CHAPTER 1

INTRODUCTION

The masses of data measured in process industry are mainly used for the purpose of process control. However, they are also useful for (a) the overview of the processes (process monitoring), (b) for fault (upset) detection, (c) for the prediction of product or process properties (soft sensors), and (e) for improved process understanding. The multivariate analysis to accomplish these objectives has been proved as a practical and useful method. Multivariate Statistical Process Control (MSPC), process monitoring based on multivariate statistical works well both for continuous processes (e.g., distillation in a refinery, polymerization plant, or Kamyr pulp digester), and for batch processes (e.g., spray-coating, fermentation, wafer etching, cosmetic formulation).

Semiconductor processes, like many chemical processes, are becoming more measurement rich all time. Large volumes of data are recorded and are often not used until the process has undergone a significant upset. This data can be very useful for process monitoring if the appropriate tools are applied. Successful applications can result in reduced costs and/or improve the final product quality through improve process control or fault detection.

However, there are significant obstacles to using the data for process monitoring and fault detection, including the sheer volume of the data, large numbers of variables, and the non-stationary of the process data due to process and monitoring sensor drift. A wide variety of data treatment methods are available, however, it is often not apparent what methods will be useful in meeting monitoring and fault detection goals.

1.1. Problem Statement

In the data storage industry today, the requirement of Hard Disk Drive (HDD: Fig 1.1) capacity is increased dramatically. The more high capacity is related to the less flying height as shown in Fig.1.2. Because if we need the same size of HDD but more capacity. Track width in media will become narrower. A;so magnetic signal in read-write head will become less. The flying height of read-write head in HDD will be less also.

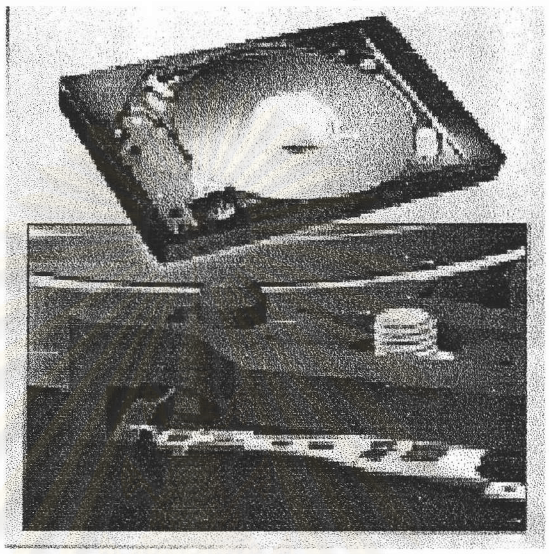

Figure 1.1 Hard Disk Drive

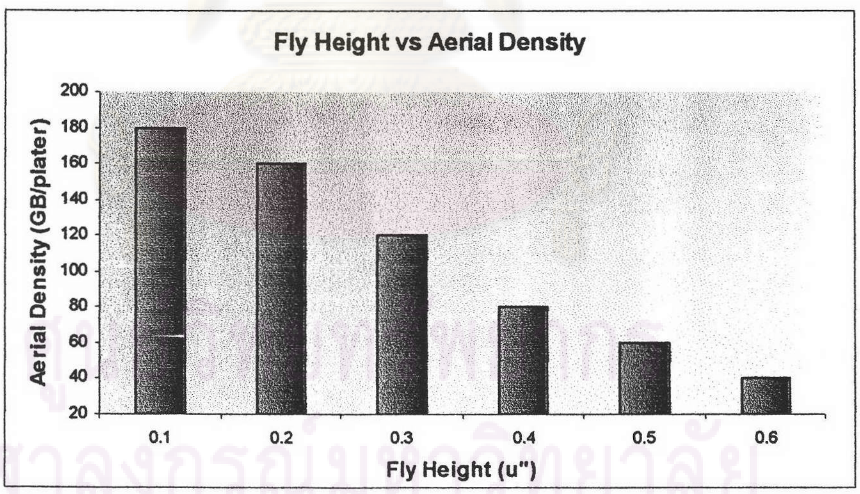

Figure 1.2 Fly Height vs. Aerial Density

To meet the consistency of flying height, all of critical process input variables must be well controlled and the uniformity of etch depth is the key process input variable, which will strongly effect on fly height performance.

There is relationship between fly height and etch depth uniformity, hence smooth etch depth surface is a most significant (Fig 1.3) to quality of read-write head.

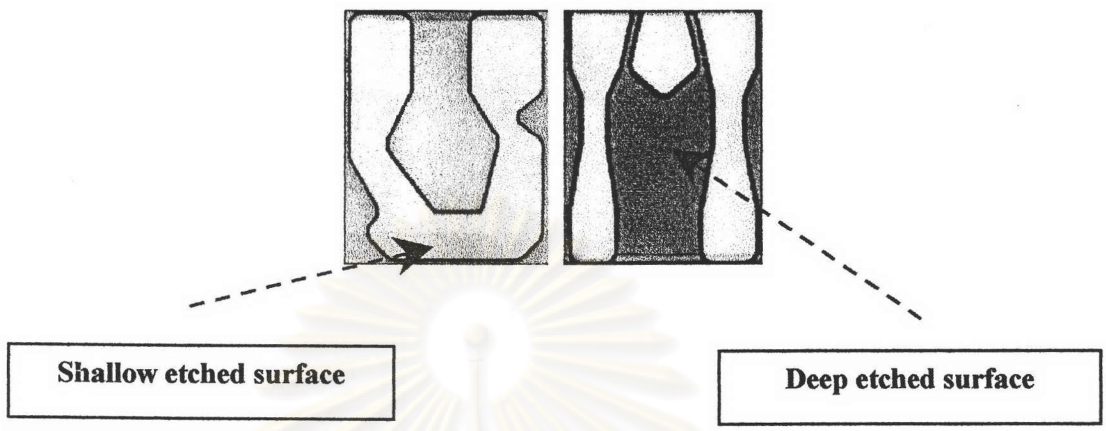

Figure1.3 Read-Write Head in Hard Disk Drive

As typical of the operating environments, statistics techniques are important tool, which is used for monitor, control, improve and prevent process from assignable causes. In order to monitor and control process, univariate control chart is very common tool for monitor response and control process input variables. In another hand, there is more than one variable play significant roll on the real process and some of them strongly correlation to each other. Therefore, multivariate statistical process control (MSPC) is introduced to fullfill the disvantage of normal statistical process control.

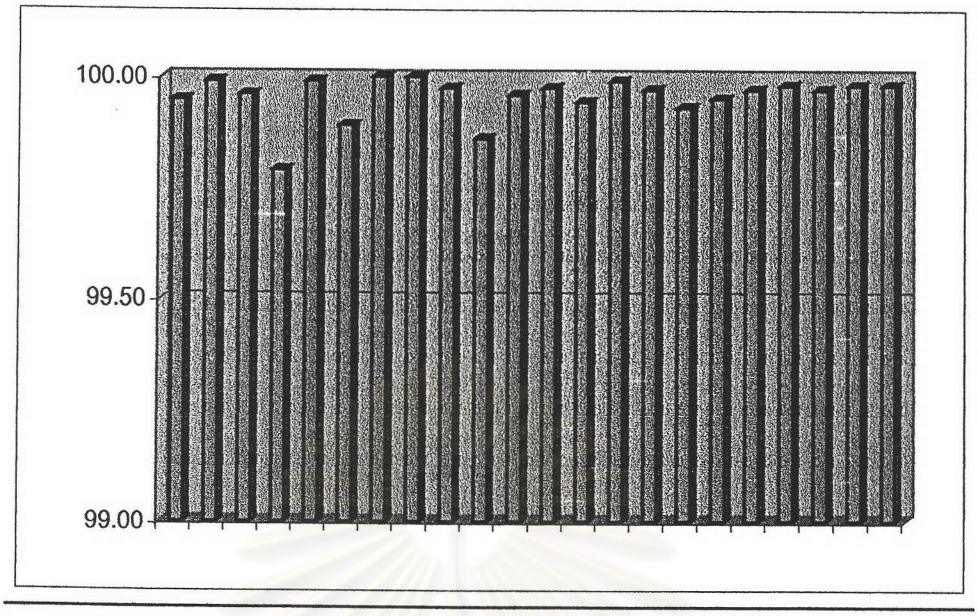

Figure1.4 Percentage of Yield of Etching Operation

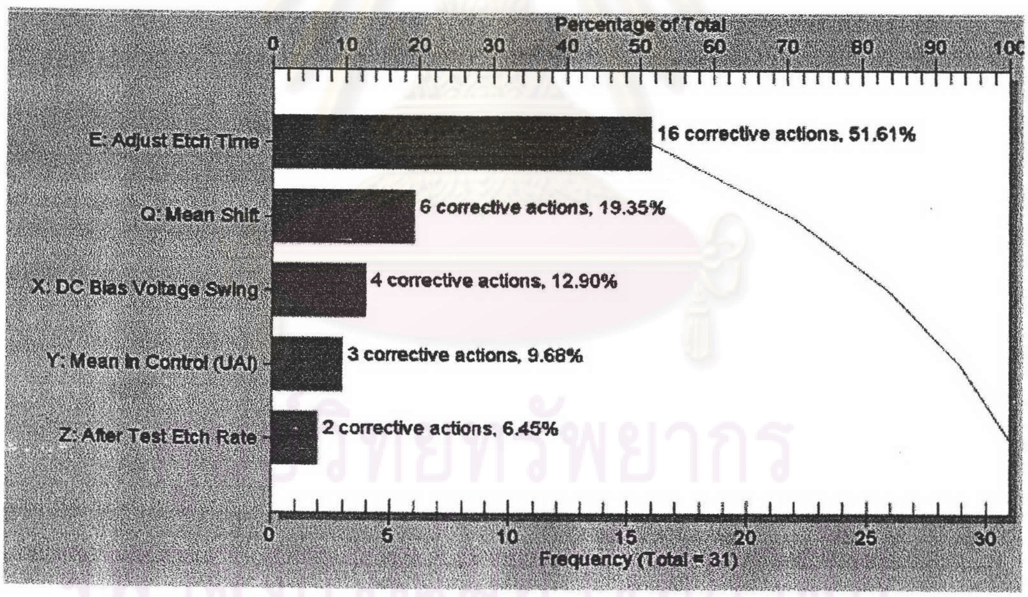

Figure 1.5 Percentage of Fault Detection

However, there are significant obstacles to using data for process monitoring and fault detection, including the sheer volume of the data, large number of variables, and the non-stationarity of the process datadue to process and monitoring sensor drift. A wide variety of data treatment methods are available, however, it is not often apparent what methods will be useful in meeting monitoring and fault detection goals.

In process applications, the data are usually highly multivariate, collinear, noisy, and typically have missing data. This makes it difficult or impossible to use full rank statistical method for their modeling and analysis, i.e., multiple regression, discriminant analysis, analysis of variance, as well as neural networks. However, projection methods such as Principal Component Analysis(PCA) and Partial Least Square (PLS) are based on realistic assumptions about variables (collinear, noisy etc.), making them suitable for the modeling and analysis of complicated process and other data.

PCA and PLS models derived from historical data measured on a well functioning process, producing products within specifications, can then be put “on-line” and be used to continuously monitor the process. Resulting multivariate control charts indicate a well or malfunctioning process and point to “faults”. The traditional control charts (Shewhart, CUSum, EMWA) are also used here, but instead of showing the values of individual variables, they now displayed scored, and score summaries, which optimally summarize the process variables. Contribution plots are used for the interpretation of the faults and for drilling down to find likely causes.

This approach of multivariate process monitoring (MSPC) works well both for continuous processes and for batch processes . An application of MSPC is used to illustrate the approach and its benefits, i.e., improved process understanding, improved product quality, and improve bottom line.

1.2. Objective of the study

i. To create the solid model that is using for fault detection in shallow etching process with respect to etch depth uniformity.
ii. Simulate and validate the solid model on actual shallow etching process.

1.3. Scope of the study

i. Study on batch process : shallow etching process on 1 product and 1 machine only.
ii. Use application of statistical software JMP5.0 to formulate Principal Component (PC) model.
iii. Test the PC model with normal and abnormal condition.
iv. Use Matlab for data processing

1.4. Methodology of the study

i. Study on Multivariate Statistical Process Control (MSPC), Principal Component Analysis (PCA) and their applications.
ii. Study on shallow etching process.
iii. Data collection and model formulation based on PCA technique.
iv. Model validation and simulation on actual process.
v. Analysis and conclusion.
vi. Documentation and presentation

Step	2003									2004			
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1.4.2													
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