ANALYSIS OF THE INFLUENCE OF NON-MACHINING PROCESS PARAMETERS ON PRODUCT QUALITY BY EXPERIMENTAL DESIGN AND STATISTICAL ANALYSIS

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I certify that this thesis satisfies all the requirements as a thesis for the degree of Master of Science.

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This is to certify that we have read this thesis and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science.

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ABSTRACT

ANALYSIS OF THE INFLUENCE OF NON-MACHINING PROCESS PARAMETERS ON PRODUCT QUALITY BY EXPERIMENTAL DESIGN AND STATISTICAL ANALYSIS

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This thesis illustrates analysis of the influence of the non-machining processes on product quality by experimental design and statistical analysis. For the analysis objective ; dishwasher production in Arcelik Dishwasher plant is examined. Sheet metal forming processes of dishwasher production constitutes the greatest portion of production cost and using the Pareto analysis technique; four pieces among twenty six pieces are determined to be investigated. These four pieces are the U Sheet, L Sheet, Inner Door and Side Panel of the dishwasher. By the help of the flow diagrams production process of the determined pieces are defined. Brainstorming technique and cause&effect diagrams are used to determine which non-machining process parameters can cause pieces to be scrapped. These parameters are used as control factors in experimental design. Taguchi's $L_{16}(2^{15})$ orthogonal array, Taguchi's $L_{16}(2^{15})$ orthogonal array using S/N transformation and 2^{8-4} fractional factorial design are used on purpose. With repetitions and confirmation experiments the effective parameters are determined and optimum level of these parameters are defined for the improvements on scrap quantity and quality of production.

Keywords : Process Parameter Optimization, Design of Experiments (DOE), Taguchi's Methods, Fractional Factorial Design, Production, Sheet Metal Forming, Non-machining Effects

ÖZ

ÜRETÝM EKÝPMANI HARÝCÝ PROSES PARAMETRELERÝNÝN ÜRÜN KALÝTESÝ ÜZERÝNDEKÝ ETKÝLERÝNÝN DENEY TASARIMI VE ÝSTATÝSTÝKSEL YÖNTEMLERLE ANALÝZÝ

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Bu tez çalýþmasý üretim ekipmaný harici proses parametrelerinin ürün kalitesi üzerindeki etkilerini deney tasarýmlama ve istatistiksel çözümleme yöntemleriyle analiz edilmesini içerir. Analiz amaçlý olarak Arçelik Bulaþýk Makinasý Ýþletmesindeki bulaþýk makinasý üretimi incelenmiþtir. Bulaþýk makinasý üretiminde soðuk sac þekillendirme proses maliyeti, üretim maliyetinin büyük kýsmýný oluþturur ve Pareto analiz teknikleri kullanýlarak bulaþýk makinasýný oluþturan 26 sac parça içinden 4'ü incelenmek üzere seçilmiþtir. Bu dört parça bulaþýk makinasýnýn U Parça, L Parça, Ýç Kapý ve Yan Duvar parçalarýdýr. Akýþ þemalarý kullanýlarak bulaþýk makinasý üretim prosesleri þekillendirilmiþtir. Beyin fýrtýnasý tekniði ve neden & sonuç þemalarýnýn (balýk kýlçýðý þemalarý) kullanýmýyla hangi üretim ekipmaný dýþý parametrelerin hurdaya yol açabileceði belirlenmiºtir. Bu parametreler

deney tasarýmýnda kontrol faktörleri olarak seçilmiþtir. Taguchi L_{16} (2^{15}) dikeysel tasarýmý , Taguchi L_{16} (2^{15}) dikeysel tasarýmýnýn S/N çevrimiyle analizi ve 2^{8-4} kesirli faktöryel tasarýmý amaç için kullanýlmýþtýr. Deneylerin tekrarý ve konfirmasyon deneyleriyle etkili parametreler belirlenmiþ ve bu parametrelerin optimum seviyeleri hurda miktarýnýn azaltýlmasý ve kalitenin artýrýlmasý için tanýmlanmýþtýr.

Anahtar Kelimeler : Yöntem Parametre Optimizasyonu, Ýstatistiksel Deney Tasarýmý (DOE) , Taguchi Yöntemleri, Kesirli Faktöryel Tasarýmý, Ýmalat, Soðuk Sac Þekillendirme, Üretim Ekipmaný Dýþý Etkiler

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INTRODUCTION

The purpose of this study is to evaluate the influence of non-machining processes on product quality. Extensively in production, machining effects are considered and evaluated for improvements in product quality. In this study, by using experimental techniques, it is analyzed whether the non-machining processes also have effect on product quality. Throughout the study the pieces which are scrapped during production are accepted to have 'zero quality'. It is examined whether the non-machining effects cause the pieces to be scrapped and consequently to have zero quality.

For this purpose sheet metal forming in Arçelik Dishwasher Plant is investigated. Metal forming is a kind of production process frequently used in industry. Metal forming may be defined as controlled change of geometry or shape of a slug or workpiece maintaining its mass without decomposition. Today, complex precise components from a large variety of metals are being produced daily worldwide, frequently in mass production.

Sheet metal forming is a special kind of metal forming process where sheet metals up to 5-6 mm. thickness are plastically deformed and given the desired shapes. Generally, sheet metal forming processes are characterized by:

- High productivity
- Low material consumption

- Product qualities designed to function

- Large variety of material specifications with steels and non-ferrous metals

- Low unit production costs

Machining effects result in low piece production costs but when non-machining effects come into picture, scrap costs can increase incredibly and consequently unit costs increase.

A targeted improvement in production processes is absolutely essential if higher quality is to be achieved. Capable production processes and ergonomically designed workplaces provide the basis for the manufacture of products of consistently high quality. In addition, continuous improvement in product quality can only be realized by means of systematic analysis and optimization of all the industrial production processes. This requires taking into account not only the machine-specific setting parameters but also consideration of factors related to non-machining factors.

In the early days of quality management (before 1950), quality costs were regarded as the cost of scrap, rework, inspection plus the costs of running the Quality Department. The definitions and importance of quality costs changed following the changes in total quality management perceptions. The first attempts at a scientific approach to quality costs was made in the 1950s. It was Juran (1951) who brought out his perception about quality costs, and he made it clear that quality cost is not the cost of running the Quality Department. His view was that there are costs that could be avoided at reasonable expense and ones that it is economically inefficient to avoid. In the 1950s, Feigenbaum (1956) categorized the quality costs in four main categories : prevention, appraisal, internal failure and external failure. This classification is still widely used.

A study by Giakatis and Rooney (2000) states that the two most important quality costs are scrap and non-productive time costs. In this study, it is found out that in three manufacturing companies, the scrap and non-productive time costs represent 56% of the total quality costs. The quality costs respectively in this research are given in Table 1.1.

Table 1.1. Quality costs (€) sorted according to their importance

		Quality Cost(€)	%
1	Scrap	246 000	43,5
2	Non-productive time	67 682	12,0
3	Troubleshooting/problem-solving	49 056	8,7
4	Complaints and complaint handling	23 532	4,2
5	Supplier quality assurance	19 355	3,4
6	Stock evaluations	14 848	2,6
7	Calibration and maintenance of equipment	13 260	2,3
8	Design FMEAs and design verification activities	13 108	2,3
9	Pre-production verification activities	12 500	2,2
10	Receiving inspection	11 811	2,1
11	Quality planning	11 714	2,1
12	Acquisition, analysis and reporting of quality data	9 556	1,7
13	Inspection and testing	9 286	1,6
14	Defect/failure analysis	9 286	1,6
15	Subcontractor faults	7 982	1,4
16	Design of test, measurement and control equipment	7 034	1,2
17	Record storage	6 987	1,2
18	Laboratory acceptance testing	5 973	1,1
19	Internal quality auditing and management reviews	5 943	1,1
20	Field performance testing	5 304	0,9
21	Quality improvement programs	2 964	0,5
22	Feasibility studies, quality function deployment and quality reviews	2 864	0,5
23	Returned products	2 227	0,4
24	Analysis and reporting of test and inspection results	1 991	0,4
25	Returned products analysis and reporting	1 991	0,4
26	Quality training	1 250	0,2
27	Approvals and endorsements	995	0,2
28	On-site repair costs	928	0,2

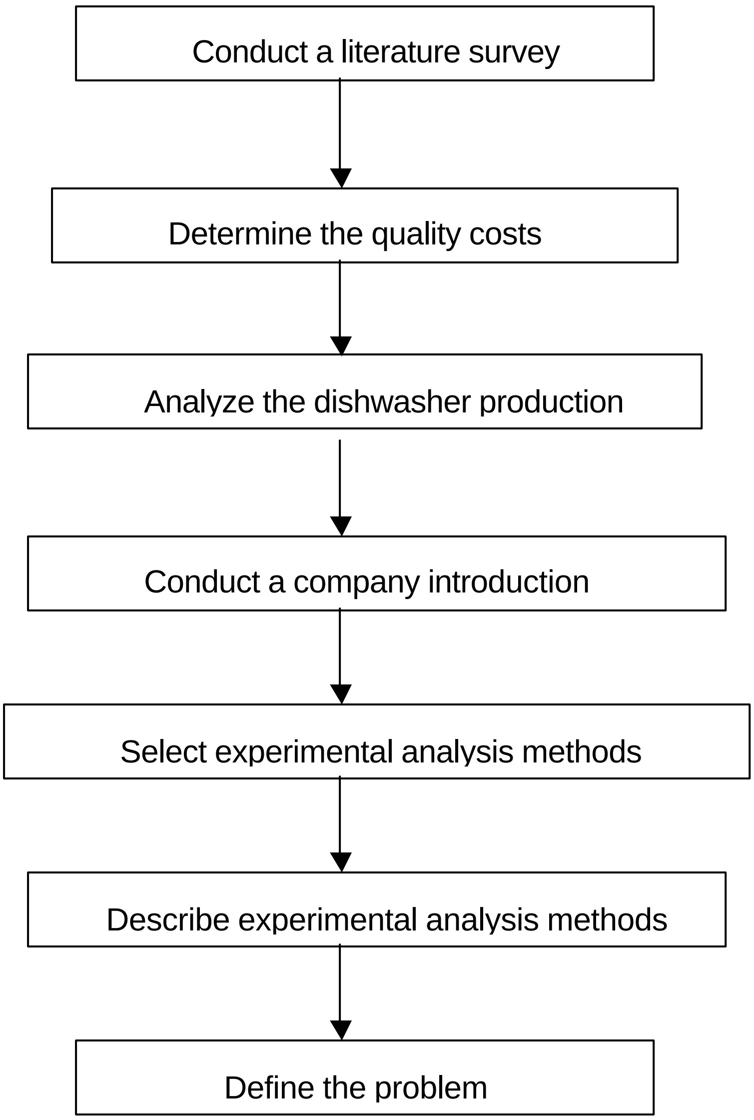
It is apparent that the scrap comes out to constitute the largest portion of the quality cost. Scrap cost represents 43.5% of all total quality costs.

In Arçelik Dishwasher Plant sheet metal forming processes are used extensively. About 1% of the pieces produced by sheet metal forming processes are scrapped from the beginning of sheet metal forming process until the minute of assembly. As well as the machining effects; non-machining effects have considerable influence on the pieces to be scrapped.

The purpose of this study is to determine the non-machining effects causing scrapping; consequently increasing the unit production costs. Thereby after the unit costs will be decreased by making improvements on these non-machining processes.

For this purpose a methodology is determined and the study is based on this methodology. The methodology is given in Figure 1.1:

METHODOLOGY



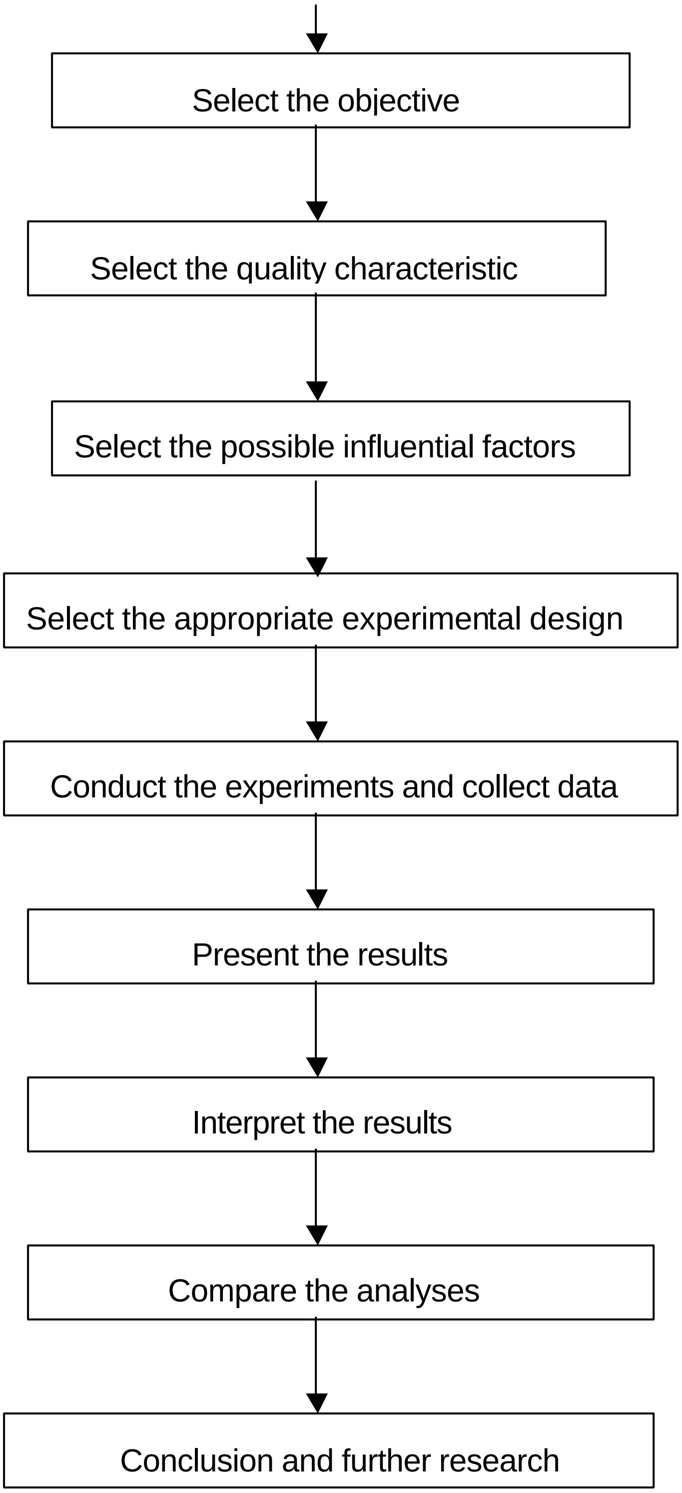


Figure 1.1 : Methodology of the study

CHAPTER 2

LITERATURE SURVEY

With competition creating an emphasis on higher quality goods, there is a greater demand for quality control to ensure no defective products are delivered to the customer. Also, the risk of product liability litigation over defective products has caused quality control to be crucial in manufacturing industries (Micalizzi and Goldberg, 1989). Many companies recognize that a targeted improvement in production processes is absolutely essential if higher quality is to be achieved. A systematic, continuous improvement in the product and process quality presupposes, however, capable processes and standardized, ergonomically designed workplaces (Monden, 1983). On the other hand machine manufacturers frequently consider a certain fabrication spread on the part of a machine to represent process capability, the concept of process capability in the course of industrial manufacture must be considerably extended in order to arrive at reliable statements about the production process. This requires taking into account not only the specific machine-setting parameters but also further influencing factors, which sometimes do not, at first sight, appear relevant to the process. In this context, increasing importance is being attached to the ergonomic design of workplaces and the realization of group-oriented working structures. Consequently, a comprehensive analysis of the quality capability production processes should consider, in addition to the influence of the machine, the influence

- of the person (qualification, reliability)
- of the material (condition at the time of supply, supplier,

characteristics of the material)

- of the work organization (material supply, parts handling, visual inspection, inspection lot size)

- of the workplace design (ergonomics, influence of the working environment)

However, more complex analytical instruments must be employed if improvements in quality are to be achieved on the basis of all of the above mentioned factors. (Klatte,Daetz and Laurig, 1996). Klatte, Daetz and Laurig uses Statistical Process Control techniques in their paper ' Quality improvement through capable processes and ergonomic design ' for process auditing and indicates that for continuous improvement not only machine-specific setting parameters but also non-machining factors must be considered.

One of the non-machining parameters mentioned is visual inspection. Visual inspection by humans is a widely used method of defect detection in industry, but we have long known inspection by humans to be less than 100% accurate. (Juran 1935; Tsao, Drury and Morawski 1979). Thus, it is necessary to seek methods to improve human inspection.

Visual inspection has been divided into two primary functions: visual search and decision making (Drury, 1975). These functions are the main determinants of inspection performance and must be executed reliably for inspection to be successful. Empirical studies have compared human inspection to the alternative of automated inspection. These studies show that automated inspection systems are superior at visual search (Hau, Lin and Drury, 1993) while humans are superior at decision-making (Drury and Sinclair, 1983). Although human visual search behavior tends to be less systematic and therefore may not have complete visual coverage, the flexibility of humans for various tasks and superior decision making ability make them desirable inspectors. Therefore, improving human visual search performance will enhance the effectiveness of humans as inspectors. In their paper, Wang, Lin and Drury (1997) show empirically that systematic behavior produces better inspection performance. On the practical side, overall inspection performance is evaluated through the measures of speed and accuracy. Since inspection is dependent on factors such as search behavior, the performance measures would reflect improvements in factors affecting inspection and indicate their impact on quality. (Schoonard, Gould and Miller,1973).

Another non-machining parameter is material handling and storage. Different practices in manufacturing sites are employed in the areas of handling, storage and movement to protect the quality of products and prevent loss, damage, deterioration, degradation or inadvertent substitution of product.

Covered, painted, plated or polished material is securely wrapped in heavy neutral papers or placed in individual plastic bags to prevent damage and scratches. Small parts are packaged in bulk providing the finish is not critical, and damage will not occur.

Parts of identically formed shapes without sharp projections can be netted provided they are wrapped with heavy neutral paper or other protective material to prevent scratches. Dissimilar materials are stored separately unless they are parts of an assembly. A quality procedure used as a policy in ‘Prime Technology’ (Prime Technology, 2000) recommends the following practices:

- Precious metals or materials plated with precious metals are handled with gloves or other anti-static devices and enclosed in bags or heavy neutral paper.
- Material returned to stock is inspected for damage and proper packaging to prevent damage and scratches during storage.
- Stacking of materials or containers is allowed to a height that tipping will not occur.

- Material is not allowed to block aisles, walkways or heavily trafficked areas.

An analysis at the pressing department of Volkswagen AG indicates the importance of material handling on quality as well. Due to the distance involved and the considerable weight of the pile of steel sheets, the ready-cut steel sheets are transported from the cutting press to the press line by crane. This can result in twisting and deformation. In addition, soiling of the steel sheets during stocking and transportation may occur as a result of particles, abraded steel cable, burr or dust. Damage to the edges of cut sheets through the use of steel cables for purposes of transportation also cannot be excluded. (Klatte, Daetz and Laurig, 1996).

One of the most critical issues in the material handling of compliant objects is excessive part deformation. The deformation of compliant sheet metal parts during the handling process can significantly impact both part dimensional quality and production rate. Increasing production rate while maintaining part quality requires an optimal design of the part transfer trajectory. (Shi and Hu, 1996). Compliant sheet metal parts are widely used in various industries such as aerospace, automobile and appliance industries. Excessive deformation during material handling may cause permanent (plastic) deformation due to material yield. Part elastic deformation also effects part/subassembly dimensional quality mainly in the following ways:

a) *Nesting error* - error positioning/dropping parts into the forming die. Part elastic deformations may cause part positional variation in a die, which can further cause mis-stamped parts in stamping press line (a stamping line for large parts usually has 4-5 presses/dies). These small deviations of the part in each die accumulate and can, at times, eventually cause, very large dimensional variation of the final part that can further lead to scrap or production line downtime.

b) *Part distortion during die contact*. At the end of the material handling process, parts are usually dropped into the die. If excessive elastic deformations exist relative to the die contour, the contact force of the part with the die could be so evenly distributed that the part could be so unevenly distributed that the part could be permanently damaged.

c) *Part-obstacle interference*. Part elastic deformation during transfer increases uncertainty in planning a part transfer trajectory. This may, in effect, cause unexpected interference of the part with the surrounding environment and therefore, damaging the part. (Li and Ceglarek, 2002)

All these factors will result in deterioration of product quality and/or reduction of production rate by an increase of down time. Material handling was identified as one of the top five causes of part dimensional variation(Li and Shi ,1993). It has also been observed that material in a sheet metal forming facility spends over ninety percent of its time waiting to be processed. (Sprow ,1991)

There exist direct relations among transfer path, transfer velocity and part deformation. Small transfer velocity causes cycle time increase, but also results in small part deformation. On the other hand, large transfer velocity reduces cycle time, but increases part deformation considerably, which has negative impact on part quality. Li & Ceglarek uses non-linear programming in the paper 'Optimal Trajectory Planning for Material Handling of Compliant Sheet Metal Parts' to minimize total time needed for the transfer of sheet metal parts. The objective function is the minimization of transfer motion, t .The first constraint is the path geometric constraint to avoid static obstacle, g=g(s) where s stands for path, g(s) represents the paths that satisfy the static obstacle avoidance condition. Second constraint is $a<a_{max}$ where a stands for the acceleration changing rate. This constraint means that in order to meet the requirement of path smoothness, the acceleration changing rate can not exceed certain value a_{max}. The third constraint is a maximum allowable part deflection constraint. The maximum deformation of every point on the part in any instant should not exceed this value. The fourth constraint is the material handling system constraint, representing the material handling system transfer capability. Lastly, the fifth constraint is the material

yield constraint to limit the maximum stress to be less than the yield stress (Li and Ceglarek, 2002).

Inspection lot size can be another effective non-machining parameter. The inspection process is necessary in order to maintain customer satisfaction but also must be kept efficient in order to reduce the cost for the company. Inspection process provides an ensurement for process and quality control.

Deming (1986) and Vander Wiel and Vardeman (1994) consider the all or none inspection in minimizing the average total cost. Deming recommends a complete –100%- inspection when the proportion of defective is greater than the break-even quality.

A paced inspection task is one in which a time limit has been imposed, while schemes of pacing deal more with the degree of control one has over the task. Three types of pacing have been discussed in literature: machine-paced, self-paced, and unpaced. A machine –paced task is defined as a fixed time in which a defect may be detected. The same amount of time is allocated whether or not a defect is found or not. Self-paced is when a maximum time limit is set, although the inspector may choose to go on before the time limit is reached. Finally, unpaced inspection occurs when there is no time restriction placed on the inspector (Garrett, Melloy and Gramopadhye 2001). Machine-paced inspection in industry offers certain obvious economic advantages such as the minimization of work in progress, maximization of floor space usage and simplification of the organization of supplying components to the right place at the right time. However, because under this type of paced condition operators are required to complete each task within a rigidly fixed time, certainly ergonomic principles are lacking. 'Stress originates from forcing longer than standard work cycle times into a rigidly fixed time cycle' (Belbin and Stammers, 1972). In a different study performed by Mc Farling and Helmstra (1975), it is determined that self-paced inspection appears to be beneficial to both performance and motivation.

Also pacing can be classified according to the lot size inspected. Per-item pacing is when a set amount of time is given for each individual item. This time is comparable to inspection on a conveyor line or indexing machines (Kochar and Jaisingh, 1980). Per-item pacing relates to a more structured condition than per-lot pacing, and would eliminate the possible problem of having some items missed entirely. On the other hand per-lot pacing is when a set amount of time is given for a batch of items.

The condition of pacing per-lot may appear to compensate for the variability of inspection times between individual items. In the paper ' The effects of per-lot and per-item pacing on inspection performance ' Garrett, Melloy & Gramopadhye uses a Latin square design, blocking for both subject and sequence of trials. Two main factors were studied, level of control and speed. The two levels of control investigated were per-lot pacing and per-item pacing. The most important deduction from this study is that even though the accuracy for per-lot and per-item were found to be similar, for practical reasons per-item pacing would be more favorable in the majority of industry settings. (Garrett, Melloy and Gramopadhye, 2001)

Another non-machining effect to be considered is the operator effect. The paper 'Effect of operator competence on assessment of quality control in manufacturing' by Loven & Helander (1997) describes the influence of operator competence on judgement of product quality. They indicate the use of high competence operators can improve the quality in manufacturing considerably. They use questionnaires, in-depth interviews, observations, company documents and quality control data but do not use any experimental design techniques. In Swedish industry there is a great interest in creating jobs, which are both satisfying and productive. Traditional techniques to design more interesting jobs include job rotation, job enlargement (horizontal extension) and job enrichment (vertical extension). The assumption is that such enhanced jobs will improve work motivation, productivity and job satisfaction.

Hackman and Oldham (1980) observe that changes should aim at improving job factors such as skill variety, task identity, task significance, autonomy and feedback. These techniques have been complemented by concepts of teamwork, groups managed by objectives, and strategies for improvement of competence and flexibility. This approach focuses more on organizational change of the entire manufacturing process and management style of a company. Only through a change of the organization of a company can one achieve solid improvements which will create desirable jobs (Martenson, 1995).

Work effectiveness and work motivation are expected to be high when jobs are high in motivating potential. People who work with highly motivating jobs like to perform well. And performing well, for most people, implies high-quality work of which one can be proud (Hackman and Oldham, 1980). Individuals who are satisfied with the work content (job security, co-workers and pay) tend to respond more positively to enriched and challenging jobs than individuals who are dissatisfied (Hackman,1990). There are, however, large individual differences in the personal need structure and attitudes to work (Hackman and Oldham, 1980). Therefore most research on these issues produce great variability in result between individuals.

Often organizational principles are implemented in manufacturing without analyzing the required worker competence. There is one obvious reason: relatively little is known about the extent to which work content and competence influence productivity. Therefore worker and organizational competence have rarely been used as a criteria in assessing organizations. The study by Loven and Helander (1997) addresses the need for competence for the purpose of improving quality.

The supplier effect can also be considered as a non-machining parameter. The analysis at the pressing department of Volkswagen AG implies that the influence of the supplier on the quality of the pressed pieces is not inconsiderable. More surface faults, in particular at the medium press setting, i.e. the normal pressure setting for the press, occurred in connection with the parts produced from the coil from one supplier than with those from another supplier. This can be explained by differences in the characteristics values for the material as well as in the thickness of the steel sheet, both of which resulted in the pieces exhibiting different deep-drawing behavior (Klatte, Daetz and Laurig, 1996).

These were some of the researches in literature examining the effects of non-machining parameters on product quality. None of these papers used experimental design techniques for identifying the effect of *non-machining parameters*. But there are some researches examining the effects of *machining parameters* on product quality by using experimental design techniques:

The paper 'Defining the operating window for an automotive sheet pressing operation' by Herron, Hodgson and Cardew-Hall developed a methodology that allows the operating window of an automotive sheet metal forming process to be defined. The method is applied to a production panel drawn on a 1200t double action press in an automotive sheet metal forming plant. The effects of corner pressure, shut height and draw speed(machining parameters) on quality were examined using a full factorial design of experiment (DOE) and a series of empirical models are consequently developed.

The DOE analysis identified punch speed (x_1) as having the most influence on severity over the variable ranges investigated. Decreased punch speed causes increased severity. Shut height (x_2) was found to be about half influential as x_1 showing that severity is increased by decreasing the shut height gap. Corner pressure (x_3) was found to have little influence and this finding was supported by plant personnel. Corner pressure only came into consideration as an interaction with shut height on severity.

An operating window in sheet metal forming is an area in the input space which corresponds to the production of a high quality part. The size of the operating window corresponds to the sensitivity of the part quality to variation in the input parameters. With an understanding of the process and associated variation, the most robust operating point within this window can be identified. (Doolan, Kalyanasundaram, Hodgson and Hall, 2001)

'Characterising frictional behaviour in sheet metal forming' by Lanzon, Cardew-Hall & Hodgson (1998) uses a two-level multi-variable design of experiment (DOE) approach to investigate the influence and interaction of lubricant type, die surface finish, contact pressure, sheet metal coating and draw speed, which are machining parameters, on product quality. Lubricant type, contact pressure, die surface roughness and blank coating are identified as having significant influence on sheet metal buckling. Lubricant type is found to have the most influence on sheet metal buckling.

There has always been a variation in the quality of a part produced using sheet metal forming. The sheet metal forming process has a large number of inputs affecting the quality of the final part produced. Each of these inputs has an associated variation which leads to the variation in the final part. A more effective method of controlling the output is to understand the output variation more thoroughly and account for this in defining the operating point to ensure robustness to this identified variation.

In literature no articles could be come across which examine the effects of non-machining parameters on product quality by using experimental design techniques. This study will use experimental design techniques for identifying effective non-machining parameters on product quality.

CHAPTER 3

SYSTEM ANALYSIS

Short description of the company :

Arçelik was established in 1955 and entered the Turkish Appliances Sector by producing its first washing machine in 1959 and its first refrigerator in 1960.

Koç Group owns the majority of the company (58.4%) and the rest of the shares belong to Burla Group (21.3%) and to the public (20.3%) including foreign investors.

Arçelik produces a full-range of major household appliances, which includes refrigerators/freezers, washing machines, dishwashers, ovens/cookers and vacuum cleaners.

In 2002, Arçelik realized 96% of the washing machine and dishwasher exports, 57% of the refrigerator exports and 39 % of the oven exports from Turkey.

Arçelik is one of the seven largest European household appliance manufacturers with net domestic sales € 820.000.000 and export sales of € 410.000.000 in 2002. In 13 out of last 16 years(1987-2002) Arçelik has been the largest private sector company in Turkey.

Arçelik Dishwasher Plant where the study and the experiments were held, was founded in 1993. The plant is located near Sincan, Ankara in an Industrial Region. The factory's total area is 109.000 m^2 and its covered area is 31.400 m^2. The plant's total workforce is 306 employees, where 66 of total workforce are white-collar employees and the remaining 240 are blue-collar employees. The plant’s total production capacity is about 700.000 dishwashers per year.

The pieces of the dishwasher which are made up of sheet metal are produced in Arçelik Dishwasher Plant. Only the raw material, that is the sheet metal coil, is purchased from different suppliers and the production is carried out by different means in the Arcelik Plant.

The electronic components, motor&pump assembly and the plastic pieces of the dishwasher are purchased from different suppliers and assembled with the sheet metal components at the assembly line in Arcelik Plant.

Analysis of dishwasher production and scraps :

Scraps to come out during dishwasher production at Arçelik is examined. The sheet metal parts of the dishwasher are produced at Arcelik Dishwasher Plant and are assembled with the electronic components, motor and pump assembly and the plastic pieces of the dishwasher which are purchased from different suppliers.

The sheet metal components produced at Arçelik Plant are as follows :

- Inner Door
- Outer Door
- U Sheet
- L Sheet
- Side Panel
- Bottom Tray
- Rail Pulley Holder
- Hinge Spring Holder
- Top Corner Bracket
- Water Supply Holder
- Top Traverse
- Hinge Arm

- Kick Plate
- Rail
- Rear Bottom Support
- Front Lower Support
- Motor Bracket
- Hinge Plate
- Frame

The flowchart of dishwasher production is given in Figure 3.1.

About 1% of the material is wasted as scrap during production and up to assembly phase in Arcelik Dishwasher Plant. The decrease of the scrap cost will consequently result in the decrease of the total cost of the machine for the company.

In Arcelik Dishwasher Plant 70% of the scrap cost is due to sheet metal scraps. To reduce the scrap cost; the effort must be concentrated on sheet metal production.

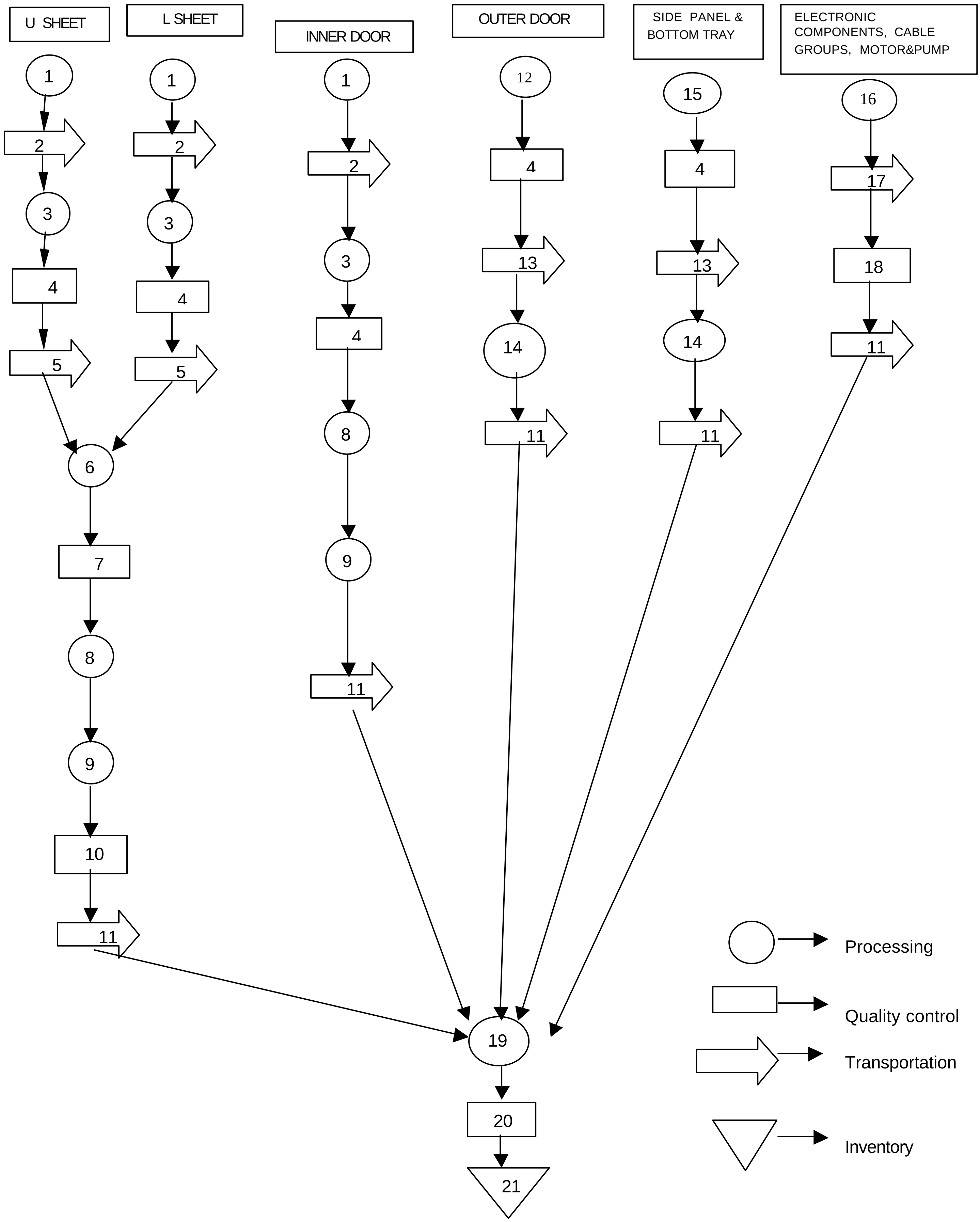


Figure 3. 1 :Flowchart of dishwasher production

1. Cutting of sheet metal to desired length
2. Transportation to the hydraulic press line
3. Processing (forming) in the hydraulic press line
4. Quality control according to the predetermined standards
5. Transportation to welding line
6. Welding of U and L sheets
7. UV test for testing leakage
8. Removal and cleansing of forming lubricant
9. Bitumen coating
10. Quality control of the inner body according to predetermined standards
11. Transportation to the assembly line
12. Processing (forming) in the outer door line
13. Transportation to the paintshop
14. Painting process
15. Processing (forming) at the eccentric press
16. Purchase from suppliers
17. Transportation to Arcelik
18. Acceptance quality control in Arcelik
19. Assembly process
20. Functioning test of the complete dishwasher
21. Storage at the warehouse

A Pareto Analysis is performed in order to determine which sheet metal components are more influential and has greater effect on the scrap cost. The information includes the data of three months - January, February &March- in 2002 .

	SCRAP COST
SIDE PANEL SCRAP COST	6.221,0Euro/3 months
INNER DOOR SCRAP COST	3.911,3Euro/3 months
U SHEET SCRAP COST	2.629,2Euro/3 months
L SHEET SCRAP COST	1.939,7Euro/3 months
TOTAL SHEET METAL SCRAP COST	18.604,3Euro/3 months

PART NAME	%(SCRAP COST)
SIDE PANEL	33,4
INNER DOOR	21,0
U SHEET	14,1
L SHEET	10,4
TOTAL	79,0
OTHER PARTS (20 ITEMS)	21,0

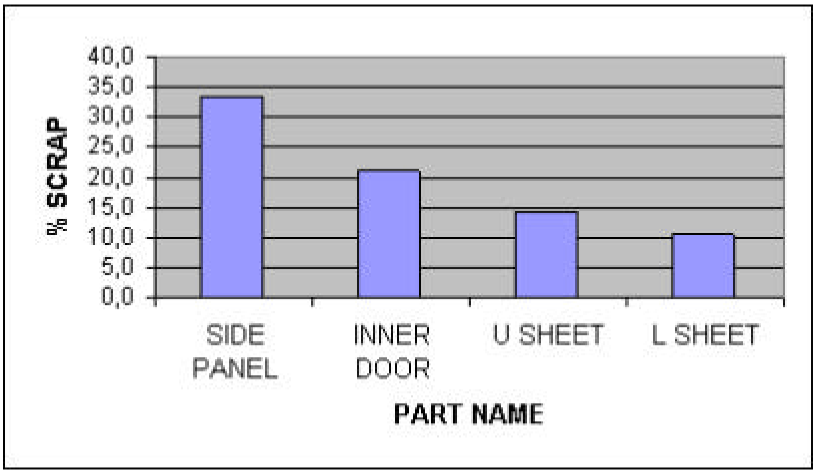


Figure 3.2 : Pareto analysis for scrap cost of sheet-metal forming process of dishwasher production

It can be concluded from the results of the Pareto Analysis that 4 of 22 pieces produced in Arcelik Plant constitutes 79.5 % of the sheet metal scrap cost, thus about 55% of all scrap cost. As a result these four pieces (U Sheet, L Sheet, Inner Door and Side Panel) will be examined throughout the analysis and experimental design will be performed for these four pieces. Information about these four pieces and the views of the dishwasher are given in the figures 3.3 through 3.9. With these views the location of the four pieces on the dishwasher can be seen.

U Sheet : U Sheet is produced from stainless steel sheet in a hydraulic press line and transferred to the welding line. In the welding line, U Sheet is welded with L Sheet and forms the inner tube of the dishwasher.

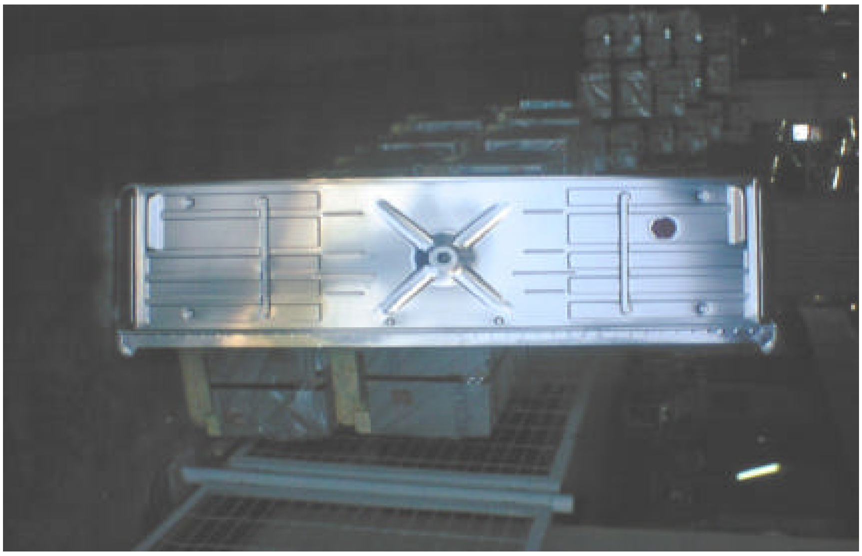


Figure 3.3 : A U Sheet

L Sheet : L Sheet is produced from stainless steel sheet in a hydraulic press line and transferred to the welding line . In the welding line, L Sheet is welded with U Sheet and forms the inner tube of the dishwasher.

Figure 3.4 : An L Sheet

Inner Door : Inner door is produced from stainless steel sheet in a hydraulic press line, coated with bitumen and transferred to the assembly line. In the assembly line, inner door is assembled with the outer door and forms the front face of the dishwasher.

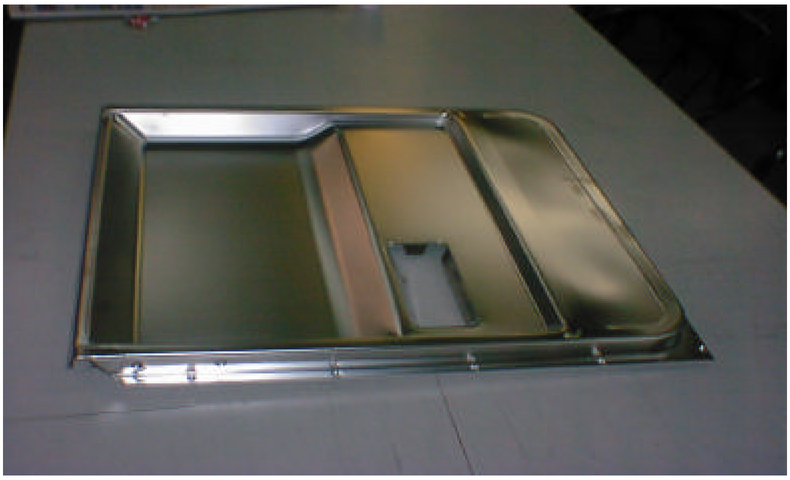


Figure 3.5 : An Inner Door

Side Panel : Side Panel is produced from cold-rolled sheet in an eccentric press. After being painted in the paint-shop it is transferred to the assembly line.

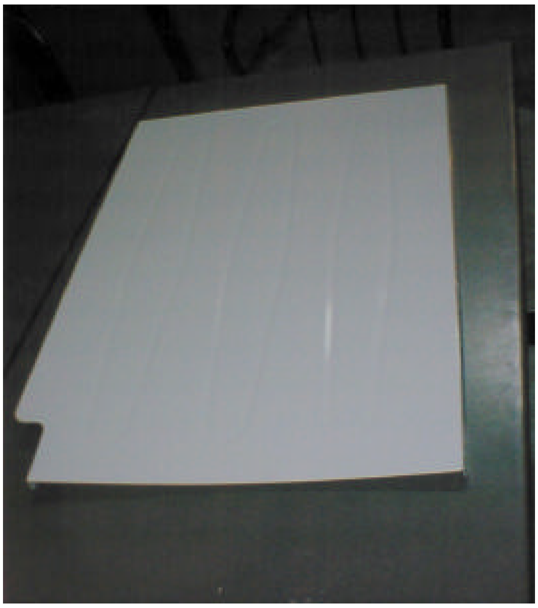


Figure 3.6 : A Side Panel

Figure 3.7 : Side view of a dishwasher

Figure 3.8 : Front view of a dishwasher

Figure 3.9 : Side view of a dishwasher

CHAPTER 4

BASIC INFORMATION ABOUT THE TECHNIQUES USED IN THE STUDY

Experimental methods are widely used in research as well as in industry settings, however, sometimes for very different purposes. The primary goal in scientific research is usually to show the statistical significance of an effect that a particular factor exerts on the dependent variable of interest. In industrial settings, the primary goal is usually to extract the maximum amount of unbiased information regarding the factors affecting a production process as few (costly) observations as possible.

The study of experimental design originated in England and in its early years, was associated solely with agricultural experimentation. The need for experimental design was very clear : it takes a full year to obtain a single observation on the yield of a new variety of most crops. Consequently, the need to save time and money led to a study of ways to obtain more information using smaller samples. Similar motivations led to its subsequent acceptance and wide use in all fields of scientific experimentation .

$2^{(k-p)}$ fractional factorial design and Taguchi design are used in this study and information for these are given in the following:

$2^{(k-p)}$ fractional factorial designs are the workhorse of industrial experiments. The impact of a large number of factors on the production process can simultaneously be assessed with relative efficiency (i.e. with few experimental runs). The logic of these type of experiments is straightforward: each factor has only two settings. For $2^{(k-p)}$ fractional factorial designs, 2 is the number of levels for the factors used in the experiment; k denotes for the number of factors analyzed and p of these factors are generated from the interactions of a full $2^{(k-p)}$ design. As a result, the design does not give full resolution; that is, there are certain interaction effects that are confounded with other effects

Things to consider in any $2^{(k-p)}$ fractional factorial experiment include the number of factors to be investigated, the number of experimental runs, and whether there will be blocks of experimental runs. Beyond these basic considerations, one should also take into account whether the number of runs will allow a design of the required resolution and degree of confounding for the crucial order of interactions, given the resolution. Resolution refers to the amount of information that can be obtained from an experiment. Resolution III, IV, and V classifications are of major interest.

In a resolution III design

1) No main effects aliased with other main effects

2) Main effects aliased with two-factor interactions

3) Two-factor interactions aliased with other two-factor interactions

In a resolution IV design

1) No main effects aliased with other main effects

2) No main effects aliased with two-factor interactions

3) Two-factor interactions aliased with other two-factor interactions

In a resolution V design

1) No main effects aliased with other main effects

2) No main effects aliased with two-factor interactions

3) No two-factor interactions aliased with other two-factor interactions

The simplicity of these designs is also their major flaw. As mentioned, underlying the use of two-level factors is the belief that the resultant changes in the dependent variable are basically linear in nature. This is often not the case, and many variables are related to quality characteristics in a non-linear fashion. Another problem of fractional designs is the implicit assumption that higher-order interactions do not matter; but sometimes this is not the case.

The other method to be used in this study is Taguchi design. Taguchi methods have become increasingly popular in recent years. The documented examples of sizable quality improvements that resulted from implementations of these methods have added to the curiosity among American manufacturers. In fact, some of the leading manufacturers in USA have begun to use these methods with usually great success. For example AT&T is using these methods in the manufacture of very large scale integrated circuits; also, Ford Motor Company has gained significant quality improvements due to these methods (American Supplier Institute, 1984 to 1988). However, as the details of these methods are becoming more widely known, critical appraisals are also beginning to appear. Pignatiello and Ramberg published a list of the top 10 triumphs and tragedies associated with Taguchi methods, shown in Table 4.1.

Table 4.1 : 10 triumphs and tragedies associated with Taguchi methods

TAGUCHI TRIUMPHS AND TRAGEDIES

Triumphs

1 Won the attention of a new audience

2 Expanded the role of quality beyond that of control

3 Formulated a complete methodology for quality improvement

4 Focused attention on the cost associated with variability

5 Demonstrated that experimentation produces results

6 Established new directions for quality engineering-research

7 Attracted a significant level of attention for education in quality engineering

8 Popularized the concept of robust product design

9 Pioneered the simultaneous study of both the mean and variability

10 Simplified tolerance analysis through designed experiments

Tragedies

1 Spawned a cult of extremists that accept only his technique

2 Experienced a backlash of criticism from Western statisticians

3 Introduced misleading signal-to-noise statistics

4 Neglected to explain the assumptions underlying his methodology

5 Ignored modern graphical, data-analytic approaches

6 Recommended potentially misleading three-level orthogonal arrays

7 Failed to advocate randomization

8 Discouraged the adaptive, sequential approach to experimentation

9 Maintained a dogmatic position on the importance of interactions

10 Advocated the invalid accumulation of minute analysis

Taguchi methods involve both experimental design and analysis aspects. Taguchi methods employ special fractional factorial experiment designs called orthogonal arrays. (Pignatiello, 1988) Selection of an orthogonal array and the assignment of the main factor and the factor interaction effects to the orthogonal array are the experimental design aspects of the Taguchi methods. The orthogonal array determines the number of the main factor effects and factor interaction effects that can be analyzed. Orthogonal means being balanced and not mixed. In statistical terminology, orthogonal means statistically independent. Notation of orthogonal arrays is L_a (b^c) where 'L' is a symbol for orthogonal array, 'a' stands for the number of experiments required for this array, 'b' shows the number of test levels for each factor and 'c' points out the number of factors that this array can examine.

In statistical terminology a matrix is said to be orthogonal if following two criteria occur;

- All possible combinations of test levels occur between pairs of columns
- And each of these combinations occur an equal number of times

Signal to noise data transformation, analysis of variance, average response plots and confirmation run procedure are the statistical analysis aspects of Taguchi methods. The signal to noise data transformation converts multiple replication results of an experiment condition to the single S/N data used for minimizing response variation. Analysis of variance is the statistical analysis technique used for determining the relative importance of main factor and factor interaction effects (Phadke,1989). The best level of a parameter is the one producing the best average response of all experiments having the same level of the analyzed parameter for response optimization. Confirmation run procedure tests optimality of the proposed best parameter levels and existence of unconsidered important main factors and/or factor interaction effects in the analysis.

Taguchi design of experiment (DOE) methods incorporate orthogonal arrays to minimize the number of experiments required to determine the effect of process parameters upon performance characteristics. Assigning interactions at random to any available column within the orthogonal array can lead to incorrect analysis and faulty conclusions. To prevent the occurrence of these experimental design errors, Dr. Taguchi has developed a system for mapping interactions to the appropriate columns of the array. By setting up a graphical representation of the relationships among factors and the interactions between them, the experimenter can systematically assign factors and interactions to columns within the orthogonal array without fear of confounding the effects of factors ad their interactions. These are called linear graphs.

Linear graphs are constructed of interconnecting dots or circles. Each dot or circle within the orthogonal array in which a factor can be assigned. The connecting line represents the interaction between the two factors represented by the dots at each end of the line segment. The number accompanying the line segment represents the column within the array to which the interaction should be assigned.

The Taguchi experimental approach allows a statistically sound experiment to be completed, while investigating a minimum number of possible combinations of parameters or factors. A Taguchi experiment can be accomplished in a timely manner and at a reduced cost with results comparable to a full factorial experiment.

Analysis of variance, ANOVA, is a statistical decision making tool used for detecting any differences in average performances of tested parameters (Ross,1996). It employs sum of squares and F statistics to find out relative importance of the analyzed processing parameters, measurement errors and uncontrolled parameters.

By using equations 4.1,4.2,4.3 total, individual and error sum of square calculations are calculated.

$$SS_{Total} = \sum_{i=1}^{N} (X_i)^2 \quad ....(4.1)$$

Where;

X_i : Number of scraps in experiment run number i

N : Total number of runs in all experiment condition

$$SS_{Parameter} = \left(\sum_{i=1}^{kA} (S_i)^2 / n_{si}\right) - (T^2 / N) \quad ......(4.2)$$

Where;

k_A : Number of levels of a parameter

n_{si} : Number of observations under i^th level of a parameter

S_i : Sum of observations under i^th level of a parameter

T : Sum of all observations in all experiments

N : Total number of runs in all experiment condition

$SS_{Error} = SS_{Total} – (T^2 / N)$……(4.3)

After these calculations, the variances are calculated by dividing $SS_{parameter}$ by degrees of freedoms. Degree of freedom indicate the number of independent comparisons that can be made from the data.

The degree of freedom(df) is equal to total number of data minus one for the total analysis, number of parameter levels minus one for the process parameters, and total degrees of freedom minus sum of degree of freedom of all processing parameters for the error in this case.

F statistics test can be employed for determining relative importance of processing parameters. F statistics is a ratio of sample variances and used for comparing variances. Ratio of a parameter variance to an error variance has an F probability distribution with the degrees of freedom of processing parameter and error. When the F ratio becomes large enough, than the two variances are accepted as being unequal with some confidence level. Confidence level is related with statistical hypothesis testing (Ross,1996). In this case, it means probability of accepting compared variances as different when they are really different. Therefore, larger the F statistics value means higher the confidence level for the difference of the analyzed parameter and the error variances. Besides, the processing parameters having a big F ratio are accepted as influencing the process response more than the ones having a small F ratio.(Ross,1996). If a parameter’s F statistics value is larger than the tabulated F value with the same confidence level and the same degrees of freedoms of the processing parameter and the error, than the parameter is accepted as an influential one with a certain confidence level.

Signal to noise data transformation, S/N, converts the results of multiple replications of an experiment condition into single S/N data. The origins of S/N can be traced to Taguchi’s initial use of an experimental design in industry in the late 1940s. Traditional analysis involved separate consideration of variability (usually expressed as standard deviation) and the mean value. This kind of two part optimization fails in the common sense of variability being related to the mean. In cases where the standard deviation gets smaller as the mean value gets smaller, it is impossible to first optimize with respect to minimizing variability and then adjust the mean on target. The two objectives conflict directly, and it is difficult to make a rational trade-off. A process simply consists of input, controllable and uncontrollable factors and output. In S/N ratio terminology, the controllable factors for a fixed target can be considered as signal factors and can be intentionally adjusted to accomplish a controlled change in the output of the system. Uncontrollable factors are named as noise factors and these are known to affect a system's performance. However, the settings of these factors can not be controlled or it is not feasible to control them. Noise factors can be splitted into three main categories as inner noise, outer noise and between-products noise. Inner noise are the internal sources of variability in a product's function such as deterioration of components in response to aging. Outer noise is the external source of variability such as operating environment, temperature and humidity. Between-products noise is caused by the variability in the manufacturing procedures or equipment. Welding amperage can be an example for between-products noise.

Using S/N ratio we can simply analyze the results of the experiments involving multiple runs, instead of extended and time-consuming analyses.

In this manner S/N offers the following two main advantages :

1) It provides a guidance to a selection of the optimum level based on least variation around the target and also the average value closest to the target.

2) It offers objective comparison of two set of experimental data with respect to variation around the target and the deviation of the average from the target value.

Three types of S/N ratios exist for static cases;

- Nominal-the-Best
- Smaller-the-Better
- Larger-the-Better

Nominal-the-best is the correct type when we have the following conditions;

L: Quality Loss = 0 when μ: Target = m and σ: Deviation = 0 ;

Nominal-the-best is a measurable characteristic with a specific user-defined target. The transformation to S/N ratio can be made by the following formula :

$$\eta = 10\mathrm{LOG}\,\frac{\bar{y}^2}{s^2}$$

where;

η = symbol for S/N; (dB)

$$\bar{y} = \text{mean} = \frac{\sum_{i=1}^{n} y_i}{n} \quad n = \text{number of data points},\ y_i = \text{result of } i^{th} \text{ data}$$

Smaller-the-better type S/N ratio can be used when we have the following requirement.

L : Quality Loss = 0 when μ = 0 and σ : Deviation = 0

$$s = \text{std.dev.} = \sqrt{\sum_{i=1}^{n} \frac{(y_i - \bar{y})^2}{n-1}}$$

This simply corresponds to the target of achieving zero which is the smallest obtainable value, without negative values. If the system is capable of attaining both negative and positive values, then this is the case for nominal-the-best type.

The transformation formula for smaller-the better type is:

$$(\text{ç} = -10\text{LOG}V_T\ ; \quad V_T = \frac{1}{n}\sum_{i=1}^{n} y_i^2\ )\text{.........}\ .(4.4)$$

where;

n = number of replications

y_i = i^{th} value

The specific examples for-smaller-the-better type problems are direct evaluation of energy, leakage of any matter or pollution.

Larger-the-better type is used when we have the following;

$$\text{L : Quality Loss} = 0 \text{ when } \quad \text{ì} = +\infty \text{, and } s \text{ : Deviation} = 0$$

If a system is defined as perfect when it approaches to infinity, larger-the-better should be used. Taguchi recommends to use the inverse of the target of zero which is similar to opposite of smaller-the-better type. Therefore the transformation to the S/N ratio can be performed by the formula :

$$\text{ç} = -10\text{LOG}V_T \qquad V_T = \frac{1}{n}\sum_{i=1}^{n} \frac{1}{y_i^2}$$

Weld strength, profit, material strength and fuel efficiency can be the examples of larger-the –better type.

The purpose of experimentation should be to understand how to reduce and control variation of a product or process; subsequently, decisions must be made concerning which parameters affect the performance of a product or process. Experimentation in any form involves expense and risk of failure. It is, therefore, imperative that each experiment conducted is planned and managed carefully to insure the highest probability of success, at the least cost. To take the proper steps in a correct sequence and to insure that each step is completed fully, is therefore vital in experimentation.

The major steps to complete an effective designed experiment are listed in the following text. The planning phase includes steps 1 through 5, the conducting phase is step 6, and the analysis phase includes steps 7 and 8.

1) Problem Definition
2) Quality Characteristic Selection
3) Selection of the Possible Influential Factors
4) Selection of the Levels for the Factors
5) Selection of the Appropriate Experimental Design and Assignment of Factors to Experimental Design
6) Conducting Experiments
7) Confirmation Experiments
8) Interpretation of the Results

These steps will be used as the main outline throughout the study

CHAPTER 5

EXPERIMENTAL DESIGN AND ANALYSIS

5.1)*Problem Definition* **:** The definition of the problem is analyzed thoroughly in the *'System Analysis'* chapter and the scrap amount is described as a major problem of production. Consequently in the light of this analysis, decreasing the scrap cost in Arcelik Dishwasher plant is selected as the objective.

5.2) *Quality Characteristic Selection* :

The key point at this step is to select a performance characteristic such that the variables evaluated in the experiment have an arithmetically additive effect with respect to this characteristic. This is a key step toward assuring a successful experiment which will yield reproducible results, but it is also the most difficult step.

In this study, the quality characteristic is selected as " the total number of scraps among selected piece's daily production". In this study experimental analysis is performed for 1500 pieces; and the number of scraps among this amount of production is considered. If more than 1500 pieces are produced in a shift, 1500 of them are selected randomly and used in the experimental analysis.

5.3) *Selection of the Possible Influential Factors* :

The goal of this phase is to develop a list of variables which should be evaluated in the experiment. If important factors are unknowingly left out of the experiment, then the information gained from the experiment may be misleading.

Brainstorming, process flow diagrams, process routings, product and process fishbone diagrams, statistical process control charts, product design specifications and process control charts are frequently used tools for selecting the factors which may influence the selected quality characteristics.

For our defined problem under the light of the literature survey and the process flow chart a cause&effect diagram can be drawn for identifying the possible influential effects. The structure for a cause&effect diagram begins with the basic effect that is produced and progresses to what causes there may be for this effect. For our problem the cause &effect diagram is given in Figure 5.1 :

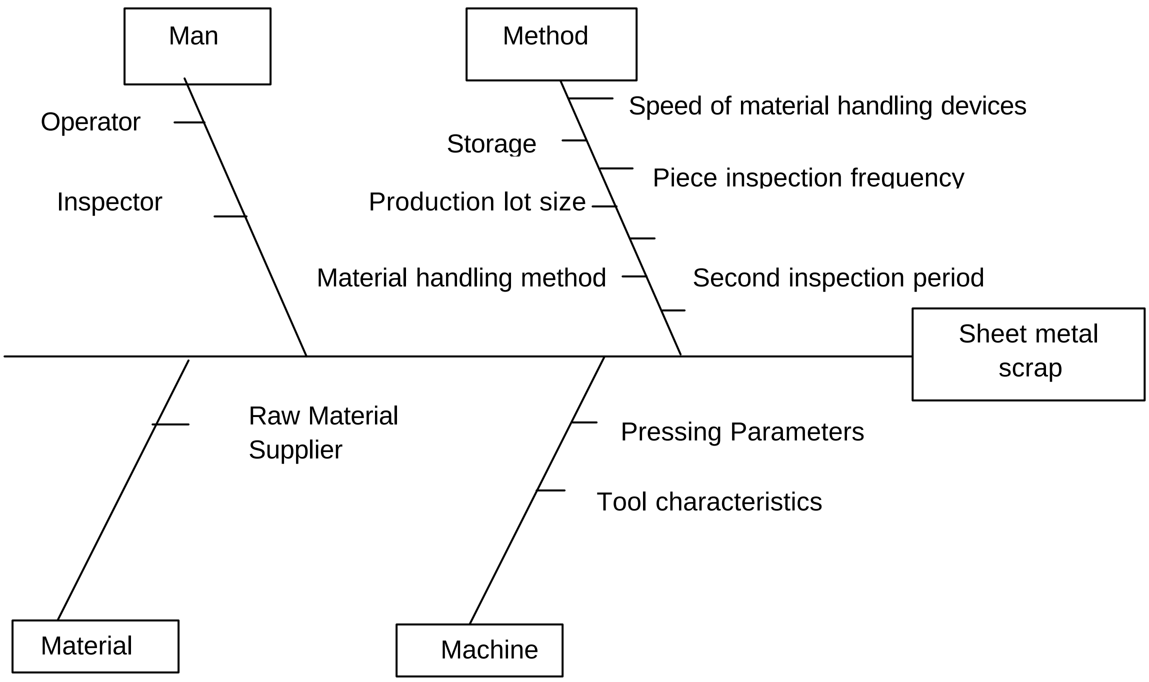


Figure 5.1 : Cause & Effect Diagram for identifying the possible influential parameters

The possible influential non-machining effects among all the effects determined from the cause&effect diagram can be listed as :

- Operator
- Inspector
- Speed of the material handling devices
- Piece inspection frequency
- Second inspection period
- Material handling method
- Storage method
- Supplier
- Production Lot Size

For U Sheet, L Sheet and the inner door the control factors are selected as:

- Operator
- Piece inspection frequency
- Used percentage of full speed of the material handling device
- Production lot size
- Inspector
- Piece storage method
- Raw material Supplier
- Second inspection period

For the side panel the control factors are determined as :

- Operator

- Piece inspection frequency
- Speed of material handling device of semi-finished product
- Production lot size
- Inspector
- Material handling method
- Raw material supplier
- Second inspection period

5.4) Selecting the Levels for the Control Factors :

Product or process technical expertise is the single most important source for the selection of appropriate values for the factor levels. In this study levels are selected by a brainstorming session with production experts and engineers in Arçelik Dishwasher Plant. Any factor can be made to look insignificant by choosing levels that are too close together and conversely, any factor can be made to look significant by choosing levels that are too far apart. The levels need to be in an operational range.

The numbering scheme for the levels is not critical, and two approaches may be considered. For continuous factors, the first level may be the lower of the two values being tested and the second level the higher level. This provides an intuitive relationship between the value of the factor and the level designation. Another approach, especially in a process development situation, is to assign the first level to all the factor values that represent the current operating conditions. With this approach, one of the trials in the experiment will automatically represent the baseline conditions.

Short Definition of the factors:

Operator : Two different operators are used during production. The operators are the levels of this factor.

Piece inspection frequency : During production the operator inspects the pieces for catching the defects. The frequency of these inspections define the levels. If the defect cannot be caught in the first inspection, then it is caught in the second inspection.

Used percentage of full speed : The full speed is defined for the material handling devices which transfer the semi-finished product.

Production lot size : The production of the piece can last for one shift of the assembly line or longer. Then production of another piece starts in the same production equipment. The period of production defines the levels. In the assembly line 1500 pieces are needed for one shift, and the first 1500 pieces produced at the presses is the production for first shift. The second 1500 pieces is the production for the second shift. Usually at the presses a piece is produced for the one week (six shifts)requirement of the assembly line; thus 1500*6 = 9000 pieces are produced. Then at the same equipment the production of another piece starts.

Inspector : The quality inspector inspects the pieces on pre-defined times. Different inspectors define the level. Two inspectors are selected for the analyses.

Piece storage method : Either the piece is stored into the storage place with robots or manually. Storage method defines the levels.

Raw Material Supplier : Sheet metal supplied by different sheet metal suppliers are used in production. The suppliers define the levels. Two suppliers are selected for each sheet examined.

Second inspection period : The difference between the first inspection and the second inspection is that the first inspection is carried out by the press operators who are the producers of the sheet metal pieces. If the operator or the assembly people cannot decide whether the piece has to be evaluated as a scrap or not; then these pieces are evaluated by the quality people. Also if the defective piece cannot be caught in the first inspection then it is caught in the period of welding and assembly by the welding or assembly operators. These processes are called as second inspection. The period of this inspection defines the levels of this factor.

Also there are noise factors such as temperature, humidity and electrical amperage. But these factors are very difficult to control so they are not used in the experiments.

With this information, the levels for the control factors for the four pieces examined, are given in Table 5.1.

Table 5.1 : Control Factors for Experimental Analysis

	Factors		Level 1	Level 2
U SHEET	A	Operator	Operator 1	Operator 2
	B	Piece inspection frequency	1/3	1/6
	C	Used percentage of full speed of the material handling device	80%	100%
	D	Production lot size	Production for first shift	Production for second shift
	E	Inspector	Inspector 1	Inspector 2
	F	Piece storage method	With Robot	Manual
	G	Raw Material Supplier	Supplier 1	Supplier 2
	H	Second inspection period	Daily	Weekly

	Factors		Level 1	Level 2
L SHEET	A	Operator	Operator 1	Operator 2
	B	Piece inspection frequency	1/2	1/5
	C	Used percentage of full speed of the material handling device	80%	100%
	D	Production lot size	Production for first shift	Production for second shift
	E	Inspector	Inspector 1	Inspector 2
	F	Piece storage method	With Robot	Manual
	G	Raw Material Supplier	Supplier 1	Supplier 2
	H	Second inspection period	Daily	Weekly

		Factors	Level 1	Level 2
INNER DOOR	A	Operator	Operator 1	Operator 2
	B	Piece inspection frequency	1/1	1/5
	C	Used percentage of full speed of the material handling device	80%	100%
	D	Production lot size	Production for first shift	Production for second shift
	E	Inspector	Inspector 1	Inspector 2
	F	Piece storage method	With Robot	Manual
	G	Raw Material Supplier	Supplier 1	Supplier 2
	H	Second inspection period	Daily	Weekly

		Factors	Level 1	Level 2
SIDE PANEL	A	Operator	Operator 1	Operator 2
	B	Piece inspection frequency	1/3	1/6
	C	Speed of material handling device of semi-finished product (stroke/minute)	10	11
	D	Production lot size	Production For second shift	Production for fourth shift
	E	Inspector	Inspector 1	Inspector 2
	F	Material handling method	Conveyor	Manual (Storage on a special car)
	G	Raw Material Supplier	Supplier 1	Supplier 2
	H	Second inspection period	Daily	Weekly

5.5) Analysis Using Taguchi Design :

5.5.1) Selection of the Appropriate Orthogonal Array and Assignment of Factors to Orthogonal Arrays for Taguchi analysis: After the conclusion of the planning phase of the experiment, the next activity is setting up the experiment or actually designing the experiment. The foundation for designing an experiment using Taguchi methodology is the orthogonal array. The orthogonal arrays efficiently make use of only a relatively small amount of data, translate it into meaningful and verifiable conclusions. Orthogonal means being balanced and not mixed. In the context of experimental matrices, orthogonal means statistically independent. If a typical orthogonal array (Table 5.4) is examined, it is observed that each level has an equal number of occurrences within each column, and each array has a different number of columns, the same rule applies. Concerning statistical independence, each level within one column will occur an equal number of times within each level in any other column.

For our problem in concern; there are 8 control factors to be used in the experimental design and if a full factorial experiment is used ;256 experiments must be conducted. (given in Table 5.2)

Table 5.2 : Calculation of the number of experiments needed for 8 control factors

Factor Effect	df Required
8 Main Effects	8
28 Two-way interactions	28
56 Three-way interactions	56
70 Four-way interactions	70
56 Five-way interactions	56
28 Six-way interactions	28
8 Seven-way interactions	8
1 Eight-way interaction	1
Total df	255
df for mean	1
Total number of experiments	256

A full factorial experiment can be effectively used to calculate an enormous amount of information about the factor effects and every possible interaction between the factors. In most industrial manufacturing and product design settings the three way or greater interaction effects are not considered. In most cases, the probability that very many of the two-way interaction effects will end-up being significant is quite low. The two-way interaction effects are examined based on previous experience, engineering knowledge and common sense.

For our problem, df required is calculated in Table 5.3.

Table 5.3 : Calculation of df needed for experimental design

Source	df_{needed}
A	1
B	1
C	1
D	1
E	1
F	1
G	1
H	1
A*B	1
B*C	1
B*D	1
A*D	1
	12
df_{error}	1
df_{total}	13

The four interaction effects used in the experiment are selected as a result of a brainstorming session with the press operators and production engineers of Arçelik Dishwasher Plant.

In our problem there are 12 factors with two levels and since with Taguchi's $L_{16}(2^{15})$ orthogonal array, up to 15 factors with two levels can be analyzed Taguchi's $L_{16}(2^{15})$ orthogonal array is used in the analyses.

Table 5.4 : $L_{16}(2^{15})$ orthogonal array

Column #	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
#1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
#2	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2
#3	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2
#4	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1
#5	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2
#6	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1
#7	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1
#8	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2
#9	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2
#10	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1
#11	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1
#12	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2
#13	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1
#14	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2
#15	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2
#16	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1

Assigning interactions at random to any available column within the orthogonal array can lead to incorrect analysis and faulty conclusions. To prevent the occurrence of these experimental design errors, Taguchi has developed a system for mapping interactions to the appropriate columns of the array. By setting up a graphical representation of the relationships among factors and the interactions between them, the factors and the interactions can be assigned to columns within the orthogonal array. These graphical representations are linear graphs.

For our problem the required linear graph is given in Figure 5.2.

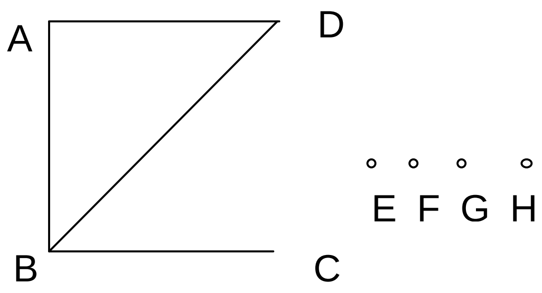


Figure 5.2 : Required linear graph for Taguchi design

The required graph matches with the standard graph in Figure 5.3.

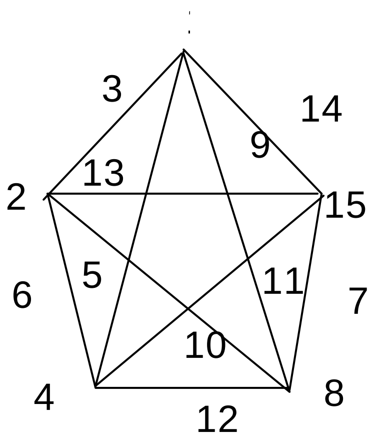


Figure 5.3 : Standard linear graph matching with the required linear graph for Taguchi Design

With this information the design given at Table 5.5 is appropriate.

Table 5.5 : The appropriate Taguchi Design for our problem

Column #	A 1	B 2	A*B 3	C 4	F 5	B*C 6	G 7	E 8	H 9	e1 10	e1 11	e1 12	B*D 13	A*D 14	D 15
#1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
#2	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2
#3	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2
#4	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1
#5	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2
#6	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1
#7	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1
#8	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2
#9	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2
#10	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1
#11	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1
#12	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2
#13	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1
#14	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2
#15	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2
#16	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1

5.5.2)Conducting Experiments :

Secondly the set-ups are established according to the Taguchi design and experiments are conducted. Each experiment lasts for one shift. The required set-ups and the observations for the four pieces examined are given in Tables 5.6, 5.7, 5.8, 5.9

Table 5.6: Taguchi design and the observations for the U Sheet

	PROCESSING PARAMETERS															RESULTS	
EXP #	A 1	B 2	A*B 3	C 4	F 5	B*C 6	G 7	E 8	H 9	e1 10	e1 11	e1 12	B*D 13	A*D 14	D 15	RUN # 1	RUN # 2
#1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	4	5
#2	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	9	3
#3	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	3	7
#4	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	10	10
#5	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	14	6
#6	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1	15	10
#7	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	11	10
#8	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2	12	10
#9	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	2	8
#10	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1	7	2
#11	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1	5	3
#12	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2	8	5
#13	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	10	12
#14	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2	10	18
#15	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	4	7
#16	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1	14	14

Table 5.7: Taguchi design and the observations for the L Sheet

	PROCESSING PARAMETERS															RESULTS	
EXP #	A 1	B 2	A*B 3	C 4	F 5	B*C 6	G 7	E 8	H 9	e1 10	e1 11	e1 12	B*D 13	A*D 14	D 15	RUN # 1	RUN # 2
#1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	12	9
#2	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	13	11
#3	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	14	17
#4	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	22	18
#5	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	20	24
#6	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1	15	17
#7	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	20	24
#8	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2	24	24
#9	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	21	19
#10	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1	22	19
#11	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1	13	7
#12	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2	11	10
#13	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	18	16
#14	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2	25	18
#15	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	15	9
#16	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1	15	17

Table 5.8 : Taguchi design and the observations for the Side Panel

	PROCESSING PARAMETERS															RESULTS	
EXP #	A 1	B 2	A*B 3	C 4	F 5	B*C 6	G 7	E 8	H 9	e1 10	e1 11	e1 12	B*D 13	A*D 14	D 15	RUN # 1	RUN # 2
#1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	10	12
#2	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	11	9
#3	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	19	24
#4	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	22	18
#5	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	13	15
#6	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1	14	14
#7	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	23	28
#8	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2	26	20
#9	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	21	18
#10	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1	23	15
#11	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1	10	13
#12	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2	6	7
#13	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	23	25
#14	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2	24	30
#15	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	16	19
#16	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1	16	16

Table 5.9: Taguchi design and the observations for the Inner Door

	PROCESSING PARAMETERS															RESULTS	
EXP #	A 1	B 2	A*B 3	C 4	F 5	B*C 6	G 7	E 8	H 9	e1 10	e1 11	e1 12	B*D 13	A*D 14	D 15	RUN # 1	RUN # 2
#1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	3	1
#2	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	5	8
#3	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	8	8
#4	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	12	8
#5	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	15	18
#6	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1	13	15
#7	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	11	11
#8	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2	8	9
#9	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	10	5
#10	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1	9	9
#11	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1	2	3
#12	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2	8	5
#13	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	6	6
#14	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2	4	7
#15	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	10	14
#16	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1	18	10

Using ANOVA and equations 4.1, 4.2, 4.3 and 4.4, results are obtained as given in Tables 5.10, 5.11, 5.12, 5.13. All ANOVA calculations throughout the study, are performed by using Minitab Release 13.32.

Table 5.10 : ANOVA of Averages- Taguchi Design for the U Sheet Scrap Analysis

Process Parameters	Degrees of Freedom	Sum of Squares	Variance	F-Ratio	p
Operator (A)	1	1,562	1,562	0,25	0,654
Piece inspection frequency (B)	**1**	**115,562**	**115,562**	**18,19**	**0,024**
Used percentage of full speed of the material handling device (C)	1	0,062	0,062	0,01	0,927
Production lot size (D)	1	4,000	4,000	0,63	0,485
Inspector (E)	1	33,063	33,063	5,20	0,107
Piece storage method (F)	1	4,000	4,000	0,63	0,485
Raw Material Supplier (G)	1	0,062	0,062	0,01	0,681
Second inspection period (H)	1	1,000	1,000	0,16	0,718
Interaction (A*B)	1	2,250	2,250	0,35	0,594
Interaction (A*D)	1	0,562	0,562	0,09	0,785
Interaction (B*C)	1	9,000	9,000	1,42	0,320
Interaction (B*D)	1	3,063	3,063	0,48	0,537
Error	3	19,063	6,354		
Total	15	193,250			

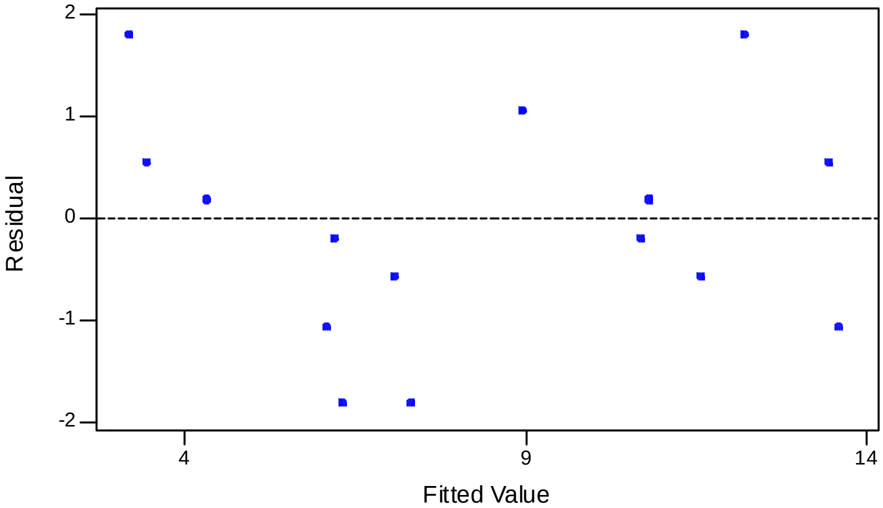


Figure 5.4 : Residuals Versus the Fitted Values

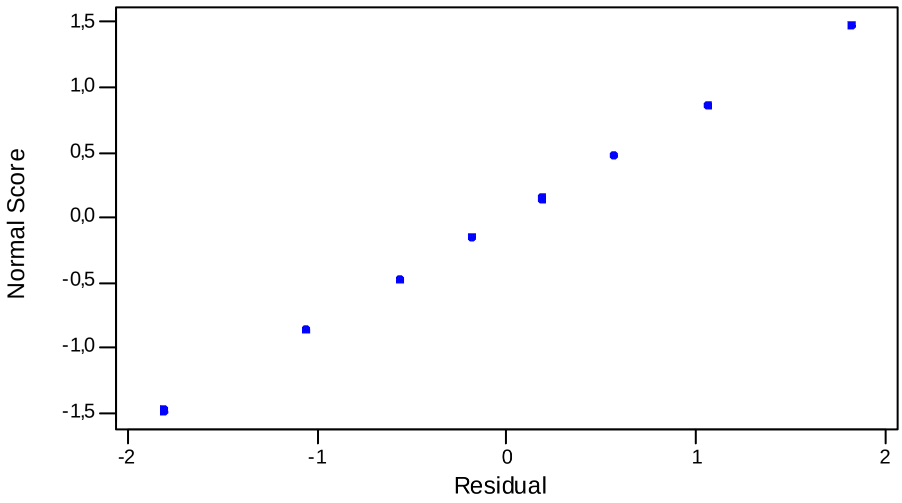


Figure 5.5: Normal Probability Plot of the Residuals

Table 5.11 : ANOVA of Averages- Taguchi Design for the L Sheet Scrap Analysis

Process Parameters	Degrees of Freedom	Sum of Squares	Variance	F-Ratio	p
Operator (A)	1	15,016	15,016	1,62	0,293
Piece inspection frequency (B)	**1**	**58,141**	**58,141**	**6,27**	**0,087**
Used percentage of full speed of the material handling device (C)	1	6,891	6,891	0,74	0,452
Production lot size (D)	1	2,641	2,641	0,28	0,630
Inspector (E)	1	9,766	9,766	1,05	0,380
Piece Storage Method (F)	**1**	**159,391**	**159,391**	**17,20**	**0,025**
Raw Material Supplier (G)	1	11,391	11,391	1,23	0,348
Second inspection period (H)	1	2,641	2,641	0,28	0,630
Interaction (A*B)	1	23,766	23,766	2,56	0,208
Interaction (A*D)	1	1,891	1,891	0,20	0,682
Interaction (B*C)	1	1,891	1,891	0,20	0,682
Interaction (B*D)	1	6,891	6,891	0,74	0,452
Error	3	27,797	9,266		
Total	15	328,109			

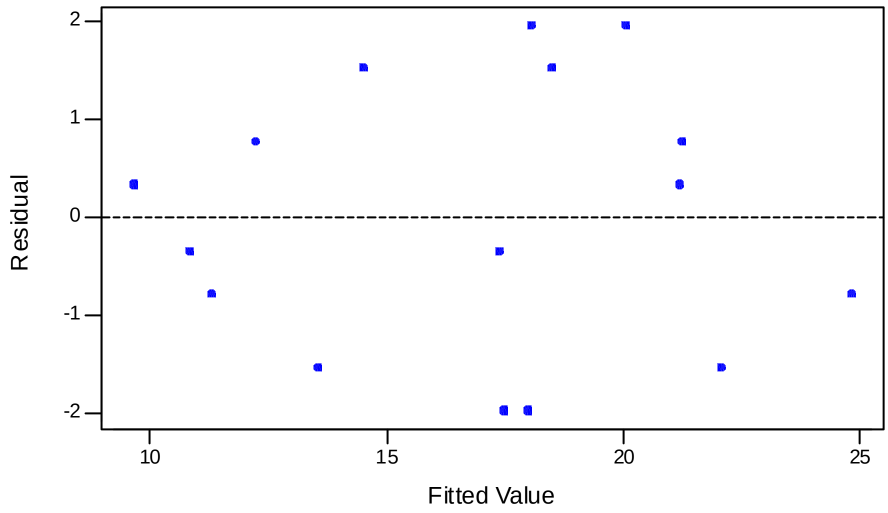


Figure 5.6: Residuals Versus the Fitted Values

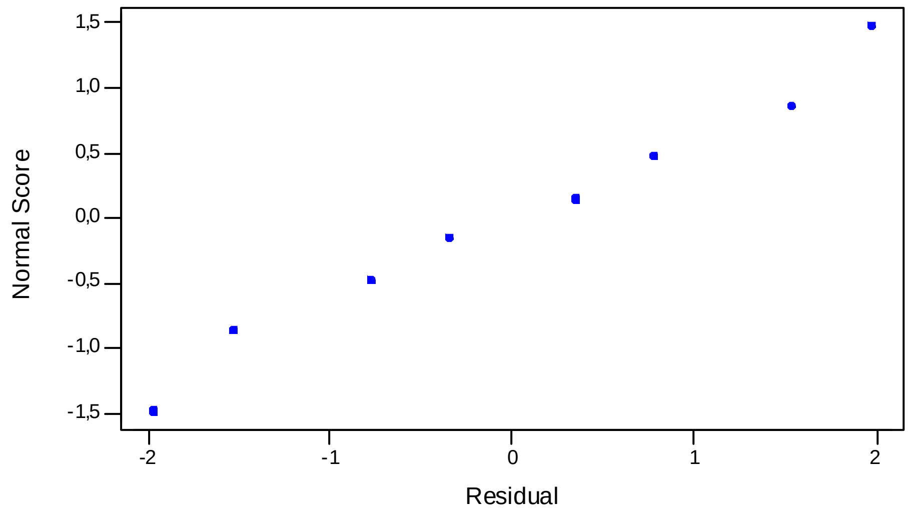


Figure 5.7: Normal Probability Plot of the Residuals

Table 5.12 : ANOVA of Averages- Taguchi Design for the Side Panel Scrap Analysis

Process Parameters	Degrees of Freedom	Sum of Squares	Variance	F-Ratio	P
Operator (A)	1	2,641	2,641	0,65	0,479
Piece inspection frequency (B)	**1**	**87,891**	**87,891**	**21,66**	**0,019**
Speed of material handling device of semi-finished product (C)	1	0,141	0,141	0,03	0,864
Production lot size (D)	1	0,391	0,391	0,10	0,777
Inspector (E)	1	1,266	1,266	0,31	0,615
Material Handling Method (F)	**1**	**346,891**	**346,891**	**85,50**	**0,003**
Raw Material Supplier (G)	1	3,516	3,516	0,87	0,421
Second inspection period (H)	1	0,766	0,766	0,19	0,693
Interaction (A*B)	1	21,391	21,391	5,27	0,105
Interaction (A*D)	1	0,391	0,391	0,10	0,777
Interaction (B*C)	1	0,141	0,141	0,03	0,864
Interaction (B*D)	1	6,891	6,891	1,70	0,284
Error	3	12,172	4,057		
Total	15	484,484			

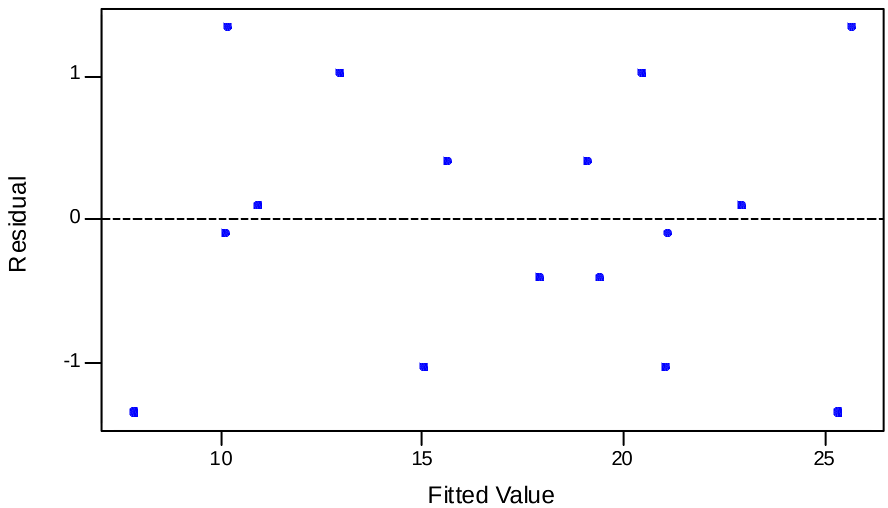


Figure 5.8: Residuals Versus the Fitted Values

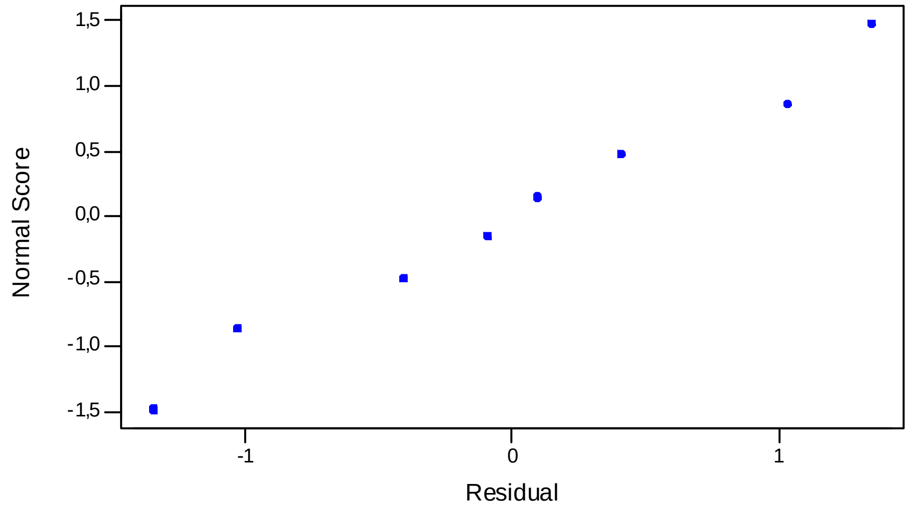


Figure 5.9: Normal Probability Plot of the Residuals

Table 5.13 : ANOVA of Averages- Taguchi Design for the Inner Door Scrap Analysis

Process Parameters	Degrees of Freedom	Sum of Squares	Variance	F-Ratio	P
Operator (A)	1	11,391	11,391	1,81	0,272
Piece inspection frequency (B)	**1**	**78,766**	**78,766**	**12,49**	**0,039**
Used percentage of full speed of the material handling device (C)	1	1,891	1,891	0,30	0,622
Production lot size (D)	1	0,391	0,391	0,06	0,820
Inspector (E)	1	4,516	4,516	0,72	0,460
Piece storage method (F)	1	4,516	4,516	0,72	0,460
Raw Material Supplier (G)	**1**	**112,891**	**112,891**	**17,90**	**0,024**
Second inspection period (H)	1	1,891	1,891	0,30	0,622
Interaction (A*B)	1	8,266	8,266	1,31	0,335
Interaction (A*D)	1	0,391	0,391	0,06	0,820
Interaction (B*C)	1	0,141	0,141	0,02	0,891
Interaction (B*D)	1	3,516	3,516	0,56	0,509
Error	3	18,922	6,307		
Total	15	247,484			

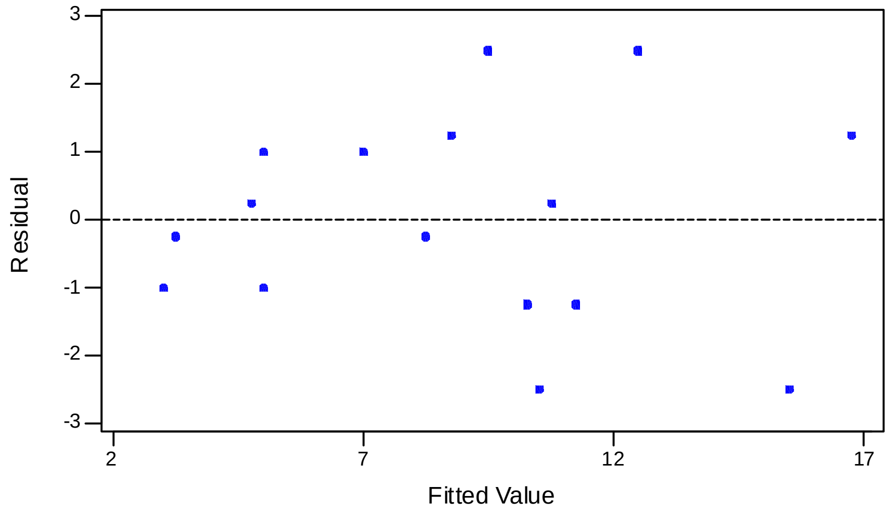


Figure 5.10: Residuals Versus the Fitted Values

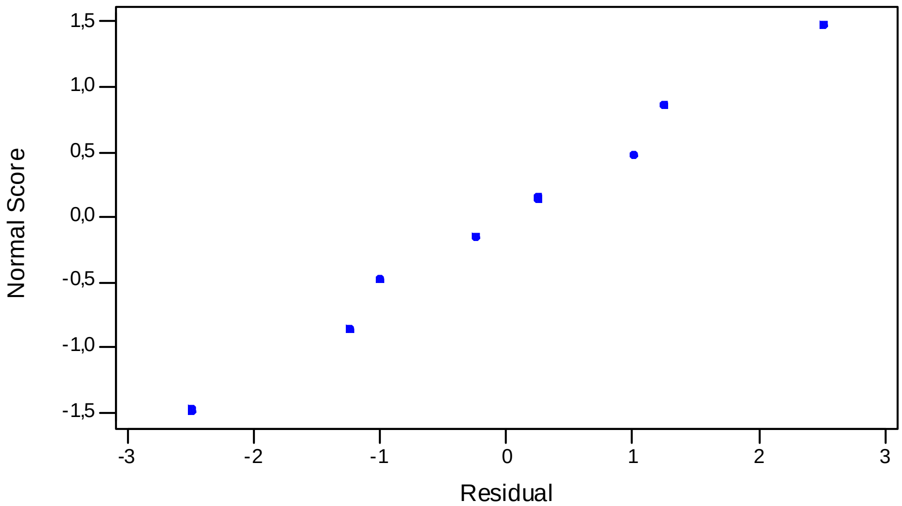


Figure 5.11: Normal Probability Plot of the Residuals

ANOVA performed for U Sheet indicates that the *piece inspection frequency* affects the scrap quantity since it has higher F-Ratio than the tabulated F values at 90% confidence level,5.54. It is also evident that none of the interaction effects have significant effect on the scrap quantity.

The *piece storage method* *and piece inspection frequency* are the significant effects on scrap quantity for L Sheet. These factors have larger F Ratios than the tabulated F Ratio value at 90% confidence level. All the remaining factors including the interaction effects have F values smaller than the tabulated F-ratio value at 90% confidence level.

For Side Panel *Material Handling Method and Piece Inspection Frequency* have significant effect on the quantity of scraps at 90% confidence level. The *Material Handling Method* also denotes significance at 99% confidence level.

The factors which come out to be significant are the *Raw Material Supplier and Piece Inspection Frequency* for the Inner Door. For this piece also none of the interaction effects indicate significance at 90% confidence level.

Residuals versus fitted values and normal probability plot indicate that errors have normal distribution with constant variance for the four sheetes analyzed.

To test the optimality of the proposed parameter levels and existence of unconsidered important factor effects and the factor interaction effects confirmation runs are held. Estimation of the expected response and the response variation with certain confidence intervals are the major steps of the confirmation run procedure. The suggested process parameter levels are accepted as optimal with the chosen confidence level if the confirmation run results are within the confidence level. The calculations for the confirmation run procedure are carried on as in the following and the factors having bigger variance values than the error variance are included in the calculations.

For U sheet one factor is included in the expected number of scrap & confidence interval calculations: *piece inspection frequency.* This factor is used since it is determined as significant at 90% confidence level.

$ì_{B1} = \overline{T} + (\overline{B}_1 - \overline{T})$

where;

$\overline{T}$: Overall average of the observations

$\overline{B}_1$: Average of the first level of process parameter B , *piece inspection frequency*. $\overline{B}_1$ is used in the calculations since $\overline{B}_1$ is smaller than $\overline{B}_2$ and we try to minimize the output response ì. ($\overline{B}_1 = 5{,}6875$, $\overline{B}_2 = 10{,}75$). In the following calculations of the expected response for the other sheets same procedure is used.

$ì_{B1} = 8{,}375 + (5{,}6875 - 8{,}375)$

$= 5{,}6875$

$CI = (F_{á,1,n_e} * V_e / N_{eff})^{1/2}$

Where

$F_{á,1,n_e}$: Tabulated F value for 1 - á confidence level 1 and n_e degrees of freedom

= 5.54 at 90% confidence level with 3 error degrees of freedom

V_e : Error variance

N_{eff} : Effective sample size

$N_{eff} = N / (1 + df_{\mu})$

$= 16 / (1+1) = 8$

where ;

N : Number of data used in design, 16

df_{μ} : Total degrees of freedom associated with items used in μ estimate.

= 1 because one parameter is used having one degree of freedom.

CI = 2,097 at 90 % confidence level

The expected number of U sheet scraps with determined parameter levels above is *5,6875 ± 2,097 .*

The process parameters *piece inspection frequency & piece storage method* are used in the calculations for determining the expected number of scrap and confidence interval for L Sheet.

$$\mu_{B_1F_1} = \overline{T} + (\overline{B}_1 - \overline{T}) + (\overline{F}_1 - \overline{T})$$

$$= 16{,}84375 + (14{,}8750 - 16{,}84375) + (13{,}6250 - 16{,}84375)$$

$$= 11{,}656$$

$$CI = ((5{,}54 * 9{,}266) / (5{,}33))^{1/2}$$

$$= 3{,}103$$

Therefore, the expected number of L sheet scraps is *11,656 ± 3,103 .*

The calculations for determining the expected number of scraps & the confidence interval for the Side Panel include two process parameters ; *piece inspection frequency and piece storage method.*

$$\mu_{B_1F_1} = \overline{T} + (\overline{B}_1 - \overline{T}) + (\overline{F}_1 - \overline{T})$$

$= 17{,}21875 + (14{,}875 – 17{,}21875) + (12{,}5625 – 17{,}21875)$

$= 10, 2187$

$CI = (5{,}54 * 4{,}057 / 5{,}33)^{1/2}$

$= 2{,}052$

The expected number of Side Panel scraps is *10,2187 ±2,052.*

For the Inner Door calculations are held with two process parameters; *piece inspection frequency & raw material supplier,* since these two parameters are determined as significant at 90% confidence level.

$$\hat{\mu}_{B_1G_1} = \overline{T} + (\overline{B}_1 - \overline{T}) + (\overline{G}_1 - \overline{T})$$

$= 8{,}71875 + (6{,}500 – 8{,}71875) + (6{,}0625 – 8{,}71875)$

$= 3{,}844$

$CI = (5{,}54 * 6{,}307 / 5{,}33)^{1/2}$

$= 2{,}560$

Consequently the expected number of Inner Door scraps is *3.844* ± *2,560.*

The setups are established again with the proper factor levels which are determined as significant and used in estimation of the expected response and confidence interval. The experiments are performed again and the results obtained are given in Table-5.14.

Table 5.14 :Results of the confirmation runs for Taguchi Design

	Result of the First Confirmation Run	Result of the Second Confirmation Run	Result of the Third Confirmation Run	Result of the Fourth Confirmation Run	Average of Confirmation Run Experiments
U Sheet	7	5	5	7	6,00
L Sheet	10	9	11	7	9,25
Side Panel	10	7	8	11	9,00
Inner Door	4	7	5	3	4,75

5.5.3)Taguchi Analysis Using S/N Transformation :

The average number of scraps of the two runs for the four pieces in consideration and their corresponding signal to noise transformed values are presented in tables 5.15,5.16, 5.17 and 5.18.

Table 5.15 : Signal to Noise Values of the Two Experiment Run Results for the U Sheet

Experiment #	Average Particle Size		S/N Ratio
	Run # 1	Run # 2	
1	12	9	-20,512
2	13	11	-21,614
3	14	17	-23,847
4	22	18	-26,064
5	20	24	-26,884
6	15	17	-24,099
7	20	24	-26,884
8	24	24	-27,604
9	21	19	-26,031
10	22	19	-26,258
11	13	7	-20,374
12	11	10	-20,434
13	18	16	-24,624
14	25	18	-26,762
15	15	9	-21,847
16	15	17	-24,099

Table 5.16: Signal to Noise Values of the Two Experiment Run Results for the L Sheet

Experiment #	Average Particle Size		S/N Ratio
	Run # 1	Run # 2	
1	4	5	-13,118
2	9	3	-16,532
3	3	7	-14,624
4	10	10	-20,000
5	14	6	-20,645
6	15	10	-22,109
7	11	10	-20,434
8	12	10	-20,864
9	2	8	-15,315
10	7	2	-14,232
11	5	3	-12,304
12	8	5	-16,484
13	10	12	-20,864
14	10	18	-23,263
15	4	7	-15,119
16	14	9	-21,414

Table 5.17 : Signal to Noise Values of the Two Experiment Run Results for the Side Panel

Experiment #	Average Particle Size		S/N Ratio
	Run # 1	Run # 2	
1	10	12	-20,864
2	11	9	-20,043
3	19	24	-26,707
4	22	18	-26,064
5	13	15	-22,945
6	14	14	-22,923
7	23	28	-28,172
8	26	20	-27,308
9	21	18	-25,826
10	23	15	-25,763
11	10	13	-21,287
12	6	7	-16,284
13	23	25	-27,612
14	24	30	-28,681
15	16	19	-24,893
16	16	16	-24,082

Table 5.18 : Signal to Noise Values of the Two Experiment Run Results for the Inner Door

Experiment #	Average Particle Size		S/N Ratio
	Run # 1	Run # 2	
1	3	1	-6,990
2	5	8	-16,484
3	8	8	-18,062
4	12	8	-20,170
5	15	18	-24,385
6	13	15	-22,945
7	11	11	-20,828
8	8	9	-18,603
9	10	5	-17,959
10	9	9	-19,085
11	2	3	-8,129
12	8	5	-16,484
13	6	6	-15,563
14	4	7	-15,119
15	10	14	-21,703
16	18	10	-23,263

Using calculated S/N ratios and equations 4.1, 4.2, 4.3; ANOVA is carried out and the results are given in tables 5.19, 5.20, 5.21 and 5.22

Table 5.19 : ANOVA-Taguchi Design Based on S/N Transformed Data Values for the U Sheet Scrap Analysis

Process Parameters	Degrees of Freedom	Sum of Squares	Variance	F-Ratio	p
Operator (A)	1	2,933	2,933	0,61	0,492
Piece inspection frequency (B)	**1**	**113,635**	**113,635**	**23,55**	**0,017**
Used percentage of full speed of the material handling device (C)	1	0,053	0,053	0,24	0,658
Production lot size (D)	1	1,154	1,154	0,22	0,672
Inspector (E)	**1**	**45,961**	**45,961**	**9,53**	**0,054**
Piece storage method (F)	1	11,384	11,384	2,36	0,222
Raw Material Supplier (G)	1	0,269	0,269	0,06	0,829
Second inspection period (H)	1	0,804	0,804	0,17	0,711
Interaction (A*B)	1	0,053	0,053	0,01	0,923
Interaction (A*D)	1	0,005	0,005	0,00	0,977
Interaction (B*C)	1	4,648	4,648	0,96	0,399
Interaction (B*D)	1	2,727	2,727	0,57	0,507
Error	3	14,475	4,825		
Total	15	199,101			

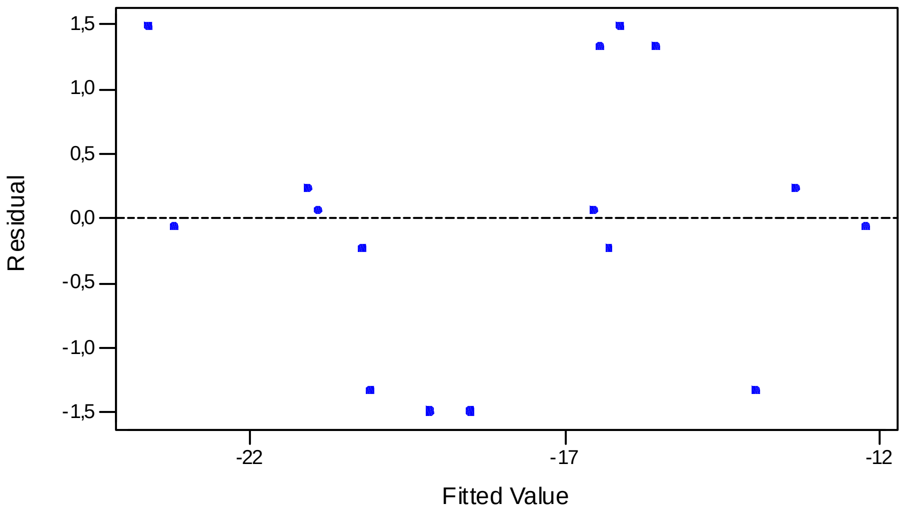


Figure 5.12:Residuals Versus the Fitted Values

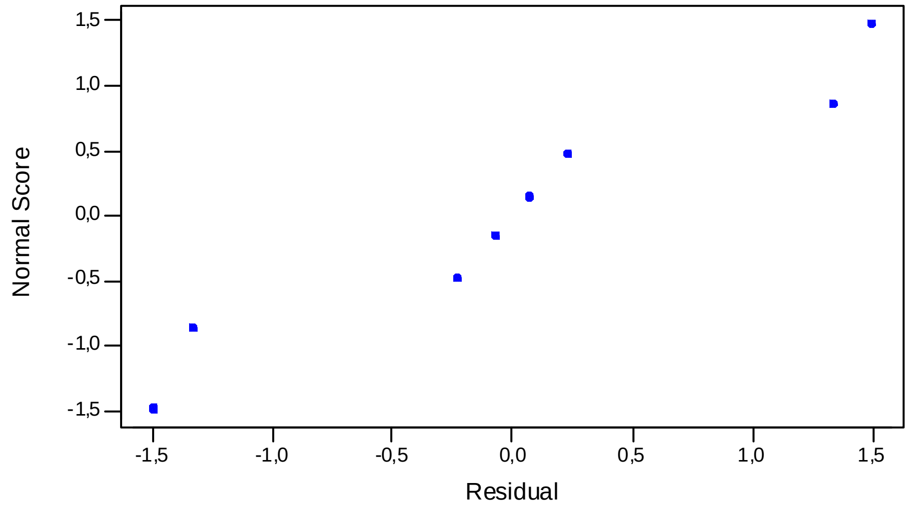


Figure 5.13:Normal Probability Plot of the Residuals

Table 5.20 : ANOVA-Taguchi Design Based on S/N Transformed Data Values for the L Sheet Scrap Analysis

Process Parameters	Degrees of Freedom	Sum of Squares	Variance	F-Ratio	p
Operator (A)	1	3,131	3,131	1,34	0,331
Piece inspection frequency (B)	**1**	**19,516**	**19,516**	**8,33**	**0,063**
Used percentage of full speed of the material handling device (C)	1	1,982	1,982	0,85	0,426
Production lot size (D)	1	0,278	0,278	0,12	0,753
Inspector (E)	1	2,199	2,199	0,94	0,404
Piece Storage Method (F)	**1**	**49,747**	**49,747**	**21,22**	**0,019**
Raw Material Supplier (G)	1	6,660	6,660	2,84	0,190
Second inspection period (H)	1	0,732	0,732	0,31	0,615
Interaction (A*B)	1	5,291	5,291	2,26	0,230
Interaction (A*D)	1	0,446	0,446	0,19	0,692
Interaction (B*C)	1	0,194	0,194	0,08	0,792
Interaction (B*D)	1	1,365	1,365	0,58	0,501
Error	3	7,032	2,344		
Total	15	98,572			

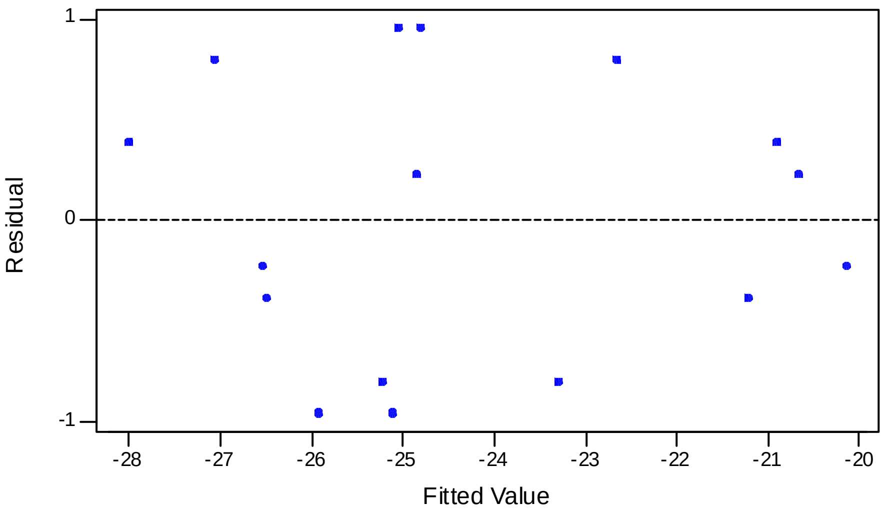


Figure 5.14 : Residuals Versus the Fitted Values

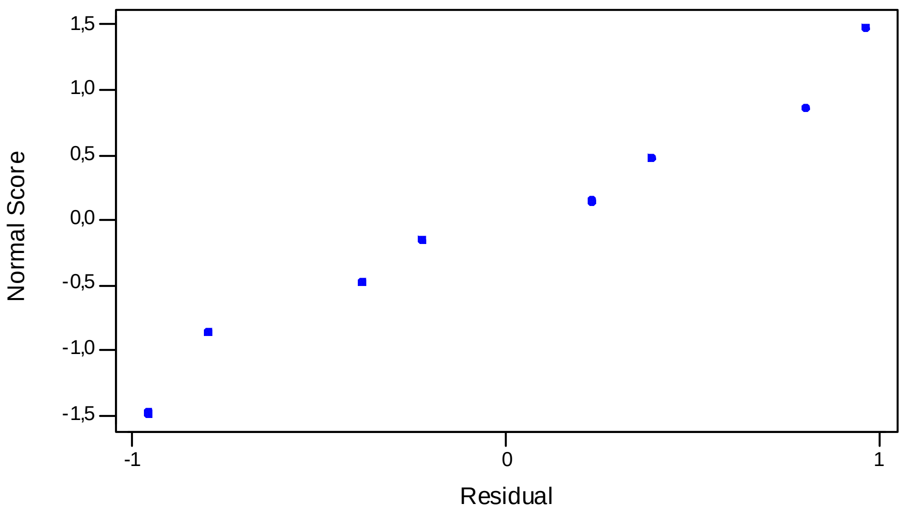


Figure 5.15 :Normal Probability Plot of the Residuals

Table 5.21 : ANOVA-Taguchi Design Based on S/N Transformed Data Values for the Side Panel Scrap Analysis

Process Parameters	Degrees of Freedom	Sum of Squares	Variance	F-Ratio	p
Operator (A)	1	0,022	0,022	0,01	0,929
Piece inspection frequency (B)	**1**	**35,331**	**35,331**	**14,96**	**0,031**
Speed of material handling device of semi-finished product (C)	1	0,001	0,001	0,00	0,983
Production lot size (D)	1	1,041	1,041	0,44	0,554
Inspector (E)	1	3,202	3,202	1,36	0,328
Material Handling method (F)	**1**	**114,56**	**114,56**	**48,49**	**0,006**
Raw Material Supplier (G)	1	5,009	5,009	2,12	0,241
Second inspection period (H)	1	0,377	0,377	0,16	0,716
Interaction (A*B)	1	4,449	4,449	1,88	0,264
Interaction (A*D)	1	0,261	0,261	0,11	0,762
Interaction (B*C)	1	1,238	1,238	0,52	0,522
Interaction (B*D)	1	2,367	2,367	1,00	0,391
Error	3	7,087	2,362		
Total	15	174,946			

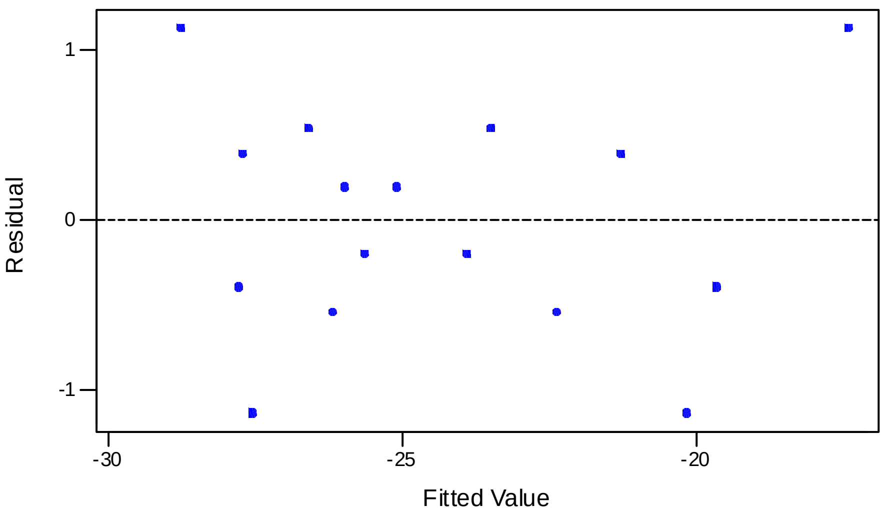


Figure 5.16: Residuals Versus the Fitted Values

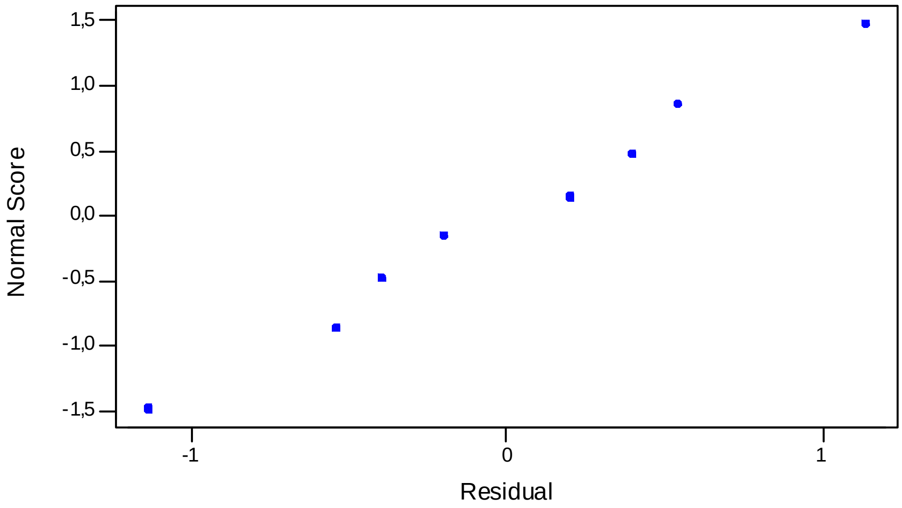


Figure 5.17: Normal Probability Plot of the Residuals

Table 5.22 : ANOVA-Taguchi Design Based on S/N Transformed Data Values for the Inner Door Scrap Analysis

Process Parameters	Degrees of Freedom	Sum of Squares	Variance	F-Ratio	P
Operator (A)	1	7,79	7,79	0,62	0,490
Piece inspection frequency (B)	**1**	**95,29**	**95,29**	**7,53**	**0,071**
Used percentage of full speed of the material handling device (C)	1	7,65	7,65	0,38	0,584
Production lot size (D)	1	8,74	8,74	0,69	0,467
Inspector (E)	1	21,47	21,47	1,70	0,284
Piece storage method (F)	1	1,57	1,57	0,12	0,748
Raw Material Supplier (G)	**1**	**152,35**	**152,35**	**12,04**	**0,040**
Second inspection period (H)	1	0,44	0,44	0,03	0,864
Interaction (A*B)	1	7,65	7,65	0,60	0,493
Interaction (A*D)	1	0,12	0,12	0,01	0,309
Interaction (B*C)	1	1,03	1,03	0,08	0,794
Interaction (B*D)	1	18,93	18,93	1,50	0,309
Error	3	37,95	12,65		
Total	15	358,08			

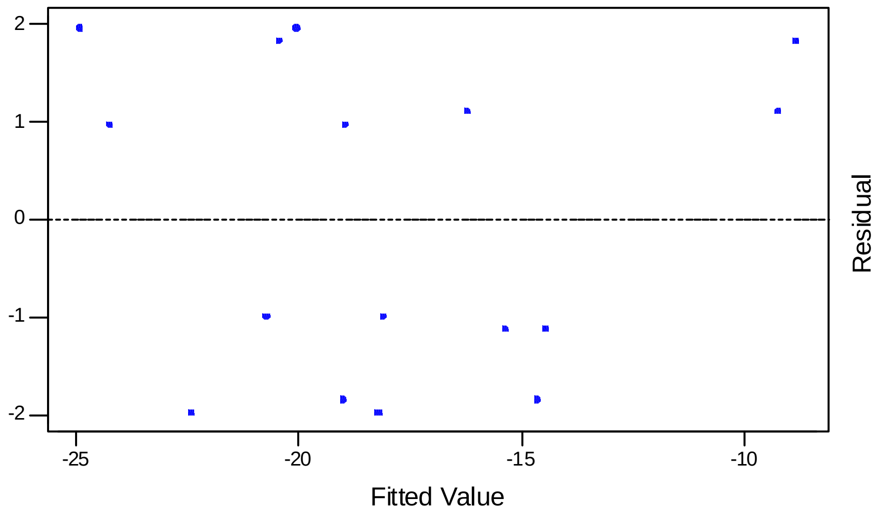


Figure 5.18: Residuals Versus the Fitted Values

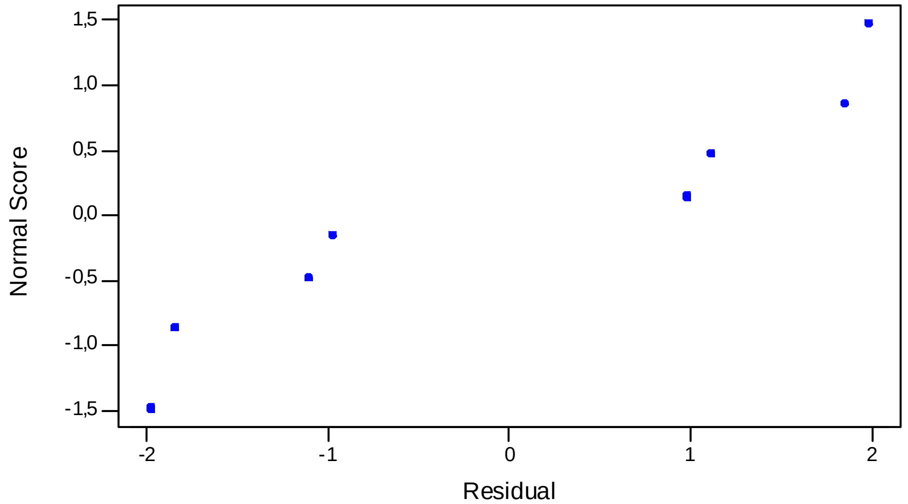


Figure 5.19 :Normal Probability Plot of the Residuals

ANOVA based on S/N transformed data values performed for U Sheet suggests that the *piece inspection frequency* and *inspector* affect the scrap quantity since they have higher F-Ratio than the tabulated F values of 90% confidence level. It is also evident that none of the interaction effects have significant effect on the scrap quantity.

For L Sheet the *piece storage method* and *piece inspection frequency* are the significant effects on scrap quantity. These factors have larger F Ratios than the tabulated F Ratio values of 90% confidence level. All the remaining factors including the interaction effects have F values smaller than the tabulated F-ratio values of 90% confidence level.

Piece inspection frequency and *material handling method* have significant effect on the quantity of scraps for 90% confidence level for the Side Panel. None of the interaction effects indicate significance.

The factors which come out to be significant are the *raw material supplier* and *piece inspection frequency* for 90% confidence level for the Inner Door. For this piece also none of the interaction effects indicate significance.

Residuals versus fitted values and normal probability plots indicate that errors have normal distribution with constant variance for the four sheets examined.

For the estimation of the expected response and the response variation with certain confidence intervals the calculations are performed as in the following, the factors having larger variance values than the error variance are included in the calculations.

Two main effects are included in the confirmation run procedure for U Sheet : *piece inspection frequency* and *inspector.*

$$\overline{S/N}_{B_1F_1} = \overline{T}_{S/N} + (\overline{B}_1 - \overline{T}_{S/N}) + (\overline{F}_1 - \overline{T}_{S/N})$$

where,

$\overline{T}_{S/N}$: Overall average of the S/N values

$\overline{B}_1$: Average S/N value of the first level of process parameter B, Piece Inspection Frequency

$\overline{F}_1$: Average S/N value of the first level of process parameter F, Piece Storage Method

$\overline{S/N}_{B_1F_1} =$ -17,9575 + (-15,3261+17,9575) + (-16,5527 + 17,9575)

= -13,9213

since S/N = -10log ((1/r)$\Sigma^r_{i=1} y_i^2$)

expected response = 4,969

$CI = (F_{á,1,n_e} * V_e / N_{eff})^{1/2}$

$F_{á,1,n_e}$: Tabulated F value for 1- á confidence level 1 and n_e degrees of freedom

Where

= 5.54 for 90% confidence level with 3 error degrees of freedom

V_e : Error variance

N_{eff} : Effective sample size

N_{eff} = N / (1+ DOF_μ)

= 16 / (1+2) = 5,33

where ;

N : Number of data used in design, 16

DOF_μ : Total degrees of freedom associated with items used in μ estimate.

= 2 because two parameters are used each having one degree of freedom.

CI = 2,239 for 90 % confidence level

Therefore the expected number of U sheet scraps is $4,969 \pm 2,239$.

For L sheet 2 factors are included in the expected number and confidence interval calculations, these factors are *piece inspection frequency* and *piece storage method.*

$$\overline{S/N}_{B_1F_1} = -24,2461 + (-23,1417 + 24,2461) + (-22,4829 + 24,2461)$$
$$= -21,3785$$

Expected response = 11,704

$$CI = ((5,54 * 2,344) / (5,33))^{1/2}$$
$$= 1,5608$$

The expected number of L Sheet scraps is $11,704 \pm 1,5608$.

For Side Panel calculations are held with two process parameters, p*iece inspection frequency* and *material handling method*.

$$\overline{S/N}_{B_1F_1} = -24,3408 + (-22,8548 + 24,3408) + (-21,665 + 24,3408)$$
$$= -19,1349$$

Expected response = 10,198

$$CI = ((5,54 * 2,362) / (5,33))^{1/2}$$
$$= 1,5668$$

Therefore, the expected number of Side Panel scraps is $10,198 \pm 1,5668$

Two process parameters are used in the calculations for Inner Door. These parameters are the *piece inspection frequency* and *raw material supplier*.

$\overline{S/N}_{B_1G_1} = -17{,}8607 + (-15{,}4202 + 17{,}8607) + (-14{,}7749 + 17{,}8607)$

$= -12{,}334$

Expected response = 4,135

CI = $((5{,}54 * 12{,}65) / 7{,}2)^{1/2}$

$= 3{,}626$

The expected number of Inner Door scraps is $4{,}135 \pm 3{,}626$.

The next step is performing confirmation runs with pre-determined levels. The levels are the levels used in the estimation of the expected response and confidence interval. The experiments are performed again and the results are given in Table 5.23.

Table 5.23 : Results of the confirmation runs for Taguchi Design using S/N transformation

	Result of the First Confirmation Run	Result of the Second Confirmation Run	Result of the Third Confirmation Run	Result of the Fourth Confirmation Run	Average of Confirmation Run Experiments
U Sheet	6	5	7	5	5,75
L Sheet	10	11	10	8	9,75
Side Panel	8	8	9	9	8,50
Inner Door	5	4	6	5	4,50

5.6) Analysis By Fractional Factorial Design:

5.6.1) Selection of the Appropriate Fractional Factorial Design and Assignment of Factors for Fractional Factorial Design analysis:

In this study, $2^{(k-p)}$ fractional factorial design will also be used as an experimental design tool. In many cases, it is sufficient to consider factors affecting the production process at two levels. The most intuitive approach to study factors would be to vary the factors of interest in a full factorial design, that is, to try all possible combinations of settings. This would work fine, except that the number of necessary runs in the experiment (observations) will increase geometrically. For example, if 7 factors are studied, the necessary number of runs in the experiment would be 2^7=128. To study 10 factors 2^{10}=1024 runs are needed in the experiment. Because each run may require time-consuming and costly setting and resetting of machinery, it is often not feasible to require that many different production runs for the experiment. In these conditions, fractional factorials are used that 'sacrifice' interaction effects so that main effects may still be computed correctly.

In the analyzed problem there are 8 possible effective factors to be examined and from Table 5.24 it is seen that both for 16 runs and 32 runs, resolution does not change for 8 factors. Design with 16 runs is selected since it shortens the time needed for experiments.

Table 5.24 : Resolution Matrix for Fractional Factorial Design

	AVAILABLE FACTORIAL DESIGNS(WITH RESOLUTION)														
	FACTORS														
RUNS		2	3	4	5	6	7	8	9	10	11	12	13	14	15
	4	Full	III												
	8		Full	IV	III	III	III								
	16			Full	V	IV	IV	IV	III	III	III	III	III	III	III
	32				Full	VI	IV	IV	IV	IV	IV	IV	IV	IV	IV
	64					Full	VII	V	IV	IV	IV	IV	IV	IV	IV
	128						Full	VIII	VI	V	V	IV	IV	IV	IV

Table 5.25 : Resolution for $2^{(k-p)}$ fractional factorial design with eight control factors

FACTORIAL DESIGN WITH 8 FACTORS			
DESIGNS	RUNS	RESOLUTION	$2^{(k-p)}$
1/16 fraction	16	IV	$2^{(8-4)}$
1/8 fraction	32	IV	$2^{(8-3)}$
¼ fraction	64	V	$2^{(8-2)}$
½fraction	128	VIII	$2^{(8-1)}$

In the experiments $2^{(8-4)}$ fractional factorial design will be used and the design is given in Table 5.26

Table 5.26 : $2^{(8-4)}$ fractional factorial design

	FACTOR								
RUN		A	B	C	D	E	F	G	H
	1	2	2	1	2	1	1	1	2
	2	1	2	2	1	1	2	1	2
	3	1	1	2	2	1	1	2	2
	4	2	1	2	1	2	1	1	2
	5	1	1	1	1	1	1	1	1
	6	2	2	1	1	2	2	1	1
	7	2	1	2	2	1	2	1	1
	8	1	2	2	2	2	1	1	1
	9	2	1	1	1	1	2	2	2
	10	1	1	2	1	2	2	2	1
	11	2	2	2	2	2	2	2	2
	12	2	2	2	1	1	1	2	1
	13	1	2	1	2	1	2	2	1
	14	1	1	1	2	2	2	1	2
	15	2	1	1	2	2	1	2	1
	16	1	2	1	1	2	1	2	2

The factors A to H are the same for the fractional factorial design as the Taguchi Design for the U Sheet, the L Sheet ,the Inner Door and the Side Panel .

Table 5.27 : Control Factors For Experimental Design

Part		Factors	Level 1	Level 2
U SHEET	A	Operator	Operator 1	Operator 2
	B	Piece inspection frequency	1/3	1/6
	C	Used percentage of full speed	80%	100%
	D	Production lot size	Production for one shift	Production for two shifts
	E	Inspector	Inspector 1	Inspector 2
	F	Piece storage method	With Robot	Manual
	G	Raw Material Supplier	Supplier 1	Supplier 2
	H	Second inspection period	Daily	Weekly

Part		Factors	Level 1	Level 2
L SHEET	A	Operator	Operator 1	Operator 2
	B	Piece inspection frequency	1/2	1/5
	C	Used percentage of full speed	80%	100%
	D	Production lot size	Production for one shift	Production for two shifts
	E	Inspector	Inspector 1	Inspector 2
	F	Piece storage method	With Robot	Manual
	G	Raw Material Supplier	Supplier 1	Supplier 2
	H	Second inspection period	Daily	Weekly

Part		Factors	Level 1	Level 2
INNER DOOR	A	Operator	Operator 1	Operator 2
	B	Piece inspection frequency	1/1	1/5
	C	Used percentage of full sped	80%	100%
	D	Production lot size	Production for one shift	Production for two shifts
	E	Inspector	Inspector 1	Inspector 2
	F	Piece storage method	With Robot	Manual
	G	Raw Material Supplier	Supplier 1	Supplier 2
	H	Second inspection period	Daily	Weekly

Part		Factors	Level 1	Level 2
SIDE PANEL	A	Operator	Operator 1	Operator 2
	B	Piece inspection frequency	1/3	1/6
	C	Speed of material handling device of semi-finished product (stroke/minute)	10	11
	D	Production lot size	Production For two shifts	Production for four shifts
	E	Inspector	Inspector 1	Inspector 2
	F	Material handling method	Conveyor	Manual (Storage on a special car)
	G	Raw Material Supplier	Supplier 1	Supplier 2
	H	Second inspection period	Daily	Weekly

5.6.2) Conducting Experiments & Analysis

The required experimental set-up is established first and then the experiments are conducted. The set-ups are first established according to the 2^{8-4} fractional factorial design. Each experiment lasts for one shift in the plant. The required set-ups and the observations for the four pieces examined are given in Tables 5.28, 5.29, 5.30 and 5.31.

Table 5.28 : 2^{8-4} fractional factorial design and the observations for the U Sheet

	PROCESSING PARAMETERS								RESULTS	
EXP #	A 1	B 2	C 3	D 4	E 5	F 6	G 7	H 8	RUN #1	RUN # 2
#1	1	1	1	1	1	1	1	1	13	9
#2	1	1	1	1	1	1	1	2	7	8
#3	1	1	1	2	2	2	2	1	9	9
#4	1	1	1	2	2	2	2	2	10	6
#5	1	2	2	1	1	2	2	1	5	8
#6	1	2	2	1	1	2	2	2	8	9
#7	1	2	2	2	2	1	1	1	7	11
#8	1	2	2	2	2	1	1	2	11	11
#9	2	1	2	1	2	1	2	1	5	12
#10	2	1	2	1	2	1	2	2	9	11
#11	2	1	2	2	1	2	1	1	12	10
#12	2	1	2	2	1	2	1	2	12	13
#13	2	2	1	1	2	2	1	1	12	12
#14	2	2	1	1	2	2	1	2	10	8
#15	2	2	1	2	1	1	2	1	9	7
#16	2	2	1	2	1	1	2	2	8	8

Table 5.29 : 2^{8-4} fractional factorial design and the observations for the L Sheet

	PROCESSING PARAMETERS								RESULTS	
EXP #	A 1	B 2	C 3	D 4	E 5	F 6	G 7	H 8	RUN # 1	RUN # 2
#1	1	1	1	1	1	1	1	1	9	11
#2	1	1	1	1	1	1	1	2	19	14
#3	1	1	1	2	2	2	2	1	8	11
#4	1	1	1	2	2	2	2	2	8	10
#5	1	2	2	1	1	2	2	1	9	7
#6	1	2	2	1	1	2	2	2	15	18
#7	1	2	2	2	2	1	1	1	16	16
#8	1	2	2	2	2	1	1	2	14	16
#9	2	1	2	1	2	1	2	1	15	16
#10	2	1	2	1	2	1	2	2	14	17
#11	2	1	2	2	1	2	1	1	17	19
#12	2	1	2	2	1	2	1	2	13	11
#13	2	2	1	1	2	2	1	1	19	18
#14	2	2	1	1	2	2	1	2	13	13
#15	2	2	1	2	1	1	2	1	13	11
#16	2	2	1	2	1	1	2	2	16	10

Table 5.30 : 2^{8-4} fractional factorial design and the observations for the Side Panel

	PROCESSING PARAMETERS								RESULTS	
EXP #	A 1	B 2	C 3	D 4	E 5	F 6	G 7	H 8	RUN # 1	RUN # 2
#1	1	1	1	1	1	1	1	1	13	14
#2	1	1	1	1	1	1	1	2	29	19
#3	1	1	1	2	2	2	2	1	6	9
#4	1	1	1	2	2	2	2	2	6	7
#5	1	2	2	1	1	2	2	1	13	10
#6	1	2	2	1	1	2	2	2	18	19
#7	1	2	2	2	2	1	1	1	18	17
#8	1	2	2	2	2	1	1	2	12	18
#9	2	1	2	1	2	1	2	1	15	20
#10	2	1	2	1	2	1	2	2	18	14
#11	2	1	2	2	1	2	1	1	18	22
#12	2	1	2	2	1	2	1	2	13	12
#13	2	2	1	1	2	2	1	1	24	20
#14	2	2	1	1	2	2	1	2	19	19
#15	2	2	1	2	1	1	2	1	10	11
#16	2	2	1	2	1	1	2	2	16	12

Table 5.31 : 2^{8-4} fractional factorial design and the observations for the Inner Door

	PROCESSING PARAMETERS								RESULTS	
EXP #	A 1	B 2	C 3	D 4	E 5	F 6	G 7	H 8	RUN # 1	RUN # 2
#1	1	1	1	1	1	1	1	1	6	9
#2	1	1	1	1	1	1	1	2	7	11
#3	1	1	1	2	2	2	2	1	13	11
#4	1	1	1	2	2	2	2	2	2	7
#5	1	2	2	1	1	2	2	1	8	7
#6	1	2	2	1	1	2	2	2	11	12
#7	1	2	2	2	2	1	1	1	6	5
#8	1	2	2	2	2	1	1	2	11	11
#9	2	1	2	1	2	1	2	1	12	18
#10	2	1	2	1	2	1	2	2	13	16
#11	2	1	2	2	1	2	1	1	16	17
#12	2	1	2	2	1	2	1	2	16	12
#13	2	2	1	1	2	2	1	1	14	16
#14	2	2	1	1	2	2	1	2	6	8
#15	2	2	1	2	1	1	2	1	12	12
#16	2	2	1	2	1	1	2	2	10	14

With this information ANOVA can be conducted and the results are tabulated in Tables 5.32,5.33,5.34 and 5.35.

Table 5.32 : ANOVA of Averages -Fractional Factorial Design for the U Sheet Scrap Analysis

Process Parameters	Degrees of Freedom	Sum of Squares	Variance	F-Ratio	P
Operator (A)	1	0,766	0,766	0,34	0,578
Piece inspection frequency (B)	**1**	**11,391**	**11,391**	**5,07**	**0,059**
Used percentage of full speed of the material handling device (C)	1	2,641	2,641	1,17	0,314
Production lot size (D)	1	6,891	6,891	3,07	0,123
Inspector (E)	1	0,391	0,391	0,17	0,689
Piece storage method (F)	1	0,141	0,141	0,06	0,810
Raw Material Supplier (G)	1	4,516	4,516	2,01	0,199
Second inspection period (H)	1	1,891	1,891	0,84	0,239
Error	7	15,734	2,248		
Total	15	44,359			

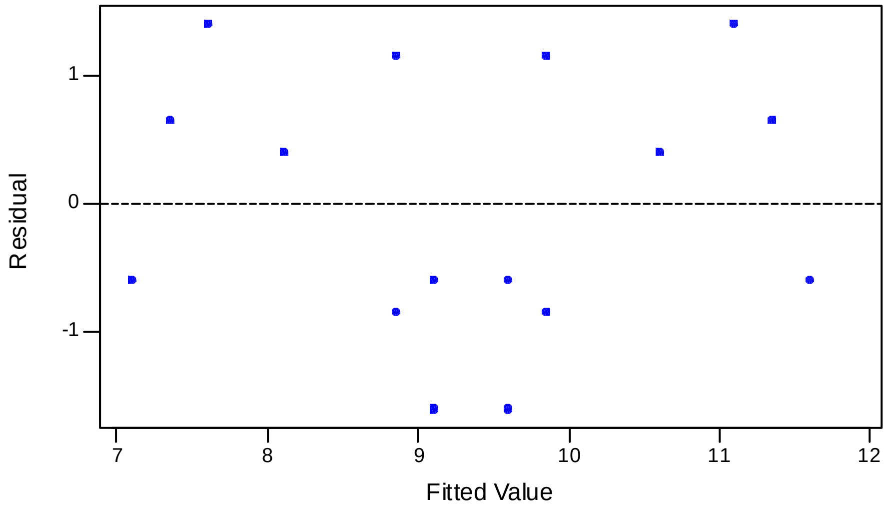


Figure 5.20 :Residuals Versus the Fitted Values

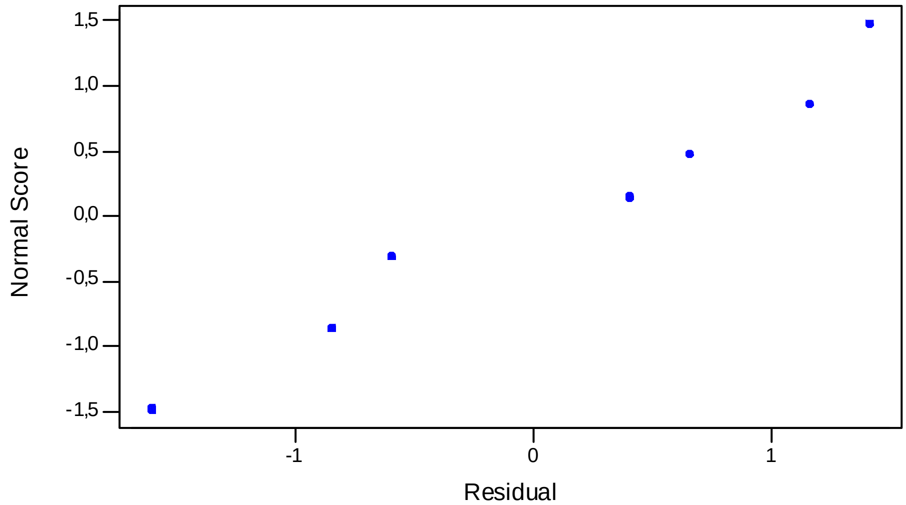


Figure 5.21: Normal Probability Plot of the Residuals

Table 5.33 : ANOVA of Averages - Fractional Factorial Design for the L Sheet Scrap Analysis

Process Parameters	Degrees of Freedom	Sum of Squares	Variance	F-Ratio	P
Operator (A)	1	0,000	0,000	0,00	1,000
Piece inspection frequency (B)	**1**	**27,562**	**27,562**	**14,56**	**0,007**
Used percentage of full speed of the material handling device (C)	1	1,563	1,563	0,83	0,394
Production lot size (D)	1	2,250	2,250	1,19	0,312
Inspector (E)	1	2,250	2,250	1,19	0,312
Piece Storage Method(F)	**1**	**105,063**	**105,063**	**55,50**	**0,000**
Raw Material Supplier (G)	1	6,250	6,250	3,30	0,112
Second inspection period (H)	1	5,062	5,062	2,67	0,146
Error	7	13,250	1,893		
Total	15	163,25			

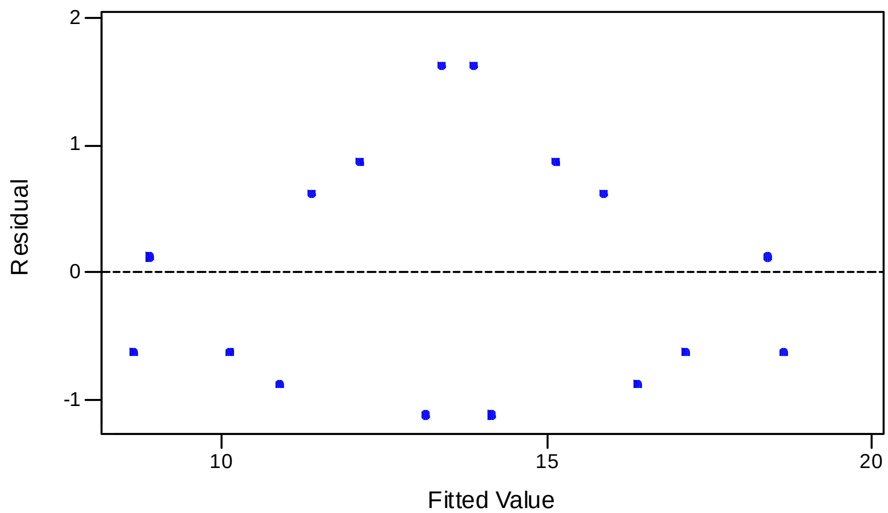


Figure 5.22: Residuals Versus the Fitted Values

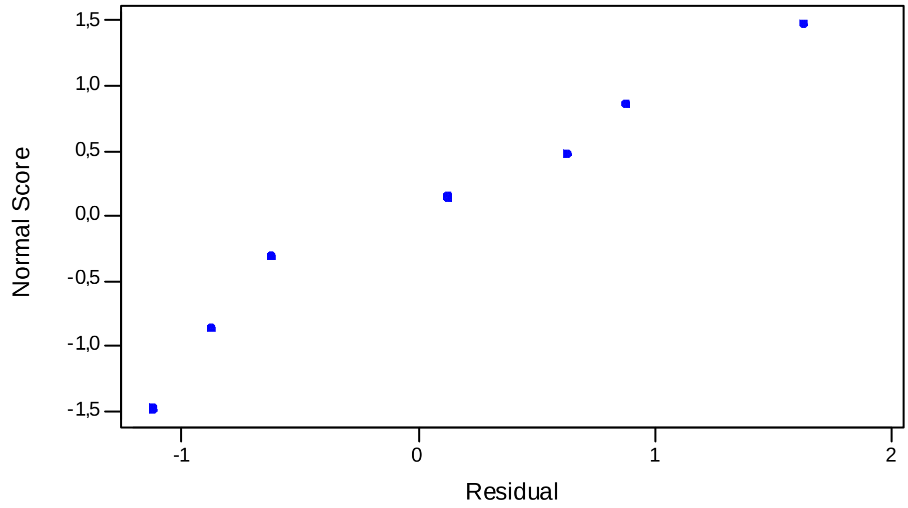


Figure 5.23: Normal Probability Plot of the Residuals

Table 5.34 : ANOVA of Averages -Fractional Factorial Design for the Side Panel Scrap Analysis

Process Parameters	Degrees of Freedom	Sum of Squares	Variance	F-Ratio	p
Operator (A)	1	9,766	9,766	2,85	0,135
Piece inspection frequency (B)	**1**	**70,141**	**70,141**	**20,47**	**0,003**
Speed of material handling device of semi-finished product (C)	1	3,516	3,516	1,03	0,345
Production lot size (D)	1	1,266	1,266	0,37	0,563
Inspector (E)	1	2,641	2,641	0,77	0,409
Material Handling Method (F)	**1**	**252,016**	**252,016**	**73,55**	**0,000**
Raw Material Supplier (G)	1	1,891	1,891	0,55	0,482
Second inspection period (H)	1	0,141	0,141	0,04	0,845
Error	7	23,984	1,893		
Total	15	365,359			

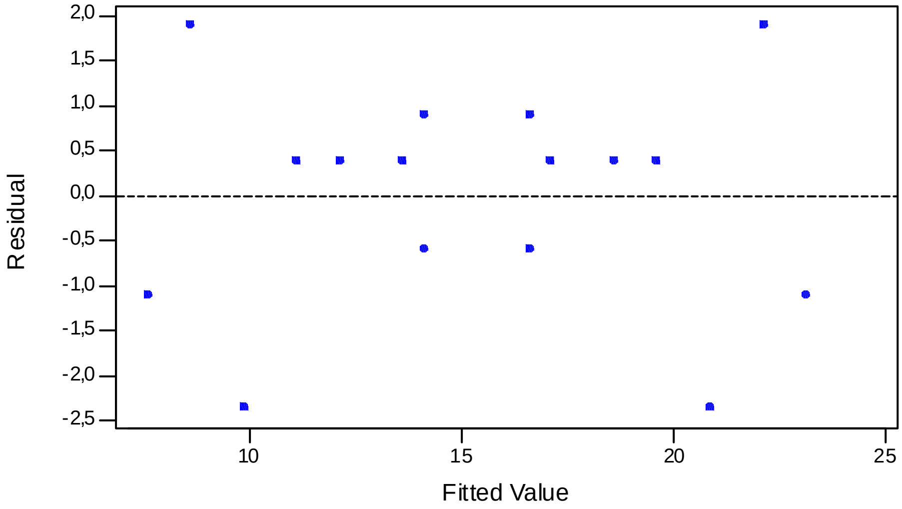


Figure 5.24: Residuals Versus the Fitted Values

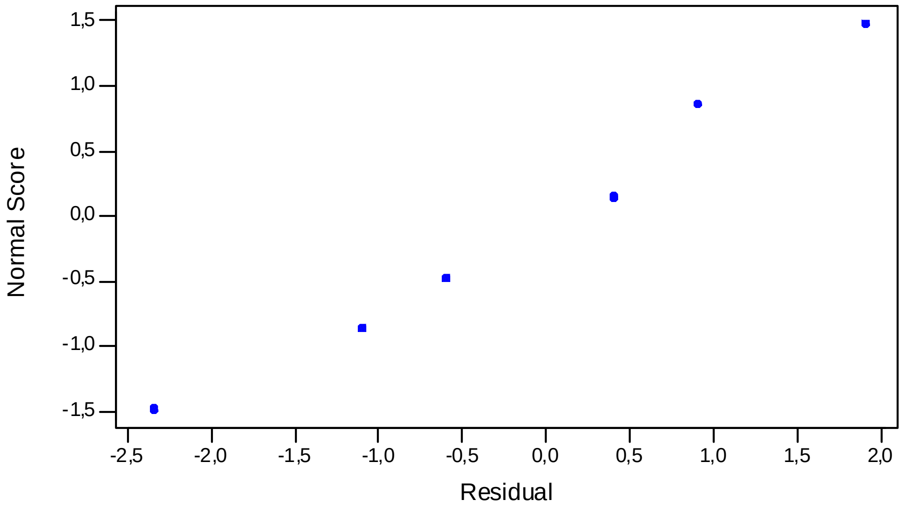


Figure 5.25: Normal Probability Plot of the Residuals

Table 5.35 : ANOVA of Averages -Fractional Factorial Design for the Inner Door Scrap Analysis

Process Parameters	Degrees of Freedom	Sum of Squares	Variance	F-Ratio	p
Operator (A)	1	0,141	0,141	0,04	0,849
Piece inspection frequency (B)	**1**	**21,391**	**21,391**	**5,93**	**0,045**
Used percentage of full speed of the material handling device (C)	1	0,016	0,016	0,00	0,949
Production lot size (D)	1	0,141	0,141	0,04	0,849
Inspector (E)	1	0,766	0,766	0,21	0,659
Piece storage method (F)	1	11,391	11,391	3,16	0,119
Raw Material Supplier (G)	**1**	**141,016**	**141,016**	**39,12**	**0,000**
Second inspection period (H)	1	3,516	3,516	0,98	0,356
Error	7	25,234	3,605		
Total	15	203,609			

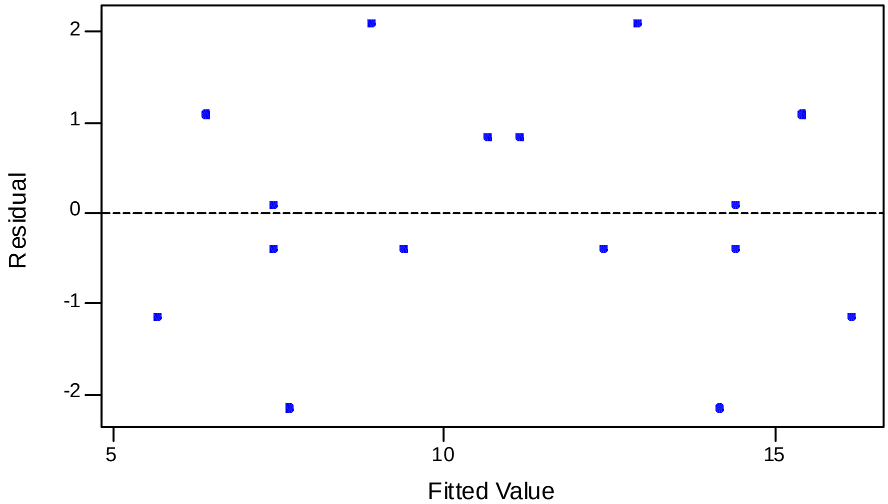
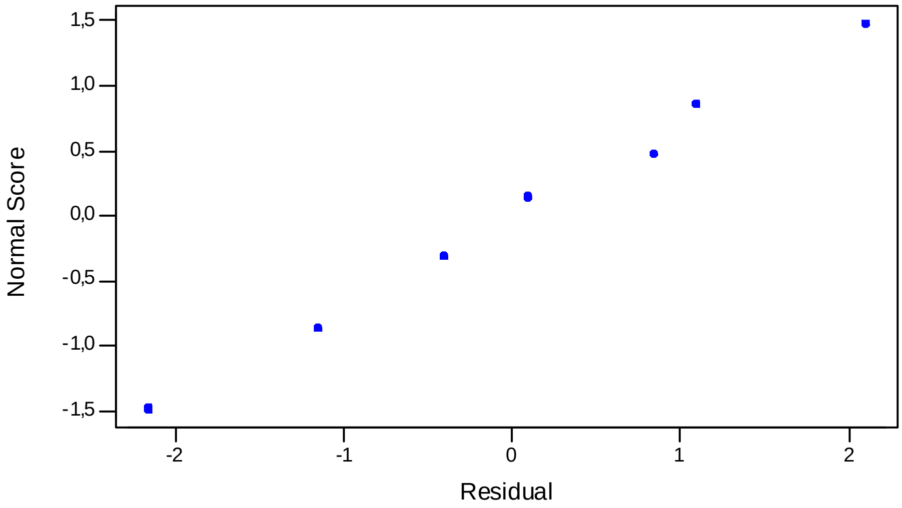


Figure 5.26: Residuals Versus the Fitted Values

Figure 5.27: Normal Probability Plot of the Residuals



ANOVA is performed for the experiment observations which uses 2^{8-4} fractional factorial design for experimental set-up. For the U sheet results of ANOVA suggests that the *piece inspection frequency* can be accepted to affect the quantity of scrap . The F-Ratio of the piece inspection frequency,5.07, is a little bit lower than the tabulated F Ratio value of 95% confidence level with one and seven degrees of freedoms for the processing parameter and the error variances, 5.59 . The remaining factors have much lower F-Ratio values than the tabulated F Ratio value of 90% confidence level.

For the L Sheet the *piece inspection frequency* and the *piece storage method* factors have higher F ratios than the tabulated F values at 90% confidence level. The remaining factors have F values indicating insignificancy for these factors.

For the Side Panel *piece inspection frequency* and *material handling method* factors have significant effects on the quantity of scraps.

For the Inner Door the factors which come out to be significant are the *piece inspection frequency* and the *supplier* effect.

For all the sheets analyzed residuals versus fitted values and normal probability plots indicate that errors have normal distribution with constant variance.

With this information available the expected response and the response variation can be estimated. This estimation is necessary for the confirmation run procedure. The calculations for the confirmation run procedure are performed in the following. The factors having larger variance values than the error variance are included in the calculations.

For the U sheet one factor is included in the expected number and confidence interval calculations: *piece inspection frequency.*

$$\text{ì}_{B_1} = \overline{T} + (\overline{B}_1 - \overline{T})$$

where;

$\overline{T}$: Overall average

$\overline{B}_1$: Average of the first level of process parameter B, piece inspection frequency

$$\text{ì}_{B_1} = 9{,}344 + (8{,}5 - 9{,}344)$$

$$= 8{,}5$$

$$CI = \left(F_{\text{á},1,n_e} * V_e / N_{eff} \right)^{1/2}$$

Where,

$F_{\acute{a},1,n_e}$: Tabulated F value for 1 - á confidence level 1 and n_e degrees of freedom

= 3.59 for 90% confidence level with 7 error degrees of freedom

V_e : Error variance

N_{eff} : Effective sample size

N_{eff} = N / (1+ DOF_{μ})

= 16 / (1+1) = 8

where ;

N : Number of data used in design, 16

DOF_{μ} : Total degrees of freedom associated with items used in μ estimate.

= 1 because one parameter is used having one degree of freedom.

CI = 1,004 for 90 % confidence level

The expected number of U sheet scraps with determined parameter levels above is *8,5* ± *1,004 .*

For the L sheet similar calculations can be held with 2 process parameters, *piece inspection frequency and piece storage method* :

$$ì_{B_1F_1} = \overline{T} + (\overline{B}_1 - \overline{T}) + (\overline{F}_1 - \overline{T})$$

= 13,625 + (12,3125 – 13,625) + (11,0625 – 13,625)

= 9,75

$$CI = ((3{,}59 * 1{,}893) / (5{,}33))^{1/2}$$

$$= 1{,}130$$

Therefore the expected number of L sheet scraps is *9,75 ± 1,130 .*

For the Side Panel two process parameters are used in the calculations, *piece inspection frequency and piece storage method.*

$$ì_{B_1F_1} = \overline{T} + (\overline{B}_1 - \overline{T}) + (\overline{F}_1 - \overline{T})$$

$$= 15{,}3475 + (13{,}25 - 15{,}3475) + (11{,}375 - 15{,}3475)$$

$$= 9{,}2775$$

$$CI = (3{,}59 * 3{,}426 / 5{,}33)^{1/2}$$

$$= 1{,}519$$

The expected number of Side Panel scraps is *9,2775 ± 1,519.*

Lastly for the Inner Door calculations are held with two process parameters, *piece inspection frequency and raw material supplier* :

$$ì_{B_1G_1} = \overline{T} + (\overline{B}_1 - \overline{T}) + (\overline{G}_1 - \overline{T})$$

$$= 10{,}90625 + (9{,}75 - 10{,}90625) + (7{,}9375 - 10{,}90625)$$

$$= 6{,}781$$

$$CI = (3{,}59 * 3{,}605 / 5{,}33)^{1/2}$$

$$= 1{,}558$$

Consequently the expected number of Inner Door scraps is *6.781 ± 1,558.*

It must also be considered that the confirmation run procedure depends on the additivity of factor effects. The additivity of the main factor effects will be poor without separately considering the factor interaction effects. Therefore strong factor interaction effects could make additive estimation model misleading (Phadke,1989).

Then the setups are established again with the proper factor levels. These factors are the factors determined as significant for 90% confidence level and used in estimation of the expected response and confidence interval. The experiments are conducted again and the results obtained are given in Table 5.36.

Table 5.36 : Confirmation runs for fractional factorial design

	Result of the First Confirmation Run	Result of the Second Confirmation Run	Result of the Third Confirmation Run	Result of the Fourth Confirmation Run	Average of Confirmation Run Experiments
U Sheet	5	8	7	7	6,75
L Sheet	9	10	12	7	9,50
Side Panel	11	9	7	10	9,25
Inner Door	8	3	4	6	5,25

5.7) Interpretation of the results **:** Two different statistical experimental designs and three analysis techniques are used to optimize parameters of the sheet metal forming process of the dishwasher production. The 2^{8-4} fractional factorial design and $L_{16}(2^{15})$ Taguchi's orthogonal array are the statistical experimental designs used. Both designs need 16 experiments and since 2 replicates are carried out for each experiment; 32 experiments are performed for each design. Since process optimization is made for four pieces of the dishwasher; 128 experiments are held for each design. For Taguchi's orthogonal array experimental design the analysis is made with using the experiment outputs directly and also using S/N transformation of the results. Tables 5.37, 5.38, 5.39 and 5.40 show all analyses results including the significant parameters, 90% confirmation intervals, best parameter level combinations and expected number of scraps.

Table 5.37 : Results of the Statistical Experimental Design and Analysis Techniques for the U Sheet

Experimental Design	Significant Parameters for 90 % confidence level	Best Levels Used in the Calculation of Expected Number of Scraps								Expected Number of Scraps	90 % C.I	Confirmation Test
		A	B	C	D	E	F	G	H			
2^{8-4} Fractional Factorial	B		1							8,500	(7,496;9,504)	6,75
Taguchi's $L_{16}(2^{15})$ Orthogonal Array	B		1							5,687	(3,590;7,784)	6,00
Taguchi's $L_{16}(2^{15})$ Orthogonal Array Using S/N Transformation	B,E		1			1				4,969	(2,730;7,208)	5,75

Results of the experiments by fractional factorial design and Taguchi's design shows that parameter B –*piece inspection frequency*- is significant for 90% confidence level. When S/N transformation is performed for Taguchi Design. *Piece Inspection Frequency* and *Inspector* are found to be the significant factors. Expected number of scraps calculated by using fractional factorial design is larger than calculated by using Taguchi's Design. This difference occurs due to the difference of overall mean of the experiments and the variance of parameters used in the calculations of finding the expected number of scraps. Yet, when the confirmation tests are performed very similar results are found. After the improvements and using the optimal level of the parameters the scrap quantity of the U Sheet can be decreased about nearly to 5.75~6.75.

Table 5.38 : Results of the Statistical Experimental Design and Analysis Techniques for the L Sheet

Experimental Design	Significant Parameters for 90 % confidence level	Best Levels Used in the Calculation of Expected Number of Scraps								Expected Number of Scraps	90 % C.I	Confirmation Test
		A	B	C	D	E	F	G	H			
2^{8-4} Fractional Factorial	B,F		1				1			9,750	(8,620;10,880)	9,50
Taguchi's $L_{16}(2^{15})$ Orthogonal Array	B,F		1				1			11,656	(8,553;14,759)	9,25
Taguchi's $L_{16}(2^{15})$ Orthogonal Array Using S/N Transformation	B,F		1				1			11,704	(10,143;13,265)	9,75

Factorial design experiment results point out that *piece inspection frequency* and *piece storage method* are significant factors in determining the number of scraps. When determined by Taguchi design, again these two parameters come out to be significant. Expected number of scraps determined by fractional factorial design is less than the number determined by Taguchi Design. This is mostly because that the average number of scraps during the experiments by fractional factorial design is smaller than the number during the experiments by Taguchi Design. With the proper process parameter levels it is evident that the number of scraps come out between 9.25-9.75 interval.

Table 5.39 : Results of the Statistical Experimental Design and Analysis Techniques for the Side Panel

Experimental Design	Significant Parameters for 90 % confidence level	Best Levels Used in the Calculation of Expected Number of Scraps								Expected Number of Scraps	90 % C.I	Confirmation Test
		A	B	C	D	E	F	G	H			
2^{8-4} Fractional Factorial	B,F		1				1			9,278	(7,759;10,797)	9,25
Taguchi's $L_{16}(2^{15})$ Orthogonal Array	B,F		1				1			10,218	(8,166;12,270)	9,00
Taguchi's $L_{16}(2^{15})$ Orthogonal Array Using S/N Transformation	B,F		1				1			10,198	(8,631;11,765)	8,50

Piece inspection frequency and *material handling method* are the two parameters which are determined as significant by both designs for the Side Panel. Expected number of scraps come out to be similar from both designs. Using the proper process parameter levels the number of scraps can be decreased around to 8.50-9.25.

Table 5.40 : Results of the Statistical Experimental Design and Analysis Techniques for Inner Door

Experimental Design	Significant Parameters for 90 % confidence level	Best Levels Used in the Calculation of Expected Number of Scraps								Expected Number of Scraps	90 % C.I	Confirmation Test
		A	B	C	D	E	F	G	H			
2^{8-4} Fractional Factorial	B,G		1					1		6,781	(5,223;8,339)	5,25
Taguchi's $L_{16}(2^{15})$ Orthogonal Array	B,G		1					1		3,844	(1,284;6,844)	4,75
Taguchi's $L_{16}(2^{15})$ Orthogonal Array Using S/N Transformation	B,G		1					1		4,135	(0,509;7,761)	4,50

For Inner Door *Piece inspection frequency* & *raw material supplier* are the process parameters occurring as significant to affect scrap quantity by fractional factorial design and Taguchi Design. When S/N transformation is used for Taguchi Design results, the outcome also does not change. Expected number of scraps found by using fractional factorial design is greater than the other results found by the two other analysis techniques because that the average number of scraps during the experiments by fractional factorial design is greater than the number during the experiments by Taguchi Design. But when the proper process parameter levels are used and the confirmation runs are performed the number of scraps come out between 4.50-5.25 interval.

CHAPTER 6

CONCLUSION

In this study two type of statistical experimental designs and three analysis techniques are employed to optimize non-machining process parameters of the sheet metal forming process of the dishwasher production. The 2^{8-4} fractional factorial design and $L_{16}(2^{15})$ Taguchi's orthogonal array are statistical experimental designs used. The 2^{8-4} fractional factorial design is analyzed with analysis of variance (ANOVA) techniques. The $L_{16}(2^{15})$ Taguchi's orthogonal array is analyzed also with ANOVA techniques using the experimental data directly and also with a S/N transformation.

The fractional factorial design and Taguchi design are used in this study for analyses purposes and are used for comparison since they both need 16 experiments and they need nearly the same time and similar set up so they are suitable for comparison. For all the sheets examined, residuals versus fitted values and normal probability plots indicate that errors have normal distribution with constant variance for all the analyses methods used. The expected number of scraps for the same sheet, found by using different experimental analysis techniques come out to be different in this study. This difference occurs due to the difference of overall mean of the experiments and the variance of parameters used in the calculations of determining the expected number of scraps. Also, since noise factors are not considered during the analyses, the effect of noise factors can be significant on the difference. Yet, when confirmation runs are performed with the optimum level of effective parameters very similar results are found. This is an indicator that although the analyses have different disadvantages and drawbacks, they give similar results; and similar effects are determined to be significant from different analyses.

The 2^{8-4} fractional factorial design with 16 experiments which is used in this study is a resolution IV design; and this means that no main effects are aliased with other main effects and also no main effects are aliased with two–factor interactions. These are the advantages of this design, but two-factor interaction effects are aliased with other two-factor interaction effects which is a main disadvantage. The simplicity of these designs can also be a disadvantage because the belief that the resultant changes in the dependent variable are basically linear in nature can sometimes be not the case.

Taguchi analysis model, based on the Taguchi's $L_{16}(2^{15})$ orthogonal array with linear main factor and two-way interaction effects, also does not consider the important three-way and the four-way interaction effects . Also, all the two-way factor interaction effects cannot be examined with $L_{16}(2^{15})$ orthogonal array; to examine all the two-way interaction effects, the number of experiments must be increased, but this results in need of more cost and more time for performing set-ups and experiments.

The previous studies show that the machining process parameters have significant effect on the number of scraps during production. Yet, with this study it is clear that also the non-machining process parameters are significant on the number of scraps. Also the non-machining effects that are significant for sheet-metal forming process are determined with experimental design techniques in this study. This study shows that only by using the optimum level of the significant non-machining effects, scrap quantity is expected to be decreased by 30%.

The analyses results point out that for all the pieces examined the piece inspection frequency is a significant non-machining process parameter or can be accepted as significant at 90% confidence level. If the inspection frequency is increased; number of scraps decrease, but there is a trade off for this point. The increase of inspection frequency affects in an opposite manner if the frequency is increased beyond to a certain limit and the operator gets tired and his inspection ability decreases because of the frequent inspection.

Furthermore, for the L Sheet the *piece storage method* is determined as a significant non-machining process parameter; for the Side Panel *material handling method* is determined as significant for 90% confidence level by the analysis methods used. For Inner Door the *raw material supplier* is the non-machining process parameter to be determined as significant. This shows that for different pieces produced by the same process different process parameters can be effective on the number of scraps.

The examination of the effects of the non-machining process parameters on scrap quantity is a new subject and can be extended in many ways. In this study the interaction of non-machining effects with machining effects are not examined. The interaction of these effects can also be significant for scrap formation during production. For further research, this can be a good point to be examined. Also, in this study the effect of non-machining process parameters on scrap formation for sheet-metal forming is analyzed; this study can also be carried out for different kinds of production. In the study, noise factors are not considered during experimental set up, since they are very difficult to control. If the experiments can be performed in an environment where the noise factors are also controlled, the process parameters can be analyzed more properly. Also, in this study all the two-way interaction effects are not examined. For examining all the main effects and two-way interaction effects 64 experiments are needed, for further research with a 64 run experimental analysis the two-way interaction effects may be clarified.

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