ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 10, October 2015

Modeling And Control Of Nonlinear Process Using Robust And Soft Controllers

M.Sridevi[1], P.Madhavasarma[2], P. veeraragavan[3]

Assistant Professor, Dept. of ECE, Vels University, Pallavaram, Chennai, India[1]

Professor & Principal, Dept. of ECE, Saraswathy College of Engineering & Technology, Tindivanam, India[2]

Assistant Professor, Dept. of Physics, Anna University, Tindivanam Campus, Tindivanam, India[3]

ABSTRACT: Level control in a hemispherical tank is a challenging task in process industries due to nonlinear variation of level with height. The need for an accurate and appropriate online or off line model to control such nonlinear process is on huge demand to avoid process complications in practical applications such as oil refineries, dye industries etc. In this work, a hemispherical tank of 40 liter capacity was subjected to dynamic analysis and level measurement was done using an on-line Honeywell capacitance sensor. Modeling was performed using first principle of mathematics, open loop analysis and Skogestad technique. The various models were validated using standard performance indices and it was observed that Skogestad model performed better with minimum model error. Real time level control was implemented using various robust, adaptive and intelligent controllers such as Smith, IMC and NMPC. The performance of the controllers was evaluated using time domain specifications. Error analysis was also performed and it was observed that NMPC and IMC controller outperformed the other controllers.

KEYWORDS: Hemispherical, Skogestad, adaptive, Fuzzy control, nonlinear process, NMPC, IMC, Smith

I. INTRODUCTION

Modeling of a nonlinear process is still a challenging task to process engineers. Many system complexity and threat arises due to imperfect modeling. Moreover in many processes involving liquid contained in vessels, such as distillation columns, re-boilers, evaporators, crystallizers, and oil refineries and mixing tanks, the particular level of liquid in each vessel is of great importance in process operation. A level which is too high upsets reaction equilibrium, causing damage to equipment, results in spillage of valuable or hazardous material. A level that is too low affects the process throughput, cost and productivity. Hence there is need for sensitive and accurate level control. The level must be maintained accurately at a predetermined height, irrespective of load conditions of the process. Chidambaram et al [1] have designed a capacitance sensor for level measurement for hemispherical tank in which the sensor was made up of a capacitor consists of two plates separated from each other by an insulating material called a dielectric. Sundaram et al [2] has designed a model based evaluation of a controller using pole placement technique for conductivity process. Chidambaram et al [3-5] have proposed method to identify the model parameters of a first order plus time delay (FOPTD) model and second order plus dead time model using a single symmetric relay feedback test. RohitRamachandran et al [6] have experimentally identified open loop and closed loop FOPDT and SOPDT model for plate heat exchanger and have also studied the response using simulated data. Wang et al [7] have designed an identification algorithm for continuous time delay signal under unknown initial conditions using step response and the obtained model best correlated with theoretical model. Antonio Visioli [8] has proposed a closed loop method for identifying the unstable FPODT parameters using PID controller. Sundaram et al [9] have designed a flow process model for both linear and non linear process with time delay by monitoring on line electrical conductivity for which process reaction curve method was used. Pankaj Swarnkare et al [10] has presented detailed theoretical and analytical insight into different adaptive and AI-based conventional control schemes used in practical applications on the basis of extensive literature review in this field. Test results are shown for Shunt Active PowerFilter(SAPF) with conventional and adaptive controllers. It is observed that under steady state the working of conventional controllers is satisfactory but during transient conditions an adaptive controller plays an important role in improving the compensation property of SAPF. Sahaj Saxenaet al [11] has presented a survey of internal model control is done through this paper, however, here IMC scheme for unstable, integrating with time delay, MIMO, and nonlinear systems are not illustrated

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 10, October 2015

extensively. Sundaram et al [12] have designed an IMC controller for flow process with varying dead time as PID type controllers do not perform well when applied to systems with significant time-delays. Sundaram et al [13] have suggested models for both linear and non linear process with time delay and have designed smith predictor controllers. Lim et al[14] has designed Smith Predictor for controlling a process with an integrator and long dead time. Ibrahimkaya[15] has proposed a modified PI-PD Smith predictor for process with large time delay. Yi-De Chen [16] has described a modified Smith predictor for periodic disturbance reduction in linear delay system. Lung Chien [17] has designed a Smith predictor for controlling integrating process with long delay time based on closed loop servo response. Marchall [18] has proposed a modification on the smith predictor structure that involves the design of extra compensators the two feedback paths in the smith predictor structure to reduce the effect of load disturbance. Astrom et al [19] have developed a new smith predictor for long time delay process. The structure decouples the set point response from the disturbance and improves set point tracking and regulatory response. Zhang and Sun [20] have developed a modified smith predictor for controlling integrator/time delay processes. Online Intelligent soft controllers using soft computing techniques having features such as robustness, adaptability, and learning has made a revolution in ease of control in process industries. Since many of industrial process are complex nature it is difficult to develop a closed loop model [21]. A.J.Hugo[22] recommends some standards that are to be fulfilled by the assessment techniques. Swanda and Seborg [23] has proposed a methodology based on dimensionless performance indices, settling time and IAE values has been proposed by. Marshall et al [24] have proposed a method for calculating ISE analytically which is based on parsevals theorem and contour integration. The above authors have not discussed about semi physical modeling of hemispherical tank. The recent advances in model based control systems necessitate the development of mathematical models inevitable for the nonlinear process. The development of suitable controller for non linear process has been studied extensively. In this paper we have designed model of the non linear process using different techniques namely semi physical modeling using mass balance equation, empirical modeling using graphical S-K technique and higher order modeling using Skogestad technique. Models are evaluated using standard Performance Indices namely Average percentage error (APE), Sum of squared errors (SSE) and Standard deviation (STD). Various basic, adaptive, and advanced controllers namely PI, IMC, Smith, NMPC, are designed and implemented in real time for level control. The controller performance was evaluated using time domain specifications namely Rise time, Peak time, and settling time and overshoot .Error analysis was performed and suitable ranking of the controller was given based on their merits and demerits. It was observed from the performance analysis that the NMPC followed by IMC controller outperform the rest of controllers. The organization of the paper is as follows the experimental set up is explained in Section 2 .Section 3 describes in brief about modeling and model validation .Section 4 discuss about design and real time implementation of various controllers. In Section 5 the ranking and merits and demerits of controllers is discussed.

II. MATERIALSAND METHODS

Figure 1 shows the experimental setup to study the dynamics of the non linear process. A Honeywell sensor was used to monitor the level. A system with a suitable interface was connected to the level sensor. The process flow model was determined experimentally by an open loop analysis. The flow rate of the water at the inlet was fixed at 1LPM. A step change in water flow rate from 1LPM to6LPM was introduced and a change in level was recorded. The experimental results are shown in Figure 2.

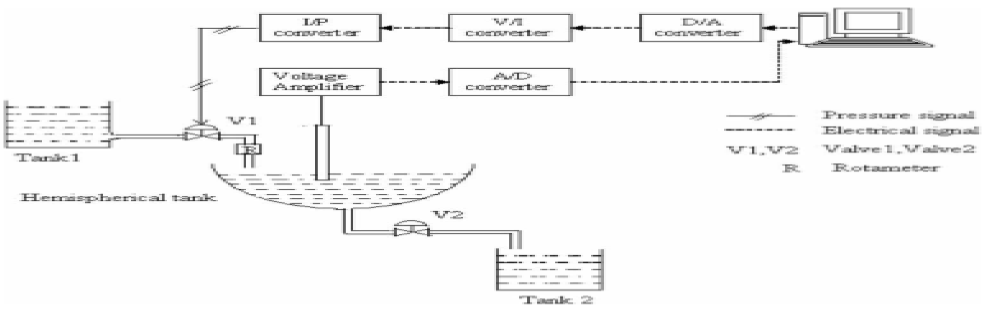

Fig. 1 Experimental setup for hemispherical process

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 10, October 2015

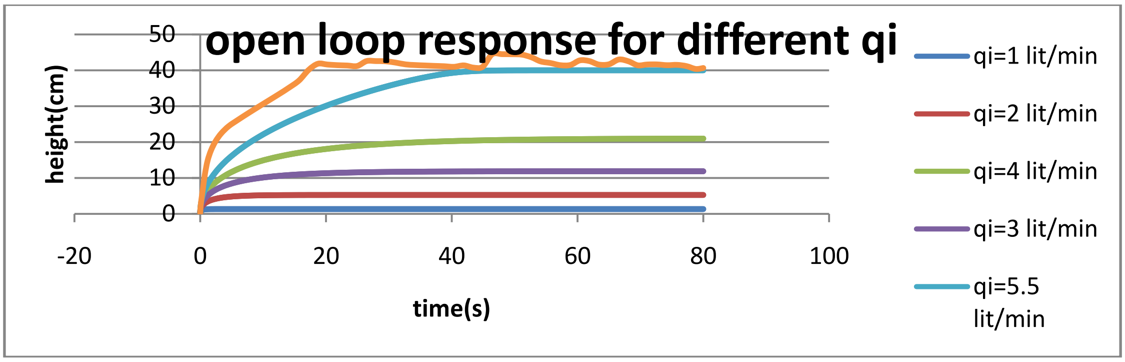

Fig. 2 Open loop Responses for different flow rates of water for hemispherical tank

III. MODEL IDENTIFICATION

A Mathematical Modeling

In this level process tank is Hemispherical in shape in which the level of liquid is desired to maintain at a constant value. This is achieved by controlling the input flow into tank. Here, the control variable is the level. The manipulated variable is the input flow rate to the tank. The schematic diagram of the system is as shown in figure (3).Let q_{out} and q_{in} be the changes in outflow rate and inflow rate in cm³/sec. Let R be the top radius of the tank in cm. Let H be the total length of the tank in cm. Let r be the radius at nominal height h in cm. using the law of conservation of mass

$$q_{out} - q_{in} = \frac{dv}{dt} \qquad [1]$$

where V-Volume of the hemi-spherical tank = $\frac{1}{6}\pi h(3r^2 + h^2)$ [2]

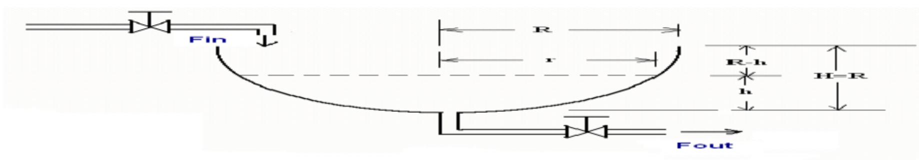

Fig. 3 Level control in hemispherical tank

From the Pythagoras theorem, $R^2 = r^2 + (r-h)^2$

Now putting the value of r in equation [2], then $V = \pi[Rh^2 - \frac{1}{3}h^3]$

The outflow rate is proportional to the square root of height of the liquid.

$$q_{out} = ch^{(1/2)}$$

Then the equation [1] becomes,

$$\frac{d\pi[Rh^2 - \frac{1}{3}h^3]}{dt} = q_{in} - ch^{1/2}$$

$$\frac{\pi[2Rh - h^2]dh}{dt} = q_{in} - ch^{1/2}, \qquad [3]$$

Let us take $q_{in} = Q_{in}$

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 10, October 2015

$$\frac{dh}{dt} = \frac{-c\sqrt{h}}{[\pi(2Rh-h^2)]} + \frac{Q_{in}}{[\pi(2Rh-h^2)]}$$

$$\frac{dh}{dt} = f(h, Q_{in})$$

Using a truncated Taylor series Expansion

$$\frac{dh}{dt} = f(h_s, Q_s) + \frac{\partial f}{\partial h} | (h_s, Q_1)(h-h_s) + \frac{\partial f}{\partial Q} | (h_s - Q_s)(Q-Q_s) + \frac{1}{2}\frac{\partial^2 f}{\partial h^2} | (h_s, Q_s)(h-h_s)^2$$

+Neglecting the higher terms. [4]

Where h_s and Q_s are steady state height of level and input flow.

And putting the value of equation [4] in [3] we will get,

$$\frac{dh}{dt} = \frac{-c\sqrt{h}}{[\pi(2Rh-h^2)]} + \frac{Q_{in}}{[\pi(2Rh-h^2)]} -+ \frac{(Q-Q_1)}{\{\pi(2Rh_s-h^2)\}} - \frac{Q_s(2R-2h)(h-h_s)}{\pi(2Rh_s-h_s)^2}$$

In the above equation, the first term of the right hand side term will be zero, since the linearization is going to be done at steady-state point, hence we will get

$$\frac{d(h_s-h)}{dt} = +\frac{Q_{in}}{[\pi(2Rh-h^2)]} - \frac{\{(h-h_s)[\{(2Rh_s-h_s{}^2)2h_s\sqrt{c}\}-2c'h(R-h)]\}}{(2Rh_s-h_s{}^2)^2} - \frac{Q_s(2R-2h)(h-h_s)}{\pi(2Rh_s-h_s)^2}$$

$$\frac{dh}{dt} = -h_a + bQ_{in} \qquad [5]$$

Where $a = \frac{c'}{2Rh_s(2R-h_s{}^2)} + \frac{Q_s(R-h_s)}{\pi(2Rh_s-h_s{}^2)^2}$ And $b = \frac{1}{\pi(2Rh_s-h_s{}^2)}$

After taking Laplace Transformation, equation [5] becomes,

$$Sh(s) = -h(s)a + bQ(s)$$

$$h(s)(s+a) = bQ(s) hence$$

$$\frac{h(s)}{Q(s)} = \frac{b}{s+a}$$

$$\frac{h(s)}{Q(s)} = \frac{2h_s{}^{(5/2)}/\{(2Rh_s-h_s{}^2)(\pi c'+4Q_s(R-h_s)h_s{}^{(5/2)})\}}{[s\{2\pi h/(\pi c'+4Q_s(R-h_s)h_s{}^{(5/2)}\}+1}$$

C = co-efficient of valve output (0.5 to 1) and hence for standard calculation the values will be R = 16 cm, h = 16 cm, c = 0.5, the model parameter for the hemispherical process as shown in table 1.

Table 1 Model parameter for the hemispherical process

Process	K_p	τ (sec)	τ_d (sec)
Hemispherical	16	12860	10

B Modeling using S-K Technique

The main drawback of the theoretical model is time consuming .Hence to identify the model an open loop test was performed and response of the process to step change was obtained. For many processes in the chemical industry from the process reaction curve which is plot of the output response of a process to step change in the input . The general from of the FOPDT model is given by Equation [6] is obtained.

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 10, October 2015

$$G_p(s) = \frac{K_p e^{(-\tau_d s)}}{\tau s + 1} \qquad [6]$$

Where K_p is the process gain, τ_d the time delay and τ is the process time constant. Several methods are available to obtain the parameters of a first–order model, The SK method proposed by Sundareson and Krishnaswamy [24] avoids use of the point of inflection construction entirely to estimate the time delay. Using this the time delay and time constant are determined experimentally for the step input using $\tau_{D=1.31t_1} - 0.29t_2$ and $\tau = 0.67(t_2 - t_1)$ where t_1-time corresponds to the 35.3 % response, t_2-time corresponds to the 85.3% response. The model parameters of the processes for hemispherical tank using S-K method are given in Table 2.

Table 2 Model parameters of the process using SK method

S.No	Process	t_1 (Sec)	t_2 (sec)	τ (sec)	τ_D (sec)	Kp
1.	Hemispherical	7	9	12860	20	16

C. Higher order modeling

Skogestad [25] has proposed a related approximation method for higher order models that contain multiple time constants. The objective is to use the resulting effective time delay to obtain the controller settings. Hence a better approach would be to find the approximation for which a given tuning method results in the best closed loop response. Using this method, an approximate FOPDT model g(s) given in equation [6] is developed for the process from the original model.

$$g(s) = \frac{K_p e^{(-\tau_d s)}}{\tau s + 1} \qquad [7]$$

Where Kp is plant gain, t is lag time constant and td is the Effective time delay. First the parameters of the original model go(s) in the form given in equation (8) are obtained.

$$go(s) = \frac{K_p e^{-\tau_d s}}{(\tau_1 s + 1)(\tau_2 s + 1)} \qquad [8]$$

than an approximate first order time delay model g(s) is obtained using 'Half rule' According to this rule the dominant time constant is retained Then one half of the neglected time constant is allocated to the retained time constant and one half of to the original time delay. The effective delay τd is the sum off of the original delay τd_0 and the contribution from the various approximated terms.

$$\tau_d = \tau_{D0} + \frac{\tau 20}{2} + \sum \tau_{i0} + \sum T^{inv}_{jo} \qquad [9]$$

Using equation 9 the FOPDT models are developed for the processes and model parameter are given in Table 3.

Table 3 Model Parameters using skogestad method

S. No	Processes	K_p	τ	τd
1.	Hemispherical	16	128	20

D Model Validation

The performance indices considered for model validation are

1. Average percentage error. 2. Sum of squared errors. 3. Standard deviation.

Average percentage error is defined by Equation [10]

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 10, October 2015

$$APE = \frac{1}{P}\sum\frac{T(i)-O(i0)}{T(i)}X100\% \quad [10]$$

where P – Number of data points, T(i)- i^{th} desired output and O(i) – i^{th} calculated output
Sum of squared errors is defined by Equation [11]

$$SSE = \sum e_{j^2} \quad [11]$$

Where e_j -error between the desired and the actual out put

The above three performance measures are calculated for all the three models of the process and are given in Table 4.

Table 4. Model validation

Process	Mathematical Modeling			S-K Method			Skogestad		
	APE	SSE	STD	APE	SSE	STD	APE	SSE	STD
Hemi spherical	1.42	0.04	0.25	1.02	0.02	0.15	0.27	0.02	0.0105

IV. DESIGN OF CONTROLLER

A. Smith predictor

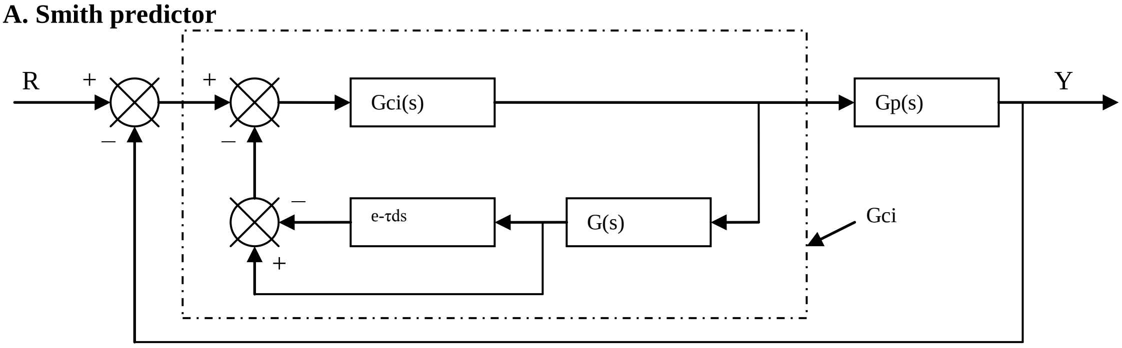

Fig 4 Smith predictor structure

Figure 4 consists of a feedback controller Gc_i, that control delay free process(s) which is easier to control than the true process Gp(s). The calculated manipulated variable resulting from controlling the model is implemented in the true process, which could yield good control as long as the model is perfect. Let Gp(s) be the transfer function of the process and Gm(s) the transfer function of the model given by equation [12] and [13] respectively

$$G_p(s) = \frac{K_p e^{(-\tau_d s)}}{\tau_{ps}+1} \quad [12]$$

and $$G_{mp}(s) = \frac{K_m e^{(-\tau_d s)}}{\tau_{ms}+1} \quad [13]$$

Let G represent the delay free model of the process given by

$$G(s) = \frac{K_m}{\tau_{ms}+1} \quad [14]$$

The resulting controller transfer function is given by,

$$GCsmith(s) = \frac{Gc_i}{1+GGe_{i(}(1-e^{\tau_{ds}})} \quad [15]$$

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 10, October 2015

where Gc_i -PI controller designed for the delay free process(S)

Let Y_{sp} and d indicate the set point and load disturbance respectively .The closed loop set point transfer function is obtained as:

$$\frac{Y}{Ysp} = \frac{Gc_i GP}{1 + Gc_i G} \quad [16]$$

and the closed loop transfer function for disturbance and a perfect model is given by

$$\frac{Y}{D} = \frac{Gd[1 + Gc_i G(1 - e^{\tau ds})}{1 + Gc_i G} \quad [17]$$

The tuning parameters of the PID controller employed in the smith predictor structure are given in Table 5.

Table 5 Tuning parameters of PID controller

S.No	Level Cm	τ	P	I	D
1.	Level 1 0-11	1.33	0.234	2.16	0.08
2.	Level 2 11-22	8.1	0.229	8.8	0.079
3.	Level 3 22-33	12.3	0.2	10	0.043

Response to set point change for a step input of magnitude 6units for hemispherical process Figure5. Regulatory response of the smith controller to a step disturbance of magnitude is shown in Figure 6.

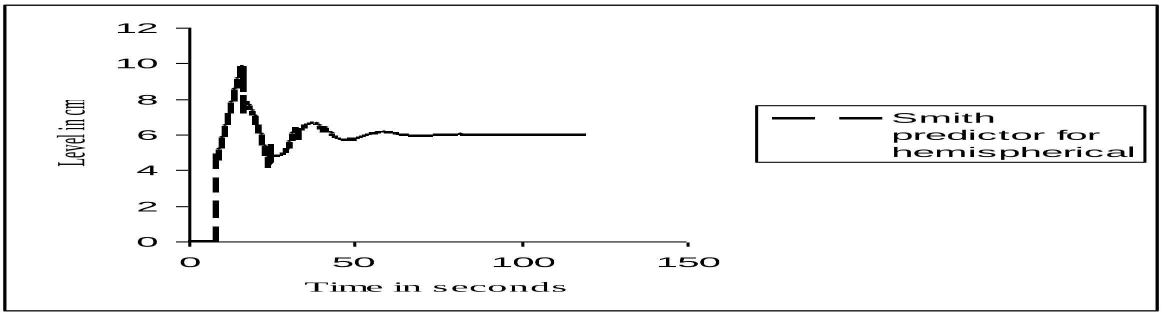

Fig 5 servo responses of the controllers for hemispherical tank level process

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 10, October 2015

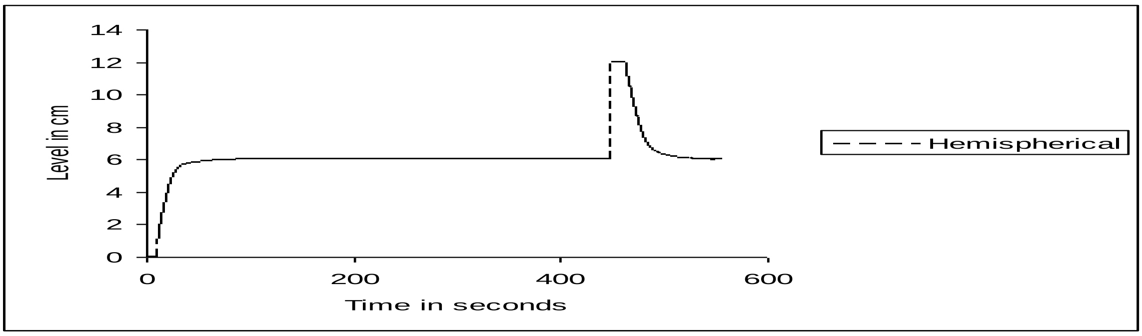

Fig 6 Regulatory response of the Smith controller to a step disturbance of Magnitude +20%at t=450seconds for hemispherical level process

The Smith predictor has the theoretical advantage of eliminating the time delay from the characteristic equation. It was observed that the advantage holds as long as the model errors are not too large (about ± 30 of the actual values). Moreover the Smith predictor approach is model based and the performance of the control strategy is affected by the accuracy with which the model represents the plant.

B. IMC Controller

The process transfer function G(s) is factorized into invertible and non invertible elements to obtain a stable controller as given in equation [18]

$$\tilde{G}(s) = \tilde{G}_+(s)\tilde{G}_-(s) = e^{(-\tau_D s)}\frac{K_p}{\tau s+1} \qquad [18]$$

where $\tilde{G}_+$ = the non invertible part and $\tilde{G}_-$ = the invertible part

An idealized IMC controller is formed. It is the inverse of invertible portion of the process model.

$$G_{IMCideal}(s) = \tilde{G}(s)_-^{-1} = \frac{\tau_p s+1}{K_p} \qquad [19]$$

A filter is added to make the controller proper. Since it is desirable to track the set point changes, the filter transfer function as given in equation [20] is used.

$$F(s) = \frac{1}{(\lambda s+1)^n} \qquad [20]$$

The general expression for designing practical IMC controller is given by equation [21].

$$G_{IMC}(s) = \tilde{G}(s)_-^{-1}F(s) = G_{IMC(ideal)}F(s)$$

$$G_{IMC}(s) = \frac{\tau_p s+1}{(\lambda s+1)K_p}; n=1 \qquad [21]$$

Based on equation (32) IMC controllers are designed for the hemispherical tank processes and are given in Table 6.

Table 6 Tuning parameters of IMC controller for various processes

S.No	Processes	Model	Tuning parameter(λ)
1.	Hemispherical	$\frac{16}{1682s+1}e-14s$	9

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 10, October 2015

The tuning parameter λ was selected to offer good servo regulatory performances and robustness. Responses to set point change for a hemispherical process was shown in Figure 7. Response to step disturbance for hemispherical process is shown in Figure 8. Regulatory response of an IMC controller to a set point change of negative step disturbance magnitude 6 units is shown in Figure 9.

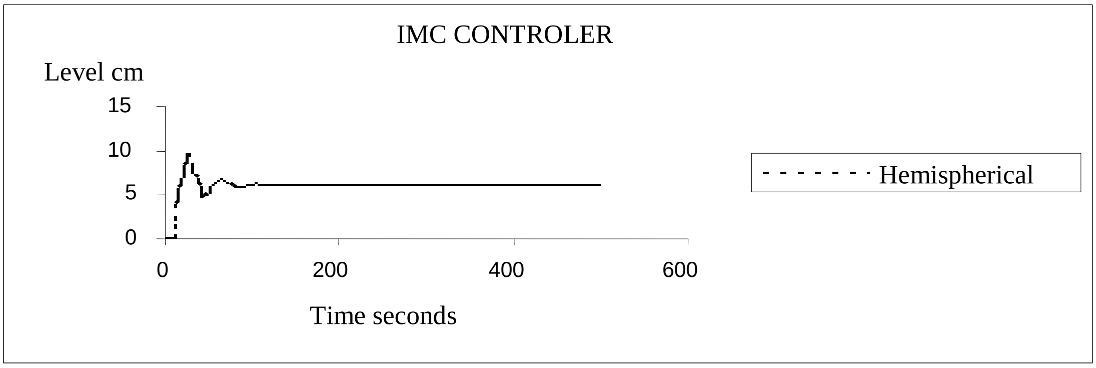

Fig 7 Servo response of the IMC controllers for hemispherical tank process

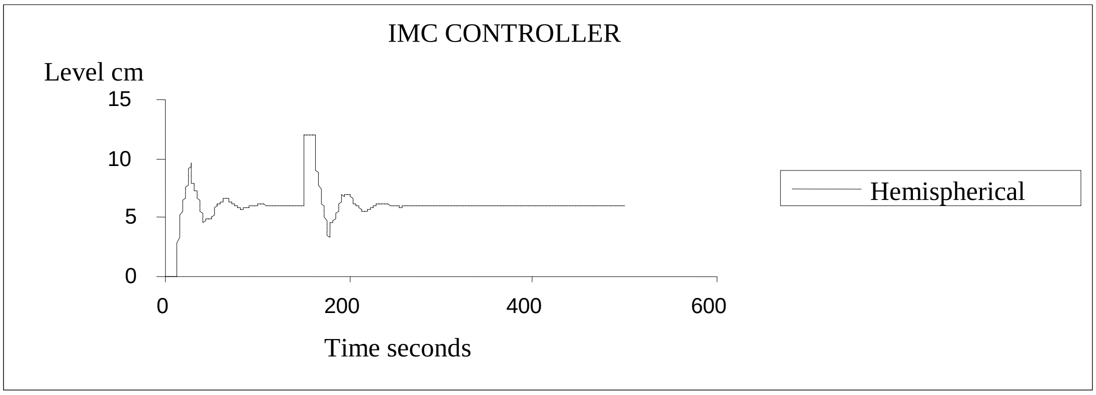

Fig 8 Regulatory responses of the IMC controllers for hemispherical tank process

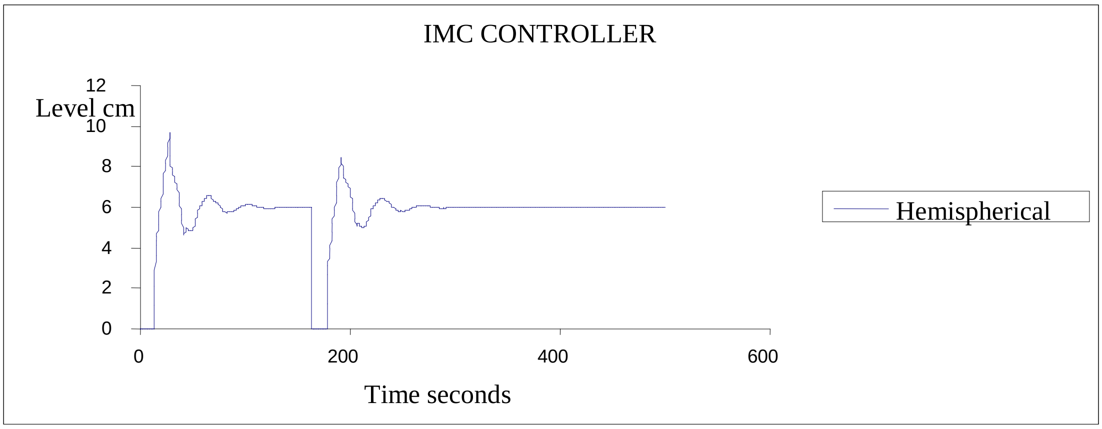

Fig 9 Regulatory response of IMC controller to negative step disturbance at t=150 sec for the hemispherical tank processes

C SOFT CONTROLLERS

The structure of neural model and neural model predictive controller is shown in Figure 10. The training of neural network is shown in Figure11. Identification of the process data was performed using neural network algorithm. The neural model network process consists of three operational steps: prediction, correction and control move

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 10, October 2015

determination. In this work flow rate was input and the output variable. A sampling time of 10 seconds was used for the simulation. For training the neural model step response data of the process was taken. A total of 2000 data were taken continuously and it was saved in file. By training the input output data the NN model of the non linear process was obtained. The neural net work used for training consists of 2 neurons in the input layer, 1 neuron in the output layer and 23 neurons in the hidden layer. The back propagation through time (BPTT) algorithm was used for training the recurrent network. Neural model was designed for the prediction horizon 2 and control horizon 3 using trained input-output data. Figure 12 shows the training performance and validation of the NN. For the network training and validation, the Levenberg-Marquardt back propagation algorithm was used. The convergence criterion was selected as 10^{-3}, and this was achieved in18and 65 epochs. Figure 13 shows the validation response for optimum alpha value of 0.07for the hemispherical process. The optimum value of alpha is based on the mean square error (MSE) of 23340 for a alpha value of 0.07 .The servo response of controllers is shown in Figure 14.

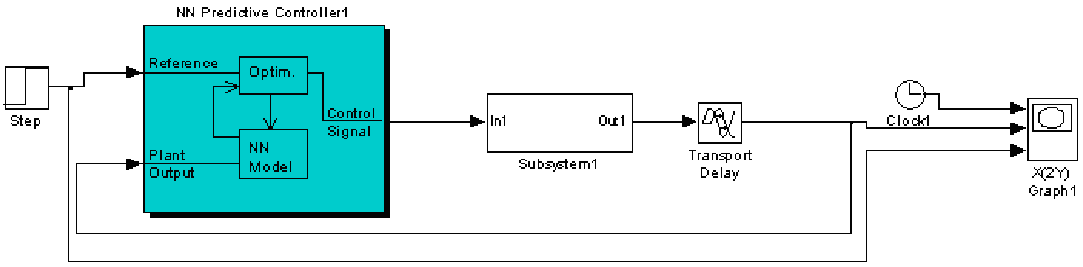

Fig 10.Simulink Structure of NN Model

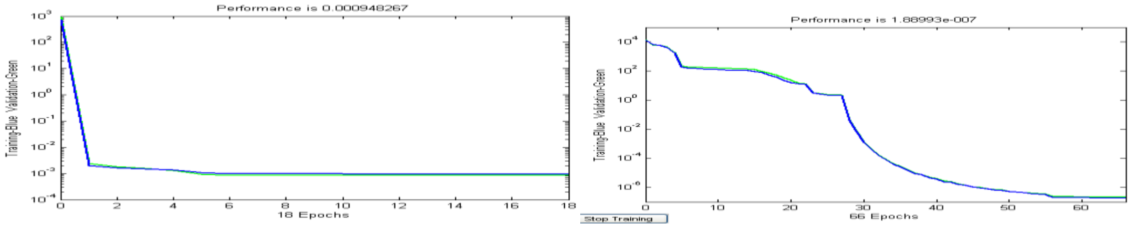

Fig 11. Training of neural network

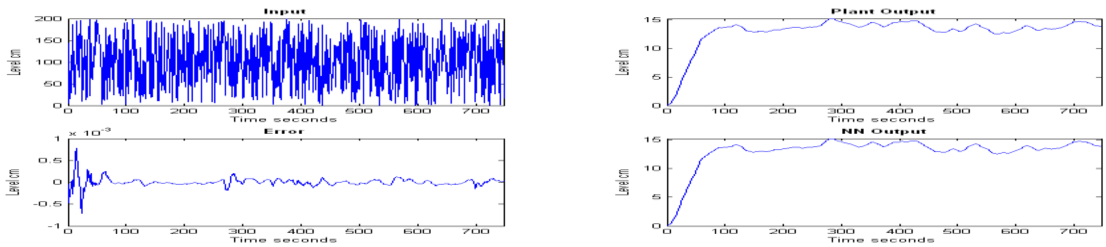

Fig 12. Training of the NN model with process for optimum alpha value 0.07 for hemispherical process

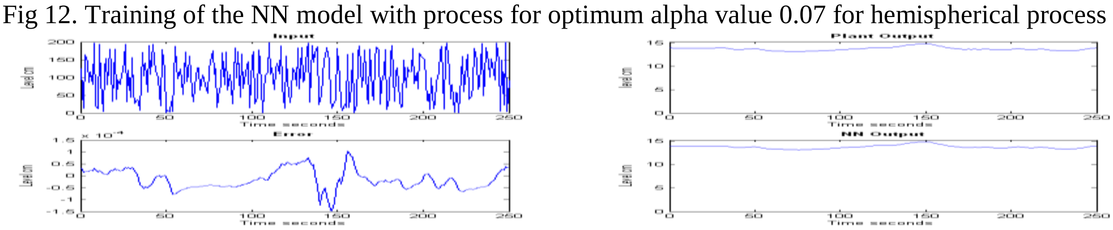

Fig 13. Validation of the NN model for optimum alpha value 0.07
for hemispherical process

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 10, October 2015

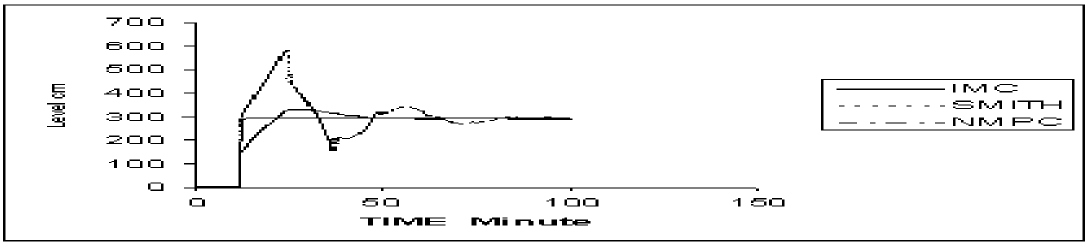

Fig 14. Comparison of servo response of the controllers for hemispherical tank

IV. RESULTS AND DISCUSSION

Model parameters and the average absolute percentage error between the model and the experimental data are also shown in Table 7 It can be concluded that model represents the processes studied with reasonable accuracy of4.9. Various controllers: Smith, IMC, and Neural controllers closed loop performance is indicated in Table 8, based on the models generated for both servo and regulator problem by a positive and negative step change of 0.2 units in flow rate. The parameters assessed for the five controllers are rise time, settling time, overshoot, ISE, IAE (5parameters). The data in Table 8 was critically analyzed and the performance of the processes shown in Table 7 were studied for the controllers and was ranked as follows based on the above 5 parameters: If all the five parameters namely, rise time, settling time, overshoot, ISE, IAE was minimum it is ranked as number 1. If all these 5 are maximum it is ranked 3. Table 9 presents the statistics of performance of various controllers. Table 10 reclassifies the controller performance according to their merit for the processes studied. It is seen that Neural is the best suited for all the process while IMC controller ranks next best. The least merited controller is Smith as it is ranked as number 3 for all the process. For real time validation the processes was connected as a closed loop with the PC and the controllers activated using software. It was found that the closed loop performance agreed with the conclusion shown in Table 10

Table 7 Model parameters and percentage error for different process

Process	Control parameter	Model generated	Average %absolute error
Hemispherical	Level	$\frac{16}{(1282s+1)}e^{-20s}$	4.9

Table 8 Comparison of time domain and servo-regulatory performance of the controllers

Tuning Method	Rise time t_r sec	Settling time t_s sec	Over shoot M_p %	+ ve step change (0.2)				-ve step change (-0.2)			
				Servo		Regulator		Servo		Regulator	
				ISE	IAE	ISE	IAE	ISE	IAE	ISE	IAE
Smith	25	120	10	0.4076	0.845	0.15	1.72	1.53	1.3	0.7	0.9
IMC	23	55	8	0.172	0.312	0.056	0.943	0.01	1.04	0.12	0.63
Neural	12	15	0	0.085	0.056	0.065	0.056	0.03	0.08	0.04	0.05

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 10, October 2015

Table 9 Performance ranking based on time domain and servo regulatory Response for controllers

Tuning Method	Performance ranking based on overall Time domain Specification		Performance ranking based on servo regulatory response							
			+ ve step change(0.2)				-ve step change(-0.2)			
			Servo		Regulator		Servo		Regulator	
	Peak Overshoot (M_p)	Settling Time (t_s) sec	ISE	IAE	ISE	IAE	ISE	IAE	ISE	IAE
Smith	3	3	3	3	3	3	3	3	3	3
IMC	2	2	2	2	2	2	2	2	2	2
Neural	1	1	1	1	1	1	1	1	1	1

Table 10 Closed loop performance ranking of the controller

Process	Control parameter	Model generated	Performance Ranking of the Controllers		
			Smith	IMC	Neural
Non linear Hemi spherical Process	Level	$\frac{16e^{-20s}}{(1282s+1)}$	3	2	1

V. CONCLUSIONS

The results given in Table 8 emphasize that the Neural Model Predictive controller shows a minimum dynamic response time than the conventional controllers. It is evident from Table 8 that the neural model predictive controller offers best time domain characteristics rise time, settling time, overshot, for the hemispherical tank level process.

REFERENCES

1. M.Chidambaram, R.Anandanatarajan, and T.Jayasingh, "Controller design for non-linear process with dead time variable transformation", Proceedings of the international symposium on process system engineering and control, IIT Mumbai, pp. 223-228, (2003).
2. P.Madhavasarma, T.K.Radhakrishnan and S.Sundaram, "Model based evaluation of a controller using pole placement technique for conductivity process", Journal of instrumentation soc., India, 36, 246-256, (2006).
3. M.Chidambaram, R.Anandanatarajan, and T.Jayasingh, "Design of controller using variable transformation for non linear process with dead time", 44 ISA, pp. 81-91, (2005).).
4. Ramakrishnan and M. Chidambaram, "Estimation of a SOPTD transfer function model using a single asymmetrical relay feedback test", Computers and Chemical Engineering, 27, pp. 1779-1784, (2003).
5. I.Ananth and M. Chidambaram, "Closed-loop identification of transfer function model for unstable systems", Journal of the Franklin Institute, 336, pp. 1055-1061, (1999).
6. R.Ramachandran, S.Lakshminarayanan and G.P.Rangaiah, "Process Identification using open loop and closed loop step responses", Journal of the Institution of Engineers, Singapore, Vol. 45, Iss. 6, (2005).
7. M.Liu, Q.G.Wang, B.Huang, and C.C.Hang, "Improved identification of continuous time delay processes from piecewise step tests", Journal of Process Control, 17 , pp. 51–57, (2007).
8. Visioli, "Time–optimal plug &control for integrating and FOPDT processes", Vol 13, pp. 95-202, (2003).
9. J.Arputha Vijaya Selvi, T.K.Radhakrishnan and S.Sundaram, "Model based IMC controller for process with dead Time", Journal of Instrumentation science and Technology, 34, pp. 463-474, (2006).
10. Pankaj Swarnkar, Shailendra Kumar Jain & R.K Nema (2014) Adaptive Control Schemes for Improving the Control System Dynamics: A Review, IETE Technical Review, 31:1, 17-33, DOI: 10.1080/02564602.2014.890838.
11. Sahaj Saxena & Yogesh V. Hote (2012) Advances in Internal Model Control Technique: A Review and Future Prospects, IETE Technical Review, 29:6, 461-472.
12. J.AVijayaselvi, T.K.Radhakrishnan and S.Sundaram, "Performance assessment of PID and IMC tuning methods for a mixing process with time delay", ISA, 46, pp. 391-397, (2007).

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 10, October 2015

13. P.Madhavasarma and S.Sundaram, "Model Based Tuning For a Non Linear Spherical Tank With Time Delay Process", J. Instrumentation Science & Technology, 36, pp. 420- 431, (2008).
14. K.J.Astrom, C.C.Hang, and B.C.Lim, "A new Smith Predictor for controlling a process with an integrator and long dead time", IEEE Trans .Automat. Control, 39, pp. 343-345, (1994).
15. I.Kaya and D.P.Athetron, "A new PI-Pd Smith Predictor for control of Process with long dead time", Proceedings of the 14th IFAC World Congress IFAC-99, pp. 283-288, (1999).
16. Y.D.Chen, P.I.Cheng Tung and C.C.Fuh, "Modified Smith predictor scheme for periodic disturbance reduction in linear systems", J. Proc. Cont., 17, pp. 799-804, (2007).
17. L.LChien., S.C.Peng and J.H.Liu, "Simple control method for integration process with long dead time", J.Proc.Cont., 12, pp. 391-404, (2002).
18. J.E.Marshall, Control of time delay systems, Peter Peregrine Ltd., stevange, UK, (1979).
19. K.J.Astrom, C.C.Hang, and B.C.Lim, "A new Smith Predictor for controlling a process with an integrator and long dead time", IEEE Trans .Automat. Control, 39, pp. 343-345, (1994).
20. W.D.Zhang and Y.X.Sun, "Modified Smith Predictor for controlling integrator Time Delay Processes", Ind.Eng.Chem.Res., 35, pp. 2769-2772, (1996).
21. P. Madhavasarma, S.Sundaram, Model based tuning of controller for non linear hemispherical tank processes. Instrum. Sci&Technol., 2007, 35, 681-689.
22. A.J.Hugo, "Process Controller Performance Monitoring and Assessment control", Arts Inc.(www.freepatentsonline.com/6594593.html), Downloaded on March, 15 2007.
23. A.Swanda, "Assessing the performance of PID feedback control loops", Ph.D dissertation, University of California, Santa Barbara, (1999).
24. J.E.Marshall, H.Gorecki, A.Korytowski and K.Walton, "Time delay systems: stability and performance criteria with applications", Ellis Horwood, (1992).
25. K.R.Sundaresan and R.R.Krishnaswamy, "Estimation of time delay, Time constant parameters in Time, Frequency and Laplace Domains", Can. J. Chem. Eng., 56, 257, (1978).