Cognitive Neuroscience Based Controller for Higher Order System in Petroleum Industries

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Abstract

A neural network is an important data modelling tool that's suitable to capture and represent complex input connections. The provocation for the development of neural network technology stemmed from the desire to develop an artificial system that could perform" intelligent" tasks analogous to those performed by the mortal brain. This research discussed about the development of cognitive neuroscience based controller for higher order non-linear system in Petroleum Industries. Interacting spherical two tanks are considered to be benchmark higher order system in this paper. Multilayer perceptron (MLP) is used as the best choice of input – output mapping in finding out architecture of neural network. Training data is obtained from open loop response of the system. Training is accomplished by a gradient descent algorithm with momentum factor included (LEARNGDM). Back propagation algorithm is implemented to find out the best fit results for the given higher order system. Performance criteria for error indices and quality indices are measured and tabulated using the neuro controller. Best fit values are identified to obtain the closed loop response of the system with zero error. The system is maintained at certain level of liquid by the fit values of controller which is the ultimo of the research.

Key Words: *Neural Network, Interacting Spherical Two Tank, MLP, Back Propagation Algorithm*

Introduction

Neural networks act the mortal brain in the following two ways: A neural network acquires knowledge through literacy. A neural network's knowledge is stored within inter-neuron connection strengths known as synaptic weights. A neural network is either a natural neural network, made up of natural neurons or an artificial neural network used for artificial intelligence problems. The connections of natural neuron are modeled in artificial neural networks as weights between bumps. An excitatory connection is represented by positive weights. An inhibitory connection means negative values. All inputs are modified by weights and added together. Amplitude of the output is controlled by activation function.

This paper discusses about implementation of cognitive neuroscience based controller for interacting spherical two tank system used in Petroleum industries. Liquid level control in spherical tank is tedious and time consuming. Shape of spherical tank is diverging from bottom to mid and converging from mid to top. Hence, system is nonlinear and controlling liquid level is highly difficult. To ease the liquid level control in spherical tank neural network is used. It uses the knowledge of brain to train the data and obtain the final fit set values to control liquid level. Most of the food processing industries, chemical industries and petroleum industries use interacting tanks for processing of chemicals and enzymes. One tank is used for storage and other is used for processing.

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In Petroleum industrial process there may be slurry and highly viscous liquids, the ordinary rectangular or cylindrical tanks does not allow flow effectively. Corners and edges of tank of regular tanks get accumulated with slurry materials which prevent smooth flow of liquids in corners. This

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shows the importance of spherical tanks in Petroleum industries.

Literature Analysis

Guoping et al. (1999) proposed a variable neural network for deriving the adaptive algorithm for a non-linear process and tuned the radial basis function center and width for adaptive control. Daniel Wu et al. (2003) presented water level control by Fuzzy logic and Neural networks and adaptive control was not discussed. Cartes Wu et al. (2005) presented experimental evaluation of adaptive three tank level control by Model Reference Adaptive Control (MRAS) technique with RLS estimator. Only cylindrical tank was considered for study. The use of neural networks for control, have increased significantly in recent years. The learning ability of neural networks helps in the development of flexible controller design, especially when plant dynamics are complex and highly non-linear. Nguyen and Widrow (1989) showed the possibility of using neural networks in controlling a plant with high non-linearity. Chen (1990) proposed a self-tuning adaptive controller with neural network and constructed a neural network controller combined with linear optimal controller to compensate for the uncertainties in model parameters. The use of neural networks in control has been focused mostly on the Model Reference Adaptive Control (MRAS) problem (Yamada et al., 1992).

Mathematical Model

There are two approaches namely experimental approach and theoretical approach. Experimental approach is time and effort consuming procedure. It is quite costly compared to other approach. Theoretical approach usually given in terms of a set of mathematical equations (differential, algebraic) whose solution yields dynamic or static behavior of chemical process. Theoretical approach is used in investigation of Interacting Spherical Two Tank System.

Inorder to investigate Theoretical approach Mathematical Modelling of liquid level system is derived using conservation principle on Total Mass Balance (George Stephanopoulos, 1990). According to which;

$$\frac{\text{accumulation of total mass}}{\text{time}} = \frac{\text{input of total mass}}{\text{time}} - \frac{\text{output of total mass}}{\text{time}}$$

Or

$$\frac{d(\rho A h)}{dt} = \rho Fin - \rho Fout \qquad (1)$$

where

ρ = density

Fin = Volumetric flow rate for inlet stream

Fout= Volumetric flow rate for outlet stream

A = Area of the tank

dh/dt= Change in height of liquid level

From above equation single spherical tank can be expressed as

$$Fin - Fout = 4/3\{ \left(A\frac{dh}{dt}\right) + \left(h\frac{dA}{dt}\right) \} \qquad (2)$$

From the general equation for a spherical tank system which is represented above, mathematical model for interacting spherical two tank system is derived, which is as follows;

For tank 1

$$Fin1 - Fout1 = 4/3\{ \left(A\frac{dh1}{dt}\right) + \left(h1\frac{dA}{dt}\right) \} \qquad (3)$$

For tank 2

$$Fin2 - Fout2 = 4/3\{ \left(A\frac{dh2}{dt}\right) + \left(h2\frac{dA}{dt}\right) \} \qquad (4)$$

For tank 1

$$Fout1 = \beta_{12}\sqrt{h1} - h2 \qquad (5)$$

For tank 2

$$Fout2 = \beta_2\sqrt{h2} \qquad (6)$$

Substitute (4) and (5) in (3)

$$Fin1 - \beta_{12}\sqrt{h1} - h2 = 4/3\{ \left(A\frac{dh1}{dt}\right) + \left(h1\frac{dA}{dt}\right) \}$$

$$\frac{dh1}{dt} = 3/4\{\frac{Fin - \beta_{12}(\sqrt{h1} - h2) - \frac{4}{3}h1\frac{dA}{dt}}{A}\}$$

(7)

Now substitute same values in equation (4)

$$Fin2 - \beta_2\sqrt{h2} = 4/3\{ \left(A\frac{dh2}{dt}\right) + \left(h2\frac{dA}{dt}\right) \}$$

Here,

$$Fin2 = \beta_{12}\sqrt{h1} - h2 = Fout1$$

$$\frac{dh2}{dt} = 3/4\{\frac{\beta_{12}(\sqrt{h1} - h2) - \beta_2\sqrt{h2} - \frac{4}{3}h2\frac{dA}{dt}}{A}\}$$

(8)

Here area (the change in area) for spherical tank

$$A = \pi r^2 - \pi(r - h)^2$$

(9)

Now substituting (7) in (5) and (6)

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$$\frac{dh1}{dt} = 3/4\{\frac{Fin-sign(h1-h2)\beta_{12}(\sqrt{h1}-h2)-\frac{4}{3}h1\frac{dA}{dt}}{\pi r^2-\pi(r-h1)^2}\}$$

$$\frac{dh2}{dt} = 3/4\{\frac{sign(h1-h2)\ \beta_{12}(\sqrt{h1}-h2)-\beta_2\sqrt{h2}-\frac{4}{3}h2\frac{dA}{dt}}{\pi r^2-\pi(r-h2)^2}\}$$

The above two equations represents the differential equations of two spherical tanks. With the help of those equations MATLAB Simulink model is developed with the modeling parameters (Nithya et al., 2008) as tabulated in table 1 for interacting spherical two tank system represented in figure 1.

Table 1. Modeling Parameters

PARAMETERS	DESCRIPTION	VALUE
D	Diameter of spherical tank	30 cm
R	Radius of Spherical tank in centre	15 cm
H	Height of spherical tank	30 cm
Fin1	Maximum Inflow to tank1	110.5 cm^3/s
β12	Valve co-efficient of MV_{12}	78.28 cm^2/s
β2	Valve co-efficient of MV_1	19.69 cm^2/s

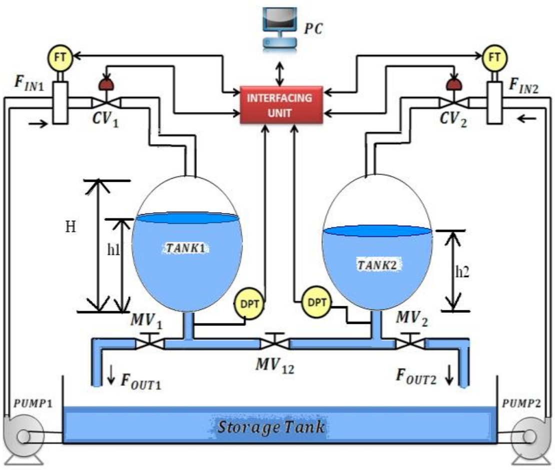

Figure 1. Liquid level control of interacting spherical two tank system (ISTTS)

Tuning of Neural Network Controller

Figure 2 represents the block diagram of neuro controlled ISTTS process. Where three inputs such as set point, error and derivative error are considered. Neuro controller is designed from the error values calculated by GSPI controller (Dinesh et al. 2012).

The major steps involved in the design of a level controller using neural networks are as follows:

Identification of the architecture of the Neural Network: Whenever the input-target patterns are known, the Multi Layer Perceptron (MLP) is the best choice as it does the exact input-output mapping. Hence, the type of neural network best suited for level control is the MLP having three layers i.e. Input layer, hidden layer, and output layer. The number of nodes in the hidden layer is determined to be five, by trial and error after considering the training error after 6000 epochs. The activation function for the hidden layer is chosen to be the binary sigmoid whose output varies from 0 to 1 and for the output layer, it is linear. The inputs applied to the neural network are the error (e) and set point (SP).

Obtaining the training data: The training data are generated from the open loop response of the system for various step changes in level corresponding to various set points and error. Care is taken to ensure that the training data set is a representative of the type of input and output patterns encountered so that the controller could be effectively designed. A number of patterns of error (e), derivative error (de), set point (SP) and controlled variable (change in liquid level) are generated for training the neural network.

Training: The most important step involved in the design of the neural network controller is the training of the Neural Network. The architecture used for the training of the neurocontroller is shown in the Figure . The training is accomplished by the use of Neural Network Toolbox (NNTOOL) available in MATLAB. The training patterns of error, derivative error and set point are concatenated into an n×3 matrix where n is the number of training patterns. The output (controlled variable) is presented to NNTOOL as a column vector. There are many algorithms present in NNTOOL for training. Among these, a gradient descent algorithm with momentum factor included (LEARNGDM), is used for training. TRAINLM is often the fastest back propagation algorithm in toolbox, and is highly recommended as first choice supervised algorithm. The stopping criterion specified is 0.25, i.e. the training is stopped when the Root mean square error (RMSE) between the network outputs and the targets is lesser than or equal to 0.25. The learning rate is fixed at 0.5. The number of

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training epochs is fixed uniformly at 10000. The number of hidden nodes is 2. Some of the patterns are also used to test the network in order to prevent over fitting of the training data. Finally the values of the weights obtained after training is used for the feed forward implementation. Neuro controller model developed in MATLAB Simulink is simulated and tracking cases are plotted for three different regions 5cm, 15cm and 30cm. The closed loop response of the Neuro controlled level process system is studied by introducing step variations in level and the responses plotted with the Neuro controller are compared with Integral Absolute Error (IAE), Integral Square Error (ISE), rise time, settling time and peak overshoot as the performance criteria.

Performance Analysis and Results

A non linear system, interacting spherical two tank system whose time constant and gain are functions of process variable is considered for testing the performance of GSPI controller and Neuro controller. The reaction curve is obtained for fixed magnitude of inflow rate at various operating points. The second order model is computed from relating the general transfer function with parameters obtained from Simulink model. In the following sections, the performance of GSPI controller and Neuro controller are summarized.

Table 2 Performance measures of Neuro controller at the operating point of 5 cm

	PARAMETERS	NEURO CONTROLLER
ERROR INDICES	Error	110.78
	ISE	900.76
	IAE	3656.53
QUALITY INDICES	Tr	316
	Ts	2008
	%Mp	0.06

Table 3 Performance measures of GSPI and Neuro controller at the operating point of 15 cm

	PARAMETERS	NEURO CONTROLLER
	Error	936.25
ERROR INDICES	ISE	11466.41
	IAE	76393.31
	Tr	440
QUALITY INDICES	Ts	1958
	%Mp	0.33

Table 4 Performance measures of Neuro controller at the operating point of 30 cm

	PARAMETERS	NEURO CONTROLLER
	Error	460.54
ERROR INDICES	ISE	1406.14
	IAE	3906.85
	Tr	666
QUALITY INDICES	Ts	1560
	%Mp	0.06

From the numerical values, it is proved that Neuro based controller continually adapt the changes in the operating time to maintain the consisted performance reasonably. Quality indices such as rise time, settling time and peak overshoot is minimum using Neuro based controller.

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Conflict of Interest

None.

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