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PATTERN RECOGNITION FOR MANUFACTURING PROCESS VARIATION USING ENSEMBLED ARTIFICIAL NEURAL NETWORK

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ABSTRACT

In quality control, monitoring and diagnosis of multivariate out of control condition is essential in today's manufacturing industries. The simplest case involves two correlated variables; for instance, monitoring value of temperature and pressure in our environment. Monitoring refers to the identification of process condition either it is running in control or out of control. Diagnosis refers to the identification of source variables (X_1 and X_2) for out of control. In this study, an ensemble artificial neural network scheme was investigated in quality control of process in Hard Disk Drive manufacturing. This process was selected since it less reported in the literature. In the related point of view, this study should be useful in monitoring and diagnose the bivariate process pattern in Hard Disk Drive manufacturing process. The result of this study, suggested this scheme has a superior performance compared to the traditional artificial intelligence, namely single isolated Artificial Neural Network. In monitoring, ANN expected to be effective in rapid detection of out of control without false alarm. In diagnosis, this scheme was effective to be applied in identifying various types of process variation such as loading error, offsetting tool, and inconsistent pressure in clamping fixture. Whereby, diagnosis cannot be performed by traditional control chart. This study is useful for quality control practitioner, particularly in manufacturing industry.

ABSTRAK

Pada hari ini dalam kawalan kualiti industri pembuatan, pemantauan dan diagnosis keadaan pembolehubah berbilang yang berada di luar kawalan adalah sangat penting. Sebagai contoh kes termudah adalah melibatkan dua pembolehubah yang berkait, seperti pemantauan nilai suhu dan tekanan dalam persekitaran kita. Pemantauan merujuk kepada pengenalpastian keadaan proses sama ada ianya berjalan dalam kawalan atau di luar kawalan. Diagnosis merujuk kepada pengenalpastian sumber pembolehubah (X_1 atau X_2) yang terletak pada keadaan luar kawalan. Dalam kajian ini, satu skema gabungan rangkaian neural tiruan telah dikaji bagi kawalan kualiti proses pembuatan cakera keras computer. Proses ini dipilih kerana ianya kurang dilaporkan dalam kajian literatur terdahulu. Dalam masa yang, kajian ini boleh digunakan dalam memantau dan mengenal pasti corak proses dwivariasi dalam proses pembuatan cakera keras komputer. Keputusan kajian menunjukkan bahawa skema ini mepunyai prestasi yang lebih baik berbanding carta kawalan tradisional yang dinamakan skema rangkaian neural tiruan tunggal. Dalam pemantauan, skim dapat mengesan dengan pantas keadaan luar kawalan tanpa amaran palsu. Dalam diagnosis, skema boleh mengenalpasti sumber pembolehubah seperti kesilapan mesin ketika memegang specimen, kesilapan mesin dalam memegang mata alat dan tekanan udara mesin yang tidak konsisten dalam memegang spesimen. Di mana diagnosis ini tidak boleh dilakukan oleh carta kawalan tradisional. Kajian ini berguna kepada pengamal kawalan kualiti terutamanya dalam industri pembuatan.

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CHAPTER 1

INTRODUCTION

1.1   Research Background

In manufacturing, quality is defined as conformance to specification. Poor quality due to process variation is known as a major issue in manufacturing processes. Variation is a disparity between an actual measure of a product characteristic and its target value. Excessive variation that found outside the upper and lower acceptable limits for a product specification tend to lead product discard or salvage.

Any source of variation at any point of time in a process will fall into one of two classes:

1) "Common Causes" - sometimes referred to as non-assignable, normal sources of variation. It refers to many sources of variation that consistently acts on process. These types of causes produce a stable and repeatable distribution over time.

2) "Special Causes" - sometimes referred to as assignable sources of variation. It refers to any factor causing variation that affects only some of the process output. They are often intermittent and unpredictable.

A key manufacturing performance objective is the establishment of stable and predictable processes that limit variation to what can be described as random, with minimum variation around target values. It becomes more difficult when

manufacturing processes involve two (bivariate) or more correlated variables, whereby an appropriate procedure is required to monitor these variables simultaneously. These techniques are often referred as multivariate SPC (MSPC) procedures.

Multivariate SPC refers to a set of advanced techniques for the monitoring and control of the operating performance of batch and continuous processes. More specifically, multivariate SPC techniques reduce the information contained within all of the process variables down to two or three composite metrics through the application of statistical modeling. These composite metrics can be easily monitored in real time in order to benchmark process performance and highlight potential problems, thereupon providing a framework for continuous improvements of the process operation.

The most common process control technique is control charting. The traditional statistical process control (SPC) charting schemes were known to be effective in monitoring aspect but they are lack of diagnosis aspect. In contrast, SPC uses statistical tools to observe the performance of the production process in order to detect significant variations before they result in the production of a sub-standard article.

The most effective technique to solve diagnosis issue is interpretation of control chart patterns (CCPs) using pattern recognizer. This technique is useful to give information on the state of a process. Control charts pattern recognition is one of the most important tools in SPC to identify process problems. Unnatural patterns exhibited by such charts can be associated with certain assignable causes affecting the process.

The pattern recognizer role to recognize the existence of abnormal function in a process production. Accurate and fast recognition is essential for efficient system monitoring to maintain the high-quality products. There are seven basic CCPs, e.g. normal (NOR), systematic (SYS), cyclic (CYC), increasing trend (IT), decreasing trend (DT), upward shift (US) and downward shift (DS). All other patterns are either special forms of basic CCPs or mixed forms of two or more basic CCPs. Only the NOR pattern is indicative of a process continuing to operate under controlled condition. All other CCPs are unnatural and associated with impending problems requiring pre-emptive actions. Advances in manufacturing and measurement technology have enabled real-time, rapid and integrated gauging and measurement of

process and product quality. Artificial Neural Network (ANN) learns to recognize patterns directly through a typical sample patterns during a training phase. ANN may provide required abilities to replace the human operator and also have the ability to identify an arbitrary. However, the existing ANN schemes were mainly utilized single isolated ANN model with raw data input representation. In this research, a combined ANN model, which is called an Ensemble-ANN, will be investigated for monitoring and diagnosing bivariate process pattern in making of Hard Disk Drive.

1.2   Problem Statement

Variation in manufacturing process is known to be a major source of poor quality products and variation control is essential in quality improvement. It becomes more difficult when involving two correlated variables (bivariate). The traditional statistical process control (SPC) charting schemes were known to be effective in monitoring aspect but they are lack of diagnosis aspect.

The hard disk drive (HDD) is a data storage device and the most important component of a computer. HDD used for storing and retrieving digital information using one or more rigid rapidly rotating disk and coated with magnetic material. Manufacturing of HDD involve many basic mechanical structure such as casing and platters. Among of brands, HDD manufacturing is spread across different factories, which are situated in different countries. Hence, the process variations in manufacture HDD become one of the research subjects of today. The production of HDD mostly in large amount hence the production required to identify variation process in order to reduce cost and time consuming. In this project, an artificial neural network, an artificial intelligence technique, is developed to successfully monitoring and diagnosing variation process variation in manufacturing of HDD. This technique can be apply on manufacturing sector in many different areas of technology in order to overcome difficulties of the experiments, minimize the cost, time and workforce waste. There is a motor in the hard disc drive in order to control the rotation of disc. The mounting of the motor (ID1 and ID2) are defined as critical characteristic that require bivariate quality control (BQC) by using the artificial neural network. However, the existing ANN schemes were mainly utilized single isolated ANN model with raw data input representation. Hence, in this project, a combined ANN model which is called an Ensemble-ANN will be investigated for

improving the quality control capability. The proposed model involves utilization of raw data and statistical features input representation technique. Representative pattern recognition scheme (framework and procedures), namely an Ensemble-ANN as a strategy of improvement. The intended scheme should be capable to identify the source variables of bivariate process variation rapidly and correctly with minimum false alarm.

1.3   PROJECT OBJECTIVES

The objectives of this project are:

i)   To design an Ensemble ANN scheme for pattern recognition of bivariate process pattern classification.

ii)   To validate the pattern recognition accuracy performance of the scheme.

1.4   PROJECT SCOPES

This research proposal project scope is listed as below:

i)   Bivariate process variables are dependent to each other based on linear cross correlation (ρ).

ii)   Three cases will be studies which are Loading Error, Off-setting Toll and Pneumatic Clamping Problem.

iii)   In a statistically out-of-control condition, predictable bivariate process patterns are limited to sudden shifts (upward shift).

iv)   Magnitudes of mean shifts in the source variables are limited within ± 3 standard deviations based on control limits of Shewhart control chart.

v)   The foundation modeling and simulation for bivariate correlated samples are based on established model (Lehman, 1977), whereas the validation tests are performed using industrial data.

CHAPTER 2

LITERATURE REVIEW

This chapter reviews the concept of SPC control chart monitoring and diagnosis. It were also review the investigation and development of previous multivariate statistical process control (MSPC) scheme in term of raw data-based input, statistical feature input representations and scheme improvement. In conclusion, explanation on why the design of synergistic ANN model recognizers was chosen to improve the monitoring-diagnostic capability was given.

2.1   Introduction

Nowadays, manufactures are on pressure to produce products that have high quality but with a low cost. Product cost and quality were influenced by many factors and one of the factors that strongly influence both was manufacturing process variation. These variations exist because the production process never can be perfect and usually controlling this variation was done by implementing process quality control especially by using SPC. The main concern of process quality control is to achieve and maintain an acceptable level of the desired process quality characteristic consistently. In this connection, accurate monitoring and control of the manufacturing system is very important and consequently, data must be gathered and analyze.

This is where statistical process control (SPC) comes in. For over 70 years, the manufacturing arena has benefited from the tools of SPC that have helped guide the decision-making process. In using control charts, samples of the products are drawn during the manufacturing process and sample statistics are then plotted on control charts (L. H. Chena & T. Y. Wang, 2004). In particular, the control chart has helped determine whether special-cause variation is present implying that action needs to be taken to either eliminate that cause if it has a detrimental effect on the process or to make it standard operating procedure if that cause has a beneficial effect on the process. If no special-cause variation is found to be present, SPC helps define the capability of the stable process to judge whether it is operating at an acceptable level.

Control charts, mostly in the form of X chart, are widely used as aids in maintaining quality and achieving the objective of detecting trends in quality variation before defective parts/products are actually produced. In any continuous manufacturing process, variations from the established standards are mainly of two types. One is assignable cause variation, such as those due to faulty manufacturing equipment or irresponsible personnel or defective material or a broken tool. The other one is normal chance variation, resulting from the inherent non-uniformities that exist in machines or operators or materials or processes.

The X chart usually exhibits various types of patterns e.g., normal (NOR), stratification (STA), systematic (SYS), increasing trend (UT), decreasing trend (DT), upward shift (US), downward shift (DS), cyclic (CYC), and mixture (MIX), as shown in Figure 2.1 (M. Bag, S. K. Gauri & S. Chakraborty, 2011).
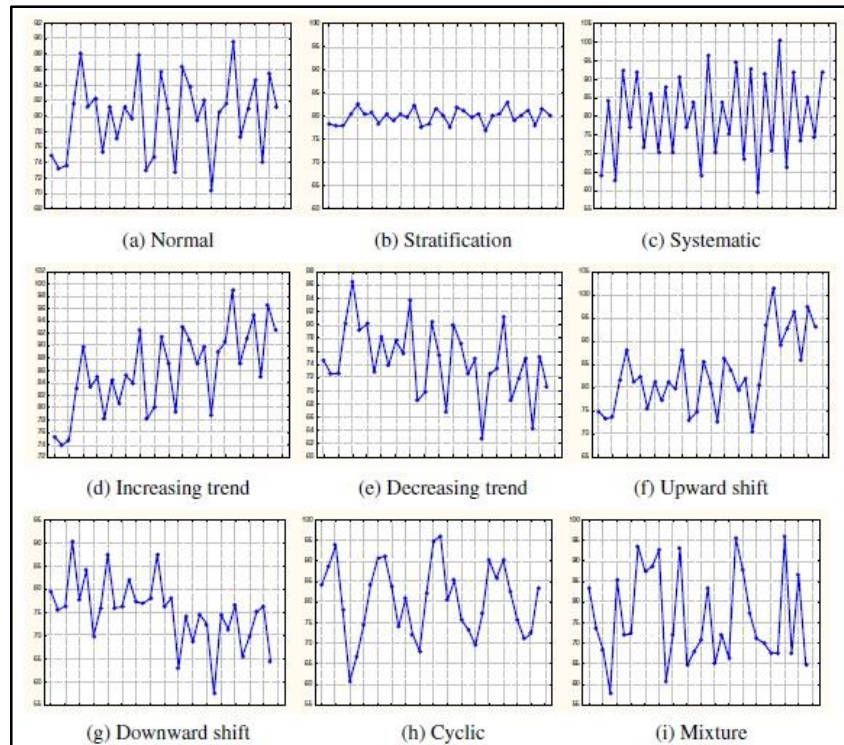
Figure 2.1: Nine control chart patterns

The patterns can be categorized as natural/normal and unnatural/abnormal process. The basic significance of a natural pattern is that it indicated a process under control. Unnatural patterns identified a process when it is out control. Natural causes are considered to be due to the inherent nature of normal process. Assignable causes are defined as abnormal shocks to the processes, which should be identified and eliminated as soon as possible. When an abnormal variation is signaled by the control chart, quality practitioners or engineers search for the assignable causes and take some necessary corrections and adjustments to bring the out-of-control process back to the in-control state (J. Yu, L. Xi & X. Zhou, 2009).

Over the years, numerous numbers of studies have been study and suggesting the quality control practitioners to detect unnatural control chart patterns. Nevertheless, this suggestion is unworthy due to lack of experience, knowledge and skill to identify, interpret and analysis the unnatural patterns from the practitioners. In a manufacturing environment, many quality characteristics must be controlled simultaneously. The usual practice has been to maintain a separate (univariate) chart for each characteristic. Unfortunately, this can give some misleading result when the quality characteristic is highly correlated. One of the solutions to overcome this issue

is to extend the univariate analysis by plotting a statistic that measures the overall deviations of the multivariate observations from the target (L. H. Chen & T. Y. Wang, 2004).

2.2 Process Variation

Process variation is the main course of quality problems, whether in business such as transactional or production processes. Process variation also can be defined as a major source of poor quality. Statistical process control (SPC) is one of the most effective tools of total quality management, which is used to monitor process variations and improve the quality of production. (M. Bag, S. K. Gauri & S. Chakraborty, 2011). Advances, variation reduction efforts as such process monitoring and diagnosis should be critically applied towards quality improvements (Masood. I & Hassan. A, 2009).

Variation occurs in all natural and man-made processes. Variation may be defined as any unwanted condition or as the difference between a current and a desired end-state. Both product performance and manufacturing processes exhibit variation. Wear and tear, vibration, machine breakdown, inconsistent raw material and lack of human operators' skills are the common sources of variation in manufacturing process. To control and reduce the variation, the source of the variation must be identified. If variation cannot be measured, it is because the measurement systems are of insufficient precision and accuracy. Process variance reduces the capacity of the industries because processes become either under- or over-utilized. Process variance reduces the ability to detect potential problems and increases the difficulty of discovering the root cause of problems.

The variation will affects in product performance and manufacturing processes and they are varying by the type of technology, maturity, and the experience of the organization and its suppliers. Variation in manufacturing processes causes significant expense in nearly every industry. Variation during production results in products that are not truly identical and thus do not perform identically in the marketplace. Some units were performing as expected, but others may fail early and incur additional costs. Some may even be unsafe and lead to recalls and lawsuit. To prevent these outcomes, manufacturers often expand large sums reworking products to address problems arising from process variation. Almost

all of these costs can be eliminated by addressing the root cause; the focus of efforts should be on reducing variation in the process as opposed to reacting to the unfortunate outcomes of variation. Tools such as statistical experimental design, analysis, and statistical process control, can be used to improve process control and reduces variation, delivering impressive bottom line savings.

2.3   Quality Engineering

In the manufacturing environment, quality practitioners often need to simultaneously monitor not only one but many product or process characteristics (O. O. Atienza, L. C. Tang and B. Ang, 1998). Quality Engineering can be describe as discipline that deals with the analysis of a manufacturing system at all stages, to improve the quality of the production process and of its output. Quality engineering also known as "the branch of engineering which deals with the principles and practice of product and service quality assurance and quality control". Absolutely, quality may be defined in many ways. Quality issues are now the concern of all organizations including the services and public sectors. Quality tools, techniques, concepts and methodologies have been enhanced, and integrated with other features to suit new challenges (A. Hassan, M. S. N. Baksh and A. M. Shaharoun, 2009).

Quality has become one of the most important consumer decision factors in the selection among competing products and services (Haridy & Wu, 2009). Therefore, process of control and improvement quality are keys factors leading to business success, growth and enhanced competitiveness. Quality engineering is the combination process of operational, managerial and engineering activities that a manufacturer uses to ensure that the quality characteristics of a product achieved the customer needs. Quality characteristics may be of several types (Montgomery, 2013):

1. Physical: depth, width, current, hardness
2. Sensory: colour, smell, taste
3. Time orientation: reliability, durability, serviceability

Most manufactures find difficulties and it's expensive to provide the customer with products that have quality characteristics that are always identical

from unit to unit, or are at levels that match customer expectations. A major cause for this situation is variability. There is a certain amount of variability in every product; consequently, no two products are ever identical. Since variability can only be described in statistical terms, statistical analysis methods play as a central role in quality improvement methods. Statistical Process Control (SPC) is one of the most widely used tools for quality control and improvement in manufacturing industries. Statistical Process Control (SPC) charts have been used widely since Shewhart first introduces them in early 1930s. The primary application domain for SPC charts has been in process control and process improvement in manufacturing business (B. L MacCarthy and T. Wasusri, 2001). The diagram of basic SPC tools classification illustrates in Figure 2.2.
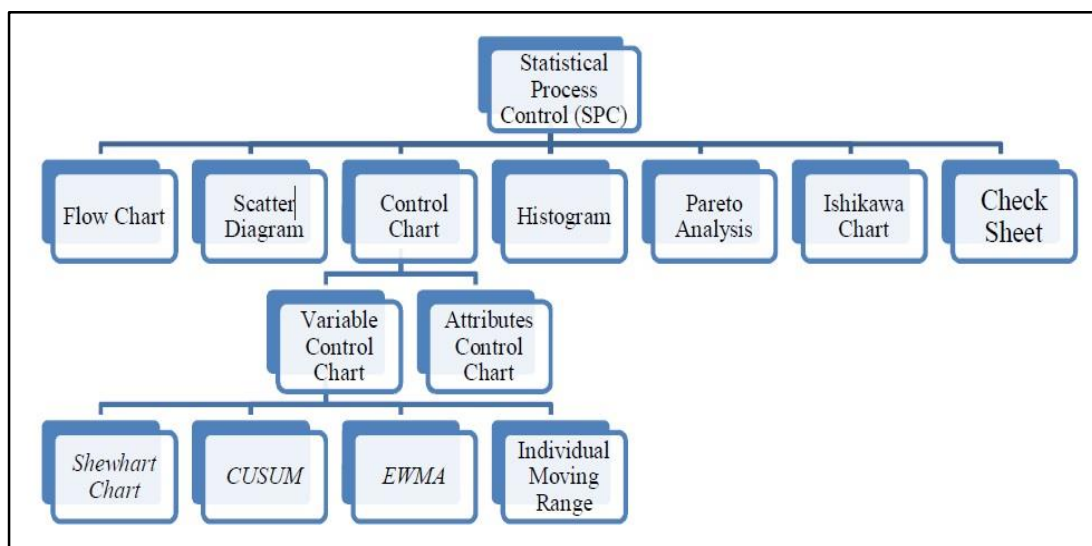
Figure 2.2: Basic statistical process control tools specification

2.4 Statistical Process Control (SPC)

For decades, statistical process control (SPC) has played a major role in controlling a product's quality, since Shewhart illustrated the technique of the control chart by applying statistical concepts in the manufacturing process (W. H. Chih & D. A. Rollier, 1993). The purpose of statistical process control is to give signal when the process mean has moved away from the target. A second purpose is to give a signal when item to item variability has increased. In either case appropriate action must then be taken by a machine operator or an engineer. Statistic can only give the signal,

the action relies on other skills. There are many ways to implement process control. There a seven basic tool as a control plan to monitor and control the manufacturing process. A control plan should be maintained that contains all pertinent information on each chart that is maintained, including:

      i. Cause-and-effect diagram (also known as the "fishbone" or Ishikawa diagram)

     ii. Check sheet

   iii. Control chart

    iv. Histogram

     v. Pareto chart

    vi. Scatter diagram

   vii. Stratification (alternately, flow chart or run chart)

One of the main tools used in statistical process control (SPC) is the control chart, also known as the Shewhart control chart, which consists of a center line and two lines drawn parallel to it. The center line represents the place where the characteristic measured should ideally be located and the parallel lines represent the control limits of the characteristic shown in Figure 2.3 (L.G. Esteban et al., 2009).
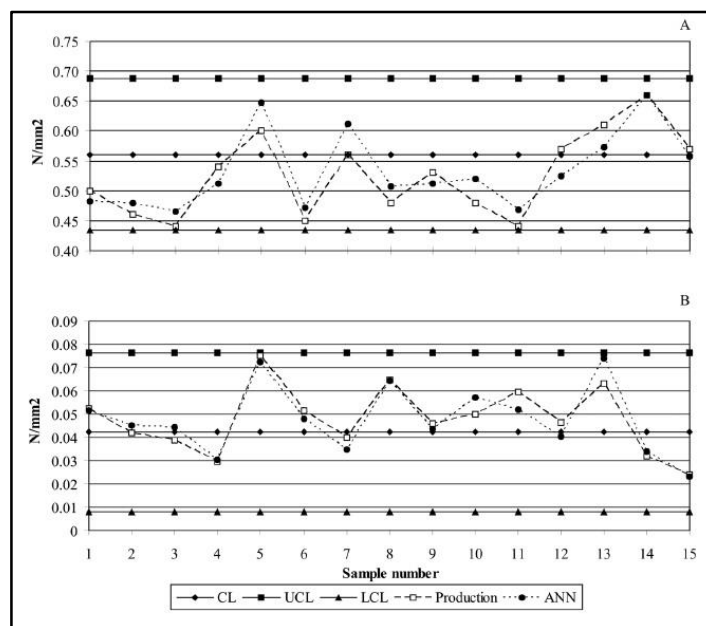
Figure 2.3: Control chart: (A) mean; (B) standard deviation. CL: center line, UCL: upper control limit, LCL: lower control limit.

The most standard display actually contains two charts, one is called an X-bar chart in Figure 2.4 and the other is called an R chart as shown in Figure 2.5.
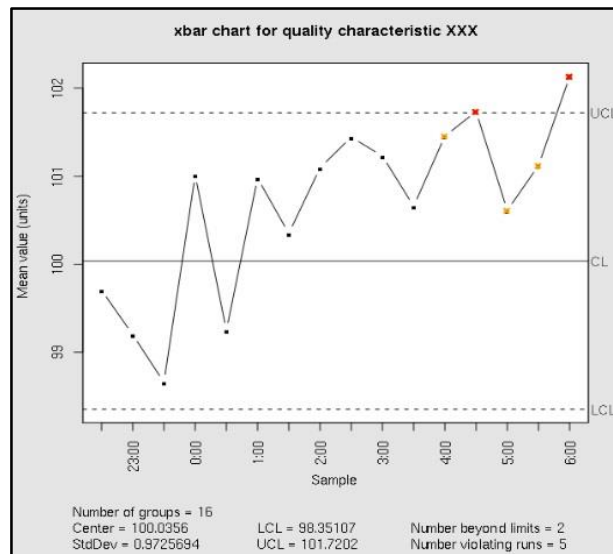
Figure 2.4: An example of *X-Bar* Chart
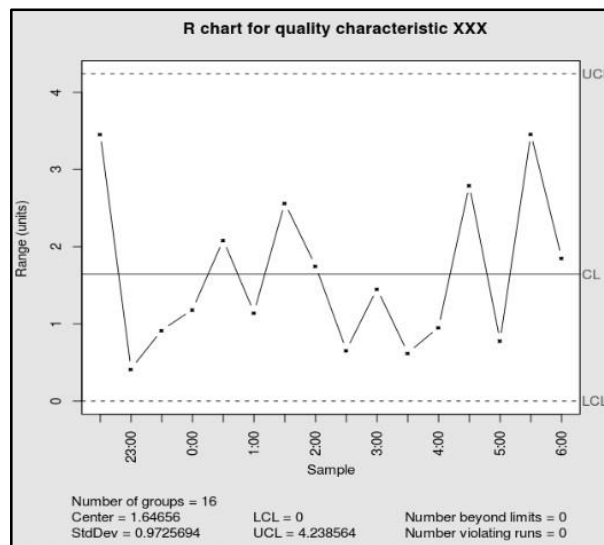
Figure 2.5: An example of R Chart

In both line charts, the horizontal axis represents the different samples and the vertical axis for the X-bar chart represents the means for the characteristic of interest. Meanwhile the vertical axis for the R chart represents the ranges. The center line in the X-bar chart would represent the desired standard or customers need specification of the product, while the center line in the R chart would represent the acceptable

within specification range of the product within samples. Thus, this latter chart is a chart of the variability of the process which mean the larger the variability, the larger the range. In addition to the center line, a typical chart includes two additional horizontal lines to represent the upper control limits (UCL) and lower control limits (LCL). If the line moves outside the upper or lower control limits or exhibits systematic patterns across consecutive samples, a quality problem may potentially exist. Upon the out of control is alarmed, the assignable causes for the abnormal process need to be identified and removed in order to bring the process back to normal. A stable production process is the key element of quality improvement. Depending on the number of process characteristics to be monitored, there are two basic types of control charts, Univariate Control Chart and Multivariate Control Chart.

2.5 Univariate Statistical Process Control (USPC)

Many manufactures use Univariate Statistical Process Control (USPC) 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 USPC (O. R. Mohana Rao et al., 2013). USPC is the monitoring and control of one quality necessary. In normal application this is usually practice by separating each quality characteristic and analysis their control chart independently (Masood, I & Hassan, A, 2010). However, in many situations the widespread use of USPC has caused a backlash as processes are frequently adjusted or shutdown when nothing is really wrong because estimates of the probability of false positives (Type I error) calculated based on USPC, were unrealistically low. USPC also takes little or no account of the multiple tests that are being performed or the correlation structure that may exist in the data (S. El-Din, Rashed & El-Khabeery, 2006).

In real time, modern continuous dynamic manufacturing processes enable process computers and sensors to record massive amount of production process data. They often present a large number of highly auto correlated and cross correlated process variables, which leads to large amount of process data to be analyzed. In this situation, the conventional univariate statistical process control (USPC) charts such as Shewhart charts and cumulative sum (CUSUM) charts may not be appropriate at

traditional production setting. One of the reason for inadequacy of traditional methods is the numbers of variables. Since 1924, when Walter A. Shewhart presented the first sketch of a univariate control chart, univariate statistical process control (USPC) charts, mainly Shewhart charts, cumulative sum (CUSUM) control charts and exponentially weighted moving average (EWMA) control charts, have been widely used. They have received considerable attention in industry due to their ease of use by the production personnel and others with minimal statistical knowledge. However, a USPC chart can only chart one variable at a time, which mean that process engineers have to look at fifty control charts to monitor the process quality if there a fifty variables measured in the process. Furthermore those univariate charts do not take any possible correlation among variables into account. In modern manufacturing environments, the characteristic of variables of a multivariate process often are interrelated and form a correlated set. Since the variables do not behave independently, they must be treated together as a group and not separately. Monitoring of processes in which several related variables are of interest is collectively known as multivariate statistical process control (MSPC).

2.5.1 Shewhart Control Chart

Shewhart charts also known as Control charts or process-behavior charts, in statistical process control are tools used to determine if a manufacturing or business process is in a state of statistical control. The Shewhart control chart certainly is not new, but its use in modern-day business and industry is of tremendous value (Montgomery 2013). These control charts are constructed by plotting product's quality variable over time in sequence plot as shown in Figure 2.6.
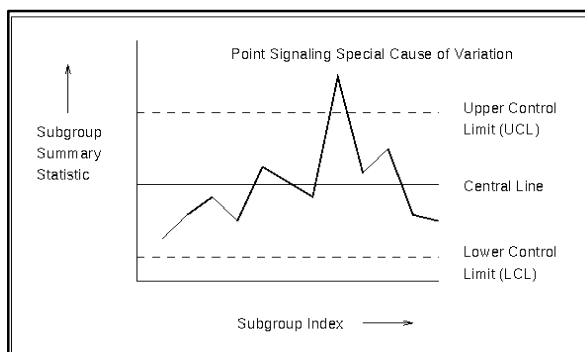

Figure 2.6: Control Chart Product Quality over Time.

A control chart contains a center line. In addition to the center line, a typical chart includes two additional horizontal lines to represent the upper control limits (UCL) and lower control limits (LCL). If the line moves outside the upper or lower control limits or exhibits systematic patterns across consecutive samples, a quality problem may potentially exist. Upon the out of control is alarmed, the assignable causes for the abnormal process need to be identified and removed in order to bring the process back to normal. Let w be a sample statistic that measure some quality characteristic of interest and suppose that the mean of w is μ_w and the standard deviation of w is σ_w. Then the center line, upper control limit and lower control limit as shows in equation (2.1).

$UCL = \mu_w + L\sigma_w$

$Center\ Line = \mu_w$

$UCL = \mu_w - L\sigma_w$ (2.1)

2.5.2 Control Limits

All the points will fall between the control limits if the process is in control. Any observations outside the limits, or systematic patterns within, suggest the introduction of a new source of variation, known as a special-cause variation. Since increased variation means increased quality costs, a control chart "signaling" the presence of a special-cause requires immediate investigation. To determine whether the process was in control when the preliminary samples were collected, plot the values of *X-Bar* and *R* from each sample on the charts and analyze the resulting display. If all points plot inside the control limits and no systematic pattern is evident, it can be conclude that the process was in control in the past, and the trial control limits are suitable for controlling current or future production. It is highly desirable to have 20–25 samples or subgroups of size n and typically n is between 3 and 5 to compute the trial control limits (Montgomery 2013). Surely it can be done by fewer data but the control limits are not as reliable.

A point falling within the control limits means it fails to reject the null hypothesis that the process is statistically in-control, and a point falling outside the control limits means it rejects the null hypothesis that the process is statistically in-control. Therefore, the statistical Type I error α (Rejecting the null hypothesis H_0

when it is true) applied in Shewhart control chart means the process is concluded as out-of control when it is truly in-control. Same analog, the statistical Type II error β (failing to reject the null hypothesis when it is false) means the process is concluded as in control when it is truly false.

This makes the control limits very important decision aids. The control limits provide information about the process behavior and have no interrelated relationship to any specification targets or engineering tolerance. In practice, the process mean (and hence the center line) may not coincide with the specified value (or target) of the quality characteristic because the process design simply cannot deliver the process characteristic at the desired level.

2.5.3 Average Run Length

Another way to evaluate the decisions regarding sample size and sampling frequency is through the average run length (ARL) of the control chart. Essentially, the ARL is the average number of points that must be plotted before a point indicates an out-of-control condition. If the process observations are uncorrelated, then for any Shewhart control chart, the ARL can be calculated easily from equation 2.2:

$$ARL = \frac{1}{P} \tag{2.2}$$

where p is the probability that any point exceeds the control limits. This equation can be used to evaluate the performance of the control chart. To illustrate, for the *X-Bar* chart with three-sigma limits, $p = 0.0027$ is the probability that a single point falls outside the limits when the process is in control. Therefore, the average run length of the chart when the process is in control (called ARL_0) as equation (2.3):

$$ARL_0 = \frac{1}{P} = \frac{1}{0.0027} = 370 \tag{2.3}$$

That is, even if the process remains in control, an out-of-control signal will be generated every 370 samples, on the average. The use of average run lengths to describe the performance of control charts has been subjected to criticism in recent

years. The reasons for this arise because the distribution of run length for a Shewhart control chart is a geometric distribution. Consequently, there are two concerns with ARL:

  (i)   The standard deviation of the run length is very large, and
  (ii) The geometric distribution is much skewed, so the mean of the distribution (the ARL) is not necessarily a very typical value of the run length.

The proposed model outperforms the conventional multivariate control schemes in terms of ARL, and can accurately estimate the magnitude of the shift of each of the shifted variables in a real-time mode (J. Yu & L. Xi, 2009).

2.5.4   Individual Control Chart

The individuals control chart examines variation in individual sample results over time as shown in Figure 2.7. While rational subgrouping does not apply, thought must be given to when the results were measured. If the process is in statistical control, the average on the individuals chart is our estimate of the population average. The average range was used to estimate the population standard deviation. For individual measurement, e.g., the sample size = 1, use the moving range of two successive observations to measure the process variability. The moving range is defined as in equation (2.4).

$$MR_i = /x_i - x_{i-1}/ \tag{2.4}$$

This is the absolute value of the first difference (e.g., the difference between two consecutive data points) of the data. Analogous to the Shewhart control chart, one can plot both the data (which are the individuals) and the moving range. For the control chart for individual measurements, the lines plotted in equation (2.5):

$$UCL = \bar{x} + 3\,\frac{\overline{MR}}{1.1.28}$$

$$Center\ Line = \bar{x}$$

$$UCL = \bar{x} - 3\,\frac{\overline{MR}}{1.1.28} \qquad (2.5)$$

Keep in mind that either or both averages may be replaced by a standard or target, if available.
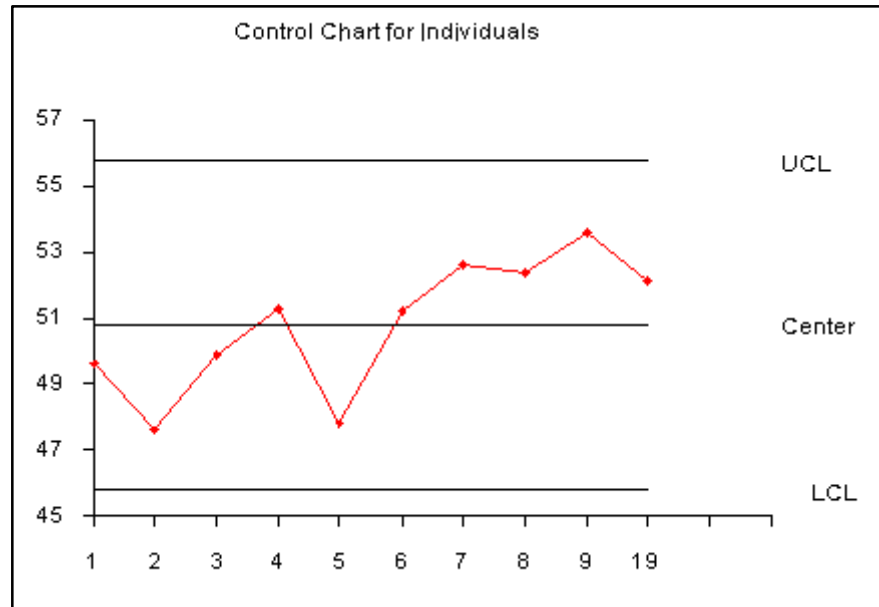

Figure 2.7: Individual chart

2.6   Multivariate Statistical Process Control (MSPC) Chart

Multivariate Statistical Process Control (MSPC) is a methodology, based on quality control charts, that is used to monitor the stability of a multivariate process. Stability is achieved when the means, variances and covariance of the process variables remain stable over rational subgroups of the observation. The conventional MSPC charts mainly include multivariate Shewhart control charts, multivariate CUSUM control charts, multivariate EWMA control charts and chart based on multivariate statistical projection methods. In manufacturing, the MSPC charts serve as well as fundamental tools for multivariate process control application. Consequently, multivariate statistical methods which provide simultaneous scrutiny of several variables are needed for monitoring and diagnosis purposes in modern manufacturing systems. (K. H. Chen, D. S. Boning and R. E. Welsch, 2001). Process monitoring of problems in which several related variables are of interest are collectively known as multivariate statistical process control. The most useful tool of multivariate statistical

process control is the quality control chart. For example found in Masood & Hassan (2013), suppose that a roller head has both an inner diameter (ID1) and inner diameter (ID2). These two dependent quality characteristics (multivariate) are needed for MSPC. Figure 2.8 shows illustration of the roller head.
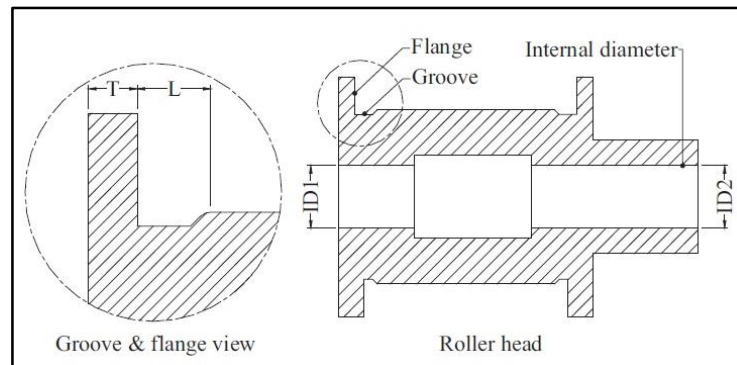
Figure 2.8: Functional features of roller head.

Multivariate process control techniques were established by Hotelling in his 1947 pioneering paper. Hotelling applied multivariate process control methods to a bombsights problem (S. Bersimis, S. Psarakis & J. Panaretos, 2006). The Hotelling's T^2 control chart was applied for bombsight data during World War II. Jackson JE, 1991 stated that any multivariate process control procedure should fulfill four conditions:

1. Is the process in control?
2. An overall probability for the event 'Procedure diagnoses an out-of-control state erroneously' must be specified
3. The relationships among the variables–attributes should be taken into account
4. An answer to the question 'If the process is out of control, what is the problem?' should be available

MSPC applies these powerful methods to process and manufacturing data and provide with a better understanding and control over your processes. Thus, will benefit the industry such as:

1. Prevent process failures

2. Improve and optimize product quality and process

3. Reduce process costs

4. Increase overall equipment efficiency

In manufacturing, although the MSPC charts serve as well as fundamental tools for multivariate process control applications, their assumptions are challenged by many modern manufacturing environments. One good example is that autocorrelation in the measurement can result in too many out of control false alarm when standard control limits are used in application where the process is sampled frequently. Most multivariate control procedures require the observation vectors to be uncorrelated over time. Unfortunately, violations of this assumption can weaken the effectiveness of the overall control procedure. Ibrahim Masood & Adnan Hassan (2014) also agreed that they are merely unable to provide diagnosis information, which is greatly useful for a quality practitioner in finding the root cause error and solution for corrective action.

2.7   Pattern Recognition in SPC

Pattern recognition is one from the need for automated machine recognition of objects, signals or images, or the need for automated decision-making based on a given set of parameters. Despite over half a century of productive research, pattern recognition continues to be an active area of research because of many unsolved fundamental theoretical problems as well as a rapidly increasing number of applications that can benefit from pattern recognition. Pattern recognition is a branch of machine learning that focuses on the recognition of patterns and regularities in data, although is in some cases considered to be nearly synonymous with machine learning A control chart pattern recognizer is to recognize any abnormal function by monitoring the behavior of the system under production. Accurate and fast control chart recognition is essential for efficient system monitoring to maintain the high-quality products. Several approaches have been proposed for CCP recognition, including rule-based, expert system and artificial neural networks (Seref Sagiroglu et al., 2000). In statistical approaches, data points are assumed to be drawn from a probability distribution, where each pattern has a certain probability of belonging to a

class, determined by its class conditioned probability distribution. In order to build a classifier, these distributions must either be known ahead of time or must be learned from the data (R. Polikar, 2011). Control charts pattern recognition is one of the most important tools in statistical process control to identify process problems. Unnatural patterns exhibited by such charts can be associated with certain assignable causes affecting the process (N.V.N. Indra Kiran et al., 2010).

2.8   Artificial Neural Network (ANN)

Artificial Neural Network (ANN) or Neural Network (NN) has provide an exciting alternative method for solving a variety of problems in different fields of science and engineering. Artificial Neural Networks are relatively basic electronic models based on the neural structure of the brain. The brain basically learns from experience. The ANN is very useful because it have ability to learn and recognize. ANN can figure out how to perform their function on their own and determine their function based only upon sample inputs.

ANN learns to recognize patterns directly through a typical sample patterns during a training phase. Neural nets may provide required abilities to replace the human operator. Neural network also have the ability to identify an arbitrary (N.V.N. Indra Kiran et al., 2010). Recently, many studies used ANNs in order to detect patterns more effectively than the conventional approach and their aim is the automatic diagnosis of the patterns such as that in Figure 2.9 (T.T. El-Midany et al., 2010).
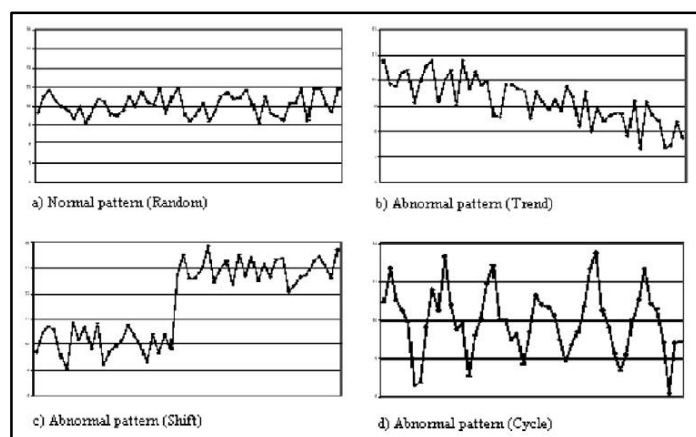

Figure 2.9: Typical normal and abnormal patterns.

In such studies, ANNs were trained in order to learn specific patterns using a training set. ANNs have been successfully applied to interpret univariate SPC charts, where ANNs have been applied to the pattern recognition task for identification of the abnormal pattern and estimation of key parameters. Since then, several other researchers have proposed various ANN-based SPC control chart pattern recognition. In general, univariate SPC frameworks average run length, $ARL_0 \geq 370$, but MSPC frameworks indicated $ARL_0 \leq 200$ (Masood, I & Hassan, A, 2013). This is so called 'imbalanced monitoring' will be effecting to the practitioner to make unnecessary and corrective action due to wrong identification. On the diagnosis side, they are also having a lack of accuracy in identifying the source (causable) variables especially when dealing small shifts. This is so called 'lack of diagnosis' would be more difficult for practitioner in searching the root cause errors. They observed a good correlation between predicted and the experimental values with the correlation coefficient ranging between 0.92 and 0.99 (Yusuf Talal F et al., 2010).

2.8.1 Generalized ANN Model

An ANN consists of massively interconnected processing nodes known as neurons. It receives the input from the external sources and combines them, performs generally a nonlinear operation on the result and then outputs the final result. A commonly used ANN model is a feed forward network which contains an input layer, some hidden layers and an output layer. Each neuron in the network accepts a weighted set of inputs and responds with an output (Shivakumar A et al., 2010). Figure 2.10 shows the architecture generalized recognizers; raw data-based and generalized feature-based respectively.
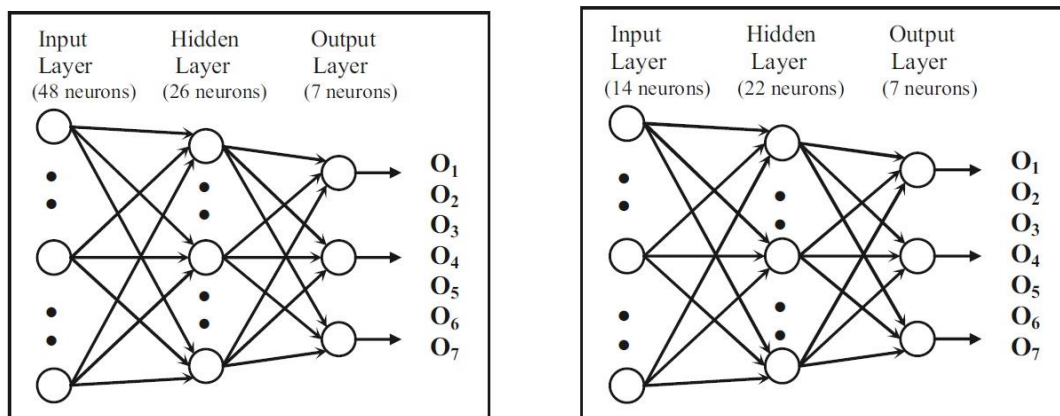
(a) Raw Data-Based ANN   (b) Feature-Based ANN

Figure 2.10: Generalized-ANN architectures based on three layer MLP model

Raw data-based input representation yields large dimensional input vectors, computational efforts and time consuming for training ANN recognizer. In addressing this issue, feature based input representation such as summary statistic features, frequency count features, shape features and statistical features have been proposed in developing univariate CCPR schemes. It involves features extraction procedure as shown in Figure 2.11 to extract the properties of the samples (Masood, I & Hassan, A, 2010).
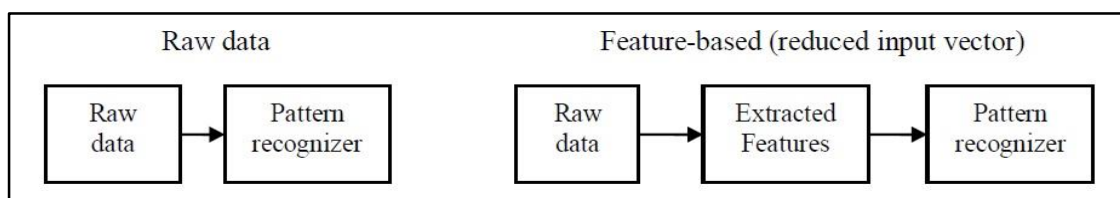
Figure 2.11: Comparison between Raw Data-Based and Feature-Based Input
Representation

2.8.2   Ensemble ANN Model

The existing ANN schemes commonly main generalized based which is only single ANN recognizer was applied. The generalization ability of ANNs can be improved by combining several ANNs in redundant ensembles, where the member networks are redundant in that each of them provides a solution to the same task, or task component, even though this solution might be obtained by different methods

(Sharkey, 1999). This approach is now formally known as an artificial neural network ensemble. An ANN ensemble is a finite number of ANNs that are trained for the identical purpose whose predictions are combined to generate a unique output. ANN ensembles offer a number of advantages over a single ANN in that they have the potential for improved generalization and increased stability (Sharkey, 1999). Ensemble methods have been successfully applied in various domains, such as time series prediction, robotics, and medical diagnosis (Chang Shu and Donald H. Burn, 2004). It has been shown to frequently generalize better than single ANN. However, for ensemble to be effective, the component ANN in the ensemble must be as accurate and diverse as possible. Figure 2.12 illustrates the basic framework of an ANN ensemble. Each ANN in the ensemble is first trained on the training examples.
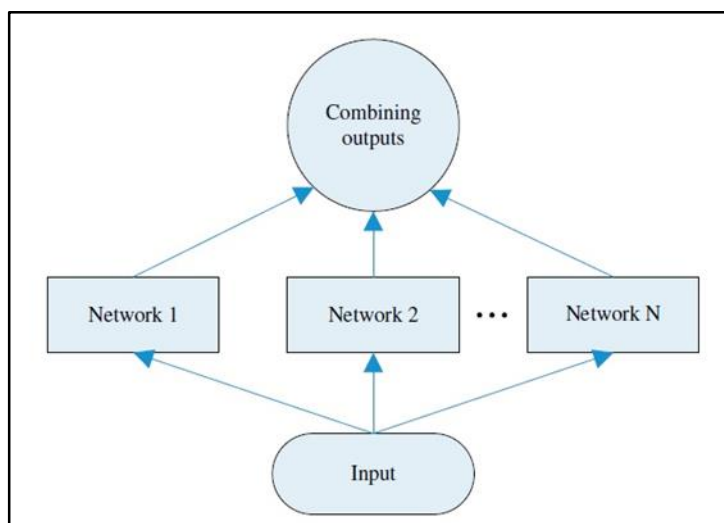
Figure 2.12: A neural network ensemble.

2.9 Modelling of Bivariate Samples and Patterns

A large amount of bivariate correlated samples and data are required to perform training and testing the ANN recognizer. Ideally, such samples should be selected from industry in real process. Unfortunately, they are not economically and limited therefore there is a need for modeling of process pattern for synthetically generating analysis data.

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