CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

Monitoring is a continuous real-time task of determining the possible conditions of a physical system, recognizing and indicating inconsistencies of the behavior (Isermann, 2011). The application of statistical method in monitoring is widely uses in chemical-based industries that involves with series of unit operations in order to convert the input materials into desired products following the qualitative and quantitative specifications of the customers. This can be considered as highly challenging as the process subjects to be affected by various unstable conditions over the time of operation. Simply avoiding or slow response in such situations may result with the decadence of product quality and even leads to catastrophic events as well as risking the profitability of the company. Thus, it has always been imperative to have a systematic mechanism which can routinely manage all of these abnormal situations automatically. These problems can be addressed quite effectively by using the process monitoring system. The method normally functioned to conduct fault detection, fault identification and fault diagnosis tasks.
1.2 RESEARCH BACKGROUND

In general, there are two popular types of process monitoring systems available for industrial application, which are univariate and multivariate monitoring systems. Since most modern industrial processes are involving multivariate in nature especially in measurements on a number of characteristics, instead one single characteristic, univariate method provides little information regarding the mutual interactions and also do not function well for multivariable processes with highly correlated variables (Nomikos and MacGregor, 1995 and Qin, 2012). The conventional univariate system, such as Statistical Process Control (SPC), has been mainly criticized for its limitation (particularly in the context of chemical-based operation), whereby it is only being operative under univariate analysis setting as well as a large number of control charts is always needed to be monitored concurrently (Bersismis et al., 2007). Besides, it always ignores the implications of harmonization between the output and input variables. Thus, the multivariate system such as Multivariate Statistical Process Monitoring (MSPM) can be regarded as the most practical method for handling complicated and large scale systems (Chiang et al., 2001).

As the process is in multivariate nature, the system will typically develop a model that correlates all of the variables simultaneously by using a set of normal operating condition (NOC) data that obtained from the historical process archive. In the other words, the system can utilize maximally all the process data stored for better use (Zhao et al., 2004). Besides, the system also has been popularly perceived as an advanced technique from the traditional SPC methodology. Unlike SPC, MSPM can extract useful information in terms of inter-related variable variations and represent it by using simplified parameters (normally in terms of multivariate scores and monitoring statistics). By applying the method, the monitoring operation can be executed much simpler (in the sense that only a small number of control charts are required) as well as critically consider the effect of all changes that contributed from various variables concurrently.
At the fundamental level application, there are two types of monitoring charts typically employed – Hotteling’s $T^2$ and Squared Prediction Errors (SPE). The first represents conceptually the magnitude of deviation of the current sample from the center, whereas, the second analyzes the consistency of the current sample correlation according to the NOC model development. Both have been used complementary, whereby, control limits for both statistics are also computed accordingly. The main task would be to observe the progressions of both statistics on a control chart (usually Shewhart-type control chart) that constructed respectively. When the process is normal, all the statistics will remain below the control limit lines. However, whenever a fault event takes place in the process, the corresponding statistics will move away from the normal region until a point where it goes beyond the control limits specified (sooner or later). If the abnormal trend persists over a period of time, the system will then initiate the alarm which signifies that one or a combination of faulty event(s) has (have) actually occurred in the process (fault detection). Contribution plot is then applied, purposely to identify the main possible variables that either contributing or being affected from that particular abnormal event that detected. Lastly, further investigation is needed to critically sort out and finally diagnose the true source of the problem that related to that particular abnormal existence.

1.3 PROBLEM STATEMENT

MSPM normally utilizes linear-based principal component analysis (PCA) as the main technique of multivariate data compression. However, PCA sometimes is improperly used especially in modeling highly nonlinear processes as a high number of principal components (PCs) are always involved may lead to inefficient and unreliable monitoring performance reflected in false alarms and missed faults (Dong and McAvoy, 1996 and Žvokelj et al., 2011). If large variable are involved, then the PCs may also be selected considerably. As a result, Zhang et al., (1997) introduced non-linear PCA which based on the combination of neural network and principal curve but the computation is very demanding and it always requires a massive amount of data for creating the optimized NOC model (Yunus, 2012).