# Fault Detection System in Gas Metering Station Using Neural Network

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***Abstract*—This research study focuses on the discussion regarding the development of fault detection in gas metering station using an Artificial Neural Network (ANN). The proposed model of fault detection applies ANN approach in order to provide a good detection method for billing purpose. However, one of the main problems faced by gas metering system is the undiagnosed faulty condition of measurement. Moreover, there are many researches regarding the Fault Detection and Diagnosis (FDD) that were conducted to enhance the reliability of the system in the plant process. Therefore, in order to address this issue, fault detection system using neural network is proposed to detect the fault data in the measured readings. The investigation of all faulty instruments was obtained from the detection model which was selected based on the performance of different ANN algorithms. Since, the artificial intelligence, such as neural network is one of the powerful tools in detecting and diagnosing the fault occurred. The ability of the neural networks to learn from the experience or past data has shown a great impact in the fault detection efficiency. Furthermore, such method based on the past data has also been established to improve the accuracy of the fault detection.**

**Index Terms—first neural network, fault detection, gas metering, fault diagnosis**

## I. Introduction

A reliable performance and quality of the metering station plays a crucial role in gas transportation system as it affects the billing integrity between the gas supplier and their customers. The incorrect value of data from the instrument can affect the credibility of the supplier that might result in customer dissatisfaction. As revealed by the internal findings, one of the key reasons was the error in energy value that was not examined thoroughly before the bills were sent to the customers. In the proposed fault detection system, the faulty instruments will be detected so that the customers could be submitted with the correct version of their bills [1].

The accurate measurement of turbine meter, temperature transmitter and pressure transmitter essentially affects the accuracy of the billing integrity process. All instruments are expected to provide and transmit reliable data to the flow computer for monitoring the gas flow and billing calculation. In this the research, one of the gas metering stations was investigated in Malaysia and the data were analyzed in order to improve the system. Basically, a metering system consists of turbine meter, measuring devices (i.e., pressure transmitter, temperature transmitter), gas chromatography and flow computer. This metering system provides the user's energy consumption [2].

Typically, during this process, there are some common unavoidable faults that might occur in instruments such as shutdown fault, hang fault and drift fault. However, the main concern here is when instruments experience a fault, the values of the readings from instruments become unreliable and this directly affects the calculation of energy consumption. In this situation, currently there is not a single innovative and advanced system exist that is capable of performing auto-correction of data during malfunctioning, as well as no fault detection system to detect and isolate the different types of fault. Thus, by having a model to detect the fault for further correction can greatly improve the reliability and availability of the metering system. In order to achieve the objectives, an intellectual approach based on the neural network is proposed to provide an appropriate fault detection model. This model will be used to detect the faulty data as well as to determine the type of faults. This fault detection system will also help the distributors to provide a reliable system to ensure the integrity of the metering system and profit to the company.

This research study is organized as follows. The development of a fault detection system based on neural network is presented in the Section 2. Moreover, in Section 3, the computational simulation is performed to illustrate the efficiency of the proposed algorithm. Finally, the conclusion of this research is provided in the Section 4.

## II. Fault Detection and Diagnosis

The detection of fault at an early stage is very crucial to maintain the reliability of the system so that the fault diagnosis strategy can be developed to perform the corrective measures for the data in any system for future consistency. In the process of monitoring and detecting the fault, efficiency and robustness are the main concerns for billing integrity. There are several methods that can be undertaken to perform fault detection and diagnostic

Manuscript received January 13, 2015; revised April 23, 2015.

©2016 Int. J. Electron. Electr. Eng.
doi: 10.18178/ijeee.4.1.52-55

(FDD). As stated in [3], FDD techniques can be divided into two parts, which are model based and data driven method. For a simple plant, the mathematical model can easily be formulated by utilizing basic fundamental laws and characterizing all the potential operational phenomena [4], [5]. This model based technique can be further expanded to qualitative and quantitative methods. Nowadays a lot of plants have been built with complex control system, where it is quite hard to reach the exact mathematical model for the system. Therefore, data driven techniques appear to be more efficient in developing a fault detection strategy. This technique uses historical data of the plant, in addition to the past information about the plant behavior. By implementing data driven approach, the data can be manipulated in several ways, according to the desired objective of FDD.

In this study, Artificial Neural Network (ANN) is proposed as a core component of the system because of its ability to model the behavior, together with describing the relationship between instruments. In other words, based on the classification of diagnostic algorithms, Neural Network is a history based process lies under quantitative method as a function of a fault detection system which uses the neural network model, for not only to detect the faulty data but also to validate the metering instrument's reliability to produce highly accurate billing reports. Other applications can also be reviewed in reference [6], [7].

### A. Neural Network

Neural networks are widely used in novelty detection and classification [8]. In designing the detection model, the system must have the capability of learning the given historical data effectively. The main aspect of the detection model is its ability to recognize the data fault and to classify the type of data fault in a short term load of large process system. Therefore, Artificial Neural Network (ANN) method is proposed to be the intelligent detection model to control the highly uncertain system of non-linear process or behavior. In developing a reliable and robust ANN system, the factors that affect the model's performance are model inputs, data pre-processing, parameter estimation and model validation [9]. Besides, there are several classifications of network architectures; such as Single-Layer Feedforward Networks (SLN), Multilayer Feedforward Networks also known as Multilayer Perceptron (MLP) and Recurrent Networks (RN). The features, operation and application of gas metering system have been explained in detail in reference [10].

Generally, the MLP is considered as the most popular and fastest network architecture. In addition, the basic form of multilayer feed-forward architecture is still most popular for load forecasting applications [11]. In fact, the MLP is relatively suitable architecture for the ANN model, which in engineers' view is proven to be the most significant factor in producing good quality product as presented in this study.

## III. Result and Analysis

### A. Data Gathering and Analysis

The data were collected from the instrument of gas metering station which is pressure, flow and volume. This experiment involved 6373 samples of data which is equivalent to a one-year of sampling data. For data analysis, the healthy and faulty data have been separated so that only the faulty data should be evaluated.

These data samples are divided into two categories, which are healthy data and fault data. The data have been further divided into several classes with respect to their frequencies as shown in Table I.

TABLE I. Frequency of Data Distribution in Measuring Instrument

| Data Classes | Type of Data | Description of Data | No of Data |
|---|---|---|---|
| 1 | Normal | Healthy data that operates within the operating range and does not classify by other type of faults | 5788 |
| 2 | Shutdown | Supervision system reads zero value from instruments when the plant is running | 12 |
| 3 | Out of range | The data lies in the range where it exceeds the allowable limit of operating range | 21 |
| 4 | Hang | The readings show a constant value for the next sampling data | 552 |

After the collection of data, each parameter reading was analyzed manually. The distribution of fault data with respect to their parameter is shown in Table II. The fault data have been separated based on three classes of faults where they can clearly be observed through the data set. The hang fault shows the highest frequency occurred in temperature and pressure measurement, while the missing fault occurred in all parameters. The percentage of fault data over available data is about 9.18%. This result shows the fault condition was happened in gas measuring instrument

TABLE II. Distribution of Fault Data for Each Parameter

| Parameter | Hang | Shutdown | Out of range |
|---|---|---|---|
| Temperature | 551 | 2 | 0 |
| Pressure | 562 | 2 | 6 |
| Volume | 0 | 8 | 21 |

### B. Development of ANN Model for Fault Detection

The method of gathering the data was crucial in presenting the input to the network that could process the data. Later on, all inputs were scaled or normalized to the range of [-1, 1] to have reasonable maximum and minimum values for each input type. Then, the one year data of 6373 were trained and validated in this experiment. Based on Table III, the best data division is 50% of the data as the training set and the remaining 50% of data is for the validation set as it provides the least value of root mean square error (RMSE) as in (1).

TABLE III. DATA DIVISION OF ANN MODEL

| Data division | Training Data (RMSE) | Validation Data (RMSE) |
|---|---|---|
| 25 % Training, 75 % Validation | 29.546 | 46.254 |
| 50 % Training, 50 % Validation | 33.908 | 36.554 |
| 75 % Training, 25 % Validation | 44.525 | 34.142 |

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_p - y)^2} \tag{1}$$

Furthermore, a few optimization parameters were taken into account such as the weights, number of hidden layer and nodes and the number of input variables. The backpropagation learning method of the network was chosen as it most frequently used in network training. A variety of input combinations were investigated based on the sequential forward method [12], and the performance of the model is defined in the result section.

The training of the network is an iterative process and it stops the process once the validation performance goal is achieved. The network calculates the output, while weight and error have repeatedly been adjusted until all targets are reached. MLP is the selected architecture to be simulated due to its good performance and fairly low percentage of errors between the actual and theoretical data [13], [14].

The neural network model trained by the MLP network used the mode of trial and error to get the best parameter of the network. Table IV shows the performance of neural network model based on percentage error of training and validation data.

TABLE IV. THE PERFORMANCE OF NEURAL NETWORK MODEL

| No of neurons | No of epoch | Training data (percentage error) | Validation data (percentage error) |
|---|---|---|---|
| 1 | 47 | 7.91 | 16.16 |
| 2 | 119 | 8.00 | 9.18 |
| 3 | 87 | 8.12 | 11.27 |
| 4 | 19 | 8.04 | 10.67 |
| 5 | 243 | 8.11 | 10.19 |
| 6 | 175 | 8.20 | 10.20 |

The neural network model chooses the best performance that provides the least percentage of errors in the training and validation data. Therefore, the best training parameters for this neural network model are having two neurons and one hidden layer with *the trainlm training algorithm*. For the purpose of fault classification, the artificial neural network for pattern recognition is used. This type of neural network is capable of classifying the data according to their attributes that can be belonged to certain classes.

Firstly, the network is trained by isolating the healthy and faulty data. The errors between the target class and actual class are small. In the confusion matrix as shown in Fig. 1, the output of the training data is being compared with the actual target class data.

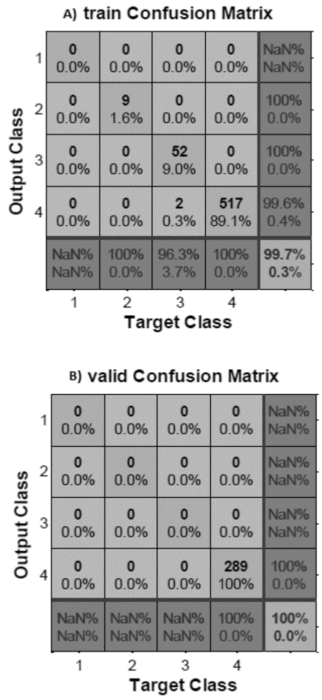


Figure 1. Confusion matrix A) training B) validation

The diagonal cell shows the data which correctly matches to the corresponding target class. The overall percentage of classification is 99.7%. Moreover, the next step is to simulate the network in the presence of healthy data to test whether the network can correctly recognize the fault. This result is shown in Table V. Here, shutdown fault and hang fault are correctly classified, where they demonstrate the percentage match of above 90%, while the out of range only classify 96.2 % of the fault. Thus, it can be said that after integrating the both healthy and unhealthy data, the model is still able to classify the types of fault in an almost accurate manner. The neural network model is then being simulated with another set of data to verify its functionality and tests for robustness.

TABLE V. FAULT CLASSIFICATION OF OVERALL DATASET

| Fault Type | Shutdown | Out of range | Hang |
|---|---|---|---|
| Match | 9 | 52 | 1095 |
| Mismatch | 0 | 2 | 0 |
| Percentage of match (%) | 100 | 96.2 | 100 |

In summary, based on Table V, the percentage of classification with respect to each class for overall data set provides high accuracy of classification which is 96.2%. Thus, artificial neural network with pattern recognition is capable in classifying the types of fault, even though it is being trained and simulated with healthy data. Hence, it obviously appears from the evidence that the proposed fault detection system can be used to detect and classify fault data.

## IV. CONCLUSION

Overall, the neural network technique is proposed in this paper to detect the fault over the years. This application has increased the reliability of the systems and eventually reduced the major loss of equipment and profit. Numerous past researches proved that there are several methods which can make the fault detection considerably easier. In this study, it has been substantiated that an artificial neural network can classify the faults according to their respective classes which is 99.7% error in training data. For the future continuation of this project is to implement the proposed algorithm to the fault diagnosis strategy. The fault diagnosis can be modeled by using intelligent approach which is neural network or another statistical method. Therefore, the best method will be selected based on the best performance result produced. Last but not least, better detection techniques can improve the time span as well as the accuracy of the detection

## ACKNOWLEDGMENT

The authors gratefully acknowledge support from Universiti Teknologi PETRONAS (UTP) and PETRONAS Gas Berhad (PGB).

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