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Radial Basis Function Neural Network Control for Coupled Water Tank

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ABSTRACT

The coupled water tank is a system consisting of a pump with two tiered tanks and a water basin, where the fundamental problem in this system is in controlling the level in the tank and controlling the flow between tanks, so that in order for this system to work as we want, it requires an appropriate control method. Therefore, in this paper will use a control method of radial basis function neural network (RBF NN) to control of level 2 in the tank 2 with 10 centimeters setpoint and 8 centimeters given at time 225 seconds. The results show that use Radial Basis Function Neural Network (RBF NN) can follow setpoint given with 0 cm for steady state error, 0% for overshoot, 48 seconds for rising time, 52 second for settling time and can follow setpoint changes in 51 seconds.

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1. INTRODUCTION

The coupled water tank is a system consisting of a pump with two tiered tanks and a water tank, where the fundamental problem in this system is in controlling the level in the tank and controlling the flow between tanks, where level control is one of the most important control system variables in process industry. The process industry requires liquid to be pumped and stored in a tank and after that it is transferred to another tank and also the level of liquid in the tank must be controlled and the flow between tanks must be controlled. All industries, such as the chemical industry, petrochemical plants, and food industry also depend on tank level control systems. So it is important for control systems engineers to understand how the tank control system works and how these level control problems are resolved. Most of the control performance in the actual design is usually determined by by steady state error, overshoot, rising time, settling time [1].

Various research attempts to control the liquid level for pair tank systems have been undertaken. Among others are the design of PI controller using characteristics ratio assignment method for linear modelled coupled tank SISO process [2], the mathematical modelling and designing of sliding mode control for a liquid level control system when tanks are coupled by using baffles [3], a direct model reference adaptive control for coupled tank system [4], comparison between PI and MRAC on coupled tank system [5] and comparative study of mamdani-type and sugeno-type fuzzy inference systems for coupled water tank [6].

Neural Network (NN) is a computerized systems as information processors that have similar characteristics to biological neural networks when capturing information from the 'outside world'. NN also has the ability to identify and study very complex relationships only from input-output data and without the need for a complete description of the system. NN can be made into a variety of architectural variations and the form of combined node design and calculations selected for each node [7]. Radial Basis Function (RBF) is a network architecture that has several advantages over other types of NN including better predictive ability, simpler network structure, and faster learning algorithms [8]. Therefore, RBF networks have been widely applied in various fields of science such as pattern recognition [9], optimization [10], and control [11]. Therefore for this research will used radial basis function neural network for controlling level of coupled water tank.

2. MATERIAL AND METHOD

Research method in this paper presents the mathematical modelling of the coupled water tank and design of radial basis function neural network control for the coupled water tank.

a. Mathematical Modelling Of Coupled Water Tank

The coupled water tank as shown in Figure 1 is a coupled tank for the experimental scale. Consists of two tanks and pumps that function to pump water vertically [6]:

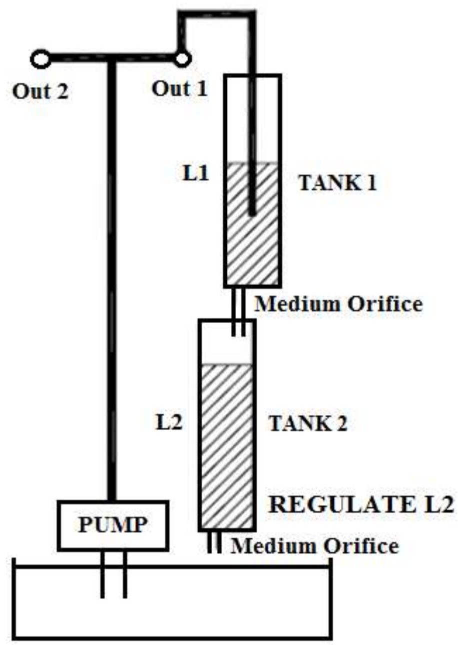

Figure 1. The Coupled Water Tank [6]

The flow into the tank 1 is:

$$F_{1in} = K_m V_p \ cm^3/sec \tag{1}$$

where K_m is the constant pump and V_p is the voltage applied to the pump. The outflow velocity is given by the Bernauli equation for small orifices:

$$V_o = \sqrt{2\ g\ L_1}\ cm/sec \tag{2}$$

where g is the gravitational acceleration in cm/ sec^2 and L_1 is the high of the water level in the tank 1 in cm.

The outflow rate is:

$$F_{1in-}F_{1out} = K_m V_p - \alpha_1 \sqrt{2\ g\ L_1}\ cm^3/sec \tag{3}$$

Then the change in level of tank 1 is then given, where A_1 is the diameter of the tank 1:

$$\dot{L}_1 = -\frac{\alpha_1}{A_1}\sqrt{\frac{g}{2\ L_{10}}} L_1 + \frac{K_m}{A_1} V_p \tag{4}$$

The equation of tank 2 for inflows and outflows is:

$$F_{1in} = \alpha_1 \sqrt{2\ g\ L_1}\ cm^3/sec \tag{5}$$

$$F_{2ou} = \alpha_2 \sqrt{2\ g\ L_2}\ cm^3/sec \tag{6}$$

Then the change in level of tank 2 is then given by:

$$\dot{L}_2 = -\frac{\alpha_2}{A_2}\sqrt{\frac{g}{2\,L_{20}}}L_2 + \frac{\alpha_1}{A_2}\sqrt{\frac{g}{2\,L_{10}}}L_1 \qquad (7)$$

If $x_1 = L_1$ and $x_2 = L_2$ then equation state of system can write as:

$$\dot{x}_1 = -\frac{\alpha_1}{A_1}\sqrt{\frac{g}{2\,L_{10}}}x_1 + \frac{K_m}{A_1}V_p \qquad (8)$$

$$\dot{x}_2 = -\frac{\alpha_2}{A_2}\sqrt{\frac{g}{2\,L_{20}}}x_2 + \frac{\alpha_1}{A_2}\sqrt{\frac{g}{2\,L_{10}}}x_1 \qquad (9)$$

and the parameter of equation (8) and (9), can we see in table 1:

Table 1. Parameter of Coupled Water Tank [6]

Parameter	**Symbol**	**Value**	**Units**
Diameter of Tank 1	A_1	15,5179	cm^2
Diameter of Tank 2	A_2	15,5179	cm^2
Gravity	g	980	
Pump Constant	Km	4,6	(cm^3/s)/Volt
Level Water of Tank 1	L_2	Measured	cm
Level Water of Tank 2	L_1	Measured	cm
Cross Section Area of Tank 1	α_1	0,17813919765	cm
Cross Section Area of Tank 2	α_2	0,17813919765	cm
Pump Voltage (max)	Vp	22	Volt
Tank 1 Work Point	L_{10}	15	cm
Tank 2 Work Point	L_{20}	15	cm

b. Design of Radial Basis Function Neural Network Control for Coupled Water Tank

In this paper we can explain 2 main parts of this design system to control level of the Coupled Water Tank, where the setpoint is 10 centimeters and the setpoint will change to 8 centimeters in 225 seconds:

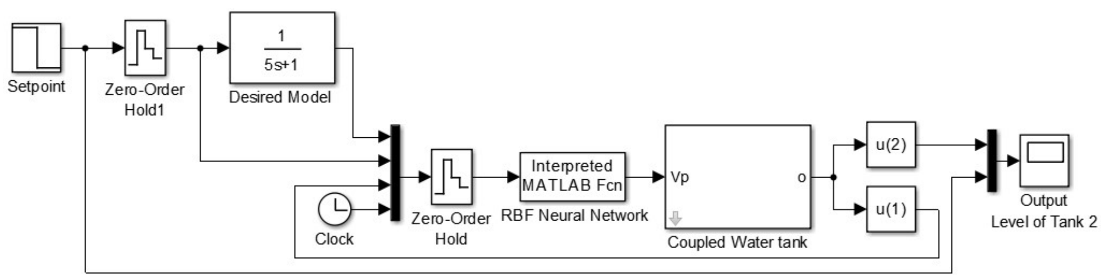

Figure 2. Design of The Coupled Water Tank and RBF Neural Network in Matlab

1) The main of Couple Water Tank can we see in figure 3 and figure 4:

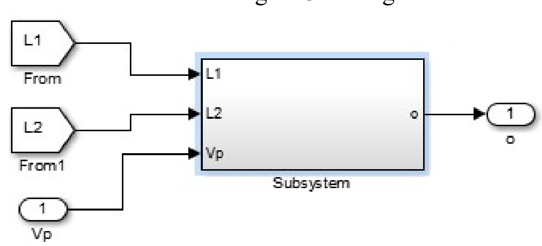

Figure 3. Design of Subsystem of The Coupled Water Tank in Matlab

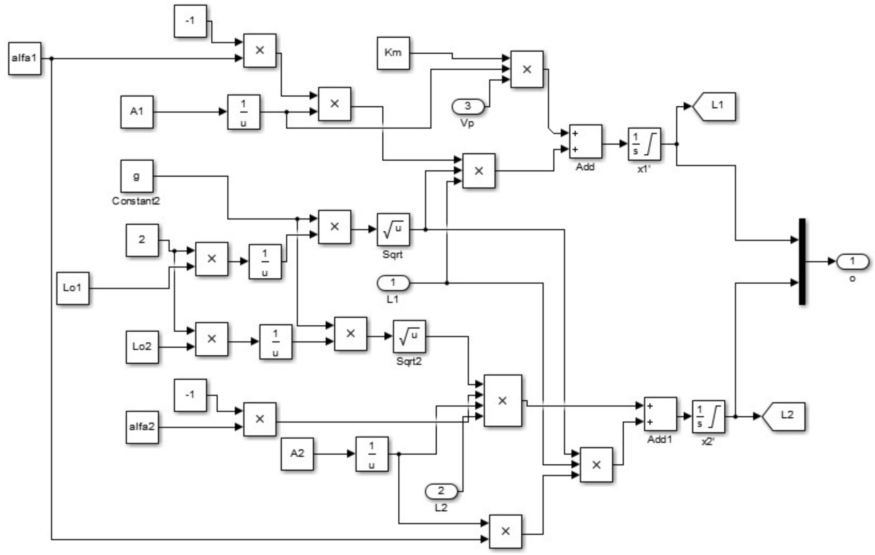

Figure 4. Design Inner of Subsystem of The Coupled Water Tank in Matlab

2) Design of Radial Basis Function Neural Network

The radial basis function neural network in this paper is designed with 1 unit input layer, 1 unit hidden layer, 1 output and 1 bias input to hidden layer using mfile in Matlab, with the following steps:

Step 1 : Determine number of inputs, in this paper will be used 3 inputs (*XX*): *X1*, *X2*, *X3*, because this plant is order 2 with na=2 , b=1. (na+nb = number of inputs)

Step 2 : Determine number of neurons in unit hidden layer, in this paper will be used 3 neurons : Zi= *Z1*, *Z2*, *Z3* $(\text{Number of Inputs} \leq \text{Number of Neurons In Hidden Layer} \leq 2.\text{Number of Inputs})$

Step 3 : Initialization value of inputs, weights, learning rate constants and maximum of epoch, in this paper will be used, i= 1,2,3 for inputs(XXi): j= 1,2,3 for neurons in hidden layer (Zi):

a. Inputs (*XXi*)= [*X1 X2 X3*] = [*ek* 0 0], where error(*ek*)= setpoint (*y_ref*) – output plant (*y_out*). Bias Input (*XB*)= 0.2. Where setpoint is 10 centimeteres and 8 centimeters.
b. Weights of input layer to the hidden layer (*WHij*) = [*WH11 WH21 WH31 WH21 WH22 WH23 WH31 WH32 WH33*], weights of input bias to the hidden layer (*WBj*) = [*WB1 WB2 WB3*], weights of hidden layer to the output layer (*WOj*) = [*WO1 WO2 WO3*] with random values between 0 to 1
c. Learning rates: for L_{WH} = 0.00005 , L_{WB} = 0.00005, L_{WO} = 0.0005, L_{OK} = 1
d. Epoch: 100
e. Target output (*OY*) = 0, as long as this target is not reached, go to step 4 to 10

Fordward Calculation

Step 4 : Calculate all of output neurons in unit hidden layer, i= 1,2,3: j= 1,2,3:

a. Add up all of the signals output with their weight:

$$ZHj = XB.WBj + \textstyle\sum_{ij=1}^{3} XXi.WHi\,j \tag{10}$$

b. Calculate the output signal using the gaussian function:
The most commonly used radial basis function is Gaussian function [12], in unit hidden layer:

$$ZYj = e^{-(ZHj)^2} \tag{11}$$

Step 5 : Calculate output neuron in output layer:

a. Add up the signal output with their weight:

$$OK = \sum_{j=1}^{3} ZYj.WOj \tag{12}$$

b. Calculate the output signal using the linear function:

$$OY = 1.OK \tag{13}$$

c. Calculate the output error:

er= (output of desired model *(y_model*) – output plant (*y_out*))/ (5/3) (14)

Backward Calculation

Step 6 : Revision weight from hidden layer to output layer, i= 1,2,3:

$$WOj\ (new) = WOj\ (old) + L_{WO}\ .er\ .L_{z0}\ .\ ZYj \tag{15}$$

Step 7 : Calculate propagation error (*ep*), j= 1,2,3:
If *OK* = 0

$$epj = er/jeh \tag{16}$$

where jeh= number of neuron in hidden layer

If not, then:

$$epj = \left(\frac{WOj\ (new)\ .ZYj}{OK}\right) er \tag{17}$$

Step 8 : Revision the weight from the input layer to the hidden layer:

$$WHij\ (new) = WOij\ (old) + L_{WH}\ .epi\ .(-2.ZHj.YHj)\ .\ XXi \tag{18}$$

Step 9 : Revision the weight from the bias layer to the hidden layer:

$$WBj\ (new) = WBj\ (old) + L_{WB}\ .epj\ .(-2.ZHj.YHj)\ .\ XB \tag{19}$$

Step 10 : Revision of input:
Where i= 1 : na-1

$$XX\ (na - i + 1) = XX\ (na - 1) \tag{20}$$

and

$$XX\ (na + 1) = OY \tag{21}$$

3. RESULT AND DANALYSIS

In the course of testing the performance of the system we can define by steady state error, overshoots, rising time, settling time and the ability to follow setpoint changes.

Design of Radial Basis Function Neural Network for Controlling Level of Coupled Water Tank

For the response output system in figure 5, we can analisys with *characteristic* time response of second-*Order System beacause the mathematical model of* Coupled Water Tank is order 2, so that 0 cm for steady state error, 0% for overshoot, 48 seconds for rising time, 52 second for settling time and can follow setpoint changes in 51 seconds.

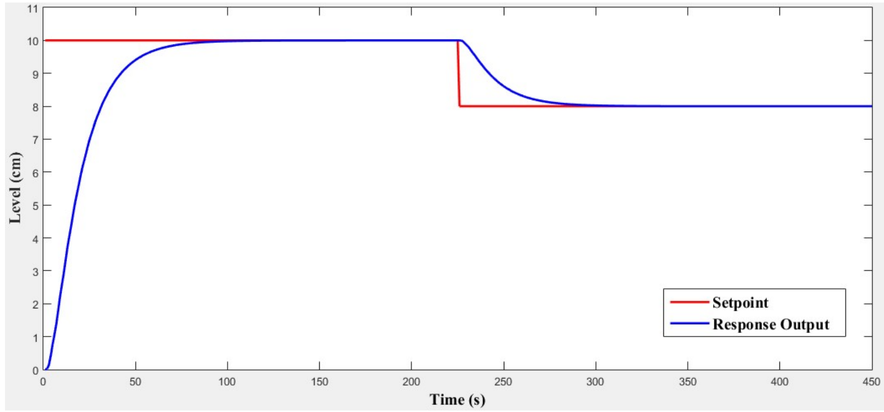

Figure 5. Response Output System for Level 2 in Tank 2 with RBF Neural network

4. CONCLUSIONS

It may be concluded from this paper, the outcome achieved from radial basis function neural network for control level 2 in tank 2 can follow setpoint given with 0 cm for steady state error, 0% for overshoot, 48 seconds for rising time, 52 second for settling time and can follow setpoint changes in 51 seconds.

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