Modeling and controller design for a Conical tank process using Radial Basis Function neural network

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Abstract: The major issue in the process industry is to control the level of the liquid in the nonlinear processes especially in a conical tank. This study addresses the efficient controller design for the conical tank process. The conical tank is divided into different operating zones and the approximated first order process model (FOPDT) was identified for each region using simple black box technique. A neural network model based on radial basis fucntion (NNRBF) was found from the FOPDT model. For the identified network, predictive controller (NMPC) was proposed using NNRBF. The performance indices and time domain specifications of the proposed controller are compared with the conventional direct synthesis PI controller (DSPI) and internal model controller (SIMC). The result showed that proposed predictive controller is more effective and robust compared with the other controllers.

Keywords: Radial Basis Function, Neural Model Predictive Control, Conical tank, PRBS.

1. Introduction

Chemical industries exhibit many challenging problems because of nonlinearity. Almost all the processes in the industries are non-linear. Controller design for the conical tank is a critical task in industries such as petrochemical industries, hydrometallurgical industries, and food processing industries, refineries. Conical tanks provide better disposal of solids, slurries, especially for viscous liquids and provide complete drainage. This is the reason for considering conical tank in this study. Since the cross-sectional area changes throughout its length, it comes under nonlinear process [1]. It is difficult to control when the liquid level is chosen as a process variable. This liquid in a preferred process varies**.** In the processes like reboiler, evaporators, distillation columns, the control of liquid level is the basic problem as it has to be transferred between the tanks during chemical or mixing treatment. It is important that the particular level has to be maintained in the conical tank. Though advanced control algorithms are available in the literature, most of the industries prefer conventional PID controller because of its simplicity and economical use. But the researchers are concentrating much on advanced and robust controllers for the industries which will be providing simple, effective and economical controllers.

The conventional approach for controlling the level in the conical tank is the proportional-integral-derivative controller (PID). PID controller can be designed based on direct synthesis approach. This controller is planned for disturbance rejection, in which set-point is frequently tuned by set-point weighing factor. Direct Synthesis Proportional Integral (DSPI) controller is designed based on desired closed loop transfer function, which can be specified by choosing the poles of closed loop [2]. Skogested based Internal Model Control uses the model of the process. Optimization is achieved in the PI controller by the proposed tuning [3]. Earlier in the past decades, controlling of the nonlinear process is done by traditional controller and self-regulating controllers, but this controller does give best results when the time delay for the process varies. The level control of two interacting conical tanks was carried using dynamic matrix control [4]. Bhuvaneswari et.al. [5] designed and implemented optimal controller for the conical tank process. Different controllers such as PI and Smith predictor based were designed for a conical tank with time delay[6]. Venkatesh et.al.[7] developed a predictive control for a conical tank process which outperformed the other conventional controllers. But the approaches used in the above literature uses either first principle models or step response models. These models do not capture the dynamics of the process effectively. The controllers in the above literature do not handle the physical constraint except predictive controllers. To enhance the advantages of modeling using artificial neural network and controllers using predictions, an attempt is made to design predictive controllers for a conical tank process using the neural network models.

The main objective of this study is to model the conical tank using neural network and to design different controllers for the identified model. Neural network which uses Radial Basis Function (RBF) is chosen for modeling the Conical Tank. RBF is an excellent network which attracts the researcher is recent years especially in modeling. Forecasting of electricity demand in west Iran was modelled using different neural network approaches in which RBF resulted with minimum error [8]. RBF neural network was utilized in modeling waste water treatment plant [9]. An electrical characteristic of photovoltaic module is estimated using radial basis function neural network [10]. A survey has been conducted to analyse the model predictive controller (MPC) design for industrial processes and the next generation MPCU [11]. Michael & Henson have addressed the problem associated with linear MPC and the future scope of MPC for nonlinear model which uses neural network models [12]. A generalized predictive controller is designed for a bench mark paper plant [13]. Model predictive controller has been developed and implemented in earth warm treatment plant using support vector regression which provided better experimental results in terms of good regression precision. This paper addresses the use of RBF model to design the predictive controller for controlling the level of the conical tank and compare the results with conventional control strategies.

2. Process modeling

In chemical industries nonlinear tanks such as conical tanks are majorly used whose level is to be controlled to run safely and efficiently. To design controller, a mathematical model of the process is required. Especially for designing an optimal controller, the selected model must be able to describe the properties of the disturbance acting on the process. Figure 1 shows the description of the process used in this study. The total height of the conical tank is designated as H which is 43 cm and D is the top diameter of the tank which is 33.74 cm. The inlet flow to the tank is the manipulating input which is varied by the application of control signal. The level 'h' of the tank will be varied to the desired set point by varying the manipulating input.

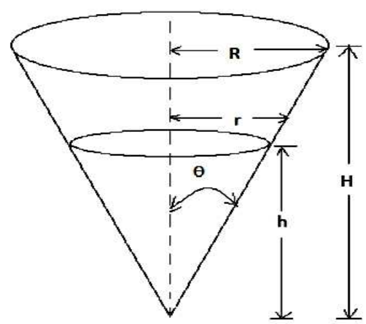

Figure. 1

Description of Conical Tank

The mathematical modeling for the conical tank is obtained as follows.

The area A of the conical tank is calculated

$$A = \pi r^2 \tag{1}$$

$$\theta = \tan^{-1} \frac{r}{h} = \frac{R}{H} \tag{2}$$

$$r = \frac{R}{H} * h \tag{3}$$

Where r, R, h, H are as shown in figure 1.

The following is the material balance equation for the process considered in this study.

inlet flow rate – outlet flow rate = rate of accumulation.

Inlet flow rate - Outlet flow rate = $A\frac{dh}{dt}$ (4)

Outlet flow rate = $k\sqrt{h}$

where *k* is the coefficient of discharge. From the above equations, we can obtain

inlet flow – outlet flow = $\frac{1}{3}\left[A\frac{dh}{dt}+\frac{h\left(2\pi R^2 h\frac{1}{h}\right)*dh}{dt}\right]$ (5)

The system is nonlinear in nature. But the nonlinear model is linearized by considering different operating zones. Each operating region is approximated to first order plus dead time model (FOPDT) as explained by Sivanandam Venkatesh et.al. The FOPDT model was obtained by introducing step change in flow rate into the tank. The response was recorded with respect to time. From this response, the FOPDT model was obtained.

2.1. Modeling of Conical Tank Using RBF

Radial Basis Function (RBF) neural network is a feed-forward network, which is trained by the supervised learning algorithm. The architecture of RBF is shown in the Figure 2. RBF has input, hidden and output layers in its structure. The input layer has source nodes, which has a dimension equal to the input vector. Hidden layer is composed of nonlinear Gaussian activation function, which has the parameters such as centre and width. Output layer has linear activation function, which executes a weighted sum of hidden unit output. RBF is mainly used in pattern recognition technique like spline interpolation, function approximation and clustering. Input of the RBF network is linear while the output is nonlinear. They have outstanding approximation capability. Due to its nonlinear approximation, RBF is capable of modeling any complex mapping.

The output of the RBF is expressed as

$$x_j = f_j(u) = w_{oj} + \sum_{i=1} w_{ij}\left(G \parallel u - c_i \parallel\right) \quad (6)$$

Pseudo random binary sequence (PRBS) was introduced into the approximated FOPDT model identified for six different operating zones. The output was obtained from the model. The input and output data thus obtained was used to train the radial basis function neural network (NNRBF). The RBF network obtained was tested by introducing the PRBS input. The network predictions thus obtained was compared with the model output. Figure 3a – 3f show the comparison of model output and network predictions for six different operating zones. It is evident from the figure 3 that the network prediction (Red in colour) and model output (Blue in colour) are almost merged together. It is manifest from table 1 that the mean squared error (MSE) is very less.

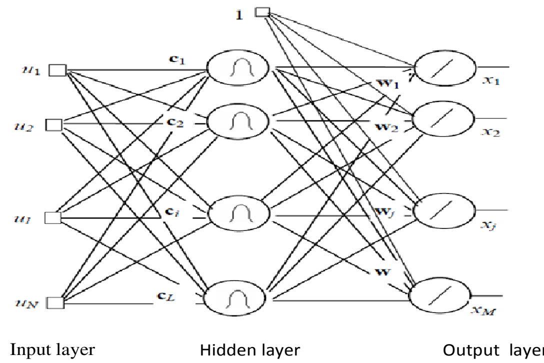

Figure. 2

Structure of Radial Basis Function Neural Network

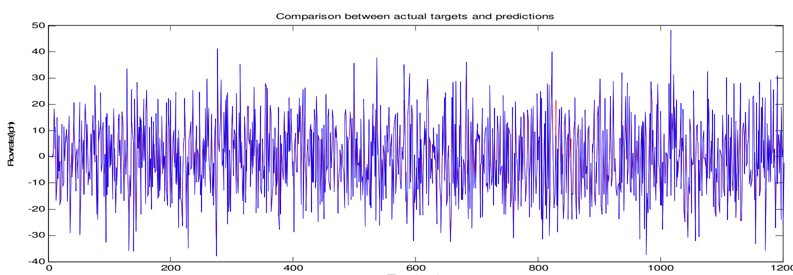

Figure. 3a. Zone 1

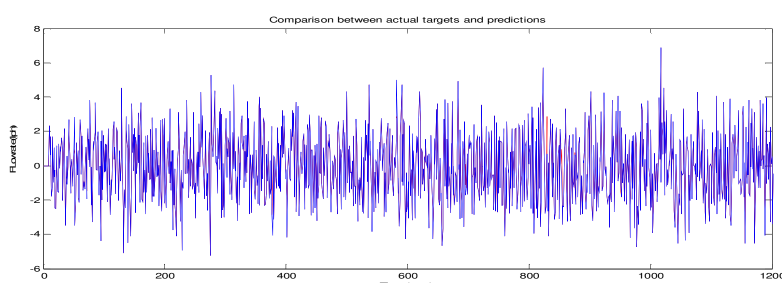

Figure. 3b. Zone 2

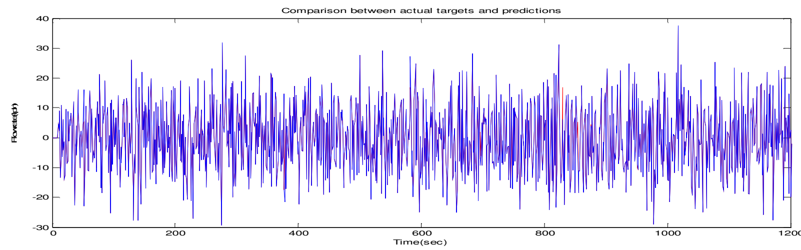

Figure. 3c. Zone 3

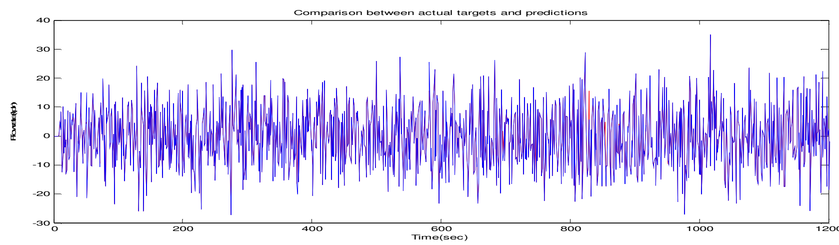

Figure. 3d. Zone 4

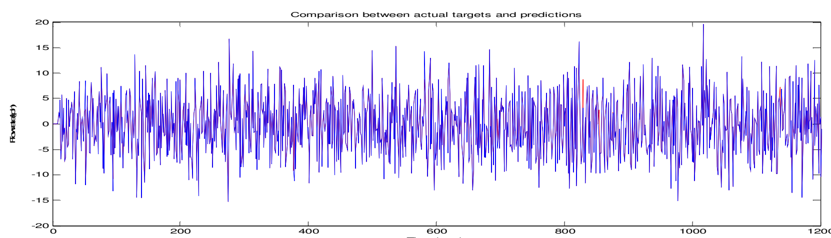

Figure. 3e. Zone 5

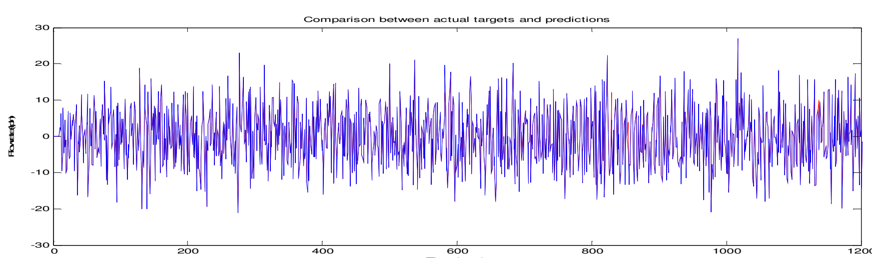

Figure. 3f. Zone 6

Figure. 3

Comparison graph between model output (blue) and network prediction (red)

Table 1. Mean squared error of the RBF network for different operating zone

Zones	MSE
I	1.6871
II	0.0322
III	1.0299
IV	0.8615
V	0.2398
VI	0.5284

3. Design of controllers

For safety operation of the plant as well as for better productivity maintaining the process parameters are essential. Design of controllers plays a key role in industries since precise control is needed for most of the process variables MPC is an advanced control strategy which also addresses the constraint handling. In this study, MPC is designed and implemented which is based on RBF neural network. To show the effectiveness of neural MPC (NMPC), other conventional controllers such as DSPI and SIMC were also designed and implemented for the conical tank.

3.1. Model Predictive Control

Model Predictive Control (MPC) is the latest control algorithms used by the number of researchers now a day. It estimates the upcoming behaviour of the process prior. The structure of MPC is shown in the fig. 4, in which the model can calculate the prospect response of the plant output, based on past input, current value and future control action. These calculations are determined by optimiser where the cost function (future error) and constraints are calculated. The model of the plant is required for the design of model predictive control systems. In this study, the model is taken as the neural network model (NNRBF) obtained from network training.

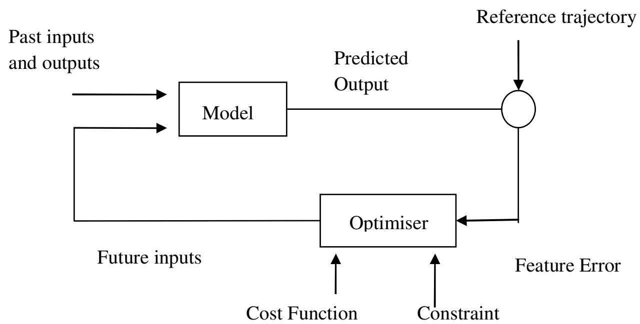

Figure. 4

Block schematic of MPC

3.2. Skogestad based Internal Model Control (SIMC)

The model of the process is utilized in designing the controllers as shown in figure 5. Skogestad has developed simple analytic rules for model-based control techniques in which tuning is expressed as a function of the process model parameter [3]. The transfer function of the process model is supposed to be continuous. The controller dynamics are represented in the transfer function G which includes process, low pass filter and the sensor. The process model obtained from step response data was used as a model. The overall transfer function relating the controlled output T(S) and the input W (S) is given as

$$\frac{Y(S)}{W(S)} = T(S) = \frac{1}{\tau_c s + 1} e^{-\tau s} \tag{7}$$

τ_c-Time constant of the process, defined by the user.

τ- Delay time of the process, given by the process model.

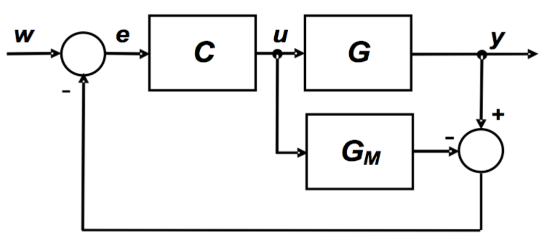

Figure . 5

Block Diagram of SIMC design.

where,

w = Set point,
C = Controller,
u = Manipulating variable,
G = Process
G_M = Model of the process
y = Filtered process measurement.

3.3. Direct Synthesis Proportional Integral Method (DSPI)

It is a well-known controller in the literature which uses the model of the process. The detailed procedure for DSPI is addressed by Seborg et.al. [15]. The main advantage of this method is to select the closed loop poles so that the desired response can be obtained. The drawback of the direct synthesis method is that it relays the on the model and requires inversion of the model which is not possible for non minimum phase systems.

4. Results and discussion

Different controllers such as NMPC, SIMC, DSPI were designed for the nonlinear conical tank process. The servo responses of these controllers for a change in set point were analyzed in MATLAB environment. Figure 6 shows the servo responses of several controllers for different operating zones. For all the operating zones, responses for different set points were analysed. Figure 6a shows the response of different controllers in the first operating zones for a set point of 15. Overshoot is well reduced in NMPC compared with the other two controllers. The servo response for set point of 21.5 is analysed for the operating zone 2 and is shown in figure 6b. Though the settling time is somewhat more for NMPC, than SIMC, the overshoot has been significantly reduced. For the operating zone 3 and 4, set point of 23 and 30 were analyzed respectively. Over shoot is very high for DSPI in both the cases whereas for NMPC it is very less which are evident from figures 6c and 6d. NMPC produce slow response for the operating zone 5 as shown in figure 6e, on the other hand over shoot is drastically reduces comparing with the other controllers DSPI and SIMC. It is manifest from figure 6a to 6f, the NMPC controller resulted with better performance for the all the operating zones. It is evident from table 2 that the rise time for SIMC and DSPI are less compared to NMPC, whereas there is no overshoot for NMPC comparing with the other two controllers. Settling time also significantly reduced for NMPC over other controllers. It is evident from table 2 that the performance indices ISE and ITAE are comparatively lesser than that of other two controllers which are applicable for almost all the operating zones. IAE for NMPC is slightly larger than that of DSPI and SIMC.

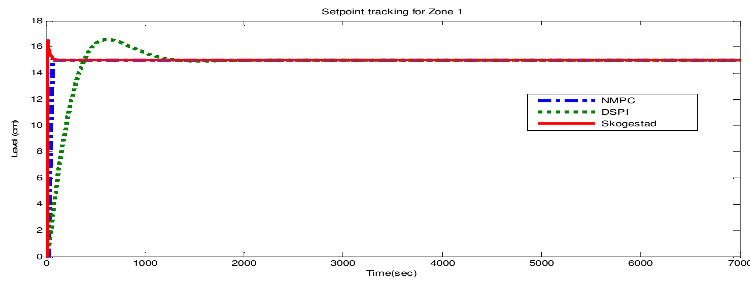

Figure. 6a. Zone 1

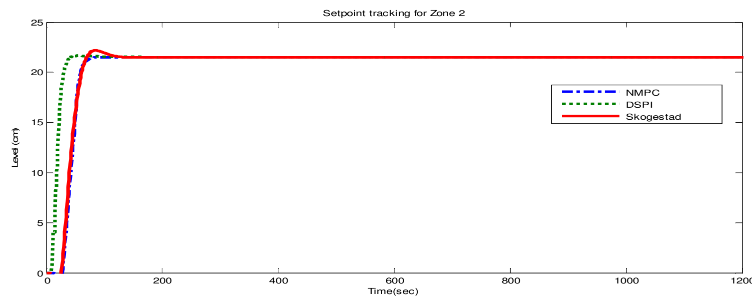

Figure. 6b. Zone 2

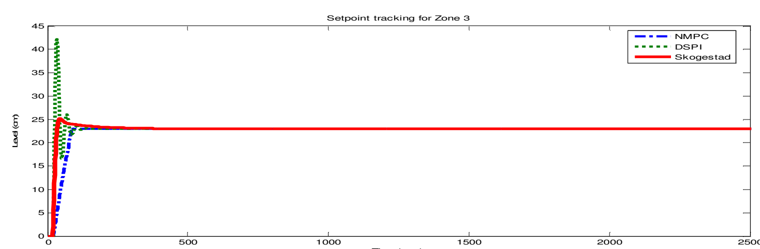

Figure. 6c. Zone 3

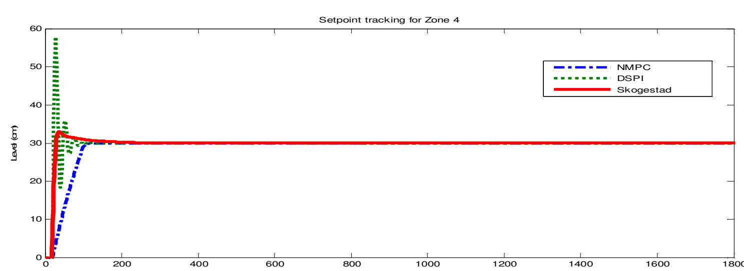

Figure. 6d. Zone 4

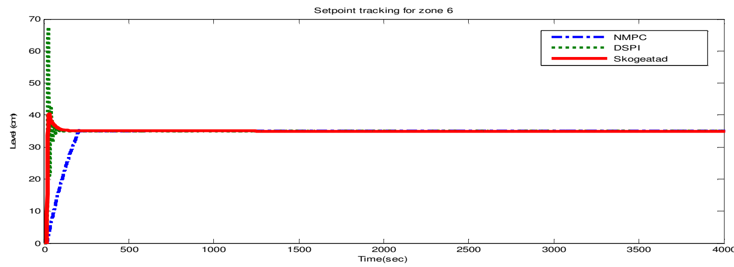

Figure. 6e. Zone 5

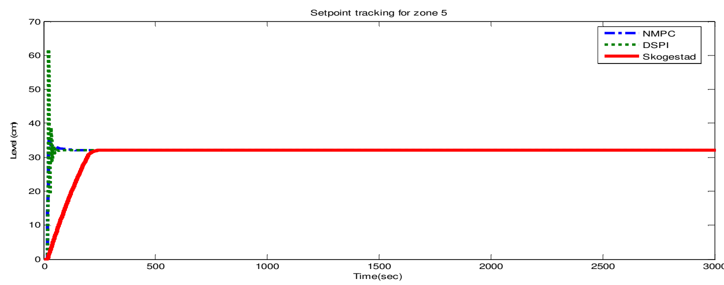

Figure. 6f. Zone 6

Figure. 6

Servo responses of different controllers

5. Conclusion

A linearized model of FOPDT kind was identified from the nonlinear process. PRBS signal was introduced into the identified model to obtain the input and output data and were used to train the neural network based on RBF. The controllers DSPI and SIMC were designed and implemented for the identified FOPDT model. NMPC controller was implemented for the process using NNRBF. The time domain specifications of settling time, overshoot, rise time and performance indices of Integral Square Error (ISE), Integral Absolute Error (IAE) and Integral Time Absolute Error (ITAE) were analyzed for the designed controllers. NMPC outperformed the other two controllers in terms of time domain specifications and performance indices. The above said parameters were considered for the study since they are the good measure of controller performance.

Table 2. Comparative Analysis for Time Domain and Performance measure Using Different Controllers

Zone	Operating Region (level in cm.)	Specification	Set point	NMPC	DSPI	SIMC
I	12-20	Rise Time(sec)	15	72	406	16
			21.5	80	34	68
			23	89	20	34
			30	109	22	29
			32	218	28.9	22
			35	238	32.48	56
II	21-22	Overshoot (%)	15	0.02	1.56	1.51
			21.5	0	0.13	0.66
			23	0	19.23	2.14
			30	0	27.8	2.85
			32	0	29.68	2.89
			35	0.32	32.48	5.35
III	22-27	Settling Time (sec)	15	89	1813	154
			21.5	80	150	141
			23	96	201	370
			30	133	275	351
			32	233	108	138
			35	268	140	197
IV	27-32	ISE	15	117.38	1832	3884
			21.5	92.32	8872.87	8410
			23	1261.12	2433	1378
			30	1302.17	5084	8755
			32	1447.02	2410	4389
			35	472.01	4611	7621
V	31-35	ITAE	15	409.21	8080	1389
			21.5	387.75	13163	8410
			23	769.96	5097	2197
			30	1644.9	63.93	6789
			32	1754.6	3526	1522
			35	1918.01	4370	3360
VI	34-38	IAE	15	1447	290.1	587
			21.5	1172	1022.2	503.3
			23	121.48	243.9	160.5
			30	159.86	353.7	455
			32	167.01	167	213.6
			35	183.01	267.6	339.3

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