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ON THE DEVELOPMENT OF MEASUREMENT SYSTEM USING ROBUST DESIGN ENGINEERING BASED ON PEEL STRENGTH MEASUREMENT

剥離強度計測に基づくロバストデザインによる

計測システムの開発に関する研究

学位請求者　機械工学専攻

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ON THE DEVELOPMENT OF MEASUREMENT SYSTEM USING ROBUST DESIGN ENGINEERING BASED ON PEEL STRENGTH MEASUREMENT

Major in Mechanical Engineering

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PART I

INTRODUCTION

CHAPTER 1 INTRODUCTORY OVERVIEW

This chapter presents the background of the thesis. The objective and delimitation are defined. A thesis outline is elaborated for better understanding of overall contents of this thesis.

1.1 Background

Measurement is very important in science and engineering field. The science of measurement is called metrology. The importance of metrology is unarguable in the world we are live in. Metrology is a field of maintaining and increasing the measurement accuracy. Metrology plays a crucial part in quality assessment and the main pillar for innovation and competitiveness [1]. Ramos and Vasconcelos [1] emphasized the metrology as factor of quality, innovation, and competitiveness and its importance cannot be neglected in daily lives. The importance of precision for productivity and quality can be illustrated by CE Johansson's gauge blocks. The gauge block, also known as Jo Blocks are a system for producing precision lengths. A gauge block is a block of metal or ceramic with two opposing faces ground precisely flat and parallel. This gauge is used in measuring the tolerance of production and any precision devices. Deming [2] shared his thought on variation and Shewhart's chart. When Walter Shewhart created the basic of statistical control chart, Deming realized that the variation in manufacturing process is inversely related to quality. Shewhart discovered variation is due to the common cause for chance causes and special cause for assignable causes. Deming emphasized the knowledge of variation which describes the range and causes of variation in quality and the use of statistical sampling in measurements [3]. This is stated in his one of the four parts in system of profound knowledge; that are appreciation of a system, knowledge of variation, theory of knowledge, and psychology. Deming's knowledge of variation has led to an interest in designing a measurement system that is insensitive to variation. In other words - a robust measurement system.

H. Imai [4] describes the recent situation in metrology, and how to obtain a reliable measurement result using the expression of metrological traceability together with measurement uncertainty. Mroczka [5] shows the philosophical threads of metrology as empirical facts verifying human hypotheses as well as the metrology intellectual superstructure. In general system development theory, a number of approaches have been suggested for the process of methodology development.

Finkelstein [6] presents an early review on the term of methodology as the science of methods of design, and as a particular system of methods of design. Design methodologies have been developed for a variety of applications and disciplines. Source of design methodology may be categorized as design education, specific methodologies, systems engineering and sciences, management, creativity and lastly problem solving and decision making. This thesis is reflecting on the design for a measurement system that lays in the systems of engineering and sciences. The development of measurement systems includes the problem solving of current measurement behavior in a system. Problem solving defined as a form of activity with a goal to be reached, a gap in the route to the goal and set of alternatives [6]. The design methodology provides a useful framework for the structuring of the design process, a design concept's generation and for evaluation and decision in design. Yano [7] emphasize the importance of measurement data in design and production. It is crucial to obtain more than one sets of data relevant to the design or production process.

Product development and related process, methodologies and tools are extremely important to the success of an organization [8]. Bergman and Klefsjö present three stages for product development that are Requirements, Concepts, and Improvement. Requirement stage is coming from the needs and expectations from customers. Concept stage describes the consideration on large numbers of different concepts that can satisfy customers. The requirement and Concept stage are corresponding to system design in robust design engineering. System design is the conceptualization and synthesis of a product or process to be used. This is where the new ideas, knowledge and concepts in science and technology are utilized to determine the right combination of materials, parts, processes, and design factors that will satisfy functional and economical specifications. Once the concepts have been selected, it should be polished and improved to a better level and cost. This stage is called improvement stage. The improvement stage corresponding to parameter design and tolerance design in robust design engineering. Design of experiments and robust design engineering that includes parameter design and tolerance design are important features in improvement stage. These systematic methodologies are used to reduce variation exist in measurement, thus produce quality product that is insensitive to variation.

1.2 Objective

The objective of this study is to contribute to the development of robust measurement systems in parameter design. A problem with measurements is that they are not always representing their corresponding measurand in a perfect way. Peel strength measurement is used for practical experiment to reflect the measurement system in parameter design. Industrial experience in implementing robust design technology is part of research methodology in developing the measurement system.

1.3 Delimitations

In the literature review of measurement system, there are many field that use different measurement systems. This thesis delimits the measurement system in parameter design of robust design engineering. The field of interest is focusing the peel strength measurement as mechanical engineering context. Thus, the scope of this thesis is presented as below.

1.3.1 Scope

The scope of this research is clearly defined to ensure the true decision problem is addressed. This research has five scopes in order to materialize the objective:

1. To provide a procedure on optimum conditions selection
2. To provide a systematic process in handling outliers in the development of measurement system
3. To establish a procedure on how to analyze variability and optimization when designing a measurement system
4. To present the difference in laboratory and industry practice on achieving quality experimental design
5. To establish a mainstream flow in order to achieve high quality experimental design

1.4 Thesis Outline

A general system design that covers not only the tool and how to use it to get the desired response, but the decision, the choice, the possibilities and its application are discussed practically and theoretically through case studies presented in this thesis. In this thesis, type of measurement in an experimental design is decided and how to evaluate the design parameters to improve the design is discussed. The elements of what to measure, how often to measure it, what evaluative measurements to make and how to use them for the best effect is emphasized in the results and discussions. Therefore, the development of such system is extremely important to discuss in this thesis.

The thesis in constructed in three parts. Part I includes Chapter 1: Introduction, Chapter 2: Theory Background, and Chapter 3: Research Methods. Chapter 1 presents the research in measurements system and its importance for productivity, quality, and innovativeness. The development methodology is described and its relation with robust design engineering is explained. Objective of research is presented. The delimitations of the research is described to narrow down the measurement system from macro-level. Chapter 2 defines the theories of importance for the research. Definition of measurement, measurement uncertainty, measurement system, robust engineering and robust measurement system are elaborated. Chapter 3 covers the research methods use in this research such as literature review and case studies that include industries and practical experiments.

Part II is further explained on parameter design of measurement systems. Here, the results from the research methods is analyzed and discussed. This part includes Chapter 4: Literature Review result, Chapter 5: Implementation of Parameter Design in Industries, Chapter 6: Parameter Design of a Measurement System, and Chapter 7: Critical to Assumptions in Parameter Design. Finally, Part III includes Chapter 8: Discussion on Parameter Design of Measurement Systems, Chapter 9: Conclusion of the research and Future research.

Figure 1.1 depicts an overview of this research. General measurement system design is the meta-level topic for this thesis. In science and engineering, the measurement starts with the existence of measurand. The measurement is surrounded by variation, anywhere. Taking the results of measurement is considered as measurement process. Then, it is completed with the existence of measurand, operand or physical arrangement, measuring task and instrumentation to form a measurement system. Further, the tool used to design a measurement system is parameter design or so-called robust design engineering. Parameter design is aimed to produce a robust measurement system. This leads us to a general design methodology to locate a robust measurement system in measurement design methodology. On top of all, the robust measurement system is capable to be used in general application of design. Not only laboratory, but practically being practiced in industries such as Fuji Xerox (Company A) and Company B mentioned in this thesis.

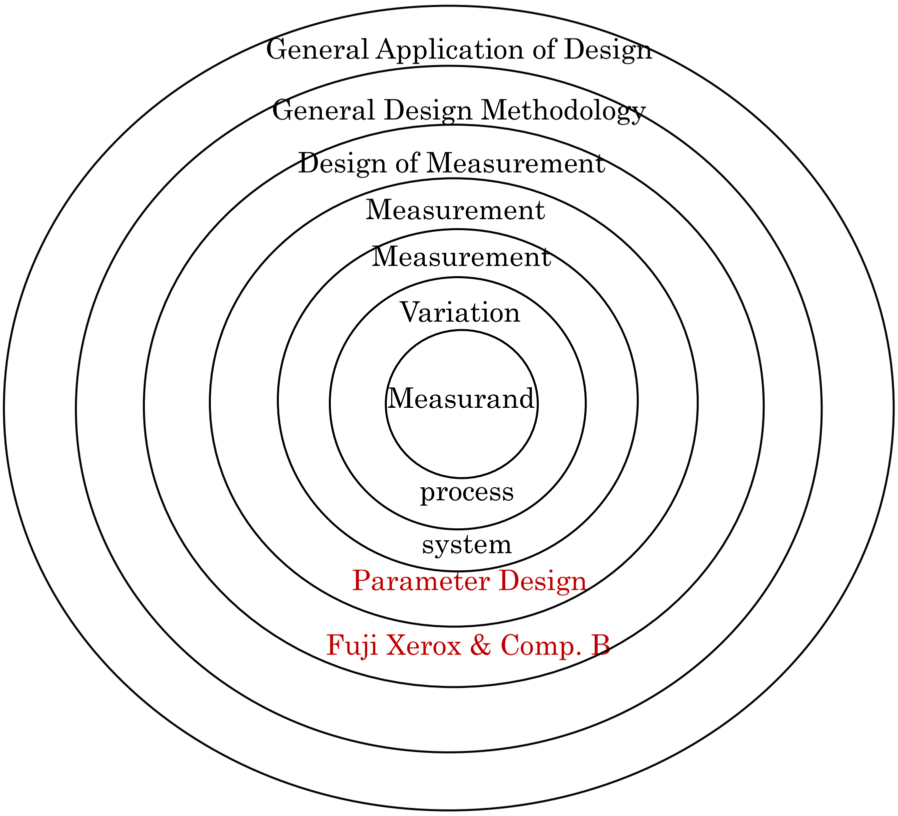

Figure 1.1: Overview of general idea of this research

The research is further narrowed for measurement system development in mechanical engineering field. Figure 1.2 shows the narrower focus that reflects what this thesis is all about. Multiple resources in general product development theories, case studies in measurement systems, application in mechanical engineering field, and manufacturing are some important key words. Next, the development in measurement system using parameter design is focused. Product development is emphasized in three stages that are requirements, concepts and improvements [8]. A systematic methodology such as parameter design is used. Application of parameter design in industries, case studies of parameter design in manufacturing and practical experiment are done at this point.

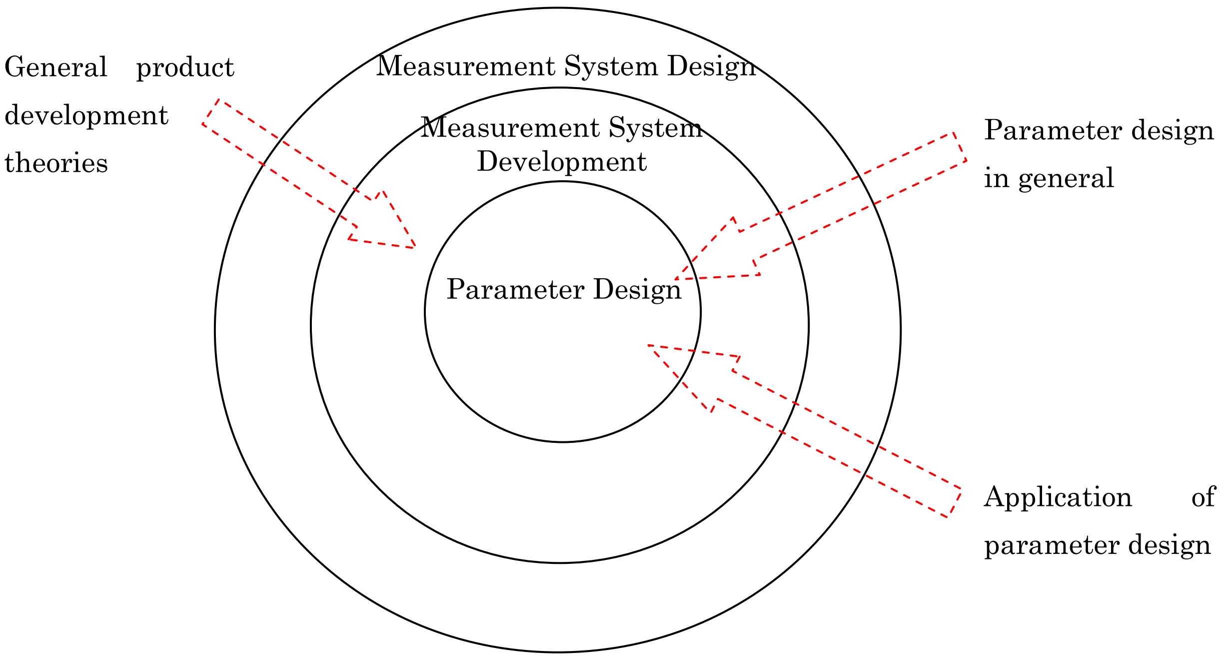

Figure 1.2: Research focus

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CHAPTER 2 THEORY BACKGROUND

The concepts in this thesis are defined. Terms and keywords are indicated and elaborated for better understanding of their usage. The theories on measurement, uncertainty, measurement system, robust engineering, and robust measurement system are presented.

2.1 What is Measurement

There are many current literature found in defining what measurement is. A New definition of measurement is made by T.L.J. Ferris [1] after rigorous definition from many literature reviews is taken into account. Ferris defined measurement as an empirical process, using an instrument, effecting a rigorous and objective mapping of an observable into a category in a model of the observable that meaningfully distinguishes the manifestation from other possible and distinguishable manifestation. It resembles everything for information capturing regardless in any field; science, engineering, technology, humanity and such. The theory of measurement has been discussed in many literature [2][3][4][5][6][7]. A system to measure result is called measurement system. Thus, it is very important on how a measurement system is carried out as it affects the result or response of a system. This thesis is to contribute to the development of a measurement system using practical experiments supported by the implementation in industries as its application. Finkelstein [6] defines measurement as empirical operational procedure which assigns numbers to members of a class of entities and to describe them by which is meant that relations between these numbers correspond to empirical relations between the entities to which they are assigned. He further defines that measurement is the process of assignment of numbers to members of a class of attributes or characteristics of objects of the real world in such a way to describe them. For instance, measurement is an operation which objectively assigns numbers to quality manifestations of objects in such a way to describe manifestations [8]. Finkelstein [9] stated that measurement is the process of empirical, objective assignment of numbers to the properties of objects and events of the real world in such a way as to describe them.

Luca Mari [3] characterizes measurement as an evaluation process able to produce objective and inter-subjective information on the measurand. An Italian standard [10] explained that measurement is an experimental activity by defining measurement as the set of empirical and processing operations performed by means of suitable devices interacting with the measured system with the purpose of assigning a value of a quantity assumed as parameter of the system. Fenten and Pfleeger [11] define measurement as a mapping from the empirical world to the formal, relational world. Consequently, a measure is the number or symbol assigned to an entity by this mapping in order to characterize an attribute.

2.2 What is Measurement Uncertainty

There are three components of measurement that are the measurand, the measuring instrument, and the environment. The result of measurement is often a value with numbers expressed with multiple of unit of measurement [12]. These numbers are associated two main aspects in measurement that are accuracy and uncertainty. High accuracy implies low uncertainty, and vice versa. In this thesis, a little part of the practical experiment reflects the uncertainty which depicted by minimizing the variation in peel strength. For example, the variation in peel strength is caused by minor deviation of peel angle. The deviation of peel angle causes variation in peel strength, thus results in uncertainty. International guidelines to assist on uncertainty are described in the Guide to the Expression of Uncertainty in Measurement or so-called as the GUM [13]. Uncertainty defined by Guide to the expression of Uncertainty in Measurement (GUM) is “a parameter, associated with the result of a measurement that characterizes the dispersion of the values that could reasonably be attributed to the measurand”. This parameter is normally a standard deviation or the width of a confidence interval. Giovanni Battista Rossi [14] states two measurement theories that are deterministic which describes an ideal measurement process and probabilistic which considering for uncertainty. K. Watanabe et al. [15] explained on optimization of paper permeability tester to increase the measurement accuracy. Robust design engineering is used to optimize the tester to make it more robust against uncertainty. More explanations on uncertainty can be found in [16], [17], [18] and [19].

2.3 What is Measurement System

Measurement system is a practice in obtaining data for certain purpose. Measurement system in this thesis refers to a process in capturing data for desired response. Considerations that need to be taken into account are laid out. Measurement system explains from the beginning stage of an experimental design until the application of the optimum condition. In many literatures, measurement system only review the way test method is carried out without explaining the previous stage before the experimental procedure is done [20], [21]. However, apart from test method, some papers discuss on the foundation of measurement and its theories. Giovanni [14] explains when performing measurements, not only the measurand object need to be considered, but also measuring system and the interaction between the two. A general probabilistic model was provided for measuring system and measurement process. The flow of measurement contains the measurand, data measurement, measured value and finally measurement result [22]. This is supported by Luca Mari [4] which found the idea that measurement results are assigned to measurands, not determined, because "values" belong to the information, not the empirical, world, and the relations between such two worlds always maintain some conventional component. By looking at these finding, the papers in the measurement journal discussed on the test method used in some case study while another pattern is discussing on the measurement concepts and theories. The experimental design is the perfect tool used in practical experiment for measurement system in parameter design. The gap in the middle between the theory and practical case study that connects the test method used for measurement and the development of measurement system is the main issue discussed in this thesis.

2.4 What is Robust Engineering

Quality is an essence in Japan. When comparing Japan products, it has no doubt in serving highest satisfactory to the user. Why is this happen? What is behind this success? How Japan can sustain the excellence of quality ahead from other countries, generally. Thus, robust engineering in general has been the backbone of the Japan's product quality performance. The excellency of robust engineering has been practised and applied by other countries of the world globally that make Japan as their role-model. Robust engineering is described using robust parameter design in which a system is insensitive to variation. M. Arvidsson and I. Gremyr [23] reviewed on robust design methodology which contains QE as part of it as systematic efforts to achieve insensitivity to noise factors which founded on an awareness of variation and can be applied in all stages of product design. B. Bergman and B. Klefsjö [24] stated that all products are exposed to different kinds of variation such as variation between customers and how they use the product, variation in environment and variation in production process or manufacturing. These variation may cause deviation from target values and lead to customer dissatisfaction. It is also emphasized that the robust design methodology and a systematic handling of tolerance are important features in "improvement" phase [25]. It is emphasized that the earlier the variation is detected, the better the product to satisfy the customer needs. L. Ilzarbe et al. [26] explained the practical applications of experimental design which has been applied for many years in industry to improve quality. M. Tanco et al. [27] described how the experimentation carried out by companies in three european regions. The findings revealed that systematic experimental design is far much better that conventional way of doing experiment to improve the performance of products or processes. R. Dolah et al. [28] presented on how an organization and laboratory works in implementing quality engineering. The real process in industy is compared with practical experiment in laboratory by taking peel test experimentation in mechanical engineering context. E. Viles et al. [29] emphasized on the importance of planning stage in industrial problems, where there are different factors that strongly affect the results of the study.

Statistical design of experiment provides a proper way of planning an experiment in selecting appropriate data. Design of experiments (DOE) such as factorial design, response surface methodology (RSM) and Taguchi methods are widely used compared to traditional one factor at a time approach. Robust engineering method have been widely applied for optimization in peel test [30], [31], [32], [33]. Robust engineering method had simplified the classical design of experiment which found too complicated to be applied by engineers in application field [34].

2.4.1 Robust Engineering Method

Back in early 1920s, Sir R.A. Fisher introduced an experimental design method of statistical technique called Design of Experiments (DOE). Started from crop optimization in agricultural experiment, research and development of DOE grew significantly in academic environment. Not many industries applied DOE in production process. The more the research grew, the more complicated it became and the less it reflects the practitioner to apply it. In 1940s, a Japanese engineer; Dr. Genichi Taguchi modified and standardized the technique into a more useful way for practitioner. Here is the significant moment where DOE techniques become extremely useful and friendlier to apply. Transforming from a sophisticated method to an applicable and easier to practice, Dr. Taguchi introduced the simplified DOE to design quality into products and is called Robust Engineering that provides the ability to produce high quality, low-cost products that fully satisfy customer needs.

G. Taguchi and Y. Wu [35] introduce his approach using experimental design as a two-step optimization:

Step 1: Reduce functional variability to increase robustness. A design that can maximize the signal-to-noise ratio which optimize the process or product function. It is more difficult to reduce variability than to adjust the mean to target value.

Step 2: Adjust sensitivity. Adjust average response to the target value.

This research is focusing on parameter design, which an investigation is done to identify settings that minimize the variation. Different setting may generate different variation in product or process performance. In classical parameter design developed by R.A.Fisher [36], the experimental design is complex and not easy to use. Main reason of this is large number of the experiments need to be carried out when the number of parameters increases. For example, a full factorial experimental design for studying four parameters at three-levels would have required 81 experimental trials (3^4). Adding in two-level noise factor with two repetitions would make number of observations to 324 (81x2x2), an unacceptable number due to experimentation constraints. From the orthogonal arrays by Taguchi, a modified L-9 orthogonal array was chosen. Only 36 observations implied (9x2x2). A loss function is then calculated from the deviation between experimental value and the desired value, or in other words; deviation from the target will create loss to customer. Value of loss function is transformed into a signal-to-noise ratio (SNR), which is a metric for robustness. SNR (unit: dB) is defined as in equation (2.1) below:

SNR, η = power of signal/ power of noise

$$= (\text{sensitivity})^2 / (\text{variability})^2$$

$$= \beta^2 / \sigma^2 \qquad (2.1)$$

Inversed SNR is the variance per unit input [37]. As in equation (2.2), loss is proportional to the inverse of the SNR. The larger the SNR, the smaller the loss, thus the better the quality is.

$$\text{Loss} \quad \alpha\ \sigma^2\ \alpha\ 1/\text{SNR} \qquad (2.2)$$

S/N ratio measures variability around the mean. It represents the ratio of sensitivity to variability. Therefore, higher S/N ratio is better as robust condition due to minimum variability. There are two categories of SNR, that are non-dynamic SNR when there is no signal factor, and dynamic SNR when signal factor is exist. Signal factor is a controllable variable to actualize the intention.

Ideally, a system with zero or minimum noise is desired. This means, after optimization, the noise level gap must be as smallest as possible to produce an ideal function as shown in Figure 2.1. In this study, Y is the output that is peel strength and represents a zero-point proportional equation [37] with dynamic SNR. M is the signal factor that is specimen width. Beta, β, is the measurement sensitivity to different inputs, thus the slope must be steep. Thus, the ideal function is $Y=\beta M$. Three elements of SNR are to improve the linearity, sensitivity and variability of a system.

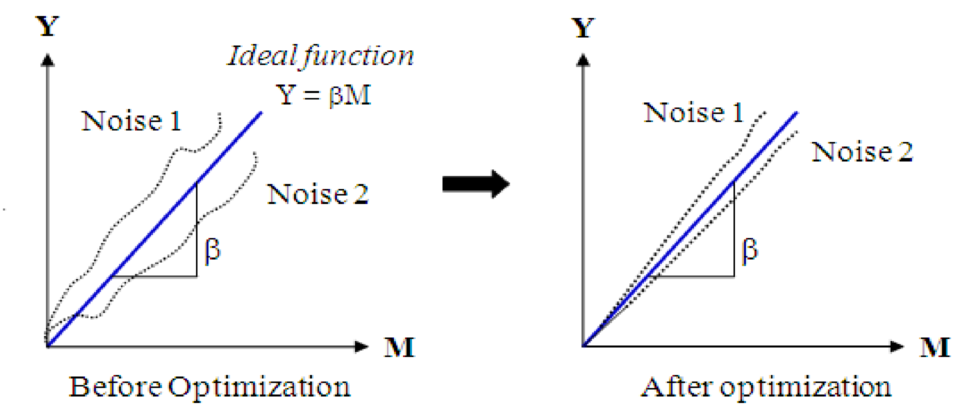

Figure 2.1: Variability improvement after optimization

In 1990's, there were many debates from the statistician and robust design practitioners about Taguchi method [38]. The concerns include the efficiency of Taguchi method providing the optimum condition, view of interactions, signal-to-noise ratio, and such. Despite many controversies over the statistically based methods advocated by Taguchi, there is broad agreement on the value of Taguchi contribution in emphasizing variation reduction and attracting industrial interest in it.

Jerome Sacks and William Welch (National Institute of Statistical Sciences and University of Waterloo) 1992 - found that robust engineering method by using parameter design is a confusion about interactions. Statistical literature states robust engineering approach assumes that interactions are absent and thus, the method is unscientific. Supposed a quality characteristic, or response is Y, depends on two control factors, X_1 and X_2, and noise factor, z. thus, Y= X_1 + X_2 + Z. However, SNR is analyzed in robust parameter design and not the response or Y. Process average in SNR is said to ignore the interaction between X_1 and X_2.

Madhav Phadke (Phadke Associates, Inc.) 1992 — views the presence of interaction between control factors is highly undesirable for some reasons; that interactions will lead to a big number of experiment and interrupts R&D productivity. Thus, every step in robust design is made to minimize or eliminate between control factors interactions be it in the choice of response (quality characteristic), maximizing SNR, control factors and their levels. Along with this, some guidelines had been established to select response in order to minimize interactions.

George Box et al. (1988) – If care is not taken during column selection, will lead to messy interaction confounding and result to wrong conclusion. Raymond Myers and Geoffrey Vining (Virginia Polytechnic Institute and State University and University of Florida) argued about the experimental planning techniques in Taguchi method. They felt that optimum condition method is a one-shot operation which is lack of proper classical experimental planning that include stage of variable screening, region movement, design augmentation, fitting model and exploration region using response surface method. James Lucas *(Du Pont Quality Management and Technology Center)* stated that all Taguchi method's design is considered response surface design because it includes environmental or noise variables and more screening design. Anne Shoemaker and Kwok Sui (AT&T Bell Laboratories and Georgia Institute of Technology) emphasized robust design as a problem in product design and manufacturing-process design. The solution method is depending on the application area.

M.S.Packianather et al. [39] used DOE and Taguchi method to optimize the multilayered feed forward neural network. Analysis of variance (ANOVA) is performed on the SNR that is called as transformed data, and also to raw data that identified the signal factors. It is assumed that signal factors have negligible effect on SNR. Through ANOVA, the effect of each variable can be analyzed.

Jiju Antony [34] summarized a framework on when to use robust engineering method and DOE based on nature of problem. Nature of problem is quite general and wide definition. But how to fit the nature of problem into the field? At which stage does the nature of that problem occur should be decided before the appropriate method is selected. This is also a motivation factor in this research.

Chang Chung Li et al. [40], stated Sprow (1992) mentioned about the problem screening in robust parameter design method is more beneficial for R&D and product-process development, rather than to fine tuning the variables. Ming-Shi Chen et.al [41] integrated Quality Function Deployment (QFD) and robust parameter design into development process. Next, the optimization of product development quality is done using SNR analysis.

Kiyoshi Saitoh et al. [42] outlined the important steps on implementing robust engineering method in Research and Development (R&D). The paper focused on problems and solutions in introducing and promoting robust engineering in corporate structure. Several experiments done by Makato Sakanobe et al. [43], Y. Sakai [44], and Kouichi Akiyama et al. [45] outlined the QE application case in different stage of product and process line in a corporate structure.

Until today, it is not very clear whether the implementation of robust engineering method are comparable or not between practical practice in laboratory and industry application. The purpose of this research is to make an attempt to address the above issue from the perspective of research and practitioner. The information gathered from practical experiment and implementation from industries is analyzed to ensure its compatibility.

2.4.1.1 Dissimilarity between DOE and Robust Engineering method

The debate between Design of Experiments (DOE) and robust engineering method so-called Taguchi Parameter Design (TPD) is well-known and has been discussed in many books and magazines. Often this question is raised "what is the best method? Should I go for DOE or Taguchi method?" In this thesis, robust engineering method is referring to the three components that are system design, parameter design, and tolerance design.

In DOE, main idea is about full factorial, response surface methods for second order model building and analysis of variance (ANOVA). On the other hand, robust engineering method often depicted as fractional factorial designs and orthogonal arrays. Both method have its own strength and purpose. The difference in technical aspect is discussed in this chapter 3. On the other hand, the differences in application due to its technical characteristic is discussed in Chapter 4 under application of robust design in industry sector. In Nair [38] , a group of practitioner and researches discuss the role of DOE and parameter design. Variation reduction, use of noise factors, interactions, selection of quality characteristics, signal-to-noise ratios, experimental strategy, dynamic systems and applications.

TPD prefers using three or more levels of the process or design parameters to estimate non-linear effects [34] . However, DOE prefers to investigate the potential interaction behaviors. Classical DOE encourages to study the parameters at two-levels so that critical process or design parameters can be identified in early phase, followed by the use of response surface designs such as central composite design (CCD) or Box-Behnken designs for studying non-linear effects. Interaction means interdependence. If a factor is independent of each other, the main effect plot will remain unchanged no matter which other factor it is with [46]. Interaction effect is when a factor behaves differently in the presence of other factors. The trend of influence changes when levels of other factors change. In DOE, ANOVA is used to analyze interaction effects. The effect of each factor is shown in ANOVA to indicate which factor gas significant effect on the response. Interaction between signal and main factors are calculated. TPD uses a performance statistic called signal-to-noise ratio (SNR) for measuring performance robustness. Signal and true data of measurement is multiplied to derive the variation caused by the linear effect, S beta. SNR contains the power of signal derived from the sensitivity of the true mean and power of noise derived from variability of variance. The SNR combines both the mean response and response variability in single performance thus may not be able to separate out those process parameters which the mean performance and response variability separately. Classical DOE performs these analyses separately and hence is powerful in achieving this objective. However, TPD approach focuses on achieving robustness in functional performance of product and process. This is done by carefully examine the outer array of the experimental design so-called “noise parameter” for those which cannot be controlled or hard to control or expensive to control using standard production conditions. TPD has a separate array for control factor and noise factor that produce variability that are inner array and outer array respectively. In DOE, blocking and randomizing strategies are done.

The interaction in TPD is distributed evenly in its orthogonal array. Orthogonal array is used to explore the design space [47] . An orthogonal array provides a balanced set of experimentation runs such that the conclusions are drawn in a balanced fashion. It is known that after the experiments had been done completely using the orthogonal array in TPD, a confirmation run confirms that no severe interaction among control factors to the SNR. Therefore, most likely the robustness will be produced at the downstream conditions. An orthogonal array is used for optimization to maximize the SNR. The gain or benefit in SNR is estimated and confirmed. This action synergize the plan-do-check-action cycle in quality management practice. Strategies of TPD are introduced in this thesis and are illustrated in practical case studies using orthogonal array L9 and L18.

2.5 What is Robust Measurement System

The purpose of measurement system is to attain an estimate of some quantity of interest and the system should be evaluated with respect to the precision of estimates obtained [48]. Robust measurement system is to design a measurement system to get a robust measurement system by taking variation into consideration. Variation is the main keyword for robust engineering. The purpose of robust engineering is explained in the previous section which means to have a system that is in sensitive to variation. Thus, the development of robust measurement system is important to obtain this objective. Robust measurement system emphasized on variation reduction that contributed by the noise factor in a measurement system. The noise factor cannot be eliminated, but the effect can be reduced by choosing the proper level for control factors. This is done in parameter design which is used to improve the quality without controlling or removing the cause of variation and to make the product robust against the noise factors. Bergman and Klefsjö [49] states that it is not always possible to completely eliminate the influence of noise factor but it might possible to decrease its influence. A transfer function of one example of a system using parameter design is shown in equation 2.3:

$$Y = f\,(X_1, X_2, X_3, \ldots Z_1, Z_2, Z_3, .. \varepsilon) \qquad (2.3)$$

with Y = response (quality characteristics)

X = process parameter/ control factor

Z = noise factor

Assume the transfer function with known values of the coefficients b_o, b_1, b_2, b_3 :

$$Y = b_o + b_1X_1 + b_2X_2 + b_3X_3 + b_ZZ + b_{2Z}X_2Z + \varepsilon \qquad (2.4)$$

ε = unknown, small residual term

For a robust solution, the influence of the noise factor, Z is decreased by utilizing the $X_2 = -\, bz / b_2Z$. It is also possible for X_1 and X_3 to be chosen in the cheapest possible way to ensure the lowest manufacturing cost.

This research presents multiple strategies of noise measurement. In a measurement, V_e represents the correction of error variance which means the variation of the data measured in a sample. V_e reflects the variation that affects the accuracy and precision of a measurement in a controlled condition. In robust measurement system, V_e is calculated with consideration of V_N, the variation of compounded noise factor. This represents the metric for robustness in robust engineering and is called signal-to-noise ratio, η. The signal-to-noise ratio is shown in equation 2.5:

$$\text{Signal-to-noise ratio, } \eta = 10 \log \left[(1/(r_o \cdot r)) (S_\beta - V_e) / V_N \right] \qquad (2.5)$$

where S_β = variation caused by the linear effect,

V_e = correction error variance (error variance/degree of freedom [DOF]),

V_N = compounded noise factor when signal factor is introduced,

r_o = total number of measurements under one signal level, and

r = effective divider representing a magnitude of input due to level changes of signal factor.

The base 10 log of standard deviation is used as a traditional statistical transformation to make a normal distribution out of the skewed standard deviation distribution.

Other approach by means of robust design of measurement systems is highlighted by Dasgupta et al. [50] and Arden Miller and C.F.J. Wu [48]. An integrated approach for estimation and reduction of measurement variation and its components using a single parameter design experiment is developed. Statistical models and performance measures are developed for measurement systems. The model for two types of variability is proposed. The first type of variability is called short term variability that is measurement-to-measurement or repeatability. The second type of variability is called ling term variability that is application-to-application or reproducibility. Two different analysis strategies- Response Function Modeling and Performance measure Modeling- have been discussed. The effectiveness of the proposed model is demonstrated with a simulation study and the data from Taguchi's drive-shaft experiment has been used to demonstrate the proposed approach. As stated by Miller and Wu [48], provide a rigorous body of theory and methodology. Signal-response systems is classified into two broad types that are measurement systems and multiple target systems. Two strategies for modeling and analyzing data is presented that are performance measure modeling and response function modeling. The proposed methodology is illustrated with injection molding experiment. Yano [51] proved the signal-response relation as one-to-one correspondence between process parameters and product characteristics. The case study shown in Yano [52] explained about anticipate the effects of signal factors and data analysis. Suitable experimental design and proper data analysis are important other than just simply measuring a product characteristic and adjust the production process accordingly.

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CHAPTER 3 RESEARCH METHODS

This chapter describes on the research methods to obtain the research results. There are two categories of methods utilized in this thesis. These are literature review and case study. Case study is divided into two sections that are from industrial experience in implementing robust design engineering and practical experiments utilizing the robust engineering approach done in laboratory.

3.1 Literature Review

3.1.1 First level Literature Review

The literature has been identified through searches in Web of Knowledge in Web of Science in three databases; SCI-Expanded, SSCI, and A&HCI. In all three databases, searches were made in topic search in advanced search. The searches were conducted in April 2013. The no.1 set of topic search is done using TS=((“Parameter design”)OR(“Taguchi”)) with result of 5114 hits. Due to parameter design often called as Taguchi method, this is the reason why the topic search is done by selecting all research papers in parameter design application field. No.2 set of topics search is done using TS=((“Measurement system”)OR(“Measuring system”)) with 14569 hits. No.2 topic search is including all measurement and measuring system in any field. Not restricted to only quality engineering field, measurement system is searched for all field that includes measuring activity. No.3 search is combining no.1 and no.2 topic search to ensure that only measurement and measuring system in parameter design and Taguchi Method only is captured. No. 3 search ends up with 15 hits.

In No.4 set, all application using robust design and robust engineering is searched because the terms for parameter design are used as well in robust design and robust engineering. The set is done using TS=((“Robust design”)OR(“Robust Engineering”)) results with 2341 hits. No.5 set is done by combining No.2 and No.4

sets to find the articles in measurement and measuring system only in robust design and robust engineering and the result is 8 hits. At the end of search, which is set No.6 ; set No.3 is combined with the set No.5 using “OR” command and the result is 19 hits. This final 19 hits are used in this literature review of the research. The final number of papers identified in the database searches is given in Table 3.1:

Table 3.1: Summary of literature review`s search

Set	Results	Search Item
# 6	19	# 5 OR # 3 Databases=SCI-EXPANDED, SSCI, A&HCI Time span=All years
# 5	8	# 4 AND # 2 Databases=SCI-EXPANDED, SSCI, A&HCI Time span=All years
# 4	2341	TS=((“Robust design”)OR(“Robust Engineering”)) Databases= SCI-EXPANDED, SSCI, A&HCI Time span=All years
# 3	15	# 2 AND # 1 Databases= SCI-EXPANDED, SSCI, A&HCI Time span=All years
# 2	14569	TS=((“Measurement system”)OR(“Measuring system”)) Databases= SCI-EXPANDED, SSCI, A&HCI Time span=All years
# 1	5114	TS=((“Parameter design”)OR(“Taguchi”))

The 19 articles are then collected and analyzed each for their contents.

3.1.2 Second level Literature Review

After the systematic search as explained in previous section, a “snow-ball sampling” search is done. Important papers in each paper’s reference is observed and analyzed to ensure no important information is missed out. Many papers from *Measurement* journal have been looked into for better understanding in measurement and metrology research. Robust measurement system is studied through the application of robust engineering method in many applications.

3.2 Case Studies

Case study is the body of content on how the research has been carried out to fulfill the research objectives. Case studies are classified into two categories that are industrial practice of applying the robust engineering method and practical experiment to illustrate the development of robust engineering measurement system.

3.2.1 Industrial Practice

First case study is looking into the procedure of industry in implementing the robust engineering method. Two companies are included in this thesis that is Company A (Fuji Xerox Co. Ltd.) and Company B. This section provides some findings from companies about their application in robust parameter design. The barriers and obstacles faced by the engineers are also discussed in this section. A Quality Engineering called as QE methodology framework is established at the end of this section to present an outline for QE implementation that suits general application and environment.

3.2.2 Practical Experiment

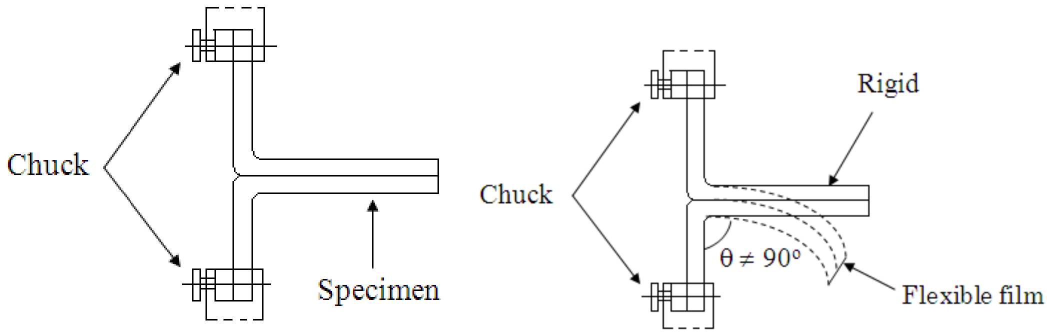
Second case study is focusing on the practical experiment done in laboratory to illustrate the measurement system in robust engineering. The specimen used in the practical experiment is flexible packaging film as shown in Figure 3.1:

Figure 3.1: Flexible packaging film Al/CPP

In order to develop the measurement system, instrumentation standard is considerably important. As for now, there is no standard for peel strength apparatus. Thus, the specimen is used as the alternative to represent as standard. This is done by implementing certain measurement level in specimen width. Three widths are used that are 5mm, 10mm and 15mm. The output; peel strength, increases periodically as the width increases. Due to this reason, specimen width is used as signal factor that actualize the intention of the output.

The practical experiment is utilizing the peel test. The T-peel test is done on the flexible packaging film as a method for measuring peel strength of an adhesive. Peel tests are most commonly used to evaluate the laminated film or bonded adhesives. Thus, peel test is preferred when working with multiple film packaging in this study that are poly ethylene (PET), polyamide, aluminum, cast poly propylene (CPP), and bonded with adhesives. There are four main types of peel tests: 90^o peel, 180^o peel, T-peel, and climbing drum peel. The 90^o peel test is suitable for a flexible adhesive material that is adhered to a more rigid substrate. The 180^o peel test is best used when the flexible substrate can be bent back by 180^o. The T-peel test is best used when both adhesive and adherend are similar or flexible. This study assesses packaging film made out of flexible material and consisting of several layers of flexible films. Therefore, the T-peel test is the most suitable peel test to measure the peel strength of this material.

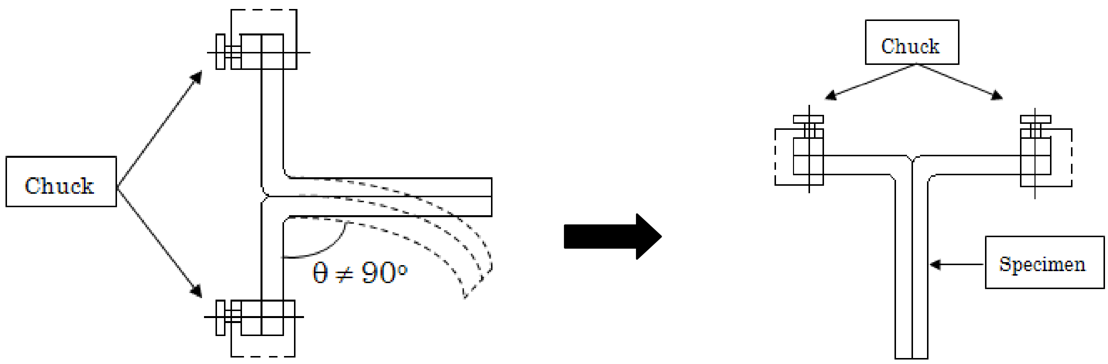
The problem of peel angle as a crucial element of peel strength [1][2][3] motivates the study to develop a new T-peel test apparatus for flexible film in order to stabilize the peel angle and further reduce variation in the measurement data of peel strength. The research motivation is initiated from the standardized method's current inability to maintain the peel angle for flexible film; this failure has led to a variation problem when it comes to measuring peel strength [1]. Hirai et al. measured the performance of the T-peel apparatus for flexible film using the standardized method of JIS K6854-3 and ASTM D1876-08 to evaluate the T-peel test jig. The variance found in the standardized method is higher than in the T-peel test jig. Hirai et al. concludes that the standardized method, although suitable for rigid material, produced a variation problem when testing flexible film. According to some scholars [2][3] described the influence of peel angle on peel strength during a T-peel test, and thus established the importance of ensuring the stability of peel angle during a T-peel test. These literatures have motivated the current study on variation reduction in peel strength occurring in the standardized test method. The new testing apparatus was developed to solve the variation problem when measuring flexible film and then used to develop an optimum condition for flexible film. The study evaluated which peel side was more influenced by peel angle in order to determine the optimum condition of the T-peel test. Figure 3.2 (a) shows the schematic diagram of the standardized test method and Figure 3.2 (b) shows the bending condition of a specimen when the standardized test method is used on flexible film.



(a) (b)

Figure 3.2(a): Standardized T-peel test method (ASTM and JIS) and (b):Failure of flexible film specimen to stabilize the peel angle

Figure 3.3 shows the difference in specimen design and variations in peel strength for the standardized method of ASTM D1876-08 and JIS K6854-3 T-peel test and the new testing apparatus. The peel angle of a flexible film is not sustained at 90^{o} with standardized method. The new apparatus with different layout of T-shape is constructed to obtained sufficient peel angle for T-peel testing thus reducing the variation of peel angle during peeling. The new test apparatus reduces variation, and further optimization was performed to achieve a smooth and minimal variation in peel strength. The Taguchi method of parameter design was used to make the new test apparatus insensitive to variation. The optimum condition was determined using the new test apparatus to ensure the robustness of the T-peel test.



(a) Test design in standardized method (b) Test design in new test apparatus

Figure 3.3: Design changes of the new test apparatus

The T-peel test apparatus is described in Figure 3.4. The angle adjuster can be used to change the peel angle from 0^o to 180^o. The flexible film specimen is attached to the drum. A weight (paper clip) was fixed on the free end of the film to keep the specimen in T-shape. The drum rotates according to peel speed as a string is attached at a fixed point and tied on the drum's pulley. Peel speed and peeling distance can be changed according to apparatus specifications. A parallel spring is pulled by pulley wire along the peeling process. Three spring thicknesses were used for this study: 0.3mm, 0.4mm, and 0.5mm. During the peeling process, displacement is triggered by a parallel spring caused by peel strength and detected by a laser sensor. This apparatus can obtain a wide range of peel strength measurements by changing the spring thickness. Peel strength increased proportionally to specimen width as shown in Figure 3.5. This can be observed using different spring thicknesses. Higher strength was needed to peel away the adherend from the adhesive as specimen width increased. A schematic diagram of the apparatus is shown in Figure 3.6.

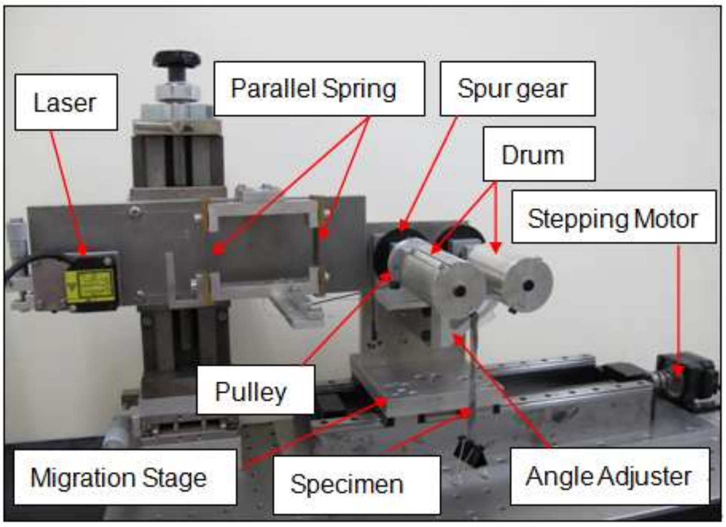


Figure 3.4: T-peel test apparatus (1cm photo:5cm actual)

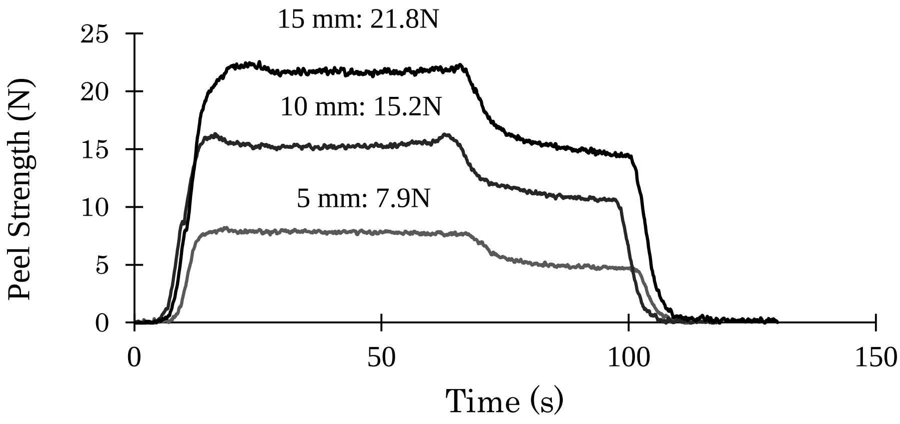


Figure 3.5: Specimen width effect on peel strength

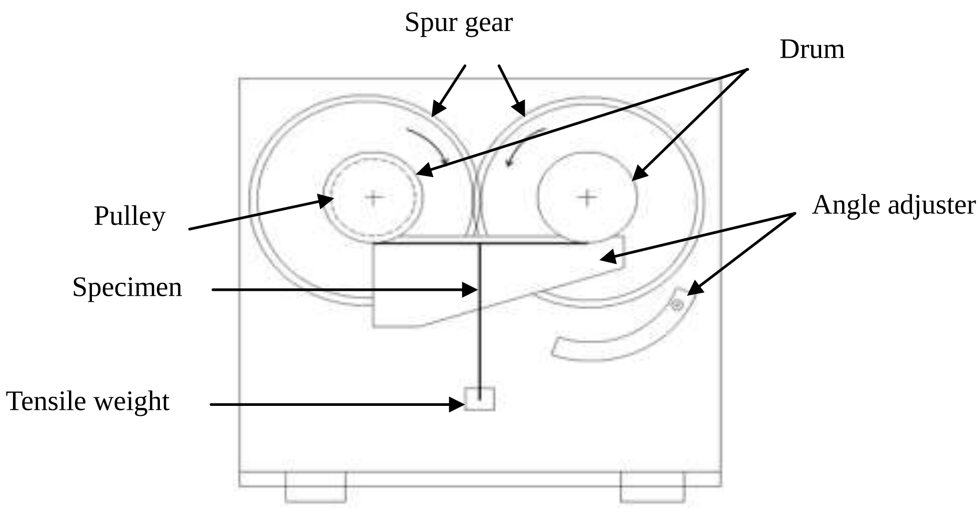


Figure 3.6: Schematic diagram of new test apparatus

The specification of test apparatus is shown in Table 3.2. This apparatus has high resolution, and thus is able to measure specimens with low peel strength.

Table 3.2: Specifications of test apparatus

Parameter	Specification
Peel speed	0 – 800mm/min
Peel length	0 – 119mm
Peel angle	0 – 180^{o}
Spring thickness	0.05 – 0.8mm
Resolution of peel strength	0.003N

The principle of how the apparatus works is shown in Figure 3.7. The specimen is attached at the bottom of the drum, and a weight (paper clip) is fixed on the free end of the film to kep the specimen in T-shape. Peel speed and peeling distance of 60mm are keyed-in using Agilent VEE Pro interface. Parallel spring is pulled by pulley wire attached with the rotating drum along peeling process. During peeling process and the displacement is detected by a laser sensor.

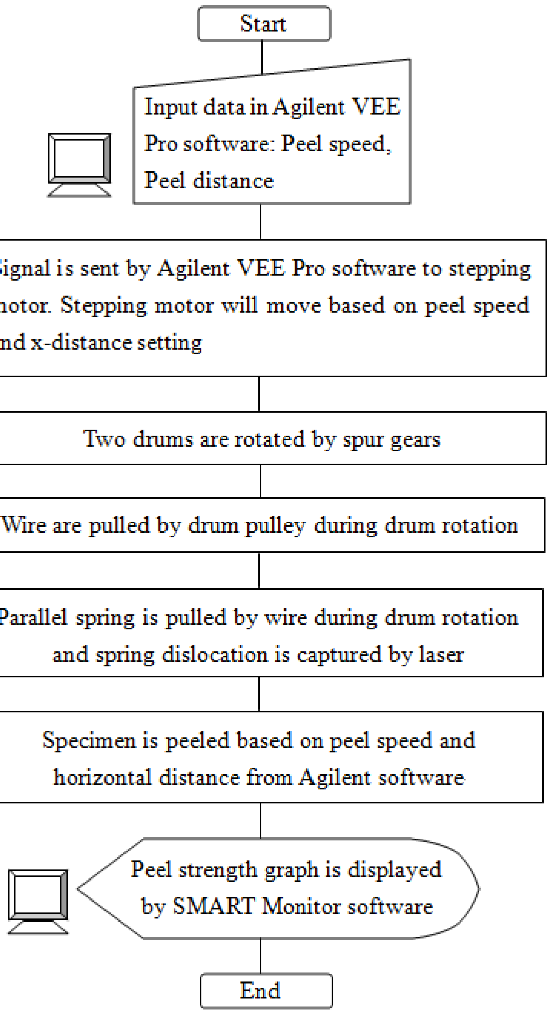


Figure 3.7: Schematic flow on peel strength measurement by peel test jig

3.2.2.1 First Practical Experiment

The first practical experiment is focusing on the multiple optimum conditions derived from the peel strength measurement. Besides, how to determine the best optimum condition is discussed. An experimental design is employed using an orthogonal array L9. L9 is used due to minimal experiment run as preliminary study. It is done to understand the behavior of the peel strength before implementing L18 in the following experiment. There is no interaction found in L9 as the ANOVA table in Chapter 6 section 6.1.2 does not show any significant relation between control factors. The variation caused by the different peel surfaces of each specimen is investigated to observe which peel side gives the best condition for the T-peel test. Three optimum conditions for flexible film are discussed: the aluminum peel side condition, the CPP peel side condition, and the harmonized condition. Based on the signal-to-noise ratio (SNR) used to evaluate the improved condition in a confirmation test, the CPP peel side has the highest SNR, followed by the aluminum peel side and then the harmonized condition. The SNR for the CPP peel side condition increased by 22% from the aluminum peel side condition; thus, it is advised that the CPP peel side condition be used. The SNR of the harmonized condition is lower than the CPP and aluminum conditions, but it provides a convenient design that can be used without regard for peel side.

3.2.2.2 Second Practical Experiment

The second practical experiment is using L18 to investigate the influence of outer array layout and noise parameter strategy. The purpose of this practical experiment is to provide the most reliable experimental design by evaluating the influence of noise parameter in outer array and reason in deciding on optimum condition. Influence of noise factor in outer array for robust parameter design is discussed experimentally. Variation reduction in peel strength from multiple noise layouts presents possible variety of optimum condition. Optimum condition is affected by signal-to-noise ratio (SNR) analysis which relates on measurement data in outer array of L18. The finding in this practical experiment is important to ensure the reliability of optimum condition. Reliability means how reliable the optimum condition is based on SNR result obtained from measurement data. Noise level plays an important role in determining the result in outer array as it affects the SNR. Three types of possible measurement data layout in outer array are studied, thus three optimum conditions are analyzed from signal-to-noise ratio (SNR). Reliability of three optimum conditions is discussed in determining the best condition. Analysis of variance (ANOVA) is employed to investigate the influence of noise parameters. Measurement data which covered the whole variation range of peel strength is chosen as the best measurement method.

3.2.2.3 Third Practical Experiment

The third practical experiment is robust engineering method using L9 in outlier effect on optimum condition. As many researches focused on application of robust design engineering in practical case study, very less concerned on the criticality to data measurement system in parameter design. This paper will emphasize on the importance to critical to assumptions in parameter design. The existence of outliers is often ignored and the impact is overlooked, thus endanger the experiment by producing false alarm and giving completely wrong parameter setting. The optimum condition from the data that contains outliers is compared with the corrected data measurement. The finding presents the indication procedure on how to confirm whether the data is reliable or not for evaluation. The data are unreliable when two main indicators are detected. Firstly, the measurement data plot detects outlier through linear regression analysis as it does not belong on the linear line. Secondly, dB gain difference from reproducibility examination of signal-to-noise ratio (SNR) between estimation and confirmation run is more than 30% shows that the experiment is a failure. This failure affects the experimental design and lead to wrong optimum condition. The practical experiment has elucidate the detection of outlier and outlier effect on optimum condition.

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PART II

ROBUST MEASUREMENT SYSTEMS

CHAPTER 4 LITERATURE REVIEW

Literature review is one of the research methods in the thesis. This chapter presents the result from literature review that covers the six key words that are measurement systems, measuring system, robust design, robust engineering, Taguchi, and parameter design. The result is then classified according to their contents.

4.1 View of Variation

How an experiment should be done is explained in Dasgupta et al. [1]. An integrated approach for estimation and reduction of measurement variation and its components using a single parameter design experiment is developed. Statistical models and performance measures are developed for measurement systems. The model for two types of variability is proposed. The first type of variability is called short term variability that is measurement-to-measurement or repeatability. The second type of variability is called ling term variability that is application-to-application or reproducibility. Two different analysis strategies that are Response Function Modeling and Performance measure Modeling have been discussed. The effectiveness of the proposed model is demonstrated with a simulation study and the data from Taguchi's drive-shaft experiment has been used to demonstrate the proposed approach.

Bovas Abraham and Mike Brajac [2] have considered two strategies to reduce variation induced by a known noise factor that are controlling the variation in the noise factor itself and secondly is exploiting the interaction between the noise factor and an easily controllable factor. The role of experiments in discovering interactions and in particular the use of robust designs to obtain the interaction between control and noise factors. Variation reduction in a measurement system is attempted using a robust design from product array and combined array. Taguchi method advocates the use of signal-to-noise ratio for analyzing data from a product array.

The problem in categorical data is overcome by V. Roshan Joseph and C.F.Jeff Wu [3] using categorical response optimization. Categorical data is used quite often in industrial experiments because of an expensive and inadequate measurement system for obtaining continuous data. This proposed categorical response optimization overcomes the inherent problems associated with categorical data. The basic idea is to select a factor that has a known effect on the response and use it to amplify the failure probability so as to maximize the information in the experiment.

A two-stage of kinematic calibration study of the measurement system is also proposed by Deuk Soo Kang et al. [4]. Constant error parameters are found in the first stage and variable error parameters are found in the second stage of kinematic calibration. After kinematic calibration the position error is reduced to within 0.5um and error reduction rate is ranged from 93.54% to 97.93%.

4.2 Taguchi's Trade-off, ANOVA and Regression Analysis

Some literatures apply Taguchi method of dynamic response and ANOVA is used to study the significance of parameters. Hsun-Heng-Tsai et al. [5] proposed a methodology using dynamic response of Taguchi method to investigate the effects of the deposited mass upon the resonant frequency output of the surface acoustic wave (SAW) gas sensor. The study integrates computer-aided simulation experiments with Taguchi dynamic method to generate a robust SAW gas sensor design that reduce the cost and increase the biosensor measuring performance. Two statistical analysis methods, namely the analysis of mean (ANOM) and the analysis of variance (ANOVA) are utilized to identify the control factors which significantly reduce the variability and bring the sensitivity towards its target value.

Der Ho Wu et al. [6] presented a measurement systems that provide an accurate and robust performance over a wide range of input conditions. The study adopted Taguchi dynamic response of piezoelectric gas sensor system whose output response is linearly to the input signal. It focuses upon the conventional quartz nanobalance (QCN) gas sensor. The goal is to increase the sensitivity of the measurement system while reducing its variability. The result produced a time and cost efficient finite element analysis method to investigate the effects of the deposited mass upon the resonant frequency output of the QCN biosensor. Besides Taguchi method, analysis of mean (ANOM) and the analysis of variance (ANOVA) are utilized to establish the optimum design condition.

P. Grob and J. Marosfalvi [7] investigated the pressure generated in the mould cavity during polyurethane integral skin foam molding using Taguchi method, ANOVA, and regression analysis. The measurement proved that the empirical correlation used in the polyurethane foam industry for mould design considerably overestimates the moulds ranges of higher average density. A multiple regression analysis was made to give a good estimation to the pressure arising in the mould. This equation can be used in the mould design instead of empirical correlation that leads to a better designed mould.

Zhisong Tian et al. [8] presented the dynamic characteristics of a scanning system which is the core of online measurement systems developed for large hot forgings. From a complete force balancing conditions of scanning systems, the correlative dynamical parameters are adjusted, the shaking forces to bearings are eliminated, and the input torques are reduced and ameliorated. This study uses simulations and experiments to verify the effect, and compare the fore-and-aft torques. The result proved that dynamical parameter design is significant to improve the dynamic characteristics of scanning systems.

Keyhwan Kim et al. [9] developed a new measurement system which can measure position and orientation of the end-effectors of a six-axis welding robot. The developed measurement system consist five digital probes. The measurement values from the digital probes are transformed into position and orientation of the end-effectors with consideration of measurement system kinematics. Calibration procedure is applied to the probe system and accuracy of the system is measured. After the calibration, the positional and orientation accuracy are observed. By using the developed measurement system, an experimental result for controller gain tuning about a welding robot is presented. Taguchi method is used to find the optimal setting and succeeded to suppress the fluctuation of the end-effectors. The fluctuation with high frequency can be reduced by 54% after gain tuning.

4.3 Taguchi Method without Noise factor, Supply Chain Taguchi Method and Expert System

There are still some research papers in the literature review not including the noise factor in Taguchi method of experimental design. Liang-Chia Chen et al. [10] presented the process characterization and optimization of the nanoparticle fabrication process known as the Submerged Arc Spray Nanoparticle Synthesis System (SANSS) by using a developed on-line nanoparticle measurement system and Taguchi method. Experiments based on Taguchi method were then conducted to investigate the optimum process parameters for producing nanoparticles with improved properties, such as particle size and uniformity. However, no noise factor involved in the L16 Taguchi experiments and repetition of response measurement is done to calculate the signal-to-noise result. ANOVA is done to investigate which process parameters significantly affect the process response; that is the quality characteristic of the SANSS. Signal-to-noise ratio of smaller-the-better is used to ensure that the averaged primary particle size is reduced. TEM pictures confirmed the average primary particle size was considerably reduced from 150 to 10nm.

H.H. Lee et al. [11] used Taguchi method to verify the precision and accuracy of the redesigned PEEK coil sensor and electromagnetic induction method. The results displayed reproducibility within 0.5 degrees and an accuracy within 2 degrees Celsius. The smaller-the-better characteristic was applied here because the difference between the ideal function and each voltage characteristic of the experimental coils should be small to yield better performance. L18 is used, and two noise parameters were chosen that are engine vibration and the temperature of the coil sensor. The Taguchi method has minimized the number of experiments in the optimization. The proposed electromagnetic induction method has many advantages over other piston-temperature-measurement methods.

Shunsuke Uchida et al. [12] presented on the optimization of crack propagation rate measurement system. The main purpose of this study was to determine the effects of H_2O_2 on the corrosive environment and crack propagation rate. In order to determine the effects of H_2O_2 on crack propagation rate, a series of measurements should be carried out while changing H_2O_2 concentration. Pre-liminary tests of crack propagation rate measurements under H_2O_2 showed a small propagation rate for the HWC condition. In order to determine such a rate accurately, the crack depth measurement system should be improved. For this purpose, Taguchi method was applied and an optimal combination of parameters for reliable measurements were proposed based on measured sensitivity, measured noise level and calculated geometrical effects. The result has optimized the crack propagation measurement system based on a 1/4-inch constant tension specimen and potential drop method allowed a crack propagation rate of 10^{-8} mm/s to be measured with less than 20% fluctuation. The crack propagation rate under H_2O_2 was less than that under oxygen, even if electrochemical corrosion potential was the same.

Nevertheless, Taguchi method is also used in supply chain system to understand business performance in an electronic component company. A model of measurement system for collaborative supply chain partners is described by Chinyao low and Ya Hsueh Chen [13]. The study adopted the signal-to-noise ratio of smaller-the-better to evaluate the robustness of a specific supply chain behavior to obtain a minimum inventory cost. Inventory strategies and how the factor delivery time and lead time of an order can improve performance are elaborated. The Taguchi method helps to ensure appropriate levels of experimental factors. The use of combination screening, system dynamics and the Taguchi method in understanding complex supply chain behavior can be extended to all areas of operation or development management.

W. McEwan et al. [14] emphasized on the human experts experience which is usually heuristic, judgmental, subjective or intuitive in nature. As the optimum procedures usually differ from one job to another, the application of Taguchi method can be used to identify optimum conditions which are robust against unwanted disturbances in the testing environment. Another important element associated with the quality of measurement systems is sensitivity, which is the ability to perceive and discriminate between two signals or samples to be measured. The study described on parameter design to increase the efficiency of non-destructive testing (NDT) by providing robust inspection parameters for a knowledge-based expert system and enhancing the industrial quality.

4.4 Without Taguchi Method

From the literature search of measurement system design of robust design, some papers did not implement any of Taguchi method. The robust design defined by C. Huhne et al. [15] is not an awareness of variation or deviation from its desired and/or specified level. The robust design is the optimal design that is determined by maximizing the buckling load of the perfect shell varying the fiber orientations of the UD-plies. Using the new deterministic design method the buckling load N_1 is maximized and the two optimal designs are compared. The new approach is used in a design example which points out that the imperfect buckling load has to be maximized to determine the optimal design for realistic shells.

Bieberle et al. [16] presented on a compact high-resolution gamma-ray Computed Tomography (CompaCT) measurement system for a multiphase flow studies and tomographic imaging of technical objects. Robust design in this paper refers to its compact design that makes it suitable for studies on industrial facilities and outdoor applications. The design has been given a special care to thermal ruggedness, shock resistance, and radiation protection. Compared to other high energy scanners the CompaCT system is transportable and can be applied to industrial facilities.

Park, T.W and Sohn, HS [17] discussed on six sigma tools for vehicle drift system, instead of Taguchi method. Vehicle drift was reduced using statistical six sigma tools through four steps: M (measure), A (analyze), I (improve), and C (control). This search appeared under measurement system's literature review. This measurement system capability were analyzed and improved before measurement. Step A analyzed critical problems by examining the process capabilities and control chart derived from the measured value. Step I analyzed the influence of the main factors on vehicle drift using Design of Experiments (DOE) to derive critical to quality (CTQ) that are tire conicity and toe angle. Thus, these CTQ will further improve the manufacturing processes. The respective toe angle tolerance for the adjustment process was obtained using Monte Carlo simulation. Step C verified and controlled the improved results through hypothesis testing and Monte Carlo simulation.

Another research paper by Kotarski, Mateusz and Smulko, Janusz [18] explained on measurement system in gas sensor by using Taguchi Gas Sensor (TGS) available on the market and the prototype monosized nanoparticle gas sensors. This research did not use Taguchi method for product's robustness, but included in the search due to Taguchi keyword and measurement system. The study presents two solutions of noise systems that can be used for noise measurements in TGS and the prototype gas sensor. The prototype gas sensor is proved to have much greater DC resistance than the sensors currently on market.

4.5 Recent research on Measurement System

Newer material in measurement research is done in order to become aware of measurement system's conceptualization. T.L.J Ferris [19] proposed a new definition of measurement as an empirical process, using an instrument, effecting a rigorous and objective mapping of an observable into a category in a model of the observable that meaningfully distinguishes the manifestation from other possible and distinguishable manifestations. A.J. Fiok et al. [20] defined measurement as an experiment of parameter identification of mathematical model of the object to be measured. This thesis includes the empirical measurement system to obtain values of parameters by means of the application of instruments. Luca Mari [21] stated that a single conceptual framework is a significant target for measurement system design, towards a generalized concept of measurement. By concerning on this issue, this thesis is initialized to ensure a general concept of measurement can be achieved. Finkelstein [22] discussed on three concepts of measurement that are wide, strong and weak defined measurement. Measurement in wide sense is defined as a process of empirical, objective assignment of symbols to attribute of objects and events of the real world. Strongly defined measurement is measurement that conforms to the physical sciences. Weakly defined measurement is measurement in the wide sense, but which is not strongly defined. Later after 6 years, in 2009, Finkelstein [23] examined the fundamental problems of widely defined measurement. Particular problems of measurand concept formation, validity, verifiability and theories for the measurand are considered. H. Imai [24] describes current situation in measurement science and how to obtain a reliable measurement result using the expression of metrological traceability and uncertainty. Variations of measured data are necessary to be considered in a process of measurement. Measurement uncertainty is also defined as non-negative parameter characterizing the dispersion of the quantity values being attributed to a measurand, based on the information used. In measurement standards, not only physics, but other fields of science are introduced effectively such as global climate change and forensic science.

Giovanni [25] discussed on some concepts and terms in measurement from different disciplines of science. The role in scientific theories are investigated and key terms such as measure value, measuring system, measurement value, and measurement model are discussed. Deterministic theory describes the ideal measurement process and probabilistic theory describes the uncertainty. Luca Mari [26] emphasized on the important role of measurement in the foundation of science. Mroczka [27] presented the philosophical threads of metrology as a set of theoretical and empirical facts verifying human hypotheses and metrology intellectual superstructure. Metrology discovers new measurement problems and unknown cognitive problems. Metrology means hypotheses from physical and mathematical models, until they are verified experimentally. There are traditional branches of metrology such as standards and patterns, measurement methods, measurement data processing for error-tracing. New section of metrology includes stochastic surveying, image recognition, technique of measurement systems and others.

4.6 Conclusion from Literature Review

The papers found in the literature reviews come from measurement system in parameter design of Taguchi method and robust design and engineering. The nature of robust design is to create insensitivity to noise factors rather than to try to eliminate or control them. Robustness and robust design in the literature have different reflection based on specific research. Mainly, robust design is produced by using Taguchi parameter design. However, some literatures found that robustness is built by optimizing the design creation in certain product or process without applying Taguchi parameter design. The measurement system presented in the literature presents the uncertainty of the results. Thus, the uncertainties have to be handled systematically in the product development process.

The literatures have been divided into four categories. In Group 1, research is focused by using statistics, variation reduction, combined array, repeatability and reproducibility, DOE and measurement calibration. Robust design is elaborated in statistic point of view and derivation of mathematics formulae. In Group 2, robustness is elaborated in quality engineering method by using signal-to-noise ratio, trade-off optimization, ANOVA, Taguchi method, regression analysis, dynamic response and noise factors. These papers are found to really utilizing the parameter design in Taguchi method. In Group 3, Taguchi method is presented in achieving product and process's robustness. However, very less concerned on noise factor in experimental design. Most of the papers are using static response of smaller-the-best, nominal-the-best, and bigger-the-best response. In addition, Taguchi method is applied in an expert system with combination of simulation program and also in business management by injecting supply chain Taguchi method. In Group 4, the papers are not using Taguchi method at all. The robustness is achieved using numerical simulations by probabilistic methods. Since the manufacturing process causes an imperfection pattern; defined as deviations from perfect shape and loading distributions, hence this probabilistic approach which revised to deterministic approach is presented derived from phenomenological test date which means of robustness in this case. Another paper explained a compact and robust design in terms of thermal ruggedness, shock resistance and radiation protection without optimization done by Taguchi parameter design.

Group 5 presents the recent research in measurement system. Majority of the papers are found in Journal of Measurement as the name implies about the measurement. There are two papers [28][29] that discuss on hard turning and flank wear optimization that did not discussed on the theory of measurement. The papers are more on the application and empirical perspective of robust design. Generally, Journal of Measurement discussed on the theory and mathematics behind the measurement result. Yano [30] is considered as a prominent researcher in metrology. However, none of the literature review papers citing his name. Yano book is really significant for practical metrology that transfer the knowledge of measurement science and metrology into application. The book emphasized on the quality engineering method that consists of system design, parameter design and tolerance design. Finding from these literatures is the opportunity to bridge the gap between the foundation or theory of measurement system with practical perspective from Yano. This thesis is hoping to embed the parameter design into the measurement journal. The journal is always been portrayed as the science of reference for the society. Parameter design is very much well-known for practical application and important for any optimization. Thus, it is very important to include the parameter design as part of the measurement system, not only on theory but also practically. In addition, Urbanski [31] stated that it is impossible to develop a theory of measurement independent from the physical nature of the measured object. In this thesis, different aspects of measurements are presented through several practical experiments and industry practice. Thus, a measurement system is developed using independent measurement from different nature of measured object. Thus, this is the research gap that this thesis intends to fulfill. Measurement and the instrumentation is the key to enable the technology of science and other practical activity [32]. It reflects a very wide variety of equipment and techniques for diversity of application. In order to make an effective measurement system, a systematically framework of general concepts and principle need to be developed. Finkelstein [23] emphasized that measurement science should address the whole range of applications of measurement and to provide a universal framework of concepts and principles to address all applications of measurement.

Therefore, a systematic measurement system is developed which results in robust product and process by using parameter design. General theory of a complete measurement system development is important to standardize the measurement system in parameter design. A mainstream flow is aimed in this research to get high quality experimental design in order to obtain quality result or optimum condition in a measurement system.

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CHAPTER 5 IMPLEMENTATION OF PARAMETER DESIGN IN INDUSTRIES

This chapter explains on the implementation of robust design engineering in industries. In addition with practitioner's application of robust design engineering in industrial fields, perhaps it provides an eagle view on measurement system in parameter design by considering the practical experiment and its application in industries.

5.1 Motivation Factor of Injecting the Implementation of Industry into Measurement System of Parameter Design

Until today, it is not very clear on how to implement robust engineering method which consists of parameter design method and Design of Experiments (DOE), apart from other quality tools such as TQM, QFD and so forth. The purpose of this chapter is to make an attempt to address the above issue from the perspective of research and practitioner. The data collected from research case study and information are gathered from industries to match between laboratory work and application fields. Robust design engineering method is analyzed from industry's experience of its implementation. The implementation information is gathered from practitioners who use robust engineering method to sustain the product and process quality. The finding in this chapter emphasizes not only on technical aspect of experimental design, but also when and how the methodology fit into the appropriate application. Thus, the finding helps to visualize the measurement system of parameter design into the implementation stage.

5.2 Introduction of Parameter Design in Industries

Engineers mainly and practitioner engaged in variety of activities such as developing new products, improving previous designs and maintaining, controlling and improving ongoing manufacturing process and others. Experiments need to be carried out with those activities for variation reduction by using statistics regardless of their background. As discussed in earlier section, Design of Experiments (DOE) and Quality Engineering of robust design engineering (Taguchi Method) have been used as a methodology for systematically applying statistics to experimentation. Martin Tanco et al. [1], provide an extensive review of the barriers faced by engineers when applying DOE. 16 barriers are identified and categorized into three different groups that are business barriers, educational barriers, and technical barriers. Resistance to change, low commitment from upper level management, insufficient resources, and absence of teamwork skills and negative image of statistics are the business barriers that hindered the usage of statistical method in industrial experimentation. Educational barriers include the publication do not reach engineers, poor statistical background, DOE is not taught to engineers at universities or badly taught and poor statistical consultancy. Finally, the technical barriers outlined the limited software aid, difficult statistical jargon, lack of methodologies in user guidelines, negative experience, absence of theoretical developments to solve real industrial problems and complexity of experimental design. It is concluded that in order to successfully implement DOE, the barriers need to be encountered. Martin Tanco et al. [2] found that the complexity in DOE is proved by only 23% of companies in three European regions namely Baden-Wurttemberg region, The Basque country, and the rest of Spain. On the other hand, 75% of companies apply one-factor-at-a-time strategy.

DOE grew significantly in academic research. The more it grew, the more complicated it became. A Japanese engineer, Dr. Genichi Taguchi simplified technique making it practical to be applied for the practitioner. By designing quality into products, a quality engineering method (robust design engineering) has been used widely not only in Japan, but throughout the world. Debates and criticism are widely spread and discussed about robust design engineering specifically Taguchi Method. However, the main contribution of Taguchi method in reducing variation in product characteristics is undeniably. Antony [3] stated that although DOE provides a quick and cost-effective method to understand and optimize products and processes, not many industries carry out experimentation with a pre-established statistical methodology.

Chang Chung Li et al. [4] highlighted that there is communication gap between statisticians and engineers. The conventional thought of professional attitudes with regard to the functions of a manufactured product is the engineers make it work and the statistician understand why it works. Taguchi pointed out that the task of an engineer is not only to make it work, but to understand the ideal function and its loss to society. Therefore, the Taguchi method of experimental design provides a way of thinking that emphasizes a philosophy of freely using the methods of DOE to solve engineering problems. The purpose does not on lay on finding response, but to reduce deviations from ideal functions. In quality improvement in a company, statisticians must not just consult after the engineers have done their work. Statisticians and engineers must work hand in hand with engineers from the beginning, and to do this the statisticians must acknowledge and become familiar with engineering issues. In order to reduce the communication gap, not only must engineers become more familiar with statistics, but the education of statisticians for industry must change. Quality problem is not only an engineering issue, but also a statistical issue. Engineers should seek engineering importance and statistical significance. Engineers must learn and gain the technical know-why and operational know-how. Finally, engineers need to strengthen the prior engineering analytical capability and posterior statistical analysis skill. Jiju Antony [5] summarized an example of Taguchi method of experimental design for the development of a new ignition coil for an automotive vehicle. An experimental design using Taguchi method with 16-trial experiment to study 14 design parameters with one interaction is presented. Each steps of the new product development is explained specifically from selection of quality characteristic, design parameters, levels, interaction, appropriate orthogonal array and execution of the experiments.

This section provides some findings from companies about their application in robust parameter design. The barriers and obstacles faced by the engineers are also discussed in this section. In addition, the comparison between robust design engineering implementation in laboratory and company is also explained. A robust design engineering methodology framework is established at the end of this section to present an outline for robust design engineering implementation that suits general application and environment.

5.3 Findings from the Observation in Company A (Fuji Xerox Co. Ltd.) and Company B

As many research focused on robustness methodology, this chapter discussed on how to implement these methodology concept from the management perspective. The experience of Fuji Xerox and Company B in implementing robust design engineering is presented. The practical data of a laboratory experiment is discussed in order to relate between the measurement result and requirement in industry. The robust design engineering implementation is explained on the strategies used in tackling organization problems. Robust design engineering methodology between the practical case and company's case study is compared. Finally, through the robust design engineering implementation in organization and method applied in experimental design, a framework is proposed for robust design engineering methodology. Robust design engineering implementation is presented from two sources, from a company and practical experiment.

5.3.1 Introduction of Robust Design Engineering Implementation

Robust design engineering has been used in Fuji Xerox and Company B to minimize product development cost, reduce time-to-market and improving the quality of product and process. Fuji Xerox and Company B found that major quality problems are coming from technological development and designs before the production phase. Company B has the same industry as Company A (Fuji Xerox). Company B is an established company that has implements robust design engineering for many years. It is common in Company B to address Taguchi method as Quality Engineering or robust design engineering. Many robust design engineering books have been published by the employee of Company B. In Fuji Xerox, robust design engineering has been used in two categories that are in management strategy and as engineering tool. Company B categorized the production or manufacturing problem into two cases; firstly – the production started without any problem; and secondly – the problem starts to occur after one to two years and need trouble shooting process. This is identified as the case without robust design engineering implementation in designing a product. The implementations in laboratory and in Fuji Xerox for management strategy and production tool are compared to establish a methodology framework for robust design engineering.

5.3.2 Implementation Methodology

The methodology is categorized into two categories that are management strategy and production strategy. Management strategy is related to the organization method in tackling the obstacles and in cultivating the interest to sustain robust design engineering practice among the practitioner. Production strategy is focusing on how the practitioners of robust design engineering apply the tools for improving the product quality.

5.3.2.1 Management Strategy

In management strategy, Fuji Xerox outlined the eight key factor for success induced from the cause and effect diagram. Firstly, support and interest in robust design engineering involvement from the top management members, and secondly; the activities for promoting robust design engineering will not show any progress although with a great effort by an eager promoter and engineers. Thirdly, continuous promotion activities and followed by continuous training to engineers who are in need to be trained is more effective in activating the activity than training many engineers at once. As the top management support is crucial, engineer portrays the training as the manager's willingness to implement robust design engineering and the discontinuance of training is interpreted as loss of interest. Structural guidance to engineers by promoters is also important as leaving the usage up to engineers will result inactive robust engineering. Promotion committee has been established under top management`s leading, so called a top-down approach. One of the functions of robust design engineering promotion system is establishing internal seminar (robust design engineering). The objective is to train engineers' ability on robust design engineering application and train the future trainer to avoid the stagnation of robust design engineering promotion on components supplier is done by the procurement department. Fifth factor is themes clarification of robust engineering project status. Sixth factor is continuous meeting involved by everybody in each management level. Seventh is continuous training from the consultant and expert support to ensure a continuous implementation. Lastly, the eighth factor is the result review and clarification. This is done through presentation review of the robust design engineering project for project or problem status.

An internal presentation forum is also held annually in June presented by the engineers regarding their achievement in robust design engineering and Design of Experiments (DOE) applications. Robust design engineering is also incorporated in existent product development process and new concept of process innovation. The concept explained on applying robust design engineering at the earliest stage consisting of optimization and confirmation evaluation, followed by building the first prototype. In consequences, occurrence of quality problem is minimized before building the prototype. The new concept is vice versa from the conventional product development process which prototype is built first then followed by improving the quality of the next prototype. It is obviously described the concept of robust engineering which robustness is confirmed before any design is finalized. Research and Development center play a key role to provide matured technologies and new technologies corresponding to business environment changes. Utilization of computer simulation has speeds up the development process and reduces the prototypes cost.

Company B has many branches in Japan. Example used in this part is namely Branch1 and Branch 2. Different approach is done for robust design engineering implementation. In Branch 1, robust design engineering applied in Material Supply

Development and Production and is using top-down approach and has ideal function of each small part. Top-down approach is emphasizing the usage of robust design engineering and DOE tools. Top-down means the implementation of robust design engineering itself. The theme is developed by manager or upper level management and engineer has to adapt the theme using robust design engineering and DOE. They learn parameter design process through robust design engineering experiments. This approach is then followed by technician and operator. In Branch 2, robust design engineering is applied in Technical and Mechanical Development by using bottom-up approach. The meaning of bottom-up is engineers learn on how to achieve development's target. Engineers need to select the best match of robust design engineering techniques and arrange it for the success of the development. The application skill of robust design engineering is learned in bottom-up approach. In bottom-up, robust design engineering means as development efficiency equipment. Figure 5.1 summarized Top-Down and Bottom-Up approach respectively:

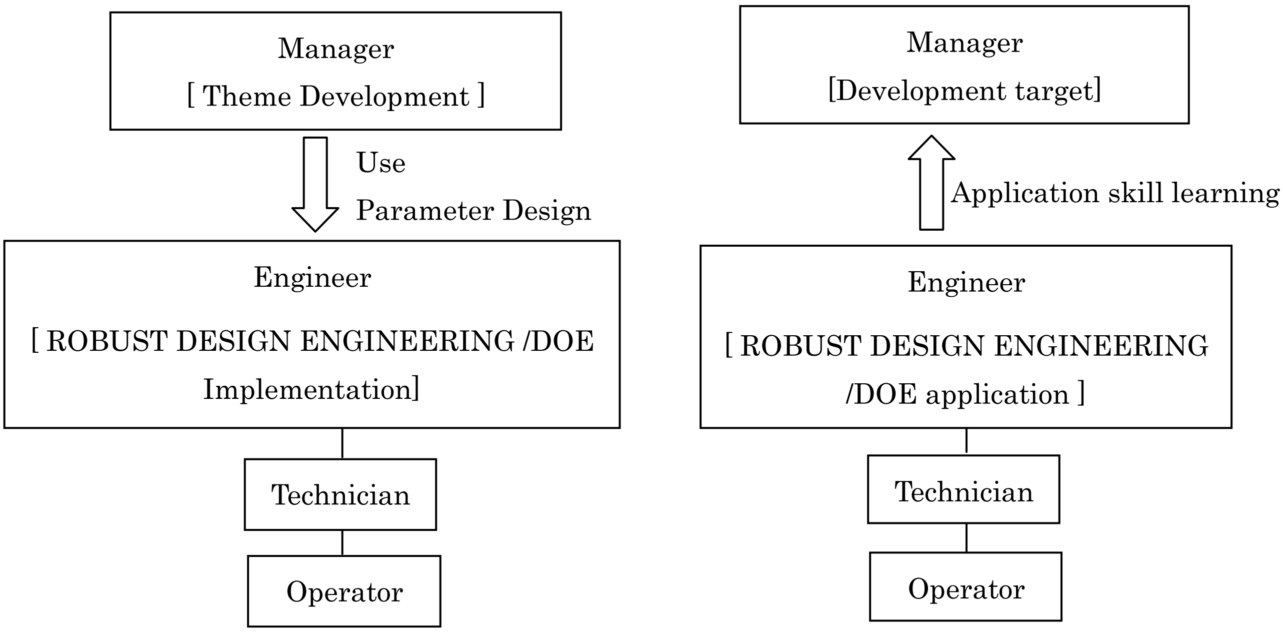

Figure 5.1: A) Top-Down Approach and B) Bottom-Up Approach by Company B

Tolerance design and Quality Loss Function (QLF) are found hard to deploy in Company B. Many simulations have been used such as CAE. One new approach currently on study is the parameter study enhanced by T-Method. T-Method is one of robust design engineering tools apart from robust parameter design. Unlike regression, variables can be more than samples in T-Method. T-Method is used when there is a continuous response and to develop a prediction model with many variables. For example, when a continuous response includes two-types of “abnormality” (good abnormality and bad abnormality), the performance is predicted with many variables. Thus, the critical variable can be identified.

5.3.2.2 Production Strategy

Annual robust design engineering forum is emphasizing on engineering tool that are robust design engineering and DOE. Fuji Xerox has differentiated the usage of robust design engineering tool based on process and purpose. DOE is utilized at the research stage to fix the themes of product and process and further verify the feasibility of the research. Taguchi method is used extensively to find the design parameters that result in the product or process robustness. It is an immensely useful tool for product development to establish the technology. Three main steps in technology development are preparing a strategy by setting the objective, selecting technology in the first development step and robust design in the second development step. Criterion in research and technology development process is defined. Objective of research is to find for “Blue Bird”[6], which means to create breakthrough technologies valuable to customers. In addition, Fuji Xerox uses DOE is when problem occurs. The purpose of DOE in troubleshooting the problem is to find the factors that change the mean value of characteristics. The difference between DOE and robust design engineering is critical to understand ensuring the suitability of the tool based on purpose. Company B divides the application into two production tools that are solving problem and optimization by changing the parameters. Design of Experiments (DOE) is used to solve problems occurred during production of a product or processes. If the problem is not due to variation, then DOE is useful to be used. On the other hand, robust design engineering is used when optimizing the performance of a product to increase its quality by changing the parameters using signal-to-noise ratio (SNR). In some cases, Company B has used both DOE and robust design engineering at a time. Robust design engineering and DOE are used most in product development phase which includes design phase and system selection phase that takes approximately 3 years. When entering online system, robust design engineering and DOE are not being used.

In management perspective, human skill to apply robust design engineering and DOE is developed tremendously in Company B which takes 5 years. Education in human resource is very important in product development stage and functionality development. Their engineers mostly have no background of robust design engineering and DOE. Therefore, Company B allocates the first hiring year to educate and train them on parameter design using MS Excel template, robust design, data analysis using robust design engineering book written by one of Company B employee, and DOE that includes ANOVA, one-way layout and two-way layout. The MS Excel template is consists of many orthogonal arrays such as L8, L9, L12, L18, L36, and such. In one year, there are ten times same training prepared by Human Resource division for engineers. In Figure 5.2, a methodology flow of robust design engineering is made after analyzing the implementation in Fuji Xerox and Company B to explain some tools used in an organization at each production process. Notice that DOE and Taguchi method have been placed separately. Other tools which are useful in each process or stage is also highlighted.

5.4 Findings from the Practical Experiment in Laboratory

Practical experiment using robust design engineering method is analyzed to compare its similarity with the measurement system in robust design engineering for industry. An optimization of T-peel test using Taguchi method is done to propose the feasibility of robust design engineering in practical experimentation. Standardized test method of T-peel test in measuring peel strength is established by JIS K6854 [7] and ASTM D1876 [8]. The limitation of the standardized method is the test only fit for rigid materials and not capable to apply on flexible film. Big variation in peel strength measurement due to specimen failure to hold the T-shape during peeling is a significant problem when standardized method is used on flexible film. This problem statement has motivated the researcher to come up with a system that can satisfy the industry requirement, which in this case is flexible packaging film. Thus, a new testing apparatus had been established to overcome this problem for flexible film. The case study is discussed on T-peel test optimization of flexible packaging film using the new apparatus. The objective is to obtain the minimum variation of peel strength. The goal of research and the technology used to deliver the goal have been integrated by applying robust design engineering. Three main steps mentioned in the Fuji Xerox's strategy of implementing robust design engineering are followed [2], that are objective setting (to satisfy the testing capability), technology selection (new apparatus for flexible film instead of using established method) to enable the functionality and finally robust design (optimization of T-peel test for minimum variation in flexible film). The study was carried out to identify factor's level that would minimize the variation in peel strength.

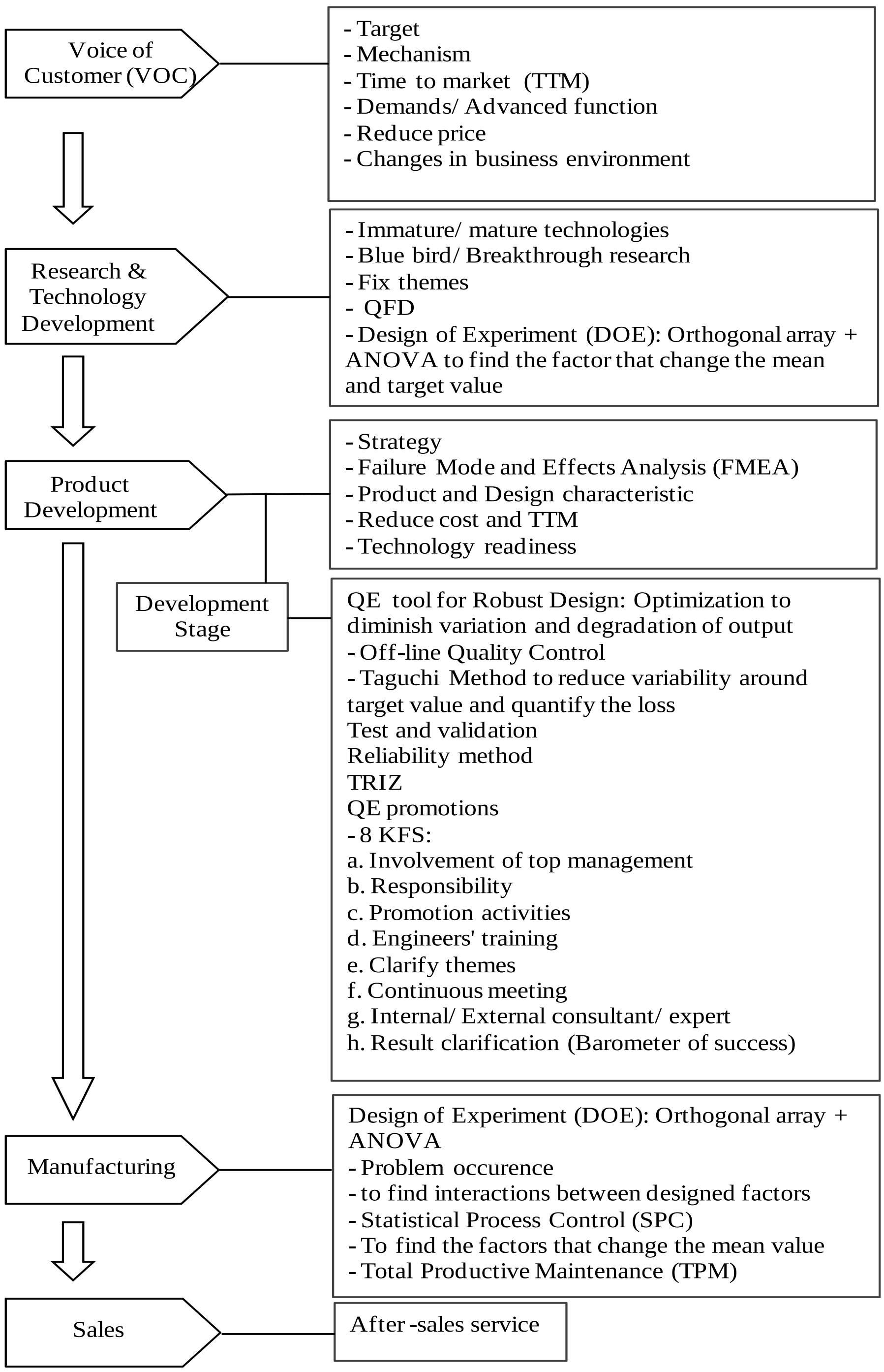

Figure 5.2: Robust design engineering implementation framework in an organization

5.4.1 Experiment Methodology

A dynamic ideal function was identified in this study, based on various range of specimen width. Y is the output energy that is peel strength. M is the input of signal factor that is various size of specimen width since it is desirable to have robustness within each width. Beta, β, is the measurement sensitivity to different inputs; thus the slope must be steep. Therefore, the dynamic ideal function is $Y=\beta M$. P-diagram in Figure 4.3 is constructed to give a whole picture on the parameters studied. The function of Al-CPP T-peel test is to measure peel strength. Thus, the response or output of T-peel test is peel strength, which measured in Newton (N). The input of T-peel test is known as signal factor. In the ideal function, the energy transformation occurs for three different specimen width that are 5mm, 10mm, and 15mm. Signal factor, in this study, is specimen width is a controllable variable to actualize the intention (variation in peel strength) to achieve robust condition regardless of various width condition [9].

In P-diagram, robustness is optimized by evaluating the control factors and their levels. Noise factor condition is varied accordingly to minimize variation that influences the response. Signal-to-Noise ratio (SNR) with dynamic response (equation 5.1) is used in this study due to the signal factor existence. A dynamic signal-to-noise ratio (SNR) has been used in this study, where the specimen width of 5mm, 10mm and 15mm as the signal factor is used to measure the peel strength linearity.

$$S/N \text{ ratio}, \ \eta = 10 \log (1/r) \left[(S_\beta - V_e) / V_N \right] \qquad (5.1)$$

where S_β = variation caused by the linear effect

V_e and V_N = error variance (error variance/DOF)

r = total number of measurements under signal

(r is also the effective divisor due to level changes of signal factor)

*DOF is degree of freedom

Then, noise strategy is done to investigate the noise factor that can reduce the variation in peel strength measurement. Noise factor is uncontrolled factor during normal production or use, but are controlled during the experiment. Noise factors are likely to produce variability in the response. For noise factor (outer array), historical data has proven that the peel angle would vary during exchanging the peel angle setting and during peeling process. Peel angle deviation will affect the peel strength; thus peel angle is considered as sources of variability. As shown in Figure 4.4, noise in peel angle is defined as deterioration in $\pm$ 2^o due to angle deviation during peeling caused by natural movement of the specimen. Maximum and minimum value of peel strength at +2^o and -2^o angle are taken for result. Thus, there are two noise levels that are N1 and N2 under each signal factor level. The intended condition is N1 has higher peel strength than N2 (N1 > N2). N1 consists of peel angle with deviation+2^o and maximum peel strength is taken as a result. On the other hand, N2 level consists of peel angle deviation

-2^o and minimum peel strength is taken as a result in outer array.

After completing the noise strategy, the selection of control factor is done. The objective of this T-peel test is to satisfy the industry requirement of getting the minimum variation for flexible film. Thus, select control factors that may affect variability in the response, and possibly the mean of the response. The controllable factors or inner array are chosen based on testing and design condition which possible to affect the variance. The controllable factor selection is also considered based on previous experiment result, preliminary test, theory and available knowledge, and expert's opinion. For example, previous experiment result in L9 orthogonal array uses tensile weight as noise factor. However, there is no significant trend in the peel strength based on 8g and 4g tensile weight. It is concluded tensile weight does not produce variability, but likely to affect the response. Thus, tensile weight is one of the control factors in L18. Tensile weight used for keeping the specimen in T-shape, peel angle, peel speed and peeling curve region are controllable factors considered based on testing condition. Parallel spring thickness, module of spur gears and drum diameter are considered based on design of apparatus condition. The factor's level is decided based on objective. The level must not be so close to each other that the effect on the response is not observable or undetected. Level must also not very far apart that there is a region of unknown process behavior. Previous process knowledge is useful to determine the level. For example, three levels is chosen to observe the curvature effect on the response. Two levels are chosen to determine whether the factor has an effect on the response. More than three levels are suitable to observe significant trend or behavior, such as sudden rise or drop at certain levels.

The experimental design space is large, and it needs a strategy to explore. After determining the control factors and factor's level, they are assigned into an orthogonal array. An orthogonal array is used for optimization to maximize the signal-to-noise ratio [10]. Balance set of experimentation runs is provided by orthogonal array. Design of experiments using orthogonal array L_{18} is utilized with one two-level factor (tensile weight) and six three-level factors (peel angle, peel speed, data region, spring thickness, module of spur gear and drum diameter) as shown in Table 5.1. In L_{18}, only 108 observations implied (18 runs x 3 signal level x 2 noise level).

Table 5.1: Experimental set up (a) and Orthogonal array (b)

(a)

Control Factor	*Unit*	*Level 1*	*Level 2*	*Level 3*
A : Tensile weight	g	4	8	
B : Peel angle	º	60	90	120
C : Peel speed	mm/s	6	9	12
D : Data region	%	30	50	70
E : Spring thickness	mm	0.3	0.4	0.5
F : Module of spur gear		0.5	1.0	2.0
G : Drum diameter	mm	20	30	40
Signal Factor			*Levels*	
M : Specimen width	mm	5	10	15
Noise Factor		*Level N1*	*Level N2*	
Peel Angle	θ	+2	-2	
Peel strength sampling	N	Maximum	Minimum	

(b)

								5mm		10mm		15mm	
	A	B	C	D	E	F	G	N1	N2	N1	N2	N1	N2
1	1	1	1	1	1	1	1						
2	1	1	2	2	2	2	2						
3	1	1	3	3	3	3	3						
4	1	2	1	1	2	2	3						
5	1	2	2	2	3	3	1						
6	1	2	3	3	1	1	2						
7	1	3	1	2	1	3	2						
8	1	3	2	3	2	1	3						
9	1	3	3	1	3	2	1						
10	2	1	1	3	3	2	2						
11	2	1	2	1	1	3	3						
12	2	1	3	2	2	1	1						
13	2	2	1	2	3	1	3						
14	2	2	2	3	1	2	1						
15	2	2	3	1	2	3	2						
16	2	3	1	3	2	3	1						
17	2	3	2	1	3	1	2						
18	2	3	3	2	1	2	3						

5.4.2 Handling the Result of Experiment

There are two main plots obtained from the measurement data of robust design engineering method that are SNR response plot and Sensitivity (beta) plot as shown in Figure 5.3 and Figure 5.4 respectively.

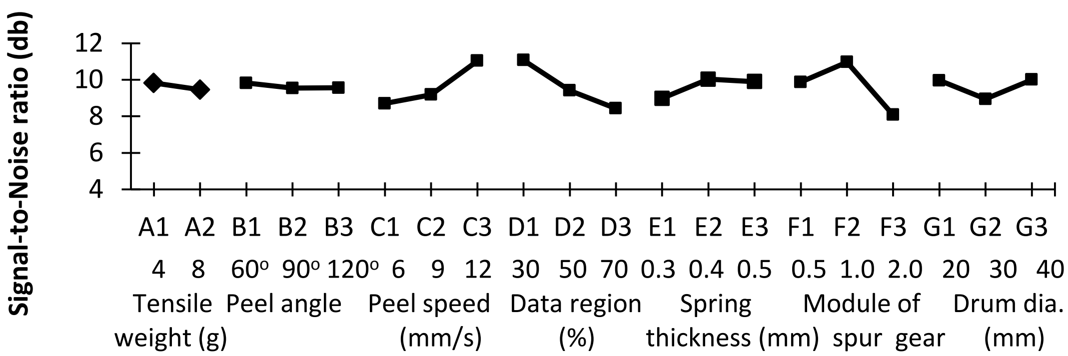

Figure 5.3: SNR response plot

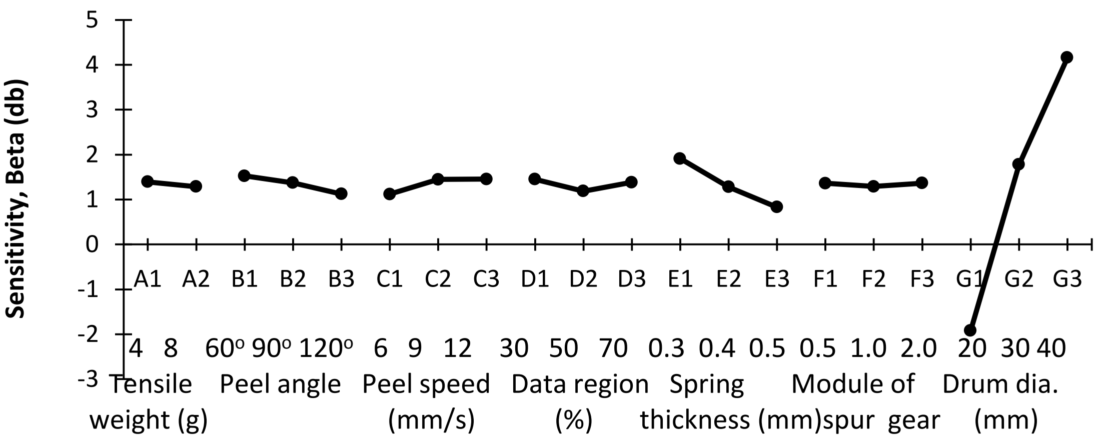

Figure 5.4: Sensitivity (Beta) Plot

SNR plot is obtained by computing the average SNR at each level of a process parameter. It explains the variation effect of each level of a factor. The maximum level of SNR value in each factor is taken as the optimum condition implies the minimum variation as the signal is bigger than noise. Sensitivity response plot, often called as Beta plot shows the sensitivity of response value at each level. It has no relation with variation, only focus on sensitiveness of response upon level's change. A confirmation run is done to check the reproducibility of the experiment. SNR in optimum condition is compared with worst condition. DB gain for confirmation SNR is differed by 2.86 dB than estimated SNR. The dB gain difference is caused by the worst condition as confirmation SNR deviates a little bit from the estimated SNR for worst condition. The repeatability of worst condition is not quite reasonable compared to optimum condition. As this confirmation experiment data is practical and actual, the dissimilarity of SNR in the worst condition is suspected due to testing condition and environment. Table 5.2 summarized the optimum and worst condition and dB gain. Second step in two-step-optimization is to adjust the controllable factor to target value. The second step is done when certain target is desired. The best factor to adjust is drum diameter (factor G) because of high sensitivity, and SNR is roughly even. Thus, the variability in peel strength is not influenced by different level of that factor. Factors with even sensitivity and uneven SNR as C, D and F are particularly useful to improve variation because the value of peel strength has no change. As this experiment data is practical and actual, the dB gain dissimilarity between estimated and confirmation result is suspected due to variation in experiment handling and environment.

Table 5.2: Optimum condition and SNR dB gain

Type	Condition	Estimated SNR (dB)	Confirmation SNR (dB)
Optimum	A1 B1 C3 D1 E2 F2 G3	14.91	14.82
Worst	A2 B2 C1 D3 E1 F3 G2	4.30	7.07
SNR dB Gain		10.61	7.75

5.5 Result and Discussion from Industry and Practical Experiment Observation

Robust design engineering implementation in Fuji Xerox is explained from the beginning of the implementation. Production tool and methodology of some case studies given by Fuji Xerox is analyzed and compared with practical experiment done in the laboratory. Figure 5.4 shows the comparison between robust design methodology in laboratory case study (Figure 5.4a) and Fuji Xerox case study (Figure 5.4b). Fuji Xerox's flow is started by problem identification that motivates what kind of improvement to be done. Based on three case studies, problems can be coming from industry requirement, customer dissatisfaction [11], technology obsoleteness [12], cost reduction driven, system improvement [13] and such. Sakanobe et al. [11] emphasized on the relationship between output (Y) and problem statement to generate signal factor that transforms the energy. Optimization is conducted with the ideal function. In laboratory, problem is known from available standards and further optimization is done for the betterment of the new developed apparatus. Similarly, the output Y (peel strength) is related with the known problem (big variation) to generate the ideal function. Both flows focused on selection of quality characteristic which describe on the desired result. Quality characteristic is defined from the measured value of the objective, which referred to response, results or output [14]. Ideal function and P-diagram are identified after problem statement is done. Confirmation run in Fuji Xerox is done on trial manufacture while case study is done with laboratory scale. In Fuji Xerox, quality is monitored after-launch to society upon the in-house quality result is official.

The methodology flow of robust design engineering is approximately similar between laboratory case study and Fuji Xerox. It is proven that robust design engineering tool can be applied in any environment, be it industrial application or research field. Results from methodology comparison in Figure 5.5a and 5.5 b is used to produce a framework on how to apply robust design engineering method to obtain robustness of a product or process. The experience from L18 in selecting control and noise level is presented and need to be carefully done. The robust design engineering methodology is developed using information from Fuji Xerox and Company B measurement data is shown in Figure 5.6 and briefly described as follows:

Step 1: Enable functionality of the system. Carefully analyze the ideal function that transforms the energy into quality characteristic. Construct P-diagram to get a whole picture of the system.

Step 2: Identify the problem by selecting the response based on experiment's objective. The response may be maximized, minimized, or taken to a target value. The mean and variance of a response can be studied simultaneously. Construct an ideal function and P-diagram. Determine the input (signal factor) and output (response) of the experiment.

Step 3: Select noise factor and level for outer array. Relate with response objective, for example if the objective is to minimize variation of peel strength, make sure the noise factor can produce the variation in peel strength and the design space is covered as best as it can. Three noise layouts are decided to be done as the possibility of variation is satisfactorily covered.

Step 4: Select control factor and level for inner array. Consideration of factor level must in line with objective or intended effect on the response such as curvature, effect presence and other behavior or trend.

Step 5: Construct an orthogonal array based on number of factors and levels. Implement an experiment based on Taguchi method. SNR and sensitivity response plot are analyzed.

Step 6: Check on reproducibility. Estimation and confirmation db gain is compared. Rule of thumb of less than 3db gain difference is preferable.

Step 7: Next step is adjustment. It is done if the intention is to move the mean to target. If there is no intention to move the mean to certain target, step 1 to 6 is sufficient enough.

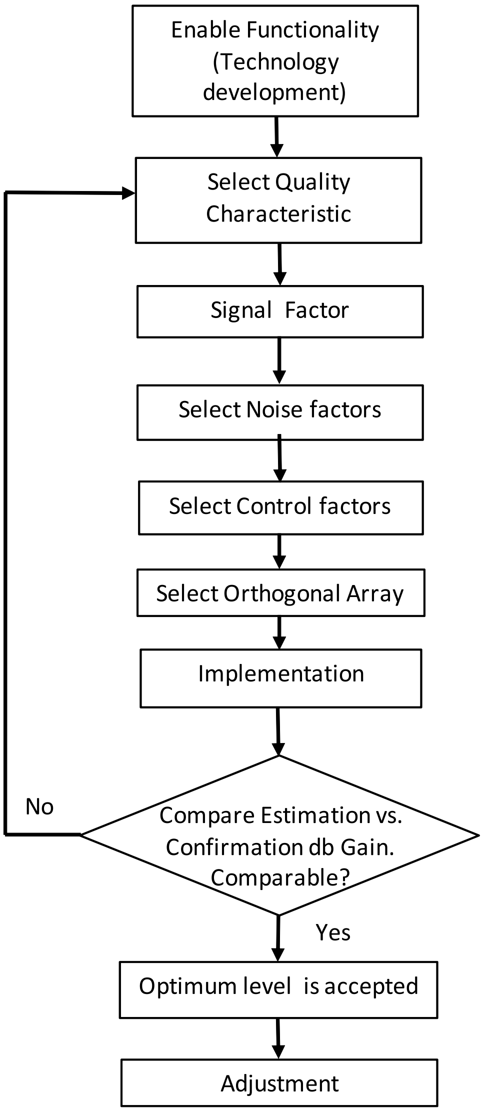

Figure 5.5 (a): Laboratory case study

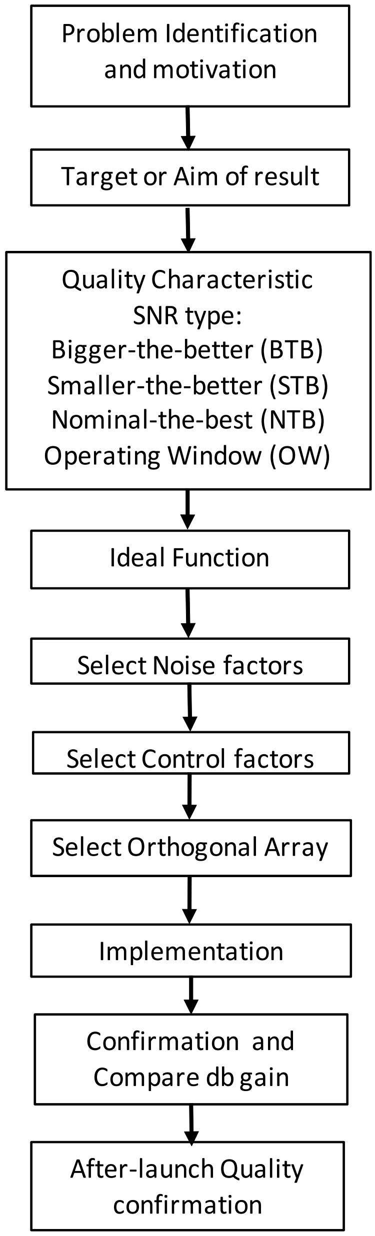

Figure 5.5 (b): Fuji Xerox case study

This chapter had presented an implementation of robust design engineering in an organization and robust design engineering application in process or product optimization through practical case study. Robust design engineering has proven successful and is emphasized during the design stage before manufacturing or production to find the design parameters and ensure the product`s robustness.

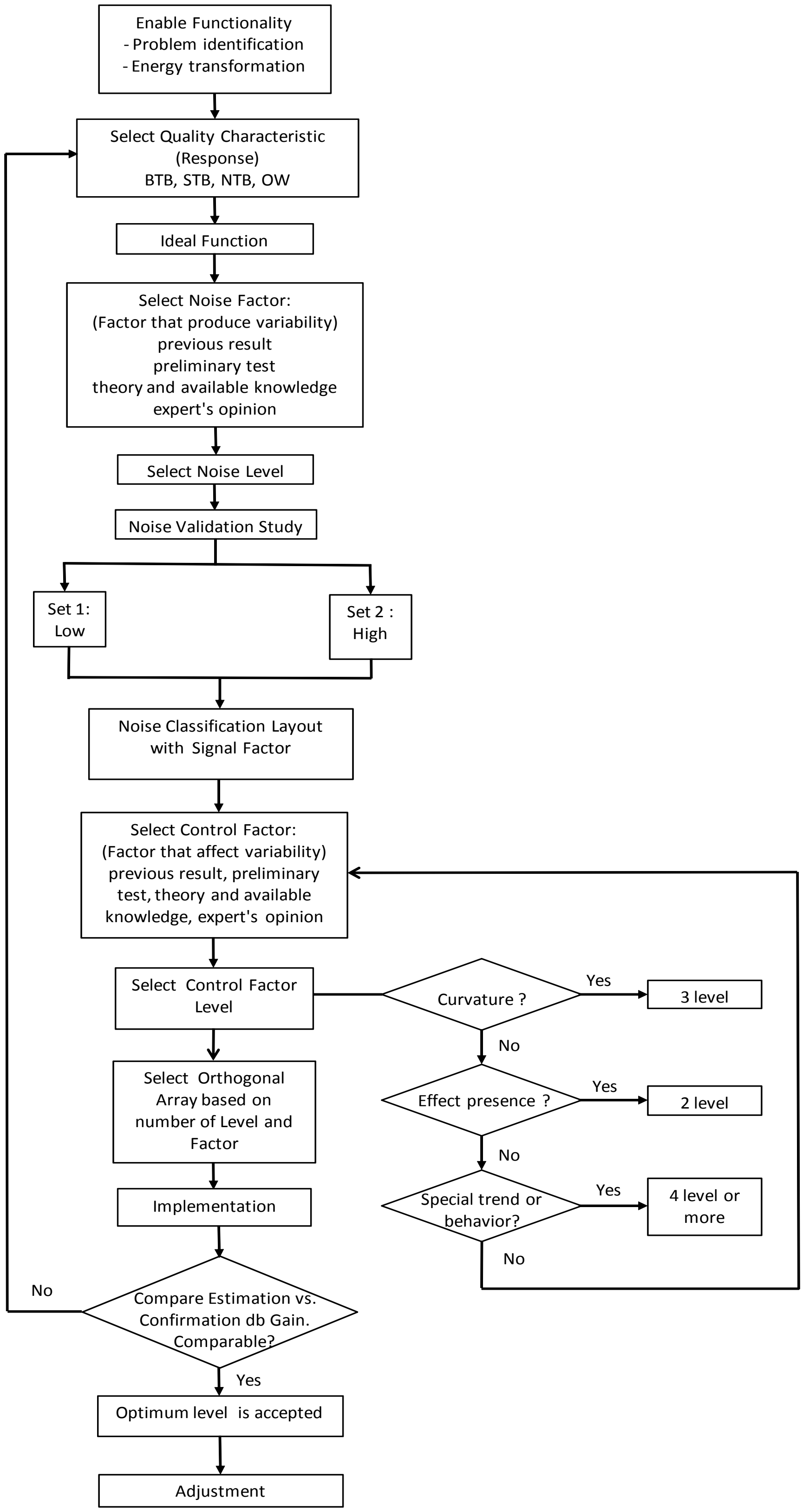

Figure 5.6: Methodology framework for robust design engineering

Fuji Xerox hypothesis of Key Factors for Success has helped promoting robust design engineering in research, technology development and product development activities. Robust design engineering promotion activities accelerate the implementation in an organization. Top-down approach is undeniably a driving force for a successful robust design engineering implementation. The case study represents on how robust design engineering is implemented in one of the product optimization.

Identifying the experiment's objective is crucial that affect the selection of noise and control factors. General guidelines are described step-by-step from selecting the response up to decision making on the optimum dB gain. The engineering tool employs the engineering and statistic knowledge to obtain product robustness. A brief framework is presented for robust design engineering implementation in organization and procedures on robust design engineering methodology. The finding of quality engineering implementation in industry and laboratory to create a methodology framework is presented in R. Dolah et al. [15]. Continuous research on improving the methodology will be done, not only focusing on one type of industry. In robust design engineering methodology, planning before implementation is a key element for performing a successful experimental design.

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CHAPTER 6 PARAMETER DESIGN OF A MEASUREMENT SYSTEM

This chapter describes the next step of research methodology using practical experiment. The measurement system in robust design engineering is further analyzed and its finding is used to develop a systematic measurement system. As previous chapter presents about the measurement in industries in terms of application, this chapter explains the basic of measurement system in terms of foundation of measurement data.

6.1 Practical Experiment using an L9: Selection of Multiple Optimum Condition and Optimum Condition Determination

An experimental design is employed using an orthogonal array with four control factors consisting of peel angle, peel speed, data region, and spring thickness. The variation caused by the different peel surfaces of each specimen is investigated to observe which peel side gives the best condition for the T-peel test. Three optimum conditions for flexible film are discussed: the aluminum peel side condition, the CPP peel side condition, and the harmonized condition. Based on the signal-to-noise ratio (SNR) used to evaluate the improved condition in a confirmation test, the CPP peel side has the highest SNR, followed by the aluminum peel side and then the harmonized condition. The SNR for the CPP peel side condition increased by 22% from the aluminum peel side condition; thus, it is advised that the CPP peel side condition be used. The SNR of the harmonized condition is lower than the CPP and aluminum conditions, but it provides a convenient design that can be used without regard for peel side.

Multilayer packaging film is produced from a single layer film product glued together by several lamination processes or coated with additional polymer layers [1] . Lamination acts as a material assembly and functions to fulfill the optimum combination. There are many methods to evaluate the lamination strength, including peel, shear, cleavage, and tension tests. Peel tests are most commonly used to evaluate the laminated film or bonded adhesives. The T-peel test is best used due to similar and flexible measurand. The peel strength of multilayer film is one of its most important properties in terms of its practical use as a packaging product. The study evaluates this property using the standardized T-peel test method of the American Society for Testing and Materials ASTM D 1876-08 [2] and Japanese Industrial Standard JIS K 6854-3 [3] . The evaluation of peel strength between interlayer films is performed by measuring the force required to peel away two layers. The T-peel test in standardized methods ASTM and JIS have been well established for a rigid adherend, but the capabilities of these methods are limited when carrying out tests on flexible film, due to the failure of flexible film to maintain the T-shape and sustain the peel angle, which leads to wide variations in test outcomes [4] . Miyagi and Koike [5] showed that peel angle is significant and recognized among the main effect, as calculated in analysis of variance in peel strength evaluation using a T-peel test. Choi et al. [6] described the influence of peel angle on peel strength as measured by a T-peel test on the Cr/BPDA-PDA interface. The peel strength increased with increased peel angles.

Peel strength is influenced by peel angle, thus, it is important to ensure the stability of the peel angle during a T-peel test. Hence, this study developed a new T-peel test apparatus for flexible materials in order to solve the variation and stability problem of the peel angle during peel testing. This testing apparatus was used to create an experimental design method to optimize peel strength with minimum variation using a parameter design method. In this paper, optimization describes the optimum setting of controllable factors that results in minimum variation in response. The optimum setting is said to have an insensitive characteristic to variation, and is thus robust. Parameter design is an engineering methodology in the robust design engineering method. It is a robust and effective approach to design quality into products and processes [7] .

The parameter design method has been widely applied for optimization in peel test [5][8]. An attempt was made to estimate the optimum condition for the T-peel strength of printing wiring boards using a robust parameter design method [5] . Miyagi and Koike analyzed the effect of drum diameter, module of spur gear, peel angle, and tension as observed using SNR. The standard deviation of peel strength in the optimum condition was reduced from that of the original condition. R. Dolah et al. [9] presented on how parameter design in quality engineering affects global product performance by considering peel strength as one of the case study. Unal and Dean [10] described the Taguchi approach to design optimization for quality and cost. R. Dolah et al. [11] addressed the benefit of the Taguchi method in an organizational context by using real industry case studies and practical T-peel adhesion tests in laboratories. The Taguchi method is often called quality engineering in Japan; it has proved undeniably useful for variation improvement and certainly increases product and process performance. Factors or parameters were selected based on previous experience, engineering knowledge, and literature reviews. Matsuda et al. [12] evaluated the reliability of the T-peel test method for laminated flexible film by controlling for specimen width, peel angle, peel speed, and diameter of drum.

This chapter presents the practical case studies that aimed to satisfy the testing capability for Al/CPP flexible packaging film by optimizing the T-peel test in order to obtain the minimum variation of peel strength. Thus, the objectives of this paper are to present the procedure to optimize the T-peel test using the new testing apparatus and determine the optimum conditions for testing flexible film by using the robust parameter design method. The benefit of the parameter design method is explained through the optimum conditions and harmonization results.

6.1.1 Robust Design Engineering – Parameter Design

The parameter design is applied to optimize the T-peel test using a new apparatus with peel strength as the measured quality characteristic. The main function of the testing apparatus is to measure peel strength. This apparatus is newly developed to encounter the variation problem that occurs when the standardized method is used. As a new apparatus, its optimum setting of parameters is unknown. This paper determines the optimum condition for peel strength by minimizing variation in flexible film testing. Robustness of the apparatus is important, as it will contribute to the improved quality of flexible film. Control factors are optimized by taking into account the variation caused by variables that cause product functions, also called noise. There are three types of noise: outer noise, which is caused by environmental conditions; inner noise, which is caused by the deterioration of elements or materials in the product; and between-product noise, which is caused by piece-to-piece variations between products. In this paper, control noise is selected from the design condition and testing condition. The design conditions are spring thickness and peel angle. The testing conditions are peel speed and data region. Noise is considered to be the factor that caused variations in peel strength measurement results using the standardized method. By adding noise into the experimental design, the testing apparatus will be made robust against variation. Deviation in peel angle during the peeling process is noise to peel strength. Therefore, the new testing apparatus undergoes parameter design to select the best control-factor-level combination, so that the effect of all the noise can be minimized.

The optimization approach starts with the research motivation to establish a procedure on T-peel test optimization followed by a determination of optimum conditions. Figure 6.1 shows step-by-step directions of the robust parameter design method used in this paper [11]. An experimental confirmation test was performed to validate the estimated condition of three optimum conditions. The first step enabled functionality of the system. The ideal function was carefully analyzed and the P-diagram was constructed. Then, SNR type was chosen based on quality characteristics. In this paper, the quality characteristic measured is peel strength [Y]. Dynamic SNR was used when signal factor (specimen width) is used. Next, noise factor and its level were selected. Outer array design was established with signal factor consideration. Control factor and level were selected for inner array design. Finally, a suitable orthogonal array was chosen based on noise and control factors. The SNR factorial effect plot and sensitivity plot were used in parameter design evaluation. Reproducibility of the optimum condition was analyzed through a confirmation test. The optimum level was determined and analyzed based on several criteria and objectives.

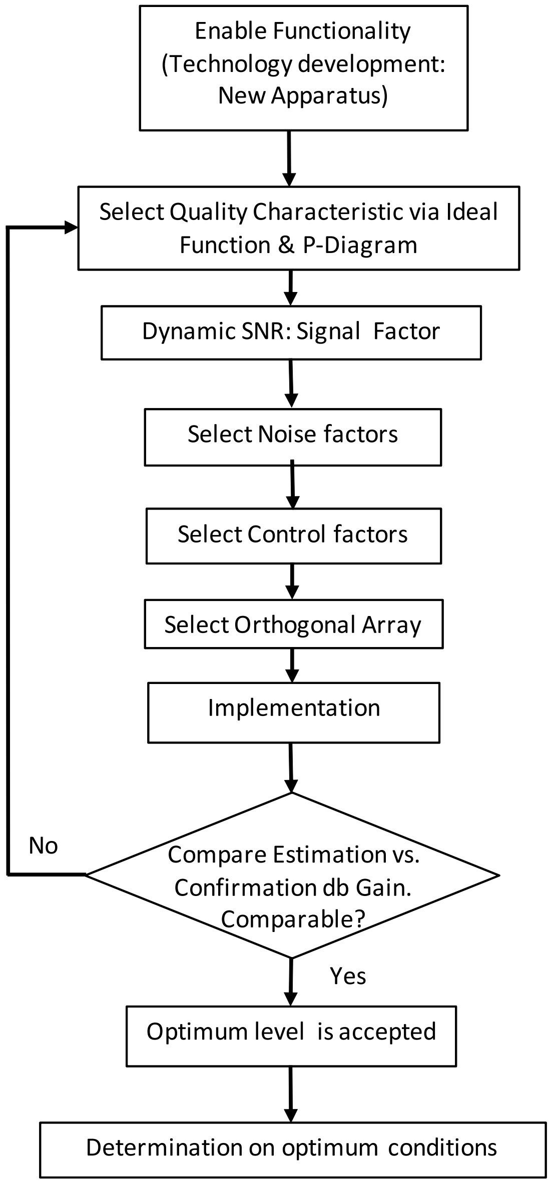


Figure 6.1: Flow chart of research methodology [11]

6.1.1.1 Ideal Function and P-Diagram

In the parameter design component of the Taguchi method, a system with zero or minimum noise is desired. Zero or minimum noise is achieved when the variation gap is the smallest possible to produce an ideal function. Peel strength (Y) is the quality characteristic or output to be measured. As a signal factor, specimen width (M) is a controllable variable used to actualize the peel strength to achieve a robust condition, regardless of the various range of specimen widths. Beta (β) is the measurement of sensitivity. The linearity of peel strength is defined as a zero-point proportional equation, where the output is zero when the signal is zero [13] . Thus, the ideal function is expressed as $Y=\beta M$, as shown in Figure 2.1, Chapter 2.

The purpose of parameter design is to evaluate the overall variation caused by noise when levels of the control factors are allowed to vary widely. The control factors vary according to the experimental design, which takes noise into account to investigate overall variation. Noise 1 (N1) and Noise 2 (N2) are noise level introduced in the experimental design. The measurement data is the result of the interaction between control factors and noise to ensure the robustness of peel strength. Variation in this study is contributed by peel angle deviation and tensile weight, as these affect the T-shape of the specimen during a peel test. The optimum condition provides a robust setting for peel strength, at the y-axis, as the noise does not affect the measurement data and peel strength is plotted ideally as a linear function under various ranges of signal levels at x-axis. Figure 6.2 shows a P-diagram that summarizes the parameters studied in this paper (signal factor [M], quality characteristic [Y], noise factor, and control factor). Constructing a P-diagram is an important step in the Taguchi method, and must be done before any experiment is carried out.

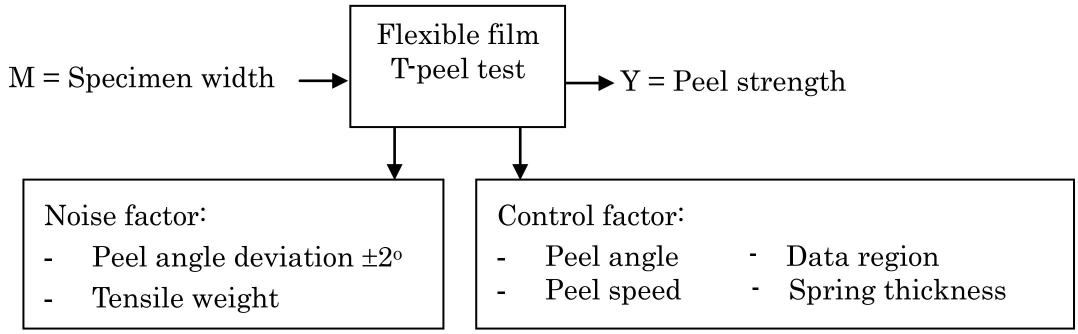


Figure 6.2: P-diagram for T-peel test

6.1.1.2 Signal Factor

Signal factor is a controllable variable that helps to actualize the intention. The width of the specimen is a signal factor used as a medium to actualize the intention of getting the peel strength result. Three widths are used (5mm, 10mm, and 15mm) to measure peel strength linearity. From preliminary studies, the wider the specimen width, the greater the peel strength is. Peel strength increase proportionally to specimen width. This can be observed solely with different spring thickness. The displacement, *d*, represented by parallel spring had increased as specimen width increased (Figure 6.3).

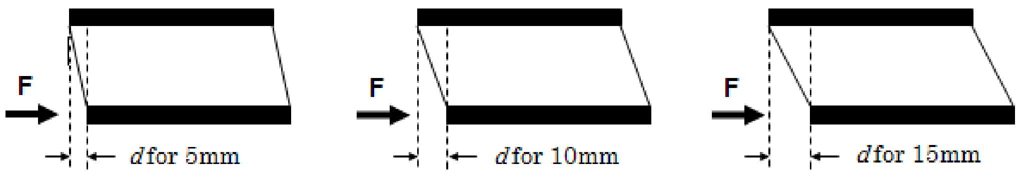


Figure 6.3: Displacement, *d*, by each specimen width

Higher strength needed to peel away the adherend from the adhesive as specimen width grow bigger. The strength of these joints between cast propylene, aluminum and adhesive in between is related to stress. Stress measures the average strength per unit area of a surface (equation 6.1).

$$\sigma = F / A \qquad (6.1)$$

where F = strength

A = cross-sectional area

σ = stress

Strength is proportional to surface area, thus higher strength needed to peel 15mm specimen width film. This is supported by Bikerman, J.J [14] , showed that the peel strength is proportional to width of adhesive tape, adhesive thickness and tensile strength of the adhesive (equation 6.2).

$F = w\ t_a\ \sigma$ (6.2)

where w = width of tape

t_a = adhesive thickness

σ = tensile strength of the adhesive

Due to tensile deformation during peel test, the cast propylene film showed necking. Tensile stress lead to expansion (necking), with the volume of the film remain constant. The film size or width decreased in cross-sectional area (Poisson effect). The necking phenomena caused a linear increase in strength [10] . During necking, the film can no longer bear the maximum stress and the strain increased. As a result, the cast poly propylene ended up with plastic deformation as shown in Figure 6.4. Necking occurred severely with higher peel rate.

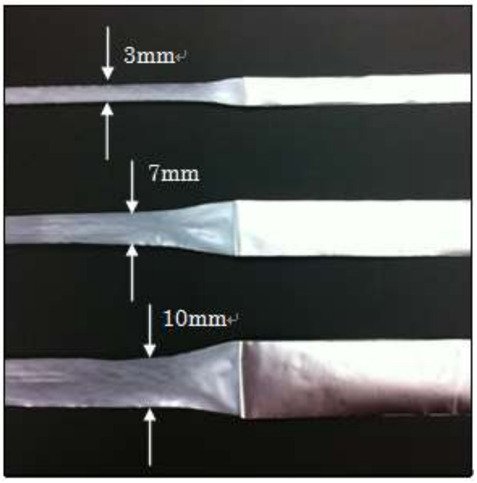


Figure 6.4: Necking example in 12mm/s peel speed for specimen width 5mm (top), 10mm (middle) and 15mm (bottom)

Hence, the signal to noise ratio (η) for dynamic response is used in this study to measure various ranges of input to ensure robustness.

SNR is a metric for robustness and is defined as:

SNR, η = power of signal/power of noise

$= (\text{sensitivity})^2/(\text{variability})^2$

$= \beta^2/\sigma^2$ (6.3)

The term σ^2 is the variation in data by noise factor conditions under Noise 1 and Noise 2. In SNR, β^2 is the numerator. Therefore, SNR, η, in decibel unit (dB) for dynamic response is

$\eta = 10 \log [(1/(r_o \cdot r)) (S_\beta - V_e) / V_N]$ (6.4)

where S_β = variation caused by the linear effect,

V_e = correction error variance (error variance/degree of freedom [DOF]),

V_N = compounded noise factor when signal factor is introduced,

r_o = total number of measurements under one signal level, and

r = effective divider representing a magnitude of input due to level changes of signal factor.

Sensitivity, β, in decibel unit, is calculated as:

$\beta = 10 \log [(1/(r_o \cdot r)) (S_\beta - V_e)]$ (6.5)

To maximize robustness one must maximize SNR; thus, the system is insensitive to variation. Sensitivity, β, is analyzed to adjust the slope, which helps determine the desired target of peel strength.

6.1.1.3 Noise Factor Selection

Noise factors are likely to produce variability in response. Two noise factors are considered in the study: peel angle deviation $\triangle \pm 2^o$ and tensile weight *w*. Peel angle is adjusted to three levels: 60^o, 90^o, and 120^o. Peel angle $\pm 2^o$ is a noise factor because it is possible to have an inaccurate reading if the peel angle is changed by the angle adjuster.

In addition, peel angle is deviated about $\pm 2^{o}$ during the peeling process because of natural movement, as shown in Figure 6.5. Thus, the noise in peel angle is defined as deviation $\pm$ 2^{o} for each level. Noise 1 is the higher level (*N1* = $+2^{o}$ and 8g) and Noise 2 is the lower level (*N2* = -2^{o} and 4g).

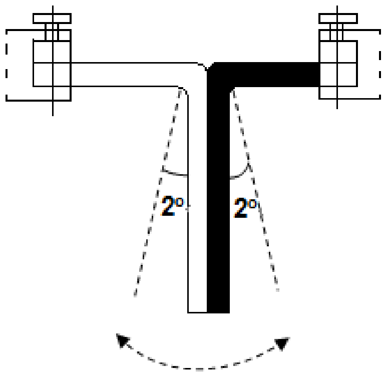


Figure 6.5: Deviation in peel angle during T-peel

6.1.1.4 Control Factor Selection

Based on the literature review, the peel test is the most common test to measure the peel strength of adhesion. Thouless [15] stated that peel strength is generally affected by geometry, essential properties of film and substrate, and cohesive properties of the interface. In this study, four three-level control factors are evaluated: peel angle, peel speed, peel strength data region percentage, and spring thickness. The geometrical terms include the peel angle (^{o}), peel speed (mm/s), and specimen width (mm).

The standard JIS analysis of peel strength data region is considered to minimize variability in data measurement. The unit for peel strength data region is percentage. JIS standard is a 30% data region. Three data regions are evaluated in this experiment: 30%, 50%, and 70%. In the 30% region, the center data is collected at a constant peak of the peeling process by discarding 35% right and 35% left of the flat region in a peel strength curve. In the 50% data region, 25% data is discarded to right and left, while in the 70% data region, 15% right and 15% left data is discarded. Figure 6.6 shows the relevance of each data region to the overall data.

Spring thickness represents the stiffness occurring when the specimen is being peeled. Three spring thicknesses were evaluated: 0.3mm, 0.4mm, and 0.5mm. All springs were 70mm in length.

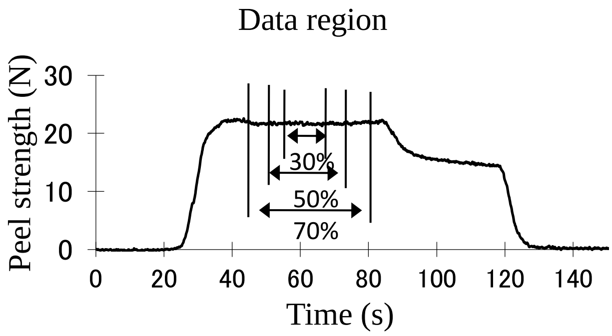


Figure 6.6: Data region in peel strength curve

6.1.1.5 Orthogonal Array

An orthogonal array is a balanced set of experimentation runs that explore the design space with a small number of experiments [16] . L9 orthogonal array was chosen to study the effect of the four three-level control factors on peel strength. Of the experiments, 54 applied for one orthogonal array (9 x 3 signal level x 2 noise level). Table 6.1 summarizes the factors used in L9. Control factor level is denoted as 1 for a level 1 setting, 2 for a level 2 setting, and 3 for a level 3 setting. Control factors are called inner array and noise factors are called outer array. The plan is referred to as a robust parameter design.

Table 6.1: Factors studied in L9

	Control factor	*Unit*	*Level 1*	*Level 2*	*Level 3*
A :	Peel angle	º	60	90	120
B :	Peel speed	mm/s	6	9	12
C :	Data region	%	30	50	70
D :	Spring thickness	mm	0.3	0.4	0.5
	Signal factor			*Levels*	
M :	Specimen width	mm	5	10	15
	Noise factor		*Level N1*	*Level N2*	
	Peel angle deviation, Δ	º	+2	-2	
	Tensile weight, *w*	g	8	4	

Notice that the peel angle of the T-peel test can be either at the aluminum side or the

CPP side. Figure 6.7 shows the schematic diagram of each peel angle layout, defined based on surface material. The peel angle of the aluminum side is called aluminum peel side (Al/CPP) and the peel angle of the CPP side is called the CPP peel side (CPP/Al).

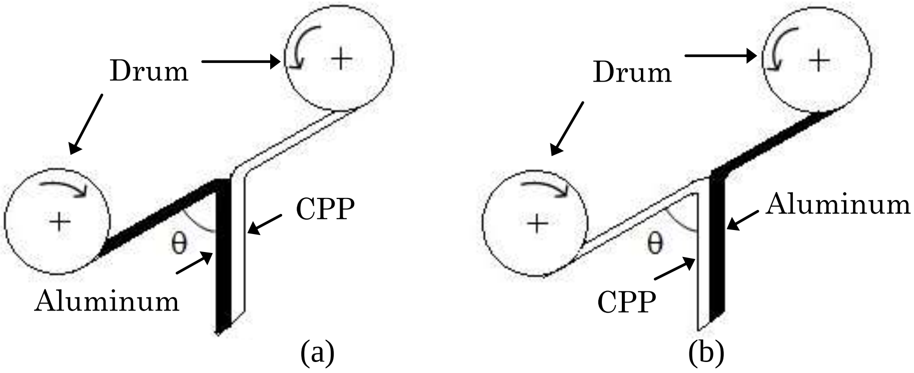


Figure 6.7: T-peel test schematic diagram of (a) Aluminum peel side: Peel angle 60^o at aluminum side and (b) CPP peel side: Peel angle 60^o at CPP side

For a clearer example, let's read the 60^o peel angle from the aluminum side. The 60^o aluminum (Al) peel angle provides a 120^o CPP peel angle, and vice versa. In the orthogonal array, all nine experiment numbers are assigned orthogonally in L9 for each parameter level. For example, in experiment number 1, the 60^o peel angle at the aluminum side is tested at a 6mm/s peel speed, 30% data region, and 0.3mm spring thickness. The peel strength is different from when the peel angle is tested from 60^o CPP peel side, because the peel angle of the aluminum side in the latter situation is 120^o. Thus, the peel side is crucial to evaluate the effect on optimum peel strength. Two sets of L9 were therefore performed. The first one used an Al peel side and the other used a CPP peel side.

Each L9 has 53 degrees of freedom with three signals and two noise levels. Two L9 were performed to study the effects of the aluminum peel side and CPP peel side on peel strength. The feasibility of the testing procedure was then evaluated, and both optimum conditions were harmonized into one condition called a harmonized design. This was done to determine an optimum condition that can be used by both peel sides. This trade-off method is useful when involving the different materials of flexible film.

6.1.2 Experimental Results and Discussions

6.1.2.1 Signal to Noise Ratio Analysis

Measurement data for all nine runs were collected under a signal factor that has a specimen width of 5mm, 10mm, and 15mm with two noise levels, *N1* and *N2*, in each signal. The results of 54 peel strength tests were measured in Newton, N (9 x 2 noise level x 3 signal level), obtained on the aluminum peel and CPP peel sides, respectively. The optimum condition for flexible film was obtained from the SNR process average. Since each peel angle surface has a different effect on the optimum condition, the aluminum peel angle surface and CPP peel angle surface results were analyzed separately. Table 6.2 shows the measurement results for the aluminum peel side.

Table 6.2: Aluminum peel side result: Peel strength, signal to noise ratio η, and sensitivity β

					5mm		10mm		15mm		SNR	Sensitivity
Run	A	B	C	D	N1	N2	N1	N2	N1	N2	η	β
1	1	1	1	1	8.70	8.37	16.62	16.78	24.96	24.09	12.40	4.35
2	1	2	2	2	8.04	8.12	15.28	16.21	23.91	24.52	11.79	4.10
3	1	3	3	3	8.72	8.09	16.59	16.36	24.49	24.30	15.15	4.28
4	2	1	2	3	7.79	8.04	15.68	15.86	23.87	24.38	15.97	4.07
5	2	2	3	1	8.45	8.41	16.49	16.20	24.12	23.99	14.85	4.18
6	2	3	1	2	8.26	8.18	15.51	15.80	24.43	24.32	13.28	4.13
7	3	1	3	2	7.59	7.74	14.77	15.15	22.16	22.20	16.76	3.45
8	3	2	1	3	7.46	7.69	15.03	15.83	22.68	23.58	11.82	3.75
9	3	3	2	1	8.49	8.27	15.87	16.29	23.76	24.09	14.43	4.11

Table 6.3 shows the measurement result for the CPP peel side result. The peel side affects the control factor of peel angle, thus presents different measurement result.

Table 6.3: CPP peel side result: Peel strength, signal to noise ratio η , and sensitivity β

					5mm		10mm		15mm		SNR	Sensitivity
Run	A	B	C	D	N1	N2	N1	N2	N1	N2	η	β
1	1	1	1	1	8.08	7.98	16.08	15.84	23.34	23.68	17.1	3.96
2	1	2	2	2	7.45	7.27	14.70	15.02	22.60	22.52	18.83	3.50
3	1	3	3	3	7.42	7.68	15.12	15.35	22.98	23.07	20.61	3.69
4	2	1	2	3	6.91	6.96	14.22	14.36	21.43	21.52	19.75	3.09
5	2	2	3	1	8.43	8.44	16.71	16.49	24.02	23.61	10.67	4.16
6	2	3	1	2	8.12	8.24	15.70	16.06	23.65	23.97	17.34	4.03
7	3	1	3	2	7.62	7.42	15.03	14.86	22.81	23.00	17.48	3.61
8	3	2	1	3	7.43	7.64	15.01	14.99	22.94	23.17	16.60	3.66
9	3	3	2	1	8.15	8.52	16.76	16.68	23.99	24.21	12.37	4.24

Peel strength (N) result was obtained upon test conditions using the parameter design. Thus, for run 1 in Table 3.3, SNR and sensitivity (unit: dB) were calculated by using equations (6.4) and (6.5) respectively.

Total variation:

$$S_T = \Sigma\, y_i^2 \qquad (6.6)$$

$$= 8.70^2 + 8.37^2 + 16.62^2 + 16.78^2 + 24.96^2 + 24.09^2$$

$$= 1907.03 \qquad (f_T = 6)$$

Variation of proportional terms:

$$S_\beta = \frac{(M_1y_1 + M_2y_2 + \ldots. + M_ky_k)^2}{r_1M_1^2 + r_2M_2^2 + \ldots + r_kM_k^2} \qquad (6.7)$$

$$= \frac{((8.70+8.37)5 + (16.62+16.78)10 + (24.96+24.09)15)^2}{2(5^2+10^2+15^2)}$$

$$= 1906.25 \qquad (f_\beta = 1)$$

Variation of differences between proportional terms, $S_{N\times\beta}$:

$$= \left\{ \frac{((8.70x5)+(16.62x10)+(24.96x15))^2+((8.37x5)+(16.78x10)+(24.09x15))^2}{(5^2+10^2+15^2)} \right\} -1906.25$$

$= \quad 0.24 \qquad\qquad (f_{N\times\beta} = 1)$

Error variation:

$S_e = S_T - S_\beta \; - S_{N\beta} \qquad\qquad (6.8)$

$= 1907.03 – 1906.25 – 0.24$

$= 0.543 \qquad\qquad (f_e = f_T - f_\beta - f_{N\times\beta} = 4)$

Error variance:

$Ve = S_e / f_e \qquad\qquad (6.9)$

$= 0.543 / 4 = 0.136$

Total error variance:

$V_N = (S_T - S_\beta) / f_{e'} \qquad\qquad (6.10)$

$= 0.157 \qquad\qquad (f_{e'} = f_T – 1 = 5)$

Thus, SNR is calculated as:

$\eta = 10 \log [\ (1/ (r_o . r)) (S_\beta - V_e) / V_N\ ]$

$= 10 \log [\ (1/ (2x350))(1906.25 – 0.136) / 0.157\ ]$

$= 12.40$ dB

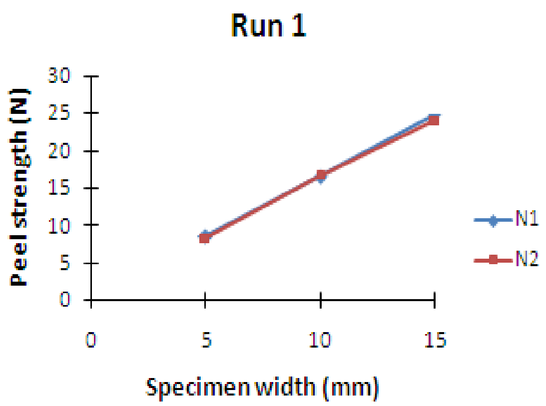
Sensitivity:

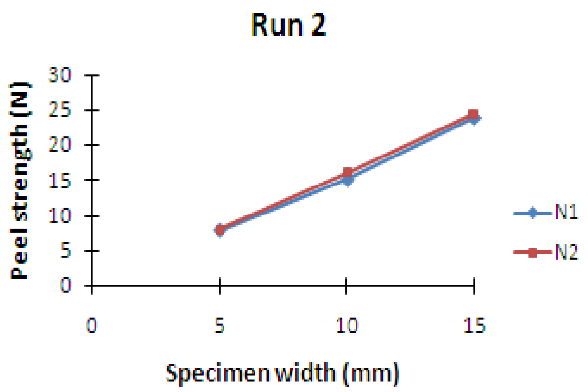
$\beta = 10 \log [(1/(r_o . r)) (S_\beta - V_e)]$

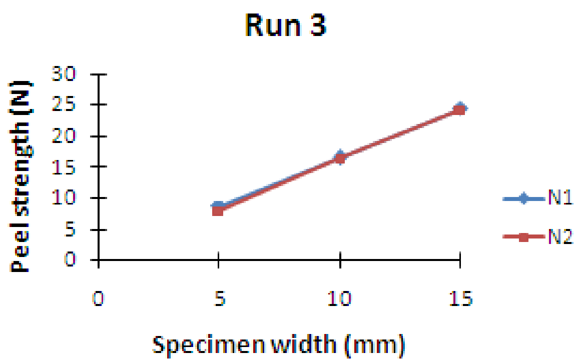
$= 10 \log [\ (1/ (2x350))(1906.25 – 0.136)]$

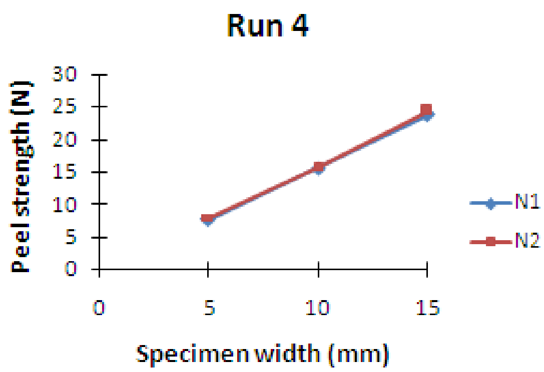
$= 4.35$ dB

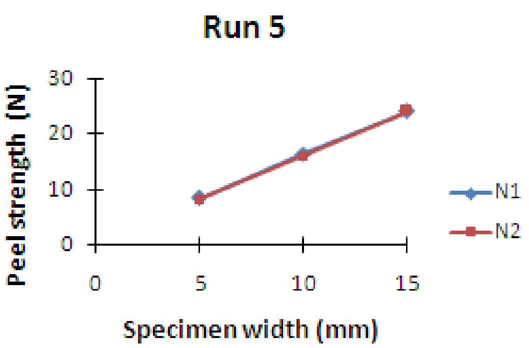
Then, the linear graph for each run is plotted for linear observation between variation N1 and N2. Figure 6.8 is the linear graph for aluminum peel angle. The line N1 and N2 are the noises or variation that is intended to be reduced using robust engineering. The smaller the gap, the less variation found in that experimental run.


Run 1
Peel strength (N)
0 5 10 15 20 25 30
Specimen width (mm)
0 5 10 15
N1
N2

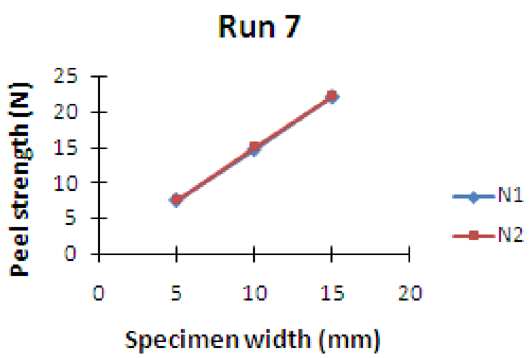

Run 2
Peel strength (N)
0 5 10 15 20 25 30
Specimen width (mm)
0 5 10 15
N1
N2

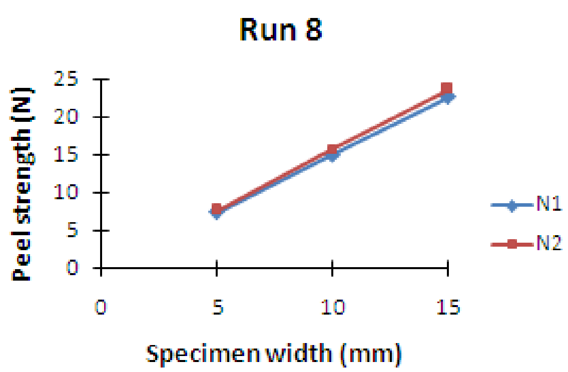

Run 3
Peel strength (N)
0 5 10 15 20 25 30
Specimen width (mm)
0 5 10 15
N1
N2


Run 4
Peel strength (N)
0 5 10 15 20 25 30
Specimen width (mm)
0 5 10 15
N1
N2


Run 5
Peel strength (N)
0 10 20 30
Specimen width (mm)
0 5 10 15
N1
N2


Run 6
Peel strength (N)
0 5 10 15 20 25 30
Specimen width (mm)
0 5 10 15 20
N1
N2


Run 7
Peel strength (N)
0 5 10 15 20 25
Specimen width (mm)
0 5 10 15 20
N1
N2


Run 8
Peel strength (N)
0 5 10 15 20 25
Specimen width (mm)
0 5 10 15
N1
N2

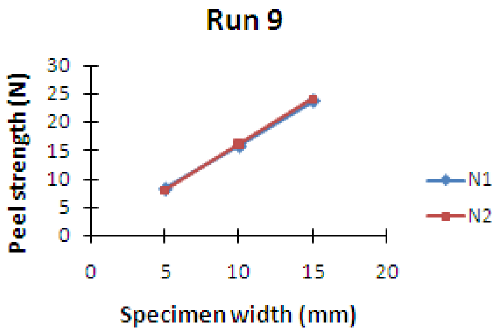
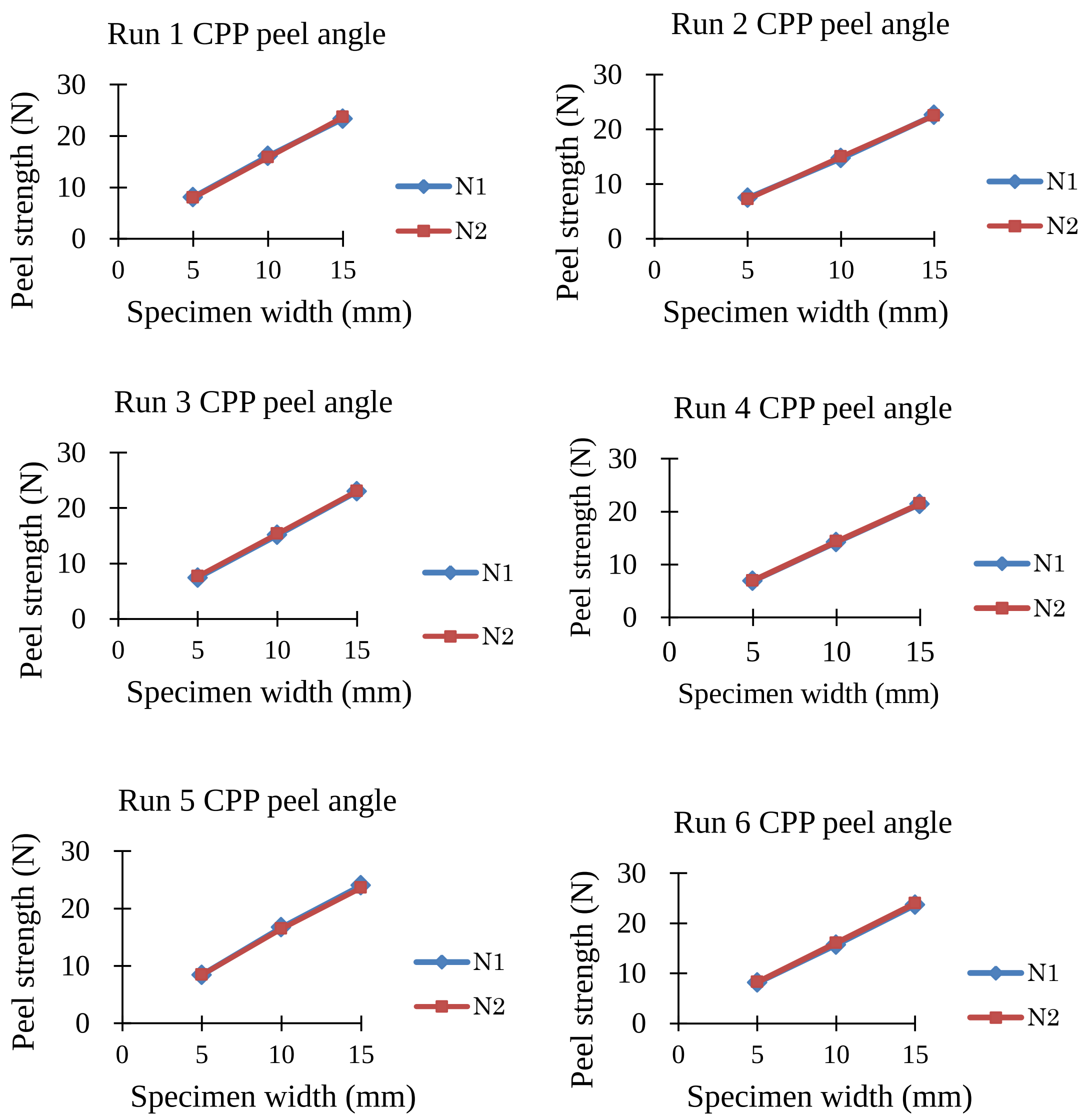


Figure 6.8: Linear graph for aluminum peel side

Figure 6.9 shows the linear graph for CPP peel side. All the nine graphs showed linear relationship as the aluminum side.



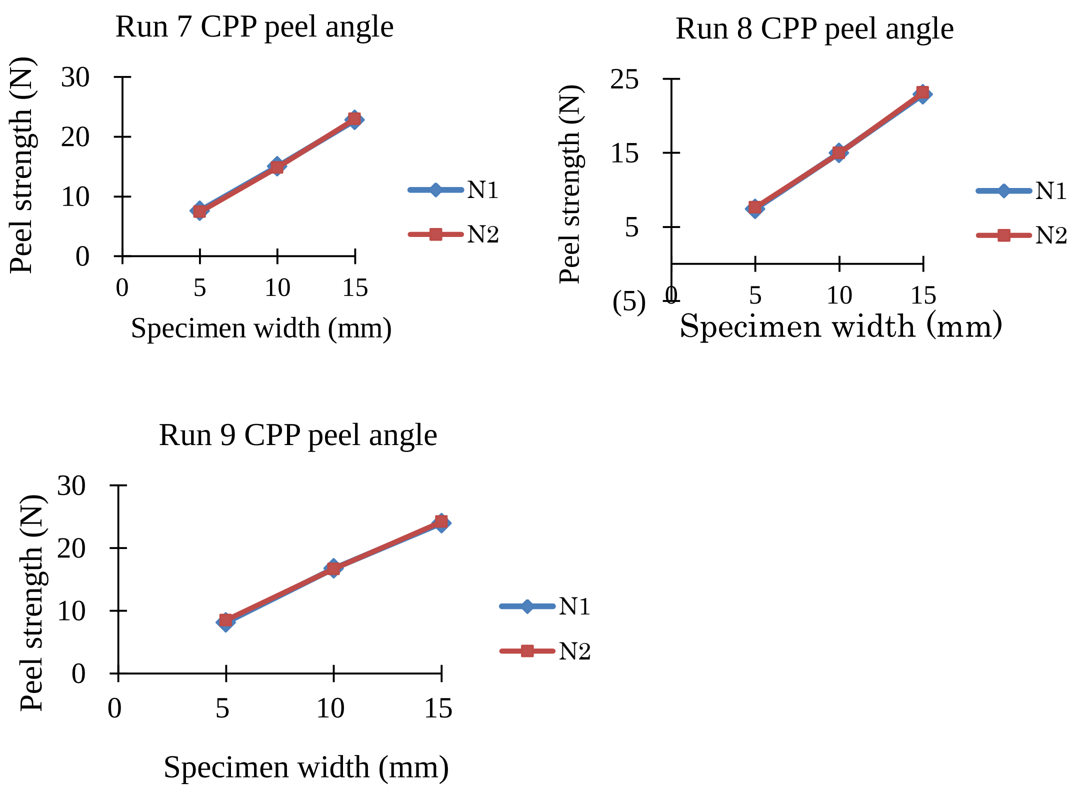


Figure 6.9: Linear graph for CPP peel side

The SNR for all nine runs was calculated using the SNR calculation above. The same calculation as above was applied for the CPP peel side result. Then, the mean SNR process average was calculated to find the effect of each control factor. The effect was separated at different levels, because the experimental design is orthogonal. For example, using the SNR result in Table 6.5, the calculation shown below will find the SNR process average for factor A (peel angle) level 1 and factor B (peel speed) level 1:

$\overline{A_1}$ = (12.40 + 11.79 +15.15) / 3 = 13.11 dB

$\overline{B_1}$ = (12.40 + 15.97 + 16.76) / 3 = 15.04 dB

The process average for each factor and level was calculated as in Table 6.4:

Table 6.4: SNR average factor effect (dB) for aluminum peel side

Label	Parameter	Level 1	Level 2	Level 3
A	Peel angle	13.11	14.70	14.33
B	Peel speed	15.04	12.82	14.29
C	Data region	12.50	14.06	15.58
D	Spring thickness	13.89	13.94	14.31

The SNR factorial effect graph for the aluminum peel and CPP peel sides is shown in Figure 6.10. The optimum condition was identified at the highest peak of SNR, as this indicates the lowest variation caused by noise factors. The worst (comparison) condition occurred at the lowest SNR, which identifies the highest amount of variation.

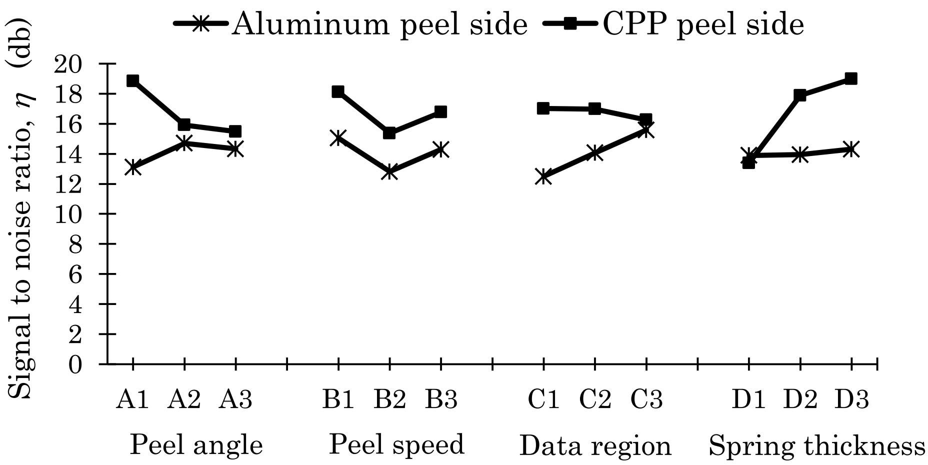


Figure 6.10: SNR factorial effect graph for aluminum peel side and CPP peel side

The result in Figure 6.10 is summarized in Table 6.5. Different optimum conditions appeared for different peel sides. For the aluminum peel side, the optimum condition for minimum variation of peel strength is a 90^o peel angle, 6mm/s peel speed, 70% data region, and 0.5mm spring thickness. For the CPP peel side, the optimum condition is a 60^o peel angle, 6mm/s peel speed, 30% data region, and 0.5mm spring thickness. Table 6.6 reveals that factors B (peel speed) and D (spring thickness) are the same for both aluminum and CPP peel sides in the optimum condition. Thus, peel speed and spring thickness have no significant different effect on the peel sides. On the other hand, factors A and C are different for each peel side; thus, the optimum condition for each side cannot be used interchangeably.

Table 6.5: Optimum and worst condition for aluminum peel side and CPP peel side

Condition	Aluminum peel side	CPP peel side
Optimum condition	A2 B1 C3 D3	A1 B1 C1 D3
Worst condition	A1 B2 C1 D1	A3 B2 C3 D1

A sensitivity graph, so-called as β graph explains the sensitivity of each factor to variation. SNR is the ratio of sensitivity to variability (eq.1). Figure 6.11 shows the sensitivity graph for both aluminum and CPP peel sides. The graph shows that factor D (spring thickness) is the most sensitive factor. High sensitivity measures an obvious change in response value when the factor level is changed. A sensitivity graph is used when there is a target in peel strength value; thus, there is not much consideration of sensitivity when determining optimum condition in this paper since there is no specific target or nominal value of what peel strength should be.

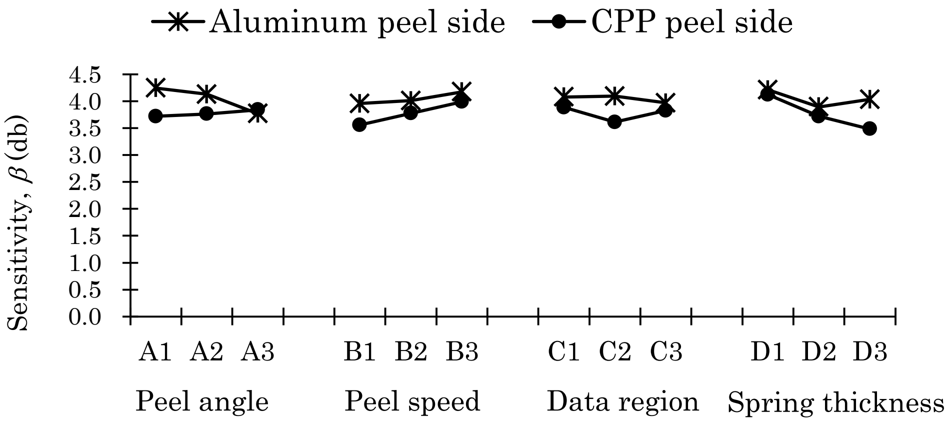


Figure 6.11: Sensitivity graph for aluminum peel side and CPP peel side

A confirmation test was performed to determine the reproducibility of the estimated SNR. Tables 6.6 and 6.7 show the dB gain for the aluminum peel and CPP peel sides according to the confirmation test. The gain percentage difference shows good reproducibility between estimated and confirmation tests for both aluminum and CPP peel sides, at 10.62% and 0.83%, respectively. The size of the dB gain or benefit is less than 3 dB, and the difference is less than 30%, which means that the experiment using the confirmed condition is highly reproducible.

Table 6.6: SNR results for aluminum peel side

	Aluminum peel side			
	Estimated		Confirmation	
	Optimum	Worst	Optimum	Worst
SNR (dB)	17.49	10.18	16.45	9.92
SNR gain (dB)	7.31		6.53	
% Gain difference	10.62			

Table 6.7: SNR results for CPP peel side

	CPP peel side			
	Estimated		Confirmation	
	Optimum	Worst	Optimum	Worst
SNR (dB)	22.71	10.24	20.11	7.54
SNR gain (dB)	12.47		12.57	
% Gain difference	0.83			

The optimum condition from the confirmation test of the Al peel side is shown in Figure 6.12(b), which represents the best SNR, as the gap between N1 and N2 is almost non-exist. Figure 6.13 shows an ideal function graph from confirmation run for the CPP peel side. The smallest gap between noises is desired, as small gaps indicate less variation among noise levels. A confirmation test of SNR for the CPP peel side reveals that it is better than the aluminum peel side, based on its higher SNR, which is at 20.11dB and 16.45 dB, respectively. This study found the optimum condition of each peel sides. The optimum condition for each peel side should be used respective to that peel side; the two conditions should not be used interchangeably.

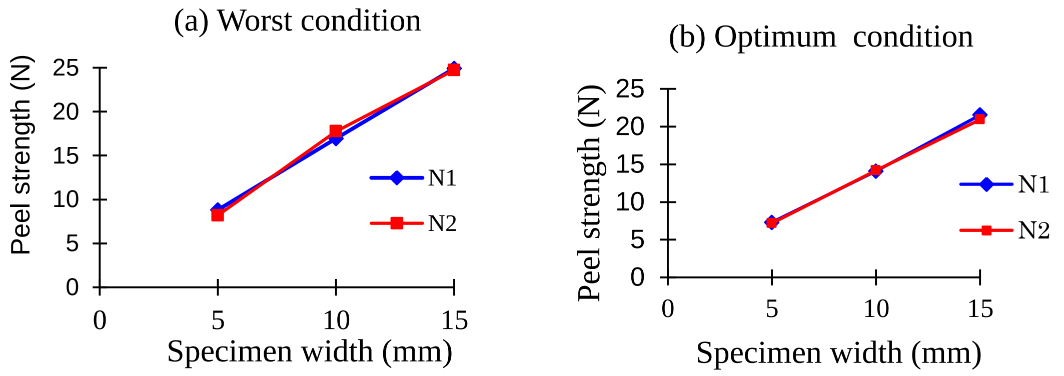


Figure 6.12: Ideal function graph from confirmation run for aluminum peel side (Al/CPP)

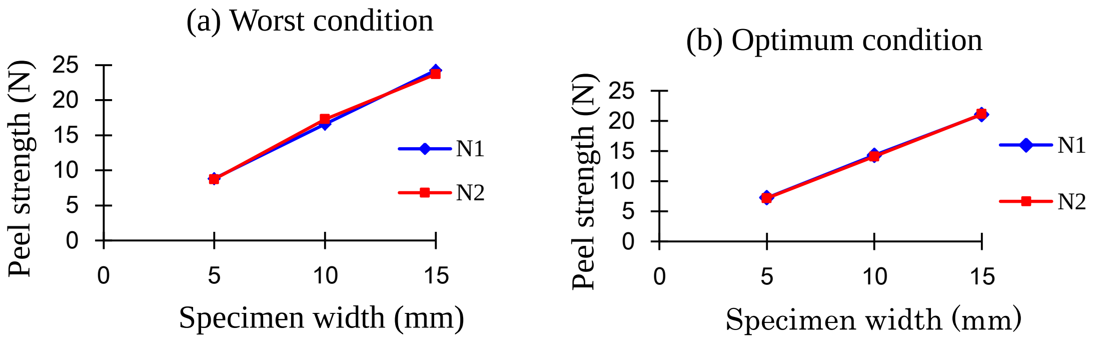


Figure 6.13: Ideal function graph from confirmation run for CPP peel side (CPP/Al)

Analysis of variance (ANOVA) is done for aluminum peel side (Al/CPP) and CPP peel side (CPP/Al). L9 for aluminum peel side and CPP peel side had shown no significant interaction as the percent of contribution between control factors are not significant. Table 6.8 and 6.9 shows the ANOVA result for aluminum and CPP respectively. L9 is used as the preliminary study due to smaller number of experiment. The purpose is to investigate the response behavior before proceeding with L18.

Table 6.8: ANOVA for aluminum peel side (Al/CPP)

Source	SS	DOF	variance,F	F ratio	% P
A	7.14	2	3.57	40.76	0.31
B	1.60	2	0.80	9.13	0.06
C	0.24	2	0.12	1.37	0.00
D	3.95	2	1.97	22.56	0.17
M	2231.82	2	1115.91	12744.35	99.17
N	0.19	1	0.19	2.13	0.00
AXM	1.50	4	0.37	4.28	0.05
BXM	0.24	4	0.06	0.69	0.00
CXM	0.83	4	0.21	2.37	0.02
DXM	0.50	4	0.13	1.44	0.01
MXN	0.29	2	0.15	1.68	0.01
e	2.10	24	0.087561	1	
total	2250.40	53		0	

Note: M = Signal factor, N = Noise factor

Table 6.9: ANOVA for CPP peel side (Al/CPP)

Source	SS	DOF	variance,F	F ratio	% P
A	0.47	2	0.24	9.65	0.02
B	5.88	2	2.94	120.51	0.27
C	2.31	2	1.16	47.39	0.11
D	14.90	2	7.45	305.44	0.69
M	2127.40	2	1063.70	43616.19	98.78
N	0.06	1	0.06	2.66	0.00
AXM	0.27	4	0.07	2.77	0.01
BXM	0.38	4	0.09	3.89	0.01
CXM	0.33	4	0.08	3.40	0.01
DXM	0.92	4	0.23	9.38	0.04
MXN	0.01	2	0.01	0.28	0.00
e	0.59	24	0.02	1.00	
total	2153.52	53		0.00	

Note: M = Signal factor, N = Noise factor

6.1.2.2 Optimum Condition Determination

The SNR analysis reveals that each peel side should apply the optimum condition respective to each side to obtain optimum performance. However, by merging the SNR factorial effect plot for both peel sides into one graph, a harmonized condition is obtained to ensure a condition that suits both sides. The harmonized condition in this term refers to the minimum or smallest gap between aluminum and CPP peel angle process average. The minimum gap indicates an agreement from both sides of the peel angle surface at that particular factor level. The minimum difference reflects an approximate point from both peel sides. This method is one of the trade-off methods used in parameter design to determine the optimum condition that universally suits the design. As shown in Figure 6.14, the harmonized condition is A3, B3, C3, and D1. The optimum condition of harmonized condition is the smallest gap between the two SNR plots that reflects the agreement of factor's level.

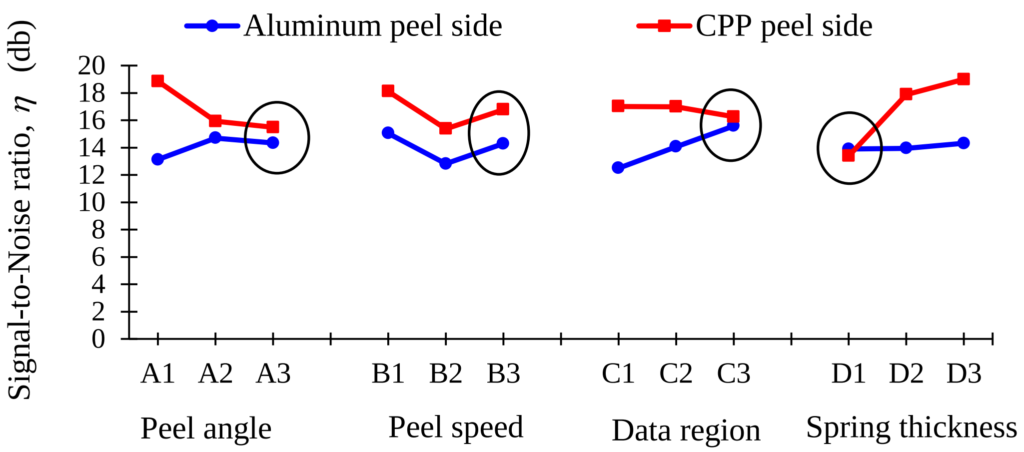


Figure 6.14: Harmonized condition that suits aluminum peel side and CPP peel side

A confirmation run was performed using A3, B3, C2, and D1; SNR was then calculated. As shown in Table 6.10, the result of the SNR (dB) optimum condition was compared to the optimum conditions for the aluminum peel side (Al/CPP), the CPP peel side (CPP/Al), and the harmonized condition.

This study identifies three optimum conditions that can be applied on flexible packaging film: the aluminum peel side condition, the CPP peel side condition, and the harmonized condition. It is advisable to use the aluminum peel side's optimum condition for the aluminum peel side and the CPP peel side's optimum condition for the CPP peel side. Swapping the aluminum peel side's condition to the CPP peel side's condition is highly inadvisable; swapping can affect SNR. The harmonized condition presents an alternative that indicates the best option to apply to both peel sides. The optimum condition for the CPP peel side has the highest SNR; thus, the CPP peel angle condition is the most advisable to use. The harmonized condition's SNR for CPP is decreased by 8.22dB from the optimum condition for the CPP peel side (20.11dB – 11.89dB) and the harmonized condition's SNR for the aluminum peel side is also decreased by 1.35dB from the optimum condition for the aluminum peel side (16.45dB – 15.10dB).

Table 6.10: Three optimum conditions obtained from confirmation run

	Optimum condition for flexible film			
	Aluminum peel side	CPP peel side	Harmonized condition	
			Aluminum peel side	CPP peel side
Parameter Level	A2 B1 C3 D3	A1 B1 C1 D3	A3 B3 C3 D1	
SNR η (dB)	16.45	20.11	15.10	11.89
% dB gain difference (reproducibility)	10.6%	0.83%	12.12%	25.7%
SNR dB gain (optimum – worst)	6.53	12.57	1.40	8.20
Improvement times	4.5 times	18 times	1.4 times	6.6 times
Average peel strength (Newton, N)	14.21	14.17	16.63	17.74

However, the convenience of the harmonized condition outweighs the low SNR. The harmonized condition provides mistake proofing against setting the wrong peel side. Therefore, the usability for the customer is more convenient when using the harmonized condition.

Harmonization is a method that can be used to evaluate different properties or merged properties, and is not limited to flexible film. Determining which optimum condition to use depends on the test objective. If the objective is focused on maximum SNR, then the CPP peel angle is the best to opt. Theoretically, the optimum condition for the CPP peel angle presents the highest SNR and gain. Practically, the harmonized condition provides a convenience design that is useful for both sides of the peel angle. The peel strength average of the harmonized condition is a bit higher than the other two optimum conditions, but this is not a significant effect. Although the confirmation run had only six observations (3 signal levels x 2 noise levels), satisfying results were obtained so that the harmonized condition may be used in flexible film application and research.

6.1.3 Conclusion

This practical experiment presents the performance of T-peel testing on flexible film to find the optimum condition for measurement. The new apparatus solved the large variation problem that occurs when using the standardized T-peel test method. The parameter design step of the Taguchi method was applied to optimize peel strength measurements for flexible packaging film. Three optimum conditions are presented; the decision for which to use was made according to the condition with the highest SNR. The study has thus achieved the following:

- The experiment describes the operation of the new apparatus created to conduct the T-peel test on flexible film. The main difference between this and the standardized method is the layout of the specimen. The specimen is set in a T-shape to ensure that no deviation occurs in the specimen's peel angle. This overcomes the variation problem caused by use of the standardized method to measure flexible film.
- The robust parameter design method was used to minimize the variation of T-peel strength. The variation problem that occurs when flexible film is measured using

the standardized methods of ASTM and JIS is addressed by the new apparatus. With a dynamic SNR equation, the maximum SNR provides minimum variation in T-peel strength. Peel angle, peel speed, data region, and spring thickness are the control factors used to evaluate the new T-peel test apparatus. The noise factors are the peel angle deviation and tensile weight. Three levels of signal factor specimen width were tested to ensure the linearity of peel strength. The control factors are arranged in a nine runs design and noise factor in 2 levels with 3 levels of signal factor. Thus, the orthogonal array L9 has 54 experimental data.

- Peel side was investigated to confirm the best T-peel test condition for flexible film. Aluminum peel side and CPP peel side have good reproducibility, as both have a db gain of less than 30% difference. Thus, the optimum conditions found for both peel sides are reliable. In order to get minimum variation, the aluminum peel side should use the optimum condition of the aluminum peel side and the CPP peel side should use the optimum condition for the CPP peel side of packaging film, and the conditions should not be swapped.
- The robust parameter design method presented the optimum process parameter obtained from SNR analysis to minimize variation and provide process robustness against noise. For the aluminum peel angle, the optimum condition that serves minimum variation is peel angle 90^o, peel speed 6mm/s, data region 70%, and spring thickness 0.5mm (A2 B1 C3 D3). For the CPP peel angle, the optimum condition is peel angle 60^o, peel speed 6mm/s, data region 30%, and spring thickness 0.5mm (A1 B1 C1 D3). It is advised that the optimum condition for the CPP peel side (A1 B1 C1 D3) be used for T-peel tests of flexible film, since the CPP optimum condition had the highest SNR (20.11dB), highest gain, smallest gain difference, and highest improvement times. The number of improvement times is calculated from the log transformation:

$$\text{SNR}, \eta = 10 \log V_e \qquad (6.11)$$

$$10^{\eta/10} = \text{number of improvement} \qquad (6.12)$$

This affects the variation in peel strength to be in minimum level.

The robust parameter design method in quality engineering benefited T-peel test optimization by presenting a harmonized condition. To achieve the same optimum condition at any peel angle surface, optimum condition for harmonized design was chosen by selecting the level with the smallest gap between the Al and CPP peel angle SNR factorial effect plots. The harmonized condition is peel angle 120^{o}, peel speed 12mm/s, data region 70%, and spring thickness 0.3mm (A3 B3 C3 D1). This practical experiment has fulfilled the research motivation to satisfy the T-peel test for flexible film. Three optimum conditions are presented to optimize the T-peel test by minimizing the variation in peel strength measurement. The CPP peel angle condition was chosen as the best optimum condition because of its highest SNR. The finding of this practical experiment is presented in R. Dolah and Z. Miyagi [17].

6.2 Practical Experiment using an L18: Influence of Outer Array Layout and Noise Parameter Strategy

The purpose of this practical experiment is to provide the most reliable experimental design by evaluating the influence of noise parameter in outer array and reason in deciding on optimum condition. The measurement process is carefully carried out to ensure the reliability of optimum condition retrieved from multiple noise strategy. In this practical work, reliability means how reliable the optimum condition retrieved from the measurement data to produce SNR result. Noise level plays an important role in determining the result in outer array as it affects the SNR. Three types of possible measurement data layout in outer array are studied, thus three optimum conditions are analyzed from signal-to-noise ratio (SNR). Reliability of three optimum conditions is discussed in determining the best condition. Analysis of variance (ANOVA) is employed to investigate the influence of noise parameters. Measurement data which covered the whole variation range of peel strength is chosen as the best measurement.

Selection of factors and levels in experimental design plays an important step in determining a satisfactory result. Factor that produces variability in the response is called noise factor and analyzed in outer array. Thus, it is important to design an experiment that capable to capture total data variability. Shin Taguchi in Nair 1992 panel discussion emphasized that in parameter design, the most important job is to select an effective characteristic to measure a data. The efficiency and effectiveness of engineering activities depend greatly on what is measured as data. This paper outlined the possibilities of measurement data layout in outer array of L18 and the procedure on choosing the best noise layout thus presenting a reliable optimum condition. The meaning of reliability in this paper is not focusing on failure rate of a system so-called bath-tub curve. Reliability in this paper means the robustness of optimum condition. There are many possible noise layout exist in outer array thus producing more than one optimum condition calculated from SNR. The decision on choosing the best optimum condition is discussed based on consideration of noise parameter criteria, gain difference in confirmation test, and noise influence in ANOVA. Different noise parameter setting affects the measurement data placed in outer array and serves different optimum condition.

6.2.1 Robust Design Engineering Method

6.2.1.1 Ideal Function and P-Diagram

Peel strength linearity is based on zero-point equation, therefore the dynamic ideal function is direct ratio $Y = \beta M$ as shown in Figure 2.1, Chapter 2. P-diagram in Figure 6.15 shows all the parameters studied in this practical experiment.

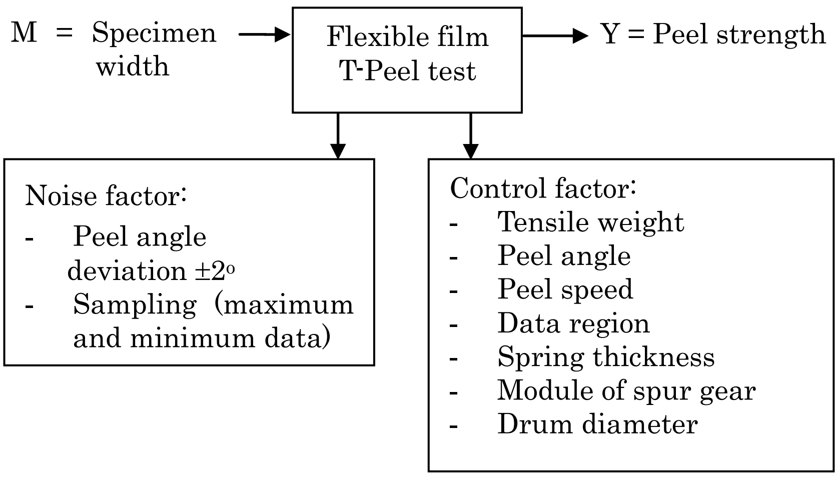


Figure 6.15: P-Diagram of T-peel Test

A dynamic ideal function is used, based on wide range of specimen width. The response, *Y*; is peel strength, the output from the measurement process with as small unwanted variation as possible. *M* is the input of signal factor from various range of specimen width for peel strength linearity. Beta,β, is the measurement sensitivity to different inputs, thus the slope must be steep.

6.2.1.2 Signal Factor

Signal factor is a controllable variable to actualize the intention to achieve robust condition regardless of various width conditions. Signal-to-Noise ratio (SNR) with dynamic response (1) is used in this study to measure different response level. A dynamic signal-to-noise ratio (SNR) has been used in this study, where the specimen width as the signal factor with 3 levels that are 5mm, 10mm and 15mm is used to measure the peel strength linearity.

Signal-to-noise ratio, η:

$$\eta = 10 \log ((1/r.r_o)(S_\beta - V_e) / V_N) \qquad (6.4)$$

where S_β = variation caused by the linear effect

V_e = correction error variance (error variance/DOF)

V_N = compounded noise factor when signal factor is introduced

r = total number of measurements under one signal level

r_o = effective divider representing a magnitude of input due to level changes of signal factor

6.2.1.3 Noise Factor

Noise factor is a factor that cause variation in measurement system arranged in outer array. Peel angle deviation $\pm 2^o$ is chosen as one of the noise factor. Peel angle is adjusted to three levels that are 60^o, 90^o and 120^o. Figure 6.16 shows the specimen condition during peel test as the peel angle would deviates in micro range during peeling process.

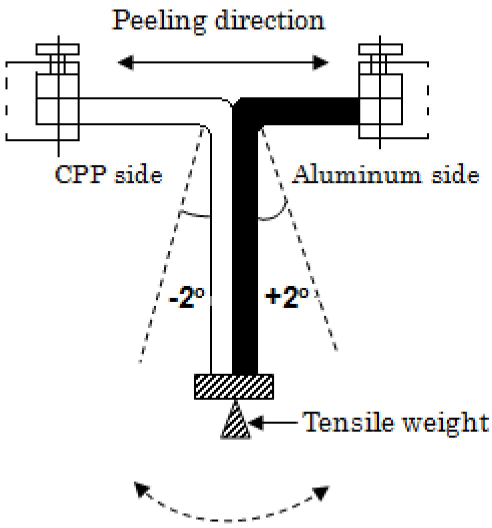


Figure 6.16: Deviation in peel angle during T-peel test

Therefore, noise in peel angle is defined as uncontrollable factor during test with deterioration at ± 2^o for each level. In previous experience, it is observed from preliminary study that ± 2^o is a rough estimation for peeling angle distribution. By using that result, it is decided ± 2^o as the level for the uncontrollable factor. Another noise factor is sampling method. Sampling is taken at maximum, minimum and average point of peel strength at constant region in peel curve. Noise factor is put in two conditions, N1 and N2. Intentionally, N1 contains higher peel strength than N2. Preliminary run is conducted to confirm the peel strength behavior. Preliminary run in Figure 6.17, is assumed as a model of peel angle effect on peel strength.

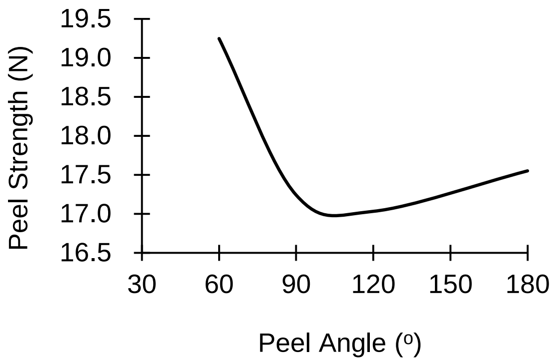


Figure 6.17: Peel angle effect on peel strength (specimen:10mm, tensile weight: 4g, peel speed: 9mm/s, data region: 30%, spring thickness: 0.3mm, module of spur gear 0.5, drum diameter: 37mm)

In this experiment, specimen of 10mm, peel speed of 9mm/s and spring thickness of 0.3mm are used. The peel strength is obviously decline from 60^o to 90^o peel angle. Deviation of peel angle gives clear value of peel strength, either high peel strength or low peel strength. However, the trend from 90^o onwards showing a very small increment. Deviation of $\pm 2^o$ for this region is hardly separated, thus peel strength for N1 is not necessarily higher than N2. As the trend of peel strength is increasing, an assumption is made on higher peel strength tends to be affected by higher peel angle. The first outer array layout; Type A, explained N1 as +2^o peel angle and sampling is taken on maximum peel strength, and N2 consists of -2^o peel angle and sampling at minimum peel strength. For example, for 90^o peel angle, measurement data in N1 is peel strength obtained using 92^o peel angle and maximum point of peel strength in 92^o is selected. Measurement data in N2 is peel strength obtained using 88^o peel angle and minimum peel strength in 88^o is selected. However, small increment in peel strength is observed in Figure 6.16 at some peel angle such as 90^o and 120^o. At this region, +2^o peel strength is not always on high side and -2^o is not always on low side. The sampling of maximum and minimum should not be classified at fixed deviation. This means, sampling of maximum peel angle might be coming from -2^o peel angle deviation and minimum peel angle might be coming from +2^o peel angle deviation due to very small incremental in peel strength. The peel strength curve between this peel angle is overlapped as shown in Figure 6.18:

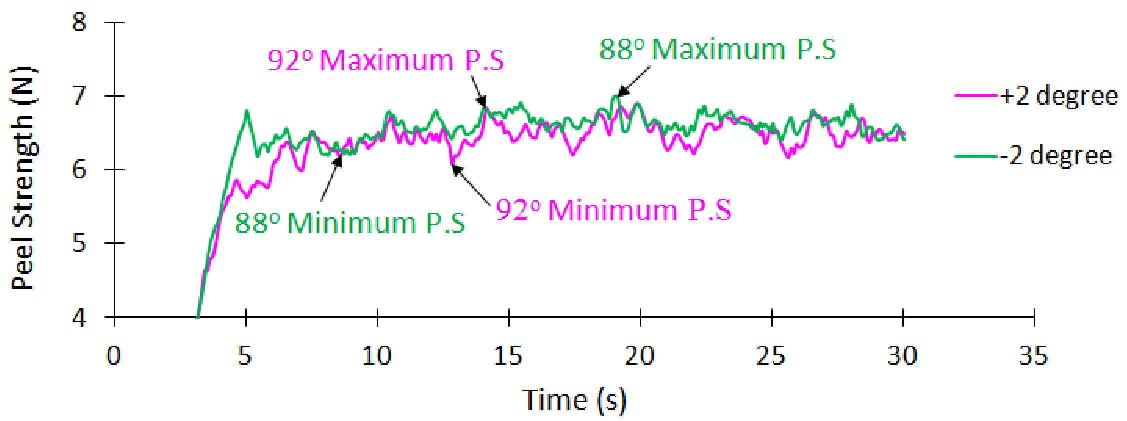


Figure 6.18: Example of maximum and minimum peel strength sampling (run 15 in L18 - specimen: 5mm, tensile weight 8g, peel angle 90^o, peel speed 12mm/s, data region 30%, spring thickness 0.4mm, module of spur gear 2.0, drum diameter 30mm)

As shown in Figure 6.19, maximum peel strength for +2^o peel angle is 6.91N, which is less than the maximum peel strength for -2^o peel angle which is 7.01N. Thus, it is not fair to state N1 as +2^o with maximum peel strength sampling because -2^o has higher peel strength.

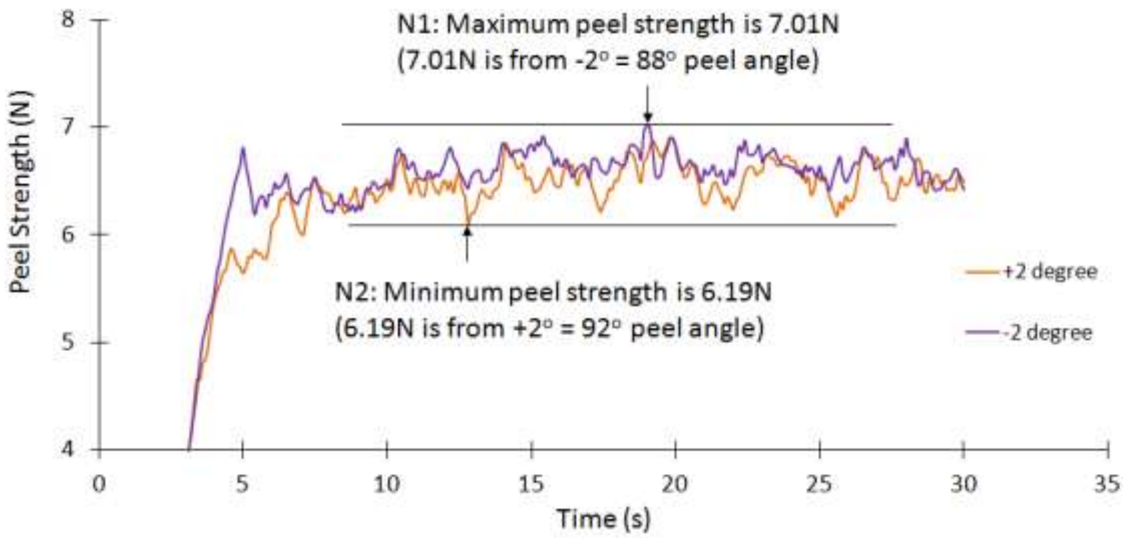


Figure 6.19: Data measurement for taking range of maximum and minimum point (run 15 in L18 - specimen: 5mm, tensile weight 8g, peel angle 90^o, peel speed 12mm/s, data region 30%, spring thickness 0.4mm, module of spur gear 2.0, drum diameter 30mm)

Table 6.11 explained the phenomena (1,2,3,4) of data measurement that could exist in peel strength measurement. The matrix description of each phenomenon is described in Table 6.12. Each number includes ‘more than’ and ‘less than’ criteria. Therefore, second outer array layout; Type B take the most maximum peel strength regardless of deviation peel angle $\pm 2^o$ to be filled in N1 and the most minimum peel strength as in N2 in outer array. In other words, Type B noise layout is measuring the range of data regardless of peel angle. In an experiment, peel strength result is differed from one data to another. A typical result can be represented by an average. Thus, in the third outer array; Type C takes average of +2^o peel angle is considered as N1 measurement and average of -2^o peel angle is considered as N2 measurement. Table 6.13 summarized all the noise factors in outer array. These multiple outer array result layouts have provided three types of SNR results, thus lead to three optimum conditions for T-peel test.

Table 6.11: Phenomena matrix for number 1,2,3, and 4

Phenomena	Criteria	Occurrence
1 (i)	+2 ^{o} max. PS > -2 ^{o} max. PS	Most of data
1 (ii)	+2 ^{o} max. PS < -2 ^{o} max. PS	Sometime
2 (i)	+2 ^{o} max. PS > -2 ^{o} min. PS	Always
2 (ii)	+2 ^{o} max. PS < -2 ^{o} min. PS	Never
3 (i)	+2 ^{o} min. PS > -2 ^{o} max. PS	Sometime
3 (ii)	+2 ^{o} min. PS < -2 ^{o} max. PS	Most of data
4 (i)	+2 ^{o} min. PS > -2 ^{o} min. PS	Most of data
4 (ii)	+2 ^{o} min. PS < -2 ^{o} min. PS	Sometime

Table 6.12: Phenomena criteria and occurrence

Item	+2 ^{o} maximum peel strength	+2 ^{o} minimum peel strength
-2 ^{o} maximum peel strength	1	3
-2 ^{o} minimum peel strength	2	4

Table 6.13 Noise factor in outer array

TYPE	N1	N2
A	+2 ^{o} peel angle with maximum peel strength	-2 ^{o} peel angle with maximum peel strength
B	Maximum peel strength of ±2 ^{o}	Minimum peel strength of ±2 ^{o}
C	+2 ^{o} peel angle with average peel strength	+2 ^{o} peel angle with average peel strength

6.2.1.4 Control Factor

The controllable factors or inner array are chosen based on testing and design condition. Tensile weight used for keeping the specimen in T-shape, peel angle, peel speed and peeling curve region are controllable factors considered based on testing condition. The meaning of data region is the percentage covered at constant peel strength. JIS standard is using 30% data region. Three data region are evaluated this experiment, that are 30%, 50% and 70%. In Figure 6.5, 30% data region means the remaining data is taken for evaluation after discarding 35% right and 35% left of constant region in peel strength curve. 25% right and left data is discarded for taking 50% data region, and 15% right and 15% left data is discarded for 70% data region. Parallel spring thickness, module of spur gears and drum diameter are considered based on design of apparatus condition. Spring thickness represents the stiffness occurred when the specimen is being peeled. Three spring thickness are evaluated, 0.3mm, 0.4mm, and 0.5mm with 70mm in length. Different module of spur gears evaluates the effect of pitch diameter over teeth number on peel strength. The three modules are 0.5, 1.0 and 2.0. The size of the drum diameter is also evaluated, that are 20mm, 30mm and 40mm.

6.2.1.5 Orthogonal Array Selection

Orthogonal array provides a balanced set of experimentation runs to explore the design space with small number of experiments. Design of experiments using orthogonal array L_{18} is used with one two-level factor (tensile weight) and six three-level factors (peel angle, peel speed, data region, spring thickness, module of spur gear and drum diameter). More controllable factors are involved to observe its influence on peel strength using orthogonal array L_{18}. A summary of all parameters used in this paper and their levels is shown in Table 6.14:

Table 6.14: Factors and their levels in L_{18}

	Control Factor	*Unit*	*Level 1*	*Level 2*	*Level 3*
A :	Tensile weight	g	4	8	
B :	Peel angle	º	60	90	120
C :	Peel speed	mm/s	6	9	12
D :	Data region	%	30	50	70
E :	Spring thickness	mm	0.3	0.4	0.5
F :	Module of spur gear		0.5	1.0	2.0
G :	Drum diameter	mm	20	30	40
	Signal Factor			*Levels*	
M :	Specimen width	mm	5	10	15
	Noise Factor		*Level N1*	*Level N2*	
	Peel Angle	θ	+2	-2	
	Peel strength sampling	N	Maximum	Minimum	

A full factorial experimental design for studying seven parameters would have required enormous number of experiment trials (2^1x3^6), an unacceptable number due to experimentation constraints. In L_{18} , 108 observations are implied (18 runs x 3 signal level x2 noise level) as shown in Table 6.15. For example, in Run 1; experiment is done using all control factors at level 1. Three specimen widths are used as signal factor level of 5mm, 10mm, and 15mm. Specimen 5mm under N1 means using all control factors at level 1 with peel angle 62^o. Specimen 5mm under N2 means using all control factors at level 1 with peel angle 58^o. The measurement data is written in outer array according to condition stated in Table 6.13. Therefore, three orthogonal arrays are produced under the same experimental run.

Table 6.15: Experimental setup

								Signal factor (specimen width in mm)					
								5		10		15	
No.	A	B	C	D	E	F	G	N1	N2	N1	N2	N1	N2
1	1	1	1	1	1	1	1						
2	1	1	2	2	2	2	2						
3	1	1	3	3	3	3	3						
4	1	2	1	1	2	2	3						
5	1	2	2	2	3	3	1						
6	1	2	3	3	1	1	2						
7	1	3	1	2	1	3	2						
8	1	3	2	3	2	1	3						
9	1	3	3	1	3	2	1						
10	2	1	1	3	3	2	2						
11	2	1	2	1	1	3	3						
12	2	1	3	2	2	1	1						
13	2	2	1	2	3	1	3						
14	2	2	2	3	1	2	1						
15	2	2	3	1	2	3	2						
16	2	3	1	3	2	3	1						
17	2	3	2	1	3	1	2						
18	2	3	3	2	1	2	3						

6.2.2 Experimental Results and Discussions

6.2.2.1 Signal-to-Noise Ratio Analysis

Peel strength result is taken to calculate SNR, η and sensitivity, β. SNR example of calculation is shown below by taking the result in Table 6.16 for run 1, using Type A outer array layout. Peel strength measurement for Type B and Type C are shown in Table 6.17 and 6.18 respectively.

SNR, $\eta = 10 \log ((1/r.r_o)(S_\beta - V_e) / V_N)$ (6.4)

$S_\beta = 542.82$

$= \underline{((4.45+4.53)5+(8.51+8.97)10+(13.51+12.94)15)^2} 2(5^2+10^2+15^2)$

$V_e = S_e/f_e = (S_T - S_\beta - S_{Nx\beta}) / 4 = 0.0689$ $\quad f_e = 4$

$S_T = 4.45^2+4.53^2+8.51^2+8.97^2+13.51^2+12.94^2$

$= 543.12$

$S_{Nx\beta} = 0.0180 = ((4.45)5+(8.51)10+(13.51)15)^2+((4.53)5+(8.97)10+(12.94)15)^2) / (5^2+10^2+15^2) - S_\beta$

$V_N = S_e' / f_e' = (S_T - S_\beta) / 5 = 0.05879$ $\quad f_e' = 5$

Signal-to-noise ratio; SNR, η :

$= 10 \log_{10}(1/2(5^2+10^2+15^2))[(S_\beta - V_e) / V_N]$ (6.4)

$= 11.20$ dB

Sensitivity, β :

$= 10 \log (1/r.r_o)(S_\beta - V_e)$ (6.5)

$= 10\log_{10}(1/2(5^2+10^2+15^2))(S_\beta - V_e)$

$= -1.10$ dB

Table 6.16: Peel strength result for Type A

Run	OUTER ARRAY						SNR	Sensitivity
	5mm		10mm		15mm			
	N1	N2	N1	N2	N1	N2		
1	4.45	4.53	8.51	8.97	13.51	12.94	11.20	-1.10
2	6.31	6.12	12.94	11.95	18.83	18.15	10.06	1.85
3	8.79	8.46	16.96	16.43	24.57	23.88	10.27	4.29
4	8.39	8.08	16.50	15.72	24.08	23.36	11.55	4.05
5	3.94	3.57	7.98	7.50	11.53	10.82	7.12	-2.46
6	7.20	7.05	13.81	13.52	19.73	18.91	6.76	2.41
7	6.38	6.38	13.28	12.74	18.97	17.83	6.91	1.95
8	7.97	7.42	16.27	15.67	24.76	23.60	10.11	4.10
9	3.93	3.75	7.51	7.28	11.33	11.10	14.44	-2.53
10	6.02	5.19	12.03	11.19	16.91	16.66	8.17	1.07
11	9.79	8.95	17.92	17.28	26.98	25.29	7.46	4.89
12	4.34	4.10	8.34	7.97	12.17	11.91	11.74	-1.84
13	7.75	7.23	15.14	14.34	22.10	21.12	9.52	3.25
14	4.74	4.44	9.17	8.81	13.38	12.90	10.44	-1.06
15	6.77	6.23	12.82	12.51	19.25	18.54	11.87	2.04
16	4.04	3.22	7.74	6.92	11.64	11.13	4.84	-2.51
17	5.95	5.52	12.22	11.56	17.84	17.09	9.90	1.36
18	8.94	8.73	16.32	16.01	24.69	25.03	11.13	4.37

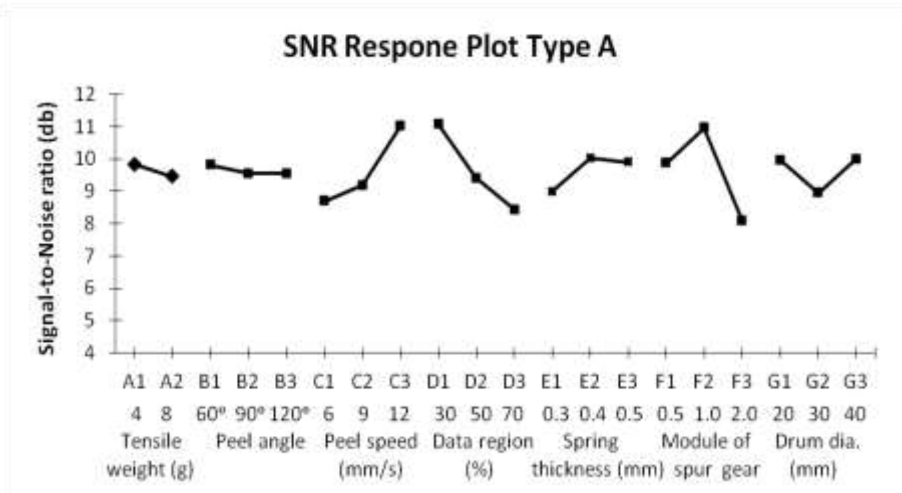
Table 6.17: Peel strength result for Type B

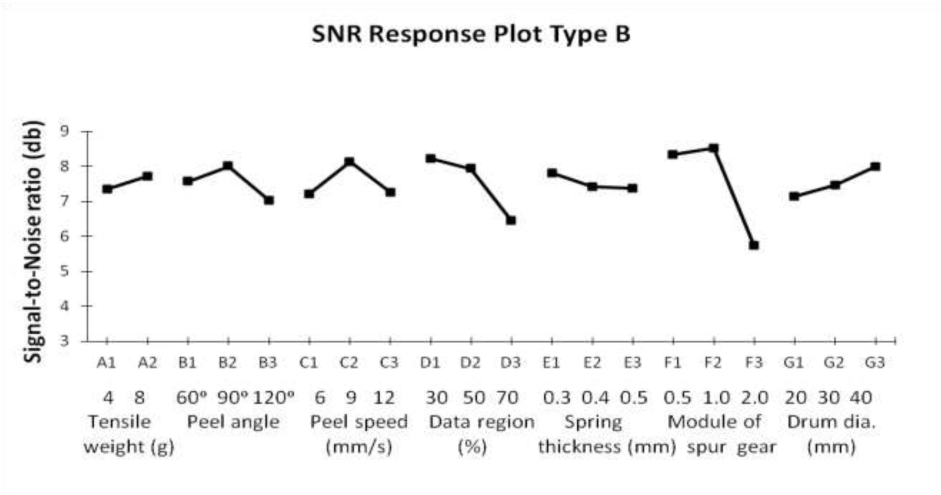
RUN	OUTER ARRAY						SNR	Sensitivity
	5mm		10mm		15mm			
	N1	N2	N1	N2	N1	N2		
1	4.66	4.34	9.12	8.36	13.51	12.94	8.6	-1.1
2	6.62	5.74	12.71	11.95	18.83	18.08	9.0	1.8
3	9.13	7.92	17.41	15.74	24.96	23.27	5.0	4.2
4	8.63	7.91	16.77	15.72	24.08	23.36	9.4	4.1
5	4.09	3.52	8.03	7.41	11.53	10.82	6.0	-2.5
6	7.36	6.90	13.81	13.44	19.73	18.91	6.6	2.4
7	6.90	6.12	13.28	12.61	18.97	17.83	6.0	1.9
8	7.97	7.07	16.27	15.36	24.76	23.60	7.9	4.1
9	4.14	3.59	7.78	7.12	11.39	11.00	7.7	-2.5
10	6.02	5.56	12.06	11.19	17.44	16.34	7.0	1.1
11	9.79	8.95	17.92	17.28	26.98	25.29	7.5	4.9
12	4.38	4.07	8.34	7.97	12.25	11.60	8.3	-1.9
13	7.75	7.23	15.14	14.34	22.10	21.12	9.5	3.3
14	4.74	4.12	9.17	8.81	13.41	12.90	9.4	-1.1
15	6.90	6.10	13.19	11.94	19.40	18.54	7.2	2.0
16	4.04	3.22	7.77	6.92	12.05	10.93	2.8	-2.5
17	6.20	5.47	12.22	11.56	17.84	17.09	9.1	1.4
18	8.94	8.59	16.32	15.91	25.62	24.37	8.7	4.4

Table 6.18: Peel strength result for Type C

RUN	OUTER ARRAY						SNR	Sensitivity
	5mm		10mm		15mm			
	N1	N2	N1	N2	N1	N2		
1	4.40	4.59	8.44	9.06	13.35	13.10	11.6	-1.1
2	6.00	6.39	12.66	12.34	18.47	18.47	16.3	1.8
3	8.45	8.74	16.38	16.92	23.92	24.41	10.9	4.3
4	8.16	8.30	16.21	16.39	23.70	23.60	13.6	4.1
5	3.73	3.84	7.69	7.79	11.21	11.11	13.1	-2.5
6	7.03	7.17	13.63	13.67	19.35	19.29	8.0	2.4
7	6.21	6.68	13.00	12.89	18.62	18.34	10.1	2.0
8	7.51	7.67	15.78	15.94	24.24	24.05	14.6	4.1
9	3.73	3.95	7.32	7.56	11.18	11.24	15.6	-2.5
10	5.81	5.43	11.76	11.74	16.64	17.03	10.8	1.1
11	9.54	9.22	17.70	17.56	26.63	25.48	9.8	4.9
12	4.21	4.25	8.19	8.09	12.03	12.11	15.7	-1.8
13	7.47	7.49	14.88	14.82	21.80	21.48	14.6	3.3
14	4.62	4.52	9.01	8.99	13.20	13.25	16.7	-14.0
15	6.45	6.61	12.42	12.84	18.91	18.98	16.3	2.0
16	3.67	3.62	7.45	7.32	11.31	11.59	12.4	-2.5
17	5.73	5.87	12.01	11.85	17.63	17.31	15.4	1.4
18	8.76	8.81	16.11	16.13	24.52	25.32	10.5	4.4

SNR response plot for Type A, B, and C outer array layout is shown in Figure 6.20. Optimum condition is determined from the highest peak of SNR and maximum SNR explained the power of signal is larger than power of noise, which means the variability is small. Thus, the condition is influenced by the noise factors.





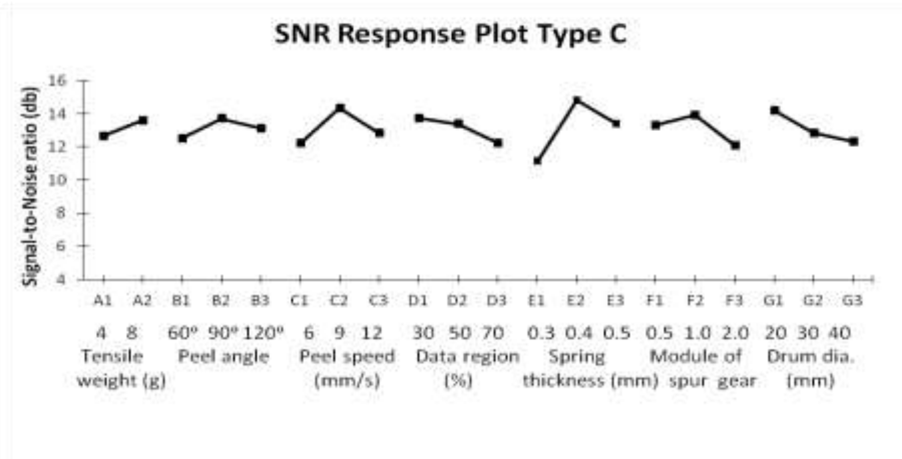


Figure 6.20: SNR response plot for Type A, B, and C

Optimum conditions can be summarized as in Table 6.19. Different optimum condition appears when different outer array applied in each L18. Factor D and F that are data region and module of spur gear have the same optimum level agreed by all three types.

Table 6.19. Optimum condition for Type A, B, and C

Control factor	Type A	Type B	Type C
Tensile weight	A1	A2	A2
Peel angle	B1	B2	B2
Peel speed	C3	C2	C2
Data region	D1	D1	D1
Spring thickness	E2	E1	E2
Module of spur gear	F2	F2	F2
Drum diameter	G3	G3	G1

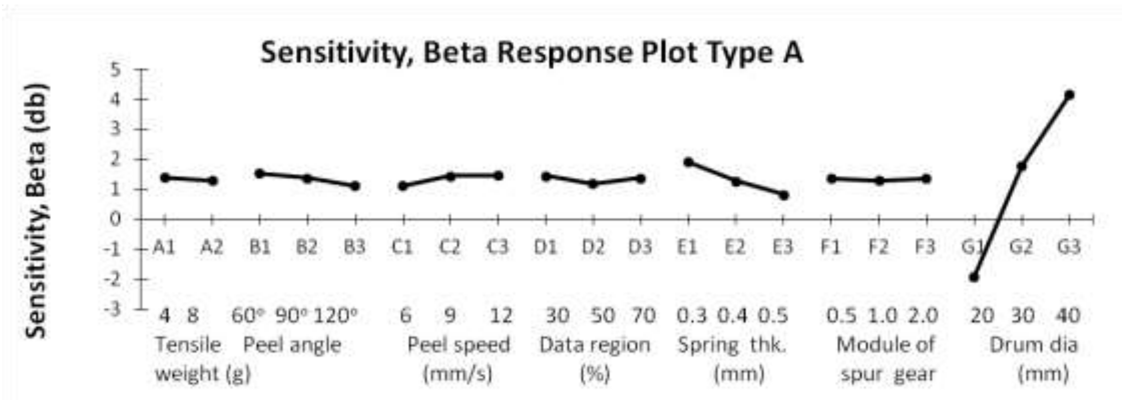
Sensitivity analysis is shown in Figure 6.21. Sensitivity plot explain the importance of adjusting the mean to the target by adjusting the level of a control factor. A control factor that is suitable to adjust must have maximum effect on sensitivity and minimum effect on robustness. In this case, factor G is the best factor to adjust for all the three types of outer array layout. Each level of drum diameter is sensitive to peel strength value. However, the change between these levels does not affect the process variance significantly, as illustrated in SNR response plot. ANOVA is calculated to investigate the noise influence to control factors between Type A, B, and C. The basic calculation of ANOVA for Type B comprises of:

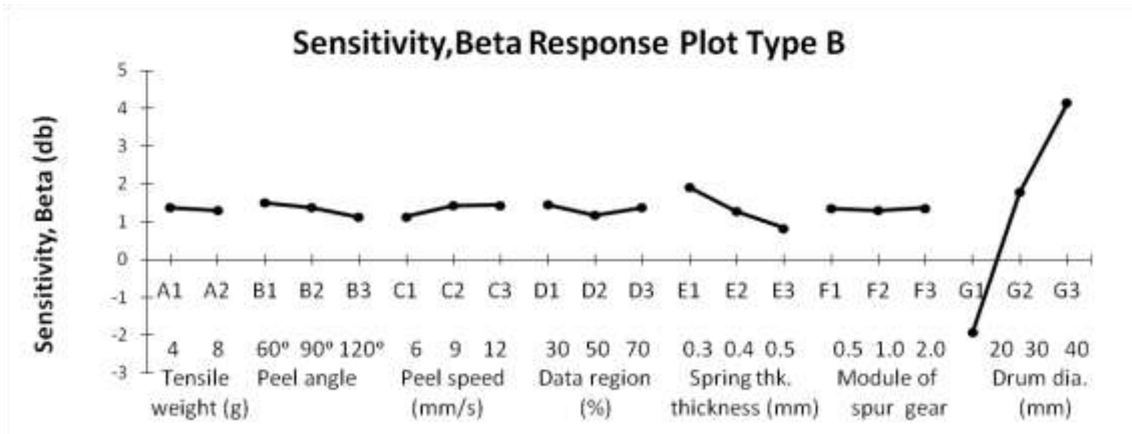
Mean square or variance, ∫$V_B = S_B / f_B$ (6.13)

F-ratio, ∫$F_B = V_B / V_e$ (6.14)

Pure sum of squares, ∫$S'_B = S_b - (V_B \text{ x } f_B)$ (6.15)

Percent of contribution, ∫$P_B = S'_B / S_T$ (6.16)





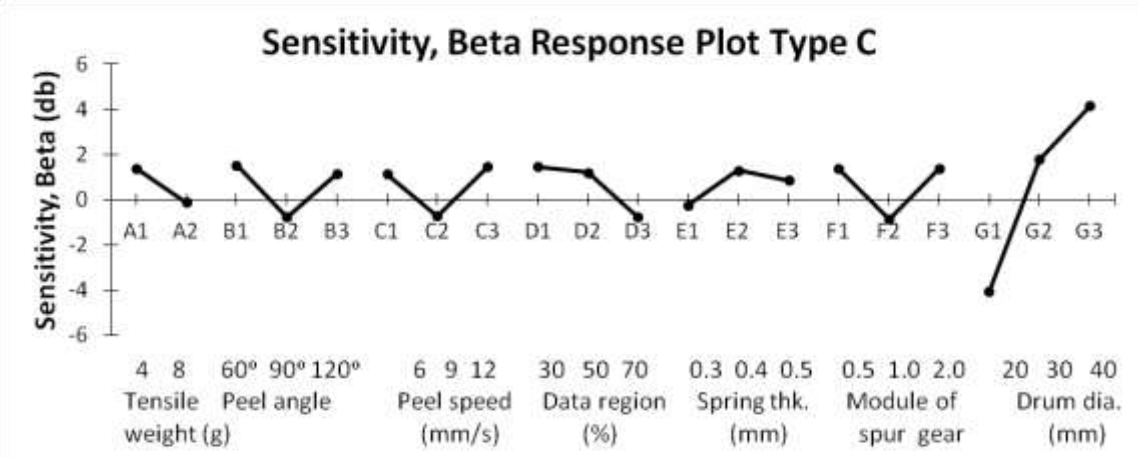


Figure 6.21: Sensitivity plot for Type A, B, and C

In ANOVA shown in Table 6.20, Type B has the largest noise influence that the percent of contribution is 0.41%. ANOVA result for Type A and C is shown in Table 6.21 and 6.22 respectively. Table 6.23 shows the summary of noise influence. Type A has 0.18% and Type C has no influence of noise factors. The noise influence showed that Type B demonstrated the variation in data measurement clearly compared to Type A and C. No contribution of noise variation is captured in Type C is observed, and little noise variation is captured in Type A. 0.41% noise effect in Type B is contributed by the range of measurement by taking the maximum and minimum point in sampling of peel strength.

Table 6.20: ANOVA for Type B

Source	DOF	SS	Mean square	F-ratio	% contribution
A	1	0.54	0.54	7.69	0.01
B	2	4.47	2.23	31.54	0.11
C	2	7.42	3.71	52.41	0.18
D	2	3.58	1.79	25.27	0.09
E	2	38.96	19.48	275.11	0.97
F	2	2.26	1.13	15.96	0.05
G	2	1197.83	598.92	8457.72	29.82
M	2	2546.77	1273.39	17982.39	63.40
N	1	16.59	16.59	234.31	0.41
AXM	2	0.26	0.13	1.82	0.00
BXM	4	0.53	0.13	1.87	0.01
CXM	4	1.68	0.42	5.93	0.03
DXM	4	0.89	0.22	3.16	0.02
EXM	4	5.02	1.26	17.73	0.12
FXM	4	0.17	0.04	0.59	0.00
GXM	4	185.21	46.30	653.86	4.60
MXN	2	0.36	0.18	2.54	0.01
Error	63	4.46	0.07		0.19
Total	107	4017.01	37.54		100.00

Note: M = signal factor (specimen width)
N = Noise factor

Table 6.21: ANOVA for Type A

Source	DOF	SS	Mean square	F-ratio	% contribution
A	1	0.80	0.80	11.04	0.02
B	2	4.80	2.40	33.10	0.12
C	2	9.19	4.59	63.34	0.23
D	2	3.22	1.61	22.22	0.08
E	2	39.48	19.74	272.14	0.98
F	2	2.26	1.13	15.57	0.05
G	2	1204.77	602.38	8305.32	30.04
M	2	2542.98	1271.49	17530.59	63.40
N	1	7.17	7.17	98.82	0.18
AXM	2	0.28	0.14	1.94	0.00
BXM	4	0.56	0.14	1.95	0.01
CXM	4	1.44	0.36	4.96	0.03
DXM	4	0.85	0.21	2.94	0.01
EXM	4	4.34	1.09	14.97	0.10
FXM	4	0.22	0.05	0.76	0.00
GXM	4	183.32	45.83	631.89	4.56
MXN	2	0.39	0.19	2.68	0.01
Error	63	4.57	0.07		0.19
Total	107	4010.65	37.48		100.00

Note: M = signal factor (specimen width)
N = Noise factor

Table 6.22: ANOVA for Type C

Source	DOF	SS	Mean square	F-ratio	% contribution
A	1	0.55	0.55	8.80	0.01
B	2	4.80	2.40	38.33	0.12
C	2	7.97	3.99	63.63	0.20
D	2	3.22	1.61	25.70	0.08
E	2	38.71	19.36	308.88	0.97
F	2	2.23	1.11	17.77	0.05
G	2	1196.62	598.31	9547.34	29.94
M	2	2547.42	1273.71	20324.81	63.75
N	1	0.05	0.05	0.81	0.00
AXM	2	0.26	0.13	2.09	0.00
BXM	4	0.64	0.16	2.56	0.01
CXM	4	1.52	0.38	6.06	0.03
DXM	4	0.70	0.18	2.80	0.01
EXM	4	4.69	1.17	18.71	0.11
FXM	4	0.10	0.02	0.39	0.00
GXM	4	182.54	45.63	728.20	4.56
MXN	2	0.08	0.04	0.62	0.00
Error	63	3.95	0.06		0.17
Total	107	3996.07	37.35		100.00

Note: M = signal factor (specimen width)
N = Noise factor

Table 6.23: Summary of noise influence of outer array layout (denoted as N in ANOVA table) for Type A, B, and C

Type	Source	DOF	SS	Mean square	F-ratio	% contribution
A	Noise	1	7.17	7.17	98.82	0.18
B	Noise	1	16.59	16.59	234.31	0.41
C	Noise	1	0.05	0.05	0.81	0.00

The new total variance is calculated to observe the difference in variance coverage by each type. The calculation for type B:

Total variance, V_T = SS_T / DOF = 4017.01 / 107 = 37.54 (6.17)

New total variance, *V all* = V_T **sum of percent of contribution for factor A to Noise*

= 37.54 (0.0001 + 0.0011 + 0.0018 + 0.0009 + 0.0097 + 0.0005 + 0.2982 + 0.6340 + 0.0041)

V all B = 35.66

The calculation for type A:

Total variance, V_T = SS_T / DOF = 4010.65 / 107 = 37.48

New total variance, *V all* = V_T **sum of percent of contribution for factor A to Noise*

= 37.48 (0.0002 + 0.0012 + 0.0023 + 0.0008 + 0.0098 + 0.0005 + 0.3004 + 0.6340 + 0.0018)

V all A = 35.61

The calculation for type C:

Total variance, V_T = SS_T / DOF = 3996.07 / 107 = 37.35

New total variance, *V all* = V_T **sum of percent of contribution for factor A to Noise*

= 37.35 (0.0001 + 0.0012 + 0.0020 + 0.0008 + 0.0097 + 0.0005 + 0.2994 + 0.6375 + 0.0000)

$V\,all\,C$ = 33.98

The new total variance shows Type B has the highest variation coverage, followed by Type A and C. Noise influence captured and variance coverage presented by Type B making this type has better outer array for experimental design when reducing variation in response.

6.2.2.2 Confirmation run

The final step is to predict and verify the improvement in peel strength variation using the optimum level in SNR response plot. Estimated and confirmation SNR between optimum and worst condition is calculated as in Table 6.24. The effect of the optimum condition is shown by the dB gain size between optimum and worst SNR. A confirmation run is done to check the SNR reproducibility of the estimation and confirmation experiment. Figure 6.22 shows the worst and optimum plot in confirmation run for all the three types; A, B, and C:

Table 6.24: Experiment result of SNR (dB) for all types of outer array layout

Type	Condition	Estimated	Confirmation
A	Optimum	14.91	14.82
	Worst	4.30	7.07
	Gain	10.61	7.75
	Gain difference	2.86	
B	Optimum	11.19	8.31
	Worst	3.09	2.27
	Gain	8.10	6.04
	Gain difference	2.06	
C	Optimum	19.60	21.00
	Worst	6.50	8.40
	Gain	13.10	12.60
	Gain difference	0.51	

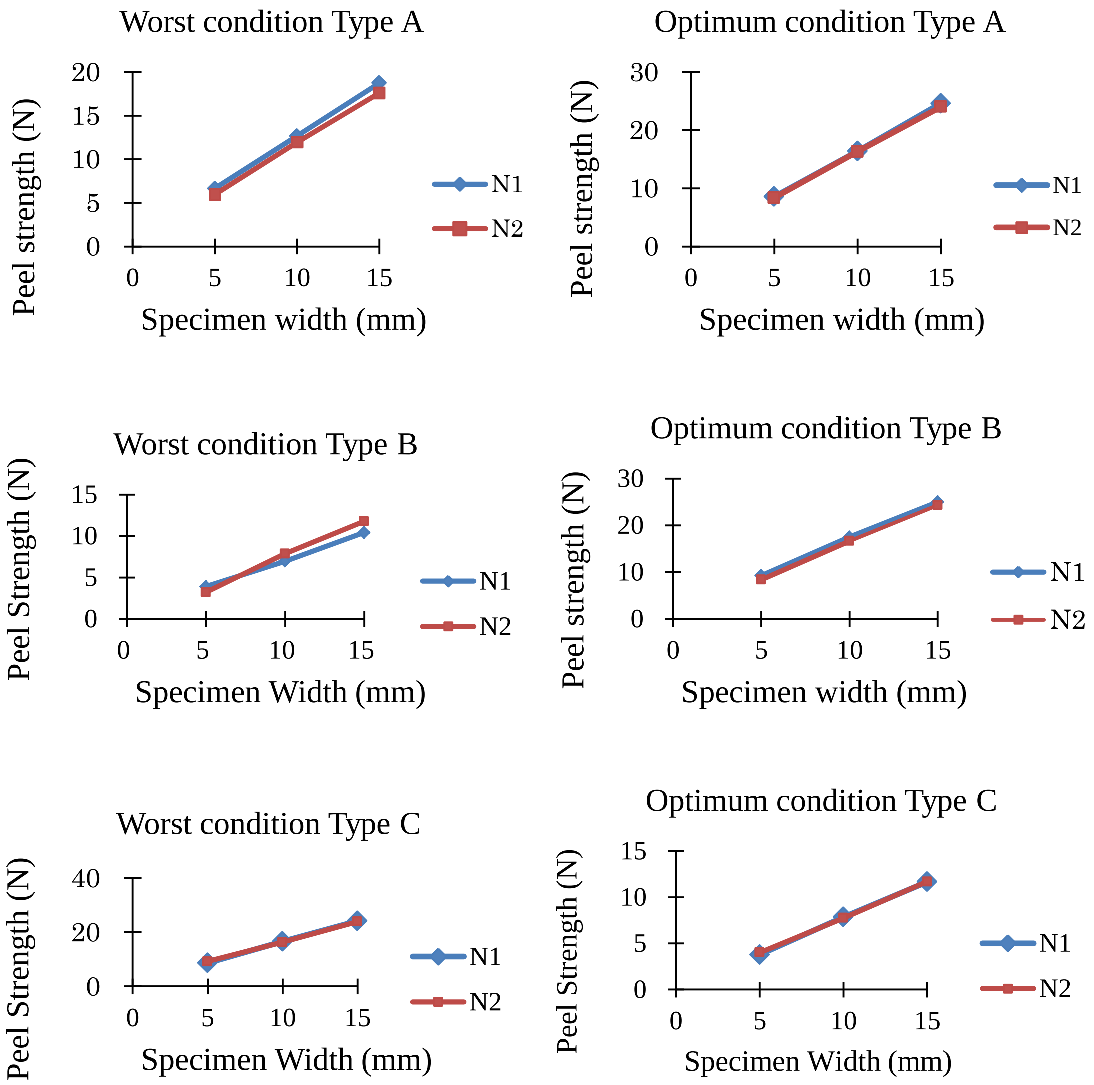


Figure 6.22: Ideal function plot from confirmation run for Type A, B, and C

For Type A, the optimum S/N ratio is confirmed at 14.82 dB, comparable to estimated value that is 14.91 dB. The difference between estimated and confirmed benefit (gain) is 2.86 dB. The gain difference is caused by the worst condition, as in confirmation SNR deviates a little bit from the estimated SNR in worst condition. The repeatability of worst condition is not very good compared to optimum condition.

Type B is considered the best type because the variation in measurement data is considered by range measurement. The gain of type B is not much differed with type A. The confirmation gain for Type B is 6.04 dB, which is just 1.71 dB difference from confirmation experiment in Type A. The gain difference for Type B is better than Type A with gain difference is 2.06 dB showing that Type B is more reproducible than Type A. Type C is considering the average, thus the gap between N1 and N2 does not deviates too much. The repeatability is very good, as the gain difference is only 0.51 dB due to average calculation. However, the variability in data measurement for Type C is not fully considered because only average value is taken. On the other hand, Type B reproducibility is affected by measurement sampling in outer array due to N1 and N2 gap which considering the most highest peel strength that is maximum peel strength of all and the least peel strength that is minimum peel strength.

All three noise parameters have less than 30% dB gain difference which shows good experiment reproducibility [15]. However, that is not the only factor to be considered when making decision on optimum condition. The logical reasons of the layout whether it covers the whole variation and the noise effect are some considerations that should be evaluated. In this study, the data measurement system on how the result is arranged in outer layout plays an important role as it relates to variability. If the measurement system does not cover the whole variation in a system, smaller gain does not mean better variation control.

In this practical experiment, reliability of optimum condition emphasized on the ability of optimum condition to perform under various range of response behavior. Three types of noise layout A, B, and C have its own characteristic, thus result three different optimum conditions. R. Dolah et al. [18] presented on Type A outer array layout. Details on noise strategy of one type are elaborated in this paper before recovering the other two types. However, the best optimum condition must be determined to ensure its reliability. Response behavior affects the way of determining noise factor and level in outer array measurement. Therefore, preliminary experiment plays an important role in experimental design before proceeding into implementation. Figure 6.23 summarized on evaluation of noise factor in outer array to provide a reliable experimental design for an optimum condition. When the noise level is selected, noise parameter need to satisfy the response behavior or process trend theoretically and practically. That is the main reason why preliminary run is conducted in Figure 6.17. Other possible measurement such as average is included to observe the effect of selected noise factor's level. Finally, the noise factor that satisfies the total response behavior is chosen as the experimental design that considered robust against variation and the optimum condition is reliable.

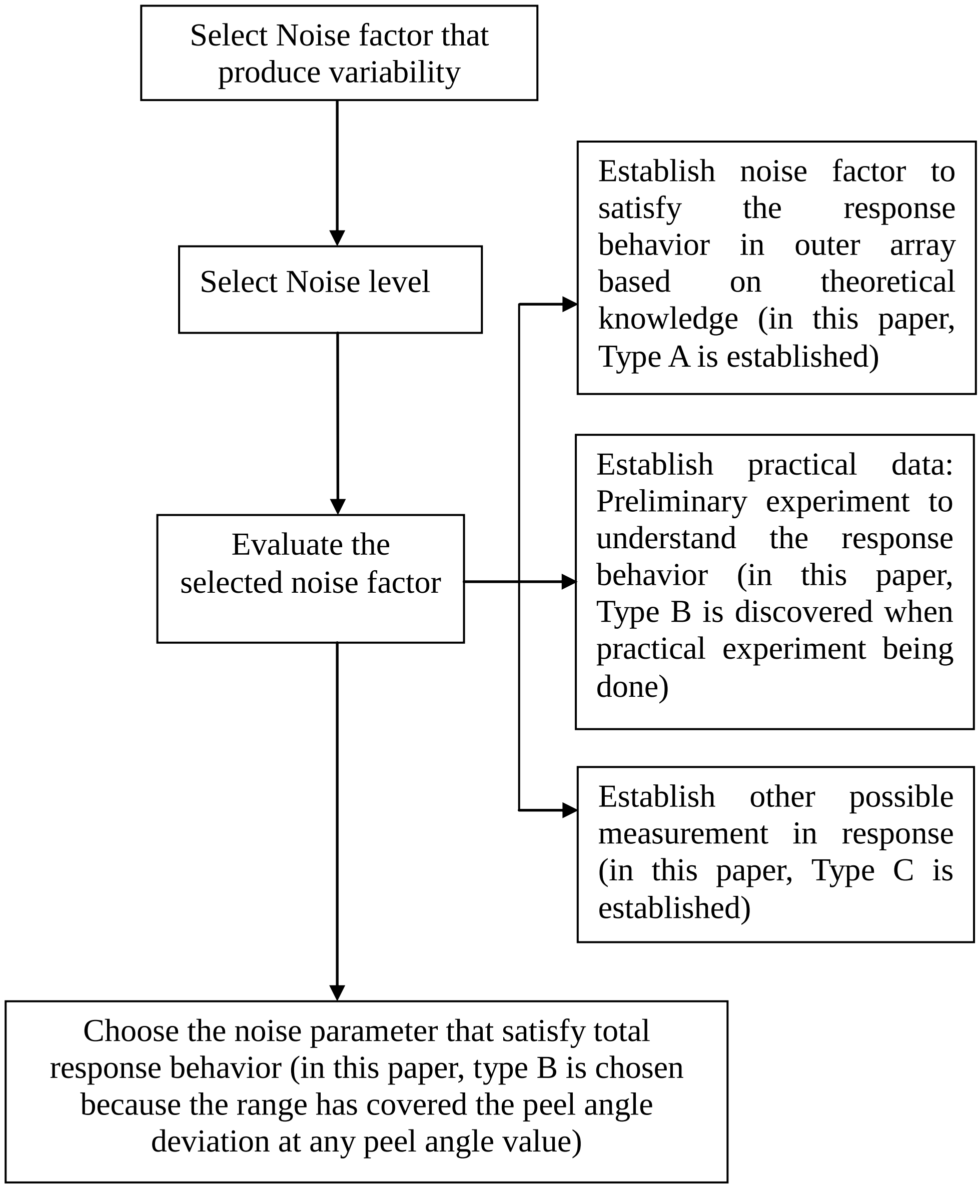


Figure 6.23: Noise factor evaluation process

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CHAPTER 7 CRITICAL TO ASSUMPTIONS IN PARAMETER DESIGN

This chapter emphasizes on the outlier effect on measurement data. The outlier problem in measurement system depicts the assumption that the process is not affected by irrelevant sources of variation. Outlier causes variation in measurement data, thus it is very important to be critical to such assumption. This chapter presents some guidelines to elucidate the detection of outlier and outlier effect on optimum condition.

7.1 Introduction

Robust design engineering is an engineering optimization strategy ideally used for the development of new technologies in product and process design [1]. One of its component focused in this paper is parameter design which defined as a systematic way to make a design robust against noise factors which takes place in improvement stage of the product development process [2]. However, the methodology of conducting robust design usually started with data analysis of sum and mean, deviation, variation and variance [3]. None emphasizes on the measurement data before the data can proceed to be analyzed.

Data which being affected by extraneous sources of variation other than variation studied in outer array could lead to wrong decision. The existence of outliers is often ignored and the impact is overlooked, thus endanger the experiment by producing false alarm and giving completely wrong parameter setting. The optimum condition from the data that contains outliers is compared with the corrected data measurement. The finding presents the indication procedure on how to confirm whether the data is reliable or not for evaluation. The data is unreliable when two main indicators are detected. Firstly, the measurement data plot detects outlier through linear regression analysis as it does not belong on the linear line. Secondly, dB gain difference from reproducibility examination of signal-to-noise ratio (SNR) between estimation and confirmation run is more than 30% shows that the experiment is a failure. This failure affects the experimental design and lead to wrong optimum condition. Investigation has to be made whenever anomalies are found, and outlier analysis is one kind of investigation analysis. In this practical experiment, the criticality to measurement data is discussed on a case study performed in T-peel adhesion test to find an optimum condition of a peel strength measurement system.

7.2 Experimental Method using Parameter Design

Parameter design in robust engineering method is used for this experiment. In order to observe the effect of outliers on optimum condition, two L9s are constructed; one with outlier data (L9A) and another one with no outliers (L9B). Experiments were then carried out to detect outlier and its effect on signal-to-noise ratio (SNR). The importance to be critical to data is presented in outlier detection procedure. The measurement data is evaluated for outlier detection through regression plot and reproducibility of experiment. The specimen utilizes the aluminum peel side [4]. Table 7.1 shows the signal factors, noise factors, and control factors used in this practical experiment.

Table 7.1: Factors and their levels in L9

	Control factor	*Unit*	*Level 1*	*Level 2*	*Level 3*
A :	Peel angle	o	60	90	120
B :	Peel speed	mm/s	6	9	12
C :	Data region	%	30	50	70
D :	Spring thickness	mm	0.3	0.4	0.5
	Signal factor			*Levels*	
M :	Specimen width	mm	5	10	15
	Noise factor		*Level N1*	*Level N2*	
	Peel angle deviation, Δ	o	+2	-2	
	Tensile weight, *w*	g	8	4	

7.3 Experimental Results and Discussions

Peel strength result is taken for SNR calculation. First measurement result is labelled as L9A and shown in Table 7.2. The data, Y*ij*, is assumed independent and in normal distribution.

Table 7.2: L9A Result

Run	Specimen width (mm)						SNR
	5		10		15		η(dB)
1	9.07	8.44	16.21	16.88	25.25	26.13	10.03
2	7.92	7.85	14.95	15.19	22.22	21.75	11.20
3	9.61	9.45	19.01	20.93	27.72	30.47	4.87
4	8.04	8.44	19.57	20.32	27.62	30.07	3.55
5	8.52	8.21	16.84	17.21	26.05	25.68	16.27
6	7.57	8.17	15.77	15.55	21.72	22.44	7.69
7	6.39	6.49	13.52	13.71	20.14	20.58	14.18
8	12.88	8.21	20.86	20.52	29.60	30.22	2.20
9	7.69	7.08	17.30	16.50	24.87	23.75	6.37

SNR, $\eta = 10 \log (1/r) \left[(S_\beta - V_e) / V_N \right]$ (7.1)

$$S_\beta = \frac{((9.07+8.44)5+(16.21+16.88)10+(25.25+26.13)15)^2}{2(5^2+10^2+15^2)}$$

$V_e = S_e/f_e = (S_T - S_\beta - S_{Nx\beta}) / 4$ (7.2)

$S_T = 9.07^2+8.44^2+16.21^2+16.88^2+25.25^2+26.13^2$

$S_{Nx\beta}=((9.07)5+(16.21)10+(25.25)15)^2+((8.44)5+(16.88)10$

$+(26.13)15)^2) / (5^2+10^2+15^2) - S_\beta$

$V_N = S_e' / f_e' = (S_T - S_\beta) / 5 = 0.29$ (7.3)

$\eta = 10 \log_{10}(1/2(5^2+10^2+15^2))[(S_\beta - V_e) / V_N] = 10.03\text{dB}$

Once the result is obtained, it is important to be critical to data before proceeding to further analysis. Otherwise, the analysis of improper data will endanger the experiment and lead to improper conclusion. Linear regression plot is one alternative to investigate the existence of outliers. Measurement data for L9A is shown in Figure 5. In 5mm, one outlier is detected as it does not belong to its population group. Peel strength of that one point is abnormally different, that is in run 8; 12.88N. The investigation is continued by plotting the regression plot for 5mm as in Figure 7.1 to investigate the problem. N1 and N2 are assumed as two variables and the correlation coefficient, r, is used to measure the linear relationship between two variables. The squared coefficient of correlation, R^2, gives the proportion of common variance between two variables, also called coefficient of determination [7]. The closer the value of R^2 is to 1, the stronger the linear association between the variables. One extremely deviant observation, so-called outlier, can dramatically influence the value of R^2 [5].

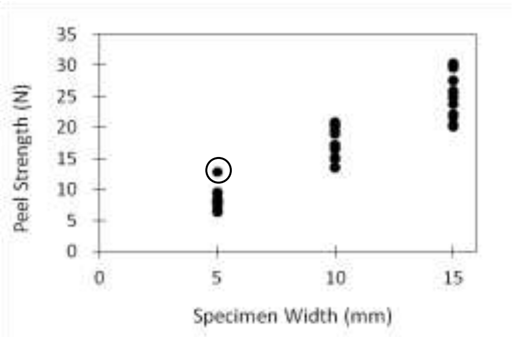


Figure 7.1: L9A measurement data

In Figure 7.2, R^2 without outlier is 0.766, but when the outlier is added to the set, the correlation is equal to -1.935. R^2 can never be negative as it is the square of r. The value of R^2 is bounded by $0 < R^2 < 1$. The existence of outlier presents a suspicious observation and the result need to be repeated to confirm the cause or else it might lead to wrong conclusion. In L9A, the outlier data is 12.88N in run 8 for specimen 5mm under N1. Outlier is not observed in specimen 10mm and 15mm as R^2 for specimen 10mm and 15mm is 0.910 and 0.895 respectively. Then, mean SNR so-called process average is calculated to find the effect of each control factor. The process average is used to calculate the optimum condition based on SNR factorial effect plot.

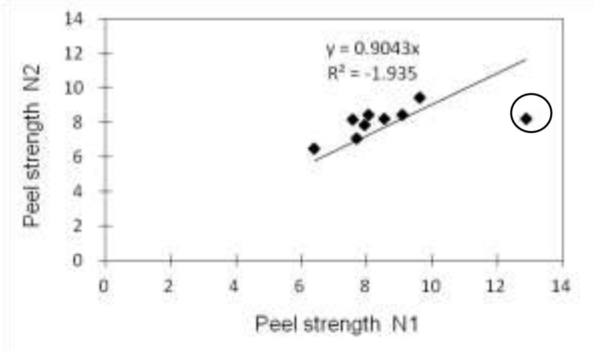


Figure 7.2: Specimen 5mm measurement result

Optimum condition for L9A derived from SNR formula in (1) is A2 B2 C3 and D2. The detection procedure is proceed by checking the experiment reproducibility through comparison of SNR estimation and confirmation dB gain. Estimation SNR for optimum condition is calculated by:

= A2+B2+C3+D2 – (DOF n-1)($\Sigma\eta$ / n) (7.4)

= (A2+B2+C3+D2) – (4 factor–1)(average SNR in L9A)

= 41.84dB – 3(8.48dB) = 16.39dB

Estimation SNR for worst condition is calculated to get the dB gain. The effect of the optimum condition is shown by the dB gain size.

= (A3+B3+C1+D3) – (4 factor–1)(average SNR in L9A)

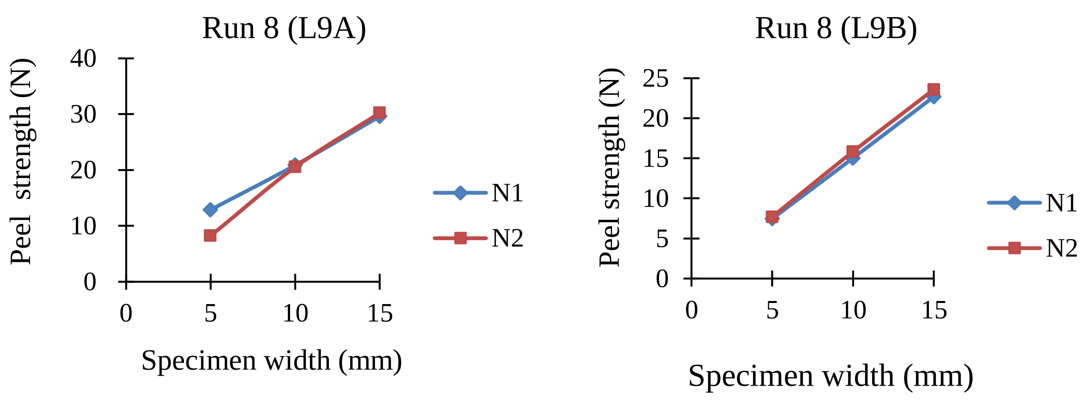
= 24.07dB – 3(8.48dB) = - 1.38dB

Thus, estimated dB gain is 17.77dB. Confirmation run is done to ensure the reproducibility of optimum condition. However, the confirmation dB gain is 9.75dB, which is 45.1% different from estimation dB gain. The result of experiment is considered not satisfactory. This indicates the possibility of wrong optimum condition resulted from outlier data. The dB gain difference should not exceed 30% difference from estimation dB gain [6]. From the anomaly of R^2 and dB gain difference, second L9 which is called L9B in Table 7.3 is employed as to repeat the experiment and confirmed the outlier reproducibility. All 9 runs are conducted again to reduce extraneous sources of variation.

Table 7.3: L9B Result (repeated experiment)

Run	Specimen width (mm)						SNR η (dB)
	5		10		15		
1	8.70	8.37	16.62	16.78	24.96	24.09	12.40
2	8.04	8.12	15.28	16.21	23.91	24.52	11.77
3	8.72	8.09	16.59	16.39	24.49	24.30	15.15
4	7.79	8.04	15.68	15.86	23.87	24.38	15.97
5	8.45	8.41	16.49	16.20	24.12	23.99	14.85
6	8.26	8.18	15.51	15.80	24.43	24.32	13.28
7	7.59	7.74	14.77	15.15	22.16	22.20	16.76
8	7.46	7.69	15.03	15.83	22.68	23.58	11.76
9	8.49	8.27	15.87	16.29	23.76	24.09	14.43

Run 8 which found to have outlier in earlier experiment, L9A; is plotted as in Figure 7.3 (a). Therefore, by repeating the experiment in run 8 as in L9B, the linear plot is shown in Figure b. The linear relationship is clearly observed in L9B for run 8 and the data is acceptable as no outlier is observed. The outlier in Figure 7.2 is clearly depicted in Figure 7.3 (a) for specimen width 5mm. Figure 7.3 (b) illustrates the repeated experiment (L9B) and linearity of peel strength is observed.



(a) (b)

Figure 7.3: Run 8 for L9A (a) and L9B (b)

Measurement data of L9B is plotted to observe any outlier. R^2 for 5mm, 10mm, and 15mm are 0.729, 0.676, and 0.645 respectively. No outlier is observed. The outlier in L9A is a special cause, due to environment noise or measurement mistake that cause the 12.88N as outlier data. SNR as in (1), SNR process average and effect plot, and estimation SNR as in (4) are calculated as same as L9A. The optimum condition for L9B is A2 B1 C3 D3 as shown in Fig. 7.4. The estimated db gain is 7.31dB and confirmation db gain is 6.53dB. Table 7.4 summarized only 10.7% difference, thus L9B is considered a success.

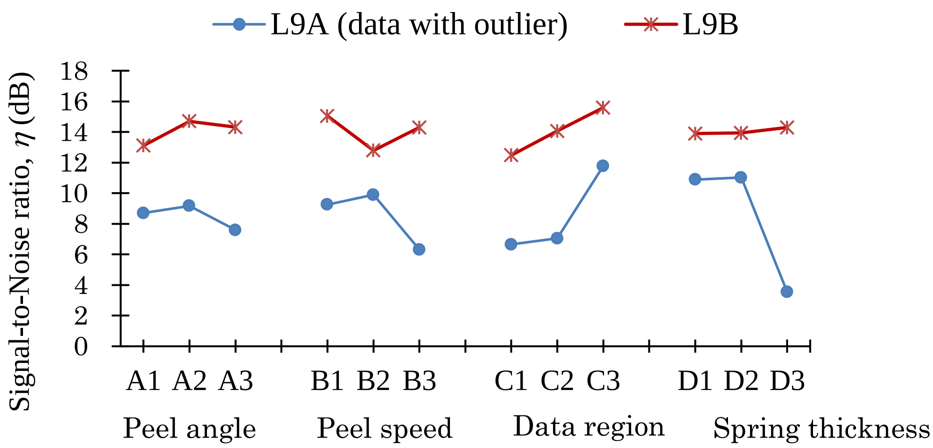


Figure 7.4: SNR factorial effect plot for L9B and L9A

Table 7.4 Reproducibility Examination For L9A And L9B

Type	Condition	Estimated	Confirmation
L9A	Optimum	16.39	15.10
A2	Worst	-1.38	5.35
B2	SNR dB gain	17.77	9.75
C3 D2	Gain difference	8.02 dB (45.1% difference)	
L9B	Optimum	17.49	16.45
A2	Worst	10.18	9.92
B1	SNR dB gain	7.31	6.53
C3 D3	Gain difference	0.78 dB (10.7% difference)	

Notice that there are some deviations between condition L9A and L9B. SNR for L9B is higher than L9A due to repetition error since L9B is done after realizing the outlier existing, which took some time gap between both experiment. The variation is also due to extraneous factors which inevitably vary during experiment such as temperature and humidity. As the practical experiment focused on the effect of outlier from response data and its influence on optimum condition, the difference in optimum condition level between separated data set is assumed has no effect in outlier examination.

7.3.1 Replacement with Regression Point

Decision must be done carefully between repeating the experiment of the whole orthogonal array or replacing the data with regression point. This is done to prevent any extraneous variation or the noise that is not under study is not affecting the measurement result. Run 8 which contains the outlier is omitted to allow normal data calculation. This method is treated as missing data treatment. Table 7.5 shows the calculation of linear regression from L9A result. N1 is considered as x-data and N2 as y-data.

Line of best fit is $Y = b_1X + b_0$ (7.5)

with slope; $b_1 = \sum Sxx / Sxy$ (7.6)

Table 7.5: L9A Linear Regression Data

					Sxx	Sxy
Run	X	Y	X - average X	Y - average Y	(X - average X)^2	(X - average X)(Y - average Y)
1	9.07	8.44	0.971	0.4257	0.94	0.413399032
2	7.92	7.85	-0.184	-0.1636	0.03	0.030141322
3	9.61	9.45	1.511	1.4351	2.28	2.168047901
4	8.04	8.44	-0.061	0.4216	0.00	-0.025510789
5	8.52	8.21	0.421	0.1925	0.18	0.081115043
6	7.57	8.17	-0.532	0.1501	0.28	-0.079834222
7	6.39	6.49	-1.711	-1.5262	2.93	2.611636619

8						
9	7.69	7.08	-0.415	-0.9352	0.17	0.388439319

Average X = 8.10

Average Y = 8.02

Sum of Sxx = 6.82

Sum of Sxy = 5.587

By using equation (7.6), $b_1 = 0.8187$. Thus, intercept; b_0 is calculated by inserting the average of X and Y into equation (7.5). Therefore, line of best fit is:

$$Y = 0.8187\,X + 1.3859 \qquad (7.7)$$

The correlation coefficient, R^2, gives the proportion of common variance between two variables, also called coefficient of determination. The closer the value of R^2 is to 1, the stronger the linear association between the variables. One extremely deviant observation, so-called outlier, can dramatically influence the value of R^2 [7]. The line of best fit is used as the predicted $\hat{Y}$ in R^2. R^2 is 0.8013. Figure 7.5 shows the regression plot for the best fit line.

$$R^2 = \frac{\sum(\hat{Y} - \bar{Y})^2}{\sum(\bar{Y} - Y)^2} \qquad (7.8)$$

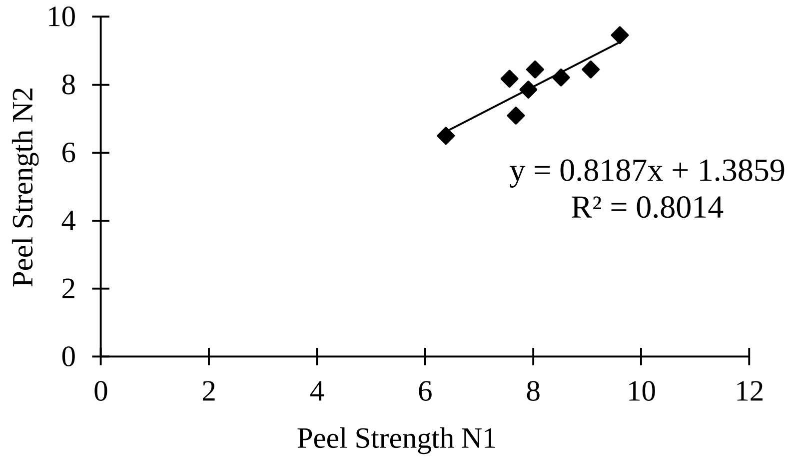


Figure 7.5: Linear regression plot for run 8

Measured data of run 8 in Y (8.21) is used in equation (7.7) to calculate the value of X. Value of X, which initially the outlier is replaced with new data obtained from equation (7.7). Thus, the replacement data of the new X is 8.33. SNR for the replacement data from linear regression point is 4.42 dB. Initial SNR with outlier is 2.20, the replacement with regression data is much better. The repeating experiment has SNR 11.76 dB. Table 7.6 summarizes the three SNR results in obtained in run 8.

Table 7.6: Treatment of outlier data using repeating L9 and replacement by regression

Type	5mm		10mm		15mm		SNR η	Sens. β
	N1	N2	N1	N2	N1	N2		
Initial outlier	**12.88**	8.21	20.86	20.52	29.60	30.22	2.20	6.12
Repeated (L9B)	**7.46**	7.69	15.03	15.83	22.68	23.58	11.76	3.75
Regression point	**8.33**	8.21	20.86	20.52	29.60	30.22	4.12	5.97

Although the SNR of run 8 in L9B is the best compared to replacement of regression data, consideration such as experimental time and cost must need to be considered. Therefore, the lifespan of specimen is studied before deciding on repeating or replacement data should be done. If changed condition of specimen is observed, it is advisable to repeat the experiment to prevent the extraneous variation. However, if there is no changed in specimen condition, treating it as missing data treatment is worth enough.

7.4 Conclusion

The importance of making thorough analysis of assumptions and possible existence of outliers have become obvious from the case study in this paper. Even though the confirmation test indicated the problem and thus trigger suspicious to data, a thorough investigation of possible anomalies in measurement data should be performed. Thus, it is very important to ensure that the data is reliable enough to draw a conclusion at the end of the experiment. Two ways to examine on data reliability:

a) Outliers examination - by observing the linear relationship in regression plot. R^2 changed dramatically when deviant observation is found.

b) Reproducibility examination – Estimation and confirmation in dB gain difference should not deviates too much or exceeds 30%. The similar the value between estimation and confirmation SNR, thus more reliable the optimum condition is.

Figure 7.6 presents the outlier checking methodology flow. Figure 7.6 summarized the outlier checking methodology to prevent any misleading conclusion from SNR analysis. Planning the experiment carefully is extremely important to ensure a smooth and reliable result. Enable the function, quality characteristic selection, and noise, control and orthogonal array selection is done in Plan stage. When planning is complete, experiment is ready to be implemented thus labeled as Do stage. Before confirming the SNR result, linear regression from the measurement data is plotted to observe any abnormalities and extraneous variation. Reproducibility in measurement is analyzed through confirmation experiment by comparing the dB gain between estimation and confirmation SNR. If the condition of sample has changed, the experiment is necessary to be repeated because variation is greater for a sample that has changed its condition. However, if the sample has no changed condition (short period of time), it is worth enough to be treated as missing data treatment through linear regression. Replacement of regression point found in linear regression analysis is done instead of doing another new experiment. Finally, the optimum level is accepted as an action for further application of the confirmed optimum condition. Measurement data should be examined immediately once the experiment is performed to prevent perils. The finding of this chapter is presented in R. Dolah et al. [8] concerning on the data criticality in measurement process.

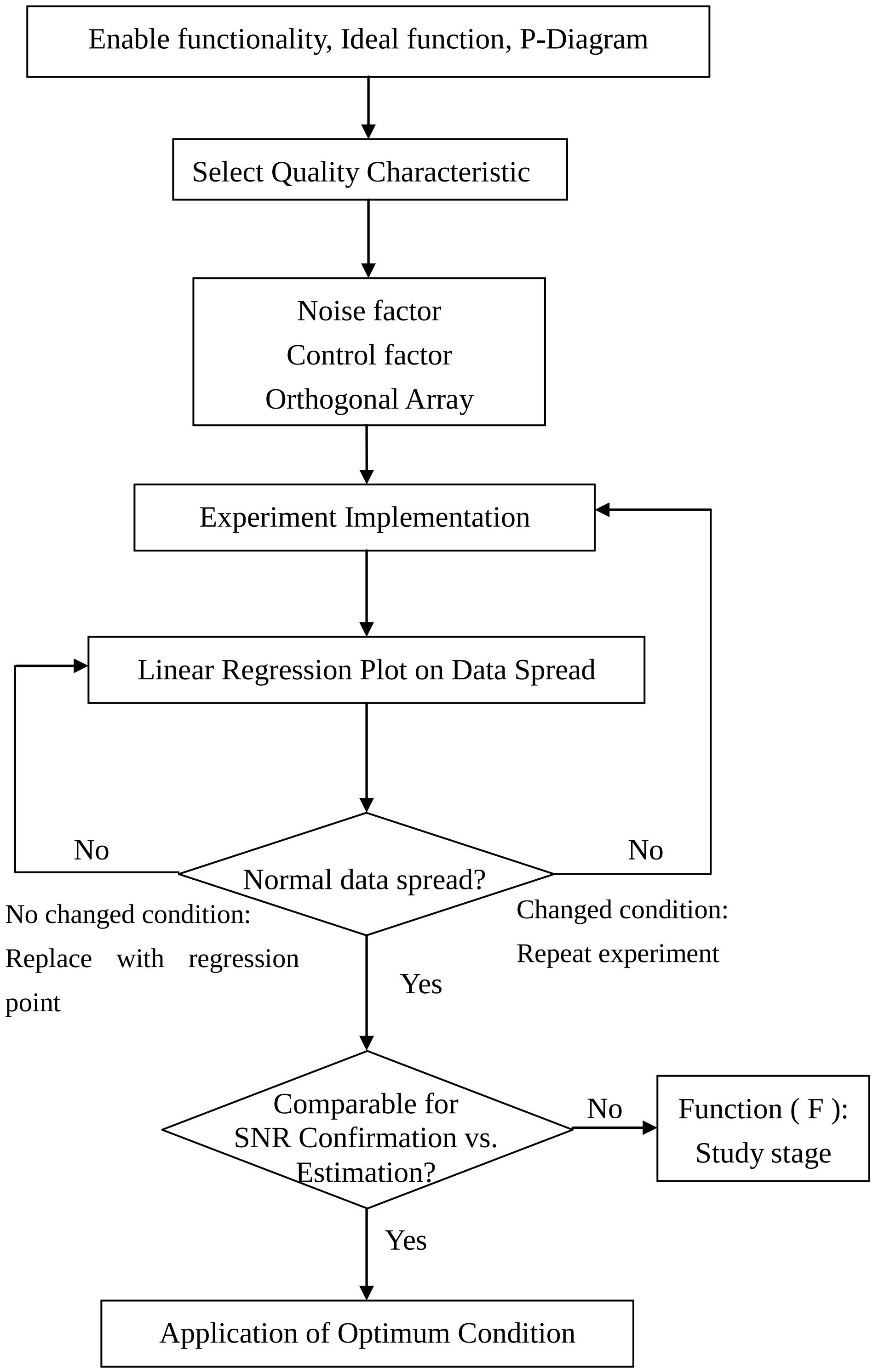


Figure 7.6: Outlier checking methodology flow

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PART III

CONCLUSIONS

CHAPTER 8 DISCUSSIONS ON CONCLUSION

Chapter 5, 6 and 7 explained the robust design methodology step by step from the ideal function stage to the experiment implementation. These findings are categorized into several stages of measurement systems. Measurement systems in each section are explained thus enhancing the general measurement system of parameter design.

8.1 Methodology for Measurement System Design of Quality Engineering

The research of measurement system design has included the three components of Taguchi Method that are System Design, Parameter Design, and Tolerance Design. The practical experiment of peel strength measurement is not suitable for tolerance design because the response is not a part to be measured exactly. This practical case study is minimizing variation in peel strength as much as possible. Tolerance design is not suitable to be applied using this practical case study. Therefore, only system design and parameter design are explained.

8.1.1 System Design

System design is the conceptualization and synthesis of a product or process to be used. This is where the new ideas, knowledge and concepts in science and technology are utilized to determine the right combination of materials, parts, processes, and design factors that will satisfy functional and economical specifications. Therefore, before going in depth to optimize a process for example the T-peel test process in this case; first one should think of the system itself whether it satisfies the function and economically designed. Mechanical testing method is studied and final conclusion is drawn from system design analysis. The practical case study is using T-peel test for the flexible film packaging as a method for measuring peel strength of an adhesive. Firstly, consideration on mechanical basic test methods to evaluate the lamination strength are studied that are peel, shear, and tension testing. Peel tests are most commonly used to evaluate the laminated film or bonded adhesives. Thus, peel test is preferred when working with multiple film packaging in this study that are poly ethylene (PET), polyamide, aluminum, cast poly propylene (CPP), and bonded with adhesives. Shear test Shear adhesion test is one of the PSA test to evaluate the holding properties. Shear adhesion is the resistance to movement of a tape specimen when a shearing load is applied. In other words, shear adhesion is holding power. The essence of the test is a given area of tape is adhered to a substrate, placed in vertical position, and loaded with a given mass for example a quartz block. The measurement includes the slippage of a specimen for the standardized loading time, or in other words the ability to adhere to a standard stainless steel plate. Another measurement of adhesive test method is tensile test or known as tension testing. Tensile test is done in which a sample is subjected to a controlled tension until failure. This test is important to predict how a material will react under other type of forces. Mechanical characteristics that usually been measured in tensile test are tensile strength, maximum elongation, and reduction in area. As the specimen focused on mechanical peeling property, thus elongation is not much concerned here. Therefore, tensile test is not being selected.

There are four main types of peel tests: 90^o peel, 180^o peel, T-peel, and climbing drum peel. The 90^o peel test is suitable for a flexible adhesive material that is adhered to a more rigid substrate. The 180^o peel test is best used when the flexible substrate can be bent back by 180^o. The T-peel test is best used when both adhesive and adherend are similar or flexible. The climbing drum peel test is suitable to determine the peel resistance of adhesive bonds between sandwiches of two layers. This study assesses packaging film made out of flexible material and consisting of several layers of flexible films. Therefore, the T-peel test is the most suitable peel test to measure the peel strength of this material. The selection of testing method is part of system design based on knowledge from specialized fields or so-called specialist’s territory, and neither quality control nor the design of experiments can help it. Figure 8.1 below summarized the selection of mechanical testing method for flexible film packaging:

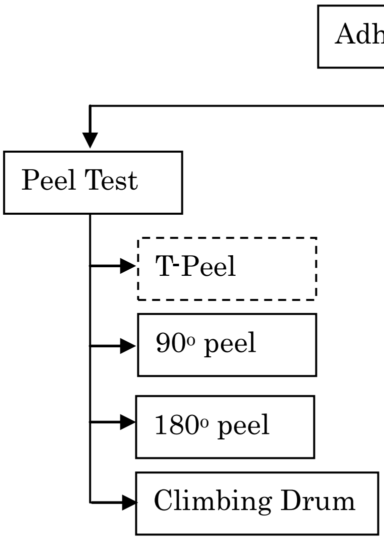

Figure 8.1: Selection of mechanical testing method in system design phase

8.1.2 Parameter Design

Dr. Taguchi has emphasized that quality must be designed into products from the start. Everywhere not only Japan, but also in Europe and United States began adopting Taguchi's robust design approaches as part of product's quality improvement and robust design. Quoted by Phadke, 1989, robust design is and engineering methodology for improving productivity during research and development so that high quality products can be produced quickly and at low cost. The idea behind robust design is insensitivity to variation in uncontrollable parameters. The minimization of variation in parameters is done in parameter design process. Parameter design is a stage where the controllable factor is observed on how the product or process reacts with uncontrollable factor in a system. Parameter design is a main thrust of Taguchi approach. Appropriate level of factors are determined to ensure the system is less sensitive to variation or in other words, to make the system robust. By doing this approach, the performance of a product or process is much better thus produce high quality product and reducing loss to the customer. Once system design is finished, the next step is to determine the optimum level of individual parameters of the system.

Bo Bergman and Bengt Klefsjö [1] explained that a robust design is considered as improvement stage of the product development process. A simple mathematic description is illustrated with an output variable denoted as y with a target value y_o. Three design parameters x1, x2, x3 and a noise factor Z as an uncontrollable variation is shown in equation 8.1:

$$Y = f\ (X_1,\ X_2,\ X_3,\ \ldots\ Z_1,\ Z_2,\ Z_3,\ ..\ \varepsilon\ ) = b_o + b_1X_1 + b_2X_2 + b_3X_3 + b_ZZ + b_{2Z}\,X_2Z + \varepsilon \quad (8.1)$$

ε is an unknown, small residual term which is independent on the design parameter.

With X_2 = -bZ / b_2Z, the influence of noise factor Z is completely disappears. The equation is said to be robust because the influence of noise factor is minimized and disappeared. The noise factors in an experiment can be varied, as assumed that it is controllable during the experiment and uncontrollable in real life. There is some case whereby noise is not detected and its appearance is not even known. These variations are caused by extraneous factors. Extraneous factor could deviate the output result unintentionally. In Chapter 3, the study on the effect of the outliers as extraneous factor is described thoroughly and method to overcome the ignorance of outliers has been presented. The existence of outliers is often ignored. Outliers may sway the output result thus giving an inaccurate optimum condition as the end result.

8.2 Flow for Measurement System in Robust Design Engineering

The findings can be gathered as one measurement system design for parameter design in Taguchi method. Literature review explained that most Taguchi method application only informed about application of the tool without discussing on the concept of variation measurement in the early of implementation [2][3][4]. On the other hand, measurement systems of robust design are explained deeply in Tirthanka Dasgupta et al., Bovas Abraham et al., V. Roshan Joseph et al., and Deuk Soo Kang et al.

As from voice of customer, the target or customer specification is aligned in Quality Function Deployment house (QFD). The findings are then being channeled to product development section to satisfy or fulfill the QFD requirements. In product development, the QE implementation is branched out through two channels that are management strategy and development implementation stage using engineering tool for QE. In the management strategy, the opponents or resistance of implementing QE is overcome and counter measured. Findings from Fuji Xerox and Company B are taken into account as to overcome the negative feedback of QE implementation in an organization. For development implementation stage, parameter design is identified as an engineering tool. Parameter design method is illustrated in laboratory using T-peel test method and is compared with implementation in Fuji Xerox. Parameter design as QE engineering tool can be applied in any environment, be it industrial application or research field. Methodology comparison in Figure 5.4a and 5.4b of Chapter 5 is used to produce a framework on how to apply QE methodology to obtain robustness of a product or process. Measurement system design is drafted from this very beginning stage of product development.

The parameter design in engineering tool is further analyzed to ensure the measurement has covered total variability in data. There are four stages in measurement systems for this flexible film. The first measurement system is the function system measurement (F). Secondly, noise strategy measurement (N) is done followed by control factor selection and determination I(C). The last stage is optimization measurement (O). Figure 8.2 showed the measurement system in parameter design.

The system is a close-loop measurement system called as F-N-C-O ladder. Problem statement is the system ignition followed by the four sub-systems; F for Function system, N for Noise system, C for Control system, and O for Optimization system. Application of the optimum condition is the output of the measurement system. The F-N-C-O is connected to each other by the Plan-Do-Study-Action so-called P-D-S-A cycle. In each sub-system, P-D-S-A cycle is used for continuous improvement from one sub-system to another. Each sub-system is started with P: Plan stage and end up with A: Act stage. The Act stage in Function system (F) is moving the Plan stage in Noise system (N).   And the Act stage in N is moving the Plan stage in Control system (C) and so on. In optimization system (O), S: Study stage analyze the normality of the data spread. If the spread of data is not good (NG), the flow is back to Function system (F) under D:Do stage of selecting the quality characteristic. If the reproducibility is low detected in O system, the experiment was a failure. The failure is often related to basic function setting, quality characteristics and others. Thus, the flow is back to F. This P-D-S-A cycle ensures the mobility of the system and dependency to each sub-system. The equation $Y = f(X_1, X_2, X_3,..Z_1, Z_2, Z_3, ..\varepsilon)$ shown at the bottom of F-N-C-O ladder represents the output; Y as the function of the Xs as in the Control system (C) and Zs as the Noise system (N). Details on each sub-system are elaborated in further sections.

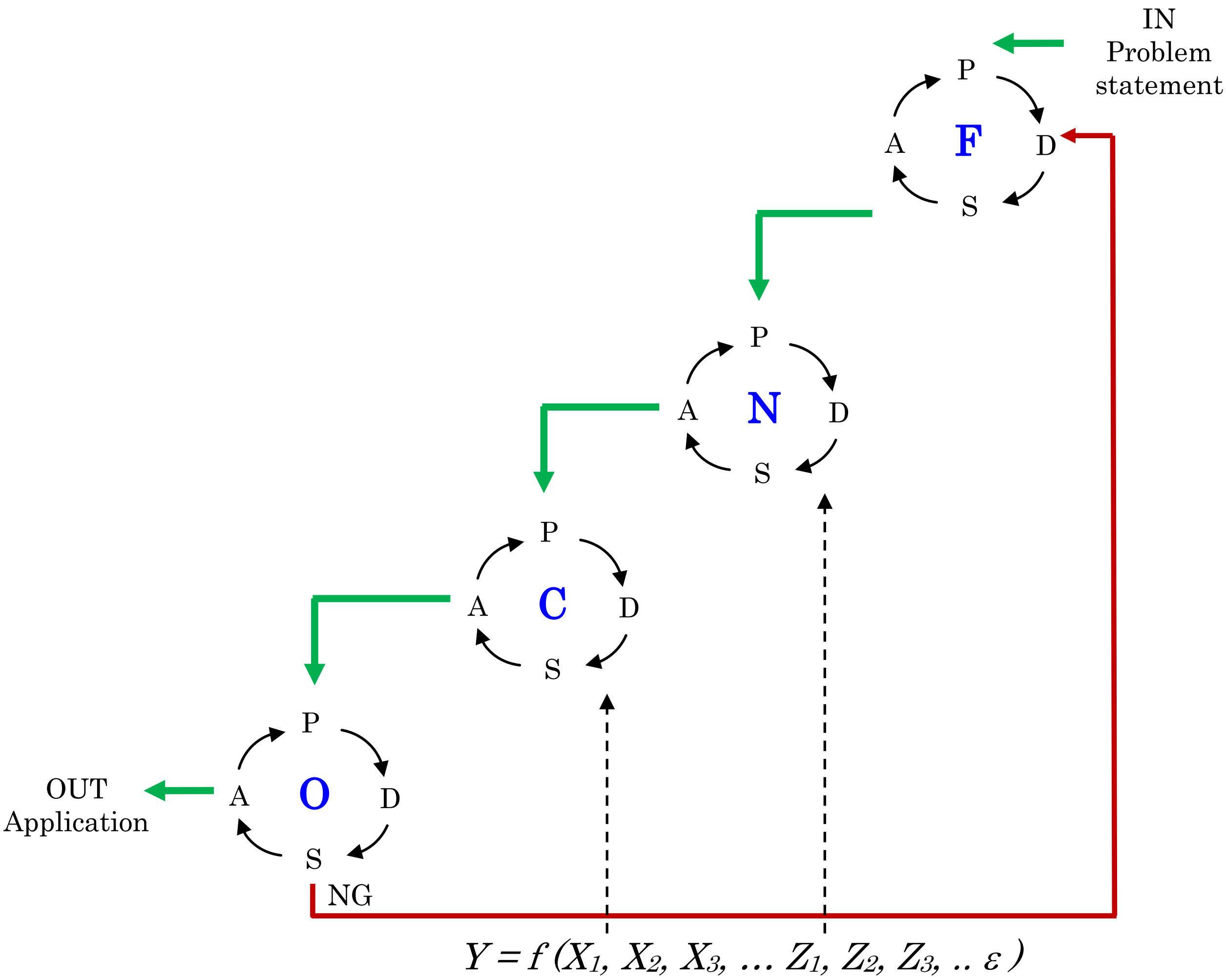

Figure 8.2: F-N-C-O ladder for measurement system in robust design engineering

8.2.1 Function System (F)

This stage consists of enabling the function, energy transformation, quality characteristic selection and finally forming the ideal function. In order to enable the functionality of the system, a careful analysis of the ideal function that transforms the energy into quality characteristic is done. This is done in "Plan" stage to define the function of the system that is being investigated. The response, Y, or also called quality characteristic represents the energy transformation of the system, then the interactions is greatly reduced because energy is additive. In order to improve quality, do not measure and analyze the response. Measure the function, that is energy related because energy has additivity.

In this research, peel strength is the energy for flexible film testing. At “Do” stage, peel strength has been used as quality characteristic for the practical experiment using parameter design. After the quality characteristic is identified, type of signal-to-noise ratio (SNR) is studied. In “Study” stage, analysis on which suitable quality characteristic is done to ensure the variation is totally captured. It is important to identify whether or not the system has the signal factor. There are static SNR without signal factor and dynamic SNR with signal factor. Measurement system is a perfect illustration of dynamic system. In a measurement system, the measurand is always in dynamic state as the range of measurement is used. The shaded area covering the static SNR means different characteristic of measurement term. Static in robust design consists of bigger-the-better (BTB), smaller-the-better (STB), nominal-the-best (NTB), and operating window (OW). In this research, dynamic SNR is chosen because signal factor that is specimen width is used. Signal factor is a controllable variable that helps to actualize or accomplish the intention. Factors cited for the purpose of expressing intention or attaining a target are called signal factor. The width of the specimen is a signal factor used as a medium to actualize the intention of getting the peel strength result. From preliminary studies, the wider the specimen width, the greater the peel strength is. Peel strength increase proportionally to specimen width.

Three widths are used (5mm, 10mm, and 15mm) to measure peel strength linearity. Hence, the signal to noise ratio (eta, η) for dynamic response is used in this study to measure various ranges of input to ensure robustness. Another application example of signal factor is in dyeing process. In dyeing process, dyeing temperature considerably affects darkness. If temperature is changed to adjust darkness, then temperature is a signal factor. Signal factor has no influence on SNR but have a significant effect on the mean. As explained in early section, the mean of peel strength changes according to specimen width.

Next, under “Act” stage, an ideal function and finally P-diagram is constructed to get a full view of the parameter design system. An ideal function shows a relationship between a signal and an output characteristic under certain conditions of use. In robust engineering, research and development are conducted by reducing the variability of a function under various conditions and bring the function as close as possible to the ideal function under standard condition [5]. Function measurement consists of below processes as shown in Figure 8.3:

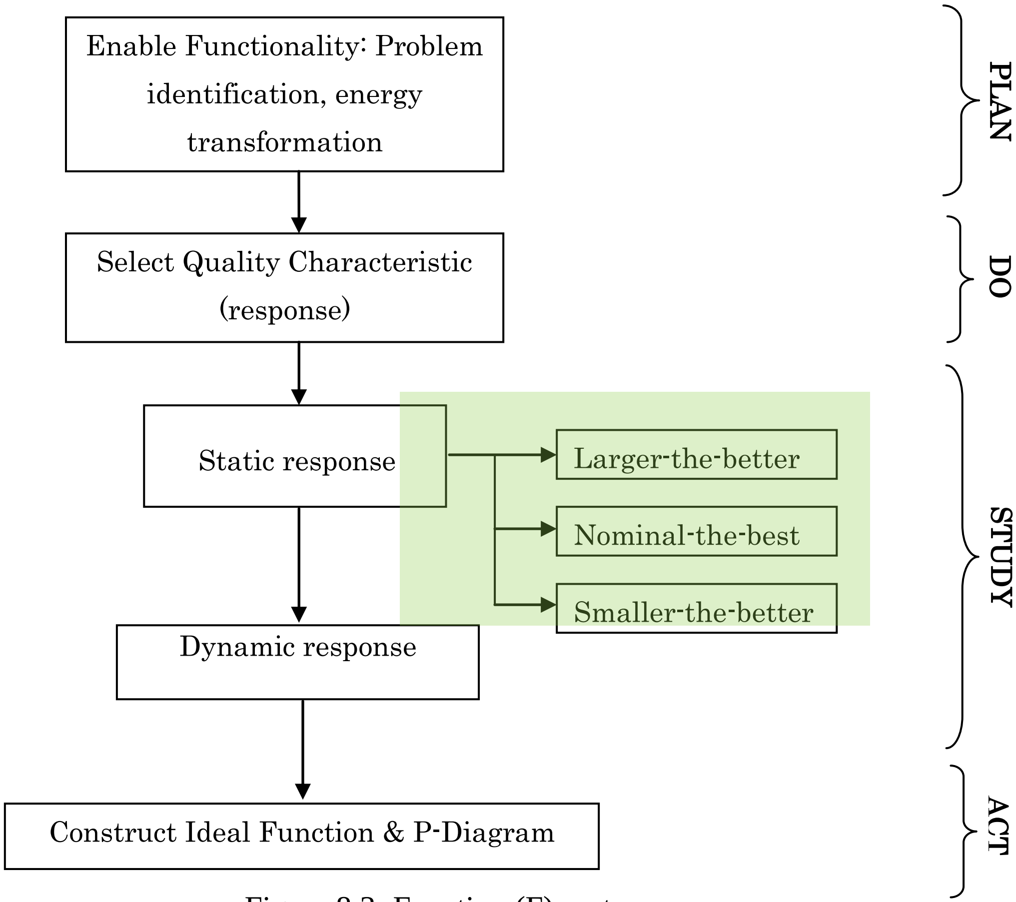

Figure 8.3: Function (F) system

8.2.2 Noise System (N)

Noise factors cannot be controlled during normal production or use. Thus, noise factor if likely to produce variability in response. In other words, noise is variables that cause product functions. Three types of noise are outer noise caused by environmental conditions, inner noise caused by deterioration of elements or materials in the product, and between-product noise caused by piece-to-piece variation between products [5]. A robust design experiment searches for values of the control factors which can be controlled during production and make the product or process insensitive to changes in noise factors. For a robust design experiment, start by selecting the response, and then choose noise factors that are likely to produce variability in response, and finally select the control factors that are likely to affect the variability and the mean of the response. After identifying the experiment objectives, it is usually preferable to select the responses before selecting the noise factor. Therefore, the "Act" stage of constructed ideal function and P-diagram in F sub-system has connected the "Plan" stage in N sub-system. After function measurement is determined for the quality characteristic, noise measurement is done. When planning an experimental design, selecting factors that affect the response and their levels of value or setting are very important. If incorrect factors and levels are chosen in the experiment, the results may be incomplete or misleading. Number of factors and levels are chosen based on objectives of the experiment. Relate with response objective, for example if the objective is to minimize variation of peel strength, make sure the noise factor can produce the variation in peel strength and the design space is covered as best as it can. Engineering knowledge of the process can be used to select noise factors and level. Historical data, previous experimental results, theoretical knowledge, expert opinion, observational data and other relevant data can be used in judging what noise factor should be. The noise strategy is very important which involves the selection of noise factor. Engineering knowledge is very useful in ensuring the stability of the optimum condition in long term. When source of variation is identified clearly, this will minimize the risk of having the unstable optimum condition. The robustness of measurement result is heavily depending on the noise factor. In long term, reproducibility of measurement must be equal or most equal to the measurand.

In selecting the noise level, the range of factor levels should be selected as the levels are not so close to each other because the effect on the response is not observable or important nearby effects will be undetected. The level also should not be so far apart that there is a region of unknown process behavior between the factor levels. The level also depends on the response being considered. Two-level is chosen when the factor either has or has no effect on the response. Three-level of a factor is chosen to study curvature in the response. Normally in two-level factor, it is possible to assess whether there is curvature in one or more factors by adding center points at the center of its range. Four-level factor or more is to study further curvature, to locate sudden rise or drop in the response. In other words, extra level is meant to understand some pattern or change behavior. Then, the noise validation study is made in "Do" stage to categorize the group of noise parameter. For example, set 1, or usually denoted as N1 gather the low setting of noise parameters. Set 2, or N2 denotes the high setting of noise parameters. This is the special characterization of Taguchi method that the noise parameter is separated in outer array. The effect of noise parameter is studied in Taguchi method and placed in outer array. The objective is to determine the best setting of those parameters which can be controlled during the standard conditions and minimize the effect of noise parameters which causes variability in product performance. Taguchi method focuses on achieving robustness in the functional performance. However in classical design of experiments (DOE), the objective is to minimize the effect of parameters using blocking or randomization strategies. Thus, in DOE all parameters are placed in one array and no distinction of control and noise parameters.

In studying the noise factor to be measured in outer array, there are three types of data measurements as explained in Chapter 3 section 3.2.2.2. This practical experiment emphasizes on the outer array layout effect on optimum condition. This is done under "Study" stage to study the selected noise factor. Firstly, the assumption of current behavior in the response is evaluated based on theoretical knowledge of peel strength. Practical experiment is done to confirm the assumption of the peel strength curve. This is called the preliminary study of the assumption. In practical experiment to proof the assumption, the peel strength is found decreasing from 60^o to 90^o peel angle. Deviation of peel angle gives clear value of peel strength, either high peel strength or low peel strength. As the trend of peel strength is increasing, an assumption is made on higher peel strength tends to be affected by higher peel angle. This assumption is an outer array derived from theoretical analysis. However, the trend from 90^o onwards showing a very small increment. Deviation of $\pm 2^o$ for this region is hardly separated, thus peel strength for N1 is not necessarily higher than N2. Thus, measurement of peel strength is further analyzed to understand the actual phenomena or response behavior. As the objective is to minimize variation in peel strength, coverage of data is an important for data measurement in outer array. Full range coverage is the noise parameter to fulfill this phenomenon. Other measurement that could possibly occur in the response is further analyzed. In this case, average measurement is done. Finally, under "Act" stage, the noise parameter that satisfies the total response behavior is chosen. Outer array which covers the whole variability is chosen to ensure the result of optimum condition is not misleading. Figure 8.4 summarized the noise strategy:

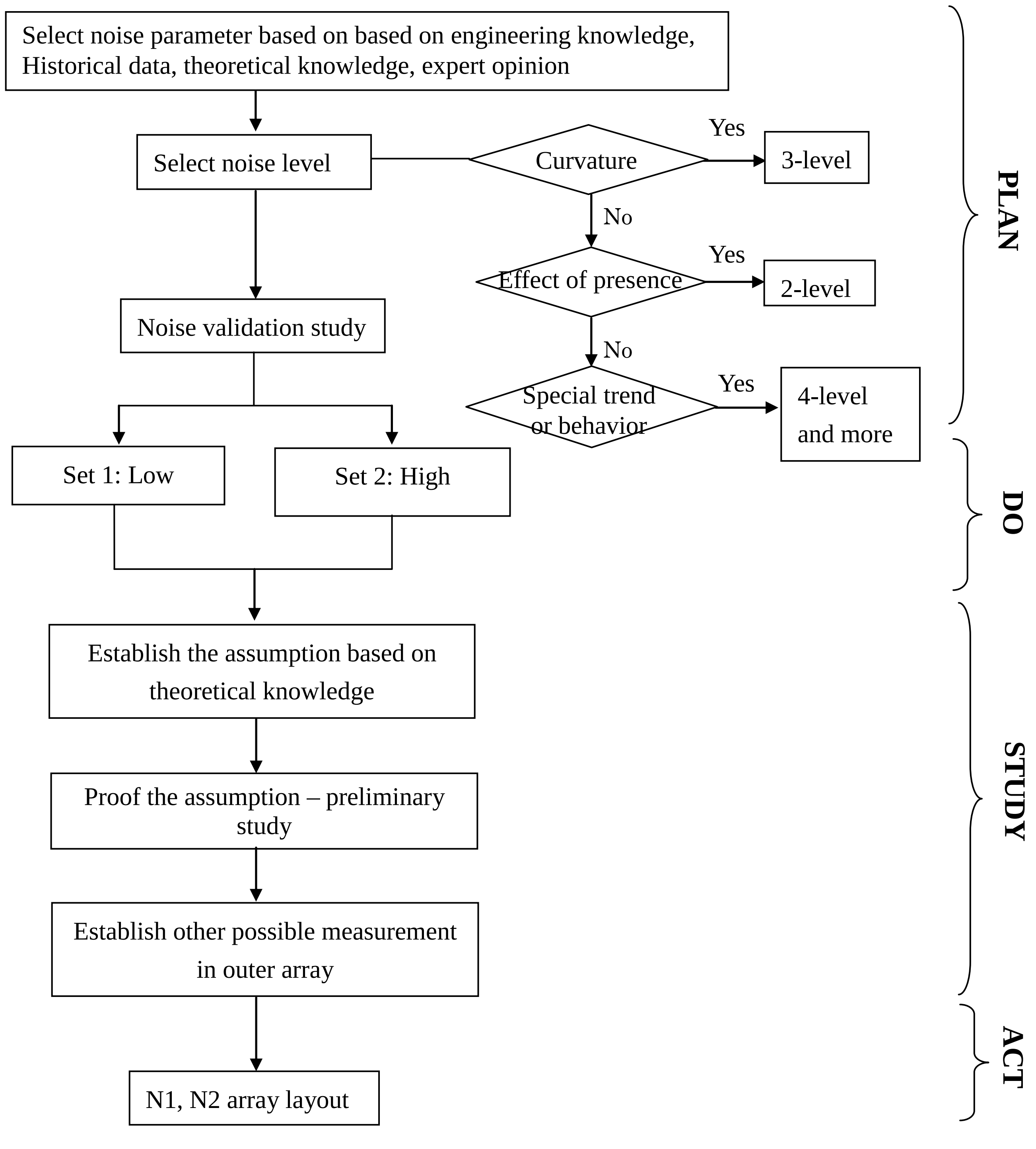

Figure 8.4: Noise (N) system

8.2.3 Control System (C)

Control factor is the factor that can be controlled during experiment and also during customer use. In this C stage, the control factor selection and determination are done. Taguchi's strongest contributions to the design of experiments were to focus the experimenter's attention on minimizing the variability of the response and not only optimizing the response. Thus, control factor and noise factor are separated in inner array and outer array respectively. Most statistical methods concentrating on modeling, predicting, and controlling the average response, new method of experimental design and analysis are crucial. Control factor is placed in inner array of orthogonal array. Control factors affect process variability as measured by the SNR. Control factor has three categories. The first category is the factor whose different settings give different average responses. These factors are said to be active but have no interaction with noise factors. Second category is a group of control factors which are active by virtue of having an interaction with noise factors. They have the dispersion effect. Finally, the third category is the factors which have no effect on the response or called as non-active. This kind of factor can be set at their cheapest or most convenient levels.

Selecting the control parameters can be started by relating with the response objective. Similarly like in selecting the noise parameter, engineering knowledge of the process can be used to select and judge the control parameters and their level apart from historical data, previous experimental results, theoretical knowledge, expert opinion, observational data and other relevant data. After identifying the noise factor, control factor evaluation is done. Noise measurement system is done before the control factor system to ensure the effect of all the noise parameter can be minimized by the best control-factor-level combination. Therefore, the "Act" stage in N sub-system is the input for the "Plan" stage in C sub-system. In this thesis, there are three characters in designing T-peel test to minimum variation that are testing condition, design or machine condition and specimen condition. Testing condition includes peel angle, peel speed, peel length, and spring thickness. Design or machine condition includes diameter of the drum and module of spur gear. Specimen condition is tensile weight to keep the specimen in T-shape position in minimizing the variation during peeling and data region coverage from constant peel strength curve. From these characters, "Do" stage presents the determined control factor. The final control factors for the T-peel test are tensile weight, peel angle, peel speed, spring thickness, data region, diameter of drum, and module of spur gear. Peel length is fixed at 60mm in x-axis direction. Control-factor-level is then been “Study” to prevent any misleading results due to incorrect control-factor-level. Final control factor and level is selected in “Act” stage thus activate the “Plan” stage in the next sub-system. Figure 8.5 summarizes the methodology flow of control measurement system (C):

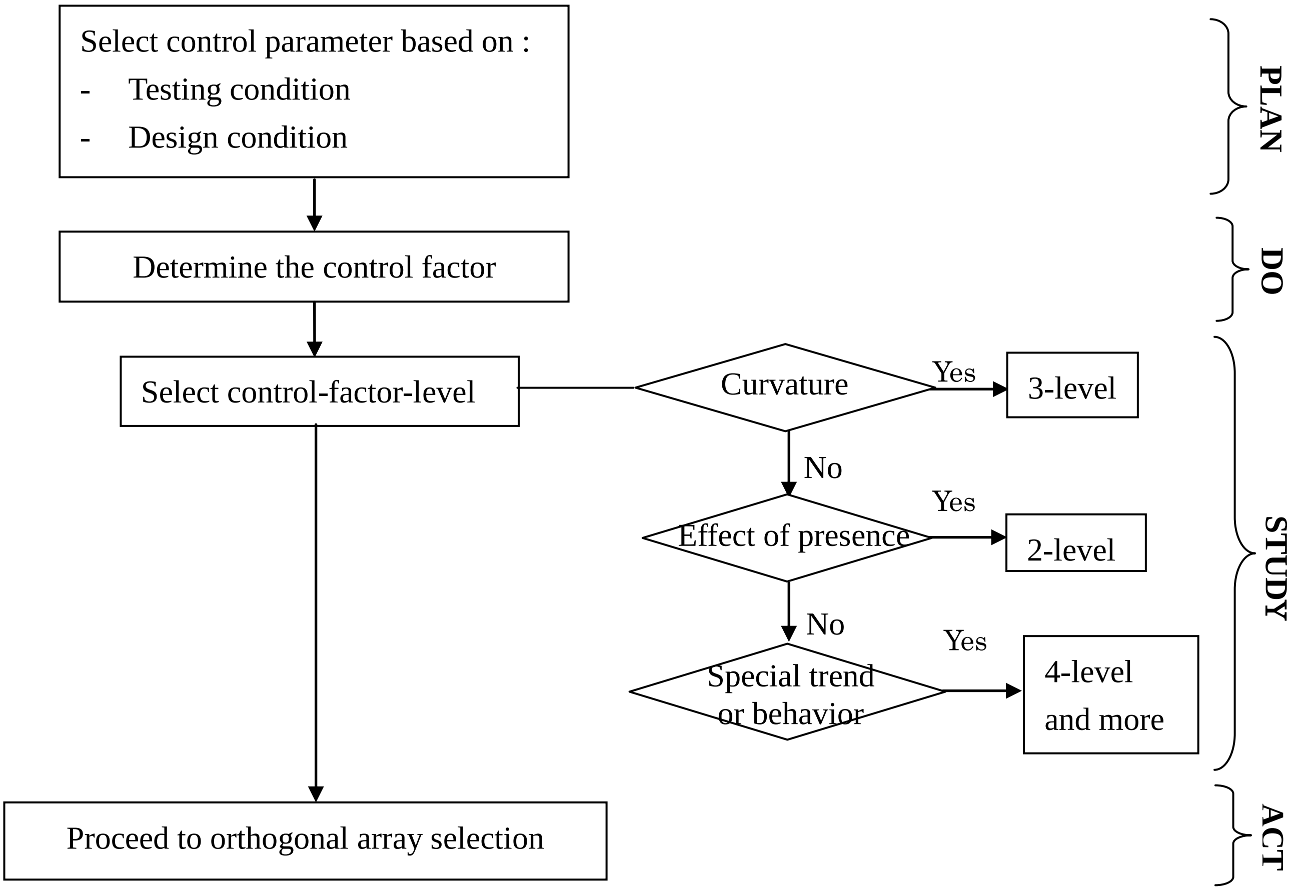

Figure 8.5: Control factor selection and determination (C) system

8.2.4 Optimization System (O)

Once the function, noise and control measurement are done, optimization stage takes place. “Act” stage in C sub-system acts to activate the “Plan” stage in O sub-system. “Plan” in Optimization sub-system is done by correctly chosen the orthogonal array based on noise and control factor strategies. Orthogonal array is chosen based on number of control factor and noise factor and their levels. Orthogonal array is the design space. It is a balance set of experimentation run. Every pair of columns, all combinations of levels occur in equal number of times. The design used in this thesis is L9 and L18. Four three-level of control factors is used in L9 that results for 54 experimental runs. One two-level factor and six three-level control factor are used in L18 that result for 108 experimental runs. Outer array of N1 and N2 with one three-level of signal factor is used. Dynamic SNR is employed. The relationship between the mean response and the levels of signal factor is linear. In “Do” stage, experiment is implemented based on the setting of levels in orthogonal array. The measurement data is recorded and further analysis on SNR is done.

In “Study” stage, the criticality of data and assumption is analyzed to ensure the measured data is genuine from extraneous variation that is not in the measurement system. The spread of measured data is checked through linear regression plot for abnormality checking. Outlier is often overlook thus giving misleading conclusion. Practical case study is given in Chapter 7 for studying the effect of outlier in measurement system. Next, the confirmation test is done for reproducibility checking. When estimation SNR gain is not comparable with confirmation gain resulting more than 30% difference, the measured data is not reproducible and investigation needs to be done. If this mistake is realized more than three months, repetition of the experiment of that particular point is needed. However, if the mistake is realized less than three months, the abnormal data can be replaced with regression point by treating it as missing data. Confirmation experiment is done once again to ensure the reproducibility is less than 30% or 3 dB. If reproducibility is low, then the loop is back to the F system under Do stage. Either to repeat or replace with regression point in a linear relation, specimen condition must be taken into account. This is done to minimize the outer noise and inner noise due to environmental condition and deterioration of elements in the sample respectively. Thus the optimum condition is accepted in “Act” stage. Figure 8.6 summarized the optimization measurement system:

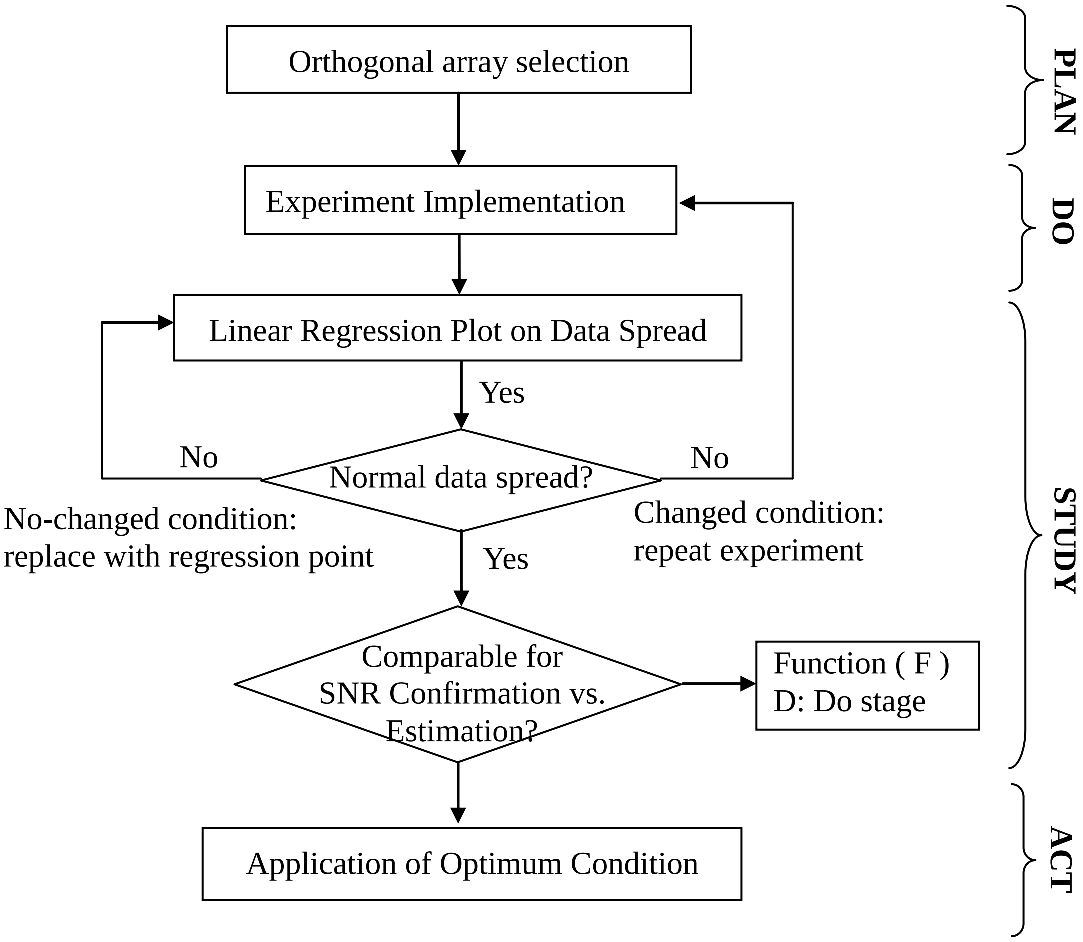

Figure 8.6: Optimization (O) system

8.3 Conclusion

The measurement procedures in Chapter 5, 6 and 7 clearly explained on the measurement system in each stage of parameter design. The system is divided into four sections for details. F (function), N (noise), C (control) and O (optimization) are the stages of parameter design measurement system. This is the mainstream of measurement system in parameter design as stated in the research objective (Chapter 1) to establish the measurement system design for parameter design achieved using the five scopes of research.

While many research focuses on application of parameter design, very less concern on the measurement system in every stage of parameter design implementation.

This thesis explained the measurement system in four categories so that to encapsulate the methodology in detail. The objective stated to present the measurement system design not only the result of experiment using parameter design in practical case but the methodology of measured data is explained. Five scopes have been decided to achieve the objective. Firstly, the procedure of optimum condition is explained in Chapter 6. Selection of multiple optimum conditions is done through L9 experiment. Three optimum conditions for flexible film are discussed: the aluminum peel side condition, the CPP peel side condition, and the harmonized condition. The signal-to-noise ratio for the CPP peels side condition increased by 22% from the aluminum peel side condition; thus, it is advised that the CPP peel side condition be used. The SNR of the harmonized condition is lower than the CPP and aluminum conditions, but it provides a convenient design that can be used without regard for peel side. Selection between CPP or harmonized condition is based on objective of the experimenters objective. It is advised that the optimum condition for the CPP peel side (A1 B1 C1 D3) be used for T-peel tests of flexible film, since the CPP optimum condition had the highest SNR (20.11dB) and thus had minimum variation in peel strength. The robust parameter design method in quality engineering benefited T-peel test optimization by presenting a harmonized condition. To achieve the same optimum condition at any peel angle surface, optimum condition for harmonized design was chosen by selecting the level with the smallest gap between the Al and CPP peel angle SNR factorial effect plots. Trade-off method is used for harmonized design to provide a convenience method to experimenter. The decision of selecting the optimum condition is explained in I (implementation) stage of measurement system design flow. Then, selection of noise strategy is done through L18 experiment which presents the possibilities exists in outer array data measurement. The most reliable optimum condition is the one which covers the whole variability of data covered by noise parameter presented in outer array. Noise parameter evaluation process is explained in N (noise) stage of measurement system design flow.

Second scope covered the systematic way in handling the outliers to prevent false alarm and wrong or misleading optimum condition. This scope is presented in O (optimization) stage of measurement system design flow under “Study” label. This paper will emphasize on the importance to be critical to data. The existence of outliers is often ignored and the impact is overlooked, thus endanger the experiment by producing false alarm and giving completely wrong parameter setting. The finding presents the indication procedure on how to confirm whether the data is reliable or not for evaluation. The data is unreliable when two main indicators are detected that are linear regression check and SNR reproducibility check. The L18 experiment of multiple noise strategy and L9 experiment on the effect of outliers had encapsulate the third scope which to establish a procedure on how to analyze variability and optimization when designing a measurement system in parameter design.

The fourth scope underlined the importance of observing the difference of parameter design practise in laboratory and industry. This scope had been encapsulated in Chapter 5 which explained the application of parameter design in two companies and management of quality engineering implementation. Barriers and counter measure procedure are presented so as to analyze not only in practical point of view but also to implementation in real working environment. Business, education, and technical barriers are the main obstacle's group that hindered the implementation widely. Fuji Xerox had revealed their way of overcoming the obstacles and Company B had explained their quality engineering culture. The laboratory way of implementing QE methodology flow is approximately similar between laboratory case study and Fuji Xerox. It is proven that QE engineering tool can be applied in any environment, be it industrial application or research field. The F (function) stage has been emphasized in industry's application in Fuji Xerox and Company B because function is very important as the initial or foundation basis before starting the quality engineering steps. C (control) and N (noise) stage in measurement system cycle have been used as guideline for both laboratory and industry practice in parameter design factor selection.

Finally, the fifth scope to establish a mainstream flow in order to achieve high quality experimental design. Four categories consist of F, N, C, and O is briefly summarized general mainstream flow of measurement system in parameter design. For instant, mechanical engineering case using peel strength standardized method is blended with the industry experience of parameter design application have served a complete measurement system design focusing in parameter design of Taguchi Method. Finally, with these findings, a mainstream flow is established to achieve high quality experimental design. Experimental is the perfect tool for measurement. The reliability of measurement depends on how well it is planned, how well the data are analyzed, and how the results are evaluated as shown in FNCO cycle of measurement systems. This research has affects the existing measurement system in parameter design by providing higher confidence level and optimization rate. By coming out with the measurement system using robust design engineering method, metrology in parameter design becomes more convergent and higher degree of confidence in reliability. It also has enlightened the black box of parameter design method by clarifying the reasons behind optimization result.

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CHAPTER 9 FUTURE RESEARCH

When a systematic general system is developed in this thesis, there are few items that need to be explored more. Firstly, the measurement system in tolerance design need to be established because tolerance design and parameter design are both included in the improvement phase of RCI [1] . Thus, comparison or gap analysis could further enhance for the betterment of this measurement system.

In addition, the context of robust measurement system should be studied due to difference perspective of robust methodology found in literature review. One of the example is the paper by Dasgupta et al. [2] presents different variation countermeasure compared to Yano's [3] approach. Miller and Wu [4] also presented on different look at dynamic parameter design and robust design measurement systems. A performance measure on signal-response relationship is one of the contradictions. Perhaps, further research on this measurement system in parameter design could connect and bridging the existence gap between these two.

The existing gap found in papers of Measurement journal with Dr. Hiroshi Yano's works could be minimized with further research. Dr. Yano's works on the importance of parameter design need to be recognized in this journal and measurement research field. Dr. Yano is known as a prominent researcher in metrology and measurement science. His outstanding book, "Metrological control: Industrial Measurement Management" presents many useful and interesting information about metrology. However, his name has not much been cited in papers for Measurement journal. Why such a prominent researcher had been left out in this specific journal that reflects his expertise?

Reference

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APPENDIX I

SNR Calculation L9

Aluminum peel side result: Peel strength, signal to noise ratio η , and sensitivity β

					5mm		10mm		15mm		SNR	Sensitivity
Run	A	B	C	D	N1	N2	N1	N2	N1	N2	η	β
1	1	1	1	1	8.08	7.98	16.08	15.84	23.34	23.68	17.1	3.96
2	1	2	2	2	7.45	7.27	14.70	15.02	22.60	22.52	18.83	3.50
3	1	3	3	3	7.42	7.68	15.12	15.35	22.98	23.07	20.61	3.69
4	2	1	2	3	6.91	6.96	14.22	14.36	21.43	21.52	19.75	3.09
5	2	2	3	1	8.43	8.44	16.71	16.49	24.02	23.61	10.67	4.16
6	2	3	1	2	8.12	8.24	15.70	16.06	23.65	23.97	17.34	4.03
7	3	1	3	2	7.62	7.42	15.03	14.86	22.81	23.00	17.48	3.61
8	3	2	1	3	7.43	7.64	15.01	14.99	22.94	23.17	16.60	3.66
9	3	3	2	1	8.15	8.52	16.76	16.68	23.99	24.21	12.37	4.24

no.1

M1		M2		M3	
N1	N2	N1	N2	N1	N2
8.70	8.37	16.62	16.78	24.96	24.09

ST= 1907.03 (fT= 6)
Sβ= 1906.25 (fβ= 1) sum of square for regression
SN×β= 0.23971 (fN×β= 1) noise level -1
Se= 0.5434 (fe= 4)
Se´= 0.78311 (fe´= 5)
Ve= 0.13585
VN= 0.15662
η= 12.402
S= 4.3505

no.2

M1		M2		M3	
N1	N2	N1	N2	N1	N2
8.04	8.12	15.28	16.21	23.91	24.52

ST= 1799.84 (fT= 6)
Sβ= 1798.99 (fβ= 1)
SN×β= 0.50767 (fN×β= 1)
Se= 0.34758 (fe= 4)
Se´= 0.85524 (fe´= 5)
Ve= 0.08689
VN= 0.17105
η= 11.7679
S= 4.09909

no.3

M1		M2		M3	
N1	N2	N1	N2	N1	N2
8.72	8.09	16.59	16.39	24.49	24.30

ST= 1875.47 (fT= 6)
Sβ= 1875.06 (fβ= 1)
SN×β= 0.09058 (fN×β= 1)
Se= 0.31901 (fe= 4)
Se´= 0.40959 (fe´= 5)
Ve= 0.07975
VN= 0.08192
η= 15.1452
S= 4.27899

no.4

M1		M2		M3	
N1	N2	N1	N2	N1	N2
7.79	8.04	15.68	15.86	23.87	24.38

ST= 1786.64 (fT= 6)
Sβ= 1786.31 (fβ= 1)
SN×β= 0.16284 (fN×β= 1)
Se= 0.15995 (fe= 4)
Se´= 0.32279 (fe´= 5)
Ve= 0.03999
VN= 0.06456
η= 15.9691
S= 4.0685

no.5

M1		M2		M3	
N1	N2	N1	N2	N1	N2
8.45	8.41	16.49	16.20	24.12	23.99

ST= 1833.66 (fT= 6)
Sβ= 1833.24 (fβ= 1)
SN×β= 0.03841 (fN×β= 1)
Se= 0.3901 (fe= 4)
Se´= 0.42851 (fe´= 5)
Ve= 0.09753
VN= 0.0857
η= 14.8511
S= 4.18097

no.6

M1		M2		M3	
N1	N2	N1	N2	N1	N2
8.26	8.18	15.51	15.80	24.43	24.32

ST= 1813.49 (fT= 6)
Sβ= 1812.88 (fβ= 1)
SN×β= 0.00101 (fN×β= 1)
Se= 0.60717 (fe= 4)
Se´= 0.60818 (fe´= 5)
Ve= 0.15179
VN= 0.12164
η= 13.2817
S= 4.13235

no.7

M1		M2		M3	
N1	N2	N1	N2	N1	N2
7.59	7.74	14.77	15.15	22.16	22.20

ST= 1548.72 (fT= 6)
Sβ= 1548.48 (fβ= 1)
SN×β= 0.03725 (fN×β= 1)
Se= 0.19617 (fe= 4)
Se´= 0.23342 (fe´= 5)
Ve= 0.04904
VN= 0.04668
η= 16.7564
S= 3.44795

no.8

M1		M2		M3	
N1	N2	N1	N2	N1	N2
7.46	7.69	15.03	15.83	22.68	23.58

ST= 1661.28 (fT= 6)
Sβ= 1660.48 (fβ= 1)
SN×β= 0.73747 (fN×β= 1)
Se= 0.05397 (fe= 4)
Se´= 0.79144 (fe´= 5)
Ve= 0.01349
VN= 0.15829
η= 11.7569
S= 3.75133

no.9

M1		M2		M3	
N1	N2	N1	N2	N1	N2
8.49	8.27	15.87	16.29	23.76	24.09

ST= 1802.55 (fT= 6)
Sβ= 1802.09 (fβ= 1)
SN×β= 0.09175 (fN×β= 1)
Se= 0.37236 (fe= 4)
Se´= 0.46411 (fe´= 5)
Ve= 0.09309
VN= 0.09282
η= 14.43
S= 4.10656

APPENDIX II

SNR Calculation L9

CPP peel side result: Peel strength, signal to noise ratio η , and sensitivity β

					5mm		10mm		15mm		SN ratio	Sensitivity
Run	A	B	C	D	*N1*	*N2*	*N1*	*N2*	*N1*	*N2*	η	β
1	1	1	1	1	8.08	7.98	16.08	15.85	23.34	23.68	17.10	3.96
2	1	2	2	2	7.45	7.27	14.70	15.02	22.60	22.52	18.83	3.50
3	1	3	3	3	7.42	7.68	15.12	15.35	22.98	23.07	20.61	3.69
4	2	1	2	3	6.91	6.96	14.22	14.36	21.43	21.52	19.75	3.09
5	2	2	3	1	8.43	8.44	16.71	16.49	24.02	23.61	10.67	4.16
6	2	3	1	2	8.12	8.24	15.70	16.06	23.65	23.97	17.34	4.03
7	3	1	3	2	7.62	7.42	15.03	14.86	22.81	23.00	17.48	3.61
8	3	2	1	3	7.43	7.64	15.01	14.99	22.94	23.17	16.60	3.66
9	3	3	2	1	8.15	8.52	16.76	16.68	23.99	24.21	12.37	4.24

no.1

M1		M2		M3	
N1	N2	N1	N2	N1	N2
8.08	7.98	16.08	15.84	23.34	23.68

ST=	1743.81	(fT=	6)
Sβ=	1743.56	(fβ=	1)
SN×β=	0.00611	(fN×β=	1) noise level -1
Se=	0.23671	(fe=	4)
Se´=	0.24283	(fe´=	5)
Ve=	0.05918		
VN=	0.04857		
η=	17.1		
S=	3.96325		

no.2

M1		M2		M3	
N1	N2	N1	N2	N1	N2
7.45	7.27	14.70	15.02	22.60	22.52

ST=	1567.96	(fT=	6)
Sβ=	1567.82	(fβ=	1)
SN×β=	0.00194	(fN×β=	1)
Se=	0.14451	(fe=	4)
Se´=	0.14645	(fe´=	5)
Ve=	0.03613		
VN=	0.02929		
η=	18.8348		
S=	3.50188		

no.3

M1		M2		M3	
N1	N2	N1	N2	N1	N2
7.42	7.68	15.12	15.35	22.98	23.07

ST=	1638.87	(fT=	6)
Sβ=	1638.76	(fβ=	1)
SN×β=	0.03553	(fN×β=	1)
Se=	0.06622	(fe=	4)
Se´=	0.10175	(fe´=	5)
Ve=	0.01655		
VN=	0.02035		
η=	20.6083		
S=	3.69414		

no.4

M1		M2		M3	
N1	N2	N1	N2	N1	N2
6.91	6.96	14.22	14.36	21.43	21.52

ST=	1426.99	(fT=	6)
Sβ=	1426.88	(fβ=	1)
SN×β=	0.01299	(fN×β=	1)
Se=	0.09496	(fe=	4)
Se´=	0.10795	(fe´=	5)
Ve=	0.02374		
VN=	0.02159		
η=	19.7502		
S=	3.09283		

no.5

M1		M2		M3	
N1	N2	N1	N2	N1	N2
8.43	8.44	16.71	16.49	24.02	23.61

ST=	1827.68	(fT=	6)
Sβ=	1826.57	(fβ=	1)
SN×β=	0.09901	(fN×β=	1)
Se=	1.01853	(fe=	4)
Se´=	1.11754	(fe´=	5)
Ve=	0.25463		
VN=	0.22351		
η=	10.6718		
S=	4.16477		

no.6

M1		M2		M3	
N1	N2	N1	N2	N1	N2
8.12	8.24	15.70	16.06	23.65	23.97

ST=	1772.51	(fT=	6)
Sβ=	1772.28	(fβ=	1)
SN×β=	0.1155	(fN×β=	1)
Se=	0.11818	(fe=	4)
Se´=	0.23367	(fe´=	5)
Ve=	0.02954		
VN=	0.04673		
η=	17.3379		
S=	4.03426		

no.7

M1		M2		M3	
N1	N2	N1	N2	N1	N2
7.62	7.42	15.03	14.86	22.81	23.00

ST=	1609.33	(fT=	6)
Sβ=	1609.13	(fβ=	1)
SN×β=	0.00011	(fN×β=	1)
Se=	0.20539	(fe=	4)
Se´=	0.20549	(fe´=	5)
Ve=	0.05135		
VN=	0.0411		
η=	17.4765		
S=	3.61479		

no.8

M1		M2		M3	
N1	N2	N1	N2	N1	N2
7.43	7.64	15.01	14.99	22.94	23.17

ST=	1626.69	(fT=	6)
Sβ=	1626.43	(fβ=	1)
SN×β=	0.02829	(fN×β=	1)
Se=	0.22573	(fe=	4)
Se´=	0.25402	(fe´=	5)
Ve=	0.05643		
VN=	0.0508		
η=	16.6022		
S=	3.66123		

no.9

M1		M2		M3	
N1	N2	N1	N2	N1	N2
8.15	8.52	16.76	16.68	23.99	24.21

ST=	1859.47	(fT=	6)
Sβ=	1858.7	(fβ=	1)
SN×β=	0.02761	(fN×β=	1)
Se=	0.74101	(fe=	4)
Se´=	0.76862	(fe´=	5)
Ve=	0.18525		
VN=	0.15372		
η=	12.3733		
S=	4.24067		

APPENDIX III

SNR Calculation L18

Peel strength result for Type A

no.1

M_1		M_2		M_3	
N_1	N_2	N_1	N_2	N_1	N_2
4.45	4.53	8.51	8.97	13.51	12.94

S_T= 543.1166 (f_T= 6)
S_β= 542.8227 (f_β= 1)
$S_{N\times\beta}$= 0.018048 ($f_{N\times\beta}$= 1) noise level -1
S_e= 0.275943 (f_e= 4)
S_e'= 0.293992 (f_e'= 5)
V_e= 0.068986
V_N= 0.058798
η= 11.2014
S= -1.10495

no.2

M_1		M_2		M_3	
N_1	N_2	N_1	N_2	N_1	N_2
6.31	6.12	12.94	11.95	18.83	18.15

ST= 1071.38 (f_T= 6)
Sβ= 1070.63 (f_β= 1)
SN×β= 0.63048 ($f_{N\times\beta}$= 1)
Se= 0.12416 (f_e= 4)
Se′= 0.75464 (f_e'= 5)
Ve= 0.03104
VN= 0.15093
η= 10.0576
S= 1.84528

no.3

M_1		M_2		M_3	
N_1	N_2	N_1	N_2	N_1	N_2
8.79	8.46	16.96	16.43	24.57	23.88

ST= 1880.266 (fT= 6)
Sβ= 1879.004 (fβ= 1)
SN×β= 0.432965 (fN×β= 1)
Se= 0.829143 (fe= 4)
Se′= 1.262108 (fe′= 5)
Ve= 0.207286
VN= 0.252422
η= 10.26655
S= 4.287817

no.4

M1		M2		M3	
N1	N2	N1	N2	N1	N2
8.39	8.08	16.50	15.72	24.08	23.36

ST= 1780.88 (fT= 6)
Sβ= 1779.99 (fβ= 1)
SN×β= 0.58464 (fN×β= 1)
Se= 0.30583 (fe= 4)
Se′= 0.89047 (fe′= 5)
Ve= 0.07646
VN= 0.17809
η= 11.5465
S= 4.05301

no.5

M1		M2		M3	
N1	N2	N1	N2	N1	N2
3.94	3.57	7.98	7.50	11.53	10.82

ST= 398.0791 (fT= 6)
Sβ= 397.5276 (fβ= 1)
SN×β= 0.428558 (fN×β= 1)
Se= 0.12296 (fe= 4)
Se′= 0.551519 (fe′= 5)
Ve= 0.03074
VN= 0.110304
η= 7.116454
S= -2.45764

no.6

M1		M2		M3	
N1	N2	N1	N2	N1	N2
7.20	7.05	13.81	13.52	19.73	18.91

ST= 1221.84 (fT= 6)
Sβ= 1220 (fβ= 1)
SN×β= 0.36446 (fN×β= 1)
Se= 1.47454 (fe= 4)
Se′= 1.839 (fe′= 5)
Ve= 0.36864
VN= 0.3678
η= 6.75518
S= 2.41131

no.7

M1		M2		M3	
N1	N2	N1	N2	N1	N2
6.38	6.38	13.28	12.74	18.97	17.83

ST= 1097.8 (fT= 6)
Sβ= 1096.206 (fβ= 1)
SN×β= 0.71918 (fN×β= 1)
Se= 0.874741 (fe= 4)
Se´= 1.593921 (fe´= 5)
Ve= 0.218685
VN= 0.318784
η= 6.912108
S= 1.947075

no.8

M1		M2		M3	
N1	N2	N1	N2	N1	N2
7.97	7.42	16.27	15.67	24.76	23.60

ST= 1799.13 (fT= 6)
Sβ= 1797.87 (fβ= 1)
SN×β= 0.9742 (fN×β= 1)
Se= 0.27827 (fe= 4)
Se´= 1.25248 (fe´= 5)
Ve= 0.06957
VN= 0.2505
η= 10.1084
S= 4.09644

no.9

M1		M2		M3	
N1	N2	N1	N2	N1	N2
3.92592	3.748278	7.51432	7.28338	11.3337	11.1027

ST= 390.6973 (fT= 6)
Sβ= 390.5968 (fβ= 1)
SN×β= 0.063396 (fN×β= 1)
Se= 0.037035 (fe= 4)
Se´= 0.100431 (fe´= 5)
Ve= 0.009259
VN= 0.020086
η= 14.43723
S= -2.5338

no.10

M1		M2		M3	
N1	N2	N1	N2	N1	N2
6.02211	5.18719	12.0265	11.1915	16.9117	16.663

ST= 896.718 (fT= 6)
Sβ= 895.743 (fβ= 1)
SN×β= 0.37744 (fN×β= 1)
Se= 0.59758 (fe= 4)
Se´= 0.97502 (fe´= 5)
Ve= 0.1494
VN= 0.195
η= 8.16971
S= 1.07013

no.11

M1		M2		M3	
N1	N2	N1	N2	N1	N2
9.78793	8.948202	17.9186	17.2788	26.9823	25.2896

ST= 2163.117 (fT= 6)
Sβ= 2160.349 (fβ= 1)
SN×β= 1.850225 (fN×β= 1)
Se= 0.917279 (fe= 4)
Se´= 2.767504 (fe´= 5)
Ve= 0.22932
VN= 0.553501
η= 7.462616
S= 4.893799

no.12

M1		M2		M3	
N1	N2	N1	N2	N1	N2
4.33775	4.10433	8.34482	7.96551	12.1671	11.9142

ST= 458.734 (fT= 6)
Sβ= 458.515 (fβ= 1)
SN×β= 0.10946 (fN×β= 1)
Se= 0.10989 (fe= 4)
Se´= 0.21935 (fe´= 5)
Ve= 0.02747
VN= 0.04387
η= 11.7407
S= -1.8377

no.13

M1		M2		M3	
N1	N2	N1	N2	N1	N2
7.74526	7.230091	15.1352	14.3358	22.0989	21.1218

ST= 1481.345 (fT= 6)
Sβ= 1480.164 (fβ= 1)
SN×β= 0.909028 (fN×β= 1)
Se= 0.271437 (fe= 4)
Se´= 1.180465 (fe´= 5)
Ve= 0.067859
VN= 0.236093
η= 9.521087
S= 3.251919

no.14

M1		M2		M3	
N1	N2	N1	N2	N1	N2
4.73624	4.43856	9.17035	8.81491	13.3823	12.898

ST= 549.376 (fT= 6)
Sβ= 549.022 (fβ= 1)
SN×β= 0.21638 (fN×β= 1)
Se= 0.13789 (fe= 4)
Se´= 0.35427 (fe´= 5)
Ve= 0.03447
VN= 0.07085
η= 10.441
S= -1.0554

no.15

M1		M2		M3	
N1	N2	N1	N2	N1	N2
6.76922	6.234301	12.8187	12.5075	19.2476	18.5376

ST= 1119.556 (fT= 6)
Sβ= 1119.036 (fβ= 1)
SN×β= 0.385953 (fN×β= 1)
Se= 0.133741 (fe= 4)
Se´= 0.519694 (fe´= 5)
Ve= 0.033435
VN= 0.103939
η= 11.86955
S= 2.037331

no.16

M1		M2		M3	
N1	N2	N1	N2	N1	N2
4.03625	3.21927	7.74181	6.92484	11.6419	11.1264

ST= 393.875 (fT= 6)
Sβ= 392.954 (fβ= 1)
SN×β= 0.57067 (fN×β= 1)
Se= 0.35068 (fe= 4)
Se´= 0.92135 (fe´= 5)
Ve= 0.08767
VN= 0.18427
η= 4.83694
S= -2.5085

no.17

M1		M2		M3	
N1	N2	N1	N2	N1	N2
5.95106	5.524713	12.2219	11.5646	17.8354	17.0893

ST= 959.1976 (fT= 6)
Sβ= 958.4972 (fβ= 1)
SN×β= 0.565505 (fN×β= 1)
Se= 0.134885 (fe= 4)
Se´= 0.70039 (fe´= 5)
Ve= 0.033721
VN= 0.140078
η= 9.901077
S= 1.364775

no.18

M1		M2		M3	
N1	N2	N1	N2	N1	N2
8.93932	8.7305	16.3191	16.0081	24.6942	25.0319

ST= 1915.1 (fT= 6)
Sβ= 1914.05 (fβ= 1)
SN×β= 0.00119 (fN×β= 1)
Se= 1.05304 (fe= 4)
Se´= 1.05422 (fe´= 5)
Ve= 0.26326
VN= 0.21084
η= 11.1283
S= 4.36796

APPENDIX IV

SNR Calculation L18

Peel strength result for Type B

no.1

M_1		M_2		M_3	
N_1	N_2	N_1	N_2	N_1	N_2
4.66	4.34	9.12	8.36	13.51	12.94

S_T=	543.6278	(f_T=	6	)
S_β=	543.0966	(f_β=	1	)
$S_{N\times\beta}$=	0.450078	($f_{N\times\beta}$=	1	) noise level -1
S_e=	0.081117	(f_e=	4	)
S_e'=	0.531195	(f_e'=	5	)
V_e=	0.020279			
V_N=	0.106239			
η=	8.634786			
S=	-1.10237			

no.2

M_1		M_2		M_3	
N_1	N_2	N_1	N_2	N_1	N_2
6.62	5.74	12.71	11.95	18.83	18.08

ST=	1062.71	(f_T=	6	)
Sβ=	1061.75	(f_β=	1	)
SN×β=	0.77189	($f_{N\times\beta}$=	1	)
Se=	0.19025	(f_e=	4	)
Se´=	0.96215	(f_e'=	5	)
Ve=	0.04756			
VN=	0.19243			
η=	8.96632			
S=	1.80903			

no.3

M_1		M_2		M_3	
N_1	N_2	N_1	N_2	N_1	N_2
9.13	7.92	17.41	15.74	24.96	23.27

ST=	1861.444	(fT=	6)
Sβ=	1857.239	(fβ=	1)
SN×β=	3.298642	(fN×β=	1)
Se=	0.906977	(fe=	4)
Se´=	4.205619	(fe´=	5)
Ve=	0.226744		
VN=	0.841124		
η=	4.988568		
S=	4.237167		

no.4

M1		M2		M3	
N1	N2	N1	N2	N1	N2
8.63	7.91	16.77	15.72	24.08	23.36

ST=	1790.79	(fT=	6)
Sβ=	1789.31	(fβ=	1)
SN×β=	0.88561	(fN×β=	1)
Se=	0.59817	(fe=	4)
Se´=	1.48377	(fe´=	5)
Ve=	0.14954		
VN=	0.29675		
η=	9.35154		
S=	4.07551		

no.5

M1		M2		M3	
N1	N2	N1	N2	N1	N2
4.09	3.52	8.03	7.41	11.53	10.82

ST=	398.3717	(fT=	6)
Sβ=	397.6615	(fβ=	1)
SN×β=	0.555452	(fN×β=	1)
Se=	0.154721	(fe=	4)
Se´=	0.710173	(fe´=	5)
Ve=	0.03868		
VN=	0.142035		
η=	6.019793		
S=	-2.45627		

no.6

M1		M2		M3	
N1	N2	N1	N2	N1	N2
7.36	6.90	13.81	13.44	19.73	18.91

ST=	1220.02	(fT=	6)
Sβ=	1218.13	(fβ=	1)
SN×β=	0.4752	(fN×β=	1)
Se=	1.42266	(fe=	4)
Se´=	1.89787	(fe´=	5)
Ve=	0.35567		
VN=	0.37957		
η=	6.61171		
S=	2.40467		

no.7

M1		M2		M3	
N1	N2	N1	N2	N1	N2
6.90	6.12	13.28	12.61	18.97	17.83

ST=	1098.276	(fT=	6)
Sβ=	1096.317	(fβ=	1)
SN×β=	1.091027	(fN×β=	1)
Se=	0.86753	(fe=	4)
Se´=	1.958557	(fe´=	5)
Ve=	0.216883		
VN=	0.391711		
η=	6.017861		
S=	1.947523		

no.8

M1		M2		M3	
N1	N2	N1	N2	N1	N2
7.97	7.07	16.27	15.36	24.76	23.60

ST=	1784.4	(fT=	6)
Sβ=	1782.32	(fβ=	1)
SN×β=	1.37082	(fN×β=	1)
Se=	0.70475	(fe=	4)
Se´=	2.07557	(fe´=	5)
Ve=	0.17619		
VN=	0.41511		
η=	7.87677		
S=	4.05845		

no.9

M1		M2		M3	
N1	N2	N1	N2	N1	N2
4.13909	3.588399	7.78079	7.1235	11.3869	10.9961

ST=	391.8712	(fT=	6)
Sβ=	391.3934	(fβ=	1)
SN×β=	0.329559	(fN×β=	1)
Se=	0.148206	(fe=	4)
Se´=	0.477765	(fe´=	5)
Ve=	0.037052		
VN=	0.095553		
η=	7.672301		
S=	-2.52526		

no.10

M1		M2		M3	
N1	N2	N1	N2	N1	N2
6.02211	5.56024	12.062	11.1915	17.4446	16.3432

ST=	909.338	(fT=	6)
Sβ=	908.043	(fβ=	1)
SN×β=	1.08309	(fN×β=	1)
Se=	0.21261	(fe=	4)
Se´=	1.29569	(fe´=	5)
Ve=	0.05315		
VN=	0.25914		
η=	6.9945		
S=	1.12983		

no.11

M1		M2		M3	
N1	N2	N1	N2	N1	N2
9.78793	8.948202	17.9186	17.2788	26.9823	25.2896

ST=	2163.117	(fT=	6)
Sβ=	2160.349	(fβ=	1)
SN×β=	1.850225	(fN×β=	1)
Se=	0.917279	(fe=	4)
Se´=	2.767504	(fe´=	5)
Ve=	0.22932		
VN=	0.553501		
η=	7.462616		
S=	4.893799		

no.12

M1		M2		M3	
N1	N2	N1	N2	N1	N2
4.37665	4.06543	8.34482	7.96551	12.2546	11.603

ST=	453.574	(fT=	6)
Sβ=	453.099	(fβ=	1)
SN×β=	0.32675	(fN×β=	1)
Se=	0.1475	(fe=	4)
Se´=	0.47426	(fe´=	5)
Ve=	0.03688		
VN=	0.09485		
η=	8.34014		
S=	-1.8894		

no.13

M1		M2		M3	
N1	N2	N1	N2	N1	N2
7.74526	7.230091	15.1352	14.3358	22.0989	21.1218

ST=	1481.345	(fT=	6)
Sβ=	1480.164	(fβ=	1)
SN×β=	0.909028	(fN×β=	1)
Se=	0.271437	(fe=	4)
Se´=	1.180465	(fe´=	5)
Ve=	0.067859		
VN=	0.236093		
η=	9.521087		
S=	3.251919		

no.14

M1		M2		M3	
N1	N2	N1	N2	N1	N2
4.73624	4.1231	9.17035	8.81491	13.409	12.898

ST=	547.39	(fT=	6)
Sβ=	546.939	(fβ=	1)
SN×β=	0.29149	(fN×β=	1)
Se=	0.15964	(fe=	4)
Se´=	0.45113	(fe´=	5)
Ve=	0.03991		
VN=	0.09023		
η=	9.37478		
S=	-1.0719		

no.15

M1		M2		M3	
N1	N2	N1	N2	N1	N2
6.89566	6.098138	13.1883	11.9434	19.4032	18.5376

ST=	1121.438	(fT=	6)
Sβ=	1119.897	(fβ=	1)
SN×β=	1.236551	(fN×β=	1)
Se=	0.304299	(fe=	4)
Se´=	1.54085	(fe´=	5)
Ve=	0.076075		
VN=	0.30817		
η=	7.152601		
S=	2.040506		

no.16

M1		M2		M3	
N1	N2	N1	N2	N1	N2
4.03625	3.21927	7.77099	6.92484	12.0504	10.9319

ST=	399.715	(fT=	6)
Sβ=	398.218	(fβ=	1)
SN×β=	1.22839	(fN×β=	1)
Se=	0.26866	(fe=	4)
Se´=	1.49705	(fe´=	5)
Ve=	0.06717		
VN=	0.29941		
η=	2.78682		
S=	-2.4505		

no.17

M1		M2		M3	
N1	N2	N1	N2	N1	N2
6.19976	5.47142	12.2219	11.5646	17.8354	17.0893

ST=	961.6335	(fT=	6)
Sβ=	960.7852	(fβ=	1)
SN×β=	0.654598	(fN×β=	1)
Se=	0.193739	(fe=	4)
Se´=	0.848337	(fe´=	5)
Ve=	0.048435		
VN=	0.169667		
η=	9.079081		
S=	1.375064		

no.18

M1		M2		M3	
N1	N2	N1	N2	N1	N2
8.93932	8.59276	16.3191	15.9104	25.6183	24.3743

ST=	1923.61	(fT=	6)
Sβ=	1921.77	(fβ=	1)
SN×β=	0.85617	(fN×β=	1)
Se=	0.97846	(fe=	4)
Se´=	1.83463	(fe´=	5)
Ve=	0.24462		
VN=	0.36693		
η=	8.73971		
S=	4.38549		

APPENDIX V

SNR Calculation L18

Peel strength result for Type C

no.1

M_1		M_2		M_3	
N_1	N_2	N_1	N_2	N_1	N_2
4.40	4.59	8.44	9.06	13.35	13.10

S_T= 543.6492 (f_T= 6)
S_β= 543.3833 (f_β= 1)
$S_{N\times\beta}$= 0.016595 ($f_{N\times\beta}$= 1) noise level -1
S_e= 0.249239 (f_e= 4)
S_e'= 0.265834 (f_e'= 5)
V_e= 0.06231
V_N= 0.053167
η= 11.64318
S= -1.10042

no.2

M_1		M_2		M_3	
N_1	N_2	N_1	N_2	N_1	N_2
6.00	6.39	12.66	12.34	18.47	18.47

ST= 1071.53 (f_T= 6)
Sβ= 1071.35 (f_β= 1)
SN×β= 0.00235 ($f_{N\times\beta}$= 1)
Se= 0.1765 (f_e= 4)
Se′= 0.17886 (f_e'= 5)
Ve= 0.04413
VN= 0.03577
η= 16.3128
S= 1.84814

no.3

M_1		M_2		M_3	
N_1	N_2	N_1	N_2	N_1	N_2
8.45	8.74	16.38	16.92	23.92	24.41

ST= 1870.875 (fT= 6)
Sβ= 1869.779 (fβ= 1)
SN×β= 0.28581 (fN×β= 1)
Se= 0.810482 (fe= 4)
Se′= 1.096292 (fe′= 5)
Ve= 0.202621
VN= 0.219258
η= 10.85689
S= 4.266451

no.4

M1		M2		M3	
N1	N2	N1	N2	N1	N2
8.16	8.30	16.21	16.39	23.70	23.60

ST= 1785.11 (fT= 6)
Sβ= 1784.56 (fβ= 1)
SN×β= 0.00124 (fN×β= 1)
Se= 0.5515 (fe= 4)
Se′= 0.55273 (fe′= 5)
Ve= 0.13787
VN= 0.11055
η= 13.6285
S= 4.064

no.5

M1		M2		M3	
N1	N2	N1	N2	N1	N2
3.73	3.84	7.69	7.79	11.21	11.11

ST= 397.4115 (fT= 6)
Sβ= 397.2733 (fβ= 1)
SN×β= 1.13E-07 (fN×β= 1)
Se= 0.138242 (fe= 4)
Se′= 0.138242 (fe′= 5)
Ve= 0.034561
VN= 0.027648
η= 13.12283
S= -2.46046

no.6

M1		M2		M3	
N1	N2	N1	N2	N1	N2
7.03	7.17	13.63	13.67	19.35	19.29

ST= 1220.22 (fT= 6)
Sβ= 1218.83 (fβ= 1)
SN×β= 2.3E-06 (fN×β= 1)
Se= 1.39168 (fe= 4)
Se′= 1.39168 (fe′= 5)
Ve= 0.34792
VN= 0.27834
η= 7.9615
S= 2.4072

no.7

M1		M2		M3	
N1	N2	N1	N2	N1	N2
6.21	6.68	13.00	12.89	18.62	18.34

ST=	1101.818	(fT=	6)
Sβ=	1101.057	(fβ=	1)
SN×β=	0.012548	(fN×β=	1)
Se=	0.748212	(fe=	4)
Se´=	0.76076	(fe´=	5)
Ve=	0.187053		
VN=	0.152152		
η=	10.14361		
S=	1.966381		

no.8

M1		M2		M3	
N1	N2	N1	N2	N1	N2
7.51	7.67	15.78	15.94	24.24	24.05

ST=	1784.52	(fT=	6)
Sβ=	1784.08	(fβ=	1)
SN×β=	0.00022	(fN×β=	1)
Se=	0.44302	(fe=	4)
Se´=	0.44325	(fe´=	5)
Ve=	0.11076		
VN=	0.08865		
η=	14.5861		
S=	4.06288		

no.9

M1		M2		M3	
N1	N2	N1	N2	N1	N2
3.72964	3.945089	7.31891	7.56099	11.1809	11.2377

ST=	391.5072	(fT=	6)
Sβ=	391.4307	(fβ=	1)
SN×β=	0.027017	(fN×β=	1)
Se=	0.049466	(fe=	4)
Se´=	0.076483	(fe´=	5)
Ve=	0.012367		
VN=	0.015297		
η=	15.62947		
S=	-2.52457		

no.10

M1		M2		M3	
N1	N2	N1	N2	N1	N2
5.8056	5.428	11.755	11.7406	16.6441	17.0324

ST=	906.32	(fT=	6)
Sβ=	905.785	(fβ=	1)
SN×β=	0.02055	(fN×β=	1)
Se=	0.5148	(fe=	4)
Se´=	0.53535	(fe´=	5)
Ve=	0.1287		
VN=	0.10707		
η=	10.822		
S=	1.11865		

no.11

M1		M2		M3	
N1	N2	N1	N2	N1	N2
9.54422	9.219345	17.6952	17.562	26.631	25.4831

ST=	2156.23	(fT=	6)
Sβ=	2154.618	(fβ=	1)
SN×β=	0.581516	(fN×β=	1)
Se=	1.031135	(fe=	4)
Se´=	1.612651	(fe´=	5)
Ve=	0.257784		
VN=	0.32253		
η=	9.796498		
S=	4.882202		

no.12

M1		M2		M3	
N1	N2	N1	N2	N1	N2
4.21458	4.2457	8.19062	8.08738	12.0319	12.1113

ST=	459.731	(fT=	6)
Sβ=	459.642	(fβ=	1)
SN×β=	0.00014	(fN×β=	1)
Se=	0.08899	(fe=	4)
Se´=	0.08913	(fe´=	5)
Ve=	0.02225		
VN=	0.01783		
η=	15.6624		
S=	-1.827		

no.13

M1		M2		M3	
N1	N2	N1	N2	N1	N2
7.46973	7.488011	14.8777	14.8209	21.7984	21.4827

ST= 1489.549 (fT= 6)
Sβ= 1489.176 (fβ= 1)
SN×β= 0.038805 (fN×β= 1)
Se= 0.334245 (fe= 4)
Se´= 0.373051 (fe´= 5)
Ve= 0.083561
VN= 0.07461
η= 14.55026
S= 3.278236

no.14

M1		M2		M3	
N1	N2	N1	N2	N1	N2
4.61861	4.5197	9.00836	8.99443	13.2035	13.2515

ST= 553.745 (fT= 6)
Sβ= 553.66 (fβ= 1)
SN×β= 1.1E-05 (fN×β= 1)
Se= 0.0848 (fe= 4)
Se´= 0.08481 (fe´= 5)
Ve= 0.0212
VN= 0.01696
η= 16.6867
S= -1.0187

no.15

M1		M2		M3	
N1	N2	N1	N2	N1	N2
6.45493	6.606822	12.4219	12.8395	18.908	18.9789

ST= 1122.185 (fT= 6)
Sβ= 1121.998 (fβ= 1)
SN×β= 0.051403 (fN×β= 1)
Se= 0.13658 (fe= 4)
Se´= 0.187983 (fe´= 5)
Ve= 0.034145
VN= 0.037597
η= 16.29732
S= 2.048806

no.16

M1		M2		M3	
N1	N2	N1	N2	N1	N2
3.67481	3.62272	7.44766	7.32046	11.3101	11.5859

ST= 397.837 (fT= 6)
Sβ= 397.673 (fβ= 1)
SN×β= 0.0097 (fN×β= 1)
Se= 0.15386 (fe= 4)
Se´= 0.16356 (fe´= 5)
Ve= 0.03847
VN= 0.03271
η= 12.3968
S= -2.4561

no.17

M1		M2		M3	
N1	N2	N1	N2	N1	N2
5.72701	5.872575	12.0083	11.8543	17.627	17.3064

ST= 962.2331 (fT= 6)
Sβ= 962.037 (fβ= 1)
SN×β= 0.045164 (fN×β= 1)
Se= 0.150872 (fe= 4)
Se´= 0.196036 (fe´= 5)
Ve= 0.037718
VN= 0.039207
η= 15.44712
S= 1.380767

no.18

M1		M2		M3	
N1	N2	N1	N2	N1	N2
8.76307	8.80506	16.1099	16.1309	24.5217	25.3155

ST= 1916.24 (fT= 6)
Sβ= 1915.02 (fβ= 1)
SN×β= 0.21706 (fN×β= 1)
Se= 1.00338 (fe= 4)
Se´= 1.22045 (fe´= 5)
Ve= 0.25085
VN= 0.24409
η= 10.4947
S= 4.37019