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Soft Computing Control Methodologies for Temperature Process System and its Performance Evaluation

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Abstract: The temperature inside a Continuous Stirred Tank Reactor (CSTR) is difficult to control when chemical reaction takes place. The coolant circulates on the outer jacket of the reactor and extracts the heat energy liberated during the exothermic reaction. The temperature inside the reactor is controlled by manipulating the flow rate of coolant. This study compares the performances of control methodologies like Proportional Integral Derivative (PID) Control, Non Linear Auto Regressive Moving Average (NARMA) model control, Neural Network Predictive (NNP) control and Model Predictive (MP) control. A novel method of control is obtained by incorporating PID method in MP control i.e., the proposed method of control is MP-PID. A significant amount of reduction in time for the control action is obtained for the proposed methods. The time domain specifications on the response for the CSTR Model with the above controllers are tabulated and analyzed.

Key words: CSTR, PID, NARMA, NNP, MP, MP-PID, ISE, IAE, ITSE, ITAE

INTRODUCTION

Chemical reactors are often the most difficult units to control in a chemical plant, particularly if the reactions are rapid and exothermic. A little increase in temperature may make rapid increase the reaction rate causing significant changes in conversion and yield. The heat removal rate is quickly increased to restore the normal temperature. A continuous stirred reactor with a constant feed rate, feed concentration and holdup time with irreversible exothermic reaction is considered. The heat generated by chemical reaction, the heat removed by the jacket and the product stream plotted against reactor temperature shows three different operating states (Harriot, 1989). The amount of heat released by exothermic reaction is sigmoidal function of temperature in the reactor. The heat removed by the coolant is linear function of temperature. The intersection of the curves yields three states (Stephanopoulos, 1984). A CSTR at steady state will have the heat generated by reaction is equal to heat removed by the coolant. A controller that ensures the stability of the operation at the middle steady state is desirable. Figure 1 shows a CSTR in which a irreversible exothermic reaction A_B takes place. The heat of reaction is removed by a coolant medium that flows through a jacket around the reactor. The comparative control strategies are discussed (Chopra *et al*., 2014; Zahraa, 2012) for CSTR process.

MATERIALS AND METHODS

Model description: The assumptions made for developing the mathematical model is that there is perfect mixing inside reactor and the jacket. Volume of reactor and jacket is constant and the parameter values are fixed. The dynamic model of the reactor is obtained by writing material and energy balance equation. The change in concentration of the reactant, temperature of the reactor and the jacket temperature is mathematically written as (Prakash and Srinivasan, 2009):

$$\frac{dC_A}{dt} = \frac{F_i}{V}(C_{Ai}, C_A) - K_o \times \exp\left(-\frac{E}{R \times T}\right) C_A \quad (1)$$

$$\frac{dT}{dt} = \frac{F_i}{V}(T_i - T) + \left(\frac{-\Delta H}{\rho \times C\rho}\right) - K_o \times \exp \left(-\frac{E}{R \times T}\right) C_A - \left(\frac{UA}{V\rho \times C\rho}\right)(T_i - T) \quad (2)$$

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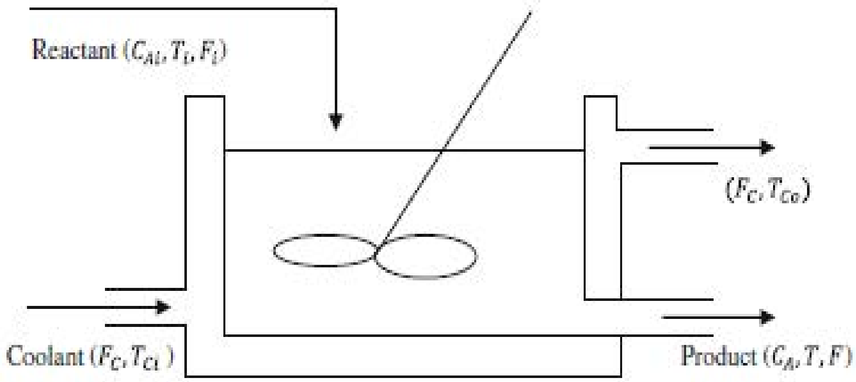

Fig. 1: CSTR with cooling jacket

$$\frac{dTj}{dt} = \frac{F_i}{V}\left(T_j in - T_j\right) + \left(\frac{-\Delta H}{\rho \times C\rho}\right) - \left(\frac{U \times A}{V \times \rho \times C\rho}\right)\left(T_i - T\right) \quad (3)$$

The transfer function model of the CSTR system (Prakash and Srinivasan, 2009) taken for performance analysis is given as:

$$G_p(S) = \frac{T}{T_j} - \frac{1.458s + 11.65}{S^2 + 3.434s + 3.557} \quad (4)$$

Control strategies: The plant transfer function model is taken and different control strategies such as PID, NARMA, NNP and MP are applied to obtain the desired response for the given reference input. All the fore said controller performances are evaluated with performance metrics such as ISE, IAE, ITSE and ITAE.

Proportional Integral Derivative (PID) controller: The Proportional Integral Derivative (PID) controller has been used for the Temperature and Concentration control for CSTR over past two decades. The time domain representation of PID control is:

$$u(t) = K_c \begin{Bmatrix} e(t) + 1/t_i \int_0^t e(t)dt + t_d \\ (de(t))/dt \end{Bmatrix} \quad (5)$$

The initial K_p, K_i, K_d values of the parameter are obtained as 0.1, 0.2 and 0.02, respectively using Zeigler-Nichols Method. The block diagram of the closed loop system with PID Controller is shown in Fig. 2.

The closed loop response of plant model with and without PID controller is obtained. A set point of 100°F is given as step input. The difference between set point and the measured temperature i.e., the error is given as a input to the PID controller. For the system with PID Controller the delay time, rise time and settling time are 1.3186, 2.5925 and 3.5485 sec, respectively. There is no over shoot in the response. The steady state error is negligible for the plant with PID controller. For a plant without controller the temperature settles at a lower stable value with overshoot. The controller performance for the plant response over a period of 5 sec is plotted with the ISE, IAE, ITAE and ITSE as metrics is shown in Fig. 3.

For a plant with PID controller the IAE and ITAE is found to be the 152.3 and 169.3, respectively at the steady state operating point when the response time is 5 sec. The typical ISE and ITSE values are 9565 and 6742 which is quiet higher.

Narma controller: The neural controller is referred to by two different names: feedback linearization control and NARMA-L2 control. It is referred to as feedback linearization when the plant model has a companion form. It is referred to as NARMA-L2 control when the plant model can be approximated by the same companion form. The central idea of this type of control is to transform nonlinear system dynamics into linear dynamics by cancelling the nonlinearities. The NARMA model is represented as:

$$y(k+d) = f\begin{bmatrix} y(k), y(k-1), \ldots, y(k-n+1), \\ u(k), u(k-1), \ldots, u(k-n+1) \end{bmatrix} + g\left[y(k), y(k-1), \ldots, y(k-n+1)\right] \quad (6)$$

where, d = 2. Using the NARMA Model, the NARMA controller model is given as:

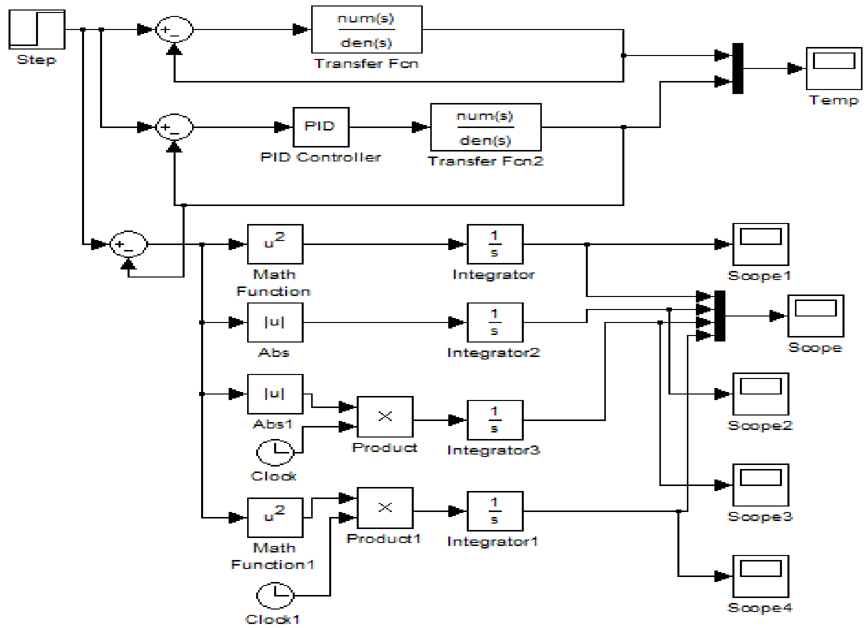

Fig. 2: Block diagram of system with and without PID controller

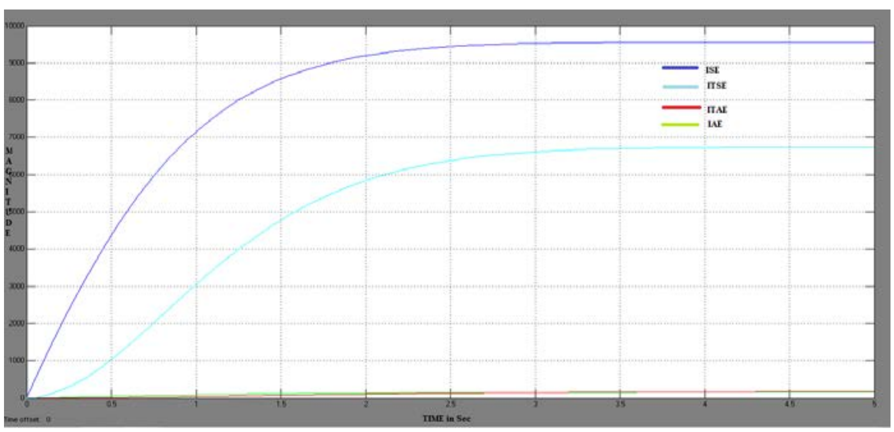

Fig. 3: Performance evaluation of PID controller

$$u(k+1)=\frac{y_r(k+d)-f[y(k),\dots,y(k-n+1),u(k),\dots,u(k-n+1)]}{g[y(k),\dots,y(k-n+1),u(k),\dots,u(k-n+1)]} \quad (7)$$

This is realizable for d≥2. The block diagram of the NARMA controller (Putrus, 2011) is shown in Fig. 4. During plant identification process the network architecture with the size of hidden layer and sampling time is 9 and 0.01 sec, respectively. The number of delayed plant inputs and outputs are chosen as 1. The training data consist of 500 samples with maximum and minimum plant input are 750 and 30.1, respectively. The maximum and minimum random plant interval values are 1 and 0.1sec, respectively. The maximum and minimum plant output is 150 and 35, respectively. The simulink plant model is kept in separate file.

The number of training epochs and training function are chosen as 300 and trainlm respectively. A set point of 100 °F is given as step input. The closed loop response of plant model with NARMA controller is obtained. For the system with NARMA Controller the delay time, rise time and settling time are 0.1685, 0.3713 and 2.1653 sec, respectively, With over shoot of 14.452% in the response. The

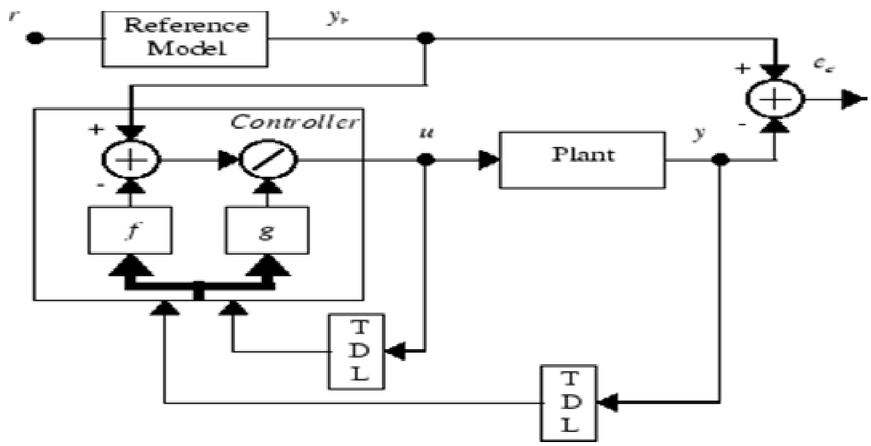

Fig. 4: Block diagram of plant with NARMA controller

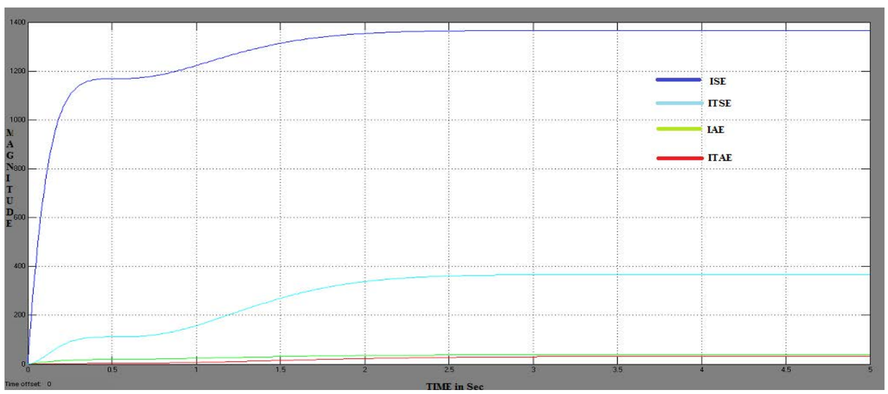

Fig. 5: Performance evaluation of NARMA controller

controller performance for the plant response over a period of 5 sec is plotted with the ISE, IAE, ITAE and ITSE as metrics is shown in Fig. 5.

For a plant with NARMA controller the ISE and ITSE is found to be the 1367 and 366.6, respectively at the steady state operating point when the response time is 5 sec. The typical IAE and ITAE values are 38.81 and 31.71. The literature (Akesson and Toivonen, 2006) shows the NARMA controller performance for the CSTR model.

Neural network predictive (NNP) controller: A plethora of Model Predictive Controller for control of temperature, concentration, Ph without neural strategy for CSTR is given in (Balaji and Maheswari, 2012; Man and Shao, 2012; Shyamalagowri and Rajeswari, 2013).The Neural network Predictive Controller uses a neural network model to predict future plant responses to relevant control signals. An optimization algorithm then computes the control signals that optimize future plant performance. The neural network plant model is trained offline, in batch form. The controller, however, requires a significant amount of online computation because an optimization algorithm is performed at each sample time to compute the optimal control input. The first stage of predictive control is to train a neural network to represent the forward dynamics of the plant. The prediction error between the plant output and the neural network output is used as the neural network training signal. The process is represented by the following Fig. 6.

The neural network plant model uses previous inputs and previous plant outputs to predict future values of the plant output. This network can be trained offline in batch mode, using data collected from the operation of the plant. The model predictive control method is based on the receding horizon technique. The neural network model predicts the plant response over a specified time horizon. The predictions are used by a numerical optimization program to determine the control signal that minimizes the following performance criterion over the specified horizon:

$$I = \sum_{j=N_1}^{N_2} \left(y_r(t+j) - y_m(t+j)\right)^2 + \rho \sum_{j=1}^{Nu} \left(u(t+j-1) - u(t+j-2)\right)^2 \quad (8)$$

where, N1, N2 and Nu define the horizons over which the tracking error and the control increments are

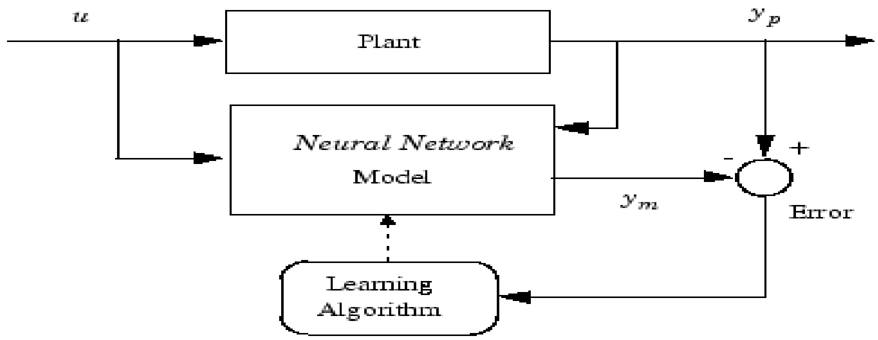

Fig. 7: NNPC structure with Plant model

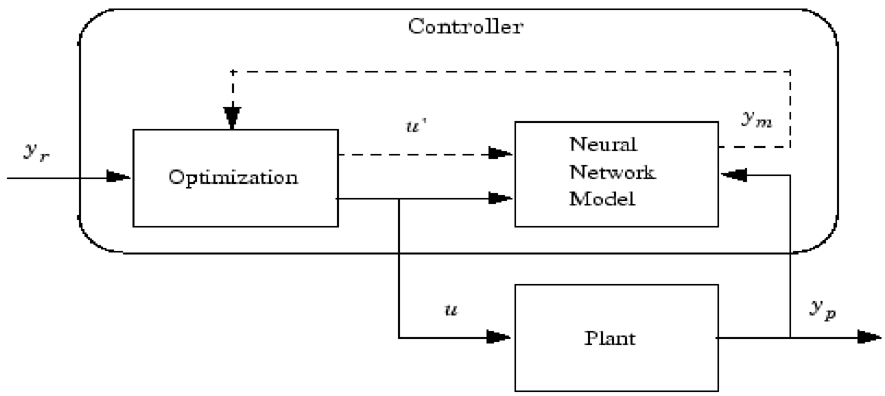

Fig. 6: System Identification Process

evaluated. The u' variable is the tentative control signal, y_r is the desired response and y_m is the network model response. The ñ value determines the contribution that the sum of the squares of the control increments has on the performance index. The following block diagram illustrates the model predictive control process. The controller consists of the neural network plant model and the optimization block. The optimization block determines the values of u' that minimize J and then the optimal u is input to the plant. The control literature (Vasikaninova and Bakosova, 2009; ZareNezhad and Aminian, 2011; Prakash and Srinivasan, 2009) have proposed neural network based model predictive control for non linear CSTR process. The structure of NNP Controller is shown in Fig. 7.

The two steps involved when using neural networks for control system are System identification and Control design. In the system identification stage, the neural network model of the plant to be controlled is developed. In the control design stage, the neural network plant model is used to design the controller. The advantage of using Artificial Neural Networks to simulate the process is that after they are trained, they represent a quick and reliable way of predicting their performance. They can also be continuously updated. The training, testing and validation of neural network model in done before the controller design.

During controller configuration the cost (N_2) and control horizon (N_u) is the number of steps over which the prediction errors and control increments are minimized, is chosen as 30 and 2, respectively. The control weighting factor (ρ) and search parameters (α) are chosen as 0.05 and 0.01 respectively. The csrchbac search minimization routine with 2 iterations per sample time is used as the performance optimization algorithm. During plant identification process the network architecture with the size of hidden layer and sampling time is 2 and 0.2 sec, respectively. The number of delayed plant inputs and outputs are chosen as 2 in both the cases. The training data consist of 500 samples with maximum and minimum plant input are 150 and 15 respectively. The maximum and minimum random plant interval values are 1 and 0.2 sec,

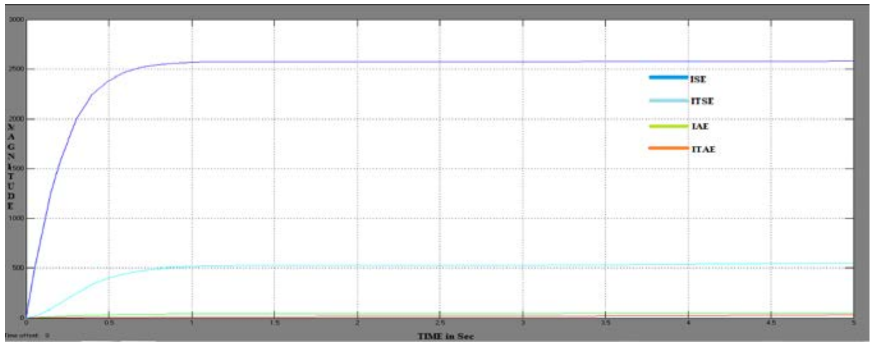

Fig. 8: Performance evaluation of neural network predictive controller

respectively. The maximum and minimum plant output is chosen as 80 and 35. The simulink plant model is kept in separate file. The number of training epochs and training function are chosen as 1000 and trainlm respectively. A set point of 100° F is given as step input. The closed loop response of plant model with NNP controller is obtained. For the system with NNP Controller the delay time, rise time and settling time are 0.352, 0.8245 and 1.1048 sec, respectively. There is no over shoot in the response. The NNP controller performance for the plant response over a period of 5 sec is plotted with the ISE, IAE, ITAE and ITSE as its metrics is shown in Fig. 8.

For a plant with NNP controller the IAE and ITAE is found to be the 47.98 and 31.59 respectively at the steady state operating point when the response time is 5 sec. The typical ISE and ITSE values are 2583 and 551.6.

Model predictive controller: The Model Predictive Control Toolbox is a collection of software that helps you design, analyze and implement an advanced industrial automation algorithm. Like other MATLAB® tools, it provides a convenient Graphical User Interface (GUI) as well as a flexible command syntax that supports customization. As its name suggests, MPC automates a target system (the "plant") by combining a prediction and a control strategy. An approximate, linear plant model provides the prediction. The control strategy compares predicted plant states to a set of objectives and then adjusts available actuators to achieve the objectives while respecting the plant's constraints. Such constraints can include the actuators' physical limits, boundaries of safe operation and lower limits for product quality.

An MPC Toolbox design generates a discrete-time controller one that takes action at regularly-spaced, discrete time instants. The sampling instants are the times at which the controller acts. The interval separating successive sampling instants is the sampling period, At (also called the control interval). Figure 9 shows the state of a hypothetical SISO MPC system that has been operating for many sampling instants. Integer k represents the current instant. The latest measured output, y_k and previous measurements, y_{k-1}, y_{k-2},.. Are known and are the filled circles in Fig. 9a. If there is a measured disturbance, its current and past values would be known (not shown). Figure 9b shows the controller's previous moves, u_{k-4}, ..., u_{k-1}, as filled circles. As is usually the case, a zero-order hold receives each move from the controller and holds it until the next sampling instant, causing the step-wise variations shown in Fig. 9b. To calculate its next move, u_k the controller operates in two phases.

Estimation: In order to make an intelligent move, the controller needs to know the current state. This includes the true value of the controlled variable, y'_k and any internal variables that influence the future trend, , y'_{k+1},..., y'_{k+P}. To accomplish this, the controller uses all past and current measurements and the models , $u \to y'$, $d \to y'$, $w \to y'$ and $z \to y'$.

Optimization: Values of set points, measured disturbances and constraints are specified over a finite horizon of future sampling instants, k+1, k+2, ..., k+P where P (a finite integer = 1) is the prediction horizon Fig. 7a). The controller computes M moves u_k, u_{k+1}, ... u_{k+M-1} where M (= 1, = P) is the control horizon Fig. 7(b). In the hypothetical example shown in the Fig. P = 9 and M = 4. The moves are the solution of a constrained optimization problem.

For a step reference input of 100°F the control interval is chosen as 0.1 time units the prediction and control horizon are chosen as 5 and 1 time intervals. The closed loop response of plant model with MP controller is obtained. For the system with MP Controller the delay time, rise time and settling time are 0.2508, 0.5604,

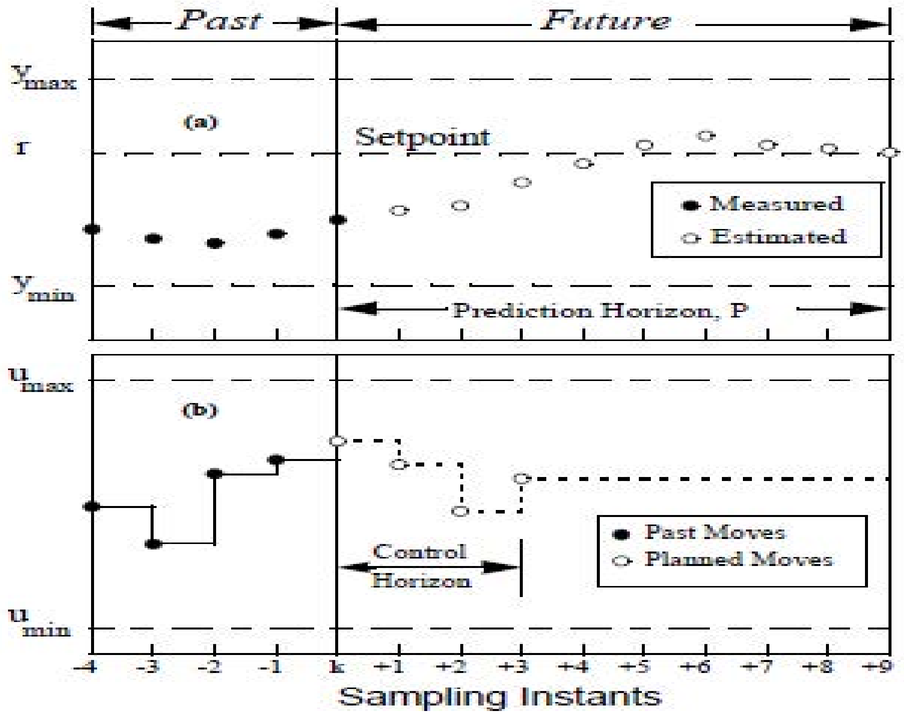

Fig. 9: Controller state at the kth sampling instant

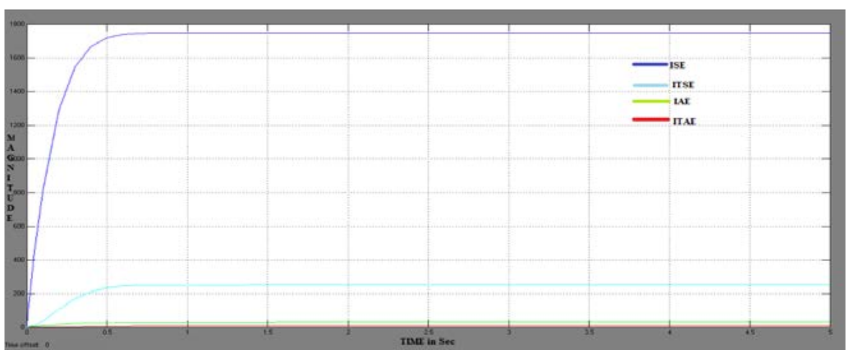

Fig. 10: Performance evaluation of model predictive control

and 0.7209 sec, respectively. There is a over shoot of 0.98% in the response. The MP controller performance for the plant response over a period of 5 sec is plotted with the ISE, IAE, ITAE and ITSE as its metrics is shown in Fig. 10.

For a plant with MP controller the ISE and ITSE is found to be the 1748 and 251 respectively at the steady state operating point when the response time is 5 sec. The typical IAE and ITAE values are 29.99 and 7.442.

Proposed MP-PID controller: The advantage of PID controller is incorporated separately in the MP controllers. This results in the formation of new MP-PID Controller. The proposed controller has good controller performance metrics and time domain specification in the response. For a step reference input of 100°F the control interval is chosen as 0.1 time units the prediction and control horizon are chosen as 5 and 1 time intervals. The closed loop response of plant model with MP-PID controller is obtained. For the system with MP-PID Controller the delay time, rise time and settling time are 0.0013743, 0.00475961 and 0.0057849 sec, respectively. There is a over shoot of 0.966% in the response. The MP controller performance for the plant response over a period of 5 sec is plotted with the ISE, IAE, ITAE and ITSE as its metrics is shown in Fig. 11.

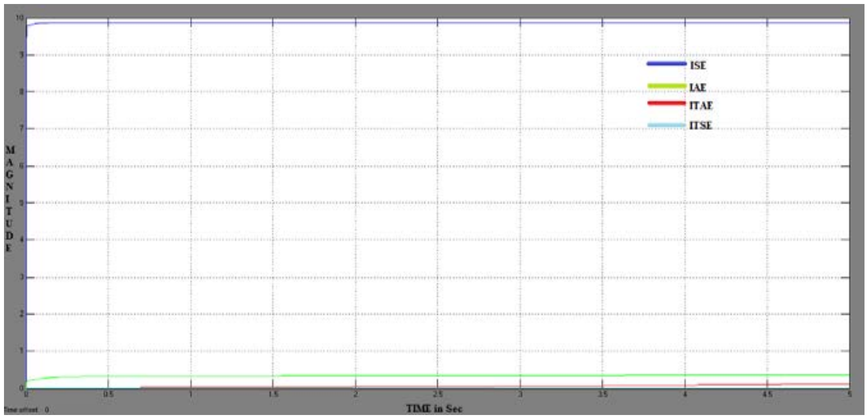

Fig. 11: Performance Evaluation of MP-PID Controller

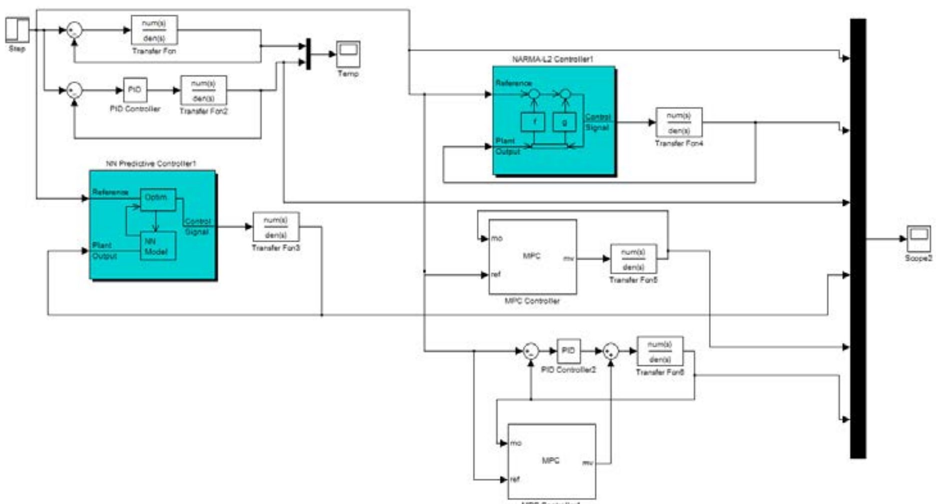

Fig. 12: MATLAB/Simulink Implementation with Various Controllers

The initial K_p, K_i, K_d values of the parameter are chosen as 0.1, 0.2 and 0.02, respectively using Zeigler Nichols Method. For a plant with MP-PID controller the ISE, IAE, ITAE and ITSE is found to be the 9.875, 0.3586, 0.1144 and 0.01332, respectively at the steady state operating point when the response time is 5 sec.

RESULTS AND DISCUSSION

The MATLAB/simulink block diagram implementation of the PID, NARMA, NNP, MP and MP-PID Controllers for the given plant model is given in Fig. 12. The combined closed loop response of the plant with PID, NARMA, NNPC, MPC, MP-PID for a reference step input of 100°F is shown in Fig. 13.

The time domain specification such as delay time, rise time, settling time and peak overshoot for various controllers are provided in Table 1.

From Table 1, it is inferred that MP-PID has the least delay time, rise time, settling time and peak overshoot values of all other controllers. From the extensive simulation study using MATLAB/Simulink software, it is found that for Non liner systems such as CSTR process the MP-PID Controller's performance is bett. The controller performance are measured using the below indices (Mishra *et al*., 2014):

- Integral Square Error (ISE)
  $ISE=\int e^2(t)\,dt$
- Integral of the Absolute Error (IAE)
  $IAE=\int |e(t)|\,dt$
- Integral Time Square Error (ITSE)
  $ITSE=\int t.e^2(t)\,dt$
- Integral Time Absolute Error (ITAE)
  $ITAE=\int t.|e(t)|\,dt$

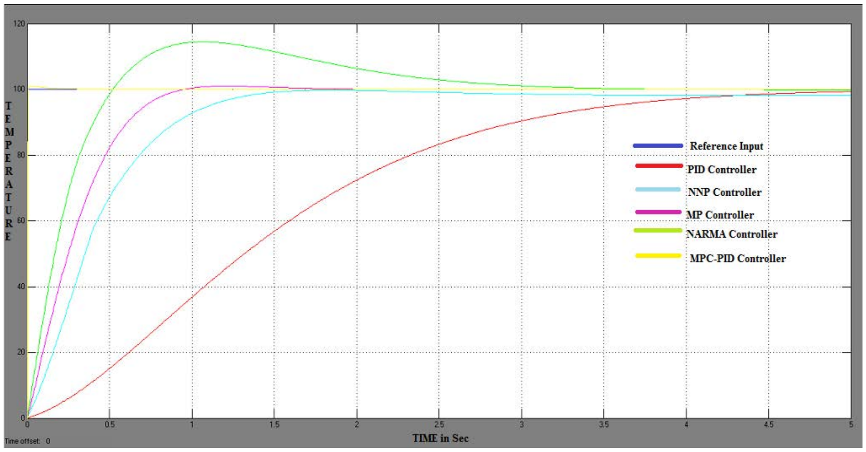

Fig. 13: MATLAB/Simulink Implementation with Various Controllers

Table 1: Comparison of controllers response parameters

Types of controller	Delay time (t_d) in sec	Rise time (t_r) in sec	Settling time (t_s) in sec	Peak overshoot (M_P) in (%)
PID	1.3186	2.5925	3.5485	0
NARMA	0.1685	0.3713	2.1653	14.452
NNP	0.352	0.8245	1.1048	0
MP	0.2508	0.5604	0.7209	0.98
MP-PID (proposed)	0.0013743	0.00475961	0.0057849	0.9666

Table 2: Comparison of controller performance metrics

Types of controller	ISE	IAE	ITSE	ITAE
PID	9565	152.3	6742	169.3
NARMA	1367	38.81	366.6	31.71
NNP	2583	47.98	551.6	31.59
MP	1748	29.99	251	7.442
MP-PID	9.875	0.3586	0.01332	0.1144

Here, e(t) is the error response of a system. Generally limit of integration is from 0-8 but integration up to infinity is not practical and hence limit 8 is replaced by T which is chosen sufficiently large so that e(t) for t>T is negligible. In this study, T = 5 sec has been taken. The above indices for the controllers are given in Table 2. From Table 2, it is inferred that MP-PID has the least ISE, IAE, ITSE, ITAE values of all other controllers.

CONCLUSION

The controller performance indices criteria like Integral Square Error (ISE), Integral Absolute Error (IAE), Integral Time Square Error (ITSE) and Integral Time Absolute Error (ITAE) are obtained.

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