Performance of Controllers for Non Linear Process

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***Abstract*—*Non-linear process control is a complex task in process industries. Due to the persistently changing cross section and non-linearity of the tank a spherical tank provides a demanding problem for the level control. In this paper the model of a spherical tank system is derived as First Order Plus Dead Time (FOPDT) from the open loop response of real time setup of the system using Lab VIEW software. The intention of this project is to preserve the level inside the process tank at preferred value. The Proportional-Integral (PI) controller is designed to direct the level of the water in spherical tank. But for a non-linear system the same PI controller will give different responses at different operating regions. Hence there is a need for non-linear controller (Model Predictive Controller- MPC) to work in this non-linear region. But the complex control problem has led to use Neural Network (NN) in MPC. The advantage of Neural Network Predictive Controller (NNPC) is that an precise depiction of the process can be obtained by training the NN. The controllers are designed and the performances of these controllers (PI controller, MPC and NNPC) are compared for set point tracking and disturbance rejection using MATLAB. From the results it is inferred that NNPC gives minimum error and better tracking performance.*

Index Terms— *Model Predictive Controller, Neural Network Predictive Controller, Proportional – Integral controller, Spherical tank.*

I. Introduction

Process control manages models, instruments and calculations for maintaining the output of a specific process within a favored range [1]. The information gathered automatically from various sensors is used to control various equipments for running the plant. The variable area process considered here is maintaining the level in a Spherical tank process [2]. Most of the process industries are in need of classical control techniques, it's simply because of the inalienable. The constantly changing cross section and non-linearity of the spherical tank provides a challenging problem for the level control [3]. In Liquid level control systems, level is the controlled variable which finds many applications in various fields. Once the model has been developed, then the controllers are designed to maintain the process under steady state [4]. The process needs controllers to maintain the level at the desired value. Designing a controller for a non-linear system is complex and difficult to implement [5] and [6]. Limitations of traditional approaches in dealing with constraints are the main reasons for emerging the powerful and adaptable methods.

The conventional Proportional - Integral (PI) controller is usually applied to industrial automation and process control because its control mode is direct, simple and robust [7]. Thus the PI controller can be understood as a controller that takes the present, past and future of the error into consideration [8]. After digital execution was introduced a certain change of the structure of the control system was proposed and has been adopted in many applications. But that change does not influence the essential part of the analysis and design of PI controllers [9-11]. Model Predictive Control (MPC) is a significant nonlinear control methodology also referred to as moving horizon control or receding horizon control [12]. MPC controller solves at each sampling instant, a finite horizon optimal control problem. But only the first value of the resulting optimal control variable solution is then applied to the plant and the rest of the solution is discarded [13]. Recently, Neural networks offer alternative nonlinear models for implementing MPC in industrial systems. But the need of such difficult control problem has led to use Neural Network (NN) in MPC [14-17]. The advantage of Neural Network Predictive Controller (NNPC) is that an accurate version of the process can be obtained by training the NN [18-20].

II. Physical Model Description

An Experimental set up of the Spherical tank system is shown in Fig. 1.

Fig 1. Experimental setup of Spherical tank system

It consists of a spherical tank, Differential Pressure Transmitter (DPT) for level measurement, Current to Voltage (I/V) converter, interface to Personal Computer (PC) using Universal Serial Bus (USB)-based Data Acquisition (DAQ), Voltage to Current (V/I) converter, Current to Pressure (I/P) converter, variable speed pump, a compressor to operate pneumatic control valve and a Rota meter are used for inflow measurement. The height of the spherical tank is 48 cm. The unpredictable speed pump adjusts the flow of water in to the spherical tank from the reservoir.

A. Working Methodology

The control factor has been chosen is the level. Pressure sensors and level transmitter arrangement senses the level from the process and converts into electrical signal. Then the electrical signal is fed to the I-V. The actual spherical tank level is sensed by the level transmitter and is fed back to the level controller. This feedback is compared with the desired level. Then the controller performs the control action and it is given to the I-V converter and then to I-P converter. The final control is actuated by the resulting air pressure. This in turn controls the inlet flow of the liquid in to the spherical tank and the level is maintained.

Figure 2 shows the block diagram of the system. The operating current for regulating the valve position is 4-20mA, which is converted in to 3-15psi of compressed air pressure. The water level inside the tank is measured with the differential pressure transmitter which is calibrated and is converted to an output current of 4-20mA.This output current is converted into 1-5V using I/V converter ,which is given to the controller through DAQ CARD. The USB based DAQ CARD is used for interfacing the personal computer with the spherical tank.

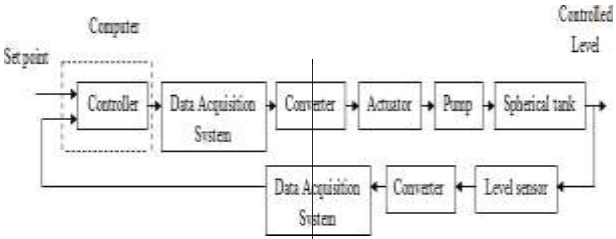

Fig 2. Block diagram of working methodology

B. Calibration of level sensor

Instrument Calibration of level sensor is done by changing the level of the spherical tank from (0-48) cm and the corresponding current value from (4-20) mA is noted. The calibrated values are shown in Fig. 3.

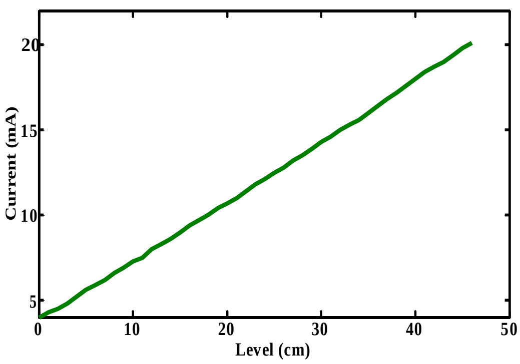

Fig 3. Calibration of level sensor

C. System modeling

The level in the tank at any instant is obtained by making mass balance as indicated below

$$F_{in}(t) - F_{out}(t) = S(h(t))\frac{dh(t)}{dt} \qquad (1)$$

In (1) h(t) denotes the liquid level and Sh(t) is the transverse section of the tank, which changes according to the liquid level as

$$Sh(t) = \pi(2Rh(t) - h^2(t)) \qquad (2)$$

Where 'R' is the radius of the spherical tank, F_{in} is the Inlet flow rate to the tank (LPH), F_{out} -Outlet flow rate to the tank (LPH). The manipulated variable is the inlet flow rate $F_{in}(t)$. The controlled variable is the liquid level in the tank h(t). The disturbance by the outlet flow rate can be described as,

$$F_{out}(t) = C_p\sqrt{2gh(t)} \qquad (3)$$

The first order transfer function is given by (4)

$$G(s) = \frac{ke^{-\theta s}}{\tau s + 1} \qquad (4)$$

D. Open loop response

From the experimental arrangement open loop response of the spherical tank system for the level control is obtained by changing the inlet flow from 190 LPH to 220 LPH. Fig. 4 indicates that the level has a steady state error of 30% enabling the design of PI controller, MPC and NNPC for the system.

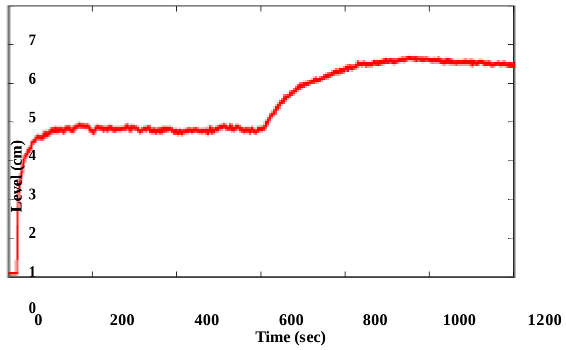

Fig 4. Open loop response

Transfer function obtained from the open loop response is

$$G(s) = \frac{0.053e^{-5.565s}}{49.8s + 1}$$

III. Design of Controller

A. PI controller

Feedback PI (Proportional - Integral) controller is used to control most processes due to its robust design and easy implementation. The control action is based on the error e(t)

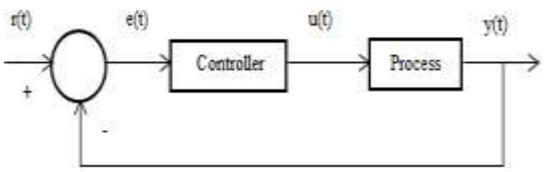

Fig 5. Open loop response

calculated at that given time. The error is the difference between the Reference signal r(t) and the Process variable y(t) is shown in Fig. 5. It is fed back into the controller continuously to determine the action the controller should take to minimize the error. A mathematical description of the PI controller is given in (5)

$$U(t) = K_P\, e(t) + \frac{1}{T_I}\int_0^t e(t)\, d(t) \qquad (5)$$

B. *Model Predictive Controller*

MPC employs a corrective controller action as shown in Fig. 6 which predicts the plant behavior and then rectifies itself to account for any irregularities in its prediction model and direct the output as close to the set point as possible. The key features of MPC are

- Predicts future behavior of the process over a finite time horizon
- Computes the future control actions while optimizing a cost objective function with the given equality and inequality constraints

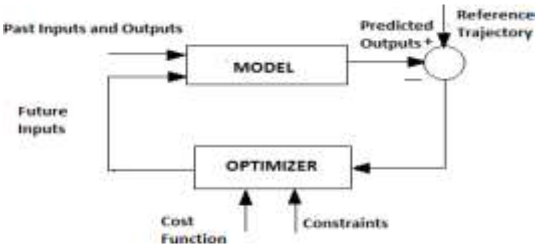

Fig 6. Basic structure of MPC

C. *Neural Network Predictive Controller*

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. Fig. 7 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.

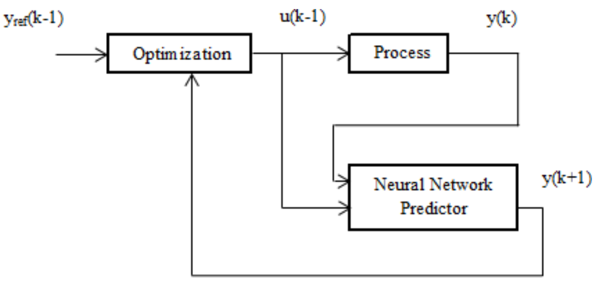

Fig 7. Basic structure of NNPC

IV. Simulation Results

The Proportional – Integral (PI) controller, Model Predictive Controller (MPC) and Neural Network Predictive Controller (NNPC) are introduced in the spherical tank by taking the level (h) as controlled variable and inlet flow (F_{in}) as manipulated variable.

A. *Closed loop responses for the level of MPC for variations in parameters*

MPC consists of prediction horizon, control horizon, input and output weights. While changing these parameters the output of MPC get varied.

CASE 1: When the prediction horizon is varied and the other parameters are fixed.

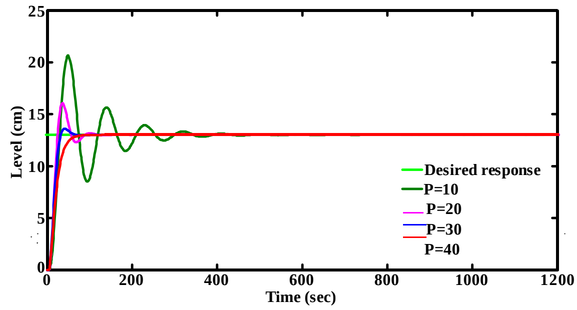

Fig 8. Effect of prediction horizon of MPC

CASE 2: When the control horizon is varied and the other parameters are fixed.

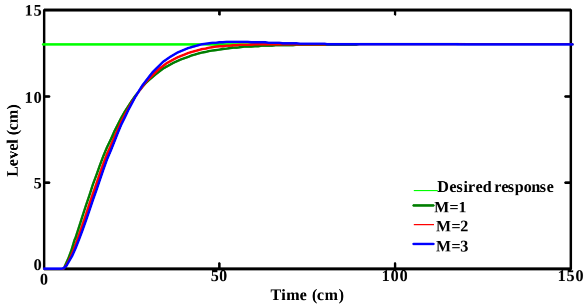

Fig 9. Effect of control horizon of MPC

CASE 3: When the output weight is varied and the other parameters are fixed.

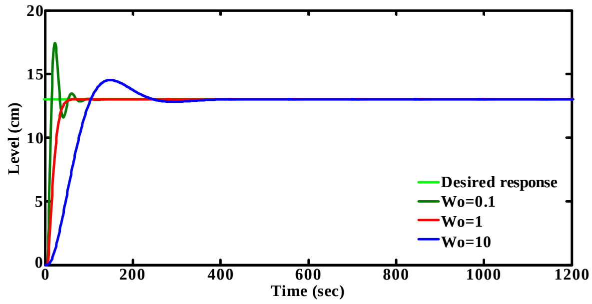

Fig 10. Effect of output weight of MPC

CASE 4: When the input weight is varied and the other parameters are fixed.

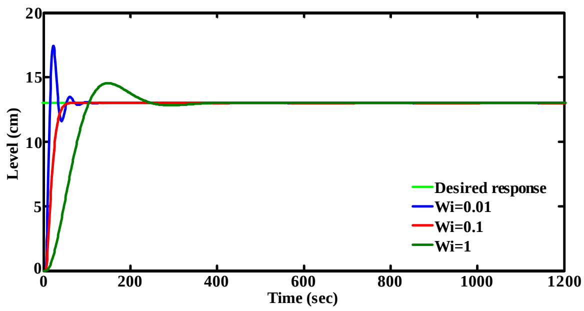

Fig 11. Effect of input weight of MPC

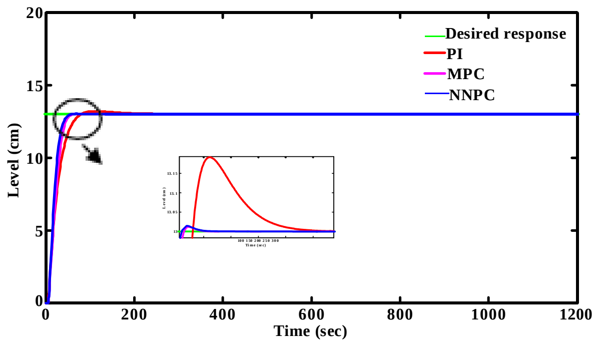

Fig 12. Closed loop responses for the level using PI controller, MPC and NNPC

B. Servo response

The servo responses for controlling the level of liquid in a spherical tank with PI, MPC and NNPC for two different step changes are shown in Fig. 13. For the level with positive step change of 50% at 1200 seconds and other negative step change of 50% at 2400 seconds are given as different step changes.

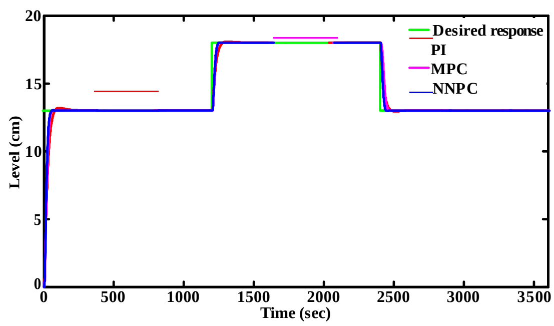

Fig 13. Servo responses for the level

C. Regulatory response

The regulatory responses for controlling the level of spherical tank level with PI controller, MPC and NNPC are shown in Fig. 14 respectively. After reaching a steady state, external disturbance of 0.05% is applied at 1200 seconds.

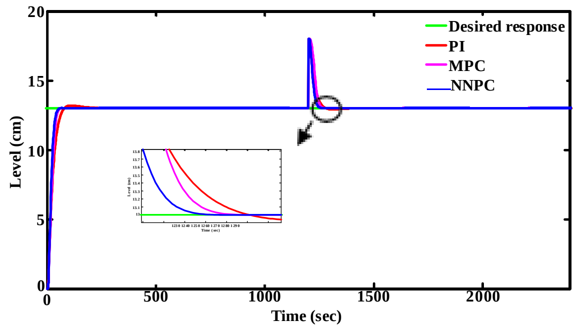

Fig 14. Regulatory responses for the level

D. Results and discussions

CASE 1: When the prediction horizon is varied and the other parameters are fixed.

The prediction horizon increment with constant control horizon, leads to lower performance because it takes more time for computation and also control them for few cycles only. But the error gets reduced while increasing prediction horizon. If control horizon is closer to prediction horizon leads to better performance. From Table I (obtained from Fig. 8) it is seen that while increasing the Prediction horizon up to 40 the response becomes more faster and the error value get reduced.

TABLE I. Effect Of Prediction Horizon Of MPC

Prediction Horizon	Time constant (sec)	Rise time (sec)	Over shoot (cm)	Settling time (sec)	ISE	IAE
10	23.1	29.8	7.5	500	4799	788.8
20	18.14	25	3	180	2368	284.8
30	19.07	32.2	0.6	100	2260	234
40	**21.31**	**60**	**0**	**60**	**2432**	**257.5**
50	23.7	110	0	110	2627	296

Also the proper selection of control interval will make the system to respond faster. If the control interval is large the control applied to the system is no longer effective, which results in unstable or slower operation. A very low value of control interval is also not possible because of the hardware limitation.

CASE 2: When the control horizon is varied and the other parameters are fixed.

According to MPC algorithm the control horizon must be lesser than prediction horizon. But the control horizon increments give better results. The values in Table II (obtained from Fig. 9) shows that the Integral Square Error (ISE) get increased while increasing control horizon closer to prediction horizon for the spherical tank.

TABLE II. Effect Of Control Horizon Of MPC

Control Horizon	Time constant (sec)	Rise time (sec)	Overshoot (cm)	Settling time (sec)	ISE	IAE
1	20.65	95	0	95	2324	256
2	**21.31**	**60**	**0**	**60**	**2432**	**257.5**
5	21.75	45	0.15	95	2503	259.9

CASE 3: When the output weight is varied and the other parameters are fixed.

The increment in the output affects the input drastically, because with the higher output weight the controller tends to optimize output rather than optimize input error, which leads to increase the performance and vice versa happens when input weight is increased. From Table III (obtained from Fig. 10) it is seen that while increasing the output weight the ISE and Integral Absolute Error (IAE) get reduced.

TABLE III. Effect Of Output Weight Of MPC

Output Weight	Time constant (sec)	Rise time (sec)	Overshoot (cm)	Settling time (sec)	ISE	IAE
0.1	21.31	60	0	60	2432	257.5
1	**65.63**	**104**	**1.5**	**400**	**7295**	**874.6**
10	11.6	15	4.4	130	1713	212.7

CASE 4: When the input weight is varied and the other parameters are fixed.

The increment in the input affects the output drastically, because when input weight is high the controller tends to optimize input rather than optimize output error, which leads to reduce the performance. The values in Table IV (obtained from Fig. 11) show that when the input weight increased from 0.01 to 1, the ISE and IAE also increased. So the minimum input weight has been taken to get better result in MPC.

TABLE IV. Effect Of Input Weight Of MPC

Input Weight	Time constant (sec)	Rise time (sec)	Overshoot (cm)	Settling time (sec)	ISE	IAE
0.01	11.6	15	4.4	130	1713	212.7
0.1	**21.31**	**60**	**0**	**60**	**2432**	**257.5**
1	65.63	104	1.5	400	7295	874.6

A comparison of performances of PI controller, MPC and NNPC are tabulated in Table V in terms of time domain specifications and performance indices (obtained from the Fig. 12). From the comparison it is observed that the response is faster and the Integral Square Error (ISE) and Integral Absolute Error (IAE) are minimized in NNPC compared to MPC and PI controller.

TABLE V. Performance Measures of Closed Loop Responses for PI Controller, MPC And NNPC

Controllers	Time constant (sec)	Rise time (sec)	Overshoot (cm)	Settling time (sec)	ISE	IAE
PI	27.45	81	0.19	325	2836	351
MPC	24.9	90	0	90	2590	289
NNPC	**21.3**	**60**	**0**	**60**	**2430**	**257**

A comparison of performances of PI controller, MPC and NNPC for Servo and Regulatory responses are tabulated in Tables VI and VII in terms of Time domain specifications, ISE and IAE (obtained from the Figures 13 & 14). From the comparison it can be observed that the error is minimized in NNPC than MPC and PI controller.

TABLE VI. Performance Measures Of Servo Responses For PI Controller, MPC And NNPC

Controllers	Step change	Settling time (sec)	ISE	IAE
PI	50% of +ve step change	1450	2836	351
MPC		1300	2793	388
NNPC		**1260**	**2681**	**356**
PI	50% of –ve step change	2680	3255	486
MPC		2500	3183	457
NNPC		**2450**	**350**	**440**

TABLE VII. Performance Measures Of Regulatory Responses for PI Controller, MPC and NNPC

Controllers	Settling time (sec)	ISE	IAE
PI	1450	3255	486
MPC	1275	2906	438
NNPC	**1260**	**2800**	**358**

V. Conclusion

The Proportional – Integral (PI) Controller, Model Predictive Controller (MPC) and Neural Network Predictive Controller (NNPC) are simulated for first order system with delay using MATLAB and the results are compared. From tracking and from the regulatory response it is inferred that NNPC has better disturbance rejection to a maximum extend of 5% when compared to MPC and PI controller.

References

[1] Reshma.K. V and Dr. S. Sumathi, “Control of Non Linear Spherical Tank Level Process”, International Journal for Research in Applied Science & Engineering Technology, Vol. 3, pp. 448-453, 2015.

[2] M. Kalyan Chakravarthi, Nithya Venkatesan, “Labview Based Tuning Of PI Controllers For A Real Time Non Linear Process”, Journal of Theoretical and Applied Information Technology, vol. 68, pp. 579-585, 2014.

[3] Mrs. A. Asuntha and Dr Andy Srinivasan, “Tuning Of Controllers for Non Linear Process Using Intelligent Techniques”, International Journal of Innovative Science Engineering & Technology, vol. 1, PP. 180-183, 2014.

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

[5] M. Vijayakarthick and P. K. Bhaba, “Optimized Tuning of PI Controller for a Spherical Tank Level System Using New Modified Repetitive Control Strategy”, International Journal of Engineering Research and Development, vol. 3, pp. 74-82, 2012.

[6] D. Pradeepkannan, Dr. S. Sathiyamoorthy, “Control of a Nonlinear Spherical Tank Process Using GA Tuned PID Controller”, International Journal of Innovative Research in Science, Engineering and Technology, vol. 3, pp. 580-586, 2014.

[7] Bequette B. W, “Process control Modeling, Design and Simulation”, Prentice Hall of India, 2004.

[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] 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.

[10] M.Bharathi and C.Selvakumar, “Model based controller design for a spherical tank”, International Journal of Computer Trends and Technology, vol. 3, pp.19-35, 2012.

[11] 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.

[12] K. Hari Krishnaa, J. Satheesh Kumarb and Mahaboob Shaik, “Real Time Implementation of Model based Controller for a Spherical Tank”, International Journal of Current Engineering and Technology, vol. 3, pp. 587-590, 2013.

[13] Keerthi Chacko, Lakshmi Ponnusamy and Sangapillai Sutha “Model Predictive Controllers for Non minimum-Phase Quadruple-Tank Process”, Springer Publication, vol. 324, pp. 853-860, 2014.

[14] P. Liu, V. Kadirkamanathan and S. A. Billinks, “Predictive control for nonlinear systems using neural networks”, International Journal of Control, vol. 71, pp. 1119-1132, 1998.

[15] 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.

[16] 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, pp. 323-335, 2005.

[17] Piyush shrivastava and A.Trivedi, “Control of nonlinear process using neural network based model predictive control”, International Journal of Engineering Science and Technology, vol. 8, pp. 2573-2581, 2011

[18] T.Yuvapriya and P. Lakshmi, “Neuro based controller for a Spherical tank process”, International Conference on Advances in engineering, science and management, pp.106-110, 2012.

[19] Ramdane Hedjar,"Adaptive Neural Network Model Predictive Control", International Journal of Innovative Computing, Information and Control, vol. 9, pp. 1245-1257, 2013.

[20] Ballekallu Chinna Eeranna, Subba Rao and G. Prabhaker Reddy, "Artificial Neural Network Based Modeling and Control of Bioreactor", International Journal of Engineering Research & Technology, vol. 3, 2014.