Neural Based pH System in Effluent Treatment Process

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Abstract

This investigation considers the application of Artificial Neural Network (ANN) techniques to estimate the pH value for effluent treatment process. ANN has the ability to identify the non-linear dynamical systems from the input-output data. An important requirement of the application is robustness of the system against erroneous sensor measurements. The simulation model of the pH system for common effluent treatment plant (CETP) is developed using MATLAB 7.5, GUI tool box. A novel off-line and on-line training scheme for the neural network is developed by error back propagation training algorithm to model the pH system for CETP, accurately. For this purpose, a simple feed forward, back propagation neural network, with only one hidden layer, and sigmoidal activation functions is used. The training of such network is based on Input-Output data which is collected from Perundurai common effluent treatment plant (PCETP). Experimentation and simulation results on this neuro identifier of pH system for common effluent treatment plant are shown.

Keywords: pH system, CETP, PCETP, ANN, Alkali wastes

1. Introduction

The textile industry occupies an important place in the economy of India and other developing countries. The low efficiency of chemical operations and spillage of chemical, cause a significant pollution hazard and make the treatment of discharged wastewater a complex problem. Group of textile industries are joined together to form common effluent treatment plant to economize the process. The industrial pollution control regime in India is based on the standards and regulation approach. Source specific concentration based standard have been laid down for polluting units and penalties for non compliance, disconnection of electricity/water supply and closure of the units. The standards are same for large and medium units as well as for small units. While most of the large and medium polluting units have been able to erect and operate effluent treatment plants, this option does not appear to be viable for many small units because of their small size, and technical, financial and managerial constraints. Common effluent treatment plants are being suggested as a cost-effective option for compliance with the standards for small polluting units in industrial clusters (Shankar, U., 2003).

Most process plants generate a wastewater effluent that must be neutralized prior to discharge or reuse. Consequently, pH control is needed in just about every process plant, and yet a large percentage of pH loops perform poorly. Results are inferior product quality, environmental pollution, and material waste. However, implementing a pH system is like putting a puzzle together. It will only work when all the components are in place. While various pH probes and actuators for pH control are available, commercial adaptive pH controllers are still in demand. The challenge is to provide a controller that is able to deal with large nonlinear gain changes in the pH loop. It will be useful for not only wastewater neutralization, but also chemical concentration control, since concentration is a key quality variable. It is impossible for a fixed controller like PID to effectively control this process (OMEGA Engineering, 2006).

In 1999, Hunt, K., J. et al said that the internal model control is used to directly incorporate networks modeling the plant and its inverse within the control strategy. Rejecting disturbances caused by coupling effects have shown a significant improvement over that achieved by fixed parameter PID control designed using a conventional method. In 2003, Yu, D., L. et al said that the Implementation of a neural network model based predictive control scheme to a laboratory sealed multivariable chemical reactor, three variables are controlled in the reactor- temperature, PH and dissolved oxygen. The optical control performance in tracking set-points and rejecting disturbances caused by coupling effects have significant improvement over that achieved by fixed parameter PID control designed using a conventional method.

In 1998, Lin-En Kuo et al said that the Neural Network based Model Predictive Controller (NNMPC) is applied to the control of coagulant dosing in a drinking water treatment plant. The hybrid system developed includes raw data validation and reconstruction based on a Kohonen self-organizing feature map, and prediction of coagulant dosage using multilayer perceptrons. The performance of the network is obviously dependent on the quality and completeness of data provided for system training. Continuous updating of training data during operational use will improve the performance of the system.

In 1996, Junhong Nie et al said that the modeling and identification of pH-processes via fuzzy neural approaches is done. Extensive simulations including on-line modeling have shown that these nonlinear pH-processes can be modeled reasonably well by the present schemes which are simple but efficient. Compared with the backpropagation neural network (BNN) modeling approach, this method is particularly suitable for real-time applications. The identification of a fuzzy model via a CPN neural network can be completed very quickly by presenting the training examples once only. This feature of fast response to new situations has been demonstrated in modeling.

In 2005, Bernt M. Akesson et al said that the process is modeled by a set of linear models constructed by velocity-based linearization in order to reduce the computational requirements associated with the solution of the continuous-time nonlinear system equations. The resulting quasi-linear models also simplify the estimation of the system state from the measured outputs. The accuracy of the neural network controller approximation which is required to ensure stability and performance is shown to be related to the fragility of the model predictive controller. The proposed approach is applied to a simulated nonlinear pH neutralization process. The study shows that it is possible to achieve good control performance with this approach, reducing the required on-line computations significantly.

Lamanna, R. et al said that the tuning procedure of a PID is very tedious and time consuming, and the controller produces responses of a quality comparable to that of the neural controller within very narrow operating limits. The weights are adjusted, depending on the task at hand, to improve performance. The ability to learn is one of the main advantages that make the neural network so attractive. Neural networks can also provide significant fault tolerance. Since damage to a few links need not significantly impair the overall performance.

Based on the literature survey, it is seen that a good amount of work has been done using ANN to control the pH value for drinking water treatment and waste water treatment process. Literature has suggested few mathematical models; few case studies on neural network approach have been attempted, how ever without a real time or simulation study. There is no research work was carried out to control the pH value in effluent treatment process. Hence the problem of pH control for effluent treatment process using neural network is pursued.

2. Effluent Treatment Plant

This section describes the wash water treatment process of Perundurai Common Effluent Treatment Plant (PCETP). The wash water treatment plant was opened in July 2002 and reduces COD and BOD by 40-60%. They regularly measure pH, TSS, TS BOD, COD and TDS. The receiving tank and the bar screens are designed for the peak flow, but the units down stream of the equalization tank are designed for an average flow and an average quality.

The wash water plant is designed to treat 3600 m3 per day of wash water effluent received from 14 member units and the plant consists of the following

2.1 Screening

The raw effluent from the plant is first passed through a bar screen of 20mm and 15 mm size removes the floating matters in the receiving sump. In the receiving sump, the variation of pH value at various intervals of time is shown in Figure 1.

2.2 Equalization

The screened effluent is collected in the equalization tank. The function of equalization tank is to homogenize the flow and characteristic of the effluent. The equalization tank is designed for a hydraulic retention time of 24 hrs. The equalization tank is provided with floating surface aerators to ensure proper mixing and to avoid settling of suspended solids. The variation of pH value at various intervals of time is shown in Figure 2.

2.3 Colour Removal

The equalized effluent is pumped to flash mixer, where lime, ferrous sulphate and poly electrolyte is dozed for precipitation of colour and coagulation of the solids formed. The dozing arrangement has been provided to adjust the dosage based on the incoming effluent's pH.

2.4 Clarification

The coagulated suspended solids and precipitate formed due to colour removal will then the let to clarilflocculator for settling and removal of suspended solids. Settled sludge will be moved continuously along the floor towards center of unit by means of slowly rotating scrapper which covers the entire floor area. The accumulated sludge will be transferred to sludge pocket of the clarifier for sludge drawn off. The excess sludge will be removed from time to time to avoid the build up of the same. The variation of pH value at various intervals of time is shown in Figure 3.

2.5 Filtration

The clarified effluent from clarilflocculator is taken to Auto Valve less Gravity Filter (AVGF) for filtration. The filter operated automatically on the loss of head principle. This is generally accepted as being the most accurate control besides the constant analysis of the filtered water turbidity which is seldom practical on a continuous basis. The head loss at which AVGF initiates backwashing is determined by the height of the inverted U-turn at the top of the backwash pipe. The level of water in this pipe is proportional to the head loss across the filtered bed. The AVGF filtered effluent is neutralized in the static mixer with HCl acid and pumped to the Activated Carbon Filter to remove odor in the effluent. Then, it is pumped to farm land for irrigation.

2.6 Sludge Treatment

The underflow from the clarilflocculator, are pumped to the sludge thickener. The thickened sludge with 6% consistency will then pumped to the centrifuge. Polymer is dosed to enhance the efficiency of thickening and dewatering. The filtrate from the centrifuge is taken back to the clarilflocculator while dewatered sludge is collected in bags and stacked in the roofed shed (Meenakshipriya, B. et al, 2008).

3. SIMULINK Block Diagram

The SIMULINK block diagram of pH identifier using MATLAB 7.5, GUI- Neural Network toolbox is shown in Figure 4. The following parameters are considered to develop the SIMULINK model of pH identifier.

net = newff([-1 1;-1 1],[2,1],{'purelin' 'tansig'},'trainscg');

net.layers{1}.initFcn='initwb';

net.inputweights{1,1}.initFcn='rands';

net.biases{1,1}.initFcn='rands';

net.biases{2,1}.initFcn='rands';

net.layers{2}.initFcn='initwb';

net.layerweights{2,1}.initFcn='rands';

net.biases{1}.initFcn='rands';

net=init(net);

net.trainparam.show=139;

net.trainparam.epochs=100;

net.trainparam.goal=0;

net=train(net,Inputs',Target');

A=sim(net,inputs');

gensim(net);

3.1 Generation of data

The values of pH before treatment, HCl dosing and pH after treatment are measured at various intervals of time. The sampled data of all these parameters are used as training and testing input pairs to model the pH identifier as shown in Table 1.

3.2 Neural Network Training

A feed forward neural architecture is selected and the training is done using TRAINLM Levenberg-Marquardt back propagation algorithm. The selected number of input variables is 2 which are pH before treatment, HCl dosing and output variable is 1 i.e., pH after treatment. The number of epochs are fixed at 100 and learning rate parameter is

selected as 0.001.The initial weights are set randomly (very close to zero) and training is carried out for the given number of epochs.

The neural network is trained with various values of hidden nodes, learning rate and number of epochs. Neural network with too many hidden nodes may over fit the network and cause unrealistic oscillation between the training samples. On the other hand network with small number of hidden nodes may fail to approximate/generalize the complex underlying relationship in the data with fine fidelity. When the number of training epochs is increased during the training process, the training error approaches to zero, but the problem of excessive training occurs and the network converges to memorization of the training data. The training error indicates the average deviation from the actual values used for training. The activation function used between the input and hidden layer is sigmoid and the one between hidden and output layer is linear.

4. Simulation Results

The simulation results are shown in Table 1 and the response of measured pH value Vs neural predicted pH value is shown in Figure 5. The value of measured pH is shown as solid lines and the neural predicted pH value is shown as dotted lines. Figure 6 shows the error analysis of pH identifier for training, validation and testing. From the error analysis, the accuracy of neural identifier is 0.004% in terms of error.

5. Conclusion

In this paper, a new method of pH identifier using neural network is proposed to increase the performance of pH control system. Neural network with linear filter architecture and back propagation through time learning algorithm is used to design the pH control system. The neural network learning process has been performed in both on-line and off-line. Model by means of data collection over a wide range of pH improves the accuracy, reduces the complexity, increases the immunity to the noise and fewer controllers are needed. In many applications, the network has to emulate nonlinear and time varying functions where the functions might change depending on the plant operating condition and parameter variation. In such cases the network requires continuous training on-line so that it correctly emulates the model. From the presented results it can be noted that the neural systems offer an attractive solution for pH control system. The neural approach show good simulated response and suggest that further research in this area would be worthwhile. Future work could include:

- An investigation of the implications of a practical implementation.
- An evaluation of learning algorithms which offer superior performance to the error back propagation algorithm.

Nomenclature

CETP - Common Effluent Treatment Plant

PCETP - Perundurai Common Effluent Treatment Plant

ANN - Artificial Neural Network

BNN - Backpropagation Neural Network

PID - Proportional Integral Derivative

AVGF - Automatic Valves Gravity Filter

ACF - Automatic Carbon Filter

TDS - Total Dissolved Solids

TSS - Total Suspended Solids

COD - Chemical Oxygen Demand

BOD - Biological Oxygen Demand

HCl - Hydro Chloride

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Table 1. Comparison of Measured pH value and Neural predicted pH value

DATE	TIME	pH before treatment	HCl dosing (ml)	pH after treatment	Neural Predicted pH value	Error value
27.02.08	12.15	8.29	0.7	7.8	7.7524	0.0476
	1.15	8.32	0.6	7.5	7.5185	-0.0185
	2.15	8.42	0.6	7.59	7.5689	0.0211
	3.15	8.51	0.6	7.61	7.5984	0.0116
	4.15	8.56	0.6	7.54	7.5938	-0.0538
	5.15	8.62	0.6	7.62	7.5828	0.0372
29.02.08	2.15	7.89	0.6	7.64	7.6403	-0.0003
	3.15	7.71	0.7	7.79	7.7859	0.0041
	4.15	7.73	0.7	7.6	7.6055	-0.0055
15.03.08	10.15	8.71	0.8	7.46	7.5124	-0.0524
	11.15	8.61	0.5	7.71	7.6135	0.0965
	12.15	8.72	0.6	7.61	7.5663	0.0437
	1.15	8.76	0.9	7.52	7.5203	-0.0003
	2.15	8.77	0.8	7.51	7.5296	-0.0196
	3.15	8.78	0.6	7.52	7.5778	-0.0578
	4.15	8.85	1.0	7.55	7.5499	1E-04
16.03.08	10.15	9.0	0.7	7.6	7.5503	0.0497
	11.15	8.7	0.5	7.7	7.6203	0.0797
	12.15	8.9	0.6	7.6	7.6281	-0.0281
	1.15	8.8	0.5	7.7	7.6084	0.0916
	2.15	8.6	0.6	7.8	7.5882	0.2118
	3.15	8.5	0.7	7.8	7.6712	0.1288
	4.15	8.6	0.6	7.5	7.5882	-0.0882
17.03.08	10.15	8.42	0.6	7.6	7.5689	0.0311
	11.15	8.52	0.6	7.61	7.5991	0.0109
	12.15	8.41	0.7	7.7	7.7445	-0.0445

	1.15	8.61	0.5	7.65	7.6135	0.0365
	2.15	8.62	0.7	7.51	7.5533	-0.0433
	3.15	8.73	0.8	7.62	7.5114	0.1086
	4.15	8.76	0.7	7.5	7.5661	-0.0661
18.03.08	10.15	8.72	0.6	7.61	7.5663	0.0437
	11.15	8.77	0.8	7.51	7.5296	-0.0196
	12.15	7.69	0.6	7.64	7.5663	0.0737
	1.15	8.32	0.6	7.5	7.5296	-0.0296
	2.15	8.61	0.7	7.63	7.64	-0.01
	3.15	8.74	0.6	7.52	7.5185	0.0015
	4.15	8.91	0.7	7.63	7.5604	0.0696
19.03.08	1.15	8.81	0.6	7.6	7.568	0.032
	2.15	8.8	0.5	7.7	7.6541	0.0459
	3.15	8.8	0.7	7.6	7.5896	0.0104
	4.15	8.96	0.7	7.5	7.6084	-0.1084
20.03.08	11	6.7	-	6.7	6.699	0.001
	12	6.3	-	6.3	6.3	0
	2	6.4	-	6.4	6.4009	-0.0009
	3	6.3	-	6.3	6.3	0
	4	6.3	-	6.3	6.3	0
	5	6.3	-	6.3	6.3	0
21.03.08	11	7.9	0.5	7.5	7.5002	-0.0002
	12	7.9	0.4	7.6	7.6	0
	2	8.1	0.7	7.7	7.6648	0.0352
	3	8.0	0.7	7.6	7.5849	0.0151
	4	8.2	0.6	7.6	7.5455	0.0545
	5	8.1	0.7	7.6	7.6648	-0.0648
22.03.08	9.35	7.0	-	7.0	7.0004	-0.0004
	10.35	7.0	-	7.0	7.0004	-0.0004
	11.35	7.1	-	7.1	7.1006	-0.0006
	12.35	7.1	-	7.1	7.1006	-0.0006
	2.35	7.2	-	7.2	7.1992	0.0008
	3.35	7.3	-	7.3	7.2996	0.0004
	4.35	7.4	-	7.4	7.4011	-0.0011
	5.35	7.5	-	7.5	7.4988	0.0012
23.03.08	9.15	7.2	-	7.2	7.1992	0.0008
	10.15	7.4	-	7.4	7.4011	-0.0011
	11.15	7.4	-	7.4	7.4011	-0.0011
	12.15	7.2	-	7.2	7.1992	0.0008
	2.15	7.4	-	7.4	7.4011	-0.0011
	3.15	7.6	-	7.6	7.6012	-0.0012

	4.15	7.5	-	7.5	7.4988	0.0012
	5.15	7.5	-	7.5	7.4988	0.0012
24.03.08	11.15	8.7	0.3	7.6	7.6029	-0.0029
	12.15	8.6	0.3	7.5	7.4999	1E-04
	2.15	8.9	0.5	7.5	7.5772	-0.0772
	3.15	9.0	0.5	7.6	7.6629	-0.0629
	4.15	9.0	0.4	7.8	7.7008	0.0992
	5.15	8.9	0.3	7.5	7.4987	0.0013
	6.15	9.0	0.4	7.7	7.7008	-0.0008
25.03.08	11.15	9.1	0.7	7.5	7.501	-0.001
	12.15	9.0	0.7	7.5	7.5503	-0.0503
	2.15	8.8	0.6	7.6	7.5854	0.0146
	3.15	8.6	0.4	7.5	7.4865	0.0135
	4.15	8.5	0.3	7.7	7.6982	0.0018
	5.15	8.7	0.5	7.6	7.6203	-0.0203
	6.15	8.8	0.6	7.5	7.5854	-0.0854
26.03.08	11.35	8.9	0.7	7.6	7.6563	-0.0563
	12.35	8.2	0.6	7.5	7.5455	-0.0455
	1.35	8.8	0.5	7.6	7.6084	-0.0084
	2.35	8.9	0.6	7.5	7.6281	-0.1281
	3.35	8.7	0.6	7.5	7.5667	-0.0667
	4.35	8.9	0.6	7.6	7.6281	-0.0281
	5.35	8.9	0.7	7.7	7.6563	0.0437
27.03.08	11.15	8.9	0.6	7.8	7.6281	0.1719
	12.15	8.9	0.6	7.8	7.6281	0.1719
	1.15	8.8	0.7	7.6	7.6009	-0.0009
	2.15	8.7	0.7	7.5	7.5342	-0.0342
	3.15	8.7	0.7	7.5	7.5342	-0.0342
	4.15	8.7	0.6	7.7	7.5667	0.1333
	5.15	8.8	0.7	7.5	7.6009	-0.1009
28.03.08	11.15	9.0	0.7	7.5	7.5503	-0.0503
	12.15	9.1	0.6	7.7	7.6981	0.0019
	1.15	9.0	0.7	7.6	7.5503	0.0497
	2.15	9.0	0.7	7.6	7.5503	0.0497
	3.15	9.0	0.6	7.6	7.6277	-0.0277
	4.15	8.9	0.6	7.5	7.6281	-0.1281
	5.15	8.9	0.5	7.6	7.5772	0.0228
30.03.08	9.15	8.8	0.5	7.5	7.6084	-0.1084
	10.15	8.7	0.6	7.7	7.5667	0.1333
	11.15	8.9	0.5	7.6	7.5772	0.0228
	12.15	8.9	0.6	7.8	7.6281	0.1719

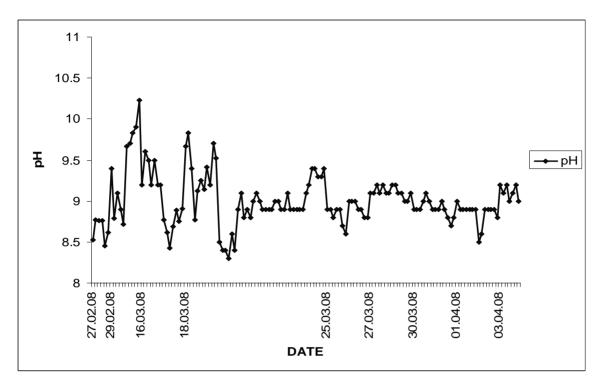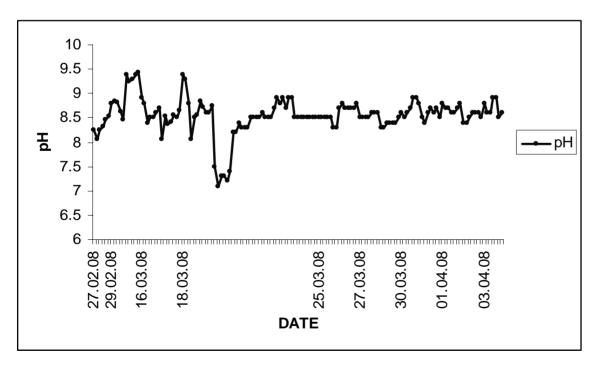|					
	2.15	8.5	0.7	7.6	7.6712	-0.0712
	3.15	8.6	0.6	7.5	7.5882	-0.0882
	4.15	8.7	0.5	7.6	7.6203	-0.0203
31.03.08	11.35	8.8	0.6	7.5	7.5854	-0.0854
	12.35	8.7	0.7	7.6	7.5342	0.0658
	1.35	8.5	0.7	7.6	7.6712	-0.0712
	2.35	8.6	0.5	7.5	7.614	-0.114
	3.35	8.6	0.6	7.6	7.5882	0.0118
	4.35	8.5	0.4	7.6	7.6128	-0.0128
	5.35	8.7	0.5	7.5	7.6203	-0.1203
01.04.08	11.35	6.7	-	6.7	6.699	0.001
	12.35	6.6	-	6.6	6.6011	-0.0011
	1.35	6.6	-	6.6	6.6011	-0.0011
	2.35	6.5	-	6.5	6.4989	0.0011
	3.35	6.5	-	6.5	6.4989	0.0011
	4.35	6.6	-	6.6	6.6011	-0.0011
	5.35	6.3	-	6.3	6.3	0
02.04.08	11.35	8.6	0.6	7.5	7.5882	-0.0882
	12.35	8.5	0.5	7.7	7.6811	0.0189
	1.35	8.9	0.6	7.7	7.6281	0.0719
	2.35	8.6	0.7	7.6	7.5683	0.0317
	3.35	8.7	0.8	7.5	7.5167	-0.0167
	4.35	8.9	0.6	7.6	7.6281	-0.0281
	5.35	8.8	0.7	7.7	7.6009	0.0991
03.04.08	11.15	9.0	0.5	7.6	7.6629	-0.0629
	12.15	8.9	0.7	7.8	7.6563	0.1437
	1.15	8.9	0.6	7.5	7.6281	-0.1281
	2.15	9.0	0.4	7.6	7.7008	-0.1008
	3.15	9.0	0.5	7.8	7.6629	0.1371
	4.15	8.9	0.6	7.6	7.6281	-0.0281
	5.15	8.6	0.6	7.5	7.5882	-0.0882

Figure 1. pH variation in Receiving Sump
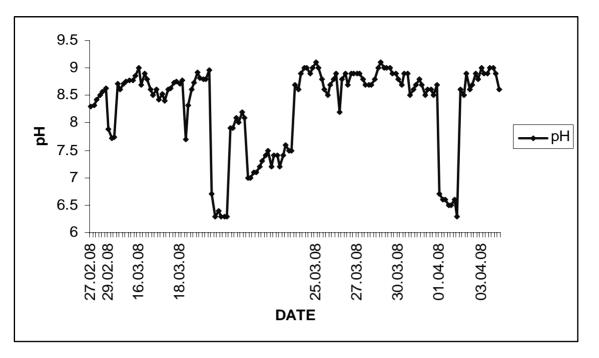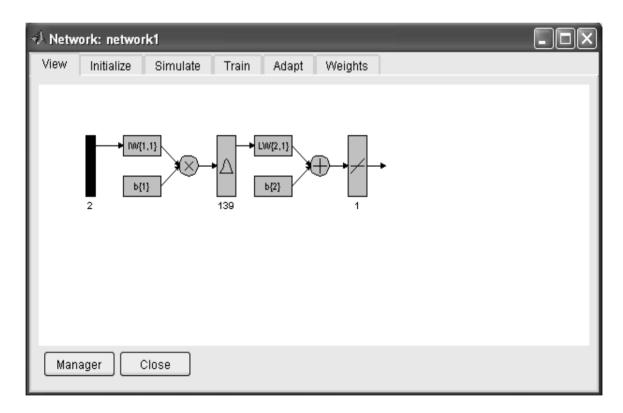

Figure 2. pH variation in Equalization Tank

Figure 3. pH variation in Clarilflocculator Overflow

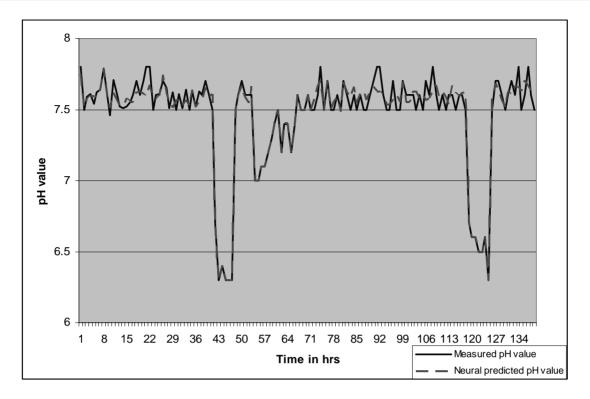Figure 4. SIMULINK Block Diagram for pH Identifier
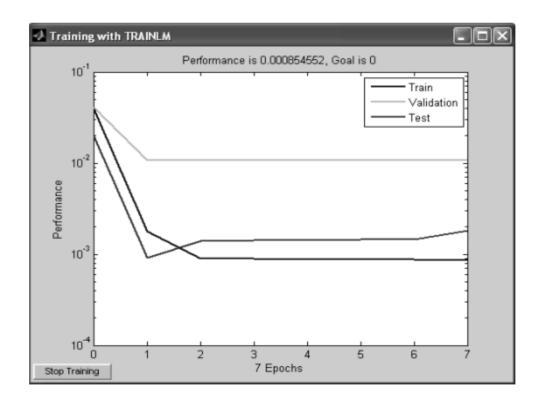
Figure 5. Measured pH value Vs Neural predicted pH value

Figure 6. Error response