A Neuro-Fuzzy Model for Fault Detection, Prediction and Analysis for Petroleum Refinery

**Abstract.** The paper describes data fusion using a neuro-fuzzy system for fault detection, prediction, and analysis of petroleum refining operations and other process industries. The model described in this paper involves algorithms applied to multi-sensor fusion using historical data to create a trend analysis. The main objective is to detect anomalies in a sensor data and to predict future catastrophes. Data mining is applied to find sensor anomalies in data sets. Neuro-fuzzy logic is used to find clusters of each sensor input using subtractive fuzzy clustering. Fault detection and prognosis are essential in a safety-critical environment such as a refinery. A new set of data is obtained and represented using the fuzzy inference system, with three linguistic values used to define and classify the patterns and failures.

**Keywords:** Fuzzy Logic, Fault Detection, Sensors, Neuron, Artificial Neural Network.

1. Introduction

A refinery is a closed system which requires numerous sensors for monitoring processing operations. It is time consuming and labour intensive to monitor all sensors for fault detection and this has in the past led to major catastrophes due to human error. It is crucial to monitor sensor operations in a refining process, to keep track of routine cyclic maintenance of sensors and to predict component failure due to time related defects and component exposure to chemicals. It could be tedious to establish useful patterns when dealing with a huge amount of data. It could mean an extra workload for operators and if extra faults were not detected, it could lead to major disaster if patterns were missed. Identifying sensor faults and anomalies early is crucial, as it determines a proper maintenance timing for systems. It could be complex to diagnosis functions but that could be solved by using pattern recognition for the data set. For a neuro-fuzzy method to work effectively, each neuron should contribute to the output.

In the last two decades, the problems involving fault detection have been studied in the literature [1-5]. Some of the methods used have been complicated and some could be limited to certain levels of non-linearity, uncertainty and complexity [6] [7].

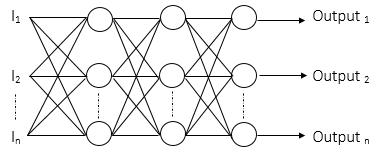
The use of multi-sensor data fusion in a neural network to classify feature output information based on individual sensors has proven to be efficient. The advantage of understanding a neural network was to identify the behaviour pattern of individual sensors to detect anomalies that could be linked to component or systemic failure.

Investigation of process monitoring activities and understanding the heterogeneous sensor (entire sensor system) information from refinery operations could help to leverage the strength of individual sensor information through sensor fusion.

This study considered experimental data from sensor information such as temperature, pressure, level control, valves, furnace temperature and feed flow.

1. Artificial Neural Networks

An Artificial Neural Network popularly referred to as ANN is a computing pattern which functions like the human brain. It comprises of cells called “neurons” and each of these neurons performs a specific operation and interacts with other neurons to make decisions (Fig. 1) [8].



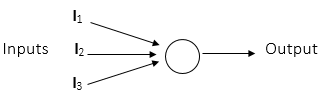
**Fig. 1**. Neural Network.

In a simple neural network, the input layer could be connected to the output layer. In most ANN including deep neural networks the input layer is connected to a hidden layer via network of neurons [8]. A key feature of ANNs is the ability of the network to learn from examples while using little or no prior knowledge about the system structure. Nonconventional ANNs give an insight into the behaviour of a system, which makes it easier to understand. Configuration could be highly trained using numerical data, while expert knowledge could not be easily incorporated. Other researchers have conducted studies on using ANNs for fault diagnosis [9] [10] [11] [12].

Authors [13] [14] suggested that for there to be a robust fault detection system, systems should be a combination of numerical attributes (Quantitative) and symbolic (Qualitative) information. ANNs provide a framework for modelling nonlinear systems by giving weighting factors and an appropriate architecture.

The input layer feeds data into the network. Input data did not change the information, but instead it passed to the input layer. The input data could be data from sensors, alarms, text logs etc. The information from each neuron is passed to a different layer of neurons, these layers could be a different type of neuron which could independently enhance the transformation on the layers of the required output solution.

The neuron explained in this paper represented information from each sensor, which input a weight dependence that contributed to the decision of the entire ANN. Fig. 2 shows inputs and an output and a neuron.



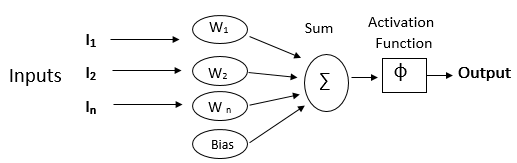
**Fig. 2.** Neuron.

Equation 1 explains the sum of products of inputs and the weights of neurons compared with a bias to determine the output of the combined neurons.

The neuron is the sum of the input weights and a bias.

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The decision-making process could be influenced by adjusting the weights with respect to the bias (Fig. 3).



**Fig. 3.** Summary of input and output Neural Network.

Where:

I1, I2, In, represented the different input data.

represented the input weight of each neuron.

∑ represented the sum of the weights of each neuron.

ɸ is the activated sum of the weight and the bias of all neuron.

Input data: The neuron in the input layer performed a simple summing which is expressed as:

( (2)

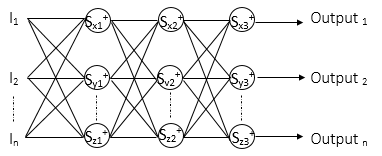
Output data: The product of this operation involving neurons of different layers is passed through a non-linear activation function and the output is the product of the neurons as shown below:

Act (3)

One main features of a neuron was its ability to train input weights and biases so that input information passed on to another neuron could change based on the input data. In order to explain neuro-fuzzy model application, it was important to expose the network to sensor input data obtained from refinery operations. To reduce the risk of data error, the method used in obtaining data is important.

The idea was to generate a new set of output information using numerical parameter values with a fuzzy-logic inference engine for decision-making such that it reflected the risk priorities of each rule. In this way, it was possible to include symbol knowledge with the quantitative information obtained and thereby allow an operator to determine the system behaviour or diagnose faults within the system using a simple rule based (IF-Then) system based on expert knowledge [15][16][17].

Fig. 4 shows a neural network with sensors providing input information obtained from a crude distillation process.



**Fig. 4.** Input neurons of sensors.

In the ANN, the input neuron in each layer represents each sensor input. That is information obtained about the crude distillation process. That represented by

Sx1+ represents input data for 1, Sx2+ = 2 and Sx3+ = 3

Sy1+ represents input data for 1, Sy2+ = 2 and Sy3+ = 3

Sz1+ represents input data for 1, Sz2+ = 2 and Sz3+ = 3

1. **Fuzzy Logic**

Fuzzy systems are based on fuzzy set and fuzzy logic theory [27] [28]. Fuzzy logic can be used within fuzzy systems, fuzzy rule based systems or fuzzy inference systems and it is formulated upon fuzzy logic theory. Fuzzy logic is a platform which provides knowledge for control systems. It considers the logical variables with truth-values between True and False statements. Fuzzy logic is a multi-valued concept used to handle concepts of partial truth, with truth-values taking real number between 0 and 1.

1. **Neuro-Fuzzy System**

A neuro-fuzzy system mimicked human thinking and that made it easier to understand the neural architecture of a system. But when there were large input and output data sets feeding into the network, it became difficult to obtain a rule base for a large monitoring system. Using a combined neural network and fuzzy logic system could address some of these problems and strengthen refinery operation process monitoring by utilizing their individual strengths and thereby overcoming some short comings.

One of the most common neuro-fuzzy systems is Mamdani’s method. The neuro-fuzzy model explained in this framework combined both numerical attributes and symbol knowledge of the crude refinery process. Three linguistic terms were introduced to explain sensor output priority; Low, High and Emergency; the terms used to differentiate the severity of fault detection of the process.

If X1 is X1x and X2 is X2x and …Xn is Xnx

Then:

Y is Yy (4)

Where X1, X2, , Xn represents system inputs and y represents output, Xziz with z=1,2,…., n and Iz=1,2,…, 1z represents the linguistic values of the output, with each linguistic variable Xu described by lk linguistic values Xz1, Xz2, …, Xzn.

Fig. 5 shows the four different layers of the neuro-fuzzy network. Layer 1 comprises of input variables for each node. Layer 2 represents the Membership Function layer where each node from layer mapping connects each input X1 to every Membership Function Xiy to the linguistic values of that input variable. Layer 3 is called the Rule layer, because it performs precondition matching using conditional statements to draw up (IF-Then) fuzzy rules and the weights of this layer were set to 1. Layer 5 is the output nodes, with each node acting as a defuzzifier. Integration of each activation function chosen for each function to perform specific operations in a fuzzy inference engine [18].

Layer 4:

(Defuzzification layer)

Layer 3:

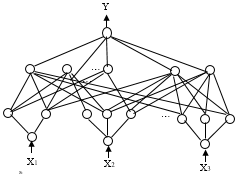
(Rule layer)

Layer 2:

(Membership function layer)

Layer 1:

(Input)



**Fig. 5.** Neuro-Fuzzy network for fuzzy model implementation.

1. **Data Collection and Feature Extraction**

The sensors contributing to the monitoring system found in a crude distillation process were identified (Table 1). These sensors played an important part in a monitoring system in a refinery and in other process monitoring systems. The sensor data measurements were obtained by observing the process. Other factors such as classification challenges and factors that trigger possible false alarms when detecting faults were considered.

**Table 1.** List of monitoring sensors.

|  |  |
| --- | --- |
| No (s) | Description |
| 1 | Temperature sensor |
| 2 | Pressure sensor |
| 3 | Level Control |
| 4 | Reboiler pressure Gauge |
| 5 | Temperature at Furnace |
| 6 | Control Valve |
| 7 | Pump Gauge sensor |
| 8 | Feed Flow |

A summarised data set were extracted from the data of each sensor comprising of numerical parameters referred to as features (Table 2). The input data of each sensor was the feature vector which determined the outcome of the output variable referred to as the label.

**Table 2.** Sensor parameter readings.

|  |  |  |  |
| --- | --- | --- | --- |
| No (s) | Description | Set points | Units |
| 1 | Temperature at Column | 135 | (C⁰) |
| 2 | Temperature at Reboiler | 137 | (C⁰) |
| 3 | Temperature at Reflux | 70 | (C⁰) |
| 4 | Temperature at Furnace | 356 | (C⁰) |
| 5 | Pressure at column | 0.69 | (Kg/cm3) |
| 6 | Reboiler Pressure | 150 | (Kpa) |
| 7 | Level Control | 40 | (%) |
| 8 | Reflux rate | 300 | (kmol/sec) |
| 9 | Feed Flow rate | 100 | (gpm) |
| 10 | Valve Control | 0n/Off | - |
| 11 | Pump | 0n/Off | - |

1. Method

Unstructured data were obtained from a refinery process (Crude distillation column). These were data from sensor readings. The information was unstructured because the information could be in form of sound alarms, log messages and signals which did not have real data structure.

To obtain a more useful dataset, some factors were considered and implemented in this study including:

* Categorization of data set.
* Identifying patterns in data.
* Assigning numerical attributes to the dataset.

Data from a crude distillation process were obtained using sentiment analysis in event process operation by combining readings from sensors in the process.

1. Results

Sensor readings were categorized into variables (below, within and above) as shown in Table 3. The results presented in Table 4 considered three sensors and the features extracted from a refinery process. A matrix of two sensors decreased the accuracy of fault detection and prediction and led to a lower level of performance. A more optimal approach using three sensors was created. A trend involving the accurate combination of different sensors can be seen in Table 4 and the effect of these sensor combinations in the refinery process were used in classifying data.

**Table 3.** Parameter readings.

|  |  |  |
| --- | --- | --- |
| Sensor | Parameter readings | Value |
| Feed Flow (FF) rate (gpm) | Below Range | 80.0 |
| Within Range | 100.0 |
| Above Range | 120.0 |
| Temperature at Column (TC)  (C⁰) | Below Range | 120.0 |
| Within Range | 135.0 |
| Above Range | 150.0 |
| Level Control (LC)  (%) | Below Range | 20 |
| Within Range | 40 |
| Above Range | 1060 point, italic |

**Table 4.** Matrix of 3 sensors.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| No (s) | Feed Flow (FF) Rate  (gpm) | Temperature at Column (TC) (C⁰) | Level Control (LC)  (%) | Result |
| 1 | 100.0 | 135 | 40.0 | Low |
| 2 | 100.0 | 135 | 20.0 | Low |
| 3 | 100.0 | 120.0 | 20.0 | Low |
| 4 | 80.0 | 120.0 | 20.0 | Low |
| 5 | 80.0 | 120.0 | 60.0 | High |
| 6 | 80.0 | 150.0 | 60.0 | High |
| 7 | 120.0 | 150.0 | 60.0 | High |
| 8 | 120.0 | 150.0 | 40.0 | High |
| 9 | 120.0 | 135.0 | 20.0 | Low |
| 10 | 100.0 | 120.0 | 60.0 | High |
| 11 | 80.0 | 150.0 | 20.0 | Moderate |
| 12 | 120.0 | 120.0 | 40.0 | Moderate |
| 13 | 100.0 | 120.0 | 40.0 | Low |
| 14 | 80.0 | 150.0 | 40.0 | High |
| 15 | 120.0 | 100.0 | 60.0 | High |

The neuro-fuzzy output information were represented using a rule-based classifier to draw up rules (IF – THEN statements) using expert knowledge as summarised in Table 5.

**Table 5.** Rules for three sensors.

|  |  |  |
| --- | --- | --- |
| No (s) | Rules | Priority |
| 1 | IF Feed flow rate within range AND Temperature at column within range Level AND within range | Low risk |
| 2 | IF Feed flow rate within range AND Temperature at column within range AND Level below range | Low risk |
| 3 | IF Feed flow rate within range AND Temperature at column below range AND Level below range | Low risk |
| 4 | IF Feed flow rate below range AND Temperature at column below range AND Level below range | Low risk |
| 5 | IF Feed flow rate below range AND Temperature at column below range AND Level above range | High risk |
| 6 | IF Feed flow rate below range AND Temperature at column above range AND Level above range | High risk |
| 7 | IF Feed flow rate above range AND Temperature at column above range AND Level above range | High risk |
| 8 | IF Feed flow rate above range AND Temperature at column above range AND Level within range | High risk |
| 9 | IF Feed flow rate above range AND Temperature at column within range AND Level below range | Low risk |
| 10 | IF Feed flow rate within range AND Temperature at column below range AND Level above range | High risk |
| 11 | Feed flow rate below range AND Temperature at column above range AND Level below range | Moderate risk |
| 12 | Feed flow rate above range AND Temperature at column below range AND Level within range | Moderate risk |
| 13 | Feed flow rate within range AND Temperature at column below range AND Level within range | Low risk |
| 14 | Feed flow rate below range AND Temperature at column above range AND Level within range | High risk |
| 15 | Feed flow rate above range AND Temperature at column within range AND Level above range | High risk |

1. **Conclusion**

This paper studied the process of diagnosing faults in a petroleum refinery. Neuro-fuzzy methods were applied, and the residual generation and classification of faults using a fuzzy inference system was used to create fuzzy set of rules based on expert knowledge.

This study showed that combining a neural network and fuzzy systems could produce a better result, especially for diagnostic results. Sensor information from a petroleum refinery process (Crude distillation column) was used in sensor fusion. Firstly, monitoring sensors were identified as described in Table 1. Then a parameter value for each sensor reading was obtained (Table 2) and data pre-processing was performed using categorization, pattern recognition of data and assigning numerical attributes. Results for three sensors were categorised into three linguistic variables (below, within and above) as shown in Table 3. It was discovered that using fusion for two sensors decreased the accuracy of fault detection and prediction. Focus was placed on to fusion for three sensors for a more optimal approach (Table 4).

Using neuro fuzzy feature extraction output information, a fuzzy set of rules was created using IF – THEN statements and a conceptual priority was assigned (Low, Moderate and High) to describe each output.

Future work will use trend analysis and investigate a more suitable approach for feature selection of sensor data.

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