Chapter

Taguchi Method as a Robust Design Tool

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Abstract

Taguchi Method is a powerful technique to optimize performance of the products or process. Taguchi's main purpose is to reduce the variability around the target value of product properties via a systematic application of statistical experimental design which called robust design. Robust Design is an important technique for product manufacturability and product life. Taguchi simplified the usage of orthogonal arrays to setup experimental design. Thanks to this development, researchers and engineers saved both time and money. Furthermore, Taguchi proposed the usage of S/N ratio in order to measure the effects of factors on the performance characteristics. In this study a brief knowledge about the Taguchi Method is given. Orthogonal Arrays and S/N ratios are described. Summary of a case study is given.

Keywords: Taguchi method, robust design, orthogonal Array, S/N ratio, Pareto ANOVA

1. Introduction

The quality of a product is the result of production process. The desired properties of the product should be revealed at the design stage. Towards the end of the 1950s, Dr. Genichi Taguchi put forward many concepts and methods to improve quality which based on robust design.

Robust Design (RD) means the design of a product that causes no problem under any case. RD signifies designing of a product which can work properly under different circumstances [1].

One of the important developments of the manufacturing industry is related to the application of modern off-line quality control techniques in product or process engineering. Many of these quality techniques were shaped by W. E. Deming. Taguchi built his philosophy on them. Deming's main success has been to convince businesses that the production process should be controlled statistically in quality improvement. Taguchi went a little further back and said that quality will be achieved at the design stage before production. Taguchi's main purpose is to reduce the variability around the target value of product properties. To achieve this, the controllable factors that cause this variability must be identified and the product and production process must be designed according to these factors. Taguchi's strategy is a systematic application of Experimental Design (DOE) and analysis in order to improve or design product and process quality. This strategy includes experimental minimization of an expected loss function to determine the best product design (or process design) [2].

Taguchi observed that the most important reason for a product to be rejected is variability in product specifications. Improving quality is through reducing variability. Efforts for quality should be made for zero deviation and zero distortion. All quality experts, especially Shewart and Deming, have addressed the issue of variability. Taguchi in one of his articles [3] -by using the **Figure 1** which has given under the title "Who is the Better Marksman?"- indicated that it is a difficult problem to eliminate variability in the production process. In this example, both gunners fire ten shots. If the average position of Gunner's A is calculated, it will be seen that the average is very close to the target. On the other hand, marksman B's average is far from the target. However, his shots are very consistent. When the variability is calculated for both marksmen, it will be seen that the variability of the gunner B is much less. Those who are interested in shooting can easily say that while it is possible to correct B's shots with a small adjustment, it will take a lot of effort to make A a good shooter. Taguchi argues that production processes are also similar to shooters in this respect. While it is possible to easily adjust the B sniper-like processes, improving the A sniper-like processes will take a lot of time, maybe even huge investments.

Taguchi proposes a two-step process to reduce product variability. These steps are as follows.

- To produce the product with the best methods, technology and techniques

- To produce all products in the same way

In order to fulfill above issues, Taguchi divides the activities into two parts as On-Line Quality Control and Off-Line Quality Control. While on-line quality control covers the quality activities during and after the manufacture of the product, off-line quality control includes market research and quality activities carried out during the development of the product and production process. These activities are design studies carried out before production begins. Taguchi defines three stages such as system design, parameter design, and tolerance design both for product and process improvement.

The most important stage of product or process design in terms of quality improvement is the parameter design stage. At this stage, DOE method is used to

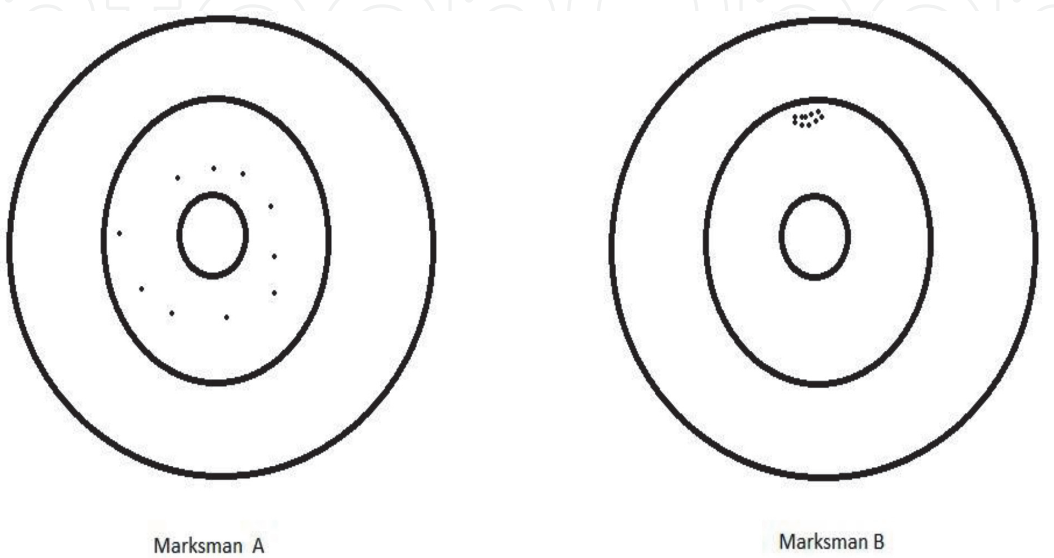

Figure 1.
Who is better gunner? (Adapted from Ref. [3]).

determine the factors affecting product performance and their effects on performance. The aim is to minimize the effect of effective factors on the product [4].

2. Literature review

RD is an important technique for product manufacturability and product life. Although the method was known by 1960's in Japan it has been used in USA by 1980's. Since its use in the USA industry in the 1980s, it has attracted a great attention from designers, manufacturers, statisticians and quality experts. Due to this success of robust design, a lot of researches such as master and PhD theses, scientific articles and case studies have been done to understand the method. Literature of Taguchi Method (TM) and RD is very large and it is still growing. When the literature is examined, it will be seen that Tagcuhi method is frequently used for the optimization of critical parameters of product and process in manufacturing industry and it gives useful results. **Table 1** presents some examples from last ten years publications about the manufacturing industry. It is important to note that TM has been applied to the service industry too. Antony [5] reports the potential applications of DOE in the service environment as follows.

- Identifying the key variables which influence the performance
- Identifying the service design parameters
- Minimizing the time to respond to customer complaints
- Minimizing errors on service orders
- Reducing the service delivery time to customers
- Providing a better understanding of cause–effect relationships between what we do and what we want to achieve
- Reducing cost of quality due to rework and misinformation that lead to bad decision-making

Recently publishings deal with the integration of TM and other approaches such as multicriteria decision making (MCDM), principal component analysis, numerical simulation, artificial neural network, and genetic algorithm. Sharma et al. [6] used the TM and PROMETHEE (which widely used MCDM tool) technique to obtain an optimal setting of process parameters for single and multi-optimization resulting in an optimal value of the material removal rate and tool wear rate. Kumar and Mondal [7] compared the results of experimental data on the electric discharge machining of AISI M2 steel by different optimization techniques such as TM, TOPSIS and gray relational analysis (GRA). Viswanathan et al. [8] aimed to investigate the effective factors in turning of magnesium alloy with physical vapor deposition coated carbide insert in dry conditions. To identify the optimal parameters setting, a combination of principal component analysis (PCA) and GRA has been conducted. Liu et al. [9] and, Land and Yeh [10] used both TM and ANSYS which widely used numerical simulation software in order to optimize and design injection molded products. Asafa et al. [11] presented integration of TM and artificial neural network (ANN) technique for the prediction of intrinsic stresses induced during plasma enhanced chemical vapor deposition of hydrogenated amorphous silicon thin films. Parinam

Article	Subject
Sekulic et al. [13]	Taguchi optimization methodology is applied to optimize cutting parameters in high-pressure jet assisted turning when machining Inconel 718.
Fei et al. [14]	The practical use of TM in the optimization of processing parameters for injection molding was reviewed. Also, integration of TM with various approaches including numerical simulation, GRA, PCA, ANN, and genetic algorithm (GA) were discussed.
Dave and Bhogayata [15]	The mix design of geopolymer concrete based on the target strength criteria by optimizing the proportions of the constituents using TM is presented.
Terzioğlu [16]	The factors which were effective in Thermoelectric Generators (TEG) used in the production of electrical energy a research is carried out by using TM to determine the performance effects.
Zhou et al. [17]	The effects of eight parameters on the value of borehole thermal resistance and internal thermal resistance are investigated. TM is carried out to obtain the optimal scenarios of parameters combination.
Hong [18]	A clustering approach based on TM for effective market segmentation is proposed. To select appropriate initial seeds, the use of TM as a tool is suggested.
Kumar et al. [19]	The objective of the article is to optimize and design nano-biosystem of Isradipine via novel bioenhancer (Rutin) loaded solid-lipid nanobioparticles using Taguchi design methodology.
Tiryaki et al. [20]	Taguchi design method for obtaining lower surface roughness values in terms of process parameters in wood machining is presented. Orthogonal arrays of Taguchi and the signal-to-noise (S/N) ratio is employed to find the optimal levels and to analyze the effect of process parameters on surface roughness.
Hamzaçebi [21]	TM was applied to determine the effects of production factors such as adhesive ratio, press pressure, and pressing time on the thermal conductivity of oriented strand board.
Alafaghani and Qattawi [22]	Taguchi's DOE is used to investigate the main effects of four processing parameters in the Fused Deposition Modeling (FDM) process; those are the infill percentage, infill pattern, layer thickness, and extrusion temperature.
Mitra et al. [23]	TM of robust optimization has been adapted along with DOE methodology and ANOVA to reduce the variability in the Ride comfort of a vehicle with respect to sprung mass of vehicle.
Çakıroğlu and Acır [24]	The optimization of the cutting parameters on drill bit temperature in drilling was evaluated by TM. TM was used to determining the settings of cutting parameters.

Table 1.
Some articles from the literature of the last ten years.

et al. [12] described integration of TM and Genetic Algorithms to optimize high transmission optical filter.

3. Robust design

Phadke defines the RD as an engineering methodology for improving productivity during research and development. Hence high-quality products can be produced quickly and at low cost [25]. The emphasis of RD is variability in product and process performance. Reducing variability will result in increased quality. The source of variability can be divided into two groups [26].

- Controllable factors: Factors determined by the manufacturer that cannot be changed directly by the customer,

- Uncontrollable factors (Noise factors): Factors that the producer cannot directly control and that vary according to customer use and environmental conditions.

Uncontrollable factors can be divided into three categories.

- External noise factors: factors such as environmental conditions, eg; environmental temperature, workers, different raw material piles etc.

- Intrinsic noise factors: time-varying factors, eg; deterioration, aging, discoloration, etc.

- Product-related factors: the difference in each product

Hence, RD means a design that has minimum sensitivity to variabilty of uncontrollable factors. Taguchi says that it is necessary to minimize the variability in the product or process by choosing the values of the controllable factors (parameters) optimally against the factors that create variability. The word robust in the statement of RD refers to uncontrollable factors which insensitive to environmental conditions such as moisture, dust, heat, different applications in customer use and differences in materials [27, 28]. The key to Taguchi Robust Design; instead of trying to control factors that cannot be controlled or that are too expensive to control, it is to determine the best values of controllable factors that will minimize their effects on the product or process [27]. RD provides answers to the following questions [29].

- How to reduce variability when the product is in customer use? How does a product consistently perform at the desired property and thus maximize customer satisfaction?

- How is the production process optimized?

As will be known, there are many factors that need to be determined and optimally adjusted in product and process parameter design stages. Moreover, many of these factors interact with each other. The most effective method to determine the effects of these controllable and uncontrollable factors on product and product performance is statistical experiment design. Through experimental design, it is possible to economically determine the effect of many factors on the product and to take precautions against factors that cause variability at the design stage. Therefore, we can say that the most important quality assurance method in Taguchi's off-line quality control system is DOE [30].

RD covers the parameter design and tolerance design steps of TM. System design consists of traditional research and development activities [31].

In order to realize RD, it is necessary to follow a systematic path. Implementation of the below steps are beneficial [26, 32, 33].

1. Determining the problem and organizing the experiment team

2. Determination of performance characteristics and measurement system

3. Determining the variables affecting performance characteristics

4. Establishing the monitoring design

5. Identifying controllable and uncontrollable variables and their levels

6. Identification of possible interactions

7. Selection of suitable orthogonal array and assignment of variables to relevant columns

8. Determination of loss function and performance statistics

9. Establishing the experiment and recording the results

10. Analysis of data and selection of optimum value of controllable variables

3.1 Determining the problem and organizing the experiment team

When a new product is to be developed, there is no need for any examination for the work to be done. If an existing product is to be developed, "why was this product chosen?" The question must be answered. Generally as an answer to this question; scrap, rework, warranty and service costs can be given. After the problem is determined, the team that will do the task should be formed. The team generally; It consists of experts of the problem of interest, DOE experts, senior management representative and people who will conduct the experiment. The other steps we try to explain below are carried out by this team.

3.2 Determination of performance characteristics and measurement system

The product may have one or more performance characteristics, so the selection of performance characteristics is important. The important point here is that the customer's view should not go unnoticed. Performance characteristics are the basis of the study. Determining the measuring system is the second step in this phase. Each of the performance characteristics may require different measuring systems.

3.3 Determination of variables affecting performance characteristics

Independent variables that affect the product performance characteristics should be determined. Previous experience and expertise are very important in this determination. Brainstorming, cause-effect diagrams and flowcharts are important tools to be used. Easily controllable independent variables are put in the group of control variables (CV) and the others into the group of uncontrollable variables (UCV).

3.4 Establishing the screening design

If the number of CV is large, it may not be possible to carry out the experiment in terms of time and cost. In such a case, there may be some variables that are believed to have no effect at the outset. Of course, making such a choice is difficult. Even after some variables are discarded, there is still the question of whether other variables are important. Screening design allows to get more realistic results with predetermined variables. In the sifter design, the level number is kept as low as possible, usually taken as two. The outputs are analyzed and junk CV is discarded. Significant CV is included in the main experimental group.

3.5 Determining the number and levels of CV and UCV

The number of levels of variables is determined by their characteristics. Thus, possible alternatives are obtained. Taguchi recommends selecting three or more test groups for each CV. Three or more test levels allow a nonlinear effect of CV on the performance characteristic to be revealed. Test levels should be chosen over a wide range so that the CV sequence covers a large region of the CV space. The next step is to determine the set of UCV. This cluster includes the values of the UCV that affect the performance variability the most or the product performance is insensitive. Due to physical impossibilities or lack of information, not all UCV can be included in the experiment. Therefore, it is important to represent all possible combinations of UCV in the experiment [34].

3.6 Identifying possible interactions

The definition of interaction can be as follows: If the effect of a factor on the response variable depends on the value of the other factor, it is said that there is an interaction between two factors as seen in **Figure 2** [30]. The interactions can have a significant impact on performance characteristics. Taguchi thinks that interaction is not that important. The reason of this; the view is that in order to detect the interaction, the experimenter has to control the two main effects, and the interaction does not contribute anything when one or more of the main factors are under control [33]. Taguchi and Wu [35] suggest that one of the following techniques should be applied to reduce the interaction effects.

1. Determining the performance characteristics by weight,

2. Determining the relationship between CV and its levels and making an adjustment accordingly,

3. Conducting an analysis for classified data, such as cumulative analysis.

However, the experimenter must have the necessary attention and knowledge. It is difficult to add all interaction factors to the experiment due to the high cost and time required. On the other hand, including interaction factors believed to be important in the experiment will increase success. The existence of interaction between two factors can be determined by graphical procedure.

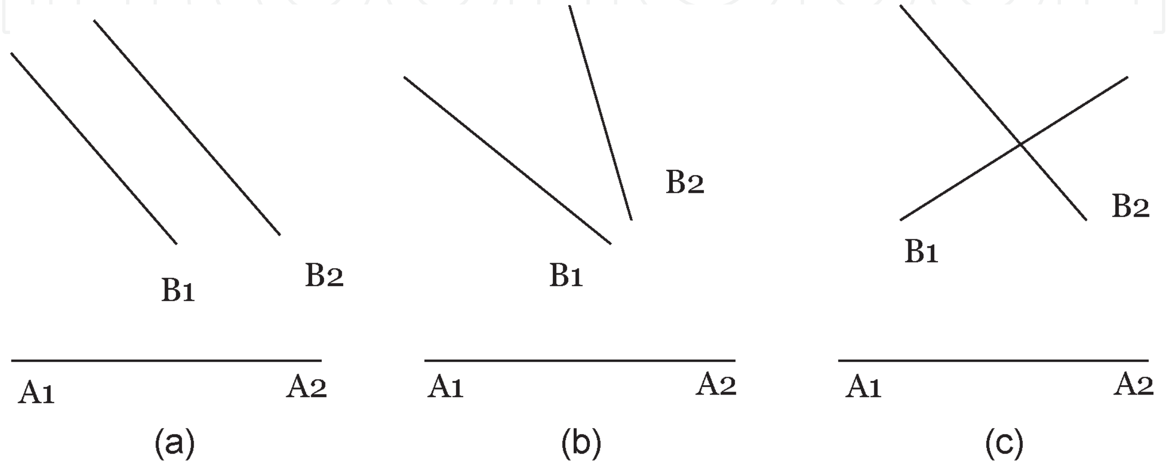

Figure 2.
Graphical representation of interaction between two factors. (a) No interaction, (b) Weak interaction, (c) Strong interaction.

3.7 Choosing appropriate orthogonal arrays

Orthogonal Arrays (OA) take us all the way to Euler's Greco-Latin squares. But in Euler's time they were not known as OA. At that time they were known as mathematical games, like 36 office workers' problems. OA is a matrix of numbers arranged in rows and columns. Orthogonal arrays have a balanced property which entails that every factor setting occurs the same number of times for every setting of all other factors considered in the experiment. In an OA, each row represents the levels of the selected factors in a given experiment, and each column represents a specific factor whose effects on the process performance or product quality characteristic can be studied.

The idea of using OA in DOE independently of each other is originated in the USA and Japan after World War II [36]. The first use of OA was in the 1930s by Fisher in England. Taguchi added three OAs in 1956. And in the following years, three OAs were added by the American NIST [31]. Taguchi makes use of OA in performing multivariate experiments with a small number of trials. Using OA significantly reduces the size of the experiment to be studied [37]. The use of OA is not exclusive to Taguchi. However, Taguchi simplified their usage. Taguchi developed tabulated standard OA and corresponding linear graphs. A typical OA table is shown in **Table 2**.

In this array the columns are bilateral orthogonal. In each column there are all combinations of factor levels with an equal number. There are 4 factors (A, B, C, D) and three levels of each. This design is called the L9 design. The letter L indicates the orthogonal array, and 9 the row number, in other words the number of trials [4].

One point we should pay attention to that how much the OA reduces the number of trials. Due to the full factorial design (2^k or 3^k), OA significantly reduces the number of attempts to be made in large numbers. For our example, 3^4 = 81 trials are required, but only 9 trials will be done to achieve the same results. It is obvious that it will provide more convenience in larger series. **Table 3** highlights the convenience that OA provides in terms of the number of trials [37].

OA allows working economically and simultaneously with many variables that are effective in product mean and variance. Two different OAs can be selected for CV and UCV. Using statistical DOE techniques, suitable subsets for CV and CIA can be demonstrated. Taguchi suggests using OA in planning DOE optimization. The multiplicity of CV and the emergence of interaction require very careful attention in the selection of OA and assignment of CV to columns. Target in establishing CV

	A	B	C	D
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

Table 2.
L9 orthogonal Array.

OA	# of Factors and levels	Full factorial design trial number
L4	3 factors 2 levels	8
L8	7 factors 2 levels	128
L9	4 factors 3 levels	81
L16	15 factors 2 levels	32,768
L27	13 factors 3 levels	1,594,323
L64	21 factors 4 levels	4.4*1012

Table 3.
Frequently used OAs and full factorial design comparison.

OA	# of Row	# of Maximum factor	# of Maximum column			
			2 Levels	3 Levels	4 Levels	5 Levels
L4	4	3	3	—	—	—
L8	8	7	7	—	—	—
L9	9	4	—	4	—	—
L12	12	11	11	—	—	—
L16	16	15	15	—	—	—
L16'	16	5	—	—	5	—
L18	18	8	1	7	—	—
L25	25	6	—	—	—	6
L27	27	13	—	13	—	—
L32	32	31	31	—	—	—
L32'	32	10	1	—	9	—
L36	36	23	11	12	—	—
L36'	36	16	3	13	—	—
....	....	...	....	....	.....	....

Table 4.
OA information table.

matrix; It should be to setup a design where the most information can be obtained with the least effort. **Table 4** presents a brief knowledge about the OAs.

Depending on the levels of CV, an appropriate OA is chosen or some changes are made on the selected OA. The assignment of the CV and interaction variables to the columns is achieved by using standard linear graphs suitable for the selected OA. To determine a suitable OA for the experiment, the following procedure should be followed.

1. Determination of the number of factors and their levels

2. Determining the degree of freedom

3. Selection of OA

4. Consideration of interaction

3.8 Determination performance statistics

Defining the optimal CV requires the determination of some criteria to be optimized such as Signal / Noise (S/N) ratio. The analysis of the data obtained from the experiment is made according to performance statistics and / or mean. Wrong selection of performance characteristics leads to erroneous determination of UCV levels and results. The S/N ratio is used to measure the best RD performance. Many different S/N ratios can be used depending on the purpose of the optimization process. Taguchi mentions that over than 60 S/N ratios can be used and that he developed most of them himself [2]. However, all S/N ratios must meet the criteria listed below [28].

1. The S/N ratio should reflect the variability of the UCV on the response variable.

2. The S/N ratio is independent of setting the mean. This means; the measuring system should be useful in predicting the quality even if the target value changes.

3. S/N ratio measures relative quality. Because it is used for comparative purposes.

4. S/N ratio should not cause unnecessary complexity.

Many S / N ratios are available. The three commonly used are as below.

- Largest - Best

- Smallest - Best

- Nominal - Best

3.9 Establishing the experiment and recording the results

The design optimization experiment can be done in two ways.

- Physical performance of the experiment,

- Computer simulation.

In both experiments, any combination of CV is tested for all combinations of UCV and the results are recorded. The order in which the experiments are performed should be random, as the process will not be constantly stationary. In order for the test results to be evaluated completely and precisely, the test conditions must be recorded.

3.10 Analysis of data and selection of the best values of CV

One of the goals of design optimization experiments is to reduce variability. Another goal is to adjust the mean to the target value. To achieve these two objectives, mean and performance statistics are calculated for each combination of CV in the design model. In order to evaluate the effects of CV on performance statistics and / or mean, Analysis of Variance (ANOVA) is made and percentage contributions are determined. Thus CV can be divided into three classes.

1. CV, which has a significant impact on performance statistics,

2. Setting variables that have a significant effect on average but have no effect on performance statistics,

3. Residual variables that do not affect the average or performance statistics at all.

Analysis results are plotted according to the levels of CV, so that the effects are displayed visually. The optimization procedure is different. If the performance statistics are Nominal - Best, TM uses the following two-step procedure.

1. Investigation of CVs and levels for which the analyst expects the least variability, using calculated performance statistics.

2. Investigation of the setting variables that will bring the sample mean to the target using the calculated sample mean or sample total.

With this method, the variability is reduced in the first step and the sensitivity increases in the second step. If the performance statistics are the smallest best, the TM uses a one-step procedure. This procedure aims to reduce the total variance using the calculated performance statistics; CV affecting the total variance is investigated. Levels of CV where the analyst expects the smallest mean square variability are determined. If the performance statistics are the greatest best, the TM uses a two-sided transformation. Performance statistics change from smallest to best, using the one-step method to reduce the total variance. In case of disagreement between different performance characteristics, one may be abandoned and then the best values selected. If the chosen CV combination is not included in the experiment, the performance values and confidence intervals of the best combination are estimated.

3.10.1 Analysis of variance (ANOVA)

As we mentioned earlier, DOE is used to develop or improve products or processes. The data obtained from the experiment should be analyzed. Variance analysis is used to interpret experimental data. Variance analysis was used for the first time by the British statistician Fisher. Experts usually work with samples. Because it is sometimes impossible to work with the whole population and sometimes it is very expensive. It should not be forgotten that; each individual case study forms part of the error. Sample statistics and assumptions allow the testing of hypotheses regarding experimental parameters. In order to analyze variance with sample data, we have four basic assumptions.

1. Samples are random,

2. Population is distributed normally,

3. Population variances are equal,

4. The choice of samples is independent of the others.

Total variance can be divided into two components such as inter-group variability and intra-group variability. The components of the model are tried to be estimated using the least squares method on the sample data. Total squares are used to show piecemeal variability. After calculating the total squares and determining the appropriate degrees of freedom for each component of variability, the hypothesis is tested using the F distribution [38]. A typical ANOVA table is as **Table 5**.

where

SSF = sum of squares of factor

SSe = sum of squares of error

SST = sum of squares of total

L = number of levels of the factor

N = total number of observations

F_{comp} = computed value of F

VF = variance of factor

Ve = variance of error.

After the experiment is set up, the ANOVA is completed, and the important factors and/or interactions are determined, some comments have already been made. However, if it will not be too expensive, it will be beneficial for the experimenter to learn the rest of the information. Here, we will talk about determining contribution percentages.

The rate of variability for each important factor and interaction observed in the experiment is reflected by the percentage of contribution. Percentage contribution is a function of the sum of squares of each significant factor. Percentage of contribution indicates the strength of factors and/or interaction in reducing variability. If the factor and/or interaction levels are fully controllable, the total variability can be reduced by the percentage of contribution. We know that the variance for a factor or interaction includes error variance. So we can arrange the variance for each factor to show the error variance as well.

The percentage contribution of the error provides an estimate of the adequacy of the experiment. If the error contribution percentage is 15% or less, it is assumed that no significant factor has been overlooked in the experiment. If the error contribution percentage is 50% or more, it is considered that the experimental conditions in which some important factors are ignored cannot be fully controlled or the measurement error is made [39].

In order to learn percantage contribution of the factors Pareto ANOVA can be used. Pareto ANOVA is a simplified ANOVA technique based on the Pareto principle. The Pareto ANOVA technique is a quick and easy method to analyze results of the parameter design and it does not need F-test. Pareto ANOVA does not use an F-test, but it identifies the important parameters and determines the percent contribution of each parameter [40, 21].

3.10.2 $^{S}\!/_{N}$ ratio

Taguchi uses the statistical performance measure known as the $^{S}\!/_{N}$ ratio used in electrical control theory to analyze the results [25]. $^{S}\!/_{N}$ ratio is a performance criterion developed by Taguchi to select the best levels of CV that minimize the

Sources of variation	Sum of squares (SS)	Degrees of freedom	Mean square variance	F_{comp}
Factor	SS_F	L-1	$V_F = \frac{SS_F}{L-1}$	$\frac{V_F}{V_e}$
Error	SS_e	N-L	$V_e = \frac{SS_e}{N-L}$	
Total	SS_T	N-1		

Table 5.
ANOVA table.

impact of UCV [41]. The S/N ratio takes into account both mean and variability. In its simplest form, the S/N ratio is the ratio of the mean (signal) to standard deviation (noise) [4]. TM uses S/N ratios for two main purposes. The first pupose is to use the S/N ratio in order to identify CVs that reduce variability and the second purpose is to identify CVs that move the mean to target. Different S/N ratios can be choosen depending on the goal of experiment. In all cases, the S/N ratio should be maximized. Although Taguchi mentions over than 60 S/N ratios three of them such as smaller-best, larger-best and nominal-best are used frequently. The formulas of them are follows.

- Smaller-Best

$$\frac{S}{N} = -10 * \log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \tag{1}$$

- Nominal-Best

$$\frac{S}{N} = 10 * \log\left(\frac{\overline{y}}{s^2}\right) \tag{2}$$

- Larger-Best

$$\frac{S}{N} = -10 * \log\left(\frac{1}{n}\sum_{i=1}^{n} \frac{1}{y_i^2}\right) \tag{3}$$

where $\overline{y}$ is the mean of observed data, s^2 is the variance of y, n is the number of observed data, and y_i is the ith observed data.

4. Experiment

In this section, a summary of Hamzaçebi [21] is given. Hamzaçebi [21] applied the TM to determine the effects of production factors such as adhesive ratio, press pressure, and pressing time on the thermal conductivity (TC) of oriented strand board (OSB). MINITAB 17 statistical software (State College, PA, USA) was used to analyze experiments in the Taguchi design.

4.1 Data

In the article of Ref [21], adhesive ratio, pressing time, and press pressure were considered as controllable factors. **Table 6** indicates the process parameters and their levels. As deduced from **Table 6**, there are 3 factors, which have 3 levels. After the factor definitions, suitable Taguchi orthogonal array was selected as L9. The L9 design sheet and output of each experiment was given in **Table 7**.

Factors	Level 1	Level 2	Level 3
Adhesive Ratio (%)	3%	4.5%	6%
Pressing Time (minute)	3	5	7
Press Pressure (kg/cm^2)	35	40	45

Table 6.
The process parameters and their levels.

Experiment	Factors			Response	
	Adhesive ratio	Pressing time	Press pressure	$\bar{y}$	s
1	1	1	1	0.129	0.010
2	1	2	2	0.153	0.028
3	1	3	3	0.152	0.025
4	2	1	2	0.142	0.023
5	2	2	3	0.143	0.026
6	2	3	1	0.146	0.025
7	3	1	3	0.163	0.027
8	3	2	1	0.154	0.018
9	3	3	2	0.170	0.019

Table 7.
The design sheet and output of each experiment.

In **Table 7**, $\bar{y}$ and s present the mean and standard deviation of the TC values, respectively.

4.2 Solution and results

Hamzaçebi [21] was used the S/N ratio and Pareto ANOVA analysis to evaluate the results of the experiment.

Figure 3 is the main effect graph of S/N ratios that states the optimal level of the factors. The biggest S/N ratio indicated the optimal combination of parameter values. The ranking of the process parameters was obtained from S/N ratio table which is given in **Table 8**. This order was determined by comparison of delta values. The delta value is equal to the difference between maximum and minimum values for levels of each factor. **Table 8** shows that the order of importance in minimizing the TC of OSB is adhesive ratio, press pressure, and pressing time. **Figure 3** shows the optimal level of the process parameters. As deduced from **Figure 3**, the second level of adhesive ratio (3%), the first level of pressing time (3 min), and the first

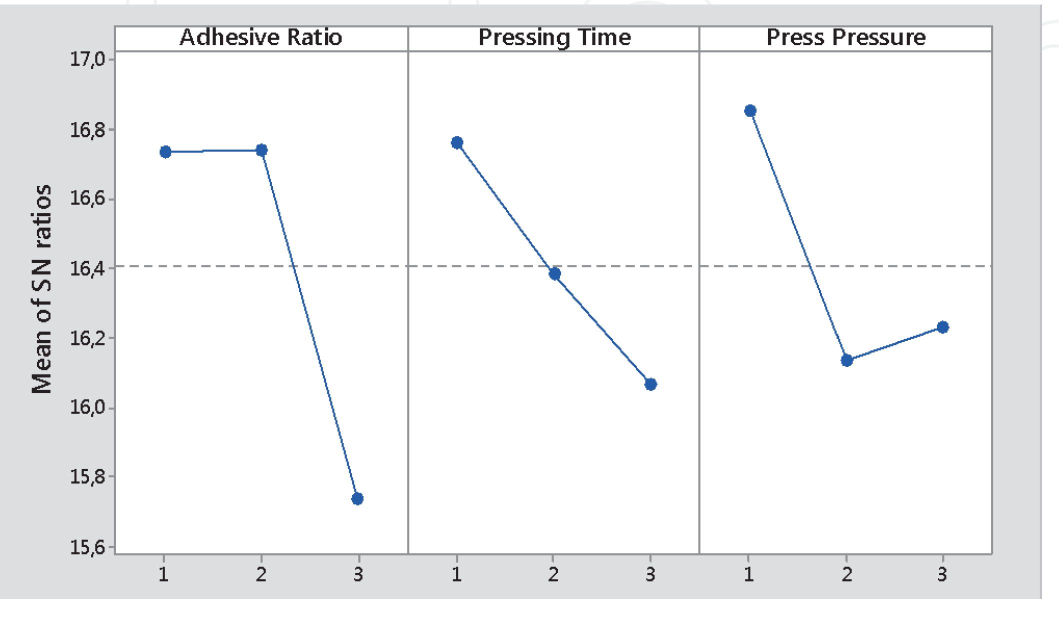

Figure 3.
Main effect plots for S/N ratios of process parameters.

Level	Adhesive ratio	Pressing time	Press pressure
1	16.74	16.77	16.86
2	16.74	16.39	16.14
3	15.74	16.07	16.23
Delta	1.00	0.70	0.72
Rank	1	3	2

Table 8.
S/N ratio values of TC.

level of press pressure (35 kg/cm^2) were the optimal values for the minimization of the TC of OSB.

Hamzaçebi [21] applied the Pareto ANOVA to determine the percent contribution of each parameter on the TC. To obtain the Pareto ANOVA of S/N ratio values, the overall mean of S/N ratios and the sum of squares due to variation about overall mean were calculated by Eqs. (4) and (5), respectively.

$$\overline{S/N} = \frac{1}{m}\sum_{i=1}^{m}(S/N)_i \quad (4)$$

where $\overline{S/N}$ is the overall mean of S/N ratio, $(S/N)_i$ is the S/N ratio for ith parameter, and m is the number of S/N ratios.

$$SS_{Total} = \sum_{i=1}^{m}\left((S/N)_i - \left(\overline{S/N}\right)\right)^2 \quad (5)$$

where SS_{Total} is the total sum of squares. Secondly, for the ith process parameter, the sum of squares due to variation about overall mean was calculated by Eq. (6).

$$SS_i = \sum_{j=1}^{k_i}\left((S/N)_{ij} - \left(\overline{S/N}\right)\right)^2 \quad (6)$$

where SS_i is the sum of the square for ith parameter, $(S/N)_{ij}$ is the S/N ratio of ith parameter of jth level, and k_im$_i$ is the number of levels of ith parameter. Finally, the contribution (Cont) of ith parameter was calculated by Eq. (7). **Table 9** presents the contribution results.

$$Cont_i = \frac{SS_i}{SS_{Total}}x100 \quad (7)$$

Process parameter	Sum of squares (SSi)	% Contribution	Rank
Adhesive ratio	0.6667	54.64	1
Press pressure	0.2456	20.13	3
Pressing time	0.3078	25.23	2
Total	1.2201	100	

Table 9.
Contribution of process parameters based on Pareto ANOVA.

4.3 Discussion

When $S/_N$ ratio results are interpreted, as it can be seen by **Table 8**, the order of importance in minimizing the TC of OSB is adhesive ratio, press pressure, and pressing time. Also, as deduced from **Figure 3**, the second level of adhesive ratio (3%), the first level of pressing time (3 min), and the first level of press pressure (35 kg/cm^2) were the optimal values for the minimization of the TC of OSB. Beside, according to the Pareto ANOVA results, the most effective factor is the adhesive ratio, the second factor is pressing time and the third one is the press pressure. The results show that the adhesive ratio is the most effective factor on the TC of OSB.

On the other hand, for this problem, if the full factorial design was used instead of using the TM, it would be necessary to set up 27 experimental setups. However, 9 experimental setups are sufficient with the TM. 18 more experimental setups are no longer required. Considering that these experiments must be repetitive, the time and cost savings gained will be appreciated. In addition, the $S/_N$ ratio criterion used to interpret the results facilitates the decision made by the decision maker.

5. Conclusion

The objective of this study is to give a brief knowledge about the TM which is used in both manufacturing and service sectors as an optimization tool for product and process. Literature of the TM applications is very large and it is stil growing. The objective of the TM is to setup a RD, hence reduce the variabilty of performance characteristcs of the product and/or process. The main advantage of the TM is cost reduction in time and budget.

In order to present an example, the summary of Hamzaçebi [21] is given. The theoretical benefits of the TM can be seen as follows from the result of Ref. [21].

1. TM is a powerful technique to analyze the effects of the process parameters.

2. Time and cost of experiments can be reduced by using TM. As a result of a selected orthogonal array, 9 experiments were performed instead of 27 experiments, which should be done for full factorial design implementation.

3. The same results were obtained by both S/N ratio analysis and Pareto ANOVA. Thus, it can be said that the outputs of the analysis is consistent.

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