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

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Date : 14 DECEMBER 2014

To my parents Haji Majid Ahmad and Hajah Zainab Mat Hassan, my sister Zairini Majid and my dearest husband Muhmmad Hafas Azmi

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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

Dalam industri pembuatan, proses variasi merupakan sumber utama yang menyebabkan kualiti sesuatu produk adalah ditahap yang rendah. Dengan itu, pemantauan dan diagnosis semakin kritikal kea rah peningkatan yang berterusan. Ini menjadi lebih mencabar apabila melibatkan dua atau lebih pembolehubah yang berkorelasi. Proses pemantauan adalah merujuk kepada pengenalpastian status sesuatu proses samada ianya bergerak didalam keadaan dalam kawalan atau keadaan luar kawalan, manakala proses diagnosis merujuk kepada pengenalpastian sumber pembolehubah terhadap proses yang berada diluar kawalan. Carta skim proses kawalan statistic tradisional (SPC) diakui berkesan dalam proses pemantauan. Bagaimanapun, bagi proses diagnosis tahap keberkesanannya masih berada di tahap yang rendah. Kebelakangan ini, rangkaian neural buatan (ANN) berdasarkan skim pengiktirafan corak telah dilaksanakan bagi menyelesaikan isu ini. Skim-skim yang sedia ada direka bagi menangani proses aliran data sepenuhnya dengan lengkap. Secara praktikal, bagaimanapun, terdapat kes-kes dimana data pemerhatian tidak lengkap kerana proses pengukuran yang ralat. Dalam kajian ini, sebuah pengecam bagi gabungan corak model ANN dikaji untuk mengiktiraf proses aliran data. Setiap model terdiri daripada perwakilan kemasukan data yang berbeza, iaitu data mentah dan ciri-ciri statistik. Data mentah diperolehi daripada industry pembuatan sebagai data sebenar yang akan digunakan semasa kajian ini dijalankan. Oleh itu, diharap skim ANN yang diperkenalkan dan dicadangkan akan memberikan perspektif yang lebih baik didalam penyelidikan ini.

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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 ± 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 = $b_1|\Sigma_0|$

$$UCL = |\Sigma_0|\,(b_1 + 3\sqrt{b_2}) \tag{2.1}$$

$$LCL = |\Sigma_0|\,(b_1 - 3\sqrt{b_2})$$

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

$$b_1 = \frac{1}{(n-1)^p} \prod_{i=1}^{p}(n-i) \tag{2.2}$$

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

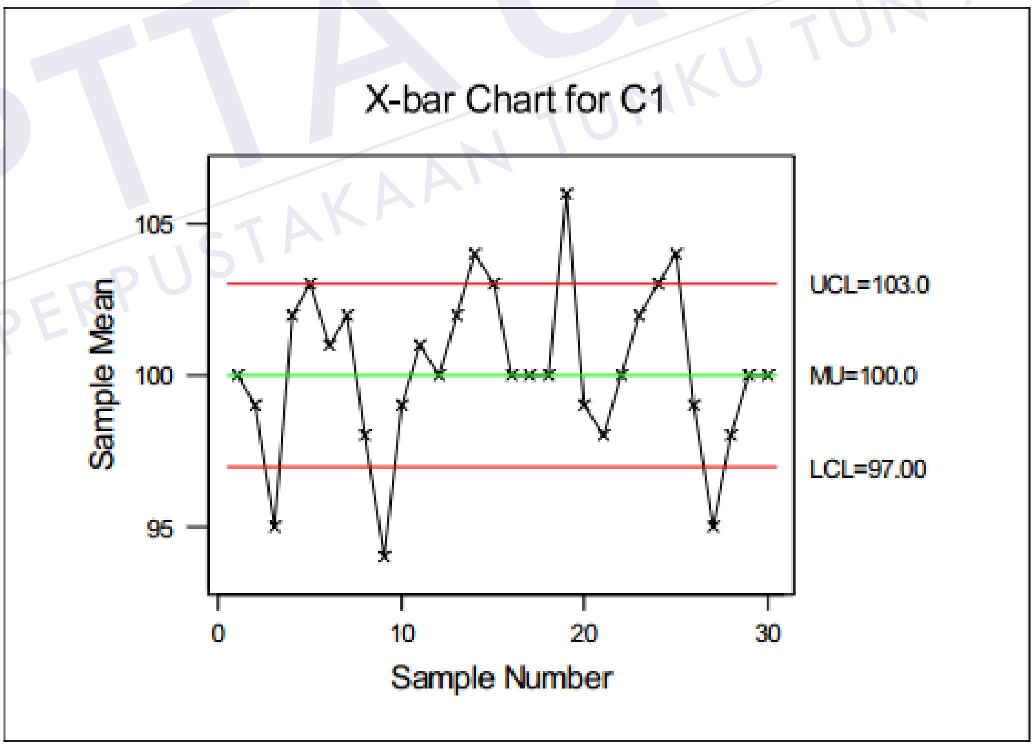


Figure 2.1: A typical X-bar Control Chart

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.

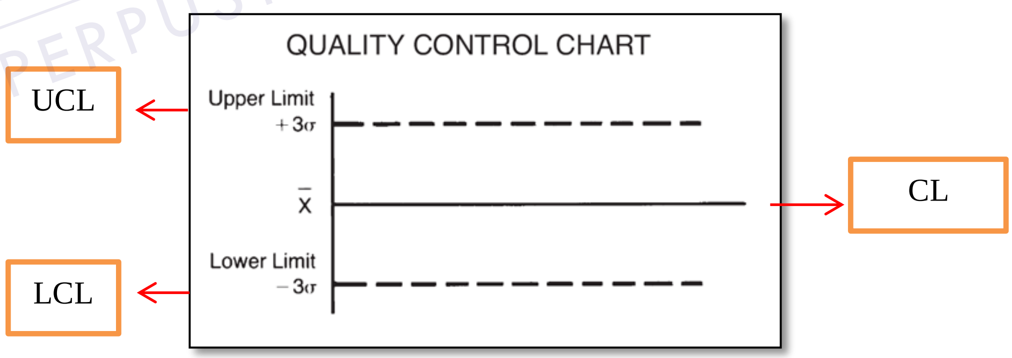


Figure 2.2: Graph of Control Limit

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:

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

$$UCL = m_0 - 3(\sigma_0 + \sqrt{n}) \tag{2.4}$$

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:

$$\textit{Center Line} = \bar{\bar{x}} = \sum_{i=1}^{k} \bar{x}\mathrm{I}$$

$$UCL = \bar{\bar{x}} + m\left(\frac{\sigma}{\sqrt{n}}\right) \tag{2.5}$$

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

When subgroup size is one, the control limit becomes:

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

$$UCL = \bar{\bar{x}} - m\sigma \tag{2.6}$$

Where, it given:

k = samples number

$\bar{x}$I = samples mean

$\sigma = \sqrt{MSE}$, Mean Square Error

Second section is R chart, as it increased in the process standard deviation σ 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:

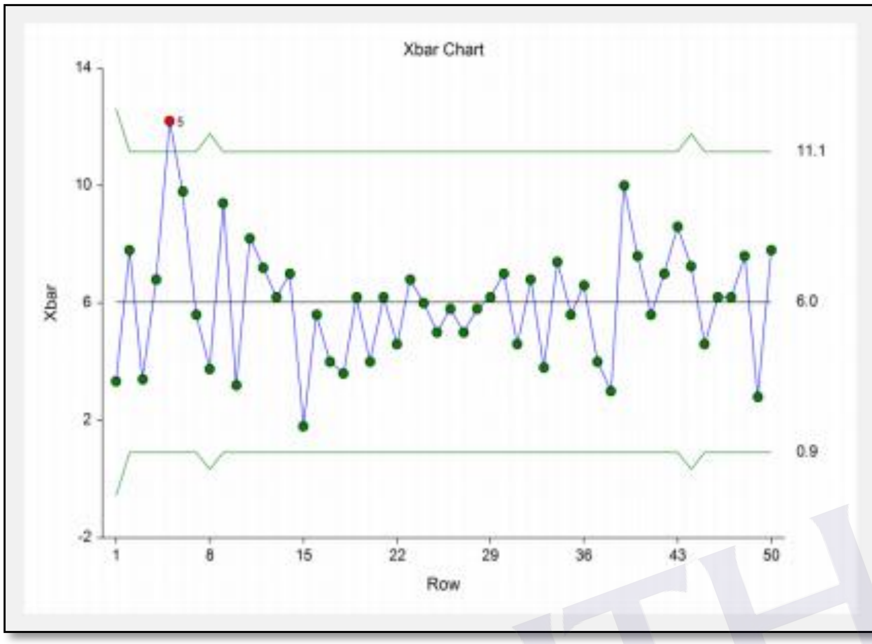
$$UCL = R_e + m\, d_3\, \hat{\sigma}_x$$
$$\tag{2.7}$$
$$LCL = R_e - m\, d_3\, \hat{\sigma}_x$$

Given that:

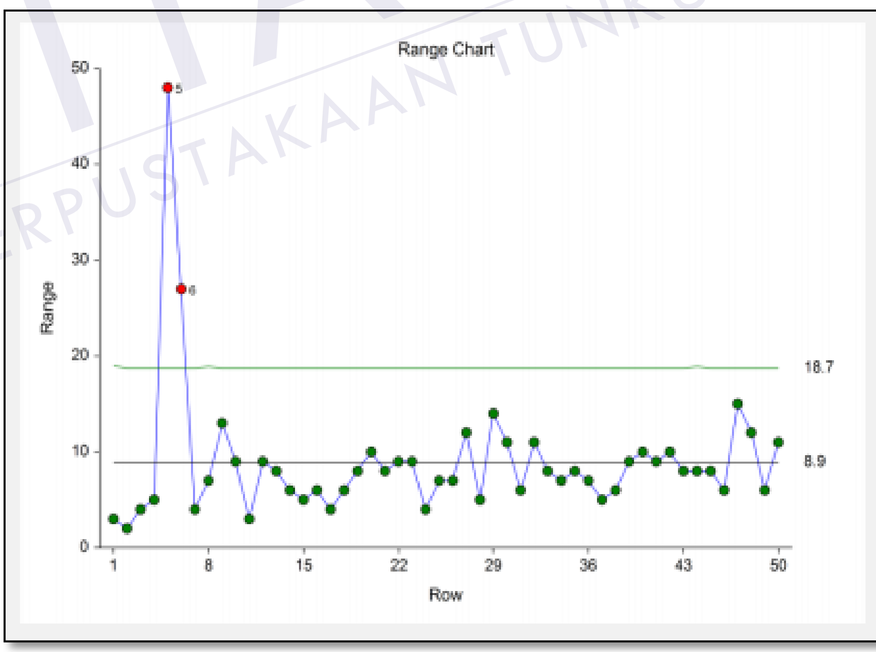
m = multiplier to reduce the possibility of false alarms

d_3 = constant depend on *n*,

$d_3 = \sigma_R / \sigma_x$



(a) X-bar Chart



(b) R bar Chart

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:

$$ARL=\mu T \quad (2.8)$$

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,…….Q_n can be modeled as random draws,

q = P [Q_1 plots outside control limit] a

nd 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:

$$Zt = \lambda \bar{x}_t + (1-\lambda)Z \qquad 0< \lambda \leq 1 \qquad (2.9)$$

Where:

λ = constant

Z_0 = equal to an estimate of the process mean

$\bar{x}_t$ = sample mean for the time period, t

In quality monitoring applications, typical values for the weight λ 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 λ in the interval $0.05 \leq \lambda \leq 0.25$ work well in practice, with λ = 0.05, λ = 0.10, and λ = 0.20 being popular choices.

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

$$Zi = \lambda \bar{x}_i + (1-\lambda)Z_{i-1} \qquad (2.11)$$

$$Z_0 = \mu_0 \qquad (2.12)$$

Center line = μ_0

$$UCL = \mu_0 + L\sigma\sqrt{\frac{\lambda\,[1-(1-\lambda)^{2i}]}{(2-\lambda)}} \tag{2.13}$$

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

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.

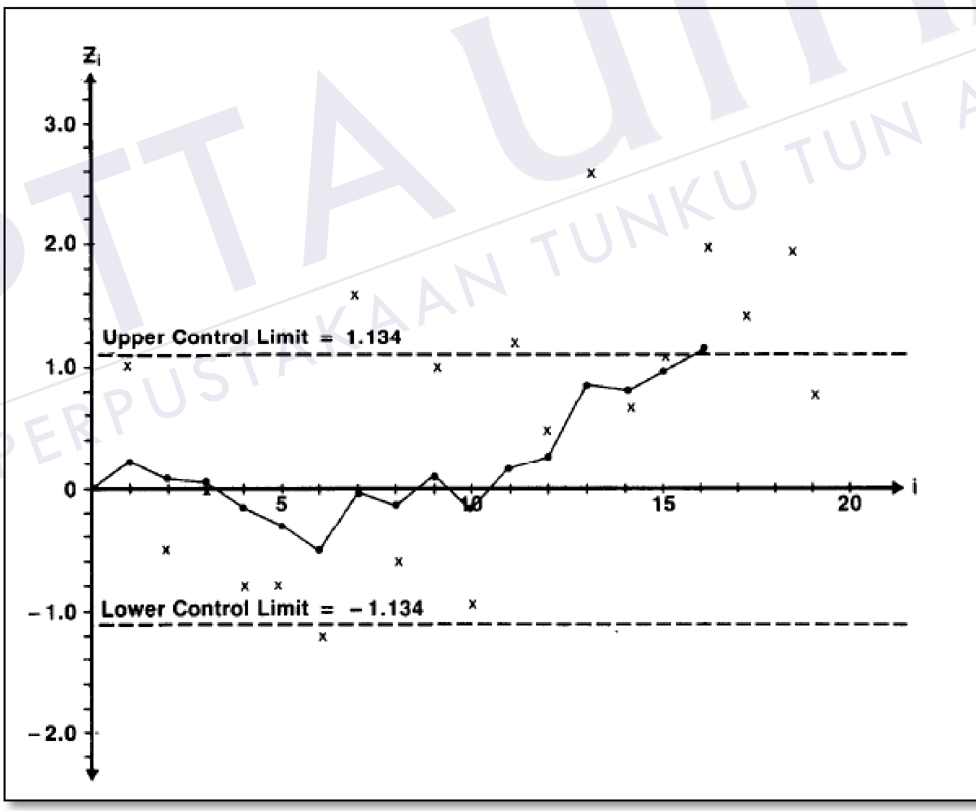


Figure 2.4: EWMA Control Chart

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/X^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 μ and covariance matrix Σ 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.

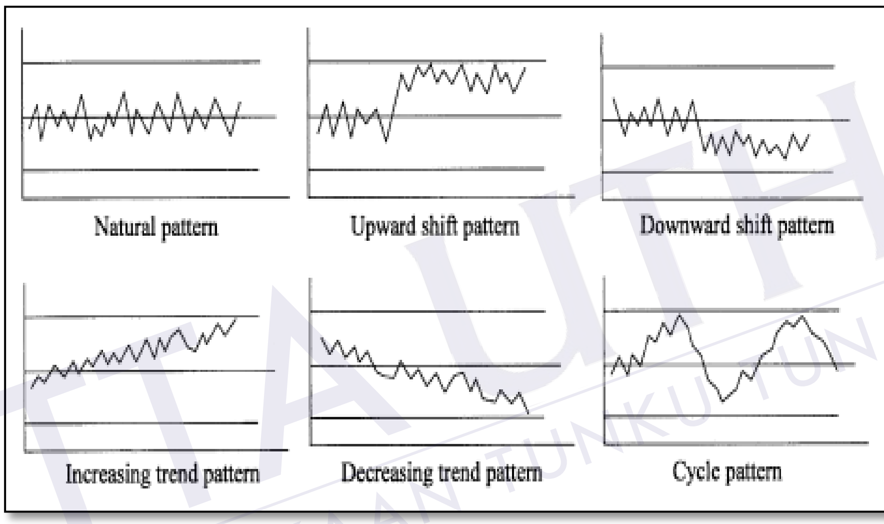


Figure 2.5: Typical pattern in-control chart (Guh, 2010)

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.

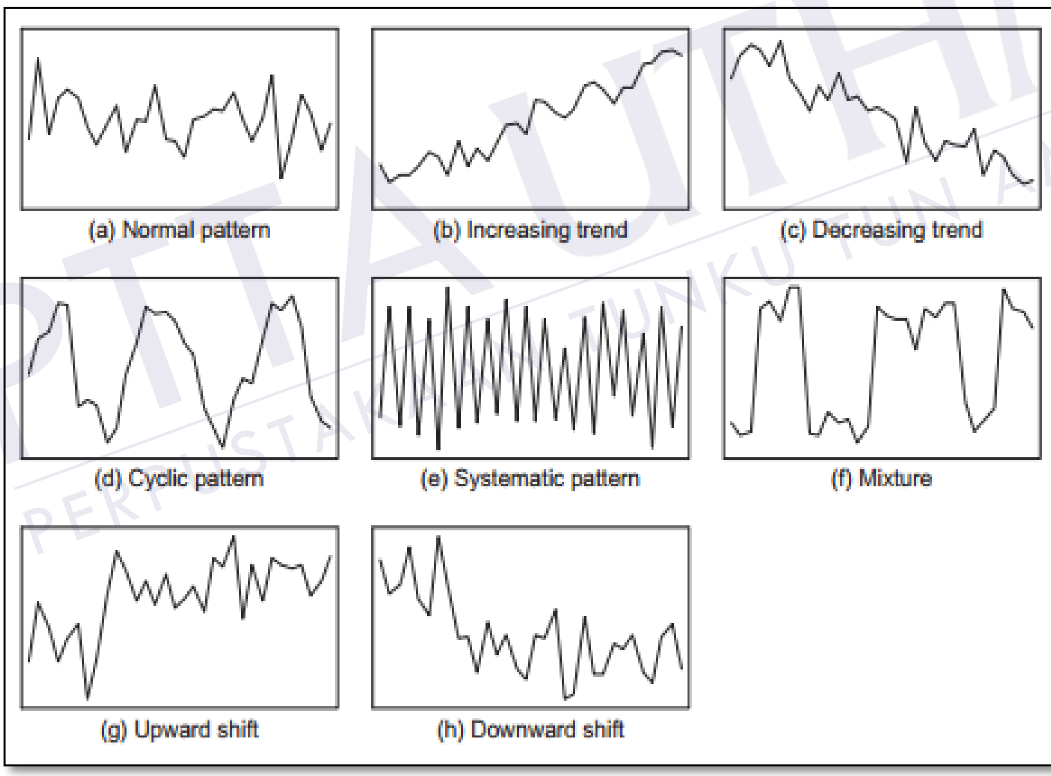


Figure 2.6: Types of CCPs (Hachicha and Ghorbel, 2012)

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.

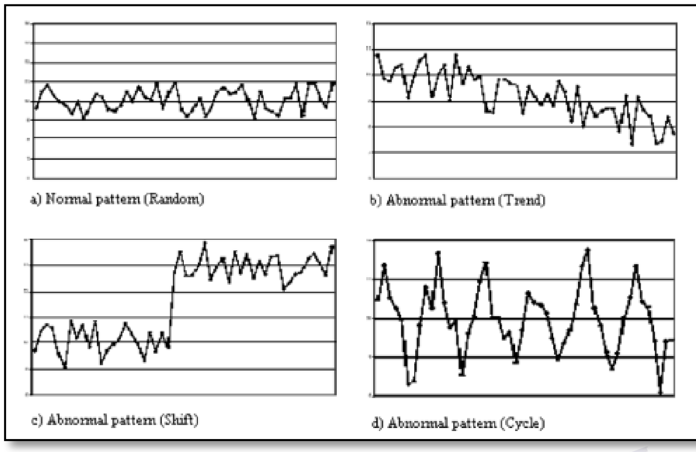


Figure 2.7: Typical normal and abnormal patterns (El-Midany *et al.*, 2010)

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.

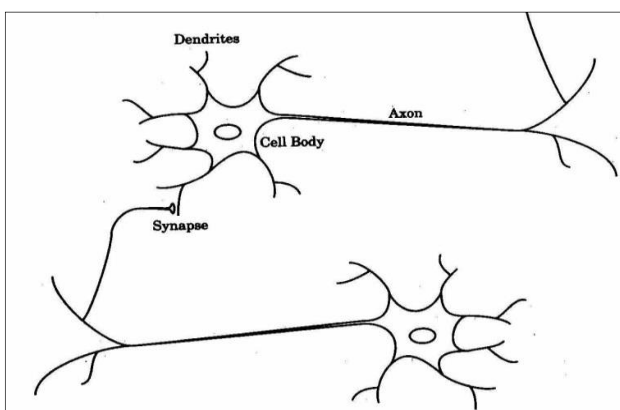


Figure 2.8: Biological neural cell

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.

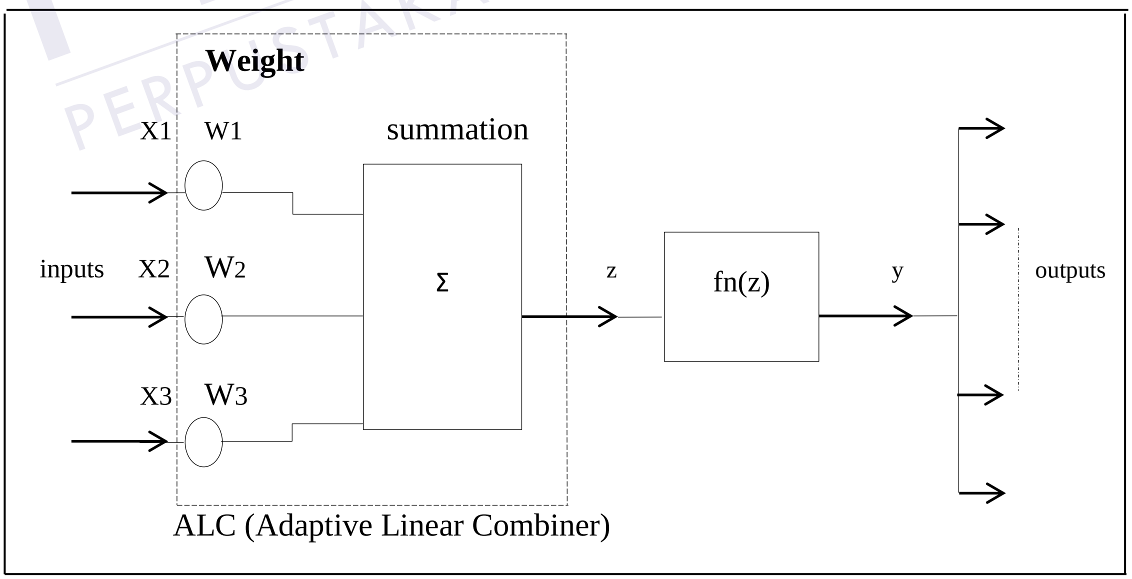
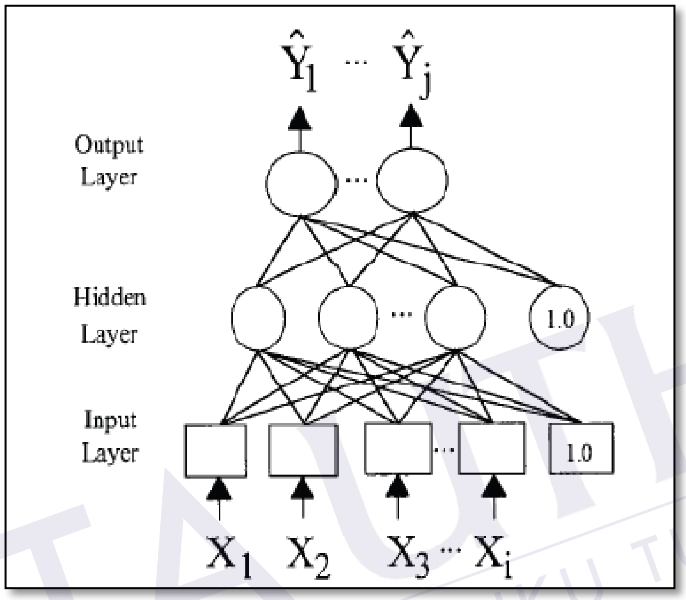


Figure 2.9: A perceptron of artificial neuron (Graupe, 2007)

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.



a) Univariate Case (Guh, 2008)

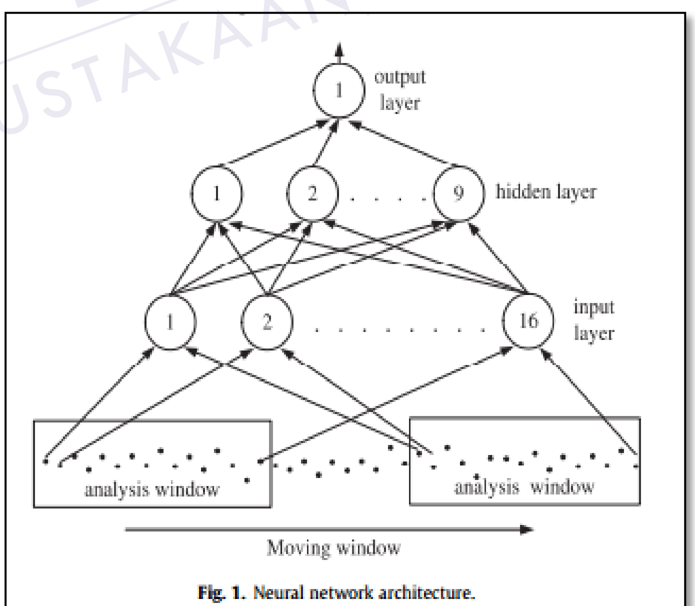


Fig. 1. Neural network architecture.

b) Bivariate Case (Cheng, 2011)

Figure 2.10: Architecture of a BPN for univariate and bivariate cases

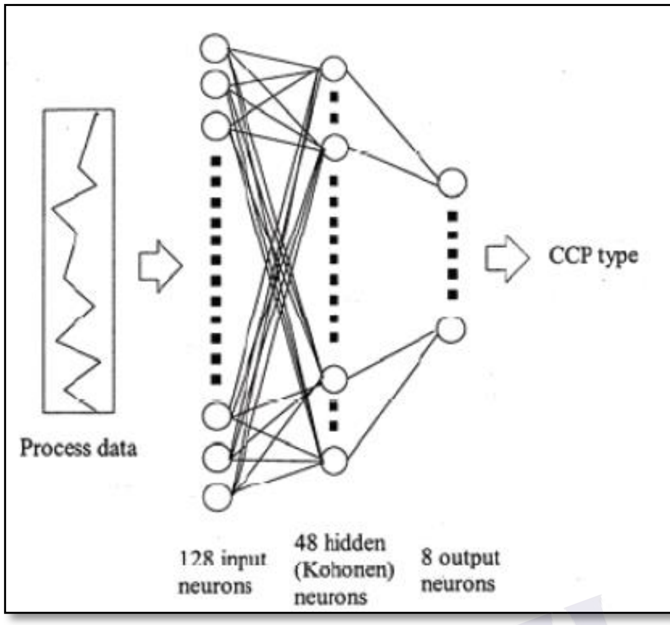


Figure 2.11: Structure of a LVQ networks

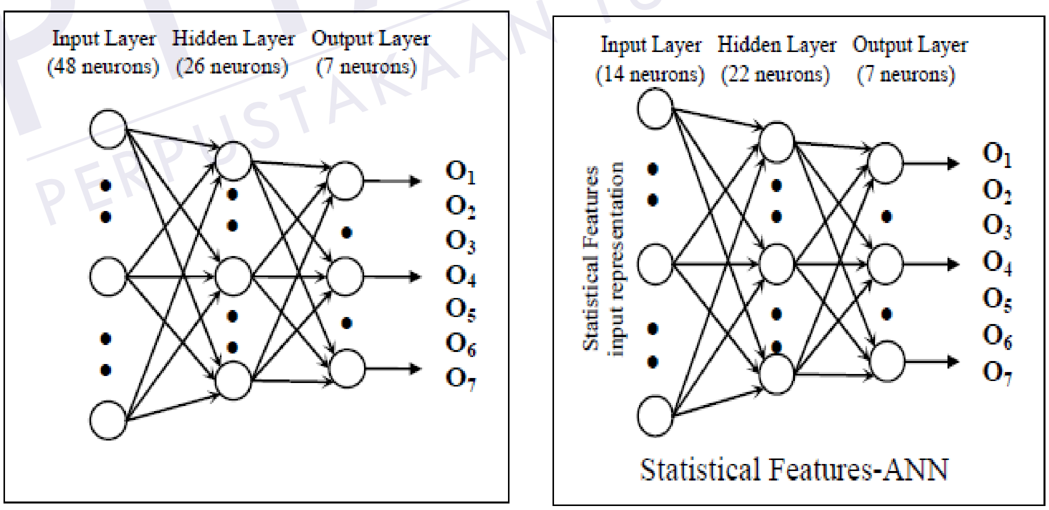
The behavior of a neural network is determined by the transfer functions of its neurons, by the learning rule, and by the architecture itself. Once the network is trained and tested it can be given new input information to predict the output. In addition, ANNs can combine and incorporate both literature-based 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, 3^{rd} 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.

Hence, MLP is a feed forward neural network with one or more hidden layers. Typically, the network consists of an input layer of source neurons, at least one middle or hidden layer of computational neurons and an output layer of computational neurons. Each layer in a multilayer neural network has its own specific function with input layer accepts input signals from the outside and redistributes signals to all neurons in the hidden layer. Neurons in the hidden layer detect the features; the weights of the neurons represent the features hidden in the input patterns.

Throughout this research, the selected MLP model as in Figure 2.12 comprises an input layer, one hidden layer and an output layer. The number of input representation determined the number of input neurons. Raw data input representation requires 48 neurons with 26 neurons of hidden layer while for the feature input representation requires 14 neurons with 22 neurons of hidden layer. Also, the output layer of both models contains seven neurons, which was determined according to the number of pattern categories. once the neurons exceed the required numbers, it did not improve the training results but yields poorer accuracy and increase training time.



a) Raw data-based ANN b) Featured-based ANN

Figure 2.12: Generalized-ANN architectures based on three layer MLP model (Masood and Hassan, 2012)

2.5.3 Synergistic-ANN Model

Synergistic-ANN recognizer is a parallel combination between raw data-based ANN and feature-based ANN to get the output which is higher. The model aims to solve complex problem through combination of the strengths offered by different recognizers and recognition technique. The basis methodology of combined ANN models is applied into this scheme since it has been proven effective towards improving recognition accuracy (Pham and Oztemel, 1993). Figure 2.13 shows the concept of combination of raw data-based and feature-based on the maximum output where O_{RD} and O_F are the outputs from both input representations. It has two ANNs recognizers for both data, where each of data was trained with seven types of bivariate mean shifts pattern as in Figure 2.14.

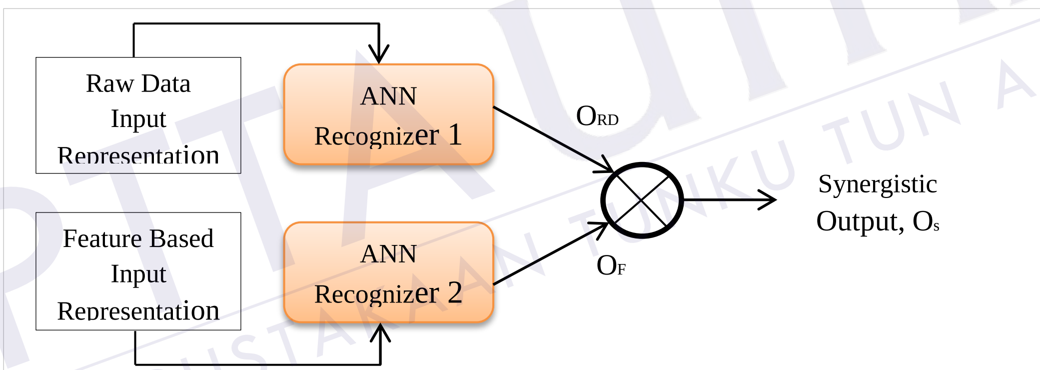


Figure 2.13: Concept of Synergistic-ANN

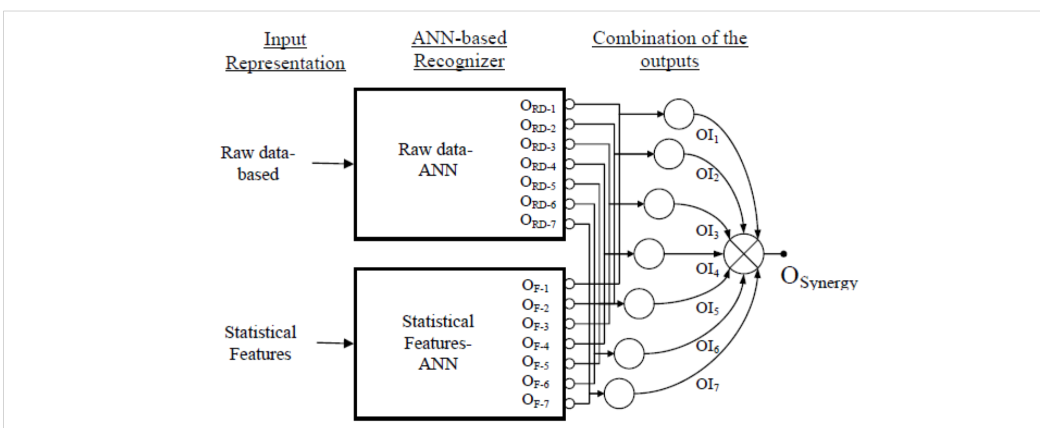


Figure 2.14: Synergistic-ANN recognizer

2.6 Bivariate Pattern Recognition Scheme

In bivariate pattern recognition (BPR) schemeS, ANN is applied as a recognizer for recognition of unnatural data streams patterns. The existing schemes were categorized into: (i) ANN-based model and (ii) Integrated MSPC-ANN model, based on the external structures. The ANN-based models such as novelty detector-ANN, modular-ANN, ensemble-ANN, multi modules-ANN scheme have been designed to perform process monitoring and diagnosis simultaneously and continuously.

2.6.1 Novelty Detector ANN model

Zorriassatine (2003) identified the abnormalities caused by mean shifts in bivariate process with several method provided using Novelty Detector (ND), where it is an effective classification technique to measure deviation and estimate unseen data point. On this paper, it only examines the upward and downward shifts in the process mean vector of a bivariate process. The shift signals are added to random normal bivariate vectors to provide shift patterns. The studied were in terms of identification shift patterns of MSPC where the number of variate is two. The method starts simulating the bivariate data by preparing for training and testing. Monitoring of mean vector μ_0 and covariance matrix Σ shows whether the system as a whole is in statistical control or not from the reference value. In MSPC, the statistic X^2 is used to identify in-control versus out-of-control vectors and each normal multivariate mean vector must result in a value of X^2. The abnormalities begin from the independent variables when simulating a pattern. GMMs are used to implement and construct ND to identify novel process patterns shown in Figure 2.15. Two sets of experiments about the feasibility at ND and sensitivity analysis of performance were conduct by producing good result when tested with sudden shift pattern. 99.98% of the test examples representing shift pattern that correctly plot below the novelty threshold.

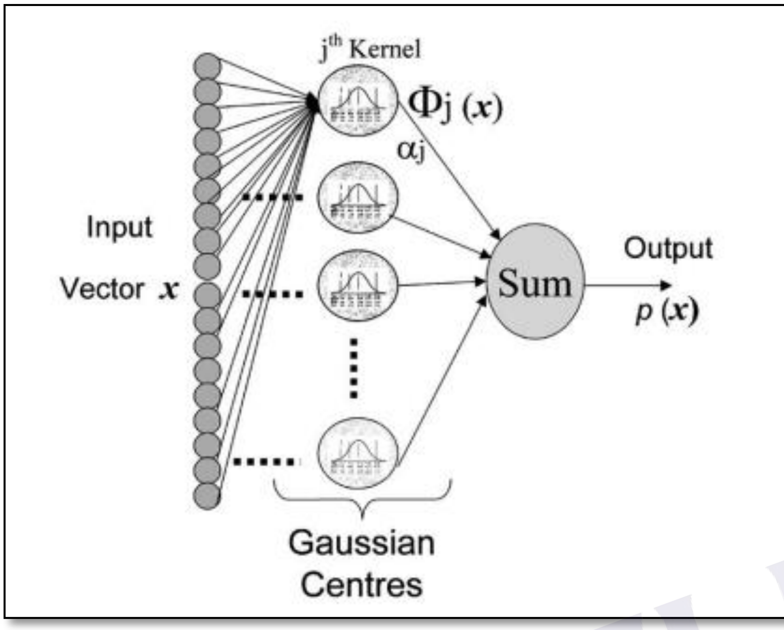


Figure 2.15: The Architecture of a Typical ND (Zorriassatine, 2003)

2.6.2 Ensemble-ANN model

In the study of Wu and Yu (2010), an ensemble neural networks consists of two steps which are training several networks and combining their prediction results. To obtain the improved generalization performance, each network in the ensemble is first trained using the training examples as illustrate in Figure 2.16. After that, each of example training, they predict the outputs of each of these networks that are combined to produce ensemble outputs.

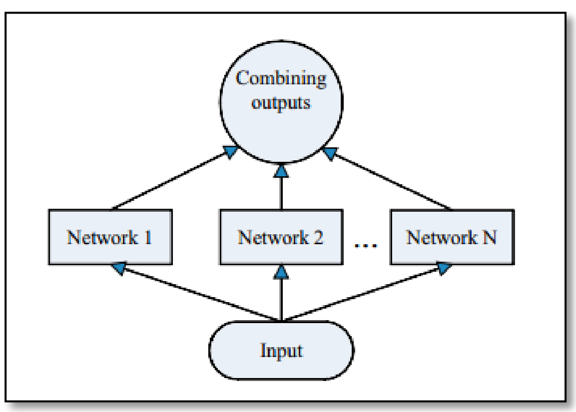


Figure 2.16: A neural network ensemble (Wu and Yu, 2010)

For the training network, creation of candidate was being produce by varying different initial condition. After each candidate network is created, the training data sets are inserted to this network to get training examples and become a part of the next candidate network. The selection of networks was selected by DPSOEN when each number of neural networks trained is obtained to construct ensemble also in order to increase mean squared error and to create ensemble with the lowest error. From the result, DPSOEN generated neural network ensembles with far smaller sizes but stronger generalization ability. Rather than that, it is also identify non-shift and shift for correlation ρ=0.00, 89.2% non-shift cases, 95.4% mean shift cases and 82% cases are accurately identified.

2.6.3 Multi-Module-Structure ANN model

El-Midany *et al.* (2010) proposed the multi-module-ANN as shown in Figure 2.14 for monitoring and diagnosis of three variates process mean shifts. The X^2-statistics (56 consecutive X^2) as shown in Block A were utilized as input representation for allindividual ANN-based recognizers. Variation in mean shifts was represented by sudden shift and trend patterns as shown in Block B, which can be recognized using the three-layered MLP neural network recognizer. In Block C, outputs from several specialized-ANN recognizers were combined to determine the sources of variation. There are seven possibility sources of variation that are: (1,0,0), (0,1,0), (0,0,1), (1,1,1), (1,1,0), (1,0,1) and (0,1,1). Notation '1' represents shifted variable, while notation '0' represents normal variable.

2.6.4 Modular-ANN model

For case of monitoring and diagnosis bivariate process mean shift of Salehi *et al.* (2012) proposed the modular ANN model to visualize the performance. In monitoring aspect, this scheme can be observed as so effective to rapidly detect process mean shifts (with short ARL_1) based on limited capability to avoid false alarms ($ARL_0 \approx 200$). This ARL_0 level was determined based on monitoring capabilities of the traditional MSPC charting schemes. In diagnosis aspect, it was also effective to accurately identify the sources of variation (with excellence RA results). A modular framework was presented through this studied for using advantages of general-purpose and special-purpose. It is impossible that one network would be performing in the required recognition and analysis because it may cause difficulty in network training. For that, we can split the main recognition problem into more manageable sub-problems by modular structure that consists of two modules (Module I and Module II) as shown in Figure 2.17. Module I is a support vector machine-base classifier as a general propose system for recognizing unnatural pattern chart and module II is a neural-network classifier as a special propose system for estimating the major parameters of the unnatural CCPs.

Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that predicts whether a new example falls into one category or the other. SVM is a related supervised learning method used for classification and regression. For the section of module II, it is responsible for identification of the key parameter of each unnatural pattern that divided into three separated specialist-NNs; Network A (Shift Recognizer), Network B (Trend Recognizer) and Network C (Cycle Recognizer).

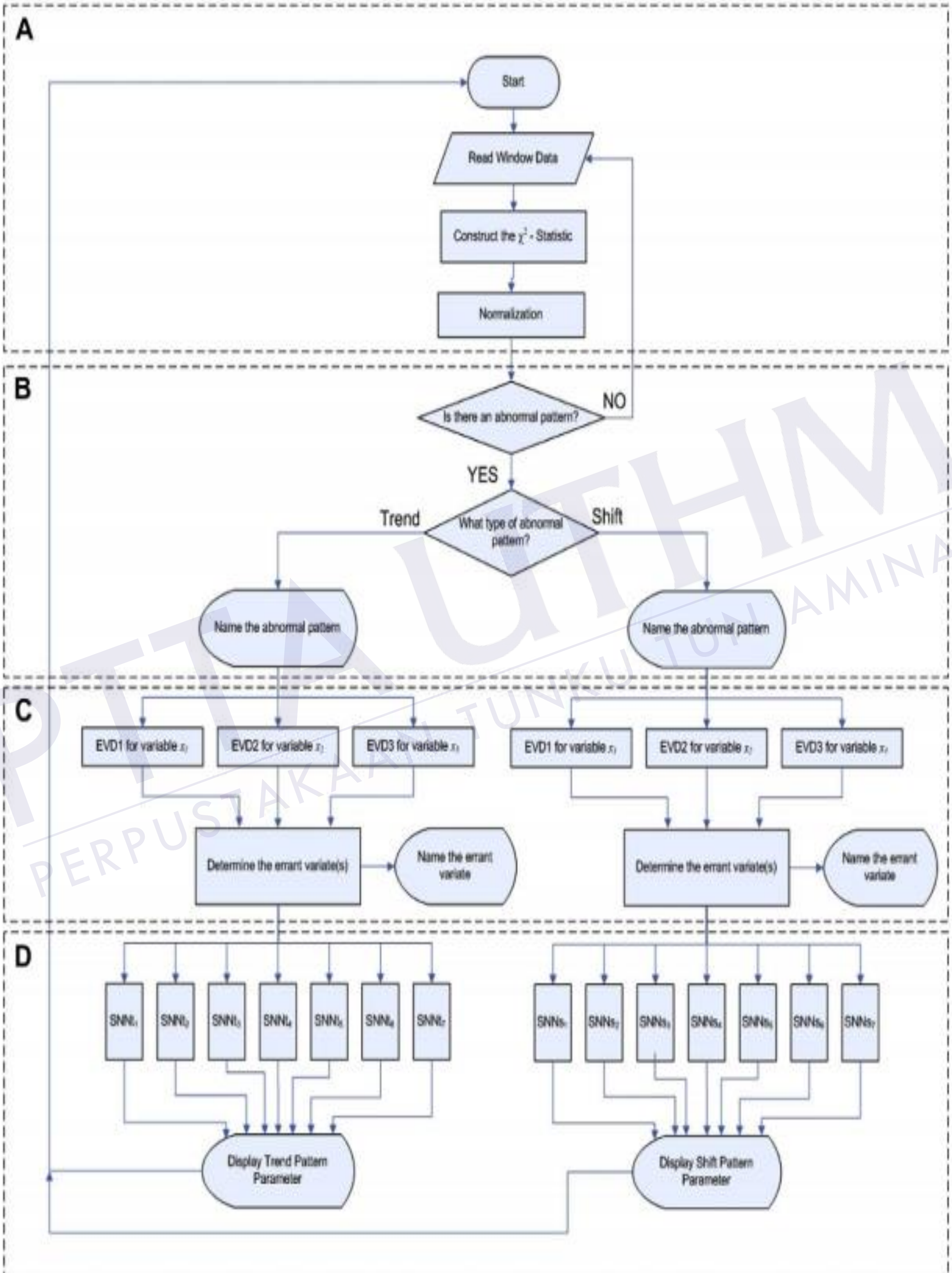


Figure 2.17: Multi-Module-Structure model (El-Midany *et al*., 2010)

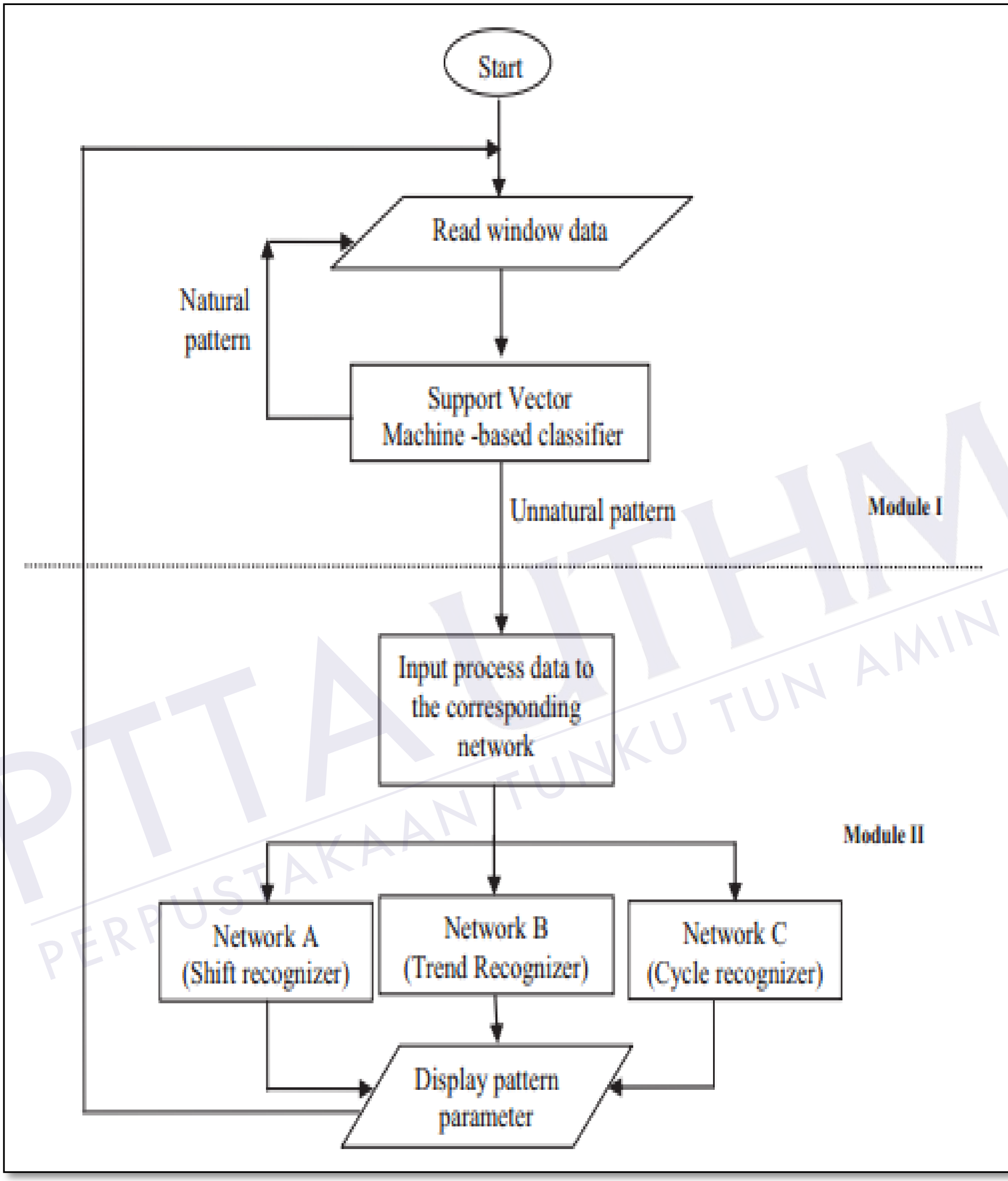


Figure 2.18: Modular-ANN model (Salehi, 2012)

2.7 Case Study

Previously, Azry (2013) had been conducted the experiments of *Multivariate Quality Control using Integrated Artificial Neural Network Scheme, a case study in Plastic Injection Molding Industry*. The studies were focused on thermo plastic part fabricated from plastic injection process machine which the dimension and weight differed base on the changes in machine parameter. The two variables of cases were being monitor in injection molding. Types of control chart were used in this study were divided to three categories of Univariate Control Chart, Multivariate Control Chart and Advance Multivariate Control Chart. For the Univariate control chart, it's divided into I-Chart and EWMA chart. The I-Chart is sensitive to large process shifts. The probability of detecting small mean shifts fast is rather small. Meanwhile EWMA (Exponentially Weighted Moving Average) is capable detect small mean shifts faster that I-Chart. Then, Multivariate Control Chart, in this experiment T Hotelling Chart and MEWMA (Multivariate Exponentially Weighted Moving Average) Chart were used to analyze bivariate dependent variables.

The process start when new plastic part tooling was fabricated and it performance was test during Engineering Trial before can be introduced to run mass production. Since the profile of the part was predicted to have problem with appearance issues, it was important to understand that the changes in injection machine parameter or material use will cause process disturbance that affected the mean and standard deviation of the continuing production part. The new tooling has been use in new model for electronic devices that consists of cavities. About 30 samples were select for this process with machine parameter and variables are fixed. For T2 Hotelling Chart, 1:24 subgroups was used to estimate the parameter, upper confidence limit bound was 8.64 and covariance matrix was calculated from 30 samples from in control process. And for MEWMA (Multivariate Exponentially Weighted Moving Average) chart, bivariate dependent variables were set with subgroup size was 1, ARL was 200 and lambda was 0.1. In advance multivariate control chart, soft computing technology (ANN) was applied for Baseline scheme, Statistical Features scheme and MEWMA-ANN scheme.

For MEWMA-ANN scheme, it is the integrated of Synergistic ANN recognizer consist of two ANN-based Recognizer (Statistical Features-ANN and Raw data-ANN) with MEWMA control chart. In the process, Holding Pressure and Injection speed been control to 5% for rising and falling the rate from the control process. As a result, the traditional control charts of I-Chart, EWMA, T^2 and MEWMA were obtained from Minitab 16 and Advance Statistical Process Control scheme of MEWMA-ANN, Statistical Features and Baseline which applied ANN recognizer were obtained from Matlab R2010a software. From the analysis, I-Chart performance was better than EWMA chart and process disturbance recognition performances are better than univariate control chart from T^2 chart and MEWMA chart. It is because the capability to detect the process was out-of-control. This shows that MEWMA-ANN scheme were unable to perform accurate diagnosis result when the process was out-of-control.

2.8 Summary

Overall, this chapter described about the terms also parameters used in way to achieve the objective of the study for monitoring and diagnosis bivariate process variation in mean shift by synergistic-ANN. The processes of control chart, univariate, bivariate and ANN have been discussed and it is depend on product process to choose which is more suitable subjected to the case. Proven that, ANN is widely used in manufacturing process due to its function and ability. Previously, most of the researchers monitor the bivariate processes with the false data and only a few of them conducted with abnormal data. However, for the purpose of verification or validation in real manufacturing industries are quite limited. Therefore, this research aims to provide more informative application in various fields of manufacturing industry.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

The review of control chart, univariate and bivariate pattern recognition for monitoring and diagnosis process variation had been discussed in the previous chapter. The focus of the research is to investigate the manufacturing industry process with two variables of X and Y in bivariate shifted. This is supported with the real data of product applied into ANN scheme and analyse the performance of product before produced. In order to generate this type of data, in this chapter the design strategy and research methodology are presented. This chapter is organized as follows: Sections 3.2 provides an overview of bivariate process mean shift and followed by the process flowchart in Section 3.3. In section 3.3, it includes the research methodology about the concept and strategy through experiments.

3.2 Bivariate Process Mean Shift

Bivariate analysis is a simple special case of multivariate analysis where multiple relations between multiple variables are examined simultaneously. Furthermore, the studies are different from univariate because it allows the researcher to analyze the relationship between two variables denoted as X and Y for the purpose of determining the empirical relationship between them. Thus, it can be helpful in testing simple hypotheses and checking to what extent becomes easier to know and predict a value for the dependent variable. The major differentiating point between univariate and bivariate is that the purpose of a bivariate analysis goes beyond simply descriptive.

According to Masood and Hassan (2012), the samples from both variables can be assumed as identically and independently distributed with zero mean ($\mu_0 = 0$) and unity standard deviation ($\sigma_0 = 1$). Depending on process situation, the bivariate samples can be in low correlation ($\rho = 0.1 \sim 0.3$), moderate correlation ($\rho = 0.4 \sim 0.6$) or high correlation ($\rho = 0.7 \sim 0.9$). This type of correlation analysis was shown in Figure 3.1. Correlation is a direction and strength of linear relationship between two variables. The correlation coefficient, r changes from -1.0 to +1.0. If the value of r equals +1.0, then a perfect positive relationship exists. But, if the value of r equals to -1.0, a perfect negative relationship exists as shown in Figure 3.2. No correlation is indicated when r equals to 0. Disturbance from assignable causes on the component variables (variable-1only, variable-2 only, or both variables) is a major source of process variation. The structure of an unstable pattern is initially vague or partially developed. Then, it will be more obvious and proceeds into a fully developed pattern.

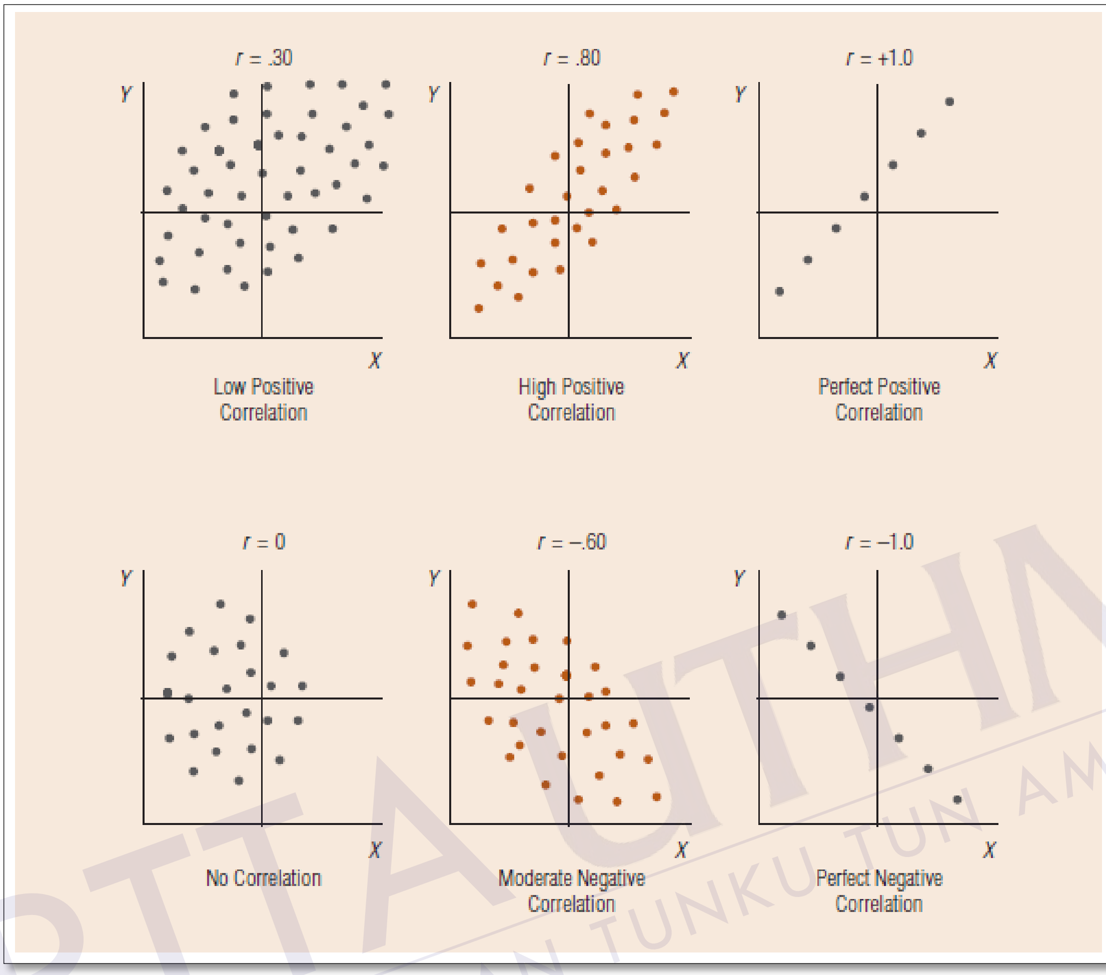


Figure 3.1: Types of Correlation Analysis

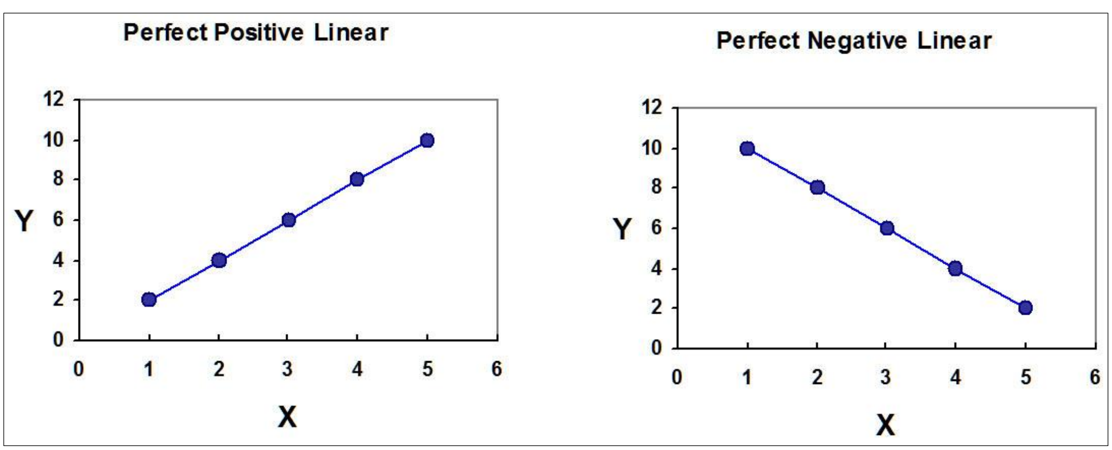


Figure 3.2: A linear scatter graph of Positive and Negative of two variables

3.3 Process of Flowchart

From Figure 3.3, it illustrates the overview and the concept of methodology in this research. The research starts by gather all the information and understand the concept of SPC, Bivariate and machine learning that use ANN scheme. For the SPC, determine the various types of control chart could be investigated for process monitoring and diagnosing. After that, it continues by identifying the problem occurred during the study, also in manufacturing industry in way to apply bivariate process pattern recognition scheme. The real data from various manufacturing process were use through this study as an input representation of bivariate to monitor and diagnose the shift condition. The selected industries are from mechanical, chemical and servicing. Each of the cases will be observed through the process and verified the defect of product. Next, data recognizer will be conduct using ANN scheme by software. As a result, it will be analyze the three sections of false alarm (ARL_0), fast detection (ARL_1) and correct classification (Recognition Accuracy, RA). Generally the ARL_0 is for in-control process where there is no point is out-of-control. However, due to probability of Type I error, ARL_0 is limited to certain condition. While, for the ARL_1 ideally the summation is equal to 1 for identify the process as out-of-control. However, due to investigating the result of this summation will be more when Type II error appears.

Meanwhile, Figure 3.4 illustrates the research flow chart that was carried throughout a year. It is more detail information than the previous figure, as it involved seven condition of bivariate correlated and the testing that are available of this research for synergistic testing. Synergistic-ANN is a parallel combination between raw data-based ANN and feature-based ANN recognizers as stated in Section 2.14 for more detail. The parameter of raw data-based and feature-based input representation can be referred in the Section 2.12 in literature review. By using ANN, the data were trained and detail parameters are composed in the next chapter. Then, validation testing was applied for training the industrial real data of injection molding. The next section discuss as the result and make a conclusion of the study.

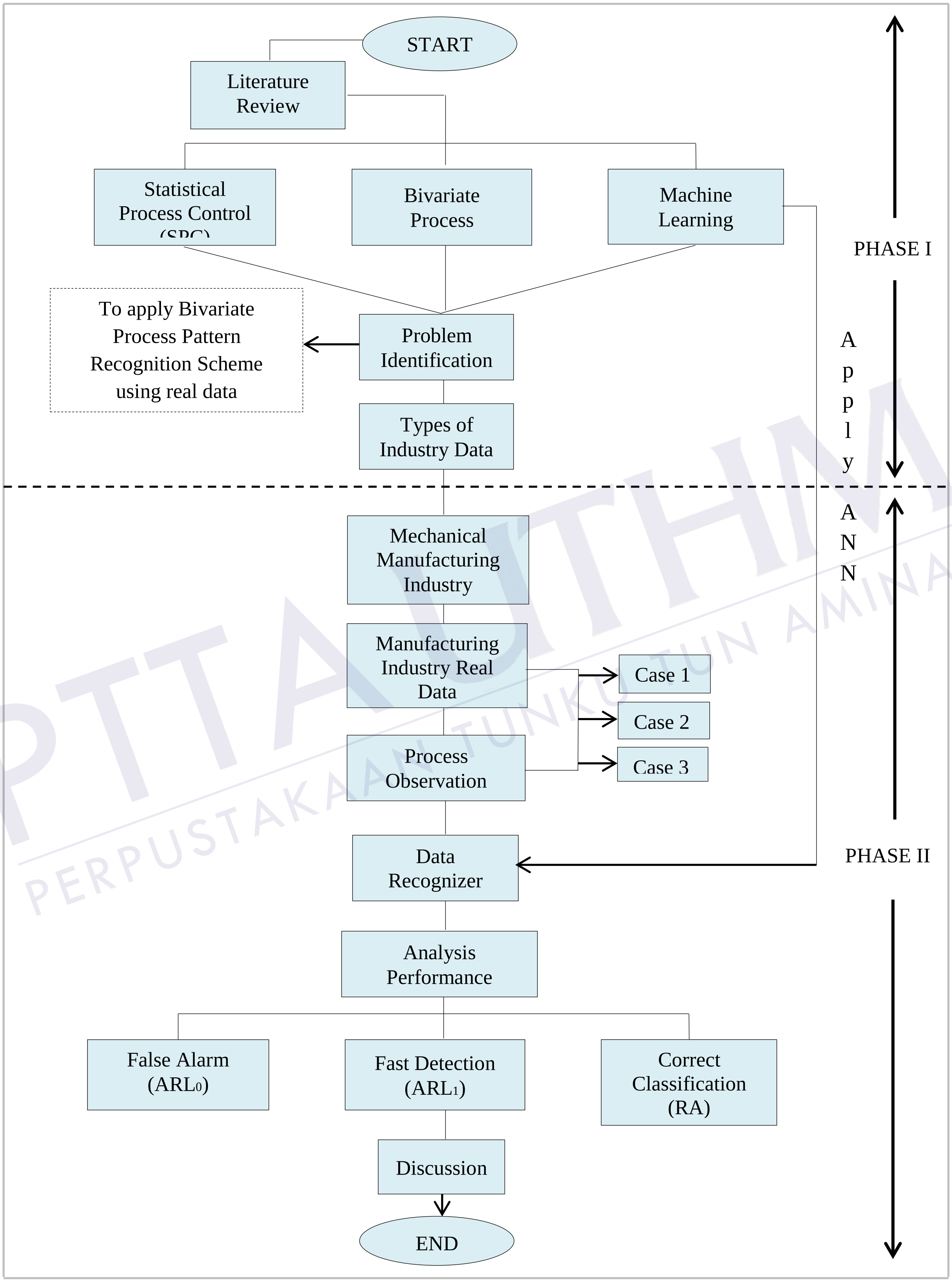


Figure 3.3: Process of Methodology

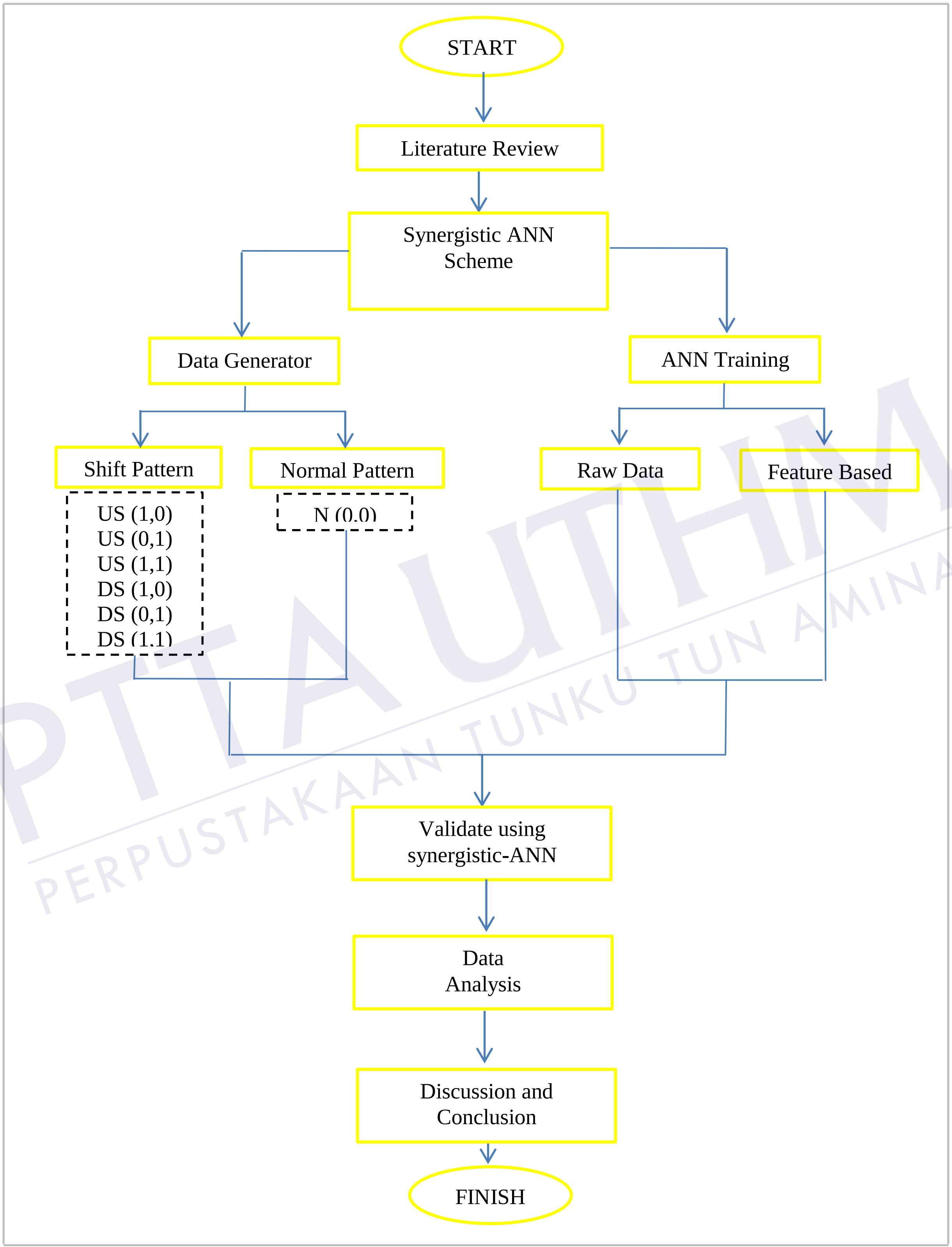


Figure 3.4: Research Flow Chart

3.4 Conceptual of Pattern Recognition Scheme

The concept of pattern recognition was implemented in this research since it is known to be effective for identifying the source of variation as shown in the Figure 3.5. In this concept, it comprised into two main phases i.e, process patterns and the input representation stated in phase one and for the process monitoring and diagnosis was stated in phase two.

Hence, in the first phase, it includes the variables that consist of bivariate pattern X_{1i} and X_{2i}. Both of variables are plotted in a scatter diagram to facilitate and identify the readings before being transformed into a vector in the input representation. Input representation contained the raw data or statistical feature where it will be tested using MatLab, after generate all seven types of patterns of shift pattern and normal pattern.

Furthermore, ANN recognizer takes a role in monitoring and diagnosis of the pattern in phase two. The ANN will recognize and monitor whether the patterns are detect or not and also was classified into some form of breakdown where it will discussed more detail in the next section. Monitoring refers to the identification of process status, either in a statistically stable state or in a statistically unstable state. In this stage, recognizer should have the capability to detect the unstable multivariate quickly as the average run length, ($ARL_1 \leq 7.5$ for shift range $\pm 1.0 \sim 3.0$ standard deviations) is shortest. While, for the stable state it should be extended run as the ($ARL_0 \geq 370$) is longest. Meanwhile, diagnosis refers to identify the source variables for unstable state with highest recognition accuracy percentage with average ($RA \geq 95\%$.for shift range $\pm$ 1.0 ~ 3.0 standard deviations). The effects of cross correlation function (ρ) and dynamic (moving) process data streams are properly considered into bivariate samples and patterns to suit on-line situation.

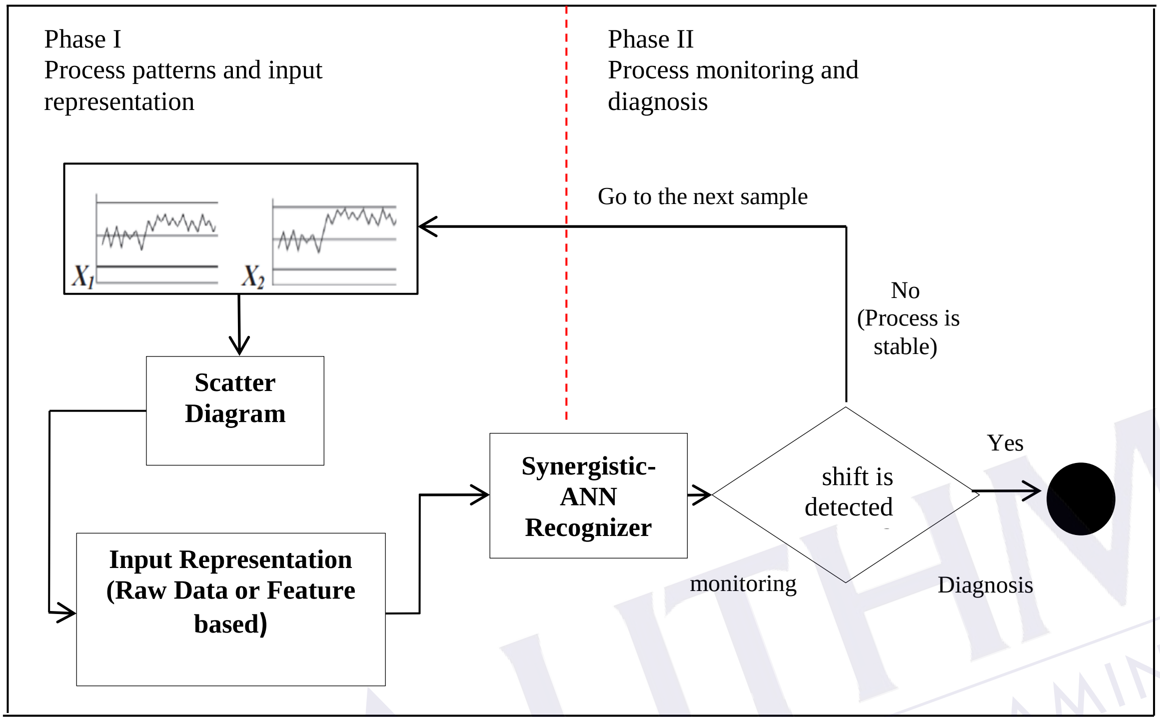


Figure 3.5: Conceptual of Pattern Recognition Scheme

An initial setting needs to be performed before it can be put into application, as follows:

- Load the trained raw data-ANN recognizer into the system
- Set the values of means (μ_{01} , μ_{02}) and standard deviations (σ_{01} , σ_{02}) of bivariate in-control process (for variables X_1 and X_2). These parameters can be obtained based on historical or preliminary samples.
- Perform in-process quality control inspection until 24 observation samples (individual or subgroup) to begin the system.

Recognition window size of baseline scheme is set to 24 observation samples (for variables X_1 and X_2) and for synergistic training it is depend on the mean shift where, window size 105 for mean shifts 1σ, window size 60 for mean shifts 2σ and window size 48 is for mean shifts 3σ.

3.4.1 Data Generator

The synthetic samples of bivariate process were generated based on the following steps (Lehman, 1977):

Step 1: Generate random normal variates for process variable-1 (n_1) and process variable-2 (n_2) which is identically and independently distributed (i.i.d) within [-3,+3]:

$$n_1 = b \text{ x } r_1 \tag{3.1}$$

$$n_2 = b \text{ x } r_2 \tag{3.2}$$

Parameters (r_1 and r_2) and b represent random normal variates (random data) and noise level respectively. Random normal variates are computerized generated data, whereby the noise level is used to rescale its variability. In this research, b = 1/3 is used to ensure that all random are simulated within ± 3.00 standard deviations (not exceed the control limits of Shewhart control chart).

Step 2: Transform random normal variates for process variable-1 (n_1) into random data series (Y_1):

$$Y_1 = \mu_1 + n_1\sigma_1 \tag{3.3}$$

Parameters μ_1 and σ_1 respectively represent the mean and the standard deviation for Y_1.

Step 3: Transform random normal variates for process variable-2 (n_2) into random data series (Y_2) dependent to (Y_1).

$$Y_2 = \mu_2 + [n_1\rho + n_2\sqrt{(1-\rho^2)}\,]\sigma_2 \tag{3.4}$$

Parameters μ_2 and σ_2 respectively represent the mean and the standard deviation for Y_2 whereas ρ represents the correlation coefficient between (Y_1,Y_2).

Step 4: Compute mean and standard deviation from (Y_1,Y_2). The values represent in-control process mean (μ_{01},μ_{02}) and standard deviation (σ_{01},σ_{02}) for part variables.

Step 5: Transform random data series (Y_1,Y_2) into normal or shift (pattern) data streams to mimic real observation samples (X_1,X_2):

$$X_1 = h_1 (\sigma_{01}/\sigma_1) + Y_1 \tag{3.5}$$

$$X_2 = h_2 (\sigma_{01}/\sigma_2) + Y_2 \tag{3.6}$$

The magnitudes of mean shift (h_1,h_2) are expressed in terms of the standard deviation for the in-control process. A pair observation sample (X_1,X_2) represents a bivariate vector measured at time t (X_t) that follows the random bivariate distribution N (μ_0, Σ_0). The notations μ_0 and Σ_0 = [(σ_1^2 σ_{12}) (σ_{12} σ_2^2)]represent mean vector and covariance matrix for bivariate in-control process with variances (σ_1^2 $_,\sigma_2$) and covariance ($\sigma_{12} = \sigma_{21}$).

Step 6: Rescale pattern data streams into a standardize range within [-3, +3]:

$$Z_1 = (X_1\text{-}\mu_{01})/\sigma_{01} \tag{3.7}$$

$$Z_2 = (X_2\text{-}\mu_{02})/\sigma_{02} \tag{3.8}$$

A pair standardized sample ($Z_{1,}$ Z_2) represents a standardized bivariate vector measured at time t (Z_t) that follows the standardized normal bivariate distribution N (0, R). Zero value and R = [(1 ρ) (ρ 1)] represent mean vector and general correlation matrix for bivariate in-control process with unity variances ($\sigma_1^2 = \sigma_2^2 = 1$) and covariance equal to cross correlation ($\sigma_{12} = \sigma_{21} = \rho$).

3.4.2 Input Representation

The description of input itself is to put the information, while representation is a something that shows the information. The both terms will provide a strong influence on the performance, especially related into this research for an ANN recognizer. Raw data-based and feature-based have been used in pattern recognition. The simplest input representation technique is using the original observation samples (raw data). Generally, the raw data-based input representation yields a large dimensional input vector. As such, it requires high compiitational efforts and time consuming for training the ANN-based recognizer (Pham and Wani, 1997). In order to overcome this problem, feature-based input representation has been proposed. Through this research, it focused on combination between raw data-based and feature-based input representation. Seven possible categories of bivariate pattern as follows were considered in representing the bivariate process variation in mean shifts:

- Normal (0,0); Both X_{1i} and X_{2i} are stable
- Up-shift (1,0); X_{1i} in upward shift and X_{2i} remain stable
- Up-shift (0,1); X_{2i} in upward shift and X_{1i} remain stable
- Up-shift (1,1); Both X_{1i} and X_{2i} in upward shift
- Down-shift (-1,0); X_{1i} in downward shift and X_{2i} remain stable
- Down-shift (0.-1); X_{2i} in downward shift and X_{1i} remain stable
- Down-shift (-1,-1); Both X_{1i} and X_{2i} in downward shift

Bivariate normal pattern (N(0,0)) represents the bivariate in-control process, whereas bivariate shift patterns (US(1,0), (0,1) and (1,1)) represent the bivariate out-of-control process on the positive direction. Thus, bivariate shift patterns for (DS(-1,0), (0,-1) and (-1,-1)) represent the bivariate out-of-control process on the negative direction. Therefore, positive magnitudes of cross correlation function (ρ = 0.1, 0.3, 0.5, 0.7 and 0.9) were applied to all pattern categories in training ANN recognizer.

CHAPTER 4

RESULT AND DISCUSSION

4.1 Introduction

The performance and enhancement for process monitoring and diagnosis of bivariate patterns were discuss in this chapter involving the result of input representation, design of the recognizer, mean shift and medium cross correlation ($\rho = 0.5$). The detail concept of research had been explained in the previous chapter. The results obtained from MatLab R2011 software to recognize Advance Statistical Process Control Scheme, Synergistic-ANN also to recognize process out-of-control by used actual industrial data. The diagnosis accuracy of synergistic-ANN schemes were compared with generalized-ANN scheme of raw data.

The discussions can be divided into three section, Baseline Scheme in Section 4.2 whereas design and development using ANN pattern recognition technique in Section 4.3 describes the improvement of the internal design by reducing neural network size using statistical features input representation. Finally, technique to combine the raw data-based and the statistical feature-based input representations, namely synergistic-ANN model is presented in the Section 4.4.

4.2 Synergistic Scheme

The synergistic scheme for monitoring and diagnosis of bivariate process variation in mean shifts was designed and developed using on an artificial neural network (ANN). Before the ANN was trained, a large amount of bivariate samples is required for raw-data recognizer. Supposedly, the samples should be trained from real world data, but according to time limited it was not necessarily. As such, there is a need for modelling of synthetic samples. The synthetic samples of bivariate process were generated based on the following steps (Lehman, 1977) used to generate seven categories of bivariate pattern where the detail of this pattern can be refer in the previous chapter.

4.2.1 Data Generator

<u>Step 1</u>: Generate random normal variates for process variable-1 (n_1) and process variable-2 (n_2) which is identically and independently distributed (i.i.d) within [-3,+3]:

$$n_1 = b \text{ x } r_1 \tag{4.1}$$

$$n_2 = b \text{ x } r_2 \tag{4.2}$$

Parameters (r_1 and r_2) and b represent random normal variates (random data) and noise level respectively. Random normal variates are computerized generated data, whereby the noise level is used to rescale its variability. In this research, b = 1/3 is used to ensure that all random are simulated within ± 3.00 standard deviations (not exceed the control limits of Shewhart control chart).

<u>Step 2</u>: Transform random normal variates for process variable-1 (n_1) into random data series (Y_1):

$$Y_1 = \mu_1 + n_1\sigma_1 \tag{4.3}$$

Parameters μ_1 and σ_1 respectively represent the mean and the standard deviation for Y_1.

Step 3: Transform random normal variates for process variable-2 (n_2) into random data series (Y_2) dependent to (Y_1).

$$Y_2 = \mu_2 + [n_1\rho + n_2\sqrt{(1-\rho^2)}\,]\sigma_2 \tag{4.4}$$

Parameters μ_2 and σ_2 respectively represent the mean and the standard deviation for Y_2 whereas ρ represents the correlation coefficient between (Y_1,Y_2).

Step 4: Compute mean and standard deviation from (Y_1,Y_2). The values represent in-control process mean (μ_{01},μ_{02}) and standard deviation (σ_{01},σ_{02}) for part variables.

Step 5: Transform random data series (Y_1,Y_2) into normal or shift (pattern) data streams to mimic real observation samples (X_1,X_2):

$$X_1 = h_1\,(\sigma_{01}/\sigma_1) + Y_1 \tag{4.5}$$

$$X_2 = h_2\,(\sigma_{01}/\sigma_2) + Y_2 \tag{4.6}$$

The magnitudes of mean shift (h_1,h_2) are expressed in terms of the standard deviation for the in-control process. A pair observation sample (X_1,X_2) represents a bivariate vector measured at time t (X_t) that follows the random bivariate distribution N (μ_0, Σ_0). The notations μ_0 and Σ_0 = [(σ_1^2 σ_{12}) (σ_{12} σ_2^2)]represent mean vector and covariance matrix for bivariate in-control process with variances (σ_1^2 ,σ_2) and covariance ($\sigma_{12} = \sigma_{21}$)

Step 6: Rescale pattern data streams into a standardize range within [-3, +3]:

$$Z_1 = (X_1-\mu_{01})/\sigma_{01} \tag{4.7}$$

$$Z_2 = (X_2-\mu_{02})/\sigma_{02} \tag{4.8}$$

A pair standardized sample (Z_1, Z_2) represents a standardized bivariate vector measured at time t (Z_t) that follows the standardized normal bivariate distribution N (0, R).

4.2.2 Input Representation

Input representation is a technique in which the process data streams or statistical properties or features of input patterns can be represented into ANN recognizer to achieve effective recognition. In this scheme, raw data-based input representation was applied and each input pattern was represented by 48 data, which is standardized data series of both process variables.

4.3 Recognizer Training and Testing

Partially developed shift pattern and dynamic patterns were applied into the ANN training and testing respectively since these approaches have been proven effective to suit for on-line process situation (Guh, 2007). Detail parameter for the training pattern is summarized in Table 4.1.

The number of training pattern for shift patterns = [100 x (total combination of mean shift) x (total combination of cross correlation)]

The number of training pattern for normal patterns = [1500 x (total combination of cross correlation)]

Table 4.1: Parameters for the Training Patterns (Massood & Adnan, 2010)

Pattern category	Mean shift (in std dev)	Data correlation (ρ)	Amount of training patterns
N(0, 0)	X1: 0.00 X2: 0.00		1,500 x 5 = 7,500
US(1, 0)	X1: 1.00, 1.25, … , 3.00 X2: 0.00, 0.00, … , 0.00		100 x 9 x 5 = 4,500
US(0, 1)	X2: 0.00, 0.00, … , 0.00 X1: 1.00, 1.25, … , 3.00		100 x 9 x 5 = 4,500
US(1, 1)	X1: 1.00, 1.00, 1.25, 1.25, … , 3.00 X2: 1.00, 1.25, 1.00, 1.25, … , 3.00	0.1, 0.3, 0.5, 0.7, 0.9	100 x 25 x 5 = 12,500
DS(1, 0)	X1: -1.00, -1.25, … , -3.00 X2: 0.00, 0.00, … , 0.00		100 x 9 x 5 = 4,500
DS(0, 1)	X2: 0.00, 0.00, … , 0.00 X1: -1.00, -1.25, … , -3.00		100 x 9 x 5 = 4,500
DS(1, 1)	X1: -1.00, -1.00, -1.25, -1.25, … , -3.00 X2: -1.00, -1.25, -1.00, -1.25, … , -3.00		100 x 25 x 5 = 12,500

4.3.1 ANN Recognizer Training

In this research, the ANN recognizers were trained using raw data-based and statistical feature-based input representation. Both networks were structured by three layer MLP model. The experiments aim to improve in-line with the increment in the number of neurons where once it exceed the require numbers, further increment did not improve the training results but indicates poor accuracy.

The first performance was using raw data-ANN recognizer model, which consists of 48 input neurons and come out with seven output neurons. The number of hidden neurons (26) was determined based on peak performance. The medium cross correlation function (ρ = 0.5) was applied to all pattern categories in training for raw data-ANN and feature-ANN recognizers. The investigation involves several types of cases (case 1, case 2, case 3) as shown in Table 4.2.

Table 4.2: Training Result for Raw data-ANN Recognizer

Raw Data-Based					
Types of Cases	Recognition Accuracy (%)		MSE x 10^{-3}	Epoch	Time (sec)
	Normal Correct (N)	Shift Correct (S)			
Case 1 N > 99 S > 95	99.3316	98.0126	867	228	159
Case 2 N > 99 S > 95	99.3146	97.7549	950	190	133
Case 3 N ≈ 98 S ≈ 98	98.6248	98.3903	844	211	114

Based on the results, case 1 gain the highest value of normal patterns (99.3316%) and shift patterns (98.0126%). These results were compared to the value of previous researcher as show in Table 4.3. The values of normal and shift patterns for each case were examined and calculated using matrix form contain in MATLAB software. One of the example matrix forms can be summarized in Figure 4.1.

	N(0,0)	US(1,0)	US(0,1)	US(1,1)	DS(1,0)	DS(0,1)	DS(1,1)
N(0,0)	1506	7	2	5	2	4	1
US(1,0)	11	922	0	16	0	3	0
US(0,1)	11	0	909	6	0	0	0
US(1,1)	17	2	4	2444	0	0	0
DS(1,0)	16	0	3	0	865	0	9
DS(0,1)	8	1	0	0	0	865	8
DS(1,1)	13	0	0	0	5	5	2430

Figure 4.1: Matrix Forms of Raw data-based

Masood and Hassan (2012) stated that the desired training performance aims to reduce the false alarm, with longer ARL_0 and trained ANN recognizer should achieve an excellent recognition accuracy percentage; above 99% in clarifying normal patterns. Meanwhile, the training performance continued by improving the sensitivity in detecting mean shifts of smaller ARL_1 and accurate diagnosis of the source variables with higher recognition accuracy percentage with above 95% in shift patterns. The results obtained in Table 4.2 clearly prove that case 1 and case 2 have achieved the requirements of ARL_0 and ARL_1 with highest accuracy. This is also been compared with the results from Masood and Hassan (2012) in Table 4.3 that gain the value lower than the requirement of recognition accuracy. The value is (Normal Pattern = 98.70% and Shift Pattern = 98.48%).

Table 4.3: Training Result for Raw data-ANN Recognizer (Masood and Hassan, 2012)

Number of hidden neuron (HN)	Recognition accuracy (in %)		MSE $x10^{-3}$	Epoch	Time (sec)
	Normal Pattern	Shift Pattern			
5	98.70	88.96	23.8	155	37
10	98.21	98.17	7.60	223	62
15	98.21	98.40	6.26	199	64
20	98.04	98.30	5.57	243	95
25	97.99	98.65	7.25	208	98
26	**98.70**	**98.48**	**3.41**	**293**	**136**
27	98.69	98.09	8.64	169	84
30	98.45	98.51	6.00	269	138
35	98.53	97.97	10.4	191	114
40	97.80	93.71	18.5	154	95

Note: Basis structure of ANN = 48 x HN x 7

The secondary performance was analysed using statistical feature-ANN recognizer. It consists of 14 neurons of input layer and seven neurons of output layer which was determined according to the number of pattern categories. The hidden layer contains 22 neurons, where number of layers could influence an ANN performance. The training result of feature-based ANN can be shown in Table 4.4.

Table 4.4: Training Result for Feature-ANN Recognizer

Feature-Based					
Types of Cases	Recognition Accuracy (%)		MSE x 10^{-3}	Epoch	Time (sec)
	Normal Correct (N)	Shift Correct (S)			
Case 1 N > 99 S > 95	99.5876	96.2175	214	149	88
Case 2 N:97~98 S:97~98	97.8892	98.3108	103	192	133
Case 3 N > 99 S > 95	99.3814	96.1596	211	198	114

Based on the results, case 1 gave the highest recognition accuracy than others with normal patterns = 99.5876% and shift patterns = 96.2175%. This feature-based ANN recognizer yields a smaller network size, less computational efforts and it should be done with shorter training time compared to the raw data-based ANN recognizer. According to Masood and Hassan (2012), the results of feature-ANN were 99.53% and 95.72% for Normal and Shift Patterns respectively as shown in Table 4.5. It shows that the value from the previous research is lowest but still in the range of specification of ANN. In addition, the ANN was trained well from time to time and it has been performed repeatedly in order to get excellent results. The value of normal and shift patterns for each cases was examine and calculated using matrix form contain in MATLAB software. One of the example matrix forms can be summarized in Figure 4.2.

	N(0,0)	US(1,0)	US(0,1)	US(1,1)	DS(1,0)	DS(0,1)	DS(1,1)
N(0,0)	1446	1	0	2	0	2	4
US(1,0)	62	842	0	12	0	0	0
US(0,1)	49	0	865	11	0	0	0
US(1,1)	25	3	17	2498	0	0	0
DS(1,0)	53	0	4	0	808	0	5
DS(0,1)	35	1	0	0	0	825	6
DS(1,1)	31	0	0	0	14	4	2475

Figure 4.2: Matrix Forms of Feature-based

Feature-based ANN and raw data-based ANN model recognizers were trained to produce the highest and excellent output with different input representation as mentioned previously. The functions of feature-based input representation to minimize processing data and computation effort into ANN training. This method will reduce the computation effort toward achieving better recognition performance as reported in previous researches (Pham and Wani, 1997; Gauri and Chakraboty, 2006; Masood and Hassan, 2012).

Previously, some other journals only examine four types of pattern and this is not enough for further studies. Generally, the original data have strong properties to distinguish between normal and shift pattern, where this type of data can get from the industry. The data is set to 24 for one variable of input representation. Furthermore, statistical features was converted from original data with length of EWMA, λ = 0.1. The properties are to distinguish between normal and shift pattern even this type of data lower than original data. Nevertheless, each input data representation has their specific capability and advantages. Therefore, it should be useful to combine both input representation technique into the synergistic-ANN, which is discussed further in the next section.

Table 4.5: Training Result for Feature-ANN Recognizer (Masood and Hassan, 2012)

No.	Candidate ANN structure	Short listed features						Recognition accuracy (%)		MSE $x10^{-3}$	Epoch	Time (sec)
		LEWMA λ= 0.10 λ= 0.15 λ= 0.20 λ= 0.25	Mean	MSD	MMS	MAT	Slope	Normal	Shift			
1	8 x 8 x 7	*						96.39	96.13	7.56	232	55
2	10x 16 x 7	*	*					96.81	97.13	5.23	213	67
3	10 x 16 x 7	*		*				97.37	96.83	6.01	176	55
4	10 x 16 x 7	*			*			98.39	95.85	10.6	205	64
5	10 x 16 x 7	*				*		98.15	94.94	11.6	225	70
6	14 x 22 x 7	*		*	*	*		99.14	94.53	10.8	238	91
7	**14 x 22 x 7**	*	*	*	*			**99.53**	**95.72**	**9.36**	**249**	**100**
8	10 x 16 x 7	*					*	95.51	96.75	6.51	255	81
9	16 x 10 x 7	*	*	*	*	*		99.46	95.16	16.9	193	49
10	12 x 16 x 7	*	*				*	96.85	97.76	5.86	197	61
11	16 x 10 x 7	*		*	*	*	*	98.79	96.35	10.1	263	64
12	18 x 24 x 7	*	*	*	*	*	*	99.05	96.64	10.2	237	98
13	16 x 10 x 7	*	*	*	*		*	97.00	97.31	8.67	312	78
	48 x 26 x 7	Raw data						98.70	98.48	3.41	293	136

4.4 Performance Result and Evaluation

The evaluation of Synergistic Scheme were continued based on the results of average run lengths (ARL_0, ARL_1) and recognition accuracy (RA) to monitor and diagnose the performance. In this research, seven pattern categories were evaluate by medium cross correlation ($\rho = 0.5$) with different input of mean shift ($\mu = 1.00$, 2.00 and 3.00). The highest input representation of raw data-based and feature-based in ANN training were used as a part of this simulation, available with (ipminn = -6.8468, ipmaxx = 7.2808) of raw data and (ipminn = -10.0849, ipmaxx = 10.5914) of features data. Detail performance of simulation can be referring as summarized in Table 4.6. The average results for each mean shift magnitudes are compared with the previous result of (Masood & Adnan, 2012) as attached in Appendix A and it be presented graphically as shown in Figures 4.3 and 4.4.

The studies conclude of two phase; phase I is focusing to the process of pattern and input representation where it had been discussed in the previous section, while the phase II is for monitoring and diagnosis the process. In this section, monitoring process includes the ARL_0, represent the average number of samples in-control process before the first point is out-of-control process signal exist. The function of ARL_0 is to measures how long a SPC charting scheme could maintain an in-control process running without false alarm. In theory, the ARL_0 is infinity which there is no point out-of-control. However, due to the probability of Type I error, ARL_0 is limited to certain condition. The longer of ARL_0, the performance is effective and accurate.

$$ARL_0 = 1/\alpha$$

$$\alpha = 1/ARL_0$$

On the other hand, ARL1 represent the average number of samples before it truly identified as out-of-control process signal. The function of ARL_1 is to measure how fast a SPC charting scheme could detect process mean shift, and it is different with ARL_0. In theory, if ARL_1 is equal to one, it is considered a process as out-of-control. However, due to the investigating of Type II error, ARL_1 will be longer depend on the probability factor. The shorter of ARL_1, the performance is effective and accurate.

$$ARL_1 = 1/(1-\beta)$$

$$B = 1-(1/ARL_1)$$

Table 4.6: Monitoring-diagnosis results for Synergistic-ANN scheme

Pattern Category	Mean Shifts		Average run lengths		Recognition accuracy	
	X_1	X_2	ARL_0 for ρ=0.5		RA for ρ=0.5	
N(0,0)	0.00	0.00			NA	
			ARL_1 for ρ=0.5		Percentage (%)	
			Current	Previous	Current	Previous
US(1,0)	1.00	0.00	9.95	11.04	96.40	92.10
US(0,1)	0.00	1.00	11.60	9.71	**97.30**	92.90
US(1,1)	1.00	1.00	10.49	9.23	92.10	**96.10**
DS(1,0)	-1.00	0.00	11.00	9.95	96.80	92.40
DS(0,1)	0.00	-1.00	10.40	10.83	95.30	91.80
DS(1,1)	-1.00	-1.00	2.95	9.46	97.10	94.50
Average			**9.72**	**10.04**	**94.57**	**93.30**
US(1,0)	2.00	0.00	5.40	5.51	96.90	95.90
US(0,1)	0.00	2.00	5.55	4.99	**98.60**	95.70
US(1,1)	2.00	2.00	4.84	4.97	97.10	**97.10**
DS(1,0)	-2.00	0.00	5.19	5.01	98.00	97.10
DS(0,1)	0.00	-2.00	5.50	5.42	93.40	96.20
DS(1,1)	-2.00	-2.00	4.37	5.06	97.80	96.70
Average			**5.15**	**5.16**	**96.71**	**96.50**
US(1,0)	3.00	0.00	3.73	3.91	97.70	97.50
US(0,1)	0.00	3.00	3.68	3.59	99.30	95.50
US(1,1)	3.00	3.00	3.29	3.60	98.00	97.70
DS(1,0)	-3.00	0.00	3.35	3.37	**99.60**	**98.30**
DS(0,1)	0.00	-3.00	3.66	3.71	94.70	96.70
DS(1,1)	-3.00	-3.00	2.88	3.60	98.00	96.80
Average			**3.53**	**3.63**	**97.48**	**97.10**
Grand Average	(1.00-3.00)		**6.13**	**6.28**	**96.25**	**95.64**

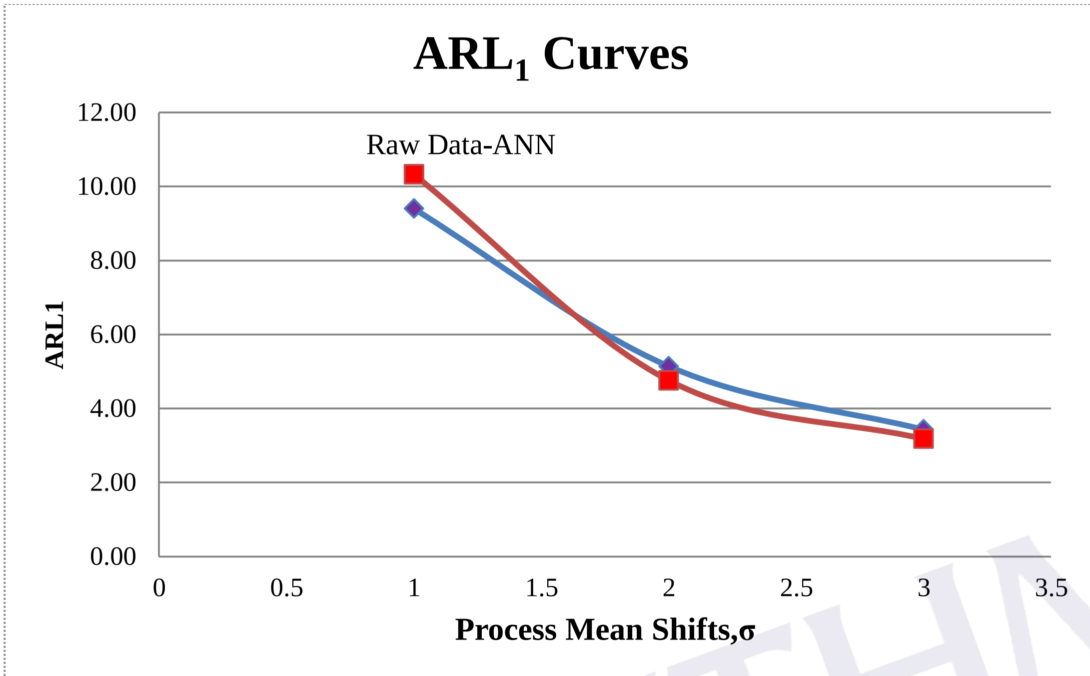


Figure 4.3: ARL_1 Curves for the Synergistic Scheme

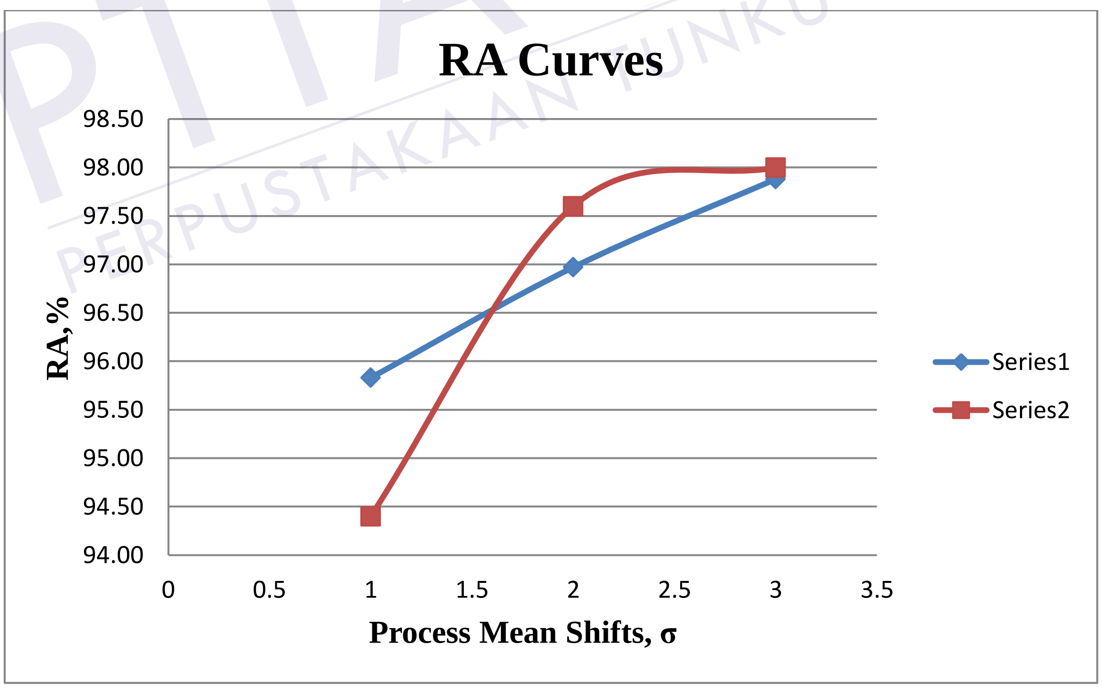


Figure 4.4: RA Curves for the Synergistic Scheme

4.5 Validation of Synergistic-ANN

The combining of raw data-ANN and statistical feature-ANN recognizers to be one unified, namely Synergistic-ANN. Thus, this section presents the study results used by actual industrial data to validate the data stream. The data was collected from previous researcher (Marian. F., 2014) in plastic injection process for panel part involved audio video device (AVD) part, namely, panel deck (Appendix B). The length and width of panel deck (A and B) were two dependent variables used as show in Figure 4.5. This scheme was proposed as the final outcome for balanced monitoring and accurate diagnosis for bivariate process mean shifts.

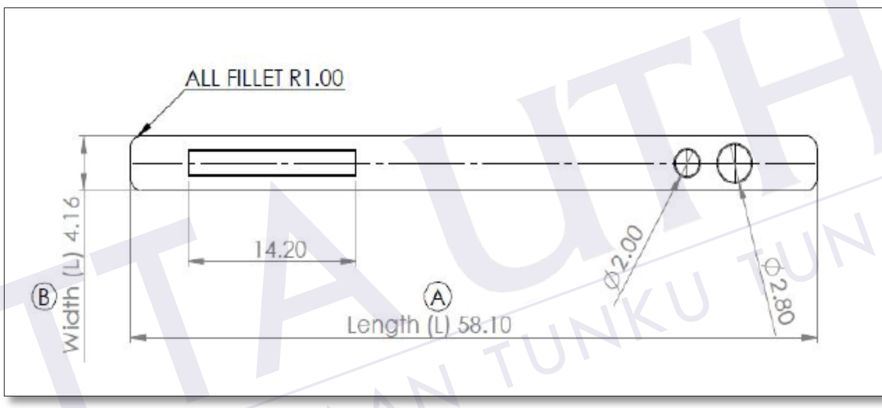


Figure 4.5: Features of Panel Deck

4.5.1 Case Studies

The selection of bivariate quality control parameters in this research involves the case study of 'pressure up', 'speed up' and 'mixed 20% regrinds'. Thus, all the variables posed a problem to the dimensions, length and width of the product is out of control, also it may cause the part or product is in imbalance monitoring. Thereby, the experiments were interpreted into I-chart and EWMA control chart to observe and identify the shift using industrial data. Table 4.7 shows the different case studies of I-chart and EWMA chart, started from in control process with in-control parameter (observation 1~40), the disturbance begins at control parameter (observation 41~50). The real raw data of the variables may refer in Appendix C, D and E.

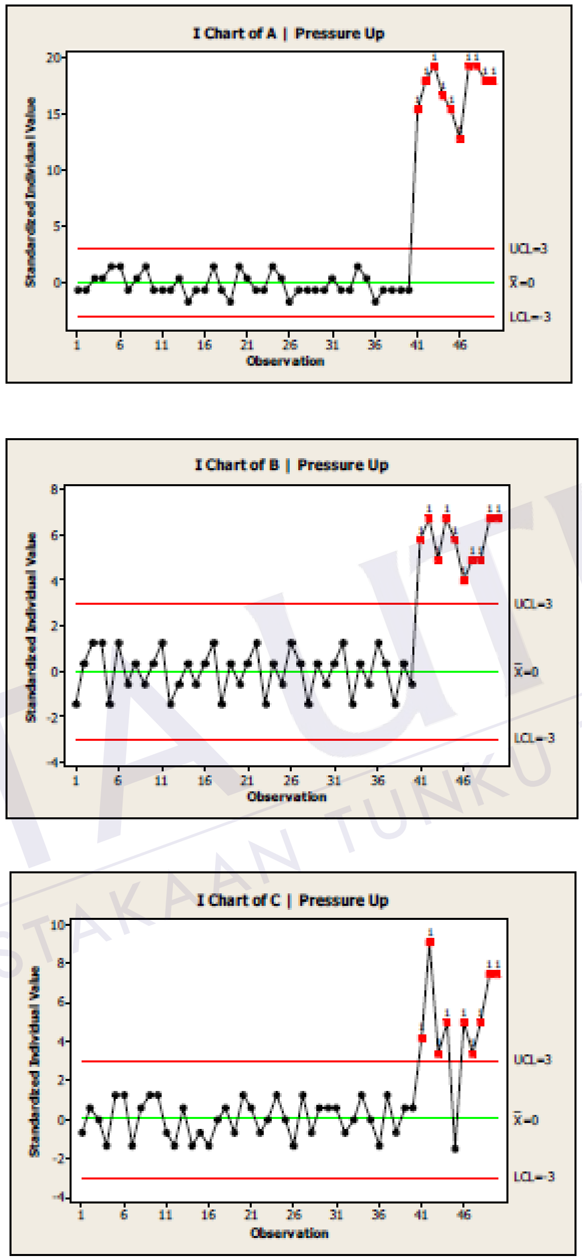


Figure 4.6: I-Chart for A, B and C in pressure increase condition

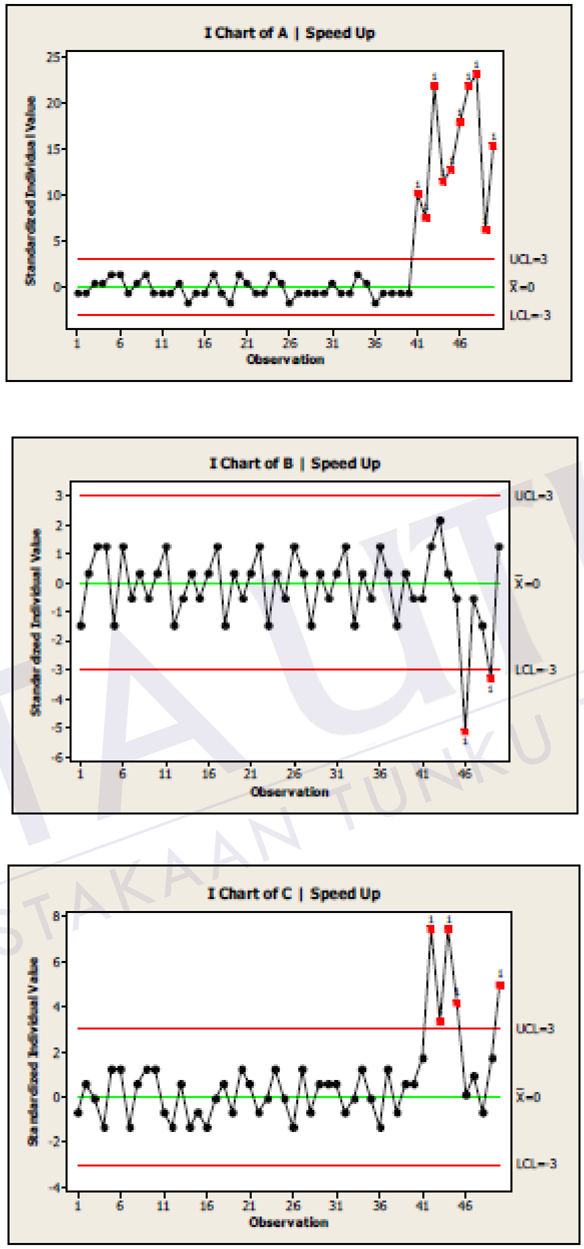


Figure 4.7: I-Chart for A, B and C in speed increase condition

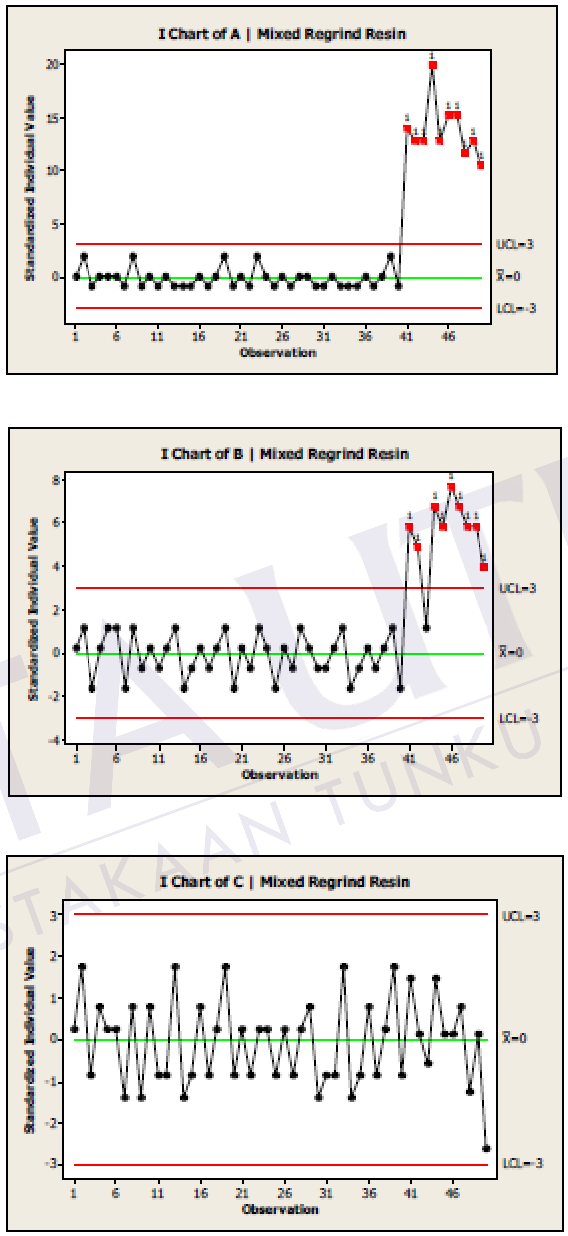


Figure 4.8: I-Chart for A, B and C in mixed 20% regrinds condition

Table 4.7: Recognition Performance between I-chart and EWMA chart

Control Chart	Variables								
	Pressure Increase			Speed Increase			Mixed 20% Regrinds		
	A	B	C	A	B	C	A	B	C
I-Chart	No. 41	No. 41	No. 41	No. 41	No. 46	No. 42	No. 41	No. 41	No. 47

Other than that, Figure 4.6, Figure 4.7 and Figure 4.8 shows the I-chart for ‘Pressure Increase’, ‘Speed Increase’ and ‘Mixed 20% regrinds’ respectively. Obviously, the disturbance has been notified started after observation sample number 41 onwards. The shift pattern for variable A of each case shows sudden highly jump up shifted trend. Meanwhile, for the case of speed increase condition, variable B start shifted to downward with number 46.

4.5.2 Out of control Recognition Performance Comparison

The study continued by the ANN recognition was design for variables which data set were combine as mentioned in order to compare the performance of synergistic-ANN scheme in term of recognition out of control condition.

i. Combination of Part Length (A) and Part Width (B);
ii. Combination of Part Width (B) and Part Weight (C);
iii. Combination of Part Length (A) and Part Weight (C);

The data from industrial was arranged as:

Data set no.1: To recognize outlier Type 1 (Holding Pressure Up)
(In control data no. 1~40 and Outlier data no. 41~50)

Data set no.1: To recognize outlier Type 2 (Injection Speed Up)
(In control data no. 1~40 and Outlier data no. 41~50)

Data set no.1: To recognize outlier Type 3 (Mixed 20% Regrinds Resin)
(In control data no. 1~40 and Outlier data no. 41~50)

For the synergistic-ANN recognizer, these three types of dependent variables selected will be combined into three probabilities, where the data set will be nine combinations. Hence, this situation can be clarified further in Table 4.8.

Table 4.8: Combination of Variables

Disturbance Factor	Combination Variables		
Case 1 Holding Pressure Up	AB	BC	AC
Case 2 Injection Speed Up	AB	BC	AC

4.6 Synergistic-ANN Scheme Detection Performance

The industrial process samples were simulated into the synergistic-ANN scheme for validating the capability in real world. The performance of the proposed scheme was compared to the traditional control chart. The first study involved ‘holding pressure increase’ and followed by ‘injection speed up’. The results of the performance were discussed in the next section and validation output was summarized into table.

Table 4.9: Validation results based on case 1 of 'Pressure Up'

I	Original Samples			Standardized Samples			Window Range	Monitoring-diagnosis decision
	X_{i-1}(L)	X_{i-2} (W)	X_{i-3} (WE)	Z_{i-1}(L)	Z_{i-2} (W)	Z_{i-3} (WE)		I-Chart
1	4.1622	58.6	10.6882	-0.6446	-1.4827	-0.7081		
2	4.1622	58.8	10.6890	-0.6446	0.3422	0.5992		
3	4.1626	58.9	10.6886	0.3867	1.2546	-0.0545		
4	4.1626	58.9	10.6878	0.3867	1.2546	-1.3617		
5	4.1630	58.6	10.6894	1.4180	-1.4827	1.2528		
6	4.1630	58.9	10.6894	1.4180	1.2546	1.2528		
7	4.1622	58.7	10.6878	-0.6446	-0.5703	-1.3617		
8	4.1626	58.8	10.6890	0.3867	0.3422	0.5992		
9	4.1630	58.7	10.6894	1.4180	-0.5703	1.2528		
10	4.1622	58.8	10.6894	-0.6446	0.3422	1.2528		
11	4.1622	58.9	10.6882	-0.6446	1.2546	-0.7081		
12	4.1622	58.6	10.6878	-0.6446	-1.4827	-1.3617		
13	4.1626	58.7	10.6890	0.3867	-0.5703	0.5992		
14	4.1618	58.8	10.6878	-1.6759	0.3422	-1.3617		
15	4.1622	58.7	10.6882	-0.6446	-0.5703	-0.7081		
16	4.1622	58.8	10.6878	-0.6446	0.3422	-1.3617		
17	4.1630	58.9	10.6886	1.4180	1.2546	-0.0545		
18	4.1622	58.6	10.6890	-0.6446	-1.4827	0.5992		
19	4.1618	58.8	10.6882	-1.6759	0.3422	-0.7081		
20	4.1630	58.7	10.6894	1.4180	-0.5703	1.2528		
21	4.1626	58.8	10.6890	0.3867	0.3422	0.5992		
22	4.1622	58.9	10.6882	-0.6446	1.2546	-0.7081		
23	4.1622	58.6	10.6886	-0.6446	-1.4827	-0.0545		
24	4.1630	58.8	10.6894	1.4180	0.3422	1.2528	1~ 24	N
25	4.1626	58.7	10.6886	0.3867	-0.5703	-0.0545	1~ 25	N
26	4.1618	58.9	10.6878	-1.6759	1.2546	-1.3617	1~ 26	N
27	4.1622	58.8	10.6894	-0.6446	0.3422	1.2528	1~ 27	N
28	4.1622	58.6	10.6882	-0.6446	-1.4827	-0.7081	1~ 28	N
29	4.1622	58.8	10.6890	-0.6446	0.3422	0.5992	1~ 29	N
30	4.1622	58.7	10.6890	-0.6446	-0.5703	0.5992	1~ 30	N
31	4.1626	58.8	10.6890	0.3867	0.3422	0.5992	1~ 31	N
32	4.1622	58.9	10.6882	-0.6446	1.2546	-0.7081	1~ 32	N
33	4.1622	58.6	10.6886	-0.6446	-1.4827	-0.0545	1~ 33	N
34	4.1630	58.8	10.6894	1.4180	0.3422	1.2528	1~ 34	N
35	4.1626	58.7	10.6886	0.3867	-0.5703	-0.0545	1~ 35	N
36	4.1618	58.9	10.6878	-1.6759	1.2546	-1.3617	1~ 36	N
37	4.1622	58.8	10.6894	-0.6446	0.3422	1.2528	1~ 37	N
38	4.1622	58.6	10.6882	-0.6446	-1.4827	-0.7081	1~ 38	N
39	4.1622	58.8	10.6890	-0.6446	0.3422	0.5992	1~ 39	N
40	4.1622	58.7	10.6890	-0.6446	-0.5703	0.5992	1~ 40	N
41	4.1684	59.4	10.6912	15.3406	5.8169	4.1942	1~ 41	NG
42	4.1694	59.5	10.6942	17.9189	6.7294	9.0965	1~ 42	NG
43	4.1699	59.3	10.6907	19.2080	4.9045	3.3771	1~ 43	NG
44	4.1689	59.5	10.6917	16.6297	6.7294	5.0112	1~ 44	NG
45	4.1684	59.4	10.6877	15.3406	5.8169	-1.5252	1~ 45	NG
46	4.1674	59.2	10.6917	12.7624	3.9920	5.0112	1~ 46	NG
47	4.1699	59.3	10.6907	19.2080	4.9045	3.3771	1~ 47	NG
48	4.1699	59.3	10.6917	19.2080	4.9045	5.0112	1~ 48	NG
49	4.1694	59.5	10.6932	17.9189	6.7294	7.4624	1~ 49	NG
50	4.1694	59.5	10.6932	17.9189	6.7294	7.4624	1~ 50	NG

Represents out-of-control

Table 4.10: Output of the scheme for the Case 1 Combination of AB

	RW	1-24	2-25	3-26	4-27	5-28	6-29	7-30	8-31	9-32
	ρ	0.7453	0.7514	0.7359	0.7349	0.7210	0.7349	0.7557	0.7594	0.7371
SYNERGISTIC-ANN	N (0,0)	**1.4762**	**1.4856**	**1.5187**	**1.4260**	**1.4866**	**1.4986**	**1.5314**	**1.3825**	**1.4644**
	US (1,0)	0.1595	0.2044	0.1941	0.1842	0.1424	0.1832	0.1681	0.1434	0.1450
	US (0,1)	0.2138	0.2098	0.2313	0.1955	0.2290	0.2700	0.2518	0.2094	0.2412
	US (1,1)	0.0971	0.0594	0.0700	0.0576	0.0809	0.0845	0.0729	0.0631	0.0645
	DS (1,0)	0.2006	0.1935	0.1925	0.1620	0.2872	0.1831	0.2476	0.2221	0.2589
	DS (0,1)	0.3244	0.2783	0.2575	0.2724	0.1998	0.1818	0.1745	0.2323	0.1919
	DS (1,1)	0.0860	0.1126	0.0835	0.1147	0.1028	0.0980	0.1095	0.1231	0.1769
	RW	10-33	11-34	12-35	13-36	14-37	15-38	16-39	17-40	18-41
	ρ	0.6414	0.6465	0.6465	0.6465	0.7364	0.7371	0.7547	0.7557	0.8931
SYNERGISTIC-ANN	N (0,0)	**1.5049**	**1.4170**	**1.2926**	**1.3578**	**1.3581**	**1.3700**	**1.4604**	**1.4512**	0.5792
	US (1,0)	0.1065	0.1318	0.1082	0.1074	0.0968	0.1079	0.1247	0.1357	**0.8418**
	US (0,1)	0.3230	0.2254	0.1738	0.2075	0.1980	0.1950	0.2398	0.2068	0.0900
	US (1,1)	0.0896	0.0615	0.0514	0.0584	0.0524	0.0586	0.0866	0.0562	0.6314
	DS (1,0)	0.3472	0.3499	0.3143	0.3714	0.4647	0.2924	0.3637	0.2431	0.1016
	DS (0,1)	0.1327	0.1537	0.1933	0.2074	0.2419	0.2215	0.2062	0.2702	0.2322
	DS (1,1)	0.0853	0.1714	0.2521	0.1700	0.2326	0.1548	0.1195	0.1615	0.0065
	RW	19-42	20-43	21-44	22-45	23-46	24-47	25-48	26-49	27-50
	ρ	0.9230	0.8348	0.8968	0.9076	0.9147	0.9251	0.9267	0.9300	0.9300
SYNERGISTIC-ANN	N (0,0)	0.1769	0.0713	0.0899	0.0589	0.0687	0.1021	0.0425	0.0729	0.0526
	US (1,0)	0.9055	**1.1584**	1.3988	1.1331	1.4411	1.3276	1.3376	1.2739	1.4081
	US (0,1)	0.1614	0.4929	0.9400	0.9784	1.0477	1.0432	1.0794	1.1274	1.0719
	US (1,1)	**1.3932**	1.1163	**1.4079**	**1.4293**	1.4393	1.4499	**1.4144**	1.4275	**1.4209**
	DS (1,0)	0.0519	0.1186	0.0390	0.1130	0.2380	0.0387	0.1336	0.0437	0.0613
	DS (0,1)	0.2351	0.7002	1.3935	1.2290	**1.5120**	**1.5365**	1.3305	**1.4844**	1.3835
	DS (1,1)	0.0051	0.0112	0.0427	0.0535	0.0545	0.0471	0.0423	0.0389	0.0364

Note: **Bolt value** represents the maximum output of ANN that determines pattern category

Table 4.11: Output of the scheme for the Case 1 Combination of BC

	RW	1-24	2-25	3-26	4-27	5-28	6-29	7-30	8-31	9-32
	ρ	0.2848	0.3377	0.2201	0.1969	0.1516	0.0845	-0.0173	0.0066	-0.0212
SYNERGISTIC-ANN	N (0,0)	**1.2717**	**1.3570**	**1.2389**	**1.3426**	**1.2634**	**1.3468**	**1.4425**	**1.1569**	0.8392
	US (1,0)	0.2184	0.1966	0.4115	0.2198	0.4404	0.3031	0.2738	0.5606	**0.8642**
	US (0,1)	0.1559	0.1521	0.1286	0.1823	0.1079	0.1507	0.2053	0.1161	0.0475
	US (1,1)	0.1196	0.0933	0.0792	0.0965	0.1069	0.0945	0.0796	0.1489	0.2269
	DS (1,0)	0.1799	0.1568	0.1014	0.1638	0.1163	0.1352	0.1868	0.1275	0.0780
	DS (0,1)	0.1751	0.2260	0.4183	0.2506	0.3422	0.2895	0.1613	0.2653	0.2772
	DS (1,1)	0.0558	0.0615	0.0624	0.0583	0.0480	0.0569	0.0719	0.0360	0.0215
	RW	10-33	11-34	12-35	13-36	14-37	15-38	16-39	17-40	18-41
	ρ	0.0451	0.2180	0.1811	0.0035	0.1209	-0.0242	-0.0187	-0.0525	0.1609
SYNERGISTIC-ANN	N (0,0)	0.7219	0.4814	0.2473	0.2054	0.1168	0.1010	0.0865	0.0637	0.0641
	US (1,0)	**1.2239**	**1.3070**	**1.6124**	**1.7729**	**1.7887**	**1.8740**	**1.8708**	**1.8770**	**1.8272**
	US (0,1)	0.0266	0.0221	0.0181	0.0130	0.0144	0.0130	0.0125	0.0133	0.0142
	US (1,1)	0.3166	0.4997	0.5165	0.4085	0.5183	0.4987	0.6063	0.6715	0.8908
	DS (1,0)	0.0843	0.1341	0.0615	0.0358	0.0408	0.0385	0.0290	0.0299	0.0372
	DS (0,1)	0.3311	0.2440	0.3158	0.4648	0.3376	0.4402	0.3958	0.3803	0.3184
	DS (1,1)	0.0142	0.0090	0.0060	0.0047	0.0032	0.0026	0.0024	0.0019	0.0018
	RW	19-42	20-43	21-44	22-45	23-46	24-47	25-48	26-49	27-50
	ρ	0.3401	0.3653	0.4537	0.3688	0.3954	0.4109	0.4606	0.5020	0.5211
SYNERGISTIC-ANN	N (0,0)	0.0132	0.0149	0.0179	0.0212	0.0340	0.0648	0.1241	0.1626	0.2044
	US (1,0)	1.2761	1.1258	0.9154	1.2673	1.0103	1.3167	1.1381	1.2099	0.9924
	US (0,1)	0.0309	0.0398	0.0364	0.0538	0.0358	0.0495	0.0661	0.0809	0.1732
	US (1,1)	**1.4728**	**1.5537**	**1.5922**	**1.6520**	**1.6920**	**1.7605**	**1.8148**	**1.8480**	**1.8758**
	DS (1,0)	0.0211	0.0268	0.0514	0.0181	0.0331	0.0183	0.0348	0.0417	0.0371
	DS (0,1)	0.2960	0.3039	0.2839	0.3691	0.2892	0.2972	0.2608	0.2622	0.2606
	DS (1,1)	0.0016	0.0015	0.0015	0.0019	0.0020	0.0025	0.0027	0.0033	0.0041

Note: **Bolt value** represents the maximum output of ANN that determines pattern category

Table 4.12: Output of the scheme for the Case 1 Combination of AC

	RW	1-24	2-25	3-26	4-27	5-28	6-29	7-30	8-31	9-32
	ρ	0.1117	0.1169	0.0570	0.0115	0.0177	0.0121	-0.0221	-0.0022	-0.1248
SYNERGISTIC-ANN	N (0,0)	**1.3859**	**1.3939**	**1.3579**	**1.3000**	**1.4006**	**1.3756**	**1.3246**	**1.3941**	**1.2572**
	US (1,0)	0.1492	0.1398	0.2198	0.1940	0.1712	0.1252	0.1259	0.2426	0.3637
	US (0,1)	0.2179	0.1882	0.1487	0.2673	0.2257	0.1934	0.2277	0.2122	0.1223
	US (1,1)	0.0950	0.0807	0.0612	0.0662	0.0655	0.0698	0.0695	0.1124	0.1358
	DS (1,0)	0.2437	0.2673	0.2034	0.2351	0.2531	0.2700	0.3134	0.2494	0.1265
	DS (0,1)	0.1798	0.1726	0.2624	0.1351	0.1972	0.1909	0.1328	0.1486	0.2385
	DS(1,1)	0.0717	0.0805	0.0955	0.0917	0.0896	0.0906	0.0960	0.0572	0.0387
	RW	10-33	11-34	12-35	13-36	14-37	15-38	16-39	17-40	18-41
	ρ	-0.0708	0.0837	0.0506	-0.0840	0.0652	-0.0663	-0.0594	-0.0726	0.2268
SYNERGISTIC-ANN	N (0,0)	**1.0875**	0.7713	0.6318	0.3670	0.2155	0.1326	0.1165	0.0708	0.0688
	US (1,0)	0.7229	**0.9178**	**1.2349**	**1.6095**	**1.6378**	**1.8281**	**1.8347**	**1.8469**	**1.7567**
	US (0,1)	0.0520	0.0377	0.0311	0.0172	0.0157	0.0140	0.0137	0.0141	0.0153
	US (1,1)	0.2074	0.3659	0.3723	0.3033	0.5291	0.4195	0.5284	0.6394	0.9059
	DS (1,0)	0.0862	0.1799	0.0694	0.0504	0.0635	0.0471	0.0323	0.0384	0.0482
	DS (0,1)	0.3664	0.2039	0.3168	0.4475	0.2881	0.3950	0.3833	0.3605	0.2817
	DS(1,1)	0.0249	0.0156	0.0106	0.0083	0.0050	0.0036	0.0028	0.0022	0.0018
	RW	19-42	20-43	21-44	22-45	23-46	24-47	25-48	26-49	27-50
	ρ	0.4234	0.4755	0.5629	0.4629	0.4936	0.5113	0.5651	0.6070	0.6154
SYNERGISTIC-ANN	N (0,0)	0.0165	0.0167	0.0166	0.0221	0.0394	0.0956	0.2374	0.3527	0.4523
	US (1,0)	1.2285	1.1131	0.9470	1.3366	1.1010	1.4275	1.2026	1.3204	1.1038
	US (0,1)	0.0293	0.0401	0.0373	0.0569	0.0401	0.0561	0.0743	0.1131	0.2131
	US (1,1)	**1.5325**	**1.5624**	**1.5854**	**1.6501**	**1.7279**	**1.8172**	**1.8875**	**1.9223**	**1.9314**
	DS (1,0)	0.0245	0.0275	0.0515	0.0160	0.0281	0.0170	0.0333	0.0430	0.0403
	DS (0,1)	0.2422	0.3021	0.2875	0.3771	0.2995	0.3081	0.2476	0.2331	0.2321
	DS(1,1)	0.0018	0.0015	0.0015	0.0020	0.0022	0.0028	0.0031	0.0034	0.0047

Note: **Bolt value** represents the maximum output of ANN that determines pattern category

In the first 40 samples, the schemes were able to recognize the bivariate process data streams as in normal pattern (N) without triggering any false alarm. The first case study involved 'pressure increase' to recognize the three combinations of variables data as stated in Table 4.10, 4.11 and 4.12. The mean (μ) and standard deviation (σ) of bivariate in-control process were computed based on the first 24 observation samples. Furthermore, the disturbance of part begins at sample 41^{st} until sample 50^{th} for those variables. The validation was train by Up-Shift pattern (US (1,1)) and supposedly at raw data 41, the shift was detect at the right path. By referring at Table 4.10, sample number of 41 shows the data was shifted at Up-Shift pattern (US (1,0)) and continue to shift at Up-Shift pattern (US (1,1)). This situation does not maintain and it is because the data was not train properly in the beginning. On the other hand, the others cases of 'pressure increase' were correctly shifted begins at sample number of 42.

The second case study involved 'speed up'. Similar as in the first case study, the mean (μ) and standard deviation (σ) of bivariate in-control process were computed based on the first 24 observation samples. The validation results and related output of the schemes were summarized in Table 4.14 and 4.15 respectively. The shift begin at sample number of 42 with late detection to achieve Up-Shift (US(1,1)) for both combination in speed up. This situation may cause the false alarm.

Based on the first 39 samples, the schemes were effective to correctly recognize the bivariate process data streams as in normal pattern (N) in-control for all cases.

Table 4.13: Validation results based on case 1 of 'Speed Up'

i	Original Samples			Standardized Samples			Window Range	Monitoring-diagnosis decision
	X_{i-1}(L)	X_{i-2} (W)	X_{i-3} (WT)	Z_{i-1}(L)	Z_{i-2} (W)	Z_{i-3} (WT)		I-Chart
1	4.1622	58.6	10.6882	-0.6446	-1.4827	-0.7081		
2	4.1622	58.8	10.6890	-0.6446	0.3422	0.5992		
3	4.1626	58.9	10.6886	0.3867	1.2546	-0.0545		
4	4.1626	58.9	10.6878	0.3867	1.2546	-1.3617		
5	4.1630	58.6	10.6894	1.418	-1.4827	1.2528		
6	4.1630	58.9	10.6894	1.418	1.2546	1.2528		
7	4.1622	58.7	10.6878	-0.6446	-0.5703	-1.3617		
8	4.1626	58.8	10.6890	0.3867	0.3422	0.5992		
9	4.1630	58.7	10.6894	1.418	-0.5703	1.2528		
10	4.1622	58.8	10.6894	-0.6446	0.3422	1.2528		
11	4.1622	58.9	10.6882	-0.6446	1.2546	-0.7081		
12	4.1622	58.6	10.6878	-0.6446	-1.4827	-1.3617		
13	4.1626	58.7	10.6890	0.3867	-0.5703	0.5992		
14	4.1618	58.8	10.6878	-1.6759	0.3422	-1.3617		
15	4.1622	58.7	10.6882	-0.6446	-0.5703	-0.7081		
16	4.1622	58.8	10.6878	-0.6446	0.3422	-1.3617		
17	4.1630	58.9	10.6886	1.418	1.2546	-0.0545		
18	4.1622	58.6	10.6890	-0.6446	-1.4827	0.5992		
19	4.1618	58.8	10.6882	-1.6759	0.3422	-0.7081		
20	4.1630	58.7	10.6894	1.418	-0.5703	1.2528		
21	4.1626	58.8	10.6890	0.3867	0.3422	0.5992		
22	4.1622	58.9	10.6882	-0.6446	1.2546	-0.7081		
23	4.1622	58.6	10.6886	-0.6446	-1.4827	-0.0545		
24	4.1630	58.8	10.6894	1.418	0.3422	1.2528	1~ 24	N
25	4.1626	58.7	10.6886	0.3867	-0.5703	-0.0545	1~ 25	N
26	4.1618	58.9	10.6878	-1.6759	1.2546	-1.3617	1~ 26	N
27	4.1622	58.8	10.6894	-0.6446	0.3422	1.2528	1~ 27	N
28	4.1622	58.6	10.6882	-0.6446	-1.4827	-0.7081	1~ 28	N
29	4.1622	58.8	10.6890	-0.6446	0.3422	0.5992	1~ 29	N
30	4.1622	58.7	10.6890	-0.6446	-0.5703	0.5992	1~ 30	N
31	4.1626	58.8	10.6890	0.3867	0.3422	0.5992	1~ 31	N
32	4.1622	58.9	10.6882	-0.6446	1.2546	-0.7081	1~ 32	N
33	4.1622	58.6	10.6886	-0.6446	-1.4827	-0.0545	1~ 33	N
34	4.1630	58.8	10.6894	1.418	0.3422	1.2528	1~ 34	N
35	4.1626	58.7	10.6886	0.3867	-0.5703	-0.0545	1~ 35	N
36	4.1618	58.9	10.6878	-1.6759	1.2546	-1.3617	1~ 36	N
37	4.1622	58.8	10.6894	-0.6446	0.3422	1.2528	1~ 37	N
38	4.1622	58.6	10.6882	-0.6446	-1.4827	-0.7081	1~ 38	N
39	4.1622	58.8	10.6890	-0.6446	0.3422	0.5992	1~ 39	N
40	4.1622	58.7	10.6890	-0.6446	-0.5703	0.5992	1~ 40	N
41	4.1664	58.7	10.6897	10.1841	-0.5703	1.743	1~ 41	NG
42	4.1654	58.9	10.6932	7.6059	1.2546	7.4624	1~ 42	NG
43	4.1709	59.0	10.6907	21.7863	2.1671	3.3771	1~ 43	NG
44	4.1669	58.8	10.6932	11.4732	0.3422	7.4624	1~ 44	NG
45	4.1674	58.7	10.6912	12.7624	-0.5703	4.1942	1~ 45	NG
46	4.1694	58.2	10.6887	17.9189	-5.1326	0.1089	1~ 46	NG
47	4.1709	58.7	10.6892	21.7863	-0.5703	0.926	1~ 47	NG
48	4.1714	58.6	10.6882	23.0754	-1.4827	-0.7081	1~ 48	NG
49	4.1649	58.4	10.6897	6.3167	-3.3077	1.743	1~ 49	NG
50	4.1684	58.9	10.6917	15.3406	1.2546	5.0112	1~ 50	NG

Represents out-of-control

Table 4.14: Output of the scheme for the Case 2 Combination of AB

	RW	1-24	2-25	3-26	4-27	5-28	6-29	7-30	8-31	9-32
	ρ	0.1074	0.0574	-0.0248	-0.0543	-0.0418	0.0494	-0.0422	-0.0400	-0.0755
SYNERGISTIC-ANN	N (0,0)	**1.5141**	**1.4427**	**1.4865**	**1.4714**	**1.4928**	**1.3654**	**1.4153**	**1.4553**	**1.4731**
	US (1,0)	0.1677	0.1670	0.1172	0.1240	0.1369	0.1037	0.1236	0.1099	0.1080
	US (0,1)	0.2304	0.2080	0.3157	0.3152	0.2499	0.2663	0.3006	0.2583	0.4404
	US (1,1)	0.0897	0.0790	0.0984	0.0985	0.0716	0.0756	0.0662	0.0767	0.0951
	DS (1,0)	0.2299	0.2079	0.3040	0.2748	0.2631	0.4318	0.2881	0.3016	0.3416
	DS (0,1)	0.2392	0.2728	0.1483	0.1481	0.1830	0.1506	0.1460	0.2003	0.0955
	DS (1,1)	0.0637	0.0829	0.0839	0.0751	0.1426	0.1235	0.1777	0.0895	0.0849
	RW	10-33	11-34	12-35	13-36	14-37	15-38	16-39	17-40	18-41
	ρ	-0.0040	0.0333	0.0458	-0.0719	-0.0598	-0.0111	-0.0279	-0.0111	-0.1466
SYNERGISTIC-ANN	N (0,0)	**1.4316**	**1.4576**	**1.4884**	**1.5095**	**1.4844**	**1.4828**	**1.4224**	**1.2427**	**1.0531**
	US (1,0)	0.1051	0.1217	0.1499	0.0986	0.1067	0.1215	0.1017	0.0981	0.8147
	US (0,1)	0.2363	0.2677	0.2584	0.2969	0.3898	0.2748	0.2505	0.2316	0.0569
	US (1,1)	0.0651	0.0801	0.0746	0.0874	0.0928	0.0700	0.0746	0.0643	0.1218
	DS (1,0)	0.3992	0.2876	0.2275	0.4166	0.3670	0.3595	0.3724	0.5417	0.0693
	DS (0,1)	0.1629	0.1953	0.2766	0.1160	0.0854	0.1490	0.1635	0.1780	0.5751
	DS (1,1)	0.2075	0.0815	0.1033	0.1038	0.0979	0.1572	0.1113	0.2412	0.0233
	RW	19-42	20-43	21-44	22-45	23-46	24-47	25-48	26-49	27-50
	ρ	0.0170	0.3825	0.3757	0.2988	-0.1380	-0.1742	-0.2323	-0.2308	-0.1406
SYNERGISTIC-ANN	N (0,0)	0.5705	0.2339	0.0466	0.1320	0.7151	0.8323	0.8379	0.8093	0.8015
	US (1,0)	**1.1901**	**1.6952**	**1.5503**	**1.9428**	**1.9412**	**1.9743**	**1.9736**	**1.9692**	**1.9910**
	US (0,1)	0.0452	0.2725	0.4164	0.5386	0.4963	0.5718	0.7890	0.8249	0.8941
	US (1,1)	0.3843	0.5751	0.6797	0.2277	0.4687	0.4127	0.5711	0.2317	0.2864
	DS (1,0)	0.0737	0.0311	0.0612	0.0583	0.1074	0.0864	0.1708	0.1525	0.1579
	DS (0,1)	0.5442	1.0867	1.3113	1.4992	1.7758	1.6985	1.6781	1.4766	1.1918
	DS (1,1)	0.0087	0.0111	0.0168	0.0277	0.0417	0.0392	0.0562	0.0484	0.0545

Note: **Bolt value** represents the maximum output of ANN that determines pattern category

Table 4.15: Output of the scheme for the Case 2 Combination of BC

	RW	1-24	2-25	3-26	4-27	5-28	6-29	7-30	8-31	9-32
	ρ	-0.0843	-0.1369	-0.2059	-0.1884	-0.0685	0.0210	-0.0760	-0.1037	-0.1562
SYNERGISTIC-ANN	N (0,0)	**1.4156**	**1.2670**	**1.3920**	**1.3437**	**1.3602**	**1.4313**	**1.3417**	**1.4539**	**1.3690**
	US (1,0)	0.1355	0.1377	0.3271	0.2025	0.1834	0.1602	0.1709	0.1824	0.1932
	US (0,1)	0.2287	0.1675	0.1555	0.1926	0.1749	0.1779	0.2663	0.2909	0.1401
	US (1,1)	0.0866	0.0822	0.0797	0.0929	0.0698	0.0782	0.0710	0.0914	0.1005
	DS (1,0)	0.2392	0.2947	0.1347	0.1567	0.2749	0.2583	0.2371	0.2975	0.2429
	DS (0,1)	0.2205	0.1628	0.2469	0.2125	0.2247	0.1601	0.1279	0.1728	0.1863
	DS (1,1)	0.0805	0.0860	0.0752	0.0665	0.0854	0.0851	0.0871	0.0721	0.0619
	RW	10-33	11-34	12-35	13-36	14-37	15-38	16-39	17-40	18-41
	ρ	-0.1186	-0.1186	-0.0779	-0.2707	-0.2242	-0.1431	-0.1563	-0.1503	-0.1678
SYNERGISTIC-ANN	N (0,0)	**1.3777**	**1.4309**	**1.3749**	**1.3234**	**1.4051**	**1.4047**	**1.3564**	**1.3979**	**1.3918**
	US (1,0)	0.1651	0.1224	0.0975	0.2878	0.1654	0.1277	0.1889	0.1355	0.1036
	US (0,1)	0.2158	0.3032	0.2614	0.1646	0.1908	0.2002	0.2229	0.2853	0.4138
	US (1,1)	0.0754	0.0926	0.0750	0.0856	0.1060	0.0813	0.0880	0.0946	0.0886
	DS (1,0)	0.2340	0.2893	0.3117	0.1458	0.2089	0.2837	0.2603	0.2655	0.4004
	DS (0,1)	0.1730	0.1175	0.1371	0.2532	0.1794	0.1783	0.1480	0.1116	0.1235
	DS (1,1)	0.0878	0.0809	0.0851	0.0677	0.0603	0.0810	0.0697	0.0665	0.0595
	RW	19-42	20-43	21-44	22-45	23-46	24-47	25-48	26-49	27-50
	ρ	0.1743	0.2998	0.2760	0.2270	0.2589	0.2450	0.2679	0.2211	0.3322
SYNERGISTIC-ANN	N (0,0)	0.6211	0.4228	0.2071	0.1748	0.1418	0.1128	0.1744	0.1888	0.1621
	US (1,0)	0.0282	0.0241	0.0125	0.0114	0.0114	0.0139	0.0175	0.0168	0.0144
	US (0,1)	**1.2969**	**1.5243**	**1.7741**	**1.9036**	**1.9049**	**1.8870**	**1.8654**	**1.8643**	**1.8744**
	US (1,1)	0.2783	0.5535	0.4752	0.4382	0.2526	0.2282	0.1964	0.1831	0.1809
	DS (1,0)	0.2857	0.1628	0.3001	0.3543	0.7038	0.5490	0.7277	0.8577	0.9628
	DS (0,1)	0.0727	0.0931	0.0626	0.0609	0.0453	0.0291	0.0324	0.0358	0.0264
	DS (1,1)	0.0149	0.0077	0.0036	0.0033	0.0039	0.0066	0.0083	0.0116	0.0054

Note: **Bolt value** represents the maximum output of ANN that determines pattern category

4.7 Summary

The objective of this chapter, that is to investigate the effectiveness of the Synergistic-ANN pattern recognition scheme in monitoring and diagnosing process variation in mean shifts have been achieved. The simulation was investigated in the fast line which is the data directly train using Synergistic –ANN differ from the previous research using two stage monitoring scheme (Masood and Hassan, 2014). The results and outputs of both schemes should have the similarity. Then, the performance of ANN was trained repeatedly to get the excellent output with required specifications. Rather than that, the investigations continued by using industrial data for the purpose of validation. Three cases of ‘pressure increase’, ‘speed up’ and ‘mixed 20% regrinds’ were applied in validating the performance of the proposed scheme.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 Introduction

The main issues in this study have been summarized and discussed in Chapter 4, relation to the existing performance of control chart. In this final chapter, the study was closed with summary of a conclusion in Section 5.2 and future work recommendation in Section 5.3.

5.2 Conclusions

This project was attempted to determine the performance of synergistic-ANN scheme using real manufacturing data in term of process out-of-control rapid recognition diagnosis the mean shifts. The principle of this research, that is to develop a synergistic-ANN pattern recognition scheme and to evaluate the scheme effectiveness in dealing with real process data as noted in Section 1.4, Chapter 1 have been successfully achieved. Rather than that, the results of this project lead to the following conclusions:

- Balanced monitoring and accurate diagnosis performance have been achieved using one stage monitoring and diagnosis approach by control chart and synergistic-ANN recognizer, although some of the result was late detecting to the shift.

- The monitoring-diagnosis performances of the design schemes are strongly dependent on input representation technique and recognizer design and training.

- Knowledge contributions and impact from this research could lead to an incremental improvement and enhancement towards balanced monitoring and accurate diagnosis in MQC, in way to minimized rework and waste products.

5.3 Future Work Recommendations

The research also opened a significant foundation for further researches in the related field of MSPC charting design and others. The following foundations are considered in further works of:

i. Further study in advance MSPC ANN scheme involving missing data in samples subgroup or in actual industry scenario when we lost some of data during data monitoring and collection should be investigate in future.

ii. The software of MatLab has to be up to date time to time for consistency data generate.

iii. Further investigation and improvement at mean shofts diagnosing accuracy to ensure correct judgement can be made to solve process disturbance from real world.

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