STUDY OF ARTIFICIAL NEURAL NETWORK SCHEME APPLICATION IN MANUFACTURING INDUSTRY FOR MONITORING-DIAGNOSIS BIVARIATE PROCESS VARIATION

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A thesis submitted in
fulfillment of the requirement for the award of
Degree of Master of Mechanical Engineering

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DECEMER 2014
ABSTRACT

In manufacturing industries, process variation is known to be a major source of poor quality. As such, process monitoring and diagnosis is critical towards continuous quality improvement. This becomes more challenging when involving two or more correlated variables (multivariate). Process monitoring refers to the identification of process status either it is running within a statistically in-control or out-of-control condition, whereas process diagnosis refers to the identification of the source variables of out-of-control process. The traditional statistical process control (SPC) charting schemes are known to be effective in monitoring aspect. Nevertheless, they are lack of diagnosis. In recent years, the artificial neural network (ANN) based pattern recognition schemes have been developed for solving this issue. The existing schemes are mainly designed for dealing with fully completed process data streams. In practice, however, there are cases that observation data are incomplete due to measurement error. In this research, an ensemble (combined) ANN model pattern recognizer will be investigated for recognizing data streams process. Each model consists of different input representation, namely, raw data and statistical features. The raw data of representation generate by manufacturing industry as a real data. The proposed ensemble ANN scheme would provide better perspective in this research area.
ABSTRAK

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CHAPTER 1

INTRODUCTION

1.1 General Introduction

The manufacturing industry faces numerous challenges in today’s marketplace. Manufacturing takes turn under all types of economic systems. In a free market economy, manufacturing is usually directed toward the mass production of products for sale to consumers at a profit. In recent year in manufacturing industries, process variation is known to be a major source of poor quality and it encourage the system introduce machine learning where define as a set of methods that can automatically detect patterns in data, and then use the uncovered patterns to predict future data, or to perform other kinds of decision making under uncertainty. As such, process monitoring and diagnosis is critical towards continuous quality improvement. When learning systems are placed at the core, interactive services in rapidly changing and statistical model need to be combined with ideas from control. The adaptive itself describe with the different meanings, which is adaption of an organism to environment and also development of anatomic structure. To ensure a stable quality, each manufacturing step needs to be repeatable by keeping it within defined specification and will costly time limit. Rather than that, industry needs the capable system to detect the defect at early stage before it over shifted.
1.2 Statement of the Problem

The study related in manufacturing industries into process monitoring and diagnosis of critical to quality (CTQ) parameters. For example, the size and position of inner diameter are two correlated CTQ parameters for a precision bearing. Process monitoring refers to the identification of process status either it is running within a statistically in-control or out-of-control condition, whereas process diagnosis refers to the identification of the source variables of out-of-control process. In order to maintain and improve the quality level, effort towards minimizing process variation in manufacturing environment has become an important issue in quality control. The average (X-bar) and (R-bar) control charts are the well-known and the most popular tools for detecting out-of-control signal in the Statistical Process Control (SPC). This control charting scheme is focused in dealing with univariate (single) CTQ parameters. The process of experiment will conduct using real data of manufacturing process on selected cases available.

In the related study, there are the cases where two correlated CTQ parameters need to be controlled jointly, as mentioned above, in manufacturing of precision bearing. The traditional multivariate SPC charting schemes are known to be effective in monitoring aspect. Nevertheless, they are lack of diagnosis. In recent years, the artificial neural network (ANN) based pattern recognition schemes have been developed for solving this issue. The existing schemes are mainly designed based on generalized (single) ANN model pattern recognizer. In this research, a synergistic ANN model pattern recognizer was investigated. This model consists of different input representation, raw data and statistical features, which were utilized in training the parallel combination of twin ANN model. Since the initial study focused on development of the scheme, further verification using real industrial data was performed to validate its effectiveness in fault diagnosis towards continuous quality improvement.
1.3 Project Objectives

The objectives of this research are:

i. To develop a Synergistic-ANN pattern recognition scheme for monitoring and diagnosis manufacturing process defect. In particular, the development process involves artificial data.

ii. To evaluate the effectiveness of the scheme in dealing with real process data.

1.4 Project Scopes

The scopes through this research are:

i. Magnitudes of mean shifts in the source variables are limited within $\pm 3$ standard deviations based on control limits of Shewhart control chart.

ii. The validation tests are performed using industrial data process as stated in Chapter 3.
CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The history of industrial manufacturing started from the 18th century until the present. What make differ it apart are in terms of technology used and quality level of satisfaction obtained. Since then, the production of quality products is emphasized in order to ensure the continuous stability of marketing. The use of technology which is more sophisticated gain built up researchers seeking for the different kind of method that can give good condition level from time to time. The concerns from industry into this problem much consider rather than cost and reliability. There are different kinds of product damages in manufactured prior to approval by the quality control. This type of damage often occurs or identified after almost all of the products had been produced. Generally, percentage of the product quality decrease due to system reputation. Artificial Intelligence (AI) is one of the machine learning exhibits by machines or software. It defines goal as making machines do things that would require intelligence if done by humans; Negnevitskyl (2011) stated that many of the problems that AI attempted to solve were too broad and too difficult. A typical task for early AI was machine translation. The types of AI are expert systems (ESs), fuzzy systems (FSs), artificial neural network (ANN), genetic algorithm (GA) and decision tree. ESs is define as a one of the computer program that use AI to solve problem with domain, knowledge base that requires human expertise providing explanations and justifications of solution to convince the user. The other types of AI system is Fuzzy well known as FSs, to realize a complex non-linear input-output (described in each rule) relation as a synthesis of multiple simple input-output relations.
The GA represents solutions for chromosomes with a genotype and searches for the best solution using GA operation of selection, crossover and mutation. Chromosome is a structure of deoxyribonucleic acid (DNA), protein and ribonucleic acid (RNA) found in cells. The crossover operation is the dominant operator. Decision trees have three kinds of nodes and two kinds of branches. A decision node is a point where a choice must be made; it is shown as a square. The branches extending from a decision node are decision branches, each branch representing one of the possible alternatives or courses of action available at that point. In general, decision nodes and branches represent the controllable factors in a decision problem; event nodes and branches represent uncontrollable factors.

In addition, ANN contains neurons which function to output pulses according to the sum of multiple signals from other neurons with the characteristics of a pseudo-step function. In this research, it more focus on ANN application in monitoring and controlling process variation when incomplete data was found. Detecting error at early phase is compulsory to avoid rework and waste materials.

2.2 Traditional Approach of Statistical Process Control

In manufacturing process, product demand from the third parties increased in line with the current development. The target value usually becomes priority to achieve the goal. Thus, it infuses to propose an approach system that will avoid the maximum waste of product. The systems are Statistical Process Control (SPC) to monitor and control a process, so that it can lead to reduction in the time required to produce product. Based on the Yu and Xi (2009) methods, the SPC is one of the most effective tools of total quality management (TQM), which is used to monitor and minimize the process variation. Control charts are the most widely applied SPC tools used to reveal abnormal variation of monitored measurements. SPC had been use in manufacturing process and non-manufacturing process of Health Care and Software Engineering sector. Many businesses use univariate (SPC) in both their manufacturing and service operations.
Automated data collection, low-cost computation, products and processes designed to facilitate measurement, demands for higher quality, lower cost, and increased reliability have accelerated the use of univariate SPC (MohanaRao et al., 2013). Generally, SPC is defined as the application of statistical techniques to control a process. SPC is concerned on conformance to standard. There are a number of tools available to the quality engineer that is effective for problem solving process. The seven quality tools are relatively simple but very powerful tools which every quality engineer should aware. According to Juran and Gryna (1998), the SPC tools consists of:

- Flow chart
- Run chart
- Process control chart
- Check sheet
- Pareto diagram
- Cause and Effect diagram
- Scatter diagram

The control charts can detect whether the manufacturing process is in control or not. If it is out-of-control, one has to find out the assignable causes and remove them. A process that operates with only common cause variability, which is define as the remainder of the variability after every component of special cause has been removed is said to be in-control while, a process that operates in the presence of special causes of variability is said to be out-of-control. Figure 2.1 show a typical control chart that are usually straight lines that stand for the upper control limit (UCL) the center line (CL) and the lower control limit (LCL) (Cheng, 2011). As the line connecting the sequence does not cross the UCL or LCL, stated that it is in under control. But, when a point is plotted outside these limits, we assume that the process is out-of-control and need to remove. For a given sample size n, the upper control limit, centerline and lower control limit of the control chart would be:
Center Line = \( b_1|\Sigma_0| \)

\[ \text{UCL} = |\Sigma_0| \left( b_1 + 3\sqrt{b_2} \right) \quad (2.1) \]

\[ \text{LCL} = |\Sigma_0| \left( b_1 - 3\sqrt{b_2} \right) \]

where, \(|\Sigma_0|\) is the determinant of the in-control covariance matrix. The coefficients \( b_1 \) and \( b_2 \) are computed as:

\[ b_1 = \frac{1}{(n-1)^p} \prod_{i=1}^{p}(n - i) \quad (2.2) \]

\[ b_2 = \frac{1}{(n-1)^{2p}} \prod_{i=1}^{p}(n - i) \left( \prod_{j=1}^{p}(n - j + 2) - \prod_{j=1}^{p}(n - j) \right) \quad (2.3) \]

Figure 2.1: A typical X-bar Control Chart
The most common types of variable control charts for variables include:

- Average and Range (X bar and R) Charts
- Average and Standard Deviation (X and S) Charts
- Individual and Moving Range (X and MR) Charts.

2.3 **Univariate Control Chart**

Control charts are constructed to decide whether a process is under statistical control and to monitor any departures from this state. This means that stability of some process properties over time is tested using certain statistical assumptions about the process (data it produces). Subsequently, the properties of mean, variance (standard deviation), distribution shape or proportion of nonconforming items are considered into the process. There are few types of control charts that had been developed, which are Shewhart, Cumulative Sum (CUSUM), Average Run Length (ARL) and Exponentially Weighted Moving Average (EWMA) also will be elaborate through this section. Shewhart chart cannot detect the small shift and sensitive to large process shift. Then, for the CUSUM the shift was easily detected and effective for the small shift, but it is not as fast as in Shewhart.

In order to improve the performance for detecting small deviations in process mean shifts, multivariate cumulative sum (MCUSUM) and multivariate exponentially weighted moving average (MEWMA) control charts were then developed based on logical extension of CUSUM and EWMA control charts, respectively (Masood and Hassan, 2012).
2.3.1 Shewhart Control Chart

The most known control charts are the Shewhart type control chart. They owe their name to Walter Shewhart who established them in his pioneering work in 1931 based on monitoring events. If there is any alarm signal, it suggesting that stability of the process was broken and the process changed. The situation is when the control limits (UCL or LCL) are exceeds with only one point. UCL is a value that indicates the highest level of product quality, while LCL is the lowest level limit of quality. Another terms use is CL that represents the mean value for the in-control process. These terms of control limit was plotted in simple way as shown in Figure 2.2 The control limits use the range of variability for quality specifications. The rules of Shewhart control chart is the nine points must be above or below the central line rather than when six consecutive points shown increasing or decreasing trend.

Through this Shewhart control chart, it will divide into 2 section of X bar chart and R chart. According to Mendenhall and Sincich (2007), control chart contains a center line, an upper control limit and a lower control limit. The point that plots within the control limits indicates the process is in control. In this condition no action is necessary.

![QUALITY CONTROL CHART](image)

Figure 2.2: Graph of Control Limit

Point that is plotted outside the control limits is evidence that the process is out-of-control. In this condition, investigation and corrective action are required to find and eliminate assignable cause(s). The Shewhart's X bar chart consists of plotting the values
of the sample mean of size $n$ on a control chart with upper and lower control limits (UCL and LCL) usually computed following a statistical criterion. These Shewhart suggested employing the 3-sigma criterion of:

$$UCL = m_0 + 3(\sigma_0 + \sqrt{n})$$

$$UCL = m_0 - 3(\sigma_0 + \sqrt{n})$$

First section of the Shewhart is the X bar chart Chart with CL, UCL and LCL. It is applied to monitor a quantitative quality characteristic base on random samples of several units of the product rather than on the characteristic of individual industrial units (Mendenhall and Sincich, 2007). The lower and upper control limits for the X bar chart are calculated using the formula:

$$Center Line = \bar{x} = \sum_{i=1}^{k} \bar{x}_i$$

$$UCL = \bar{x} + m \left( \frac{\sigma}{\sqrt{n}} \right)$$

$$LCL = \bar{x} - m \left( \frac{\sigma}{\sqrt{n}} \right)$$

When subgroup size is one, the control limit becomes:

$$UCL = \bar{x} + m\sigma$$

$$UCL = \bar{x} - m\sigma$$

Where, it given:

- $k = \text{samples number}$
- $\bar{x}_i = \text{samples mean}$
- $\sigma = \sqrt{MSE}$, Mean Square Error
Second section is R chart, as it increased in the process standard deviation $\sigma$ means that the quality characteristic variable will vary over a wider range, thereby increasing the probability of producing an inferior product (Mendenhall and Sincich, 2007). The lower and upper control limits for the range chart are calculated using the formula:

\[ UCL = R_e + m d_3 \hat{\sigma}_x \]

\[ LCL = R_e - m d_3 \hat{\sigma}_x \]

Given that:

- $m$ = multiplier to reduce the possibility of false alarms
- $d_3$ = constant depend on $n$
- $d_3 = \sigma_R / \sigma_x$
Figure 2.3: X-bar, R control chart
2.3.2 **Cumulative Sum (CUSUM)**

Cumulative sum (CUSUM) charts for attributes data were proposed at early stage in the development of statistical process control. These charts measure a cumulative deviation from the mean or a target value. Depending on the type of test used, the chart either displays the standardized deviation from the target or the mean value of the subgroup size. The CUSUM chart is very effective for small shifts and when the subgroup size \( n = 1 \). Therefore, Montgomery (2009) also stated that CUSUM charts are effective even with rational subgroups of size one which makes them an attractive option for many applications in chemical and process industries. The advantage of CUSUM is relatively slow to respond to large shifts but, got the special patterns are hard to see and analyze. It is considerably more effective over the whole shift domain instead of widely used for the efficient monitoring of internal quality control parameters and in analytical laboratories (Abbasi *et al.*, 2012).

2.3.3 **Average Run Length (ARL)**

The most effective means known for issuing out of control signal based on process monitoring data is ARL. The Average Run Length (ARL) at a given quality level is the average number of samples in subgroups taken before an action signal is given. In order to determine the parameters of a CUSUM chart, the acceptable and rejected quality levels along with the desired respective ARLs are usually specified. It is the expectation of the time before the control chart gives a false alarm that an in-control process has gone out-of-control. The equation of ARL for the process-monitoring scheme is:

\[
ARL = \mu T
\]  

(2.8)

where,

\( T \) = the period at which a process-monitoring scheme first signal also as run length distribution.
The ARL is possible to illustrate the meaning and usefulness based on the situation:

i. The process-monitoring scheme employs only the single alarm rule "signal the first time that a point Q plots outside control limits,"

ii. It is sensible to think of the process as physically stable (though perhaps not at standard values for process parameters).

The value of $Q_1, Q_2, Q_3, \ldots, Q_n$ can be modeled as random draws,

$q = P[Q_i \text{ plots outside control limit}]$

and will prove useful,

$$\text{ARL} = \frac{1}{q}$$
2.3.4 Exponentially Weighted Moving Average (EWMA)

In 1959, Roberts introduced the exponentially weighted moving average (EWMA) control scheme. EWMA control charts and other sequential approaches like Cumulative Sum (CUSUM) charts effective in detecting small persistent process shifts (Montgomery, 2005). For monitoring the process mean, the EWMA control chart consists of plotting:

\[ Z_t = \lambda \bar{x}_t + (1-\lambda)Z \quad 0<\lambda \leq 1 \quad (2.9) \]

Where:

\[ \lambda = \text{constant} \]
\[ Z_0 = \text{equal to an estimate of the process mean} \]
\[ \bar{x}_t = \text{sample mean for the time period, t} \]

In quality monitoring applications, typical values for the weight \( \lambda \) are between 0.05 and 0.25, although larger values may be used in forecasting and control applications. In the limiting cases, with \( \lambda = 1 \), the EWMA chart is the same as a Shewhart X bar control chart. Using a EWMA chart, the process is considered out-of-control whenever the test statistic \( Z_t \) falls outside the range of the control limits. Commonly, (Sharaf El-Din 2006) mention that in “Statistical Process Control Charts Applied to Steelmaking Quality Improvement” the values of \( \lambda \) in the interval 0.05 ≤ \( \lambda \) ≤ 0.25 work well in practice, with \( \lambda = 0.05, \lambda = 0.10, \) and \( \lambda = 0.20 \) being popular choices.

\[ \bar{X}_i = \frac{1}{n} x_i + \frac{1}{n} x_{i+1} + \frac{1}{n} x_{i+2} + \ldots + \frac{1}{n} x_{i+n-1} \quad (2.10) \]

\[ Z_i = \lambda \bar{x}_i + (1-\lambda)Z_{i-1} \quad (2.11) \]

\[ Z_0 = \mu_0 \quad (2.12) \]
Center line = $\mu_0$

\[
\text{UCL} = \mu_0 + L\sigma \sqrt{\frac{\lambda [1-(1-\lambda)^2]}{(2-\lambda)}}
\]

\[
\text{LCL} = \mu_0 - L\sigma \sqrt{\frac{\lambda [1-(1-\lambda)^2]}{(2-\lambda)}}
\]

The plotting graph of EWMA control statistic as shown in the Figure 2.4. The solid line connects the EWMA values, and the individual observations are represented by X’s.

Figure 2.4: EWMA Control Chart
2.4 Bivariate Control Chart

Bivariate can be described as a simplest form of quantitative of statistical analysis that involve two variables; X and Y to determine the relationship between them. In other way, it is also able to measure how it changes together. The investigation of bivariate control chart was found out in Masood and Hassan (2012). This study mainly focused on two variables, well known as bivariate pattern recognition (BPR). From the studies, the existing BPR schemes revealed disadvantages in terms of reference bivariate patterns and excess false alarms. For the reference bivariate patterns, two approaches had been used using Shewhart and $T^2/\chi^2$ control charts. Another term that effects the process stability is the false alarm where it should be maintain at minimum rate. These disadvantages may cause limited scope and slow development in this area.

There are many situations in which a process is characterized by more than one quality characteristics. Multivariate control charts are best suited to monitor such processes. Most of the multivariate control charts are based on the assumption that the underlying distribution of the process is multivariate normal. In reality this assumption may not hold in all the situations. In such situations, development and application of control charts that do not depend on a particular distributional assumption is desirable. The Hotelling’s $T^2$ is an appropriate control chart to monitoring the process location when the process distribution is normal. The purpose of control charts are to be used for detecting shifts in the location of a bivariate process. In order to develop a nonparametric control chart for monitoring bivariate process location, Ghute and Shirke (2012) conducted the process based on signed-rank test statistic. The use of location $\mu$ and covariance matrix $\Sigma$ had been choosen for the sample. The performance of the proposed chart was improved by using the runs rule and the synthetic chart and compared with the parametric chart under the bivariate normal and the bivariate double exponential distributions.
2.4.1 Pattern Recognition

Over the years, most of the studies in control charts emphasized on the pattern recognition rather than the estimates of pattern parameters, such as shift magnitude, trend slope or cycle period, etc. In general, there are six various basic patterns of control charts namely normal, upward shift, downward shift, upward trend, downward trend and cycle. Several typical patterns that commonly occur in control charts are shown in Figure 2.5.

![Figure 2.5: Typical pattern in-control chart (Guh, 2010)](image)

Hachicha and Ghorbel (2012) found that the types of control chart patterns (CCPs) were 15 based on Western Electric Company, 1958. However only eight of them were used as basic CCPs as shown in Figure 2.6. Identification of unnatural patterns can facilitate early detection of an out-of-control process the typical unnatural patterns on control charts are defined in the following:

- Trends: A trend can be defined as a continuous movement in one direction (either upward or downward).
- Sudden shifts: A shift can be defined as a sudden or abrupt change in the average of the process.
Systematic variation: one of the characteristics of a natural pattern is that the point-to-point fluctuations are unsystematic or unpredictable. In systematic variations, a low point is always followed by a high one or vice versa.

Cycles: Cyclic behavior of the process can be recognized by a series of high portions or peaks interspersed with low portions or troughs.

Mixtures: In a mixture, the points tend to fall near the high and low edge of the pattern with an absence of normal fluctuations near the middle. A mixture is, actually, a combination of data from separate distributions.

Figure 2.6: Types of CCPs (Hachicha and Ghorbel, 2012)
2.4.2 Bivariate input representation

The raw data, statistical features, cobination between raw data and statistical features have been used as bivariate input representation. According to Zorriassatine et al. (2003), it used the raw data and the $T^2$-statistics as different input representations to evaluate the recognition performance of novelty detector-ANN recognizer. Then, the combination of the raw data and the $T^2$-statistics had been used by Guh (2007) in a series as input representation of the four-layered MLP neural network recognizers in the modular-ANN scheme. Bivariate input representation was also applied in the forms of means and combination between raw data and means or variances (Chen and Wang, 2004; Cheng and Cheng, 2008).

2.5 Artificial Neural Network

Artificial Neural Network (ANN) is networks of artificial neurons and hence constitutes crude approximations to parts of real brains. They could be physical devices, or simulated on conventional computers. The role of ANN is a computational networks which attempt to simulate in a gross manner and the networks of nerve cell; neurons of the biological either human or animal central nervous system. This simulation is a gross cell-by-cell (neuron-by-neuron, element-by-element) simulation (Graupe, 2007). In pattern recognition problems, ANN was applied from noisy or incomplete representations. The function is to model how the human brain processed visual data and learned to recognize objects. Thus, it operates by creating connections between elements, each analogous to a single neuron in a biological brain. The neurons are connected by weight links passing signals from one neuron to another. Each neuron receives a number of input signals through its connections but it never produces more than a single output signal Cheng (1997) stated the application of ANN to control chart include two approaches. The first uses neural networks to detect deviation in mean and variance.
The second approach uses the neural network to identify abnormal patterns on control charts consist of trend, shift, cycle and random as shown in Figure 2.7.

![Typical normal and abnormal patterns](image)

Figure 2.7: Typical normal and abnormal patterns (El-Midany et al., 2010)

### 2.5.1 ANN Development Process

In 1958, perceptron is the earliest computational model of ANN development. Serving a building block to most later models and possesses the structure as in Figure 2.8 shows a neural cell. ANN is capable of learning it is used to improve their performance. Then, it consists of a number of processors known as neurons, which are connected by weighted links passing signals from one neuron to another.

![Biological neural cell](image)

Figure 2.8: Biological neural cell
Figure 2.8 explains the outputs were connected with the inputs of dendrites, neuron of cell body, weight of synapse and output of axon. The neuron’s cell body (soma) processes the incoming activations and converts them into output activations. Dendrites are fibres which emanate from the cell body and provide the receptive zone that receive activation from other neurons while axons are fibres acting as transmission lines that send action potentials to other neurons. Yet, the units of several weighted inputs or cell or outputs are the perception, where the weighted are adjustable and provision for an output that is function of weighted input had been illustrates in Figure 2.9. The weights are the basic means of long-term memory in ANNs because they express strength of each neuron input. Many activation function used by neuron have been tested, but only a few found practical applications. The four common choices are the step, sign, linear and sigmoid function. All of these functions are illustrated in Figure 2.9. From the figure, the step and sign function also called hard-limit functions that are often used in decision-making neurons for classification and pattern recognition events. For the sigmoid functions, its transform the input, this can have any value between the range 0 and 1. These types of neuron usually use in back propagation network. The output equal to the neuron weighted input its providing the linear activation function.

Figure 2.9: A perceptron of artificial neuron (Graupe, 2007)
According to Guh (2008), most ANN applications in CCPR (Control Chart Pattern Recognition) have been using static supervised ANNs, such as back propagation networks (BPNs) as shown in Figure 2.10 and learning vector quantization (LVQ) networks as shown in Figure 2.11.

Figure 2.10: Architecture of a BPN for univariate and bivariate cases
The behavior of a neural network is determined by the transfer functions of its neurons, by the learning rule, and by the architecture itself. Once the network is trained and tested it can be given new input information to predict the output. In addition, ANNs can combine and incorporate both literature-based and experimental data to solve problems. The various applications of ANNs can be summarized into classification or pattern recognition, prediction and modeling.

2.5.2 Generalized-ANN Model

Generalized means that the architectures used in recognizer design is either raw data-based or features-based ANN and it was trained with back propagation. Then, each of the models has the numbers of layer respectively by using multilayer perceptron, MLP, where it has been proven effective for MQC (Guh, 2007). According to the book of Artificial Intelligence, 3rd edition (2011), perceptron is based on the McCulloch and Pitts neuron model that consists of linear combiner followed by a hard limiter. The weighted sum of the inputs is applied to the hard limiter which produces an output equal to +1 if the input is positive and -1 if it is negative.
REFERENCES


