Imperial Journal of Interdisciplinary Research (IJIR)
Vol-3, Issue-9, 2017
ISSN: 2454-1362, http://www.onlinejournal.in

Control of Continuous Stirred Tank Reactor Using Neural Network based Predictive Controller

Durgadevi. A , Priyadarshini. S. A , Anbumozhi. R
Department of Electrical and Electronics Engineering,
K.Ramakrishnan college of Engineering, Trichy, India

Abstract*—This paper proposes Model Predictive Controller(MPC) for control of a Continuous Stirred Tank Reactor (CSTR). CSTR is one of the most important units in chemical industry which exhibits highly nonlinear behavior and usually has wide operating range. In CSTR system, reactor temperature and concentration control are the challenging tasks due to the strong non-linearity. The need of such difficult control problem has led to use Neural Network (NN) in MPC. The advantage of Neural Network Predictive Controller (NNPC) is that an accurate representation of the process can be obtained by training the NN. In this the conventional Proportional- Integral- Derivative (PID) controller, MPC and NNPC are designed to maintain the reactor concentration for getting the desired product.The controller's performances are supported with better tracking and disturbance rejection in terms of time domain specifications and performance indices. Model design and simulation are done in MATLAB software using Simulink.*

Keywords *—CSTR, PID controller, MPC, NNPC.*

I. INTRODUCTION

The Continuous Stirred Tank Reactor (CSTR) is generally modeled as having no variations in concentration and temperature throughout the vessel. Chemical reactions in a reactor are either exothermic or endothermic and the heat is added or removed by virtue of the temperature difference between a jacket fluid and the reactor fluid. The heat transfer fluid is pumped through agitation nozzles that circulate the fluid through the jacket at a high velocity to maintain a temperature.

The mathematical modeling of first order irreversible process [1] for both ideal and non-ideal CSTR is considered and the operating points for the local linear models of the non- ideal CSTR for various cases are taken for the process [2]. To get the desired product from nonlinear system the concentration inside the reactor is maintained at the desired level using the Proportional-Integral-Derivative (PID) controller [3]. It is widely applied to process control because the control mode is direct, simple and robust. Many variations of the controller structure are proposed and it summarizes the
tuning rules of controllers using the classical, Ziegler-Nichols and Cohen- Coon methods for a system with and without delay are explained in [4]. Limitations of traditional approaches in dealing with constraints are the main reasons for emerging the powerful and flexible methods. Hence predictive control techniques are introduced [5]. MPC is an important nonlinear control methodology and referred as receding horizon control [6]. It solves at each sampling instant but only the first value of the resulting optimal control variable solution is then applied to the plant is explained in [7] and [8]. The design of PID and MPC for concentration control of CSTR is described in [9]andthe comparisons of controller performances are developed.MPC gives better performance when compared to PID controller [10]. The design procedure and the concepts of MPC for a four tank system using an experimental set up are explained in [11] and [12].

The designing of controller includes disturbances and constraints with the system and advantages of MPC are discussed in [13] and [14]. The need of such difficult control problem has led to use Neural Network (NN) in MPC and has recently attracted a great deal of attention. NN has found wide applicability in modeling and control of non-linear systems because of their inherent capability of capturing the non-linear behavior of the system [15] and [16]. The basics of Neural Network Predictive Controller (NNPC) are explained in [17]. In this the NN is used for process identification and the process is controlled under parameter variations. NN which is able to approximate any continuous nonlinear function has been used for modeling and control of complex nonlinear processesis given in [18] and [19]. Indeed the proposed new scheme is simple, robust against parameters uncertainties and does not need to estimate the parameters uncertainties from the output are described in [20 - 22]. PID, MPC and NNPC are designed for nonlinear system. The PID controller gives sluggish response and the MPC is used to reduce that. From the performance comparison showed that NNPC gives smoother and better control performance than MPC and PID controllers [23].

This paper is organized in the following manner. Section II describes the modeling of non-ideal CSTR.Section III describes about the designing of controllers. Section IVpresents the simulation results and Section V summarizesthe results.

II. CONTINUOUS STIRRED TANK REACTOR

The model of CSTR system is shown in Fig. 1. It consists of a tank of constant volume and a stirring system to mix the

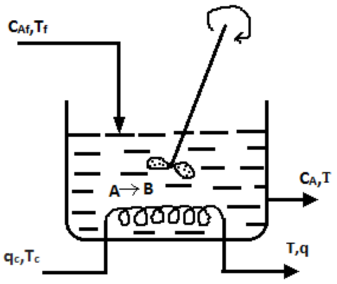

Fig. 1. CSTR system

reactants together. Reactants are continuously introduced into the reactor, while products are continuously removed. This CSTR process represents a first order, irreversible and exothermic kinetic reaction (A→B).The heat of the reaction is removed by a coolant medium that flows through a jacket around the reactor. The fluid inside the reactor is perfectly mixed and sent out through the exit valve. The jacket surrounding the reactor has feed and exit streams. The jacket is assumed to be perfectly mixed and at a lower temperature than the reactor [1].

where,

C_{Af} - Feed concentration, T_f - Feed temperature

T_c - Coolant temperature, q_c - Coolant flow rate

C_A - Output concentration, T - Output temperature

Model of CSTR

The following assumptions are made to obtain the simplified modeling equations of an ideal CSTR

- Perfect mixing in the reactor and jacket
- Constant volume of reactor and jacket

The mathematical model for this process is formulated by carrying out mass and energy balances in appropriate constitutive Equations 1& 2.

$$\frac{dC_A}{dt} = \frac{Q_f}{V}(C_{Af} - C_A) - k_0 C_A e^{-E_a/R_1 T} \quad (1)$$

$$\frac{dT}{dt} = \frac{Q_f}{V}(T_f - T) - \frac{k_0 C_A}{C_p}(-\Delta H) e^{-E_a/R_1 T} - \frac{UA_h}{VC_p}(T - T_c) \quad (2)$$

Most of the reactors have been modeled as ideal CSTRs. But in the real world the behavior of the real CSTR is very different from that of an ideal CSTR [2]. For an ideal CSTR, it is assumed that the reactor is well-mixed i.e. the concentration at different positions of the CSTR are identical throughout the reactor. But the mixing in the non ideal CSTR is not uniform dueto bypassing (β) and dead space (α).The parameters of a non-ideal CSTR are tabulated in TABLE I. In the dead space the fluid does not enter hence there is less reactor volume than in the case of perfect operation and the flow passing through the reactor will be less than the total volumetric flow rate due to bypassing. As a result there will be slower decay of the transients in the concentration response. The mathematical modeling of the CSTR considering non ideal mixing is found from Equations 3 & 4 including α and β.

$$\dot{x}_1 = -\alpha\ x_1 + D_\alpha(1 - x_1)e^{x_2/(1+(x_2/\gamma))} \quad (3)$$

$$\dot{x}_2 = -\alpha\ x_2 + D_\alpha(1 - x_1)e^{x_2/(1+(x_2/\gamma))} - \beta x_2 + \beta u(t) + \alpha d(t) \quad (4)$$

State variables in Equations 3 & 4 are

$$x_1 = \gamma\frac{C_{Af} - C_A}{C_{Af}};\ x_2 = \gamma\frac{T - T_{f0}}{T_{f0}};\ u = \gamma\frac{T_c - T_{f0}}{T_{f0}} \quad (5)$$

where,

x_1 -Ratio between theconcentrations

x_2 -Ratio between the temperatures

Disturbance,

$$d = \gamma\frac{T_f - T_{f0}}{T_{fo}} \quad (6)$$

TABLE I. STEADY STATE PARAMETERS(NON-IDEAL CSTR)

Sl.no	Parameters	Symbols	Constant values
1	Dead space	α	1
2	Boundary layer thickness	β	0.3
3	Tuning constant	γ	20
4	Constant coefficient	D_α	1

III. CONTROLLER METHODS

A. Proportional-Integral-Derivative (PID) controller

PID controllers are widely used in various process industries due to their effectiveness and simplicity. It is a type of feedback controller whose output and control variable is based on the error betweenset point and measured process variable. The error signal e(t)used to generate the proportional, integral and derivative actions are shown in Fig.2.

A mathematical description of the PID controller is

$$U(t) = K_P\, e(t) + \frac{1}{T_I}\int_0^t e(t)\ d(t) + T_D \frac{de(t)}{dt}$$

(7)where,

K_P - Proportional gain
T_I- Integral time constant
T_D- Derivative time constant.

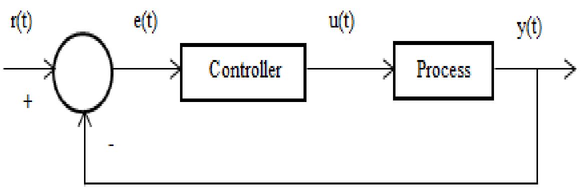

Fig. 2. Basic structure of PID

B. Model Predictive Controller(MPC)

MPC is an optimal control strategy based on numerical optimization. Future control inputs and future plant responses are predicted using a system model and optimized at regular intervals with respect to a performance index constraints on system inputs and states [4].

Primary components of MPC

MPC consists of three main components as shown in Fig. 3 namely

- The process model
- The cost function
- The optimizer

The process model includes the information about the controlled process and it is used to predict the response of the process values according to manipulated variables.The minimization of cost function ensures that the error is reduced. In the last step different optimization techniques are applied and the output gives the input sequence for the next prediction horizon.

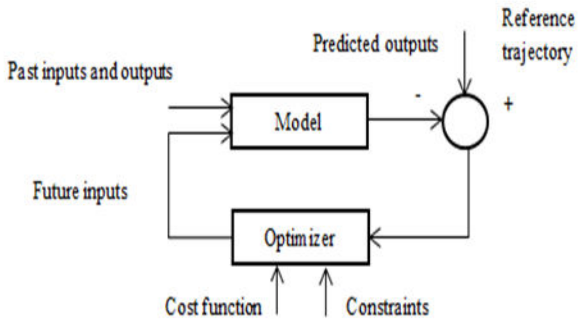

Fig. 3. Basic structure of MPC

Concept of MPC

An objective function is based on output predictions over a prediction horizon of 'P' time steps is minimized by a selection of manipulated variable moves over a control horizon of 'M' control moves. Although 'M' moves are optimized only the first move is implemented. After uk is implemented, the measurement at the next time step yk+1 is obtained. A correction for model error is performed since the measured output yk+1 will not be equal to the model predicted value. A new optimization problem is then solved again over a prediction horizon of 'P' steps by adjusting 'M' control moves. The feedback strategy is derived by solving this problem at each sampling time and using only the current control horizon. This is called as Receding horizon control [2].

C. Neural Network Predictive Controller (NNPC)

Neural Network Predictive Control (NNPC) is basically a model based predictive control. It uses a neural network model of the process, a history of past control moves and an optimization cost function over the receding prediction horizon to calculate the optimal control moves [12].

There are typically two steps which are combined to design the NNPC algorithm:

- System identification using neural network
- MPC design using NN model as a predictor

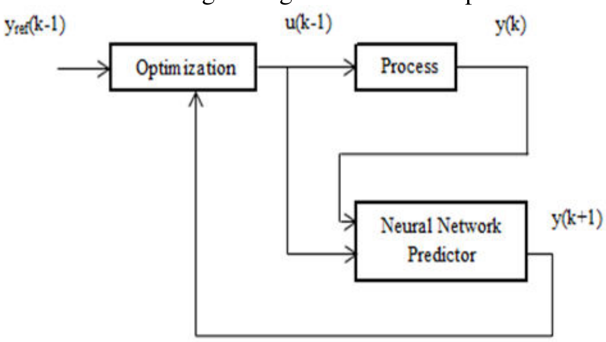

Fig. 4. Neural Network Predictive Controller

Figure 4 shows the structure of NNPC. The neural network model predicts the plant response over a specified horizon. The predictions are used by a numerical optimization program to determine the control signal that minimizes the performance criterion over the specified horizon.

Figure 5 shows the architecture of NN and the data for training the network is given in TABLE II.

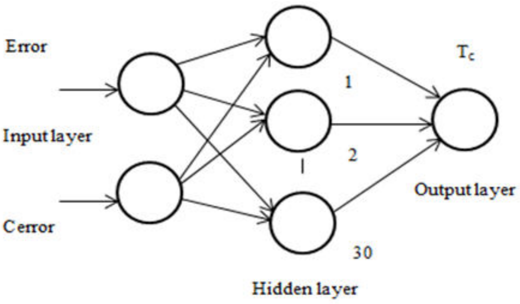

Fig. 5. Architecture of NN

TABLE II. DATA FOR TRAINING NEURAL NETWORK

No of layers	3
No of input layers	2
No of neurons	30
Network type	Feed forward back propagation
Training function	Levenberg-Marquardt
Transfer function	TANSIG
Learning function	LEARNGDM
No of iterations	9
Performance function	Mean Squared Error

Indeedusing NN model as the predictor in NNPC always causes a steady state tracking error due to the parameters variations of the process.

IV. SIMULATION RESULTS

A. Open loop response of CSTR

The open loop response is shown in Fig.6 indicates that the reactor concentration has a steady state error of 15% enabling the design of PID controller, MPC and NNPC for the system.

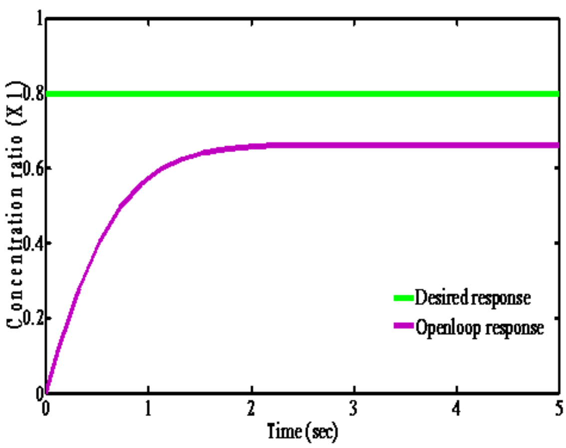

Fig. 6. Open loop response of concentration ratio (X1)

B. Closed response

The closed loop responses of reactor concentration with PID, MPC and NNPC reactor concentration is shown in Fig. 7.

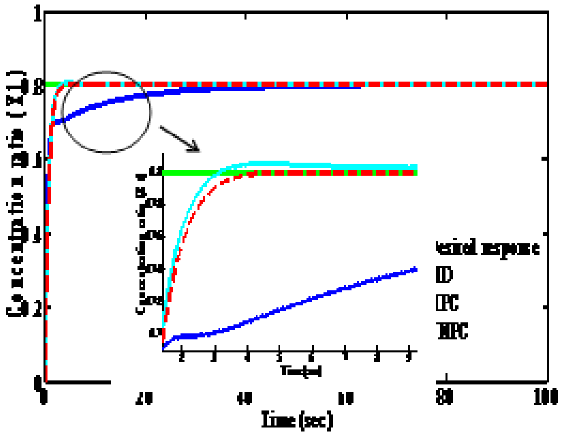

Fig. 7. Closed loop responses of concentration ratio (X1)

C. Servo response

The servo responses of reactor concentration with PID, MPC and NNPCwith the negative step change of 20% at 100 seconds and other positive step change 20% is given at 200 seconds are shown in Fig. 8.

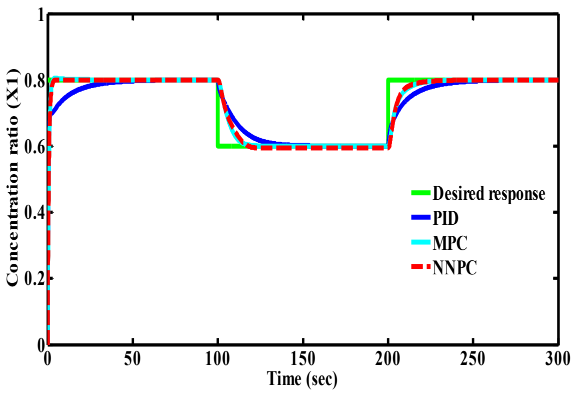

Fig. 8. Comparison of Servo responses of PID, MPC and NNPC

D. Regulatory response

The regulatory responses of reactor concentration with PID, MPC and NNPC are shown in Fig. 9. After reaching a steadystate, input disturbance of 0.01% is applied at 100 seconds.

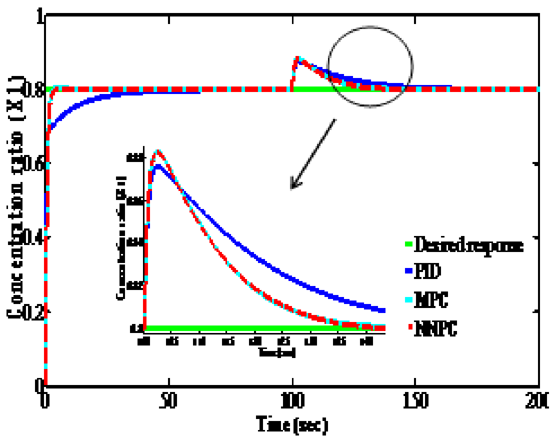

Fig. 9. Comparison of Regulatory responses of PID, MPC and NNPC

E. Control effort forNNPC

The control effort required for obtaining the desired concentration is shown in Fig.10.

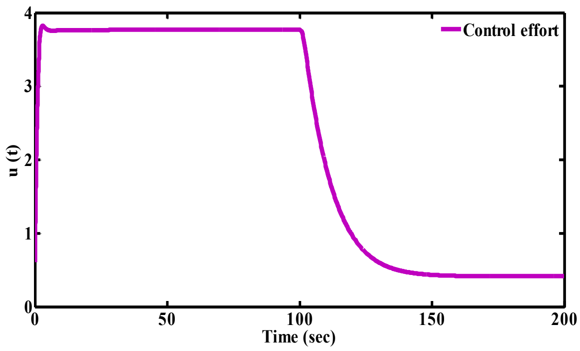

Fig. 10. Control effort for NNPC

V. RESULTS& DISCUSSION

A comparison of performances of PID, MPC and NNPC are tabulated in TABLEIII in terms of time domain specifications and performance indices (obtained from the Fig. 7). From the comparison it can be observed that the response is faster and Integral Square Error (ISE) and Integral Absolute Error (IAE) are minimized in NNPC better than MPC and PID.

TABLE III. TIME DOMAIN SPECIFICATIONS AND PERFORMANCE INDICES OF CLOSED LOOP RESPONSES FOR PID, MPCAND NNPC

Controllers	Rise time(sec)	Settling Time(sec)	ISE	IAE
PID	60	60	0.258	1.892
MPC	3	17.2	0.22	0.576
NNPC	**4**	**4**	**0.16**	**0.4**

A comparison of performances from servo and regulatory responses of PID, MPC and NNPC are tabulated in TABLE IV and TABLE V (obtained from the Fig.7&Fig. 8). It shows that NNPC gives better results in terms of Time domain specifications and performance indices than MPC and PID.

TABLE IV. PERFORMANCE INDICES AND TIME DOMAIN SPECIFICATIONS OF SERVO RESPONSE FOR PID, MPC ANDNNPC

Step Change	Controllers	Settling Time(sec)	ISE	IAE
20% of negative step change	PID	170	0.452	3.887
	MPC	125	0.38	1.81
	NNPC	**118**	**0.2**	**1.6**
20% of positive step change	PID	270	0.611	5.88
	MPC	240	0.5	2.95
	NNPC	**215**	**0.38**	**2.7**

TABLE V. PERFORMANCE INDICES AND TIME DOMAIN SPECIFICATIONS OF REGULATORY RESPONSE FOR PID, MPC ANDNNPC

Controllers	Rise time(sec)	Settling Time(sec)	ISE	IAE
PID	60	60	0.332	3.553
MPC	3	17.2	0.287	1.719
NNPC	**4**	**4**	**0.2**	**1.5**

Conclusion

The controllers (PID, MPC and NNPC) are developed for controlling the concentration of the CSTR and the results are compared. From the servo response it can be seen that NNPC has better tracking and from the regulatoryresponse it is inferred that NNPC has better disturbance rejectionto a maximum extend of 5%when compared to MPC and PID.

REFERENCES

[1] M.M.Pottman and D.E.Seborg,"Identification of non-linear process using reciprocal multi quadratic functions", Journal of Process Control, vol.2, pp.189-203, 1992.

[2] Bequette B.W, "Process control Modeling, Design and Simulation", Prentice Hall of India, 2004.

[3] Aidan O'Dwyer, "Handbook of PI and PID Controller Tuning Rules", Imperial College Press, 2006.

[4] K. Prabhuand V. MuraliBhaskaran, "Adaptive Controller Design for Continuous Stirred Tank Reactor", Research Journal of Applied Sciences, Engineering and Technology, vol. 8, pp. 1217-1224, 2014.

[5] V.Ghaffari, S.VahidNaghavi and A.A. Safavi, "Robust model predictive control of a class of uncertain nonlinear systems with application to typical CSTR problems", Journal of Process Control,vol.23, pp.493-499, 2013.

[6] K.Prabhu and V.MuraliBhaskaran, "Controller Design for Continuous Stirred tank Reactor Using Adaptive Control", Research Journal of Applied Sciences, vol.8, pp. 489-495, 2014.

[7] KeerthiChacko and LakshmiPonnusamy,“Model Predictive Controllers for Non minimum-Phase Quadruple-Tank Process”, Springer Publication, vol. 324, pp. 853-860, 2014.

[8] Omkar P.Dahale and Sharad P.Jadhav, “Design and Implementation of Controller using MPC Toolbox”, International Journal of Applied Information Systems, vol.5, pp.2249-0868, 2014.

[9] Anurag M. Deulkar and Ajay b. Patil, “Temperature Control Of Continuous Stirred Tank Reactor Using Model Predictive Controller”, International Journal of Industrial Electronics and Electrical Engineering, vol. 3,pp. 57-60, 2015.

[10] S.Allwin, S.Bikshanatesan, S.Abirami, H.Kalaand A.Udhayaprakash, “Comparison of Conventional Controller with Model Predictive Controller for CSTR Process”, International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, vol.3, pp.2278-8275, 2014.

[11] S.Abirami, Zahirhussain. A. S, SaravanaMuthu. D and Aravindkumar. C. B, “Performance Comparison Of Different Controllers For A Level Process”, International Journal of Engineering Research and Applications, vol. 4, pp.341-344, 2014.

[12] Tobias Raff, “Nonlinear Model Predictive Control of a Four Tank System- an Experimental Stability Study”, Proceedings of the IEEE International Conference, vol.2, pp.237-242,2006.

[13] Liuping Wang, “Model Predictive Control System Design”, Springer Publication, 2009.

[14] R.Sivakumar and Shennes Mathew,“Design and Development of Model Predictive Controller for Binary Distillation Column”, International Journal of Science and Research (IJSR), vol. 2, pp. 2319-7063, 2013.

[15] RamdaneHedjar, “Adaptive Neural Network Model Predictive Control”,International Journal of Innovative Computing, Information and Control, vol.9, pp. 1245-1257, 2013.

[16] P.Liu, V.Kadirkamanathan and S. A.Billinks,“ Predictive control for nonlinear systems using neural networks”, International Journal of Control, vol.71, no.6, pp.1119-1132, 1998.

[17] M.Akesson, H. T.Toivonen, J. B. Waller and R. H. Nystrom, “Neural network approximation of a nonlinear model predictive controller applied to a pH neutralization process”, Journal of Computers and Chemical Engineering, vol.29, no.2, pp. 323-335, 2005.

[18] Mohammad Anwar Hosen, MohdAzlanHussain andFarouq S.Mjalli, “Control of polystyrene batch reactors using neural network based model predictive control (NNMPC): An experimental investigation”,Journal of Control Engineering Practice, vol.19, pp. 454-467, 2011.

[19] BallekalluChinnaEeranna, SubbaRao and G. Prabhaker Reddy, “Artificial Neural Network Based Modeling and Control of Bioreactor”, International Journal of Engineering Research & Technology, vol. 3, issue 8, 2014.

[20] S.S.Ge, “Nonlinear adaptive control using neural networks and its application to CSTR systems”, Journal of Process Control, vol.10, pp.313-323, 1998.

[21] Piyushshrivastava andA.Trivedi, “Control ofnonlinear processusing neural network basedmodel predictive control”, International Journal of Engineering Science and Technology, vol. 8, pp. 2573-2581, 2011

[22] P.Poongodi and R.MadhuSudhanan, “Simulation of temperature control methodologies for chemical reactor”, Journal of Chemical and Pharmaceutical Research, vol.7, pp.682-689, 2015.

[23] Neha Sharma and Kailash Singh,“Model predictive control and Neural Network predictive control of TAME reactive distillation column”, Journal of chemical engineering and processing, vol. 59, pp. 9-21, 2012.