IMPLEMENTING OF AHS FOR PROCESS MONITORING EVALUATION SYSTEM

FATIN SYAZWANA BINTI HASHIM

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UNIVERSITI MALAYSIA PAHANG

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ABSTRACT

This research is about implementing of Analytical Hierarchy System (AHS) for process monitoring evaluation. Multivariate Statistical Process Monitoring (MSPM) system is an observation system to validate whether the process is happening according to its desired target. It will detect and diagnose the abnormality of the process behaviour and maintain consistent productivity by giving an early warning of possible process malfunctions. A significant development in MSPM has led to the introduction of principal component analysis (PCA) for reduction of dimensionality and compression of the historical operational data prior to the MSPM's two statistics which are Hotelling's T^2 and SPE models are used. This paper presents about developments of AHS in PCA-based multivariate statistical processes monitoring (MSPM) system. The procedures in MSPM system consists of two main phases basically for model development and fault detection by using Matlab. This research will be focused on implementing of AHS by using Microsoft Excel for AHS part. From the MSPM framework, the fault identification may trigger the results in contribution plot, SPE statistics and T^2 statistic models. Fault detection that produced from PCA in terms of contribution plot are then is applied in AHS as a selection tool to rank or make the priorities of the variables involved. The contribution plot produced from fault identification will be implemented in AHS parts. Normally, decision making involves the following elements which are the decision makers, criteria or indicators and decision methodology. Next, AHS will come out with the hierarchy for six types of contribution plots. Comparison is made based on the ranking and types of faults. In the field of decision making, the concept of priority is essential and how priorities are derived influences the choices one makes or decides. So, AHS is used to make the best selection. As a conclusion, it is proven that the proposed system is able to detect the fault as efficient as the MSPM. Thus, it can be the other alternative method in the process monitoring performance. Finally, it is recommended to use data from other chemical processing systems for more concrete justification of the new technique.

ABSTRAK

Penyelidikan ini tentang melaksanakan Analytical Hierarchy System (AHS) untuk penilaian pemantauan proses. Sistem Proses Monitoring Statistik Multivariate (MSPM) ialah satu sistem cerapan mengesahkan sama ada proses berlaku mengikut kehendak target. Ia akan mengesan dan mendiagnosis ketidaknormalan kelakuan proses dan mengekalkan konsistensi dalam produktiviti dengan memberi satu amaran awal proses kemungkinan tidak berfungsi. Satu perkembangan penting di MSPM telah menyebabkan pengenalan analisis komponen utama (PCA) bagi pengurangan dimensi dan memampatkan data operasi sebelum dua statistik MSPM yang mana ialah model-model T^2 and SPE digunakan. Kertas ini membentangkan tentang pembangunan AHS di proses statistik multivariat berasaskan sistem pengawasan PCA. Prosedur di sistem MSPM ini terdiri daripada dua fasa utama pada asasnya untuk pembangunan model dan pengesanan ketidaknormalan dengan menggunakan Matlab. Penyelidikan ini akan ditumpukan dalam melaksanakan AHS dengan menggunakan Microsoft Excel. Dari rangka kerja MSPM, pengenalpastian ketidaknormalan boleh menghasilkan keputusan dalam bentuk plot kontribusi, SPE statistik dan T^2 statistik. Pengesanan ketidakbiasaan yang dihasilkan daripada PCA dalam soal plot kontribusi kemudian diaplikasikan di AHS sebagai alat pemilihan untuk menempatkan atau membuat prioriti pembolehubah terlibat. Contribution plot yang dihasilkan dari pengenalpastian kesalahan akan dilaksanakan dalam bahagian-bahagian AHS. Biasanya, proses membuat keputusan melibatkan elemen-elemen berikut iaitu pembuat keputusan, kriteria atau penunjuk dan kaedah keputusan. Berikutnya, AHS akan menghasilkan hierarki untuk enam jenis plot kontribusi. Perbandingan dibuat berdasarkan kedudukan dan jenis kesalahan. Dalam proses membuat keputusan, konsep keutamaan sangat penting dan bagaimana prioriti diklasifikasikan akan mempengaruhi pilihan suatu keputusan. Jadi, AHS digunakan untuk membuat pilihan terbaik. Sebagai satu keputusan, ia terbukti bahawa sistem yang dicadangkan mampu mengesan ketidaknormalan sebaik MSPM. Maka, ia boleh dijadikan kaedah alternatif yang lain untuk prestasi pemantauan proses. Akhirnya, ia disyorkan untuk menggunakan data dari sistem-sistem pemprosesan kimia lain untuk lebih konkrit justifikasi teknik terbaru.

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LIST OF SYMBOLS

C_{mxm}	Variance-covariance matrix
$P_{i,j}$	i^{th} score for Principal Component *j*
Q_i	SPE statistics
W_i	Priority value
$\breve{X}$	Standardised data
X_z	Standardized matrix of original matrix, X
e_i	i^{th} row in residual matrix
$\overline{x}$	Data means
z_α	Standard normal deviate corresponding to the upper (1- α) percentile
λ_j	Eiganvalue corresponds to Principal Component *j*
A	Number of PCS retained in PCA model
E	Residual matrix
i	Row
I	Identity matrix
j	Column
J	Centring matrix
k	Principal component
m	Variables
n	Number of nominal process measurements per variable
N	Samples
P	PC scores
q_i	Loading vector of PCA
Λ	Diagonal matrix
V	Eigenvectors
V^T	Normalized orthogonal matrix
x	Data
X	Normal operating data
X^T	Normal operating data transpose
α	Level of control limit
σ	Standard deviation
λ	Eigen values

LIST OF ABBREVIATIONS

AHS	Analytical hierarchy system
CSTRwR	Continuous stirred tank reactor with recycle
CUSUM	Cumulative sum control chart
EVM	Eigen vector method
EWMA	Exponentially-weighted moving average
F1a	Fault 1 for abrupt
F1i	Fault 1 for incipient
F2a	Fault 2 for abrupt
F2i	Fault 2 for incipient
F3a	Fault 3 for abrupt
F3i	Fault 3 for incipient
KPCA	Kernel PCA
MCDM	Multi-criteria decision making
MDS	Multidimensional scaling
MPCA	Multi-way PCA
MSPC	Multivariate statistical process control
MSPCA	Multi-scale PCA
MSPM	Multivariate statistical process monitoring
MWPCA	Mowing window PCA
NOC	Normal operating data
PC	Principal component
PCA	Principal component analysis
PLS	Partial least square
PV	Priority value
R&D	Research and development
SPC	Statistical process control
SPE	Squared prediction errors

1 INTRODUCTION

1.1 Research background

Research and development has become an integral part of process development. Through research, science and technology evolve. New and innovative alternatives were invented. Such issues can be addressed systematically by the use of process monitoring techniques. Basically, there are various types of process monitoring system such as statistical process control (SPC) and multivariate statistical process monitoring (MSPM). SPC is the individual based monitoring whereas MSPM is multivariate based monitoring. Unfortunately, SPC have its own weaknesses. The main limitation of SPC is that it ignores the correlations among the monitored variables (Cinar, et al., 2007). So, MSPM is been introduced as an extension of conventional statistical process control (SPC). MSPM can be considered as the most practical method for monitoring complicated and large scale industrial processes (Chiang et al., 2001). It used the Shewhart control charts as a tool to determine the process parameters. This limitation is addressed by MSPM for further enhancement in the quality control mechanisms. MSPM method normally utilizes two types of monitoring statistics which are Hotelling's T^2 and squared prediction errors (SPE) (MacGregor and Kourti, 1995; Wise and Gallagher, 1996; Martin et al., 1996; Raich and Cinar, 1996). T^2 is for measure the centrality whereas SPE describes the consistency of correlations among the monitored process variables. Then, principal component analysis (PCA) is used as a tool to detect fault in process with highly variables and to characterize the multivariate process.

1.2 Motivation

MSPM has important task to detect and diagnose the abnormality of the process behavior that may cause the evolution of a range of statistically based condition monitoring approaches. In recent years, a significant development in MSPM has led to the introduction of principal component analysis (PCA) for compression of the historical operational data prior to the MSPM's two statistics which are Hotelling's T^2 and SPE models are used. (Kresta et al., 1991). Although there are various variations of MSPM models, the fundamental idea of MSPM is still the same. Therefore, faults that produced from PCA are then is applied in analytical hierarchy system (AHS) as a selection tool to rank or make the priorities of the variables involved. In the field of decision making, the concept of priority is essential and how priorities are derived influences the choices one makes or decides. Sometimes to decide on an option is not an easy task when many factors influence the decision. So, AHS is used to make the best selection. Normally, decision making involves the following elements which are the decision makers, criteria or indicators and decision methodology. To compliment this drawback, AHS is adopted a decision making methodology in selecting a sustainable design option. Through its hierarchical and systematic approach it provides an excellent option to solve multi criteria problems. Because of this, it has been a popular option for solving multi criteria problems in various fields from sports to engineering problems.

1.3 Research aims and objectives

Aiming at performing fault detection in MSPM by using PCA technique and introducing the concept of decision making in selection the fault contribution for different cases and system will be covered in the following scopes: Therefore, the main objectives of this research are:

i. To run the conventional PCA based on MSPM system.
ii. To study about the implementation of AHS for process monitoring evaluation.
iii. To develop the new process decision tools from combination of AHS in process monitoring.

1.4 Research scope

The research scopes of this research are listed as follow:

i. To develop the conventional MSPC procedure in which the linear PCA algorithm is used for lowering the multivariate data dimensions.
ii. Using Matlab software as a tool to achieve the objectives stated earlier.
iii. Focusing on the fault detection scheme only.
iv. The nature of the fault in this research includes incipient and abrupt.
v. Using Shewhart chart to monitor the process performance.
vi. Using CSTRwR system as a case study.
vii. To develop NOC data model using one operating mode.

viii. Using Microsoft Excel software to implement AHS in process monitoring evaluation.

1.5 *Significance of study*

This study produces a new idea on how to decide the monitoring performance by using AHS method in modelling all the variables involved. The method is expected to improve the monitoring progressions especially in terms of fault detection sensitiveness.

1.6 *Chapter organization*

The thesis is divided into five main chapters. The first chapter introduces the background of the research which includes the problem statement and motivation, objectives, scopes and significance of this research. The literature review is presented in Chapter 2, where it describes the fundamental of MSPM, process monitoring issues and AHS. Chapter 3 explains the methodology for both conventional PCA and AHS methods. Chapter 4 is discussing on the result and discussion of the research and finally, conclusion and recommendations have been discussed in Chapter 5.

2 LITERATURE REVIEW

2.1 *Introduction*

In today's climate of major data monitoring there has been an increment in interest in the multivariate statistical techniques of principal components analysis for process performance monitoring. The statistical technique is a method to detect the changes on occurrence. The techniques include collection, classification, analysis and interpretation of data (Cinar, et al., 2007). This chapter is divided into four sections which are introduction, fundamental and theories, justification of AHS in MSPM and summary.

2.2 *Fundamentals and theories*

These subtopics will be divided into three parts which are multivariate statistical process monitoring (MSPM), principal component analysis (PCA) and analytical hierarchy system (AHS). Those three parts will be discussed about the definition, theories, fundamentals and its application.

2.2.1 *Multivariate statistical process monitoring (MSPM)*

Process monitoring is an activity to select the process, observe the result systematically to make comparison with others and discuss the observation on how to conduct and examine the process. Whereas, a monitoring system is defined as an observation system to monitor either the process is happening according to the planning and in appropriate manner. The system should provide the process with a continuous flow of information to make it possible to decide the right decisions.

Generally, multivariate statistical process monitoring (MSPM) is to detect and identify the abnormality in the process behavior which may cause the development of a statistical range based on condition of monitoring approaches. The aim of MSPM is to remove the often observed high degree of redundancy in the data by defining a reduced set of statistically uncorrelated variables (MacGregor et al., 1995; Martin et al., 1996; Wise et al., 1996). A number of multivariate approaches have been proposed for the development of statistical process control schemes which is to monitor the dynamics processes performance. There are well known multivariate statistical tools followed these approaches such as principal component analysis (PCA), partial least squares (PLS) and multidimensional scaling (MDS) that have been extended to be included in system dynamics. Although there are various types of variations in MSPM models, the fundamental idea of MSPM is still the same. For example, the reduction of the dimensionality is used to calculate the statistic T^2.

Multivariate statistical control chart is basically used to monitor fault detection process based on scores using Hotelling's T^2 statistic and the residuals using squared prediction error (SPE). Hotelling's T^2 statistic is measured the variability that explained by the model, while the SPE statistic measured the non-explained variance (Wise et al., 1999). Confidence limits for the Hotelling's T^2 statistic will be assumed that scores are normally distributed based on the Fisher's F-distribution. Confidence limits for the SPE statistic are based on the chi-square distribution (Wise et al., 1999). Martin and Morris have described a method (M^2 statistic) to produce confidence limits based on a density estimator (Martin & Morris, 1996).

There are four main steps in MSPM in terms of the process monitoring performance and fault diagnosis. The four main steps are the fault detection, fault identification, fault diagnosis and process recovery. For the fault detection, it is used to detect the departure of the sample by using a set of parameters within the acceptable range. Meanwhile for fault identification, it is to identify the process variables that has tendency to the fault or malfunction which can be identified by using the plot contribution technique. Then, fault diagnosis is to determine the specific type of fault involved or occurred and confirmed their contribution to the signal. Finally, the process recovery is to remove the root of causes that is contributed in fault detection.

Table 2.1: Examples of industrial applications of MSPM

Process		Industrial Applications
Continuous process	i.	Fermentation industry (Lopes and Menezes, 2004)
	ii.	Steel industry (Kano and Nakagawa, 2008)
	iii.	Polypropylene Catalyzer Reactor (Xiong Li et. al., 2007)
Batch and semi-batch process	i.	Sugar crystallization process (Simoglou, 2005)
	ii.	Wastewater treatment (Lee et. al.,2006)
	iii.	Fed-batch fermentation system (B. Lennox et. al., 2000)

2.2.2 Principal component analysis (PCA)

In this research, PCA is been chosen as the multivariate statistical tools because it is widely used in multivariate statistical process monitoring (MSPM). Principal component analysis (PCA) is a reliable and simple technique to capture the variable relation and allowed extension of principles of univariate statistical process monitoring (SPM) to multivariate process monitoring (Jackson, 1991). PCA has been introduced for compression of the historical operational data prior to the MSPM's two statistics which are Hotelling's T^2 and SPE models are used (Kresta et al., 1991). The mathematical concepts that involved in PCA include standard deviation, covariance, eigenvectors and eigenvalues. PCA model is built based on the data collection from different periods of plant operation when the performance of operating condition for a particular process is normal. Moreover, both linear and nonlinear correlations can be extracted from the process data in the PCA technique to obtain more precise description of the original data. Since the PCA is used to reduce the dimensionality, the number of principal components used for reconstruction is usually smaller than the original variables. So, the major trends in a data set can be found easily.

The principal component analysis (PCA) to MSPM and extended it to on-line monitoring using Hotelling's T^2 and squared prediction error (SPE) (Kresta et al., 1991). Dynamic PCA extracts the time-dependent relationship in measurements by augmenting data matrix by time lagged variables (Ku, Storer & Georgakis, 1995).

Nonlinear PCA extends to extracting nonlinear relationships among process variables (Dong & McAvoy, 1996). Although there are many literatures on process faults detection with PCA techniques, there are few reports of PCA models addressing fault isolation in order to diagnose the root causes of the faults. PCA is the best suitable technique is used for the analysis of steady-state data with uncorrelated measurements. Because of nonlinearity of the real processes, it is recommended to use nonlinear models.

2.2.3 Process monitoring extension based on PCA

PCA plays an important role to the statistical approach in projecting the high dimensional correlated measurements to a low dimensional and un-correlated space of latent variables. However PCA also like many other classical techniques which is very sensitive to a few outlying observations. For examples, sometimes a principal component (PC) might be created just by the presence of one or two outliers. So, to overcome those outlying observation problems, there are several extension proposed by other researchers based on PCA which are Non-Linear PCA, Kernel PCA, Multi-Way PCA, Dynamic PCA, Multi-Scale PCA and others. In this research, only three process monitoring extensions based on PCA will be described more details, which includes Non-Linear PCA, Multi-Scale PCA and Moving Windows PCA.

Basically, in nonlinear PCA, the straight line straight line in PCA is replaced by a curve. Nonlinear PCA is based on neural networks builds a statistical model in the process of finding the low-dimensional nonlinear structure (i.e. the nonlinear principal component) characterizing the original data set. Without having to re-calculate neural network parameters, the nonlinear PCA model can be used to extract nonlinear principal components from new data presented to the model. If it is found during the evaluation of nonlinear principal components that the new data exhibit particular variability, only then may it become necessary to build a new neural network model using both the old and new data. Nonlinear principal components are defined for normal random vectors. Their properties are investigated and interpreted in terms of the classical linear principal component analysis (Salinelli E, 2009).

Besides, multi-scale PCA (MSPCA) also is one of the extensions for PCA. MSPCA shown the ability of PCA to decorrelate to the variables by extracting linear relationship with wavelet analysis to extract deterministic features and approximately decorrelate auto-correlated measurements at each scale is combined. MSPCA usually works on non-stationary process data and represent the cumulative effect of many underlying process phenomena, each operating at different scale. The deterministic process characteristics are extracted in the model by decomposing the data into multiple scales, so that Shewhart-type fault detection based on T^2 statistics can be used. In this way, the best statistic for a specific scale can be selected (such as Shewhart, CUSUM and EWMA) for detecting abnormal operations. Furthermore, MSPCA can separate the noise from the deterministic signal. However, the weaknesses of this method is that, it requires basic understanding of the physical and chemical principles control the process operation to help in clustering the highly correlated variables together before constructing the PCA model (Bakshi, 1998).

Next, moving window principal component analysis (MWPCA) is one of the diagnostic tools to detect the presence of peak shift. The moving window is constructed from a small data segment along the wavenumber axis. For each window bound by a narrow wavenumber region and PCA analysis is applied separately. The number of principal components (PCs) required to adequately will describe the difference in spectral intensity depends on the position of the window. This data is visualized by constructing the Scree plot for individual windows. Scree plot is log eigenvalue vs number of PC.

One may arbitrarily set the threshold for the nominal rank of the window to be the number of eigenvalues which are greater than or equal to some fraction of the first eigenvalue (Ryu et al, 2011). When the rank of each window is established, the number of eigenvalues vs the position of the window on the wavenumber axis graph is plotted. The increase in the effective rank indicates a region of the possible peak shift.

2.2.4 Analytical hierarchy system (AHS)

Generally, there are two commonly approaches to derive the answer from the modelling variables (Satay, 2001). First one is by using deductive logic with assumptions and carefully deduce an outcome from them. The second is by laying out all possible factors in a hierarchy or in a network system and deriving answers from all possible relative influences. Therefore, it is very important to have a convincing method for decision making since what we decide today shapes the future world. So, there are two types of modelling techniques which is created from those approaches which are fuzzy logic and analytical hierarchy system (AHS) (Nefeslioglu et al., 2013).

Analytical hierarchy system (AHS) was introduced in 1980 by Thomas L. Saaty. AHS is a classic and powerful decision support tool. It is one of the multi-criteria decision-making (MCDM) methods. It has been applied in wide variety of areas such as in planning, resource allocation, and bench marking. Besides, it also helped to determine the conflicts in various types of fields such as engineering, business, ecology, food, health, and government. AHS is defined as a discrete measurement theory that derives ratio scale values from pairwise comparisons and ratings (Saaty, 2000). This means that AHS is used to determine relative ranking of alternatives and the importance of criteria in a decision. AHS forms the trade-off decision between multiple objectives in a hierarchical structure.

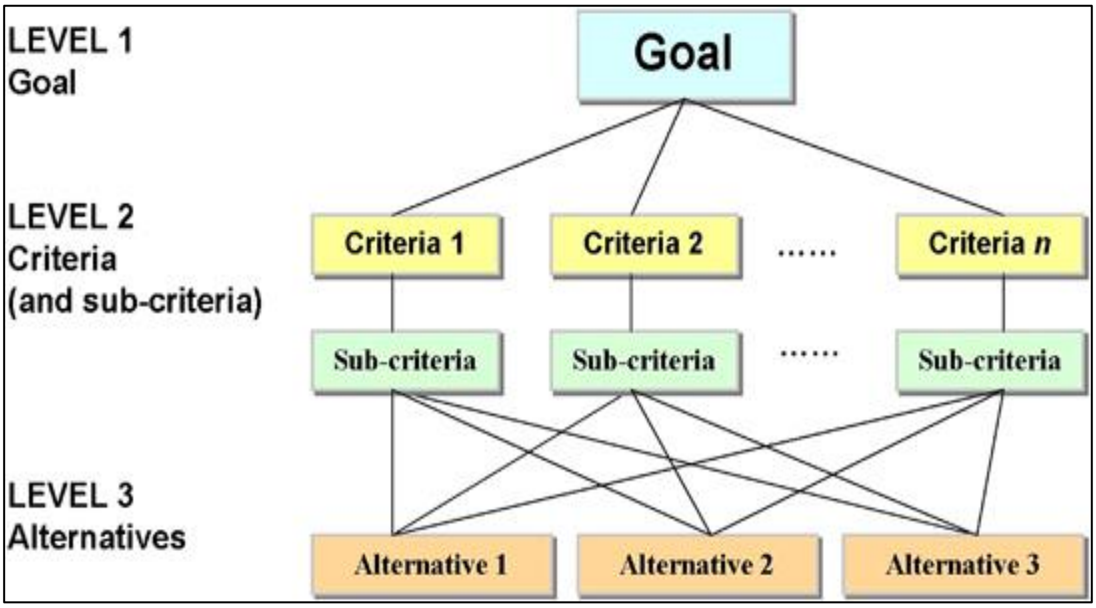
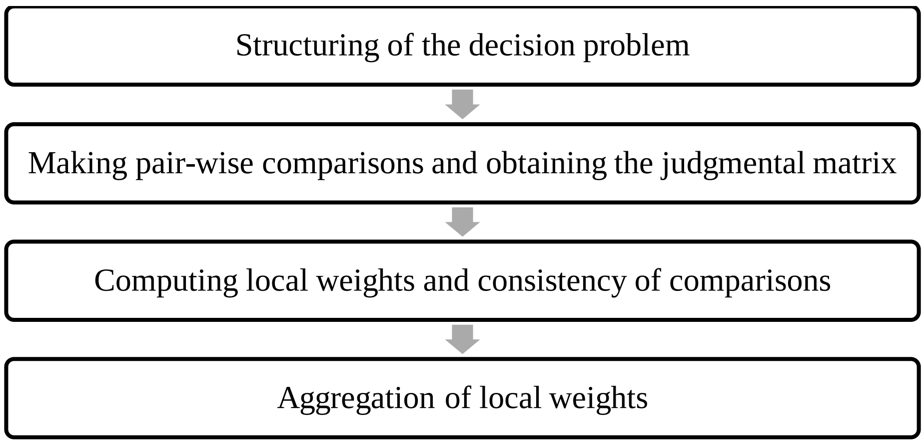


Figure 2.1: Hierarchy tree for AHS

Sources: Yung Yau, Journal of building appraisal, Multi-criteria decision making for urban built heritage conservation: application of the analytic hierarchy process

A decision-making problem is designed in hierarchy that consists of goal, criteria, sub-criteria, and decision alternatives (Saaty, 1980). An important part of AHS is to accomplish these three steps which are state the objective, define the criteria and pick the alternatives. Then, all the information is arranged and listed down in a hierarchical tree as shown in Figure 2.1. There are some of the advantages of AHS which provides a systematic and simple approach, it is hierarchy-based and offers multiples and specific criteria for decision inclusion. AHS accepts any particular constitutive criterion for inclusion and allows individual decisions to be aggregated into overall criteria, which allows other members to review and participate in that aspect of the decision making process at an appropriate level of detail.

Application of AHS to a decision problem involves four steps (Kim, M. & Cho, D., 2013). Those steps are shown graphically in Figure 2.2.



Fiqure 2.2: Step of Analytical Hierarchy System (AHS)

Researchers have found many usages of AHS have been increasing exponentially and its usages have been dominated in the manufacturing sector. They have also found growing number of recent applications in the service sector. Recent overviews about AHS have been provided by Forman and Gass (2001), and Sipahi and Timor (2010). Forman and Gass (2001) have discussed applications of AHS for decision such as choice, prioritization or evaluation, quality management, resource allocation, benchmarking, health care, public policy and strategic planning. The applicability of AHS is illustrated to wide variety of real problems with cases in different sectors beyond simple choice problems. Besides, a comprehensive literature review of recent applications of AHS over a period of five years is presented by Sipahi and Timor (2010). The studies are divided according to the application area which consists of manufacturing, environmental administration and agriculture, common decision problem, power industry, transportation industry, construction industry, health and others. In addition, the articles also categorized in terms of subject titles, publication date, origin country, academic journals and integrated methodologies.

However, since AHS has been applied in a huge variety of application fields, Table 2.2 some recent reviews have focused on the application of AHS in specific fields.

Table 2.2: Examples of industrial applications of AHS

Specific field		Application
Marketing	i.	As portfolio decisions and desired target portfolio, directions for new product development, and generation and evaluation of marketing mix strategies. (Wind and Saaty, 1980)
	ii.	Used of adaptive AHS to customize marketing decision problems and reviewed standalone AHS application and recommended that knowledge base to be incorporated in complex marketing decision problems. (Mark, 2001)
Energy	i.	Applicability of multi criteria decision making methods in 90 published articles related to renewable energy planning, energy resource allocation, building energy management, transportation energy systems, project planning and electric utility planning (Pohekar and Ramachandran, 2004).
Medical and health care	i.	Based on 50 published articles which are categorized in diagnosis, patient participation, human resource planning, organ transplantation, therapy/ treatment, project and technology evaluation and selection, and health care evaluation and policy (Liberatore and Nydick, 2008)
Research and development (R&D) project	i.	Application of AHS in R&D project selection and resource allocation. (Heidenberger and Stummer, 1999)

2.3 Justification of AHS in MSPM

Generally, AHS is commonly used as a decision making tools to identify or select the best criteria. Researchers have found the useful of AHS in different sector such as agriculture, health and marketing. Examples of some research that used AHS as a selection medium are in designing and evaluate three alternatives highway roads (Effat & Hassan, 2013), landslide susceptibility mapping (Kayastha et al., 2013) and assessing environmental impacts of municipal solid waste (Abba et al., 2013). The result from other researcher in different sector gave an idea to come out with new invention or design based on MSPM. So, this study is held to introduce the new invention where AHS is implemented in process monitoring and evaluation system or MSPM.

Several chemical plant case studies contain variables are selected to be tested in different types of fault detection based on contribution plot. Then, each contribution plot will detect and diagnose various fault or malfunction in an abnormal operating condition. With large number of variables measured in each chemical plants case, multivariate statistical process monitoring (MSPM) approaches is proposed in order to obtain useful information from large amount of process data and to detect and diagnose various faults in an abnormal operating condition. Then, the process data from the diagnosis will be used in AHS to identify the major criteria that cause the fault detection by derive the alternative composite priorities which helped to determine the conflicts happened in fault. AHS will be ranked the system to select the priorities which variables have the high tendency that lead to the fault detection.

2.4 Summary

As a conclusion, there are four main steps in MSPM performance and fault diagnosis which are fault detection, fault identification, fault diagnosis and process recovery. The PCA technique is applied in this research in order to diagnose the fault. Besides that, a decision-making problem is designed in hierarchy that consists of goal, criteria, sub-criteria, and decision alternatives. Furthermore, AHS is one of the multi-criteria decision-making (MCDM) methods and the best decision making tools. New invention is held to introduce that monitoring network also can be applied in AHS by implementing AHS in process monitoring and evaluation system.

3 METHODOLOGY

3.1 Introduction

This chapter discusses a methodology on AHS based on MSPM. Generally, the software used to develop the analytical hierarchy system (AHS) is Excel. Then, the data from the Excel is implementing to the Matlab software as the multivariate statistical process monitoring (MSPM) use to run the system. This chapter can be divided into three sections which are introduction, methodology of this research and summary.

3.2 Methodology on AHS-based MSPM

In this research, the main focuses of the methodology is fault detection in MSPM system and proceed to the AHS system. Fault detection is used to design the departure of observed samples from an acceptable range by using a set of parameter. According to the study of Yunus and Zhang (2010), the complete procedures of fault detection consists of two main phases namely as off-line modelling and monitoring (Phase I) and on-line monitoring (Phase II). Meanwhile, the third phase is performing AHS (Phase III).

Basically, Phase I is for model development which is to gain understanding about the process and to form a statistical benchmark for the future process outcomes by using NOC data to develop the model. Meanwhile, Phase II is for fault detection operation. It describes to observe the process in actual time by comparing the new process data with the pre-specified model that is formed during the first phase. From the comparing data, the result of the process may be normal or abnormal. If the process is normal it means no changes in the process whereas if the process is abnormal, it means there are fundamental changes in the process which requires intervention. Then, Phase III is procedure to develop AHS. AHS is in hierarchical and systematic method makes it a popular technique to solve multi criterion decision making (MCDM) problem. It will perform the decision between multiple objectives in a unihierarchical structure. This AHS is used to come out with conclusion about the major fault contribute and finalise the fault identification’s results from Phase II.

The overall procedures of the proposed monitoring framework are shown as in Figure 3.1. From Figure 3.1, the first phase relates to the model development of normal operating condition (NOC) data (off-line modelling) whereas the second facilitates for monitoring of the new process data (on-line monitoring). The third phase is about the development of AHS in the form of hierarchy according to its priorities from the fault identification.

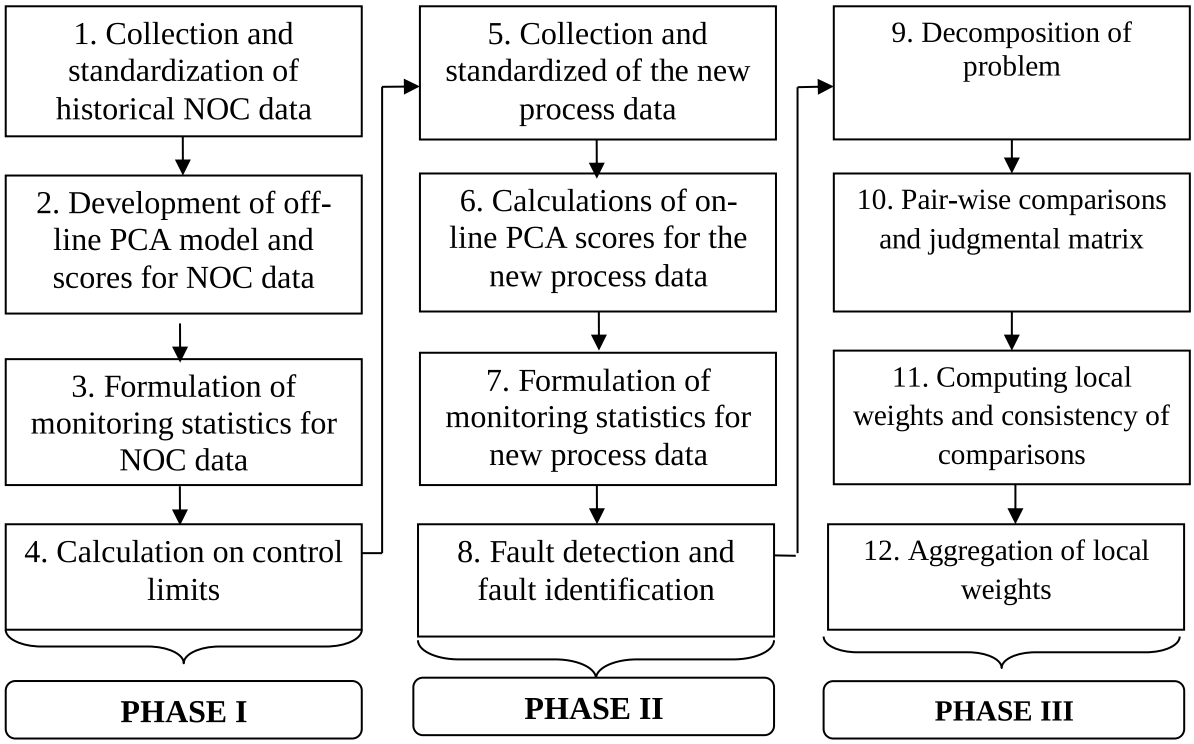


Figure 3.1: Generic MSPM & AHS framework

3.2.1 Phase I (Off-line modelling)

Firstly (**1st step**), a set of normal operating condition (NOC) data, $\mathbf{X}_{n\times m}$ (*m*: samples, *n*: variables), are identified off-line based on the historical process data archive. The data is in the matrix, $\mathbf{X}_{n\times m}$form where *m* stands for the number of variables and *n* stands for the number of samples.

$$\mathbf{X} = \begin{bmatrix} X_{1,1} & X_{1,2} \cdots & X_{1,m} \\ X_{2,1} & X_{2,2} \dots & X_{2,m} \\ \vdots & \vdots \;\; \vdots & \vdots \\ X_{n,1} & X_{n,2} \dots & X_{n,m} \end{bmatrix} \tag{3.1}$$

Then, the NOC data are standardized to zero mean and unit variance because the data involved with various sets of process units. The data also need to be set respect to each variable because PCA results depend on the scale.

$$\breve{X}_{j,i} = \frac{(X_{j,i} - \bar{X}_i)}{\sigma_i} \tag{3.2}$$

Where, $X_{j,i}$ represent the NOC data, $\bar{X}_i$ represent mean and σ_i is variance.

The mean and standard deviation can be calculated as Equation 3.3 and equation 3.4. Then, the calculated value is substituted back into Equation 3.2 to find the standardisation for each sample.

$$Mean, \bar{X}_i = \frac{\sum_{j=1}^{n} x_{j,i}}{n} \tag{3.3}$$

$$Standard\ deviation, \sigma_i = \frac{1}{n-1} \sum_{j=1}^{n} \left(X_{j,i} - \bar{X}_i\right)^2 \tag{3.4}$$

Where, n is the number of sample.

Next in **step 2**, the development of PCA model for the NOC data required the establishment of a set of correlation (or variance-covariance) matrix, $\mathbf{C}_{m\times m}$. The correlation matrix, $\mathbf{C}_{m\times m}$ will be in the diagonal matrix.

$$\mathbf{C} = \frac{1}{n-1}\breve{X}'\breve{X} = \begin{bmatrix} C_{1,1} & C_{1,2} \cdots & C_{1,m} \\ C_{2,1} & C_{2,2} \cdots & C_{2,m} \\ \vdots & \vdots \quad \vdots & \vdots \\ C_{n,1} & C_{n,2} \cdots & C_{n,m} \end{bmatrix} \tag{3.5}$$

Next, **C** is transformed into a set of basic structures of eigen-based formula.

$$C = V\Lambda V^T \tag{3.6}$$