CHAPTER 2

THEORY AND LITERATURE SURVEYS

This chapter study related theory and literature surveys to perform quality improvement and also determine the optimum condition for controlling the image printing defects in image printing process. This starts from using a cause and effect diagram to explore all the potential influence factors affecting the image printing defects in image printing process and analyse the influence factors using statistical methods and then perform experiment to conduct the optimum condition for controlling the image printing defects in image printing process. The details are as follows.

2.1 Cause and Effect Diagram

According to Kume (1985), the cause and effect diagram is developed byKauro Ishikawa of Tokyo University in 1943 using to explore all the potential or real causes (or inputs) that result in a single effect (or output). Causes are arranged according to their level of importance or detail, resulting in a depiction of relationships and hierarchy of events. This can help to find root causes, identify areas where there may be problems, and compare the relative importance of different causes. The sample of cause and effect diagram is shown in figure 2.1.

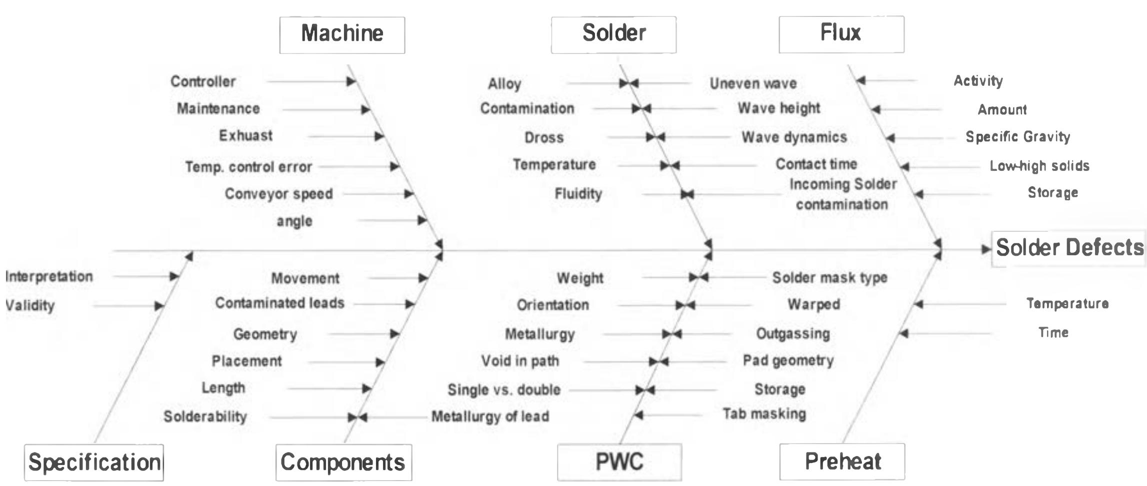

Figure 2.1 The cause and effect diagram

The cause and effect diagram is also known as the fishbone diagram because it was drawn to resemble the skeleton of a fish and can also be drawn as tree diagrams resembling a tree turned on its side.

Generally, the cause and effect diagram is the most useful for generating a list of factors for a test in the preliminary experiment becauseit is easy to learn and apply. For manufacturing, causes in the cause and effect diagram are frequently arranged into four major categories. There are man, machines, materials, and methods.

To successfully construct the cause and effect diagram: (http://www.isixsigma.com, 2002:1)

1. Be sure everyone agrees on the effect or problem statement before beginning.
2. Be concise.
3. For each node, consider what could be its causes and add them to the tree.
4. Pursue each line of causality back to its root cause.
5. Consider splitting up overcrowded branches.
6. Consider that root causes are most likely to merit further investigation.

However, Reshef (2002) has recommended that it would be a mistake to approach this diagram without mastering at least some organisational learning skills such as working together with others, seeking the truth, being open to different ideas, see others who might seem to be in opposition as colleagues with different ideas. Without such skills, internal politics can dominate the process by the most powerful opinion dominates or team members bring to the diagram construction process a political agenda.

Next, the potential influence factors affecting the image printing defects are determined as follows.

Clyde (1988) presented the image transfer processes as used in printed wiring board manufacturing by applied a resist material to a copper clad substrate. The two basic image transfer processes consist of screen-printing and photo printing that includes liquid resists and dry film resists. In term of screen-printing process, it is a stencil-printing technique that uses a circuit pattern defined on the woven mesh of a screen fabric. The ultraviolet (UV) curing ink is used as liquid resist material forced through the open areas of the screen mesh onto the copper clad layer by the pressure of squeegee passes across the top surface of the screen. He had described that the factors affecting to quality of this process consists of screen fabric, screen stencil, squeegee hardness, environment, ink, printing speed, screen-printing equipment, etc.

Refer to Handbook for screen printers of Sefar (1999), the printing systems should be determined as influence factors affecting to quality of screen printing process. These systems are flat bed printing, cylinder bed printing, and rotary printing.

In addition, Prasad (2002) had recommended to determine and monitor carefully to squeegee type, emulsion thickness, and snap off distance.

2.2 Statistical techniques

In this section, there are many statistical techniques determined to perform the experiment to conduct the optimum condition for process control. These statistical methods are introduced as follow.

2.2.1 Design of Experiment

R.A. Fisher introduced design of experiment in 1920's in England. This is a test or series of tests in which purposeful changes are made to the input variable or a process so that it might be observed and identified corresponding change in the output response.

According to a process model in figure 2.2, the process can be visualized as some combination of machines, methods and people that transforms an input material into an output product. In a design situation, the inputs might be design decisions, and the outputs would then be performance-oriented metrics. This product has one or more observable quality characteristic or responses. Some of process variables X1, X2,...,Xp are controllable, while other variables Z1,Z2, ..., Zq are uncontrollable.

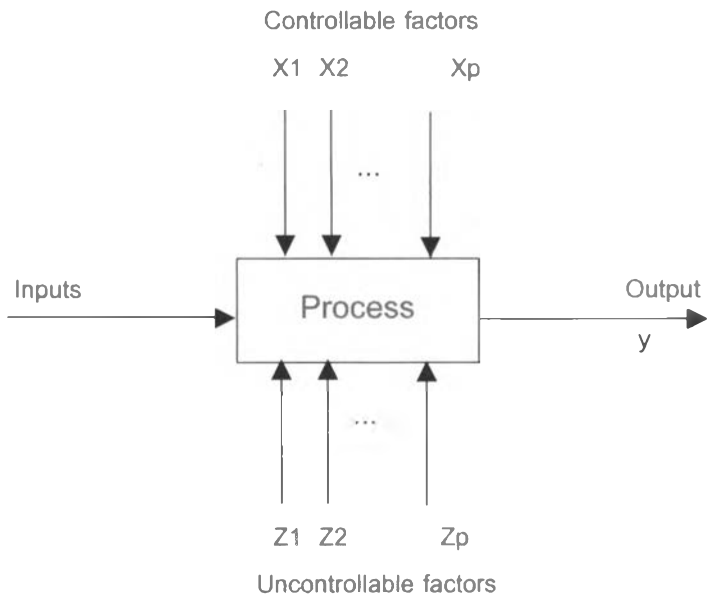

Figure 2.2 General model of a process

Besides the input and output described above, they both deal with multiple inputs e.g. two, three, five, or more input decisions to make all affecting some measurable output. It would be good if an experimenter could perform experiment with these inputs one at a time, optimizing the output for each input in turn, until the experimenter has selected ideal values for all input parameters. Unfortunately, this doesn't usually work, because the inputs generally interact with each other to some extent. Then design of experiment is used to deal with multiple inputs and how they interact with each other.

Montgomery (1991), he had described that experimental design is a critically important engineering tool for improving the performance of a manufacturing process as well as extensive application in the development of new processes. In addition, he recommended that the application of these techniques early in process development could result in

- ☆ Improve the field performance, reliability, and manufacturing aspects of products
- ☆ Reduced variability and closer conformance to nominal or target requirements
- ☆ Reduced development time
- ☆ Reduced overall costs
- ☆ Design and develop new processed and products
- ☆ Evaluate material alternatives in product design

To achieve optimal levels of simplicity and efficiency in designing an experiment, three basic principles should be considered: replication, randomization and local control (blocking).

1. Replication

   This means the repetition of treatments in an experiment in order to obtain a more precise estimate of the main effect as well as to obtain a more precise estimate of experimental error.

2. Randomization

   This is an important underlying the use of the statistical test of significance of observed differences between the treatments. The process of randomization involves random allocation of treatments to the experimental units. Thus the process makes the law of chance applicable to our experimental data and ensures that the data are free from any systematic error. Randomization tends to make experimental errors independent of each other and provides an unbiased estimate of the experimental error and treatment means.

3. Local control

   This refers to grouping of the experimental units in such a way that the units within a group are more homogeneous than are units in different groups. The experimental materials or conditions are more alike within a group. Thus the variation among experimental units within a group is less than the variation would have been without grouping.

As quoted by Montgomery (1991), an outline of recommended procedure in designing and analysing an experiment is shown as below.

1. Recognition of and statement of the problem
2. Choice of factors, levels, and ranges
3. Selection of the response variable
4. Choice of experimental design
5. Performing the experiment
6. Statistical analysis of the data
7. Conclusions and recommendations

2.2 Orthogonal array

According to Kleinman and Song (1990), "Orthogonal arrays have a pairwise balancing property so that every level of a parameter occurs in the experiment with every level of every other parameter the same number of times. Thispairwise balancing property enables parameters to be studied at the same time without distorting the effects of any individual parameter. By using orthogonal arrays..., the number of simulation runs can be greatly reduced." The orthogonal array method allows the maximum amount of information to be derived by using the fewest experiments. In addition, the orthogonal array aids in the study of the relationship between process input parameters and their corresponding output functions.

The orthogonal array method, the focus of attention in North America and Europe for the last decade, originated as an approach to quality engineering advocated by Genichi Taguchi. The orthogonal array method solves quality problems during development. Taguchi (1993) had descried that the use of orthogonal arrays could achieve the optimization of control factors in the presence of nuisance factors.

An orthogonal array is always presented in a matrix format consisting of a left-hand column and a top row, with various numbers occurring at the intersections of each column and row. Each element in the top row represents an independent input parameter, or factor, and each element in the left-hand column represents an experimental run. The numbers at the intersections indicate the level settings that apply to the various factors for various experimental runs. A matrix is orthogonal only if the following requirements are met:

- ☆ The number of occurrences of each level setting must be equal within each column.
- ☆ All rows having identical level settings in a given column must have an equal number of occurrences of all other level settings in the other columns.
- ☆ The matrix for a given number of columns must be the one with the minimal number of rows that satisfy the above conditions.

The nomenclature used is generically $L_x(Z^y)$, where y is the number of factors, Z is the number of level settings, and x is the number of experiments that must be run to complete the matrix. The concept of orthogonal arrays is used to efficiently explore the parameter domain and reduce simulation costs and time. Some available orthogonal arrays are shown in table 2.1.

$L_4\ (2^3)$	$L_8\ (2^7)$	$L_{16}\ (4^5)$	$L_{16}\ (4x2^{12})$
$L_{12}\ (2^{11})$	$L_{20}\ (2^{19})$	$L_{64}\ (4^{21})$	$L_{16}\ (4^3x2^6)$
$L_{16}\ (2^{18})$	$L_{32}\ (2^{31})$	$L_8\ (4^1x2^4)$	$L_{32}\ (4^9x2^4)$
			$L_{128}\ (4^{41}x2^4)$
$L_9\ (3^4)$	$L_{12}\ (3^1x2^4)$	$L_{25}\ (5^6)$	
$L_{18}\ (3^7x2^1)$	$L_{18}\ (6^1x3^6)$	$L_{50}\ (5^{10}x10^1)$	$L_{50}\ (5^{11}x2^1)$
$L_{24}\ (3^1x2^{16})$	$L_{24}\ (3^1x4^2x2^{13})$		$L_{125}\ (5^{31})$
$L_{27}\ (3^{13})$	$L_{36}\ (2^1x6^2x3^5)$	$L_{49}\ (7^8)$	
		$L_{98}\ (7^{14}x14^1)$	$L_{98}\ (7^{15}x2^1)$
$L_{36}\ (3^3x6^3)$	$L_{54}\ (3^{25}x2^1)$	$L_{64}\ (8^9)$	$L_{27}\ (9x3^9)$
$L_{54}\ (6^3x3^{24})$	$L_{81}\ (3^{40})$	$L_{16}\ (8x2^8)$	$L_{81}\ (9^{10})$
$L_{81}\ (3^4x9^1)$		$L_{121}\ (11^{12})$	$L_{169}\ (13^{14})$

Table 2.1 Some Orthogonal array tables

As an example, the orthogonal array table L_{18} $(2^1 x\ 3^6)$ is shown in table 2.2.

Experiment No.	Factors							Exp. Results
	A	B	C	D	E	F	G	
1	1	1	1	1	1	1	1	f_1
2	1	1	2	2	2	2	2	f_2
3	1	1	3	3	3	3	3	f_3
4	1	2	1	1	2	2	3	f_4
5	1	2	2	2	3	3	1	f_5
6	1	2	3	3	1	1	2	f_6
7	1	3	1	2	1	3	2	f_7
8	1	3	2	3	2	1	3	f_8
9	1	3	3	1	3	2	1	f_9
10	2	1	1	3	3	2	2	f_{10}
11	2	1	2	1	1	3	3	f_{11}
12	2	1	3	2	2	1	1	f_{12}
13	2	2	1	2	3	1	3	f_{13}
14	2	2	2	3	1	2	1	f_{14}
15	2	2	3	1	2	3	2	f_{15}
16	2	3	1	3	2	3	1	f_{16}
17	2	3	2	1	3	1	2	f_{17}
18	2	3	3	2	1	2	3	f_{18}

Table 2.2 Orthogonal array table L_{18} $(2^1 x\ 3^6)$

This L_{18} $(2^1 x\ 3^6)$ orthogonal array applies to seven input factors, each of which is varied over three level settings. Eighteen experimental runs are required to complete the matrix. All runs are needed to test 7 factors indicated by the number 1, 2, or 3 under the column header A, B, C, D, E, F, or G. In the results column, f_i denotes the result of theith simulation. After the f_i are obtained, the mean effects of the parameter, value of the objective function F with respect to each factor, are calculated by combining the simulation results as follows.

$$F_{A1} = (f_1 + f_2 + f_3 + f_4 + f_5 + f_6 + f_7 + f_8 + f_9)/9$$

$$F_{A2} = (f_{10} + f_{11} + f_{12} + f_{13} + f_{14} + f_{15} + f_{16} + f_{17} + f_{18})/9$$

$$F_{B1} = (f_1 + f_2 + f_3 + f_{10} + f_{11} + f_{12})/6$$

$$F_{B2} = (f_4 + f_5 + f_6 + f_{13} + f_{14} + f_{15})/6$$

$$F_{B3} = (f_7 + f_8 + f_9 + f_{16} + f_{17} + f_{18})/6$$

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$$F_{G1} = (f_1 + f_5 + f_9 + f_{12} + f_{14} + f_{16})/6$$

$$F_{G2} = (f_2 + f_6 + f_7 + f_{10} + f_{15} + f_{17})/6$$

$$F_{G3} = (f_3 + f_4 + f_8 + f_{11} + f_{13} + f_{18})/6$$

Table 2.3 the mean effects of the parameter

Where the value of objective function F with respect to factor X at leveli, denoted by F_{Xi}, is calculated by averaging the results of simulations in which parameter X is set to level i. Optimal setting of the factor can be found by simply comparing the F values related to each factor. For example, if $F_{A2} > F_{A1}$, then the optimal setting for factor A is level 2. The optimization process is very simple, since the optimization for different factors is separable due to the additive feature of the design.

According to Maynard (2002), the results obtained from the orthogonal array are then analysed to achieve the following objectives.

- ☆ To estimate the contribution of individual quality influencing factors in the product design stage.
- ☆ To gain the best, or optimum, condition for a process, or a product, so that good quality characteristics can be sustained.
- ☆ To approximate the response of the product design parameters under the optimum conditions.

Additionally, he had described advantages and disadvantages of the orthogonal array in this way. The advantages of the orthogonal array are such that they can be applied to experimental design involving a large number of design factors. The orthogonal array design experiments, analysis, and cost guidance based on the loss function have made this approach more attractive. The limitation of the orthogonal array is that it can only be applied at the initial stage of the product or process design system. There are some situations whereby these techniques are not applicable, such as a processes involving influencing factors that vary in time and cannot be quantified exactly.

It can be seen that the orthogonal array will assist in determining how many trials are necessary, and the factor levels for each parameter in each run. A parameter is an independent variable that may influence the final product, whereas a level is a distinction within that parameter. Initially, it needs to be made that the number of levels is the same for each parameter.

There are several discussions of the various aspects of the orthogonal array as belows.

According to Box, and Hunter (1998), Taguchi performed the research to finding which factors effect a product in a design of experiments and to dramatically reduce the number of trails required to gather necessary data. Taguchi Experimental Design can be described as an engineering technique with a statistical base. It is a powerful approach to solving complicated technical problems in all types of manufacturing environment. These experimental designs are based on the orthogonal arrays usually identified with a name such as L_{18}, to indicate an array with 18 runs. On the other hand, classical experimental designs are also based on orthogonal arrays, but are identified with a superscript to indicate the number of variables.

Renee, Jimmy, and Judy (1999) had compared the number of trails required by the orthogonal array method with the number of trails required by a full factorial experiment as in table 2.4.

Orthogonal Array	Number of Factors	Number of Levels per Factor	Number of Trials Required by Orthogonal Array	Number of Trials in a Traditional Full Factorial Experiment
L_4 (2^3)	3	2	4	8
L_8 (2^7)	7	2	8	128
L_9 (3^4)	4	3	9	81
L_{12} (2^{11})	11	2	12	2.048
L_{16} (2^{15})	15	2	16	32.768
L_{16} (4^5)	5	4	16	1.024
L_{18} (2^1x3^7)	1 7	2 3	18	4.374

Table 2.4 Compares the number of trials

Refer to table 2.4, for a design involving 11 factors, each with two levels to test, the number of runs required for a full factorial design is 2^{11}=2,048, but this number is reduced to 12 by using the L_{12} (2^{11}) orthogonal array.

According to Renee, Jimmy, and Judy (1999), " The property of orthogonality defined above allows statistical analysis of the data that fills in the blanks in the full factorial analysis that are not run as experiments in the orthogonal design. When the average value of an output function is taken for a group of runs having the same level setting for a given factor, the first order effects of the other factors cancel out, since the level settings for the other factors occur with equal frequency within this set of experiments. Thus the first-order correlation between the level settings of the factors and the output function values can be implicitly obtained without having to complete the much larger number of experiments required by full factorial analysis.frequency within this set of experiments. Thus the first-order correlation between the level settings of the factors and the output function values can be implicitly obtained without having to complete the much larger number of experiments required by full factorial analysis. "

2.3 One-factor-at-a-time

The one-factor-at-a-time (OFAT) experiment consists of selecting a starting point, or baseline set of levels, for each factor, then successively varying each factor over its range with other factors held constant at the baseline level. It meant that only one factor is varied at a time while keeping others fixed.After all tests are performed, a series of graphs are usually created showing how the response variable is affected by varying each factor with ail other factors held constant. The major advantage of this method is that it the can be used to estimated curvature in the factors and find out the best condition for each factor. However, this method cannot detect the interaction between variables when varying only one factor at a time.

2.3 Literature Surveys

All literature surveys related to quality improvement and also determined the optimum condition are present as below.

There are several studies about quality improvement and optimum condition for systems with few potential factors influencing in the manufacturing process. Phichatwattana (1998) applied the design of experiment for quality improvement of pull strength of Read/Write head in Hard Disc Drive. Beginning at study factors that are influential in pull strength between slider and flexure of Read/Write head in Hard Disc Drive and then propose the optimum condition for the higher quality of pull strength within practicable solution. The potential factors to pull strength are defined using a cause and effect diagram. From this diagram, 4 factors are considered to have major contribution. There are epoxy mixing ratio, curing temperature, curing time and weight type. At that time, the factorial design technique, 2^4 factorial experiment, is used to analyse the significant parameters and the interaction to the strength of pull test. The experiment reveals that only 3 factors that are epoxy mixing ratio, curing temperature, and curing time are significantly influential. Factorial design is reapplied by increasing replication of each factor in order to explore the appropriate working condition to achieve the highest pull strength without interfere with electrical performance of the Read/Write head.

In the same way, Intapun (2000) had used a cause and effect diagram to explore potential factors influencing on silver-plating efficiency of mirror glass. These are 1) glass temperature before silver plating, 2) liquid quantity on glass related to DI water pressure inputted console and 3) water pressure of Rinse bar. By using 2^kFactorial Design in 2 levels of each factor to perform screening experiment, these three factors are significant to silver plating efficiency. Next, he had used 2^3 factorial experiments to find out the optimum operating condition and then compared with a current silver-plating condition used statistical comparison. The result shows the arrange silver-plating efficiency of experiment condition is significantly higher than current condition.

Some others studies about determine the suitable condition, Kiatharoenpol (1995) had studied factors affecting the lacquering process on tin plate and then determine the suitable condition by using design of the experiment method. Four factors used to perform the principle of design and analyses of experiments are lacquer types, lacquer film weight, curing temperature and curing time. Next Lacquer coating was tested in 6 characteristics: flexibility test, scratch resistance test, rub test, blushing resistances test, adhesion test and cooking resistance test. Finally, affecting factors and suitable condition are analysed. Silavisesrith (2000) had determined the suitable conditions for reactor process control in the melamine compound process to reduce the variation of melamine compound's curing time. In the reactor process, the potential factors are the molar ratio of formalin to melamine crystal, the acid-base indicator of melamine crystal, formalin, and water. Subsequently the factorial designed experiment, 2^4 factorial experiment, is performed. The result reveals two influence factors, which are molar ratio of formalin to melamine crystal and the acid-base indicator of melamine crystal. Consequently, the two-factor factorial designed experiment is used to find the suitable condition by using more levels of the molar ratio and more replicates. Finally, the confirmation experiment with hypotheses testing is applied to test the differences between the two means and the two variances between the laboratory and the process. The result reveals that the two curing time means and variances of the laboratory and the process are not different.

There is another studies related to quality improvement and optimum condition for systems with 6 potential factors influencing in the manufacturing process.Sae-ung (2001) studied factors that are influential on plating thickness distribution to pure tin plating process, which is a new process technology of IC manufacturing. A cause and effect diagram is used to define potential factors affecting to plating thickness. As a result, 6 factors are considered to have major contribution. These are comprised of tin, additive and electrolyst concentration, shield height, plating time and current density. The technique of Taguchi design, Orthogonal array$L_8(2^6)$, has been applied to analyse which parameter are significant to mean and robustness of plating thickness. The experiment reveals that only 3 factors are significant influential in means of plating thickness. There are electrolyst concentration, plating time and current density. After that factorial design is applied to explore the appropriate condition to obtain nominal and least variation of plating thickness without interfere with physical quality in plating, trim and from operation and solderability test. The result shows 2 factors are significantly influential. The factors are plating time and current density. Finally, the optimum plating parameter are defined and tested before run in production line.