Design of Plant Estimator Model Using Neural Network

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Abstract
The construction of a parameter (or state) estimator can be basically considered as a function approximation problem. To design an estimator, it is first necessary, to obtain the training data set 'G' such that, this training data set contains as much information as possible about a system 'g'. Once trained properly, the estimator will adaptively follow the slope of 'g' at all times. In this paper, signals are processed in real time and combined with previous monitoring data to estimate, using the neural network, the process variable level in a nonlinear process control plant.

Key words:
Estimator, Neural Network, Nonlinear control, Sensor validation.

1. Introduction

In the area of process engineering, process design and simulation, process supervision, control and estimation, and process fault detection and diagnosis rely on the effective processing of unpredictable and imprecise information. In such situations, the neural network, which can achieve the sophisticated level of information processing the brain is capable of, can excel. The neural networks are generally viewed as process modeling formalism and given the appropriate network topology, they are capable of characterizing nonlinear functional relationships [3]. Furthermore, the structure of the resulting neural network based process model may be considered generic, in the sense that little prior process knowledge is required in its determination. The knowledge about the plant dynamics and mapping characteristics is implicitly stored within the network.

2. Design of Estimator Using Neural Network

Training a neural network using input-output data from a nonlinear plant is considered as a nonlinear functional approximation problem. A generic neural network estimator model, used to detect a sensor failure is shown in figure 1. Neural networks have effectively been used in many applications to predict performance degradation of operating systems in real-time. Neural networks are data driven models and data under a variety of conditions need to be obtained. In the present work the experimental setup was used to gather data and the key measurable signals that were collected for training the network consisted of the inflow, outflow rate and the process value level. Different operating conditions were simulated and the change in inflow, outflow and the level were recorded. The data collected from the plant were pre-processed for normalization and fed to the

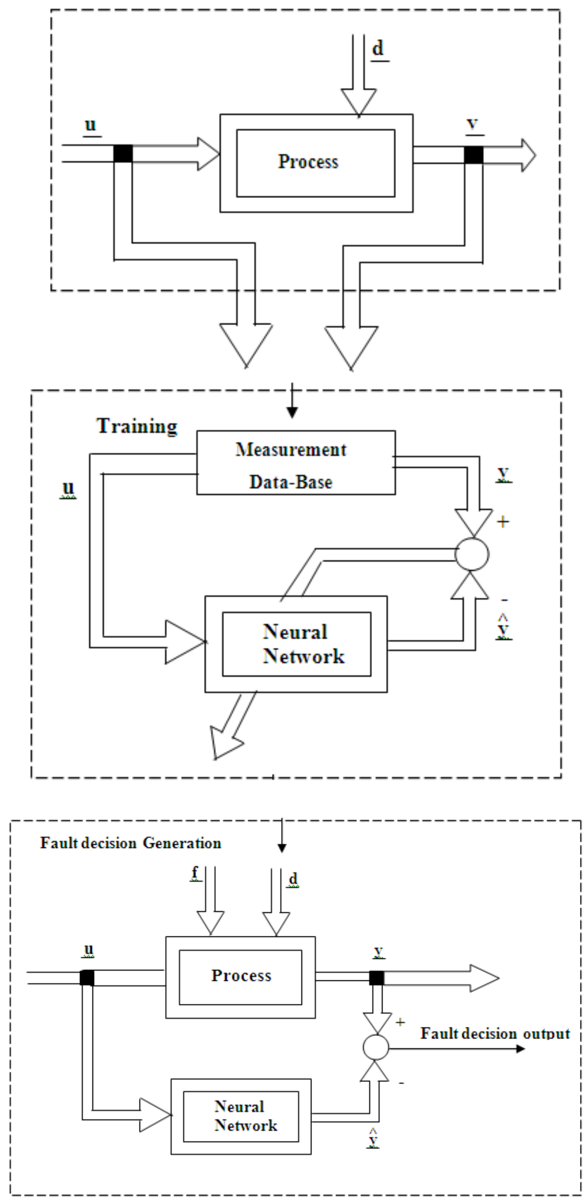

Figure 1 **Neural network estimator model**

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Neural network for training. Data pre-processing was performed as the data obtained from the experiment in not ready to use for training directly. The first step in pre processing is to identify and remove outliers [7]. Outliers are treated in statistics as samples that carry high leverage. Outliers can result from sensor failure, misreading from lab tests and other possible unknown upsets to the process. A distinctive feature of outliers is that they have extremely large influence on the model. As a sequence, it is necessary to perform outlier detection and pretreatment before training the network. The presence of outliers in the present data set is identified, by observing the signals in frequency domain. The network was trained with the back propagation algorithm is shown in figure 2.

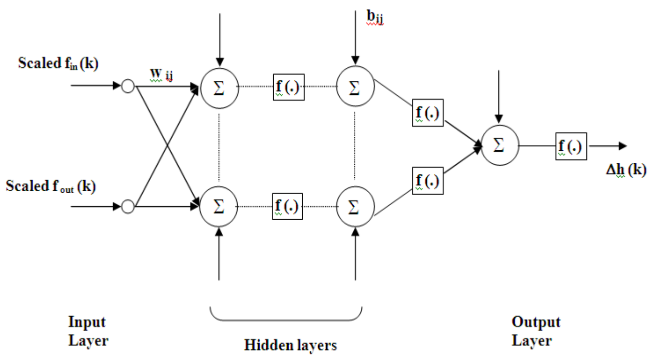

Figure. 2. BPN model of the neural estimator (2-3-(5-5-5)-1) network

3. Plant Description

The prototype model constructed for experimental study consists of the cylindrical tank with a conical bottom open to the atmosphere at the top end. The experimental model is to be used, to study the performance of the proposed intelligent control algorithms by obtaining the servo and regulatory response, in the presence of disturbances, feedback sensor failure and sensor noise. Suitable signals are given to a pneumatic operated control valve to regulate the manipulated variable inflow. Disturbances in the form of random variations in outflow (measurable) and/ or changes in outflow coefficient are considered to enter the process. The schematic diagram of the plant is shown in figure 3. The process variable level is sensed by means of an RF capacitance probe and using suitable electronics circuitry, a voltage output is obtained. The analog voltage is converted into digital form using an 8- bit A/D converter. The inflow and outflow rates are measured using suitable flow transmitters.

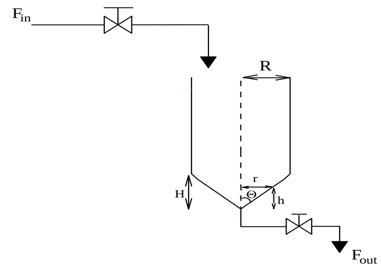

Figure 3. Geometric cross section of the tank.

Note: (i) 'b' instantaneous tank height
(ii) 'H' total conical tank height
(iii) 'R' total radius of tank
(iv) 'r' instantaneous radius

4. Plant With Sensor Validation Model Using Neural Estimator

The plant failure model with the neural estimator to take care of feedback sensor failure is shown in figure 4.

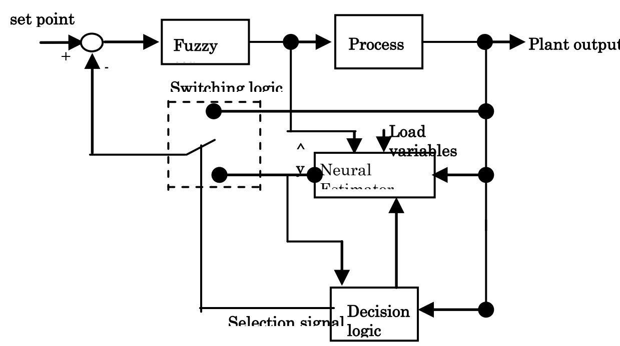

Figure. 4. Plant model with Neural Estimator to take care of feedback sensor failure

In the model, the decision logic determines the feedback signal to be provided to the controller, by computing the deviation between the estimator output and the plant output, and comparing this deviation with a pre-defined threshold value. It is proposed to construct a neural state estimator to estimate a single parameter in the plant 'g'. For this purpose, random excitation inputs were chosen to form the training data set. Excitation with random inputs was chosen, since, it had a better tendency to place the data points over a whole range of locations and also it is difficult to choose other inputs 'u' that result in a better data set G.. A set of experiments were conducted with system 'g' by varying the parameters $f_{in}(k)$ and $f_{out}(k)$ about its steady state values. The parameters were varied individually over a specified range of values to account for the possible failure scenarios the system might encounter. The random variations in inflow rate, outflow rate about its steady state values (that were used as excitation inputs for forming the training data set) and the resultant plant response obtained experimentally is shown in Appendix I (figure A and B). The parameters fin(k) and fout(k) were varied between –50% and +50% of its nominal value i.e. Δfin(k) and Δfout(k) ε [-0.5,+0.5], and the steady state deviations of the plant output was recorded.

5. Training data for Neural Network

Sample values of input-output patterns obtained from the response and subsequently used for training the network is given in Table 1. . The training data should be spread over the input space uniformly to ensure that there is a regular spacing between points and not too many more points in one region than another [5]. This is essential to get a good coverage of the whole input space. The information as to how the mapping ‘g’ is shaped in all regions should be implicitly presented as much as possible in the training data set.

Table .1. Sample values of input-output patterns

Sample values	$f_{out}(k)$ (in%)	average change in liquid level/sample (cms/sample)
100%	0%	0.10625
100%	20%	0.09
100%	40%	0.0812
100%	50%	0.06818
100%	65%	0.03846
100%	80%	0.02666
90%	0%	0.0941176
90%	20%	0.081632
90%	40%	0.074
90%	50%	0.059259
90%	65%	0.053333
90%	80%	0.026229
80%	0%	0.0805
80%	20%	0.0744186
80%	40%	0.05927
80%	50%	0.05317
80%	65%	0.04
80%	80%	0.0
65%	0%	0.057142
65%	20%	0.04507
65%	40%	0.034408
65%	50%	0.02758
65%	65%	0.01333
50%	0%	0.03368
50%	20%	0.01758
50%	30%	0.013636
50%	40%	0.0056818
40%	0%	0.0125
40%	20%	0.01
40%	30%	0.006818
30%	0%	0.012
30%	10%	0.006

6. Experimental Response With The Neural Estimator

The performance of the designed neural estimator was tested on the nonlinear hopper type tank by introducing feedback sensor failure at random time instants during the experimental run. The decision logic of figure 4 selects the neural estimator output as the feedback signal to the controller at those time instants when the deviation between the actual sensor value and the estimated value exceeds a set threshold. The actual plant response that would have been obtained with a faultless sensor was compared with the estimator response for different operating conditions such as variations in set point and outflow. These responses were obtained independently with fuzzy controller present in the forward path of the control loop. The ISE is calculated for both the servo and regulatory control with the estimator alone in the loop.

6.1 Response to set point variations

In the servo tracking experimental study on the real time plant, step signal with randomly varying magnitudes were used as the excitation input. The chosen variations of input signal $\Delta_{sp}(k)$ in the interval [-20,20] is shown in fig 5, for the first 500 samples. The obtained servo and neural estimated response of the nonlinear plant with the fuzzy controller in the forward path of the control loop is shown in Figure.6. The objective of this experimental study is to study the input signal adaptation capability of the designed neural estimator.

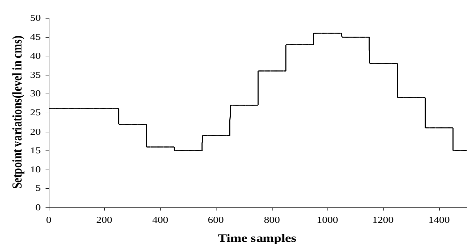

Figure 5. Set point variations chosen for the experimental study

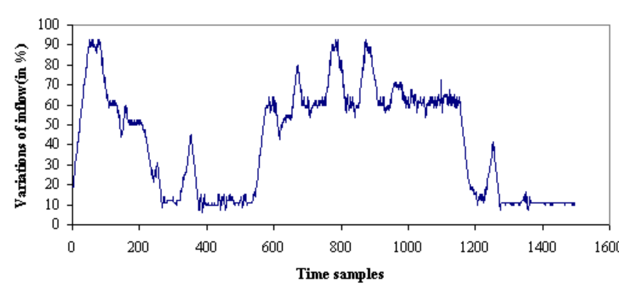

Figure 6. Measured variations of manipulated variable inflow (%)

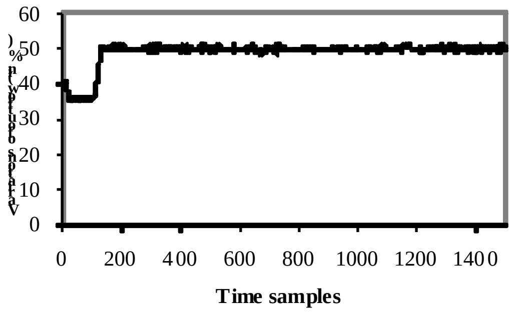

Figure 7. Measured variations of load variable outflow (%)

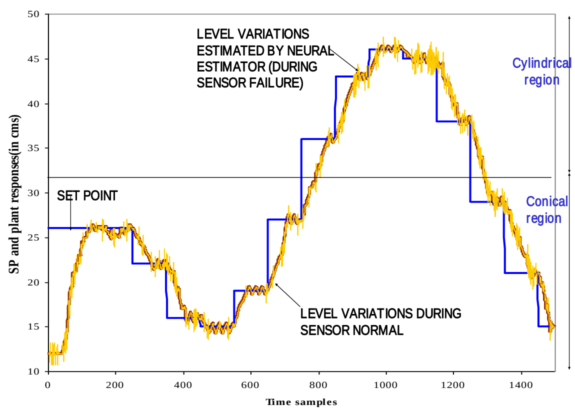

Figure 8. Actual and neural network estimated level variations of the real time plant with neural estimator

6.2 Response to variations in load variable outflow

The regulatory response of the plant estimated by the neural estimator during level sensor failure, with the fuzzy controller in the loop is shown in figure 9. The perturbations introduced in the load variable outflow were exactly the same.

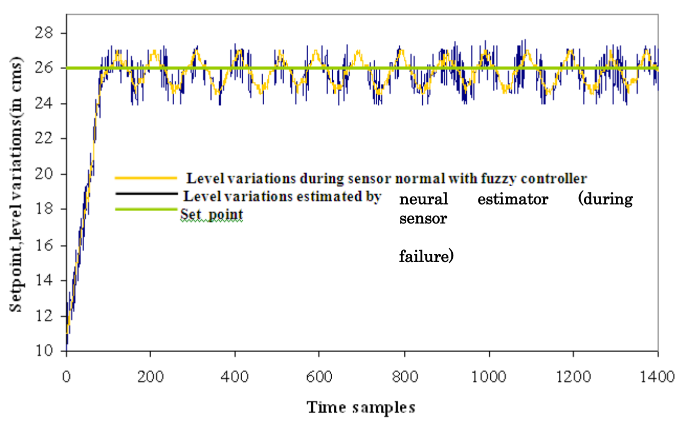

Figure 9. Measured and neural estimated level variations of the real time plant with fuzzy controller in response to perturbations in load variable outflow.

6.3 Online acquired plots

The on line acquired plots for the process variable of level, outflow, estimated value for regulatory tracking and set point tracking are shown in figure 10 and 11.

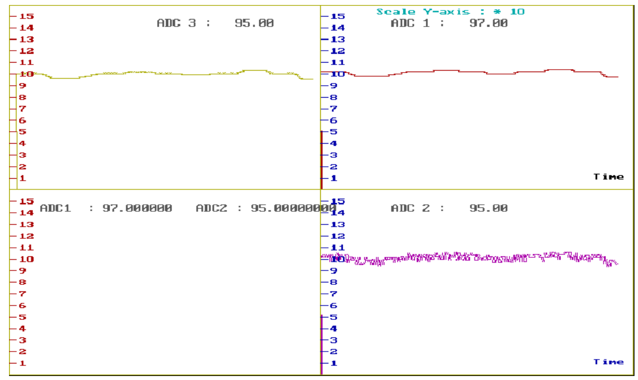

Figure 10. On-line acquired plots showing the true process value of outflow (1st quadrant), Neural network estimated value (2nd quadrant) and fuzzy estimator o/p value (4th quadrant). (Plot obtained during regulatory tracking)

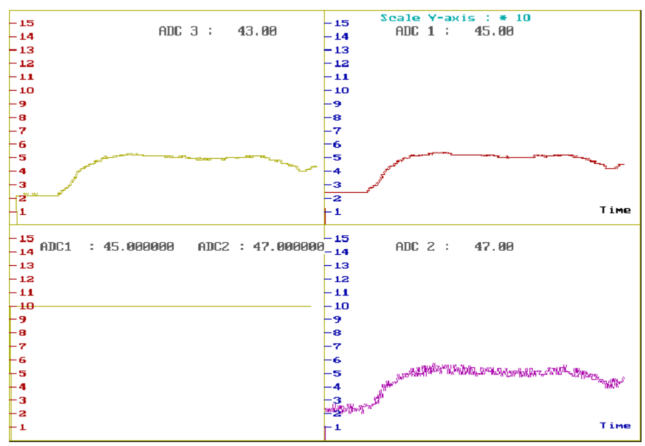

Figure 11. On-line acquired plots showing the true process value of level (1st quadrant), Neural network estimated value (2nd quadrant) and the fuzzy estimator o/p value (4th quadrant). (Plot obtained during set point tracking)

7. Comparison Results

The experimental servo and regulatory response of the system with the two designed estimators were obtained for the following cases, and shown in table 2.

1) Fuzzy estimator with fuzzy controller for servo tracking
2) Fuzzy estimator with fuzzy controller for regulatory response
3) Neural estimator with fuzzy controller for servo tracking

4) Neural estimator with fuzzy controller for regulatory response

Table 2. Normalized MSE

Typeof estimator /controller	Setpoint tracking	Regulatory response
Fuzzy estimator with Fuzzy controller	404.37	360.03
Neural estimator with fuzzy controller	402.83	346.08

8. Conclusion

In this paper, signals are processed in real time and combined with previous monitoring data to estimate, using the neural network, the process variable level in a nonlinear process control plant. Neural Estimator and Fuzzy Estimator are designed for hopper type tank process. Experimental results were carried out for servo and regulatory problems, and improved results were obtained for Neural Estimator.

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Biographies

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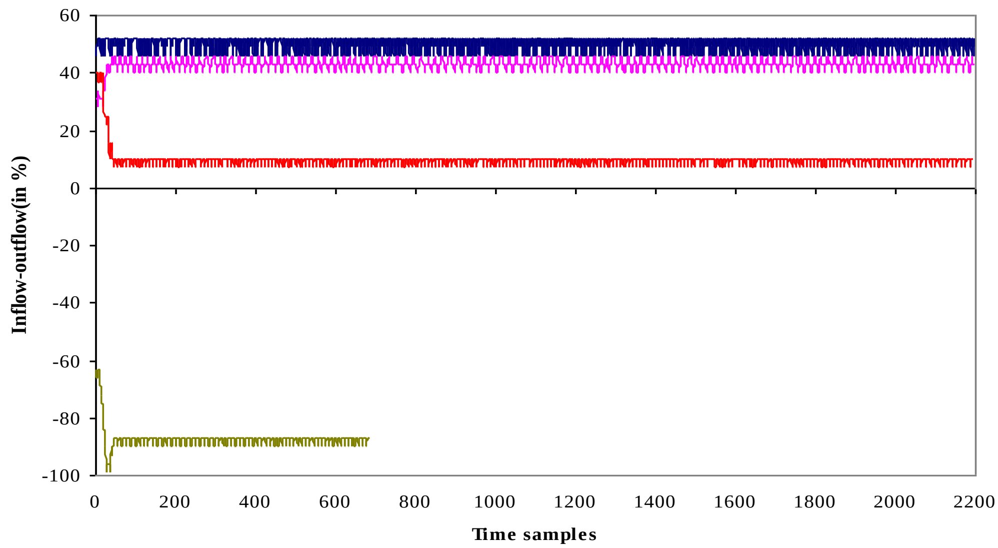
APPENDIX I



A- Inflow fluctuating between 90-100% and outflow fluctuating between 40-50% after 50 samples
B- Inflow fluctuating between 90-100% and outflow fluctuating between 50-60% after 50 samples
C- Inflow fluctuating between 0-10% and outflow fluctuating between 70-80% after 50 samples
D- Inflow fluctuating between 90-100% and outflow fluctuating between 90-100% after 50 samples

Figure A. Combined plot of (inflow-outflow) for four different experimental conditions

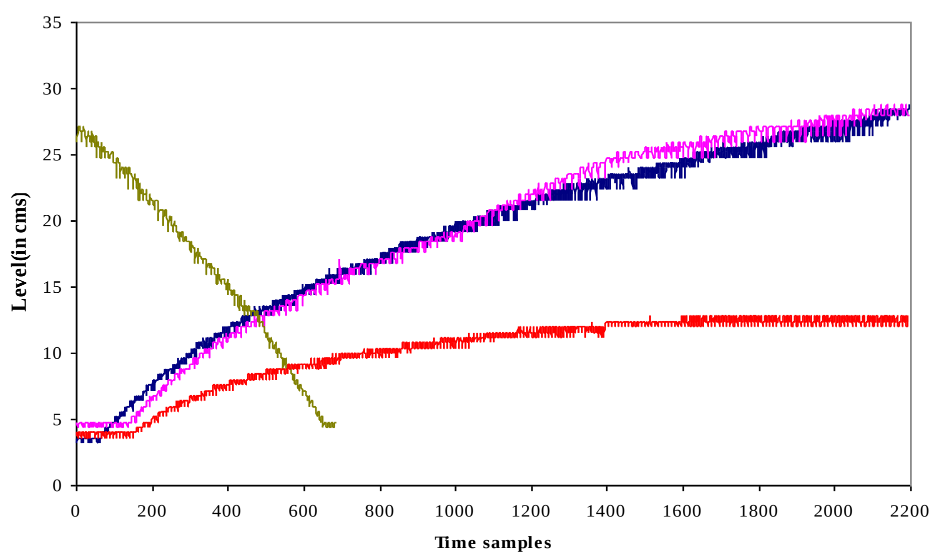


Figure B. Combined plot of resultant level response corresponding to the case A,B,C,D of figure A