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Design and simulation of a model predictive controller for level control in a single tank system

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ABSTRACT

Process control refers to the methods that are used to control and manipulate process variables in manufacturing a product. The main aim of this work is to design and simulate the working of a single input-single output (SISO) tank system using model predictive control (MPC) and conventional control and comparing the performances of both systems. The controlled variable is the liquid level in the tank and the manipulated variable is the inlet flow rate of the liquid. Control systems based on the servo and regulatory control schemes are designed and simulated in Scilab. Tuning methods like Ziegler-Nichols, Coon-Cohen, and Tyreus-Luyben are used for the design of conventional controllers (P, PI, and PID). MPC system is designed using Differential Evolution heuristic. From the results obtained, it is revealed that the model predictive control scheme developed was able to control the liquid level in the tank with no offset and a settling time which was considerably lower than those offered by the conventional control schemes. The validated MPC system provides zero offset, better settling times, self-learning control action and incorporation of non-linear models with ease. This model can serve as a base for future improvement studies on the said model predictive control scheme.

Keywords— *Model predictive control, SISO system, Scilab, Differential evolution*

1. INTRODUCTION

Model predictive control is a digital control which is used in chemical and process industries for solving complicated processes since the 1980's. It needs process parameters to control the process in desired value, which has been obtained pragmatically by modeling the process. It keeps future time slots into an account and allows the current time slot to be optimized. MPC can anticipate future events and takes control actions accordingly. The conventional controllers, on the other hand, are incapable of the same. Depending on how many controlled outputs and manipulated inputs we have in a chemical process, we can distinguish the control configurations as SISO (Single Input Single Output) systems and MIMO (Multiple Input Multiple Output) systems. When a process has only one input variable to be used in controlling one output variable, then that system is called as SISO system. A MIMO system is one with multiple inputs, u1, u2, u3, u4…, um and multiple outputs, y1, y2, y3, y4…, yn, where m is not necessarily equal to n; it could be a single process, such as the stirred mixing tank, or it could be an aggregate of many process units constituting part of an entire plant, or it could be the entire plant itself. Predictive Control should be used when: (a)Processes are difficult to control with standard conventional control algorithms – long time constants, substantial time delays, and inverse responses are present (b)There is substantial dynamic interaction among controls, i.e., more than one manipulated variable has a significant effect on an important process variable.

2. MODEL

The model that is used takes into consideration, the dynamic behaviour of a tank system, wherein, the controlled variable is the liquid level of the tank and manipulated variable is the inlet flow rate of the liquid. A setpoint of magnitude 1 was provided for the liquid level in the process tank. The liquid used in this case is water. Hence, by varying the inlet flow rate, the water level can be varied according to the process requirements. Water from the storage tank is pumped out using a $1/7^{th}$ hp fractional pump. The flow rate is measured using a rotameter. Water then passes through a control valve and then, is fed to the process tank. A setpoint value for the water level inside the process tank is predetermined. As water enters inside, a pressure sensor measures the pressure head and sends the analog signal to an A to D card where it is converted into a digital signal. This digital signal is fed to the controller and it takes the necessary action. The action is sent as a digital signal, to a D to A card where it gets converted to an analog signal and is fed to the control valve. Receiving this signal, the control valve adjusts the actuator as per the signal received from the control system and the flow rate is adjusted. This gives rise to the desired value of water level inside the tank. In this manner, the flow rate of water is varied with respect to change in level. A bypass valve is used to prevent backflow of the water to the pump. This prevents cavitation and eventual failure of the pump. A manual valve is fitted for controlling the outflow of water from the process tank to the storage tank.

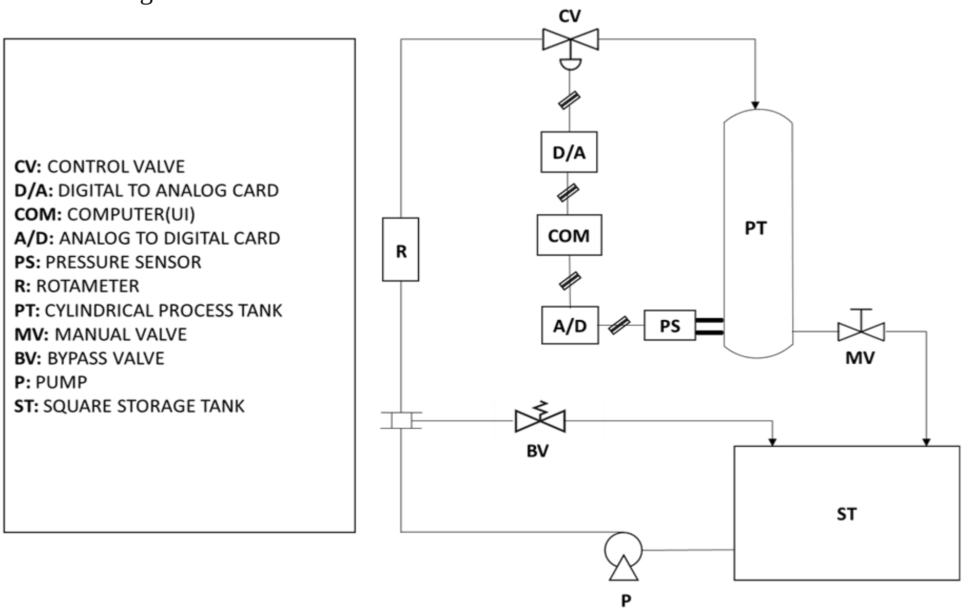

Fig. 1: SISO water level tank system

Table 1: System specifications

No.	System	Dimensions	MOC
1	**Process Tank (Cylindrical)**	Volume= 7.496 lt	PP
		Area= 100 cm^2	
		Diameter=11.28 cm	
		Height=75 cm	
2	**Bottom Plate**	Thickness=0.6 cm	PP
3	**Storage Tank (Square)**	Volume= 60 lt	PP
		Area= 750 cm^2	
		Length=30 cm	
		Breadth= 25 cm	
		Height= 80 cm	
4	**Pump**	Capacity= 1/7 hp	-
5	**MV & BV**	Ball valves	-
6	**Control Valve**	Ball/globe valve	-
		Line size= 1.27 cm	
		Electric actuator	
		Input signal= 4-20 ma	
7	**Connection Line**	Line size= 1.27 cm	PP

3. DESIGN OF CONVENTIONAL CONTROLLERS

3.1 Proportional (P) Controller

A proportional controller attempts to perform better than an on-off type by giving output in proportion to the difference (error, ε) in level between the measured and the set point,

$$p(t) = p_s + K_c^* \varepsilon(t)$$

This P-controller requires biasing or manual reset when used alone because it never reaches the steady-state condition. It provides stable operation but always maintains the steady state error. As the controller gain becomes larger, the issue arises with the stability of the feedback loop. For a P-controller as K_c increases, offset decreases.

3.2 Proportional-Integral (PI) Controller

For an integral control action, the controller output depends on the integral of the error signal over time. Consequently, the integral control action is normally used in conjunction with proportional control as the Proportional-Integral Controller.

$$p(t) = p_s + K_c * \varepsilon(t) + (K_c/\tau_I) * \int_0^t \varepsilon(t)dt$$

3.3 Proportional-Integral-Derivative (PID) Controller

The output depends on the rate of change of error with respect to time, multiplied by derivative constant. It gives the kickstart for the output thereby increasing system response.

$$p(t) = p_s + K_c * \varepsilon(t) + \left(\frac{K_c}{\tau_I}\right) * \int_0^t \varepsilon(t)dt + K_c * \tau_D * \frac{d\varepsilon(t)}{dt}$$

Table 2: Conventional controller characteristics

P	- Simplest controller to tune (K_c) - Offset with sustained disturbance or setpoint change
PI	- More complicated to tune (K_c, τ_I) - Better performance than P - No offset introduces oscillatory response - Reset windup
PID	- Most complicated to tune (K_c, τ_I, τ_D) - Better performance than PI - No offset, stabilizing or anticipatory response

3.4 Tuning

Table 3: Zeigler-Nichols tuning parameters

Z-N settings	P	PI	PID
K_c	$K_u/2$	$K_u/2.2$	$K_u/1.7$
τ_I (min)	-	$P_u/1.2$	$P_u/2$
τ_D (min)	-	-	$P_u/8$

Table 4: Luyben-Tyreus tuning parameters

TLC settings	K_c	τ_I	τ_D
PI	$0.31K_u$	$2.2P_u$	-
PID	$0.45K_u$	$2.2P_u$	$P_u/6.3$

Table 5: Coon-Cohen tuning parameters

Type	Parameters
P	$K_c = (\frac{T}{Kp*td})(1+\frac{td}{3T})$
PI	$K_c = (\frac{T}{Kp*td})(\frac{9}{10}+\frac{td}{12T})$ $\tau_I = t_d * (\frac{30+3td/T}{9+20td/T})$
PID	$K_c = (\frac{T}{Kp*td})(\frac{4}{3}+\frac{td}{4T})$ $\tau_I = t_d * (\frac{32+6td/T}{13+8td/T})$ $\tau_D = t_d * (\frac{4}{11+2td/T})$

4. DESIGN OF MPC

4.1. MPC on discrete time models

Time-delay compensation techniques predict process output one-time delay ahead. Here we are concerned with predictive control techniques that predict the process output over a longer time horizon.

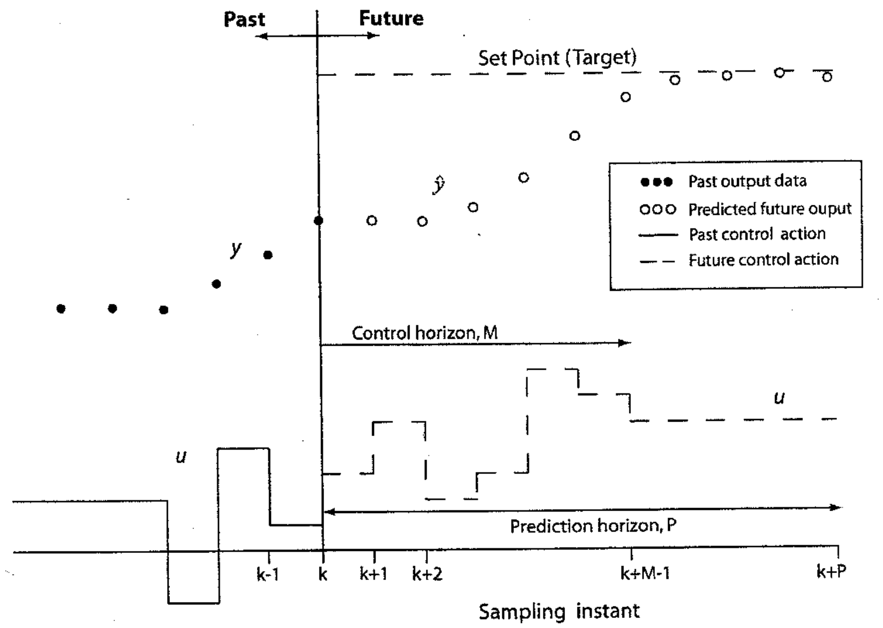

Fig. 2: MPC on discrete time models

4.2. General characteristics of MPC

Targets (set points) are selected by real-time optimization algorithms based on current operating and economic conditions. The main aim is to minimize the square of deviations (least square method) between predicted future outputs and specific reference trajectory to new targets.

4.3. Discrete step response model and response coefficients

The framework provided can handle multiple inputs, multiple outputs (MIMO) control problems with ease. Equality and inequality constraints on controlled and manipulated variables are solved as per the model specifications. Quadratic programming problem is solved at each sampling instant. The disturbance is estimated by comparing the actual controlled variable with the model prediction. The first move out of M calculated moves is implemented.

Fig. 3: SISO process

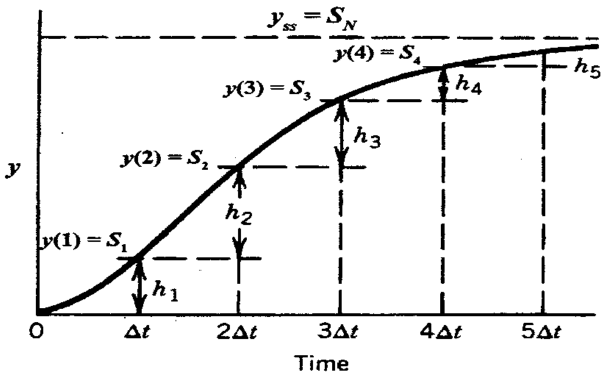

Fig. 4: Step response coefficients

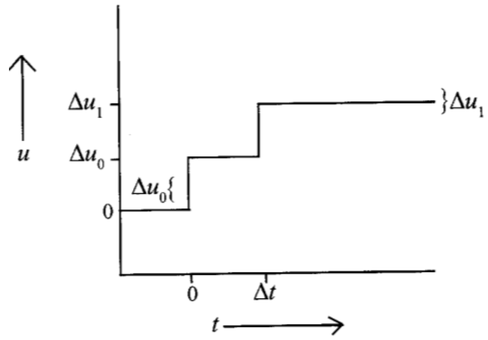

Fig. 5: Multiple step inputs

For a single input, single output process in figure-3, from the Principle of Superposition for linear system,

$y_1 = y_0 + S_1 Du_0$

$y_2 = y_0 + S_2 Du_0 + S_1 Du_1$

$y_3 = y_0 + S_3 Du_0 + S_2 Du_1$

. .

. .

$y_N = y_0 + S_N Du_0 + S_{N-1} Du_1$

4.4. Method of least squares

For an equation $\tilde{y} = m_1 x_1 + m_2 x_2$ {1}

We define, the objective function, also known as the 'Performance Index', as the sum of the squares of the differences between the actual data points and the values calculated from {1}:

Performance index: $J = \sum_{i=1}^{Np} (y_i - \tilde{y}_i)^2$ {2}

At each of the N_p data points, the values of y_i, $x_{i1,}$ and x_{i2} are known. The objective is to find the values of m_1 and m_2 that do the best job of fitting the data to the proposed equation. Substituting the predicted values from {1} into the performance index {2} and differentiating the objective function with respect to the parameters and setting the partial derivatives to zero, we obtain:

$$m_1 \sum_{i=1}^{Np} (x_{i1}^2) + m_2 \sum_{i=1}^{Np} (x_{i1} x_{i2}) = \sum_{i=1}^{Np} (x_{i1} y_i) \text{ and } m_1 \sum_{i=1}^{Np} (x_{i1} x_{i2}) + m_2 \sum_{i=1}^{Np} (x_{i2}^2) = \sum_{i=1}^{Np} (x_{i2} y_i)$$

This can be simply represented as: $X^T X m = X^T Y$

$$Where, X = \begin{bmatrix} x_{11} & x_{12} \\ x_{21} & x_{22} \\ \vdots & \vdots \\ x_{Np1} & x_{Np2} \end{bmatrix}, m = \begin{bmatrix} m_1 \\ m_2 \end{bmatrix}, and\ Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_{Np} \end{bmatrix}$$

4.5. Differential Evolution (DE)

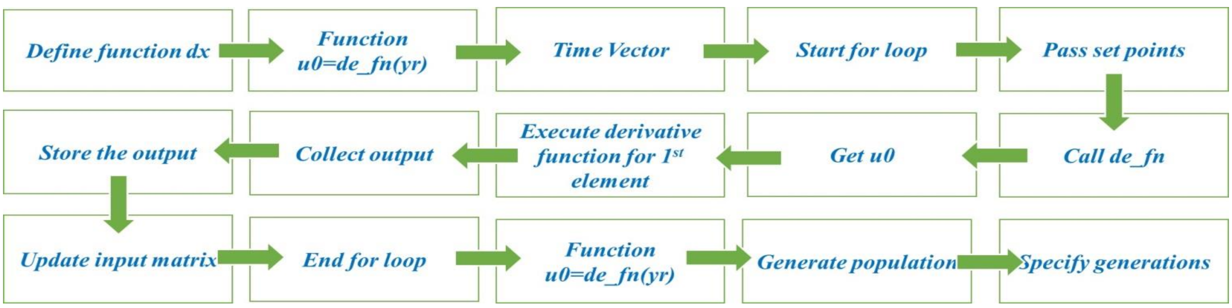

Fig. 6: DE algorithm

5. RESULTS

Table 6: Conventional controller tuning values

ZEIGLER-NICHOLS TUNING

CONTROLLER	Kc	τI	τD
PROPORTIONAL	17.6	-	-
PI	15.84	26.44	-
PID	21.12	15.86	3.99

LUYBEN-TYREUS TUNING

CONTROLLER	Kc	τI	τD
PI	10.91	69.81	-
PID	15.84	69.81	5.03

COON-COHEN TUNING

CONTROLLER	Kc	τI	τD
PROPORTIONAL	17.09	-	-
PI	14.74	13.43	-
PID	22.22	10.99	1.65

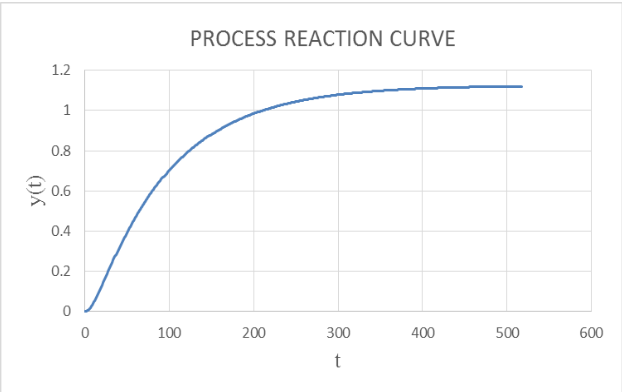

Fig. 7: Process reaction curve

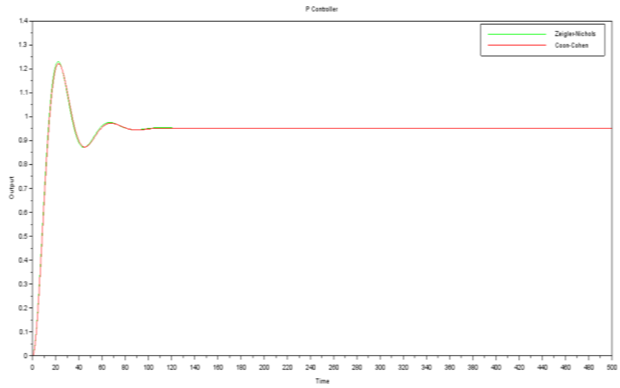

Fig. 8: P controller system output vs time (seconds)

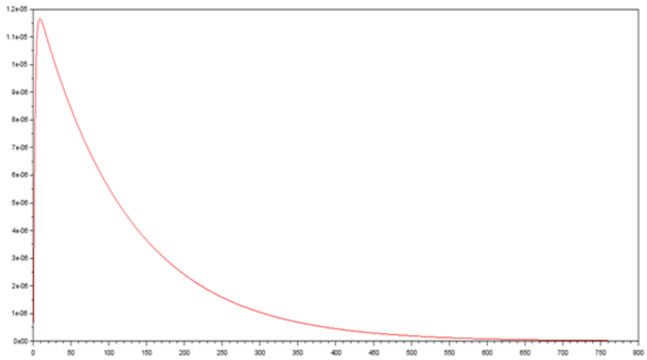

Fig. 9: PI controller system output vs time (seconds)

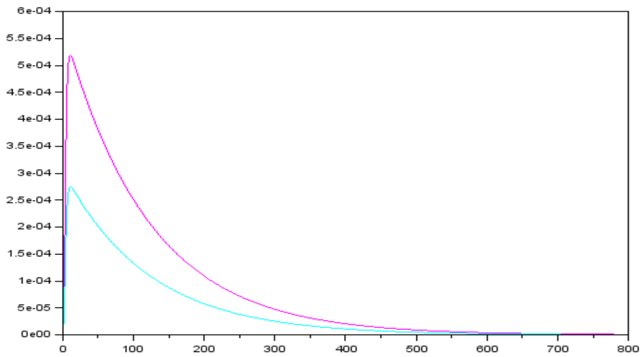

Fig. 10: PID controller system output vs time (seconds)

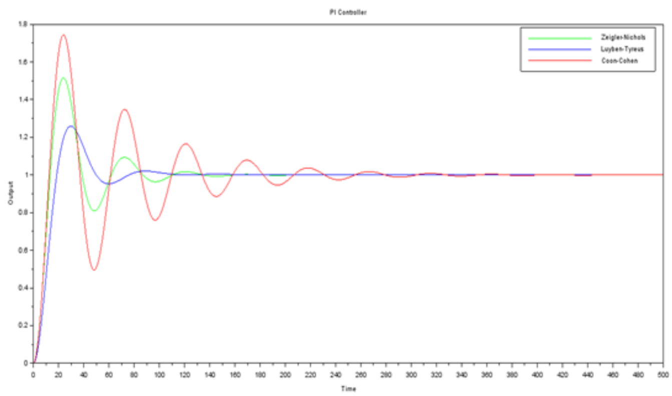

Fig. 11: Impulse input response vs. time (seconds)

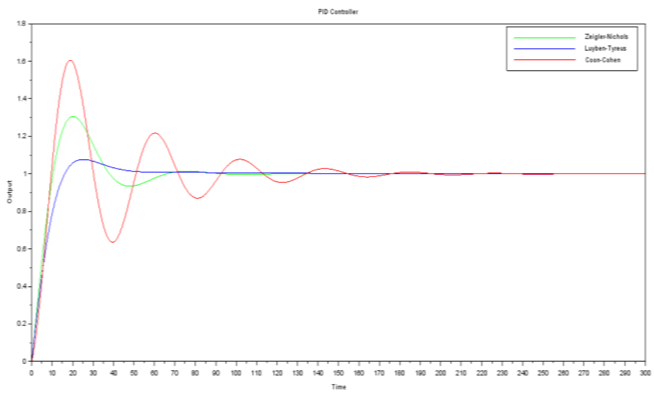

Fig. 12: Comparison of impulse input responses (csim & addition of coefficients) vs. time (seconds)

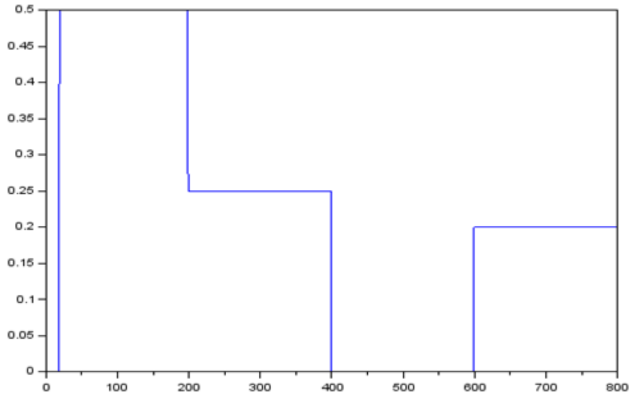

Fig. 13: Providing set path

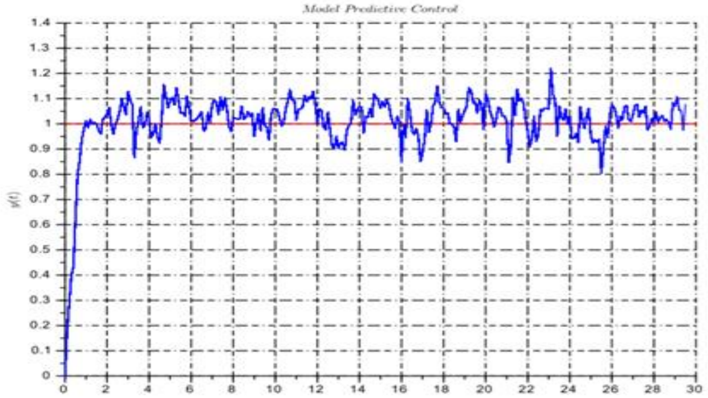

Fig. 14: MP controller system output-1 vs. time (seconds)

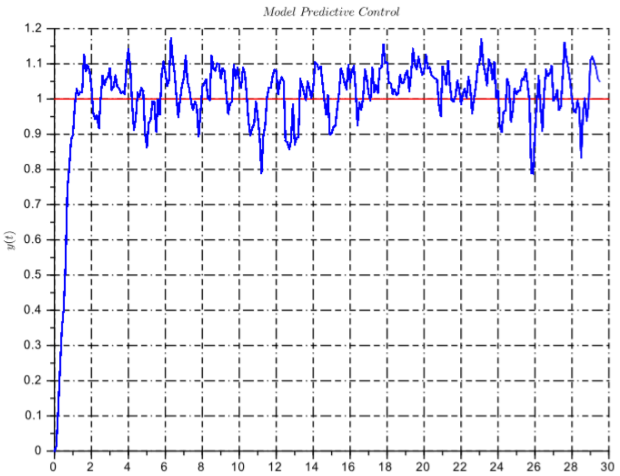

Fig. 15: MP controller system output-2 vs. time (seconds)

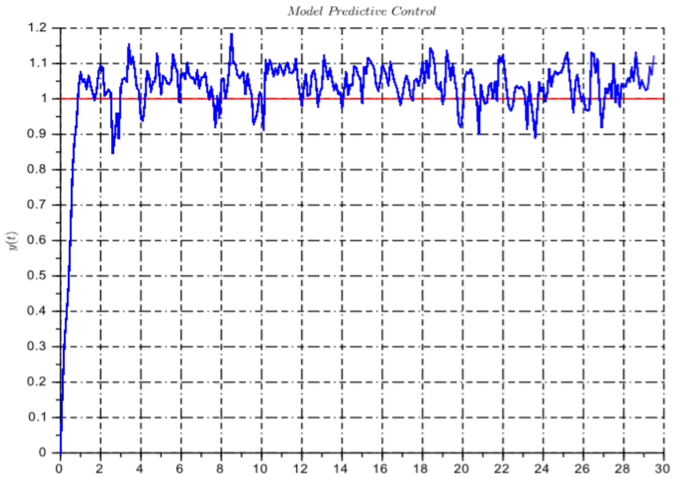

Fig. 16: MP controller system output-3 vs. time (seconds)

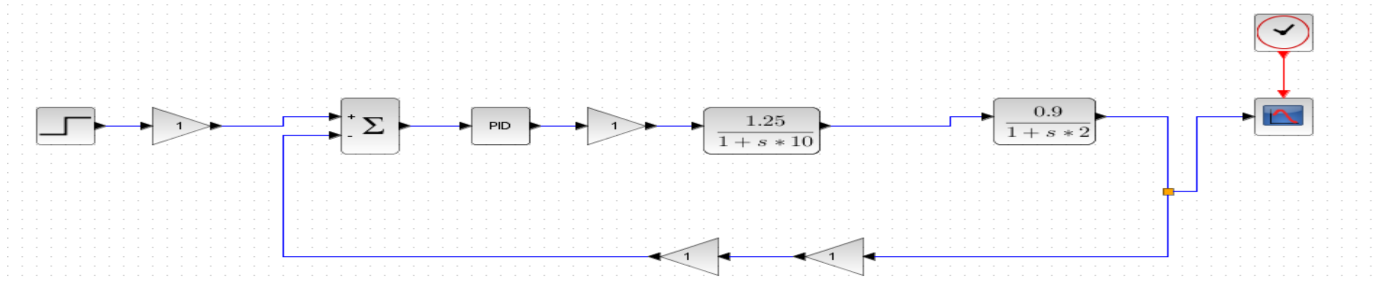

Fig. 17: Xcos model

```
//DE Parameters for output [1] in figure-14:
Initialization of Time vector
t0 = 0;
tf = 30;
dt = 0.1;
tt = [t0:dt:tf];
Nt = length(tt);
// Initialization of DE parameters
Np = 200;                                            // Number of population
Nc = 6;                                              // Prediction Horizon
Ng = 20;                                             // Number of generations
sf = 0.25;                                           // Scale Factor
ul = 1000;                                           // Lower bound on input
uh = 5000;                                           // Higher bound on input
// Defining the Weight MatrixNw = Nc + 1;W = ones(Nw,Nw);W(1,1) = 10;

//DE Parameters for output [2] in figure-15:
sc = grand(1,Nw,'unf',0,sf);ci = pop(i,:) + sf .* di;

//DE Parameters for output [3] in figure-16:
// Initialization of Time vector
t0 = 0; tf = 30; dt = 0.1; tt = [t0:dt:tf]; Nt = length(tt);
// Initialization of DE parameters
Np = 500;                  // Number of population
Nc = 6;                    // Prediction Horizon
Ng = 20;                   // Number of generations
sf = 0.25;                 // Scale Factor
ul = 1000;                 // Lower bound on input
uh = 5000;                 // Higher bound on input
```

Fig. 18: DE parameters

6. DISCUSSION

Figure 7: Represents the process reaction curve that was generated in response to a disturbance. This process curve is then used to calculate controller gain, integral time and derivative time using Coon-Cohen tuning parameters. The method is performed in open loop so that no control action occurs and the process response can be isolated.

Figure 8: Shows the output of the tank system when a proportional controller is used. It should be noted that although the response settles to a steady value after 150 seconds, a constant offset is introduced in the output which is undesirable.

Figure 9: Shows the output of the tank system when a PI controller is used. In this case, the response settles to a steady value after 290 seconds with zero offset. An undesirable oscillatory behaviour in the output can be seen.

Figure 10: Shows the output of the tank system when a PID controller is used. The response settles to a steady value after 100 seconds with zero offset and the oscillatory behaviour is also taken care of. Hence, the PID controller is vastly used in the current process industry scenario.

Figure 11: Represents the output of the system when a unit impulse input is provided using csim in Scilab.

Figure 12: Represents the comparison between csmin response and addition of coefficients response of the system to an impulse input. It should be noted that the difference between the two curves is negligible (2.3×10^{-4}).

Figure 13: Represents a set path given to the system using multiple step inputs.

Figure 14: Shows the output-1 of the tank system when an MPC controller is used.

Figure 15: Shows the output-2 of the tank system when an MPC controller is used.

Figure 16: Shows the output-3 of the tank system when an MPC controller is used.

Figure 17: Represents the Xcos simulation model of the tank system.

Figure 18: Shows the different DE parameters that were used for obtaining output-1, output-2 and output-3.

7. CONCLUSION

By comparing the graphs in Figure 14, Figure 15, Figure 16 with graphs in Figure 8, Figure 9 and Figure 10, it is revealed that the model predictive control scheme developed was able to control the liquid level in the tank with no offset and a settling time of 2 seconds as compared to the settling times of 100 seconds, 290 seconds and 150 seconds which were offered by P, PI and PID control schemes respectively. It should be noted that conventional controllers tuned with Luyben-Tyreus settings (blue curve in Figure 9 and Figure 10) yielded a smooth output curve with settling times of around 100 seconds. The output using MPC system was relatively unstable as compared to Luyben-Tyreus settings because these settings have fixed parameters and do not take into account the dynamic behavior of the system which keeps on changing with time. MPC is able to accommodate such behavior and it updates the past output matrix while optimizing and executing the current control action. Based on the comparison of the two control methods, the process model that MPC used enables the MPC controller to predict the future state of the plant during the dynamic operation, which is particularly attractive as compared with conventional control schemes because the dynamics change as the water level changes in the tanks. Work needs to be done for further linearizing the output that was obtained using the MPC controller. There is scope for incorporating nonlinear models and models that contain multiple inputs and multiple outputs. The use of Fuzzy Logic on MPC to linearize and streamline the output can be done.

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