CHAPTER 2

Theory and Literature Surveys

2.1 Introduction

This chapter represents the theory background used in developing the improved process of monitoring tester performance. Not only theories concerned are described, the related literatures that were researched by many authors have been summarised. They are used as a basis in making an analysis and improvement process.

Firstly, the measurement system is defined its definition. Then, what measurement system is usually concerned are interpreted that are calibration and measurement process control. Moreover, Six Sigma is studied what it is used for, what it is concerned about, how to implement it, and what are the steps concerned in six sigma process. In addition, tools and techniques used in statistical analysis are explained. They are Statistical Process Control (SPC), regression and correlation, power of test, inferential statistical analysis, and Analysis of Variance (ANOVA). Finally, the techniques that are used in machine condition monitoring are identified from literature surveys.

2.2 Measurement System

2.2.1 Measurements

"*Measurements are defined as the assignment of numbers to material things to represent the relations existing among them with respect to particular properties*" (**Farnum, 1994**). Measurements are important to the manufacturing processes. Without measurement system, inaccuracies of products produced or non-conforming products is not discovered. Having reliable measurement system leads to successfulness of process control and process analysis.

The quality of a measuring instrument or machine affects the reliability of process data and the statistical methods based on these data. It is important to check the reliability and reproducibility of measurement system. It would be waste much time and effort in analysing processes and searching for assignable causes when many of out of control points may be due to measurement error or unknown causes.

According to **Farnum (1994),** factors that affect measurement quality are differences among operators, differences in measuring procedures, instrument calibration and drift, instrument repeatability and reproducibility, and instrument resolution. Those create uncertainties that can be defined into two types of errors, systematic error and random error. Systematic errors are defined when the instrument's readings, on average, are off from its true value that obtained from standard process. On the other hand, random errors cannot be predicted. They come from differences among instrument, different among operators, instability over time, environmental changes, and different setups.

To control those sources of variation or error, Farnum proposed "*operational definitions*" that different operators should be addressed to arrive at equally reliable results.

Factors that affect the quality of a measurement system

1. What is the repeatability of the measuring instrument?
2. Does the time between measurements have an effect on the measurements?
3. Do different instruments measuring the same property give different results?
4. To what extent do different operators add to the magnitude of the measurement error?
5. Does the measurement result depend on the procedure or the sequence of procedures used?
6. What is the effect of environmental conditions on the resulting measurements?
7. Is the measurement process in statistical control?

When operator does not recognise operational definition, errors in measurement have high potential to take place. Measurement error can be determined from following equation:

$$X_m = X + \varepsilon$$

where X_m is the measured value, X is the true value, and ε is the error of measurement.

2.2.2 Calibration

The acceptable true value is obtained from National Institute of Standards and Technology (NIST). It creates the accepted standard for measured quantities through international agreements. This standard will be transferred to measuring instruments that are used everyday in manufacturing work called "*Calibration*".

The process of transferring NIST standards to the company's measuring instruments is accomplished by means of a hierarchical system of transfers. First, the company will establish a primary standard of each measured quantity that is directly calibrated to the NIST. Then, the primary standard will be used to calibrate secondary standards which will be further used to calibrate the instruments used in the production as working standards. Figure 2.1 shows the typical hierarchy of calibrations within a company. The strength of linkage is called tractability which is "*the ability to relate individual measurement results to national standards or nationally accepted measurement systems through an unbroken chain of comparisons*" (U.S. Dept. of Defense, Military Standard 45662).

Calibration is to compare the measurement system or instrument to a higher reference standard, and compensate instrument with offset when that instrument has inherent systematic biases in its measured values. Calibration intervals are usually established based on how much use the instrument experiences. Intervals can be lengthened or shortened depending on how many times the instrument required adjustments during past calibrations (**Sobralske, 1989**).

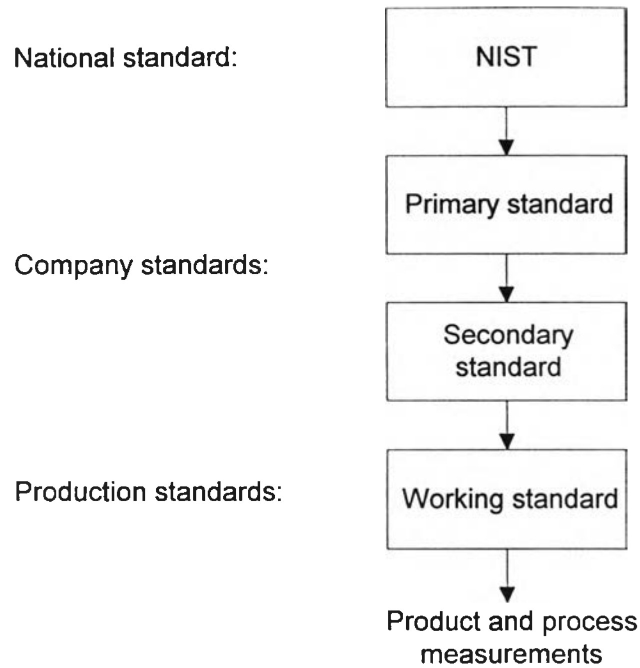


Figure 2.1: Tractability of measurements to the National Institute of Standards and Technology (NIST)

(Source: Statistical Quality Control and Improvement, Nicholas R. Farnum, 1994)

2.2.3 Measurement Process Control

Ideal measurements should show no variation that measuring the same object should give identical values whose uncertainty is limited only by the rated accuracy or resolution of the particular instrument. It can be said that the instrument has perfect repeatability. However, there are many sources of variation, such as environment and changes in measuring system, in real measurement systems.

Since many sources of variation are presented, measurement process should be controlled, like production process, by control chart techniques. This is to assure the reliability of the measurement system. **Eisenhart (1967)** stresses that "*unless a measurement system is brought into a state of statistical control, it cannot be regarded in any logical sense as measuring anything at all*".

Control chart can be constructed by using of check standards or standard parts, believed to be relatively stable, periodically measured by the system. These measured values will be plotted on control charts to monitor system performance. Any shifts or drifts on the control charts are the signal of changes in performance of measurement instrument. The control charts can be expressed as either in terms of original readings or in terms of the deviation of these measurements from the nominal or reference values.

Bishop, Hill, and Lindsay (1987) recommends to use check standards that are similar to the parts that are measured during normal production. One reason for this is that no changes needed be made in the measuring system to accommodate such check standards. Also, it is convenient to draw the check standards from normal production parts so that the standard parts experience exactly the same conditions found in the production environment.

2.3 Six Sigma

Six sigma is a system which provides managerial, statistical, and problem solving methods that enable a company to achieve function improvement capabilities. It provides the company the strategies, tools, and focus necessary to make significant gains in operating efficiencies and quality, and as a result, profitability.

According to **Redinius (1998)**, the techniques used in six sigma aim to identify the problems and sources of errors, and then finding out for the ways to eliminate them. That means six sigma can be achieved by continuously and formally improving the weaker areas of the business with higher operating efficiencies, shorter cycle time, better design robustness, and minimised defect levels, no more than 3.4 defects per million opportunities in any process, product, or service.

Hoerl (1998) has proposed the major elements of Six Sigma implementation that are defined as follows:

1. The initiative is driven by leaders at the highest levels of the organisation and passes through all levels of management and operations.

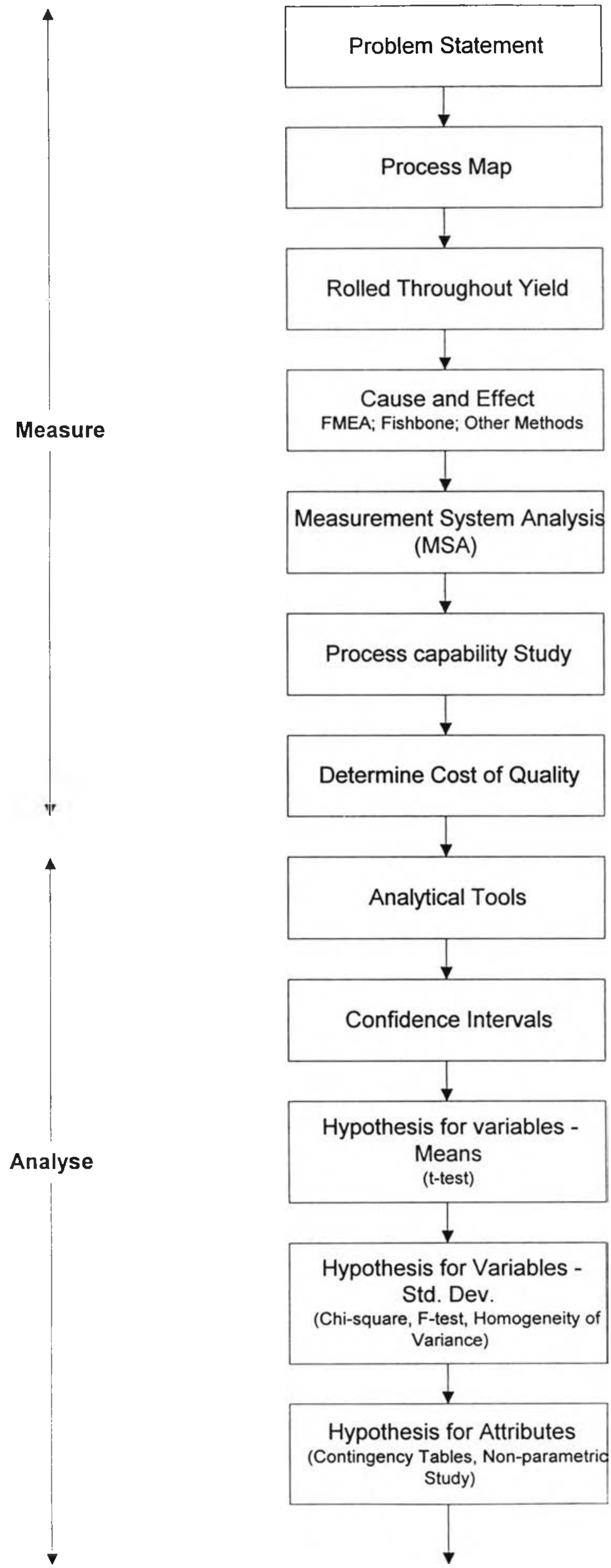
2. Six sigma initially focuses on manufacturing. It concerns on cost and waste reduction, yield improvement, and operations with opportunities to improve capability without major capital expenditure. It also emphasises on customer requirements.
3. Performance matrices are established that directly measure the improvement in cost, quality, yield, and capacity.
4. Typical projects should be targeted.
5. Practitioners, such as engineers, accountants, and computer scientists, are identified to work on the six sigma projects 50% to 100% of their time, with help from other team members.
6. Blackbelts, who dedicate 100% of their time on the six sigma projects and have responsibility in implementing the projects, are trained 4 or 5 weeks of intensive to knowledge the four steps of the Six Sigma methodology.

Six sigma involves a series of steps to achieve the improvement projects. Every projects of six sigma have to be implemented through four phases: measurement, analysis, improvement, and control. **Harry (1998)** has defined the main activities necessary to fulfill each phase as follows:

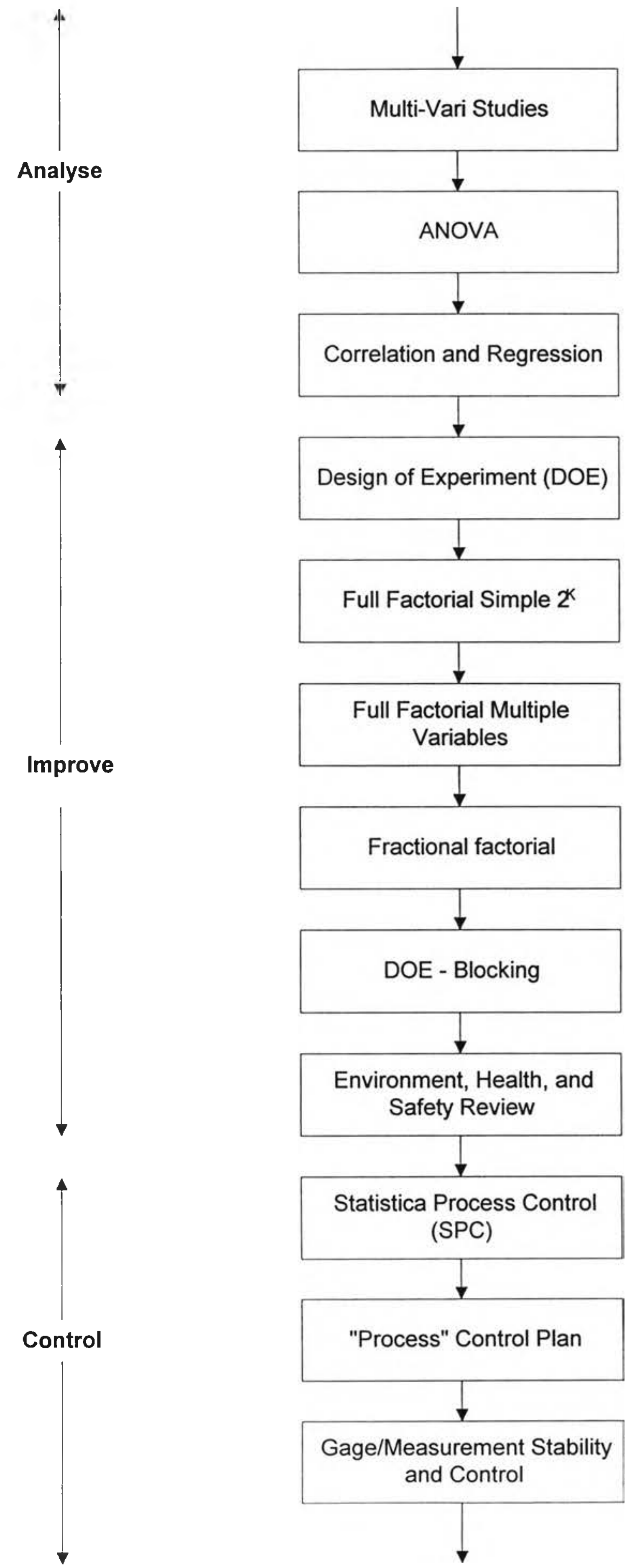
- Measurement phase: One or more Critical to Quality (CTQ) characteristic would be selected, and they are mapped with the respective processes. Then, the necessary measurements will be established to records the results. Also, short-term and long-term process capabilities are estimated.
- Analysis phase: The benchmarks of key product performance metrics are identified. Then, the gap between benchmarks and company's performance are evaluated to find the factors of successful performance.
- Improvement phase: Product characteristics that need improvement are identified so that performance and financial goals can be achieved. Then, these characteristics will be found out for the major sources of variations. Next, the key process variables (the x's) that have affected to the response variable (the Y's) are identified as $Y = f(x)$. Each key process variables will be established the performance specification (tolerances).
- Control phase: The new process conditions will be documented and monitored via statistical process control methods. Then, the process capability will be reassessed to

ensure the gains are being maintained. Based on follow-up analysis, one or more preceding phases may be reviewed.

Figure 2.2 shows the flow diagram of steps involved in Six Sigma process. When these four phases are completed for all key processes within the business, breakthrough improvement occurs in economics and customer satisfaction.



Measure
Analyse
Problem Statement
Process Map
Rolled Throughout Yield
Cause and Effect
FMEA; Fishbone; Other Methods
Measurement System Analysis (MSA)
Process capability Study
Determine Cost of Quality
Analytical Tools
Confidence Intervals
Hypothesis for variables - Means
(t-test)
Hypothesis for Variables - Std. Dev.
(Chi-square, F-test, Homogeneity of Variance)
Hypothesis for Attributes
(Contingency Tables, Non-parametric Study)


Analyse
Improve
Control
Multi-Vari Studies
ANOVA
Correlation and Regression
Design of Experiment (DOE)
Full Factorial Simple 2^k
Full Factorial Multiple Variables
Fractional factorial
DOE - Blocking
Environment, Health, and Safety Review
Statistica Process Control (SPC)
"Process" Control Plan
Gage/Measurement Stability and Control

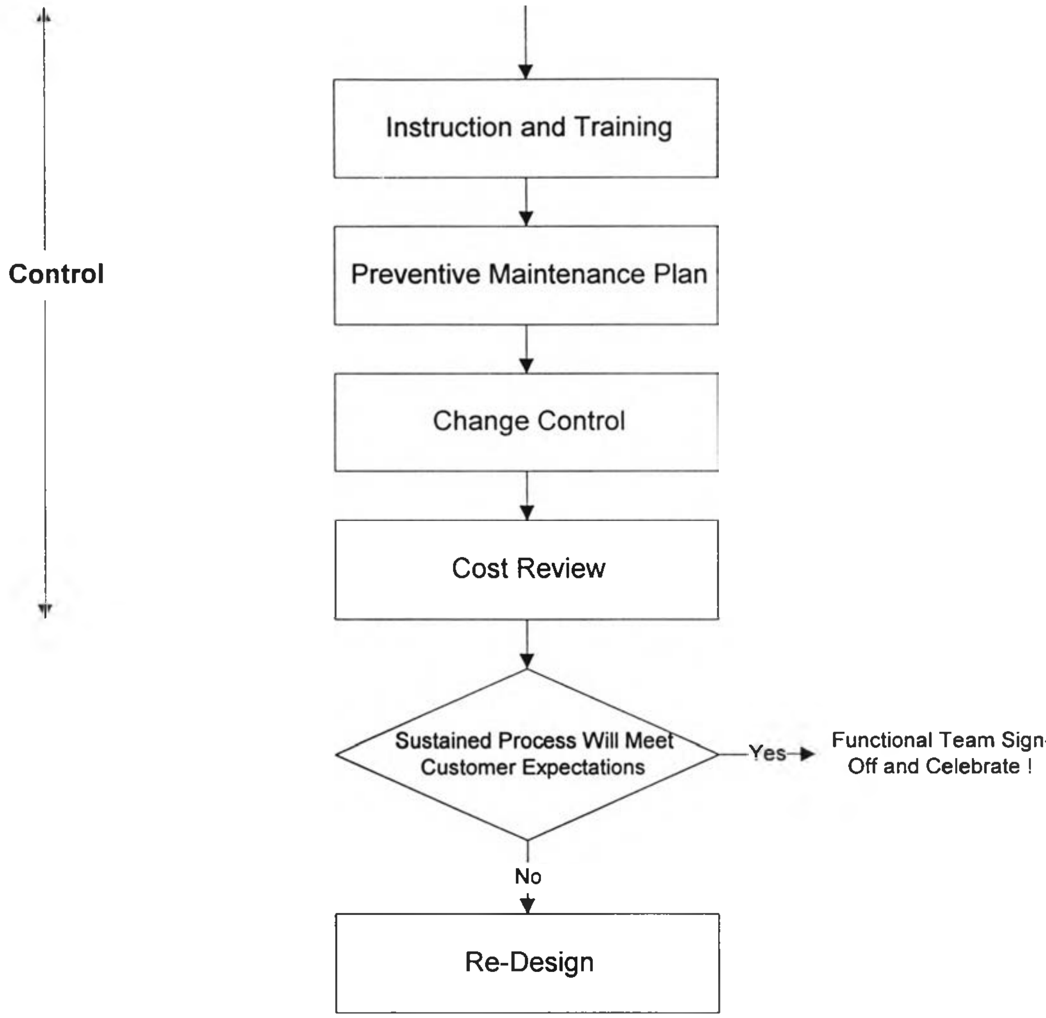


Figure 2.2: Flow diagram of Six Sigma roadmap

(Source: Blackbelt training package, 1998)

Implementing six sigma provides a lot of benefits toward the company who implements it. It can save huge amount of money due to fewer defects, and cycle time has been reduced. It also increases customer satisfaction. Six sigma is providing the right people and the right tools to accomplish the right project that results in business improvement.

One of the projects applying Six Sigma to solve the problem is done by **Pornpitakpong (1997)**. He attempted to reduce percent out of control on two parameters, High Frequency Amplitude (HFA) and Low Frequency Amplitude (LFA) of TSPC to be zero that initially was 55%. His implementation on the project is based on six sigma program.

From measurement phase, he proved that the process capabilities of both parameters are poor. They showed the negative values. He found four key input variables that are:

- TSPC understanding of TTOs
- Reference accuracy of TSPC parts
- Incorrect factoring values
- Performance change of TSPC parts

From analysis phase, he concluded that both parameters have significant improvement after TSPC training class was arranged for TTOs. They had more understanding in taking out of control corrective actions.

From improvement phase, he found that HFA parameter has significant improvement after desported part removal while LFA parameter did not have significant improvement because TSPC parts were desported in HFA greater than LFA parameter. He mentioned that both parameters have significant improvement after buy-off procedure, that is the process to ensure the assigned value of standard TSPC parts, was implemented.

From control phase, he summarised as Table 2.1:

Table 2.1: Control phase of "0% HFM and LFM out of control in TSPC "

Mech/Oper. Check	Characteristic/ Parameter	CL	Specification/Requirement	Measurement Method	Sample Size	Frequency	Who Measures	Where Recorded	Decision Rule/ Corrective Action	Reference Number
All ET Testers	Tech/TTO Qualification	CQ	100% Understand OCAP	Examination	100%	Quarterly	TTC	Paper	Re-Train and Re-Qualify	N/A
All ET Testers	TSPC Reference Accuracy	CQ	TSPC Shift > STD Tolerance	Buy-off	100%	New Inventory Implementation	TTS	TSPC Chart	Reject This New Inventory	N/A
All ET Testers	Factor Assigned Value Accuracy	CQ	TSPC Shift > STD Tolerance	Buy-off	100%	New Inventory Implementation	TTS	TSPC Chart	Reject This New Inventory	N/A
All ET Testers	TSPC heads Performance Shifted	CQ	Desported more than 5 times	TSPC Calculation	100%	Everytime running TSPC	TTC	TSPC Chart	Replace by New Heads	N/A

Scobbo (1998) also applied six sigma approach to the project "Designing engineering resins for six sigma performance". This project tried to challenge a resin supplier to develop products that meet this criterion. It had been applied to the development and commercialisation of a polyphenylene ether/polyamide blend for electrostatic painting applications.

Normand and Draper (1997) studied "Resolution of insulation related manufacturing problems using the six sigma methodology and tools". They found that resolution of manufacturing problems could be particularly challenging when making high voltage stator coils or bars. Manufacturing a virtually void free integral laminate is difficult due to variation of resin reactivity, flow, compression, and a large number of factors. Applying six sigma approach and its data analysis tools to the resolution of manufacturing issues had yielded significant results. Six sigma is the upcoming quality improvement process and is proving to be powerful tool for solving complex problems.

Not only was six sigma applied to many projects, but its application combined with other approaches also played a role in manufacturing sectors. **Turmel and Gartz (1997)** had combined the existing quality tools mixed with some basic six sigma concepts in "Designing in quality improvement: a systematic approach to designing for six sigma". Moreover, **Hoehn (1995)** used integration of six sigma approach and robust design approach in "Robust designs through design to six sigma manufacturability". It was done by Hughes Aircraft Company to ensure that a design is both manufacturable and also serves the needs of the customers by linking six sigma and robust design.

2.4 Statistical Approach

Statistical methods can be used in many situations to solve the problems. Researches concerning on statistical tools are presented. They have brought the statistical techniques to help in problem solving so that the solution can be solved systematically.

2.4.1 Statistical Process Control (SPC) and Control Charts

Statistical Process Control (SPC) is a methodology that uses the problem-solving tools and statistical methods to analyse, monitor, control, and reduce variability within a process. As a way it monitors and controls a system, the maximum potential could be obtained. It helps to define problems, analyse the process, identify causes of problems, and find out for the solutions. Those problems cause variability within the process resulting in lower quality process and product. SPC is mainly concerned on the processes working to get the finished product that satisfies customer's needs.

SPC is used for process improvement. It can be applied in which any works or activities that variations exist. Variation is a huge obstacle in succeeding the business. Attaching it with the product or process causes risks to the company. Also, variations have affected to quality and profitability of the company. Customers may be dissatisfied if the product they occupy has not met the specification or even faced uncertainly to meet the specification. As a result, loss of sales will be occurred. To eliminate the variation, SPC is a tool that helps the company to achieve this.

There are two kinds of sources resulting in variation, common cause and assignable cause. Common causes are inherent by the process such as poor process layout, poor instructions, badly maintained machines, etc. It cannot be got rid of, but it can be reduced by narrowing down the standard deviation of the process that are done by management level. On the other hand, assignable cause shows that there is something happen to the process and it should be corrected immediately such as change in raw materials, broken tools, equipment malfunction, and so on. Operator who has done activity that the causes occur is in charge of finding for solution with the helps from technicians and engineers. SPC tries to separate between these two kinds of variation to detect the assignable cause. If all assignable causes are eliminated, the process will be in state of statistical control. In state of statistical control is the place where it shows that the process is stable and predictable.

SPC respects to prevention strategy rather than detection because it believes that defects and reworks are waste because of time and resources invested in the product that are not usable. So, we should have early warnings before those things will be taken place that is prevention strategy. SPC provides the warning sign when something goes wrong in the system so that the processes will be stopped to take the corrective action before they are continued.

Juran et al (1993) mentioned that lower variation provides many benefits to the company. It results in improved product performance, less need for inspection, premium price on a product, and competitive factor in determining market share.

According to **Module Handout of Quality Management and Techniques (1999)**, in spite of improving the process by avoiding variation, SPC also presents data in a meaningful context that helps in decision-making when taking an action so that the activities will be done in more effective way.

SPC uses the statistical tools to achieve the objectives on three main areas as discussed below.

Analysing the process

Before the process is going to be improved, understanding of the process is a basic requirement. SPC helps to achieve this by providing tools to analyse the process situation. It helps to clarify where process variation is existed, which parameters are sensitive to variation, what is the behaviour of those processes, whether it is in statistical control, and so forth. Control chart is the most important tool to provide this information. All are done for eliminating the assignable causes to reach in statistical control.

Monitoring for control system

Since the process always gets change from other external factors, maintaining at an appropriate level of capability can be done by monitoring and controlling the processes. When undesirable changes are introduced, they should be eliminated immediately. In the other words, as the assignable causes are detected using SPC techniques that the most popular one is control charts, those causes should be investigated and take corrective actions before unusable products are manufactured that will induce the waste to the company.

Continuously improving the process

Always reducing variation results in continuous improvement. As common causes are reduced, customer satisfaction could be increased because of improved quality. If the company does not conform this stage, it may get competitive disadvantage causing loss in market share and profitability.

As the process is in statistical control, the process will be repeatable, consistent, and stable that provides ability in predictability. Therefore, the company could gain the benefits from this. Additionally, SPC helps to eliminate waste so that the cost could be reduced. It provides competitive edges because of low cost with higher quality of product.

As mentioned above, control chart offers many benefits to SPC. "*It provides evidence of whether a process has been operating in a state of statistical control and signals the presence of assignable causes of variation so that corrective action can be taken*" (**Kiemele et al, 1997**). Therefore, it should be concerned when SPC is implemented.

Control chart which is the most important part of SPC program should be applied. Therefore, the assignable causes will be early detected to reduce variability of the process and create stabilisation to the process performance. According to **Montgomery (1997)**, there are at least five reasons for the popularity of control charts.

- Control charts are a proven technique for improving productivity because scraps and reworks are reduced.
- Control charts are effective in defect prevention because it is based on "*do it right at the first time*" philosophy.
- Control charts prevent unnecessary process adjustment. The actions will be taken only when there is a sign of abnormal in the process.
- Control charts provide diagnostic information based on experiences of operators.

- Control charts provide information about process capability when the process is in statistical and stable over time.

He also mentioned that there is a close connection between control chart and hypothesis testing. To illustrate this, the centerline represents μ_0. If the process mean is in control, it is said that it is equal to μ_0. On the other hand, if process mean exceeds either control limit, the process mean is out of control illustrated as $\mu_1 \neq \mu_0$. Thus, the control chart is a test of the hypothesis that the process is in a state of statistical control. A point plotting within the control limits is equivalent to failing to reject the hypothesis of statistical control, and a point plotting outside the control limits is equivalent to rejecting the hypothesis of statistical control. However, there are the differences in some ways for control chart and hypothesis testing. For example, when testing statistical hypotheses, they are used to check the validity of assumptions, while control charts are used to detect departures from an assumed state of statistical control. Furthermore, control charts can detect different types of shifts in the plotted data such as a sustained shift that the mean shifts instantaneously to a new value and remain there, contemporary shift that assignable cause could be short lived and the mean could then return to in control state, and shifts from assignable causes that could result in a steady drift or trend in the means. Unfortunately, hypothesis testing can detect only the sustained shifts.

Hypothesis testing is useful in analysing a control charts. It can be used to consider the probability of Type I error that concluding the process is out of control when it is really in control and the probability of Type II error that concluding the process is in control when it is really out of control. Hence, hypothesis testing would be an indication of the ability of the control chart to detect process shifts of different magnitudes.

A control chart can be constructed by a run chart that normally 20-25 points were plotted. Centerline of the control chart is the average of those points and variability of a measure calculated from variance, s^2, found as follows:

$$\bar{y} = \frac{1}{N}\sum_{i=1}^{N} y_i$$

$$s^2 = \frac{1}{N-1}\sum_{i=1}^{N}(y_i - \bar{y})^2$$

Additionally, the data used to plot on control charts are assumed to be approximately normally distributed allowed to make use of the empirical rule. Then, this rule can assist in developing and interpreting the control charts. Most control charts establish the upper and lower control limits at ±3 standard deviations from the centerline as shown below that 99.73% of data should fall within these control limits.

$$\bar{y} \pm 3s$$

Then, out of control conditions can be detected. However, points outside the control limits are not the only indicators that assignable causes may be affected the process. There are other symptoms that may occur in a chart that will indicate when a process is changing significantly and when there is more than just random variation or common causes present. These symptoms usually involve shifts, trends, or pattern in the data that there are mainly seven out of control symptoms (**Kiemele et al, 1997**).

i) One or more points are outside 3-sigma control limits indicating as outliers.
ii) Seven consecutive points are on the same side of the centerline.
iii) Seven consecutive intervals are either entirely increasing or entirely decreasing.
iv) Two out of three consecutive points are on the same side of centerline and beyond 2-sigma.
v) Four out of five consecutive points are on the same side of centerline and beyond 1-sigma.
vi) Fourteen consecutive points alternate up and down repeatedly.
vii) Fourteen consecutive points are within 1-sigma.

Control charts are classified into two major categories that are control charts for variable data and control charts for attribute data. Figure 2.3 is the flow diagram providing a logical path to follow when deciding which chart to be used.

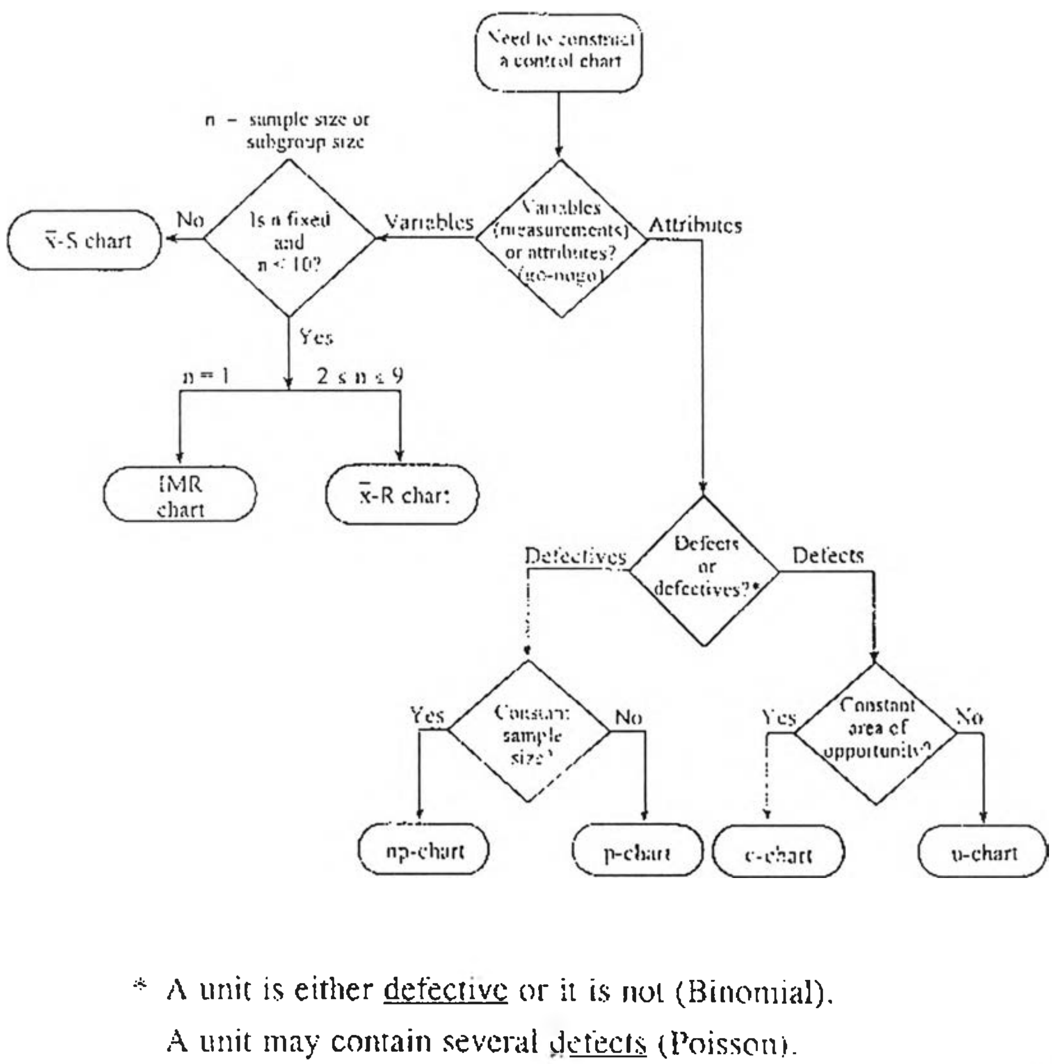


Figure 2.3: Logical flow for selecting a control chart

(Source: ESD Guide to Total Quality Control, Electronic Systems Division, Hanscom AFB, MA)

Since this thesis is focused on the continuous parameters which follow normal distribution, only control charts for variable data is explained. Control charts for variables are usually prepared and analysed in pairs that one chart for measuring the variability between groups as location difference and another chart for measuring the variability within group as dispersion. Control chart for location commonly used is $\bar{X}$-chart, and control charts for dispersion are usually R-chart and S-chart. All of those are explained as below:

$\bar{X}$ and R charts

$\bar{X}$ and R charts could be used when subgroups or samples plotted each point on control chart is fixed and has size n where $2 \leq n \leq 9$. Normally, R-chart is first plotted and evaluated for control limits. Then, $\bar{X}$-chart is followed that if R-chart is out of control, it is impossible to make conclusions about the $\bar{X}$-chart.

After the data collected is plotted on run chart, the centerline and control limits are constructed to detect out of control symptoms. For R-chart, centerline (CL), upper control limit (UCL), and lower control limit (LCL) are given by

$$
\begin{aligned}
CL &= \bar{R} \\
UCL &= D_4 \bar{R} \\
LCL &= D_3 \bar{R}
\end{aligned}
$$

Where

$\bar{R}$ = the average of subgroup range values

D_3 = a constant dependent on the subgroup size n (See Table 2.2)

D_4 = a constant dependent on the subgroup size n (See Table 2.2)

For $\bar{X}$-chart, CL, UCL, and LCL are given by

$$
\begin{aligned}
CL &= \bar{\bar{x}} \\
UCL &= \bar{\bar{x}} + A_2 \bar{R} \\
LCL &= \bar{\bar{x}} - A_2 \bar{R}
\end{aligned}
$$

Where

$\bar{\bar{x}}$ = the average of the subgroup averages

$\bar{R}$ = the average of the subgroup range values

A_2 = a constant dependent on the subgroup size n (See Table 2.2)

These control limits will be adjusted when there are removals of out of control from 20-25 points that are used to construct the control limits. They are re-calculated based on data that already removed the out of control points. When the appropriate control limits are obtained, they would be extended out in time to observe the process behaviour. Those control limits would be changed when there is a shift on process average or process standard deviation.

$\bar{X}$ and S charts

$\bar{X}$ and S charts are appropriate when the sample or subgroup size n is large where $n \geq 10$ or when the subgroup size n varies from one time increment to the next.

For S-Chart, CL, UCL, and LCL are given by

$$CL = \bar{s}$$
$$UCL = B_4 \bar{s}$$
$$LCL = B_3 \bar{s}$$

Where

$\bar{s}$ = the average of subgroup standard deviation values

B_3 = a constant dependent on the subgroup size n (See Table 2.2)

B_4 = a constant dependent on the subgroup size n (See Table 2.2)

For $\bar{X}$-chart, CL, UCL, and LCL are given by

$$CL = \bar{\bar{x}}$$
$$UCL = \bar{\bar{x}} + A_3 \bar{s}$$
$$LCL = \bar{\bar{x}} - A_3 \bar{s}$$

Where

$\bar{\bar{x}}$ = the average of the subgroup averages

$\bar{s}$ = the average of the subgroup standard deviation values

A_3 = a constant dependent on the subgroup size n (See Table 2.2)

When sample size varies, centerlines of $\bar{X}$-chart and S-chart can be calculated from

$$\bar{\bar{x}} = \frac{\sum_{i=1}^{m} n_i \bar{x}_i}{\sum_{i=1}^{m} n_i}$$

Where

$\bar{\bar{x}}$ = centerline of $\bar{X}$-chart

$\bar{s}$ = centerline of S-chart

n = the number of observations in the *i*th sample

m = the number of data used to calculate the control limits

The control limits can be calculated as mentioned earlier, but the constants A_3, B_3, and B_4 will depend on the sample size used in each individual subgroup. Each point has the same centerline but has its own UCL and LCL.

For IMR-chart and control charts for attribute data are not explained here, they can be read in statistical textbook.

TABLE 2.2 Factors Used When Constructing Control Charts

NUMBER OF OBSERVATIONS IN SAMPLE	CHART FOR AVERAGES			CHART FOR STANDARD DEVIATIONS						CHART FOR RANGES						
	FACTORS FOR CONTROL LIMITS			FACTORS FOR CENTRAL LINE		FACTORS FOR CONTROL LIMITS				FACTORS FOR CENTRAL LINE		FACTORS FOR CONTROL LIMITS				
n	A	A_1	A_2	c_2	$1/c_2$	B_1	B_2	B_3	B_4	d_2	$1/d_2$	d_3	D_1	D_2	D_3	D_4
2	2.121	3.760	1.880	.5642	1.7725	0	1.843	0	3.267	1.128	.8865	.853	0	3.686	0	3.276
3	1.732	2.394	1.023	.7236	1.3820	0	1.858	0	2.568	1.693	.5907	.888	0	4.358	0	2.575
4	1.500	1.880	.729	.7979	1.2533	0	1.808	0	2.266	2.059	.4857	.880	0	4.698	0	2.282
5	1.342	1.596	.577	.8407	1.1894	0	1.756	0	2.089	2.326	.4299	.864	0	4.918	0	2.115
6	1.225	1.410	.483	.8686	1.1512	.026	1.711	.030	1.970	2.534	.3946	.848	0	5.078	0	2.004
7	1.134	1.277	.419	.8882	1.1259	.105	1.672	.118	1.882	2.704	.3698	.833	.205	5.203	.076	1.924
8	1.061	1.175	.373	.9027	1.1078	.167	1.638	.185	1.815	2.847	.3512	.820	.387	5.307	.136	1.864
9	1.000	1.094	.337	.9139	1.0942	.219	1.609	.239	1.761	2.970	.3367	.808	.546	5.394	.184	1.816
10	.949	1.028	.308	.9227	1.0837	.262	1.584	.284	1.716	3.078	.3249	.797	.687	5.469	.223	1.777
11	.905	.973	.285	.9300	1.0753	.299	1.561	.321	1.679	3.173	.3152	.787	.812	5.534	.256	1.744
12	.866	.925	.266	.9359	1.0684	.331	1.541	.354	1.646	3.258	.3069	.778	.924	5.592	.284	1.719
13	.832	.884	.249	.9410	1.0627	.359	1.523	.382	1.618	3.336	.2998	.770	1.026	5.646	.308	1.692
14	.802	.848	.235	.9453	1.0579	.384	1.507	.406	1.594	3.407	.2935	.762	1.121	5.693	.329	1.671
15	.775	.816	.223	.9490	1.0537	.406	1.492	.428	1.572	3.472	.2880	.755	1.207	5.737	.348	1.652
16	.750	.788	.212	.9523	1.0501	.427	1.478	.448	1.552	3.532	.2831	.749	1.285	5.779	.364	1.636
17	.728	.762	.203	.9551	1.0470	.445	1.465	.466	1.534	3.588	.2787	.743	1.359	5.817	.379	1.621
18	.707	.738	.194	.9576	1.0442	.461	1.454	.482	1.518	3.640	.2747	.738	1.426	5.854	.392	1.608
19	.688	.717	.187	.9599	1.0418	.477	1.443	.497	1.503	3.689	.2711	.733	1.490	5.888	.404	1.596
20	.671	.697	.180	.9619	1.0396	.491	1.433	.510	1.490	3.735	.2677	.729	1.548	5.922	.414	1.586
21	.655	.679	.173	.9638	1.0376	.504	1.424	.523	1.477	3.778	.2647	.724	1.606	5.950	.425	1.575
22	.640	.662	.167	.9655	1.0358	.516	1.415	.534	1.466	3.819	.2618	.720	1.659	5.979	.434	1.566
23	.626	.647	.162	.9670	1.0342	.527	1.407	.545	1.455	3.858	.2592	.716	1.710	6.006	.443	1.557
24	.612	.632	.157	.9684	1.0327	.538	1.399	.555	1.445	3.895	.2567	.712	1.759	6.031	.452	1.548
25	.600	.619	.153	.9696	1.0313	.548	1.392	.565	1.435	3.931	.2544	.709	1.804	6.058	.459	1.541
Over 25	$\frac{3}{\sqrt{n}}$	$\frac{3}{\sqrt{n}}$	—	—	—	a	b	a	b	—	—	—	—	—	—	—

a $1 - \frac{3}{\sqrt{2n}}$

b $1 + \frac{3}{\sqrt{2n}}$

Source: ASTM Manual on Quality Control of Materials, American Society for Testing Materials, Philadelphia, Pa., 1951. Copyright ASTM. Reprinted with permission.

As it can be obvious that SPC and control charts are useful in analysing, monitoring, and controlling the process, they can be applied in a number of ways. Many authors used them to improve the process and others that the examples are given.

Tesara (1987) proposed "Control charts and quality related statistical applications in industry". The study focused on two operations in semiconductor sub-assembling that are lead bonding and molding. Control chart techniques were applied to the lead bonding operation in order to monitor machine performance. Multivariate analyses were used in the molding operation to derive casual relationships between input and output variables. Them the empirical approach was undertaken on the relationships to find out for safe operation region in the molding parameters.

She summarised that maintaining a control chart is practical and necessary. It had ability to detect the drift in the process. Also, it was used as an aid to decide whether the machine needs repair or not. She found that the past data could not be used as a basis for finding the safe operation region because noise in the historical data obstructed finding the relationships between input and output variables.

Wu (1998) studied "Adaptive acceptance control chart for tool wear". An acceptance control chart (ACC) is used to monitor certain processes, in which the natural dispersion of the process is much less than the specified tolerance in design. Typical examples are the process subjected to tool wear. This project presents an adaptive acceptance control chart (ACCC). Its sample size can be adjusted during the process control so that the average number of measurements may be significantly reduced. ACCC can also minimised linear combination of the Type I and Type II errors, based on the user's specifications.

McAlister (1998) uses Statistical Process Control (SPC) in "Continuous process monitoring leads to reduced scrap and shorter cycle times". The system provides real-time SPC information derived directly from sensors interfaced to each die casting machine. This system achieved significant reductions in scrap and cycle time.

2.4.2 Power of Test

Power of test (1-β) indicates the probability of rejecting the null hypothesis for which the null hypothesis is false that the correct course of action, not committing Type II error (β). Power of test is a function of sample size (n), detection difference (δ), and significant level or Type I error (α). δ represents the detection difference when the shift can be detected. It is the difference of the true mean, μ_1 from the hypothesised value μ_0. The larger the value of δ, the smaller the probability of Type II error or larger power of test for a specified sample size and α. It means the test will detect large differences more easily than small ones. On the other hand, at fixed δ and α, the probability of Type II error gets smaller when the sample size n increases. From this, operating-characteristic (OC) curves in Figure 2.4 are useful in determining how large a sample size is required to detect a specified difference with a particular probability. On OC curves, the parameter on vertical axis of these curves is β, and the parameter on the horizontal axis is d which is defined as $|\delta| / \sigma$.

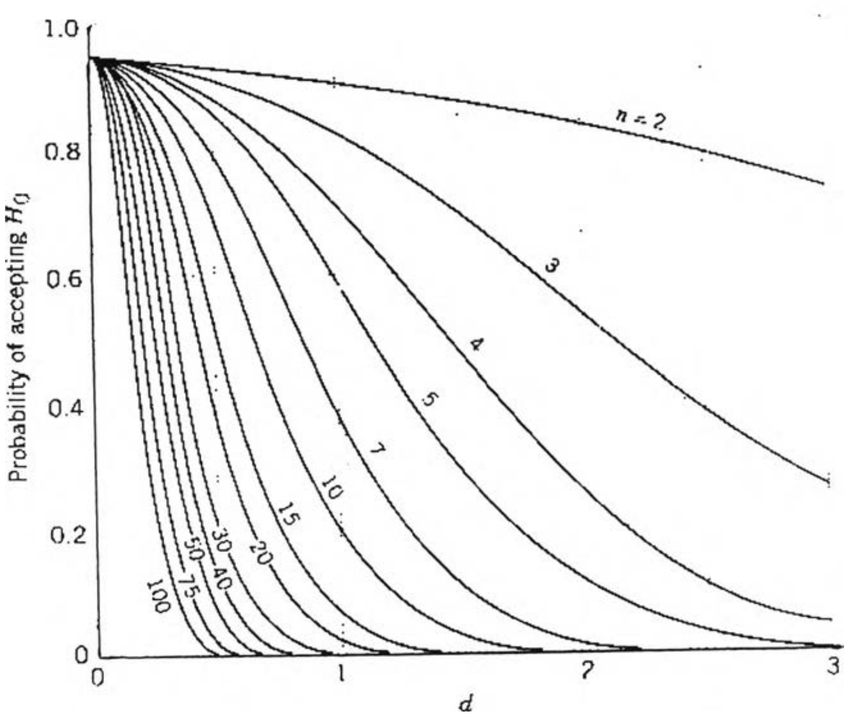


Figure 2.4: Operating-characteristic curves for two-sided normal test with $\alpha = 0.05$

(Source: C.L. Ferris, F.E. Grubbs, and C.L. Weaver, "Operating Characteristic Curves for the Common Statistical tests of Significance", Annals of Mathematical Statistics, June 1946)

2.4.3 Regression and Correlation

Regression is concerned on the relationship fit to a set of experiment data of one or more independent variables, $x_1, x_2, \ldots, x_k$, to a single dependent variable or response Y. This relationship is expressed as regression equation. In this thesis, simple linear regression is deal with.

For simple linear regression, it can be said that Y is linearly related to x that is illustrated as

$$Y = \alpha + \beta x$$

where α and β are regression coefficients that can be estimated from sample data as a and b, respectively. The relationship of the sample data or fitted regression line can be illustrated below.

$$\hat{y} = a + bx$$

where the estimates a and b represent the y intercept and slope, respectively. $\hat{y}$ is the estimated or predicted value given by the sample regression line while y is the actual observed value for specified x. It is assumed that the observed value of y are normally distributed around $\hat{y}$.

Given the sample $\{(x_i,y_i); i = 1, 2, \ldots, n\}$, the least squares estimates a and b of the regression coefficients α and β are computed from the formulas (**Walpole et al, 1993**)

$$b = \frac{n\sum_{i=1}^{n} x_i y_i - \left(\sum_{i=1}^{n} x_i\right)\left(\sum_{i=1}^{n} y_i\right)}{n\sum_{i=1}^{n} x_i^2 - \left(\sum_{i=1}^{n} x_i\right)^2} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} = \frac{\sum_{i=1}^{n} x_i y_i - \bar{y}\sum_{i=1}^{n} x_i}{\sum_{i=1}^{n} x_i^2 - \bar{x}\sum_{i=1}^{n} x_i}$$

$$a = \frac{\sum_{i=1}^{n} y_i - b\sum_{i=1}^{n} x_i}{n} = \bar{y} - b\bar{x}$$

After the regression is plotted, expression that could be drawn from relationship is

The sum of squares of y about regression	= The sum of squares about the mean	- The sum of squares due to the regression

$$\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 = \sum_{i=1}^{n}(y_i - \bar{y})^2 - \sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2$$

From this relationship, estimate of variance (σ_0^2) or error mean square can be calculated from ANOVA as below.

Sources of variation	Sum of squares	Degree of freedom	Mean square	Quantity estimated by mean square
Due to regression	$b^2\Sigma(x - \bar{x})^2$	1	(Sum of square)$_{\text{due to}}$ / 1 $= b^2\Sigma(x - \bar{x})^2 / 1$	$\sigma_0^2 + \sigma_R^2$
About regression	$\Sigma(y-\hat{y})^2$	n-2	(Sum of square)$_{\text{about}}$ / n-2 $= \Sigma(y-\hat{y})^2 / n-2$	σ_0^2
Total	$\Sigma(y - \bar{y})^2$	n-1		

$$\hat{\sigma}_0^2 = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n-2}$$

The (1-α)100% confident intervals for β and α in the regression line Y = α + βx are

$$\beta = b \pm \frac{t_{\alpha/2}\hat{\sigma}_0}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}}$$

$$\alpha = a \pm \frac{t_{\alpha/2}\hat{\sigma}_0\sqrt{\sum_{i=1}^{n}x_i^2}}{\sqrt{n\sum_{i=1}^{n}(x_i - \bar{x})^2}}$$

where $t_{\alpha/2}$ is a value of the t-distribution with n-2 degrees of freedom.

To test the null hypothesis H_0 that $\beta = \beta_0$ against a suitable alternative, calculated t is compared against t-critical from t-distribution with n-2 degrees of freedom that t could be calculated from

$$t = \frac{b - \beta_0}{\hat{\sigma}_0 / \sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2}}$$

Likewise, the null hypothesis H_0 that $\alpha = \alpha_0$ against a suitable alternative can then be evaluated. Calculated t is compared to t-critical from t-distribution at n-2 degrees of freedom as below.

$$t = \frac{a - \alpha_0}{\hat{\sigma}_0 / \sqrt{\left(\sum_{i=1}^{n} x_i^2\right) / \left(n \sum_{i=1}^{n} (x_i - \bar{x})^2\right)}}$$

In both cases, if t is in the acceptance region, also indicated by P-value more than 0.05 (at 5% significant level), there are no sufficient evidences to reject null hypothesis. In contrast, when null hypothesis is rejected with P-value less than 0.05 (at 5% significant level), it has strong evidence to conclude as alternative hypothesis.

Correlation analysis is to measure the strength of the relationships between two variables by a correlation coefficient (ρ). The population correlation coefficient (ρ), can be estimated from sample correlation coefficient or Pearson product moment correlation coefficient (r). If it is near zero, it can be said that little or no correlation or no linear association between two sample variables. Sample correlation coefficient (r) can be calculated from

$$r = b \sqrt{\frac{\sum_{i=1}^{n} (x_i - \bar{x})^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}}$$

where r is between -1 and +1. Sample coefficient of determination (r^2) expresses the proportion of the total variation in the value of variable Y that can be accounted for or explained by a linear relationship with the values of the random variable x (**Walpole, 1993**).

A hypothesis test of $\rho = 0$ versus an appropriate alternative against the critical region calculated from r-critical can be evaluated for how strong the relationship between two variables. This evaluation is equivalent to the hypothesis test of $\beta = 0$ by using t-distribution at n-2 degrees of freedom and F-value calculated from the proportion of mean square due to regression and mean square about regression in ANOVA table against critical region from F-distribution at 1 and n-2 degrees of freedom.

From the results of hypothesis testing, if the null hypothesis is rejected (P-value < 0.05 at 5% significant level), it can be concluded that there is a significant amount of variation in the response accounted for by the linear regression model. On the other hand, when null hypothesis cannot be rejected (P-value > 0.05 at 5% significant level), it can be said that there is no sufficient evidence to support the linear relationship model.

From those analyses, both regression and correlation can then be applied in many ways to be used as a tool in problem-solving. An example of using multiple linear regression is given to know its benefits.

Boonyachai (1981) proposed the project titled "A statistical approach for analysing the quality problem in a sanitaryware manufacturing system". He first determined unit production for each production stage, cast shop and kiln shop.

For cast shop, cause and effect diagram was developed. Then, materials used for cast shop was studied. Multiple regression models were taken to test the significant of materials properties and types of products on defects. Factor analysis model was subsequently used to group the materials properties. After that, each group were used in multiple regression models to determine their significance in case of reducing the number of materials properties.

For kiln shop, the contingency tables and chi-square tests were used to test the significance of kiln and types of product on product quality. Then, Bayes' rule is applied to determine the probability of the defectives appearing.

He concluded that types of product affected the quality of the product in the cast shop as well as in the kiln shop. Materials properties had affected to the quality of finished products. Therefore, he identified the effects and indicated the ways to prevent defects. Also, he found that types of kiln had affected on the quality of finished products.

2.4.4 Inferential Statistical Analysis

Inferential statistical analysis is the hypothesis testing that the conclusions are drawn from the inference samples. Since the true population is seldom known, the sample data is used as the inference about the entire population with a measurable amount of uncertainty. Those uncertainties cause Type I and Type II errors that could be denoted as α and β, respectively. Probability of errors are between 0 and 1. Type I error is more critical so it is set at a minimum level that this thesis allows $\alpha = 0.05$ so the hypothesis statement to be tested has at least 95% confidence on concluding alternative hypothesis.

In setting the hypothesis statement, attempting is on proving and finding evidence to reject null hypothesis. When the null hypothesis is rejected, it cannot be said that alternative is correct. It just has a high level of confidence in concluding alternative hypothesis. In the same way, concluding on null hypothesis means that the evidence does not enough to convince the alternative.

To test the hypothesis testing, samples drawn must be representative of the overall population. Based on sample data, the difference whether in means or variance is investigated to determine if it is large enough to provide overwhelming evidence of rejecting H_0 with at least $(1-\alpha)100\%$ confidence. If there is not sufficiently large, the conclusion is failed to reject H_0 that the evidence is not overwhelming.

In making conclusion, confidence can be high as $(1-P)100\%$ confidence which P is the probability of obtaining a sample mean at least as extreme in either direction (in case of two-tails), or it is a exact probability of making Type I error of sample that could be drawn from hypothesis testing. If P is larger than α (usually 0.05 at 5% confidence level), the test fails to reject H_0. On the other hand, if P is less than α, H_0 is rejected, concluding H_1, with (1-P)100% confidence.

The general procedures in implementing hypothesis testing are as follows. (Source: Applied Statistical Methods Module Handout, 1997)

1) Select the appropriate statistical model and hence hypothesis tests relating to the situation.
2) Specify the null and alternative hypothesis
3) Choose the significant level (Type I error).
4) Calculate the sample size.
5) Obtain a random sample of observations.
6) Compute the test statistic.
7) Look up the level of significance in the appropriate table.
8) Draw conclusions.

In this thesis, it focuses on continuous data which is expected to be Normal distribution. The test purposes to compare two samples to see if samples are from a same distribution. Thus, the tests concerned are on location testing means of samples and spread testing variances of samples. On this thesis, it is comparing based on same wafer quads so sample size is small. The sample size is provided only from all same wafer quads that is matching to same tester at different time or different testers at same time and other time.

Before testing the means of samples, their variances should first be tested to see if they are equal. Difference in variances means samples are not from the same distribution that test of mean difference for variances not equal is provided. However, when variances are equal, test of mean difference for equal variance can then be used.

To compare the means and variances of samples, two-tailed test is appropriate. The alternative hypothesis is a complement of the null hypothesis. The significant level for making a conclusion is based on at least 95% confidence. Sample size is provided by same wafer quads matching. The test statistic is calculated from formula in each hypothesis test. Then, the results of testing could be obtained. The calculated result can be compared to the appropriate tables. If the result is fallen in the acceptance region, it is failed to reject null hypothesis that could be concluded that variances or means are equal at 95% confidence. Otherwise, there is a significant difference between samples based on available evidence. The other method to conclude the results is the use of P-value. If P is less than 0.05, H_0 is rejected. Otherwise, there are no evidences to see the difference between the samples.

In this section, only the hypothesis tests concerning on this thesis is explained. They are the test for a significant difference between two means for small samples when variances are different and when variances are not significantly different. Furthermore, the test for a significant difference of two means when the samples are dependent, paired t-test, is included. Additionally, the test for the significant difference between two variances is also taken into account. On those tests, it is assumed that data is from Normal distribution.

Two-sample hypothesis test of the means when population variances are unknown and not significantly different

H_0: $\mu_1 = \mu_2$

H_1: $\mu_1 \neq \mu_2$

Confident level at 95%

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\hat{\sigma}_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}}$$

$$\hat{\sigma}_p = \sqrt{\frac{(n_1 - 1)\hat{\sigma}_1^2 + (n_2 - 1)\hat{\sigma}_2^2}{n_1 + n_2 - 2}}$$

Where

$\bar{x}_1$ = average of sample data from n_1 observations

$\bar{x}_2$ = average of sample data from n_2 observations

$\hat{\sigma}_1$ = estimated standard deviation from n_1 observations

$\hat{\sigma}_2$ = estimated standard deviation from n_2 observations

$\hat{\sigma}_p$ = pooled estimate of the unknown standard deviation

For large sample size, normal distribution approximation or Z-test can be used. The t-critical can be seen from table of t-distribution with $\nu = n_1 + n_2 - 2$ degrees of freedom to estimate the area in the tail beyond $|t|$. If t is beyond the tabulated value or P-value is less than 0.05, H_0 is rejected so there is a significant difference in means based on evidence available. Otherwise, it fails to reject H_0 (P-value greater than 0.05) that concludes there are no significant difference on means of two populations.

Two-sample hypothesis test of the means when population variances are unknown and significantly different

H_0: $\mu_1 = \mu_2$

H_1: $\mu_1 \neq \mu_2$

Confident level at 95%

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{\hat{\sigma}_1^2}{n_1} + \frac{\hat{\sigma}_2^2}{n_2}}}$$

$$\upsilon = \frac{\left(\frac{\hat{\sigma}_1^2}{n_1} + \frac{\hat{\sigma}_2^2}{n_2}\right)^2}{\frac{1}{n_1 - 1}\left(\frac{\hat{\sigma}_1^2}{n_1}\right)^2 + \frac{1}{n_2 - 1}\left(\frac{\hat{\sigma}_2^2}{n_2}\right)^2}$$

Where

$\bar{x}_1$ = average of sample data from n_1 observations

$\bar{x}_2$ = average of sample data from n_2 observations

$\hat{\sigma}_1$ = estimated standard deviation from n_1 observations

$\hat{\sigma}_2$ = estimated standard deviation from n_2 observations

ν = degree of freedom

It is suitable for small sample size. For large sample size, normal distribution approximation can be used instead. The t-critical can be gotten from table of t-distribution with calculated degrees of freedom from above formula to estimate the area in the tail beyond $|t|$. If t is beyond the tabulated value or P-value is less than 0.05, H_0 is rejected so there is a significant difference in means based on evidence available. Otherwise, it fails to reject H_0 (P-value greater than 0.05) that concludes there are no significant difference on means of two populations.

Two-sample hypothesis test of the means when the samples are not independent, but paired

Hypothesis testing usually assumes for independence of samples. However, when samples are dependent to each other, a paired comparison test is appropriate. Especially, the comparison is on two testing processes that the samples taken are based on same separated parts. Hence, it can be seen that two samples are not independent from each others.

H_0: $\mu_{1j} = \mu_{2j}$ (for all j) or $\mu_d = 0$

H_1: $\mu_{1j} \neq \mu_{2j}$ or $\mu_d \neq 0$

There are n pairs of measurements which j = 1, 2, …, n

Confident level at 95%

$$d_j = x_{1j} - x_{2j}$$

$$\bar{d} = \frac{\sum_{j=1}^{n} d_j}{n}$$

$$t = \frac{\bar{d}}{\hat{\sigma}_d / \sqrt{n}}$$

Where

x_{1j} = sample data of machine 1 where j is the observation number (j = 1, 2, …, n)

x_{2j} = sample data of machine 2 where j is the observation number (j = 1, 2, …, n)

$\hat{\sigma}_d^2$ = estimated population variance

The t-distribution is appropriate for small sample size. The t-critical can be seen from table of t-distribution with n-1 degrees of freedom to estimate the area in the tail beyond $|t|$. If t is beyond the tabulated value or P-value is less than 0.05, H_0 is rejected so there are significant differences on two dependent means. Otherwise, it is fail to reject H_0 that concludes there are no significant difference on means of populations.

Two-sample hypothesis test of the population variances

H_0: $\sigma_1^2 = \sigma_2^2$

H_1: $\sigma_1^2 \neq \sigma_2^2$

Confident level at 95%

$$F = \frac{\hat{\sigma}_1^2}{\hat{\sigma}_2^2}$$

Where

$\hat{\sigma}_1^2$ = estimated population variance from n_1 observations

$\hat{\sigma}_2^2$ = estimated population variance from n_2 observations

The F-critical can be seen from table of F-distribution with $v_1 = n_1$-1 and $v_2 = n_2$-1 degrees of freedoms. If F is beyond the tabulated value or P-value is less than 0.05, H_0 is rejected so there is a significant difference in population variances based on evidence available. Otherwise, it is concluded that there are no significant differences on population variances given the evidence available.

2.4.5 Analysis of Variance (ANOVA)

Single Factor ANOVA or One-way ANOVA

Analysis of variance (ANOVA) is a test for difference in population means of samples from different populations. It is appropriate for more than two independent samples that t-test cannot afford. ANOVA assumes the data is from a normal distribution. However, it is not affected much when data is from non-normality distribution.

Single factor ANOVA or one-way ANOVA is the testing of multiple independent samples for the equality of population means by considering only one factor causing the difference in means such as different machines, different operators, or different time. It would be indicated that the samples are not drawn from the same population if the variation between samples (e.g. different machines) is significantly greater than the variation within samples (e.g. within machines). In the other words, there is a significant difference in means if the null hypothesis stating that there is no difference between two means denoted as $\mu_1=\mu_2$ is rejected. On the other hand, if null hypothesis cannot be rejected, it can be said that there is no evidence of a difference in means of different machines.

To determine the equality of population means, the hypothesis statement has to be clarified. Then, ANOVA table is prepared to test the difference between variation between samples and variation within samples based on mean square errors. When there is a significant difference between samples, mean square between samples should be greater than mean square within samples. Otherwise, it is concluded that there are no significant different between samples.

Null hypothesis: $\mu_1 = \mu_2 = \mu_3 = \ldots = \mu_n$ or $\sigma_\mu^2 = 0$

Alternative hypothesis: Not all μ_i are equal

Variation	**Sum of squares**	**Degree of freedom**	**Mean square**	**Estimated mean square**
Between machines	$\Sigma_j(\bar{x}_j - \bar{x})^2$	n-1	$\Sigma_j(\bar{x}_j - \bar{x})^2 / n-1$	$r\sigma_\mu^2 + \sigma_0^2$
Within machines	$\Sigma_{ij}(x_{ij} - \bar{x}_j)^2$	n(r-1)	$\Sigma_{ij}(x_{ij} - \bar{x}_j)^2 / n(r-1)$	σ_0^2
Total	$\Sigma_{ij}(x_{ij} - \bar{x})^2$	nr-1		

$$F = MSB / MSE$$

$$F = \frac{\sigma_0^2 + r\sigma_\mu^2}{\sigma_0^2}$$

Where

MSB = Mean square between machines calculated by way of the variance of sample average

MSE = Mean square error calculated by way of the average sample variances

n = Number of machines (i = 1, 2, 3, …, n)

r = Number of data in a sample or machine (j = 1, 2, 3, …, r)

Calculated F is compared against F-critical from F-distribution with n-1 and n(r-1) degrees of freedom. If F is in critical region (P-value < 0.05 at 5% significant level), null hypothesis is rejected. It means there is a difference between $r\sigma_\mu^2 + \sigma_0^2$ and σ_0^2 that indicates $\sigma_\mu^2 \neq 0$. It is concluded that there is a significant difference in means of different machines. In contrast, when F cannot be rejected, it indicates $\sigma_\mu^2 = 0$ that the samples are drawn from the same normal distribution.

Two Factor ANOVA or Two-way ANOVA

Since one factor ANOVA has one source of possible difference, when there are two sources of possible difference, two factor ANOVA is then considered. Here, machines and wafer quads are given as the examples of sources of difference. Then, variation could be from different between machines, different between wafer quads, and residual, that the first two are focused for the sources of differences. ANOVA can be prepared as shown.

Variation	**Sum of squares**	**Degree of freedom**	**Mean square**	**Estimated mean square**
Between machines	$\Sigma_j(\bar{x}_j - \bar{x})^2$	n-1	$\Sigma_j(\bar{x}_j - \bar{x})^2 / n-1$	$r\sigma_m^2 + \sigma_0^2$
Between wafer quads	$\Sigma_i(\bar{x}_i - \bar{x})^2$	r-1	$\Sigma_i(\bar{x}_i - \bar{x})^2 / r-1$	$n\sigma_w^2 + \sigma_0^2$
Residual	$\Sigma_{ij}(x_{ij} - \bar{x}_i - \bar{x}_j + \bar{x})^2$	(n-1)(r-1)	$\Sigma_{ij}(x_{ij} - \bar{x}_i - \bar{x}_j + \bar{x})^2 /$ (n-1)(r-1)	σ_0^2
Total	$\Sigma_{ij}(x_{ij} - \bar{x})^2$	nr-1		

$F_{machine}$ = Mean square between machines / Mean square error

F_{wafer} = Mean square between wafer quads / Mean square error

If $F_{machine}$ is above F-critical, there is a significant difference between different machines that rejects null hypothesis that there are no differences between machines. When null hypothesis cannot be rejected, it can be said that no evidence of a difference between machines. As well as machines, there is strong evidence of difference in wafer quads if F_{wafer} is greater than F-critical. In contrast, different wafer quads have no significant difference when null hypothesis is failed to reject.

Two Factor ANOVA with Replication

From two sources of variability, the result of one variable might be depended on level of another variable that is called interaction. Thus, test of interaction is necessary to know how interaction affects the difference results. Then, more than one data of each machine on each wafer quad is required. ANOVA can be prepared as follows.

Variation	**Sum of squares**	**Degree of freedom**	**Mean square**	**Estimated mean square**
Between machines	$\Sigma_j(\bar{x}_j - \bar{x})^2$	n-1	$\Sigma_j(\bar{x}_j - \bar{x})^2 / n-1$	$mr\sigma_m^2 + m\sigma_{mw}^2 + \sigma_0^2$
Between wafer quads	$\Sigma_i(\bar{x}_i - \bar{x})^2$	r-1	$\Sigma_i(\bar{x}_i - \bar{x})^2 / r-1$	$mn\sigma_w^2 + m\sigma_{mw}^2 + \sigma_0^2$
Interaction	By subtraction	(n-1)(r-1)	$SS_{interaction} / (n-1)(r-1)$	$m\sigma_{mw}^2 + \sigma_0^2$
Residual	$\Sigma_{ij}(x_{ijk} - \bar{x}_{ij})^2$	nr(m-1)	$\Sigma_{ijk}(x_{ijk} - \bar{x}_{ij})^2 / nr(m-1)$	σ_0^2
Total	$\Sigma_{ijk}(x_{ijk} - \bar{x})^2$	mnr-1		

$F_{interaction}$ = Mean square interaction / Mean square error

From calculated F, it is compared against F-distribution to determine the effect of interaction on machine and wafer quad. If $F_{interaction}$ does not affect indicated by F less than F-critical, it is combined to the residual to get more accurate σ_0^2. Then, $F_{machine}$ and F_{wafer} can be calculated from

$F_{machine}$ = Mean square between machines / Mean square error and interaction

F_{wafer} = Mean square between wafer quads / Mean square error and interaction

However, if interaction is affected that is indicated by P-value less than 0.05, there usually are machine and wafer quad differences.

Many authors used ANOVA to improve and develop in different areas. An example of those is shown here.

Fuang-arom (1990) used statistical methods for quality improvement in a gypsum board manufacturing process. Her problem was the uneven surface board caused by the poor quality of paper. So, she aimed to set the best level of each important paper quality characteristics to reduce the variation of gypsum board quality from target value.

She was testing for uniformity to measure the consistency of paper quality throughout the roll and testing for validity of the vendor sample for representing the samples of the company to reduce loss from the existing sampling procedure.

She concluded that some quality characteristics that are air resistance, water absorption, ply bond strength, and expansion were uniform throughout a roll while some were not uniform that are thickness, tensile strength, saturation, and moisture content. She suggested that the company should ask supplier for uniformity. Additionally, the paper quality characteristics were vendor samples were not represented the self-samples. She recommended that the company should ask the vendor to modify the sampling plan by trying to use the sampling plan as the company.

2.5 Monitoring Machine Condition

There are a variety of methods to monitor the machine condition. Most of them concern on detecting the machine performance degradation of hardware. They use sensor, measurement tool, physical appearance of workpiece, and so on in deciding whether the machine is in normal condition. Therefore, this section tries to discuss those methods used in monitoring machine condition.

Wieser et al (1997) did research in "Condition monitoring of inverter fed induction machines by means of state variable observation". They suggested a method to monitor defects such as cracked rotor bars in induction machines. Rotor bar faults cause an asymmetric magnetic flux pattern in the air-gap. Thus, the current phasor and the air-gap torque differ from those of an ideal symmetric machine. The proposed condition monitoring method compared the outputs of a reference model that represents an ideal machine to a measurement model. Observing the deviations of these two models makes it possible to detect and even locate rotor faults. It can be applied to inverter fed machines as no frequency analysis is used.

Jennings and Drake (1997) researched in "Machine condition monitoring using statistical quality control charts". The method of measurement normalisation is included to compensate for performance parameter inter-dependence. The method is based on a normalisation chart which defines the normal relationships between performance parameters. The difference between a current measurement and the corresponding value from a normalisation chart is then used to calculate the residual. By using the principles of statistical quality control, the residual is then plotted on a control chart to monitor the condition of the machine tool.

Third-order spectrum analysis is used in condition monitoring of electric machines by **Chow (1996)**. This study is based on a three-phase induction machine with power supply asymmetrical fault. The machine vibration signals operating at different conditions are thoroughly analysed. The result and analysis is indicated by third-order spectrum approach that very useful for the analysis of machine fault.

Parekhji et al (1996) studied "Monitoring Machine Based Synthesis technique for concurrent error detection in finite state machines". They discussed a new design methodology for concurrent error detection in synchronous sequential circuits based on the use of monitoring machines. In this approach, monitoring machine, which is an auxiliary sequential circuit, operated in lock-step with the main machine such that any fault in either of the two machines was immediately detected. It also provides a systematic framework for the combined optimisation of the main and monitoring machines, and for exploring tradeoffs in their implementation. This method is suitable for the design of low cost sequential circuits with concurrent error detection. The monitoring machine is less costly than the main machine.

According to **Baccigalupi et al (1997),** Digital-signal-processors-based measurement system was used to detect on-line fault. The two parallel digital signal processors (DSP's), for on-line fault detection in electric and electronic devices is designed, constructed, and set up as measurement apparatus. In the proposed architecture, the first DSP monitors a device output on-line in order to detect faults, whereas the second DSP estimates and updates the system-model parameters in real-time in order to track their eventual drifts.

Monitoring machine operations and production process condition using on-line sensors has drawn increasing attention recently. **Gong and Tang (1997)** discussed a situation where an on-line sensor is used to monitor a randomly deteriorating machine operation. The machine condition is described by a finite number of states, and the machine deterioration follows a Markov process. The statistical relation between sensor measurement and the true machine condition is created to determine when a machine corrective actions should be made, based on the observed sensor measurement.

Moreover, **Long (1999)** did the project aimed to advance the technology available for on-line condition monitoring. He developed a modular approach utilising Smart technologies, Data Fusion and multiple sensor technologies which allowed for a comprehensive on-line monitoring and diagnostic capabilities.

Neural Network Technology was applied to monitor machine condition by many authors. For example, **Chetty (1996)** created "Neural network based signal processing scheme for automatic tool wear recognition". He focused on monitoring of tool wear in automatic metal drilling systems. Tool wear detection systems was to actually track down the wearing process of the machining tool, allowing the estimation of the quality of the parts being machined by tool and prediction of the useful life of tools. Conventional methods of detecting the tool wear from processing the sensor measured signals had let to tool wear detection system which perform well in set of machining parameters, but are not capable of meeting performance requirements in real manufacturing operations where the machining parameters are more varied. Because of potential of neural network to operate in real time mode and to handle data that may be distorted and noisy, it provides an improved tool wear recognition alternative.

Furthermore, **Li and Elbestawi (1996)** had proposed a strategy for unsupervised classification for automated tool condition monitoring by using fuzzy neural networks. This algorithm used three major components of soft computation; fuzzy logic, neural network, and probability reasoning. The proposed network functioned successfully in clustering the data obtained from cutting tests performed within a reasonable range of cutting conditions. Experiments in turning were implemented to test the performance of the proposed algorithm. Several sensors were used for monitoring feature selection.

Neural network solution using self-organising maps (SOM) is used in automated machinery monitoring and diagnostics by **Zhang et al (1996)**. After statistical parameters if the vibration signal are used to form the data set, SOM is then employed to perform the clustering and feature extraction.

Additionally, there still are many authors studied and tried to apply neural network to their works; for instance, **Sick (1998)** in "On-line tool wear monitoring in turning using time delay neural networks", **McCormick and Nandi (1997)** in "Classification of the rotating machine condition using artificial neural networks", **Lowes and Shippen (1996)** in "Investigating into the transferability of neural network for condition monitoring", and **Murray and Penman (1997)** in "Extracting useful higher order features for condition monitoring using artificial neural networks".

Vibration signal is another measure used to indicate the machine condition. As **Spoerre (1997)** studied in "Application of the cascade correlation algorithm (CCA) to bearing fault classification problems", a set of vibration signal is collected and used in training CCA. Each vibration signal contains unique information about the particular machine condition that is occurring. As well as Sporre, many authors did researches in the same way. They use vibration analysis techniques to monitor and diagnostic the machine condition. For example, **Ansari and Biag (1998)** did the research in "PC-based vibration analyser for condition monitoring of process machinery", and **Gupta (1997)** studied in "Vibration - A tool for machine diagnostics and condition monitoring".

Acoustic Emission (AE), as a non-destructive testing technique (NDT), is one of the popular techniques used for machine condition and process monitoring. The success of this technique is based on the high sensitivity of AE techniques to the background noise sources as **Holroyd (1997)** mentioned in "Acoustic Emission - an NDT technique evolving into a versatile industrial monitoring method". AE contributes the great challenge because of the diversity of applications and the specific nature the applications required. There are other researchers concerning on this AE such as **Venkatesan et al (1997)** who used AE for automatic detection of microcrack formation or growth in machine components and **Javed and Littlefair (1993)** who were using AE for detecting an early development of failure in rolling elements bearings.

2.6 Conclusion

Measurement system should be reliable and reproducible to provide the valid measured values. Measurement system should periodically re-calibration to adjust the instrument to be accurate. However, measurement system should be verified its performance from measuring variation. Control charts are used to control the measurement system to be reliable.

Six sigma is collection of variety tools and techniques to find out the causes of problems and make an improvement. It is done for process quality and customer satisfaction. With following the six sigma guidelines, the objective aimed can be thoroughly succeeded.

Statistical approach can be applied in various ways. It can be used to improve the process, reduce defects, analyse the process behaviours, and so on. Examples of the uses of SPC, control charts, and regression, are given.

Lastly, many techniques used in monitoring machine conditions are collected. Some of them use their results in predicting the machine condition. Some use the additional equipment or machine equipped to the monitored machine. However, all of them aim to be known when machines face problems.