CHAPTER 4

DESIGN OF PLANT ESTIMATOR MODEL USING FUZZY
LOGIC AND NEURAL NETWORK

The construction of a parameter (or state) estimator can be 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 the system ‘g’. 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. 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. Once trained properly, the estimator will adaptively follow the slope of ‘g’ at all times.

4.1 EXTRACTING LINGUISTIC INFORMATION FOR FUZZY
ESTIMATOR DESIGN

It is proposed to construct a fuzzy state estimator (Li guo et al 2006) for 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 Figures 4.1 and 4.2.

Figure 4.1 Combined plot of (inflow-outflow)

**Case (i)** : Inflow fluctuating between 90 to 100% and outflow fluctuating between 40 to 50% after first 50 samples

**Case (ii)** : Inflow fluctuating between 90 to 100% and outflow fluctuating between 50 to 60% after first 50 samples

**Case (iii)** : Inflow fluctuating between 0 to 10% and outflow fluctuating between 70 to 80% after first 50 samples

**Case (iv)** : Inflow fluctuating between 90 to 100% and outflow fluctuating between 90 to 100% after first 50 samples
Figure 4.2  Combined plot of resultant level (for the cases consider in Figure 4.1)

The parameters inflow and outflow ($f_{in}(k)$ and $f_{out}(k)$ respectively) were varied between $-50\%$ and $+50\%$ of its nominal value i.e. $\Delta f_{in}(k)$ and $\Delta f_{out}(k) \in [-0.5,+0.5]$ and the resultant variations of the plant output was recorded. The numerical data obtained from the response is then used to form the linguistic information required for the design of the fuzzy estimator. Extracting the linguistic information consists of partitioning the data set into multiple regions (usually three, five or seven). In the present work the difference between the inlet and outlet flow rates is quantized into seven linguistic regions over their universe of discourse. They are labeled as Negative Maximum (NMAX), Negative Medium (NM), Negative Small (NS), Approximately Zero (AZ), Positive Small (PS), Positive Medium (PM) and Positive Maximum (PMAX). This is shown in Figure 4.3a. Similarly $y(k-1)$, which is used to capture the dynamics of the process, is quantized into seven linguistic regions and assigned triangular membership functions as shown in Figure 4.3b. They are labeled as Very Very Fast (VVF), Very Fast (VF), Fast (F), Medium (MED), Small (SMALL), Very Small (VS) and Approximately Zero (AZ). The resultant variations of level are assigned the membership functions shown in Figure 4.3c.
Figure 4.3a Membership function for (inflow-outflow) (in %)

Figure 4.3b Membership function for the dynamics of y(k-1) (in cms)

Figure 4.3c Membership function for change in level (in cms/sample)
4.2 RULE BASE FOR THE FUZZY ESTIMATOR

In usual practice, the fuzzy logic rules are developed based on operators experience or from experimental data collected on a real plant. In the present work, the rules were formed using the experimental response obtained in section 4.1. Each rule is a triplet \((f_{in}(k) - f_{out}(k)), y(k-1), \Delta h(k)\) where \((f_{in}(k) - f_{out}(k)), y(k-1)\) and \(\Delta h(k)\) \(\in\) \(L\).

The rule takes a given pair \((f_{in}(k) - f_{out}(k)) \in [-50\%, +50\%]\) and \(y(k-1) \in [0,H]\) as input, and assigns an output \(\Delta h(k) \in [-1,+1]\). Typical rules used are,

(i) “if \((f_{in}(k) - f_{out}(k))\) is PM and \(y(k-1)\) is F then \(\Delta h(k)\) is PM”

(ii) “if \((f_{in}(k) - f_{out}(k))\) is NM and \(y(k-1)\) is VVF then \(\Delta h(k)\) is NMAX”.

(iii) “if \((f_{in}(k) - f_{out}(k))\) is AZ and \(y(k-1)\) is AZ then \(\Delta h(k)\) is AZ”.

The rule base for the fuzzy estimator is given in Table 4.1.

<table>
<thead>
<tr>
<th>(y(k-1))</th>
<th>VVF</th>
<th>VF</th>
<th>F</th>
<th>MED</th>
<th>SMALL</th>
<th>VSMALL</th>
<th>AZ</th>
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4.3 PLANT MODEL WITH THE FUZZY ESTIMATOR

The fuzzy estimator with the membership functions of manipulated variable, load variable and the process variable stored in the knowledge base (section 4.2) and the control rules stored in the rule base (Table 4.1) is incorporated into the existing plant model and shown in Figure 4.4.

![Diagram of Plant Model with Fuzzy Estimator]

**Figure 4.4** Plant model with the fuzzy estimator to take care of feedback sensor failure

The knowledge base and rule base are used by the fuzzy inference mechanism to fire the individual rules. The center of gravity method of defuzzification is used to obtain a crisp output.

For example, if the measured value of \((f_{in}(k) - f_{out}(k))\) lie in the linguistic regions NM and NS with \(\mu_{NM}=0.66\) and \(\mu_{NS}=0.33\), and \(y(k-1)\) lie in the linguistic regions MED and SMALL with \(\mu_{MED}=0.66\) and \(\mu_{SMALL}=0.33\), then the following if-then rules are fired.
(i) “If \((f_{in}(k) - f_{out}(k))\) is NS and \(y(k-1)\) is MED then change in estimator output is NS”

(ii) “If \((f_{in}(k) - f_{out}(k))\) is NS and \(y(k-1)\) is SMALL then change in estimator output is AZ “

(iii) “If \((f_{in}(k) - f_{out}(k))\) is NM and \(y(k-1)\) is MED then change in estimator output is NM”

(iv) “If \((f_{in}(k) - f_{out}(k))\) is NM and \(y(k-1)\) is SMALL then change in estimator output is NS”

The defuzzified estimator output using the center of gravity method for the above four fired rules is then obtained using the relation

\[
\Delta h(k) = \frac{\left(\min \mu_{NM}, \mu_{NMAX}\right) \mu_{PM} + \min \mu_{NM}, \mu_{NM} \mu_{AZ}\right)}{\left(\min \mu_{NM}, \mu_{NMAX} + \min \mu_{NM}, \mu_{NM} + \min \mu_{AZ}, \mu_{NMAX} + \min \mu_{AZ}, \mu_{NM}\right)}
\]

The four rules fired for the above example are shown highlighted in Table 4.2.

**Table 4.2 Fired rules in the rule base for the example considered**

<table>
<thead>
<tr>
<th>( f_{in} )</th>
<th>( f_{out} )</th>
<th>( y(k-1) )</th>
<th>( VFF )</th>
<th>( VF )</th>
<th>( F )</th>
<th>( MED )</th>
<th>( SMALL )</th>
<th>( VSMALL )</th>
<th>( AZ )</th>
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<td>PMAX</td>
<td>PMAX</td>
<td>PM</td>
<td>FM</td>
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4.4 EXPERIMENTAL RESPONSE WITH THE FUZZY ESTIMATOR

The performance of the designed fuzzy estimator was tested on the nonlinear hopper type tank by introducing feedback sensor failure at random time instants during the experimental run (Ashok Kumar Goel et al 2005). The decision logic of Figure 4.4 selects the fuzzy 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 (Chyi – Tsong Chen and Shih-Tein Peng 1999).

The actual plant response that would have been obtained with a faultless sensor was compared with the estimator response (obtained during sensor failure) for different operating conditions such as variations in set point and outflow. These responses were obtained independently with the two controllers (adaptive PI and FLC) designed in Chapter 3 and the mean square error (MSE), calculated for each case. The pseudo code of the fuzzy estimator algorithm is given as follows:

4.4.1 Pseudo Code of the Estimator Algorithm

Repeat steps (i) to (iv) for n=1,2,3…

(i) read level sensor value \( h(k) \)

(ii) read inflow \( f_{in}(k) \) and outflow \( f_{out}(k) \) from flow sensors

(iii) calculate fuzzy estimator output \( h'(k) \) using the knowledge base (section 4.1) and rule based (section 4.2) with \( (f_{in}(k) - f_{out}(k)) \) and \( y(k-1) \) as the fuzzy inputs

(iv) if \( \text{abs}(h(k) - h'(k)) > \) a predefined threshold value


\{
    \text{assign controller input} = \text{estimator output}
\}

\text{and}

\text{assign } y(k-1) = h'(k)
\}

\text{else}

\{
    \text{assign controller input} = \text{sensor output}
\}

\text{and}

\text{assign } y(k-1) = h(k)
\}

### 4.4.2 Response of the Fuzzy Estimator during Setpoint Variation

In the setpoint tracking experimental study on the real time plant, step signal with randomly varying magnitudes were used as the excitation input. The chosen variation of set point is shown in Figure 4.5 for the first 500 samples. The actual (sensor normal) and fuzzy estimator response (during sensor failure) of the nonlinear plant with adaptive PI controller is shown in Figure 4.6. From the response, the input signal adaptation capability of the designed fuzzy estimator is studied.

![Figure 4.5 Set point variations chosen for the experimental study](image-url)
Figure 4.6  Measured and fuzzy estimated level variations of the real time plant with adaptive PI controller in response to changes in set point

The variations of manipulated variable inflow and load variable outflow are plotted in Figures 4.7 and 4.8 respectively.

Figure 4.7 Measured variations of manipulated variable inflow (in %)
Figure 4.8 Measured variations of load variable outflow (in %)

The estimator response with the FLC for the same input (Figure 4.5) is shown in Figure 4.9.

Figure 4.9 Measured and fuzzy estimated level variations of the real time plant with fuzzy controller in response to changes in set point
4.4.3  Response of the Fuzzy Estimator during the Regulatory Variations

The objective of this experimental study is to observe the effect of load variations on the performance of the dynamic fuzzy estimator. The chosen variations in load variable outflow, about its steady state value of 50% is shown in Figure 4.10.

![Figure 4.10](image_url)

*Figure 4.10  Random perturbations in the load variable outflow (in %) about its nominal value of 50%*

The regulatory response of the plant with the adaptive PI controller, during sensor normal, and the fuzzy estimated response during sensor failure is shown in Figure 4.11. The variations of manipulated variable inflow are shown in Figure 4.12.
Figure 4.11 Measured and fuzzy estimated level variations of the real time plant with adaptive PI controller in response to perturbations in load variable outflow.

Figure 4.12 Measured variations of manipulated variable inflow (in %)

The response of the fuzzy estimator to the same load variations of Figure 4.11 with the fuzzy controller is shown in Figure 4.13.
Figure 4.13 Measured and fuzzy estimated level variations of the real time plant with fuzzy controller in response to perturbations in load variable outflow

4.5 DESIGN OF ESTIMATOR USING NEURAL NETWORK

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.

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. Training a neural network using input-output data from a nonlinear plant is considered as a nonlinear functional approximation problem.
Figure 4.14 Generic neural network model that can be used for sensor validation
In the present work, signals are processed in real time and combined with previous monitoring data to estimate, using the neural network, the process variable level in the nonlinear process control plant. A generic neural network estimator model, used to detect a sensor failure is shown in Figure 4.14.

4.6 PLANT WITH SENSOR VALIDATION MODEL USING NEURAL ESTIMATOR

The plant failure model with the neural estimator to take care of feedback sensor failure (Alessandri 2003) is shown in Figure 4.15.

![Diagram of plant failure model with neural estimator](image)

**Figure 4.15** The plant failure model with the 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.

4.7 DESIGN OF NEURAL NETWORK BASED ESTIMATOR

Neural networks have effectively been used in many applications to predict performance degradation of operating systems in real-time (Alessandri et al 1999). 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 neural network for training. Data pre-processing is performed as the data obtained from the experiment in not ready to use for training directly.

The primary step in pre processing is to identify and remove outliers. Outliers are treated in statistics as samples that carry high leverage. Outliers may 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 prerequisite, it is necessary to perform outlier detection and process them prior to training the network. The presence of outliers in the present data set is identified, by observing the signals in frequency domain (Olga Chibirova et al 2008). The network was trained with the back propagation algorithm discussed in chapter 2. The network used for training is shown in Figure 4.19. The frequency distribution graph of the outflow and inflow variable corresponding to servo and regulatory conditions with the experimental data collected from the plant for training pattern for neural network is shown in Figures 4.16 to 4.18. Once trained, the neural network recognizes patterns similar to those already trained and classifies new pattern accordingly.
Figure 4.16 Training patterns (obtained experimentally) for the neural network (initial 350 samples)

Figure 4.17 Continuation for samples 351 to 750
Figure 4.18 Continuation for samples 751 to 1050

Figure 4.19 BPN model of the neural estimator (2-3-(5-5-5)-1) network
4.8 EXPERIMENTAL RESPONSE WITH NEURAL ESTIMATOR

The proposed plant failure model was tested on the laboratory setup. Different operating conditions such as set point changes and load flow variations were introduced and the estimator output was compared with the level sensor output. In all the cases, during the period of level sensor failure, the decision logic of Figure 4.15 has selected the estimator output as the feedback signal to the controller.

4.8.1 Response of the Neural Estimator during Set Point Variations

The objective of this experimental study was to demonstrate the capability of the dynamic neural network estimator to adapt to step changes in input. The chosen variations of set point were identical to the one used in section 4.4 and the response of the neural estimator with the adaptive PI controller in the loop is shown in Figure 4.20. The response of the estimator to the same input signal variations but with the fuzzy logic controller in the loop is shown in Figure 4.21.

![Figure 4.20 Measured and neural network estimated level variations of the real time plant with adaptive PI controller in response to changes in set point](image-url)
4.8.2 Response of the Neural Estimator during the Regulatory Variations

The regulatory response of the plant estimated by the neural estimator during level sensor failure, with the adaptive PI controller in the loop is shown in Figure 4.22. The perturbations introduced in the load variable outflow were exactly the same as shown in Figure 4.10. The regulatory response for a similar situation but with the FLC in the loop is shown in Figure 4.23.
Figure 4.22  Measured and neural network estimated level variations of the real time plant with adaptive PI controller in response to perturbations in load variable outflow. (ISE =14.9)

Figure 4.23  Measured and neural network estimated level variations of the real time plant with fuzzy controller in response to perturbations in load variable outflow. (ISE =5.609)
4.9 COMPARISON OF RESULTS

The experimental servo and regulatory response of the system with the two designed estimators were obtained in the previous sections for the following cases:

1) Fuzzy estimator with fuzzy PI controller for setpoint tracking
2) Fuzzy estimator with fuzzy PI controller for regulatory response.
3) Neural estimator with fuzzy controller for setpoint tracking
4) Neural estimator with fuzzy controller for regulatory response

The mean square error (MSE) is computed using the relation

\[ MSE = \frac{1}{N} \sum_{k=1}^{N} \left[ y(k) - \text{estimated}(k) \right]^2 \]

where, \( N \) is the number of samples and \( y(k) \) is the process output with the sensor normal corresponding to the \( k^{th} \) sample. The computed MSE is used as a measure of performance index to compare the two estimators. It is observed that both the fuzzy and neural estimators are consistent. However, the fuzzy estimator has an added advantage that it is less dependent compared to the neural estimator. The MSE values are presented in chapter 6.