ISSN: 0975-8585

Research Journal of Pharmaceutical, Biological and Chemical Sciences

ARMAX Identification and Robust control of Hybrid Non-Linear Systems using Soft Computing Method.

P Madhavasarma[1]*, M Sridevi[2], and P Veeraragavan[3].

[1]Sarswathy College of Engineering, Tindivanam, India
[2]Agni College of Technology, Chennai, India.
[3]University college of engineering Anna University, Tindivanam, India.

ABSTRACT

In Chemical and process industries control of non-linear interactive systems posses a major challenging task to control Engineers due to multivariable process interactions. Need of innovative technology for process identification is on huge demand. Hence an Online model identification using ARMAX technique for the hybrid non interacting systems in series is proposed and designed using Conductivity as a measured parameter and level as manipulated variable. Robust PID controller and NMPC controller were designed using the identified model to control the process level. The performance of the controllers was evaluated using MATLAB software. The performance of NMPC controller was compared with PID controller based on rise time, settling time, overshoot and ISE and it was found that the NMPC controller is best suited for this process.
Keywords: Neural, Conductivity, NMPC, hybrid, ARMAX, ISE

**Corresponding author*

INTRODUCTION

The design of process control systems are highly challenging especially for non linear and multivariable process with interactions due to constraints on manipulated , controlled variablestime delays and environmental disturbances. System uncertainties, system modeling errors, other problematic dynamic characteristics arise from imperfect modeling of the system. The design of most of this control system is based on process model. A traditional modeling technique is to describe the process models such as hemispherical, spherical, and cylindrical vessels, which may contain dead time and bypass flows. In traditional design the process is usually assumed to be in a nominal operation point so that the flow rates and volumes are constant, but this assumption is not always valid. The goal of process identification is to determine a suitable model to represent the dynamics of a physical process for a specific purpose, such as control system design. Sundaram et al [1-6] have developed a conductivity measurement setup for designing control system. Neelemagam et al [7] have developed a conductivity measurement circuit using micro controller for ionic solution. Munoz et al [8] have used electrical conductivity measurement for Kcl solution. Lu et al [9] have discussed uncertainty in chemical sensor. Tse et al [10] have developed a model using neural network algorithm for air handling unit. Karacan [11] has used neural networks to extend the capacity of linear MPC to control nonlinear systems. Radhakrishnan et al [12] have designed a modified recurrent Elman network using back propagation through time algorithm (BPTT) for non linear plants. Silva et al [13] have designed a new NMPC algorithm for SISO and MIMO systems. Henriques et al [14] have modified the Elman network for higher order systems. Margrave et al [15] have detected the flaw in the engineering materials using neural networks. In this work ARMAX model identification technique and Neural Network Predictive Controller for nonlinear hybrid system has been designed. Model parameters were established from open loop analysis of a non linear process. The model was compared with experimental data and error analysis was done. Robust PID controller and Neural Network Predictive controller were designed and there performances were evaluated using MATLAB software.

EXPERIMENTAL SETUP

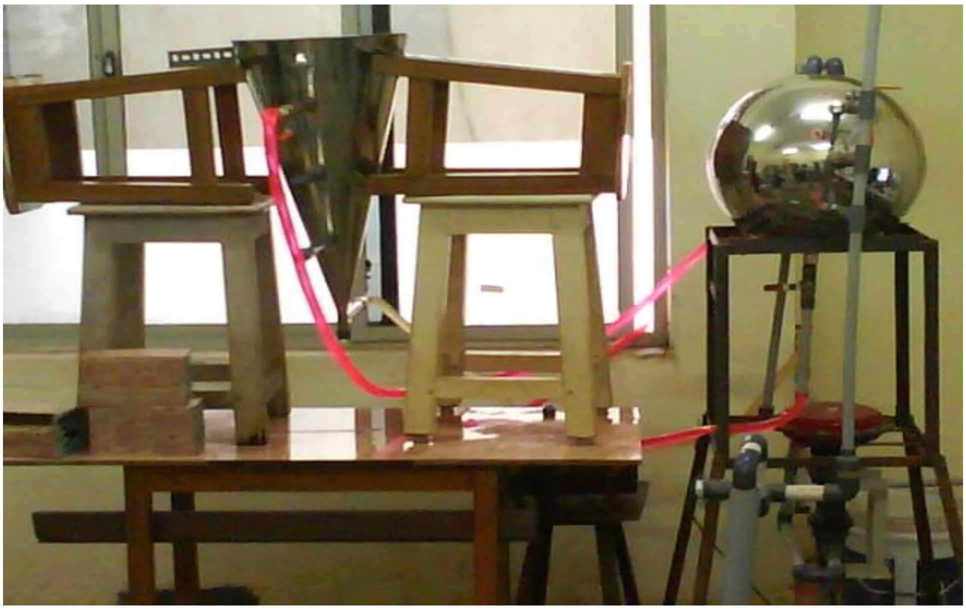

Fig 1 Real time Experimental setup of Non Linear Hybrid Systems

The schematic view of experimental setup is shown in the figure 1. The experimental assembly consists of a non linear spherical tank which is coupled to a conical tank. The mixing of water and tracer takes place in the spherical tank. The inlet flow rates of water and tracer can be varied. A rotameter is placed to determine the flow rates of water and tracer. The tracer is pumped in to the spherical tank by a pump. Sodium chloride (NaCl) was used as the tracer. The concentration of the tracer was maintained at a same concentration (10 g/L) throughout the experiment. The conductivity of the water and tracer mixture is measured through a Honeywell conductivity sensor. The current signal from the conductivity sensor was fed to a current to voltage converter. The voltage signal was fed to an Analog to Digital Converter (ADC). The digitized voltage signal was fed to the computer (Pentium IV) and conductivity was continuously recorded as a function of time. The conductivity of the mixture is measured for various flow rates of water and tracer. Figure 2 shows the response curve for a step change in tracer for 5lpm

Table 1. Experimental Parameters

Variables	Meaning	Initial Settings
V	Volume of the tank	40 liters
Fw	Flow rate of water	2 L/min
Ft	Flow rate of tracer	0.250 L/min
Cw	Conductivity of water	150 milli mho
Ct	Conductivity of tracer	1000millimho
U1	Step input response	5lpm
Y1	Actual open loop response of hybrid system	5lpm

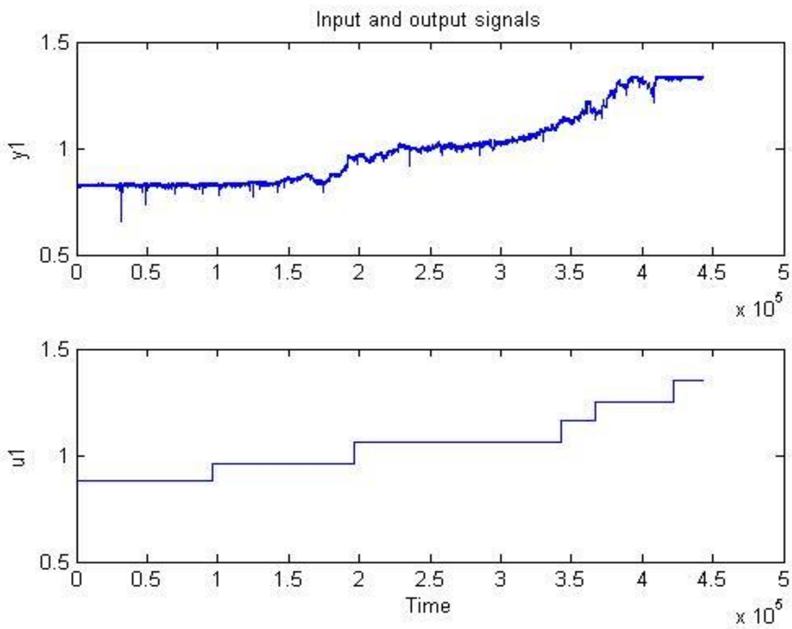

Fig 2 Open loop Response of conductivity with time for 5 LPM flow rate of water

Model identification

Model Identification of the system was done using Auto Regressive Moving Average Extended input (ARMAX) technique [16]. The identified model output was verified with actual process output. Neural network prediction of output was also carried out with the identified model. It was observed that error in predicted model was minimum.

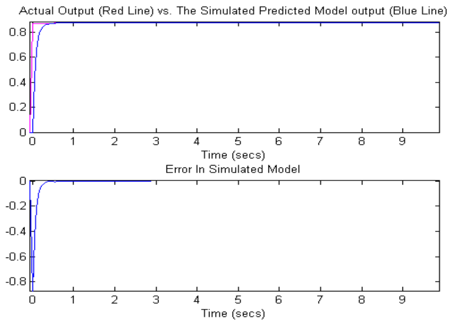

Fig 3a) Spherical tank identification

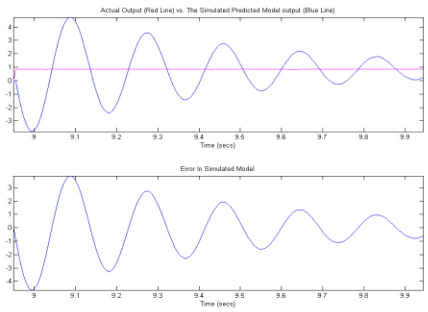

Fig 3b) Conical tank identification

The Transfer function of the hybrid system is given as below.

-6528 s^3 - 1.275e007 s^2 - 6.846e009 s + 2.026e010
----
s^5 + 2026 s^4 + 1.194e006 s^3 + 7.593e007 s^2 + 4.813e008 s + 2.098e010

Figure 3c) shows the comparison of process output and Neural Network predicted output.

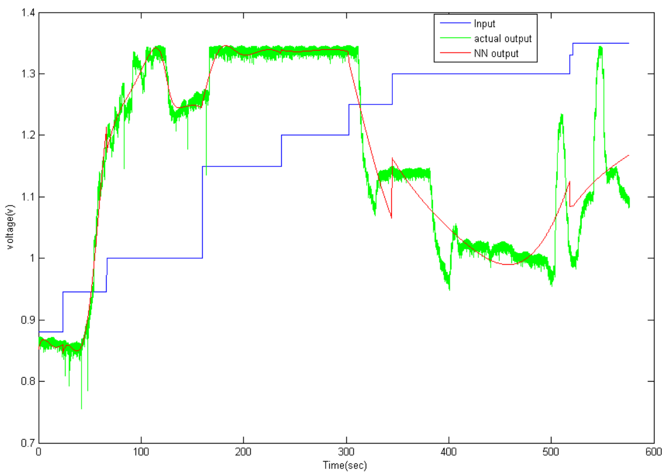

Fig 3c) Comparison of Process output and Neural Network output

Robust controller design

Identification of the process data was performed using neural network algoritham.The neural model network process consists of three operational steps: prediction, correction and control move determination. In this work water and tracer flow rate was input variable and conductivity was the output variable. A sampling time of 10 seconds was used for the simulation. For training the neural model the experimental step response data of the process was used A total of 2000 data were taken continuously and it was saved in file .By training the input output data the Neural Network(NN) model of the non linear process was obtained . The neural network used for training consists of 2 neurons in the input layer, 1 neuron in the output layer and 21 neurons in the hidden layer. The back propagation through time (BPTT) algorithm was used for training the recurrent network. Figure 4a) and 4b) shows the training and validation of the NN respectively.

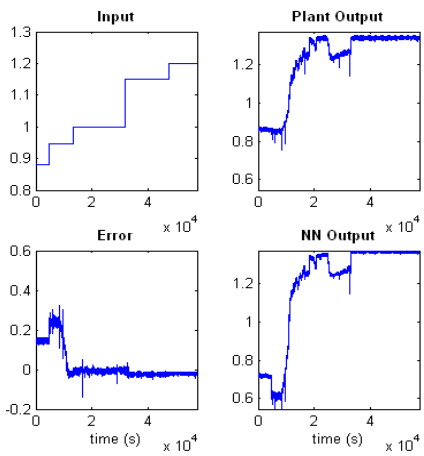

Fig 4a) Training of Neural Network

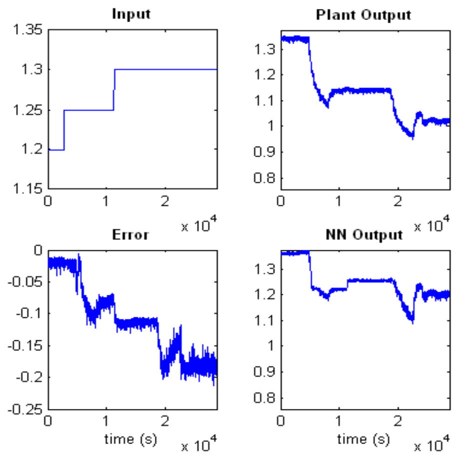

Fig 4b) Validation of Neural Network

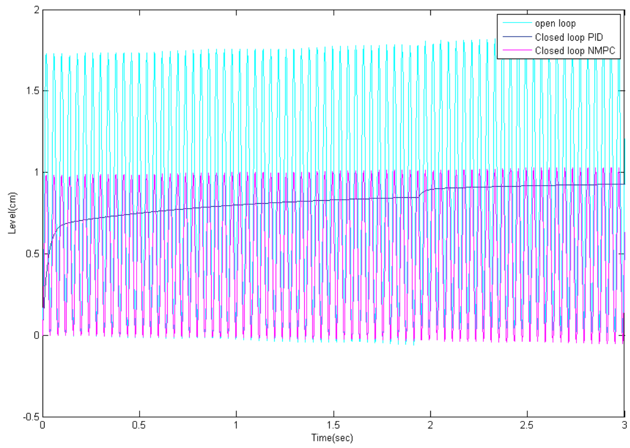

Fig. 5.Comparison of output response of the controllers

RESULT ANALYSIS

Neural model was designed for the prediction horizon 2 and control horizon 3 using trained input-output data. For the network training and validation, the Levenberg-Marquardt back propagation algorithm was used. The convergence criteria were selected as 10^{-3}, and this was achieved in18 epochs. The mean square error for validation are calculated and shown in Table 3. The optimum value is based on Table 3 choosing the mean square error (MSE) of 23340 for an alpha value of 0.05. The results are compared with PID controller.

Table 3. Selection of optimum alpha value (Tuning Parameter)

S.No	Alpha	MSE
1	0.01	25527
2	0.02	25898
3	0.05	23340
4	0.4	24040
5	0.5	24081
6	0.9	25605

On comparing the performance of controllers from the Fig 5 it is observed that PID controller never maintains the level (set point), while Neural Network controller maintains the set point within 1.5 second of settling time and almost zero overshoot with an ISE of 0.002.

ISSN: 0975-8585

CONCLUSION

Hybrid non linear system is identified using ARMAX and validated using Neural Network prediction. It has been observed that uncertainty in model can be eliminated by practicing ARMAX modeling technique and accuracy in the model is also achieved. For evaluating the closed loop response of the hybrid system Neural Network Predictive Controller (NNPC) was designed and its performance was evaluated against PID controller. The conventional PID controller does not achieve the desired level in case of Hybrid Systems while NNPC achieves the set point within one second. Hence NMPC is best suited for this hybrid process.

REFERENCES

[1] P.Madhavasarma, S.Sundaram, Model based tuning of controller for non linear hemispherical tank processes. Instrum. Sci&Technol., 2007, 35, 681-689.
[2] P.Madhavasarma, S. Sundaram,.Model Based Tuning For a Non Linear Spherical Tank With Time Delay Process, Instrum Sci & Technol, 2008 36, 420 – 431.
[3] P.Madhavasarma, S.Sundaram, Model based evaluation of controller using flow sensor for conductivity process, J. Sensors & Transducers, 2007, 79,1164-1172
[4] A.Rajenderan, A.Neelamegam,Measurement of conductivity of liquids using AT89C55WD microcontroller, Measurement , 2004,35, 59-63
[5] D.R Munoz, S.C Berga, An analog electronic interface to measure electrical conductivity in liquids, Measurement,2005,38,181-187
[6] T.Lu, C.Chen, Uncertainty evaluation of humidity sensors calibrated by saturated salt solutions, Measurement , 2007,40,591-599
[7] W.L Tse, W.L Chan, An automatic data acquisition system for on line training of artificial neural network- based air handling unit modeling, Measurement, 2005 37, 39-46.
[8] S.Karacen, Application of non –linear long range predictive control to a packed Distillation column, chemical engineering and processing, 2003. 42,43-953
[9] N.Sivakumaran, T.K Radhakrishnan, .Identification and control of Bio reactor using recurrent neural networks, Instrum.Sci&Technlogy2006, 34,463-474
[10] Silva, R.G .Wong, W.H.K Nonlinear Model predictive control of chemical Process, Braz.J.chemical Engineering, 1999, 16, 83-99.
[11] J.Henriques,P.Gill,. A. Douardo, H.D.Ramos ,. Applications of a recurrent neural network in on –line modeling of real time systems, Informatics engineering Department UC p'oloII 3030 Coimbra, Portuga, l, 2001.
[12] F.W Margrave, Rigas, K Bradley, D.A Barrowcliffe, The use of neural networks in ultrasonic flaw detection, Measurement, 1999,25, 143-154...
[13] P .Madhavasarma, S.Sundaram, Leak Detection and Model Analysis for Nonlinear Spherical Tank Process Using Conductivity Sensor. J. Sensors & Transducers, 2008, 89, pp. 71-76 [08]
[14] M.Sridevi, P.Madhavasarma, P.Prakasam, Model identification of nonlinear System Soft Computing Techniques, TIMA proceedings of the international Conferences, 2013, 180- 183.ISSN: 0975-
[15] M.Sridevi, P.Madhavasarma, P.Prakasam, Model identification of nonlinear Systems Using soft computing Techniques, IEEE explore, 2014, 1174-1178.
[16] M.Sridevi, P.Madhavasarma, P.Prakasam, Model identification and control of Spherical tank process using soft computing method. J. Sensors & Transducers, 2012,145, 10, pp,41-49.
[17] M.Sridevi, P.Madhavasarma, Model Identification and structural vibration control using Hinfinity controller J.Smart Sensing and intelligent system ,2010.