f shows comparison of the step responses of MPC and DTPID controllers for six different operating regions. It is evident from those graphs that Model Predictive Control gives less overshoot in all six operating zones, at the same time, rise time and settling time is also less than the conventional DTPID controller. Table 2 shows the time domain specifications for different controllers considered for this study. It is evident from Table 2 that the MPC controller provides better performance in all the six operating regions in terms of rise time, settling time and overshoot.

Table 2: Time domain specifications for DTPID and MPC controllers

Description	Rise time (sec)	Settling time (sec)	Overshoot (%)
Zone 1			
DTPID	45	209	3.22
MPC	8	28	0.727
Zone 2			
DTPID	17	133	0.283
MPC	3	69	1.601
Zone 3			
DTPID	235	1144	1.993
MPC	14	53	0.075
Zone 4			
DTPID	228	1056	1.590
MPC	16	50	0.032
Zone 5			
DTPID	252	1016	0.527
MPC	19	60	0.088
Zone 6			
DTPID	338	1249	1.060
MPC	19	60	0.079

CONCLUSION

The nonlinear system used for analysis is conical tank. System identification is performed using process reaction curve method and SK method. SK method was found to give minimum error compared with the process reaction method. Different controllers like DTPID and MPC were designed and implemented in MATLAB environment. The performance is compared with conventional controller and the results prove the effectiveness of the proposed Model Predictive Controller. The performance parameters used for the comparison are rise time, settling time and percentage overshoot.

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