Optimization of Sheet Metal Blanking Process Parameters For Aluminium By Using Taguchi Based GRA

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Abstract- *Metal blanking is a widely used process in high volume production of sheet metal components. Blanking consists of a metal forming operation characterized by complete material separation. Low carbon steel is a very common material used in fabrication of sheet metal components. The experimental studies are conducted under varying sheet thickness, clearance and wear radius & Shear Angle.*

The Main Objectives is to present the development of a model to predict the shape of the cut side. The model investigates the effect of potential parameters influencing the blanking process their interactions. This helped in choosing the process leading parameters for two identical product manufactures from two different materials blanked with reasonable quality on the same Tool/Die.

Optimization is one of the techniques used in manufacturing sector to arrive for the best manufacturing condition. This is an essential need of industries towards manufacturing of quality product at lower cost. The main objective of this study is to treasure optimal parameters such as sheet thickness, clearance & wear radius in blanking to find out the variations in three performance characteristic such as burr height, accuracy & circularity value for blanking of Aluminium. Based on experiments are conducted on L-9 orthogonal array, analysis has been carried on by using Grey Relational Analysis, a Taguchi method. Response tables &graphs are used to find optimal level of parameters in blanking process. The obtained results shows that the Taguchi Grey Relational Analysis is being effective technique to optimize the parameters for Blanking Process

In this work involved some computational issues on modeling blanking processes and investigates the effect of clearance between punch and die in the stress distribution during the penetration phase of cutting process and deformation during blanking process using FEA.

Keywords- Blanking, GRA, GRG, Taguchi method, Orthogonal Array, Finite Element Analysis (FEA)

I. INTRODUCTION

Die design is a large division of tool engineering, is complex, fascinating subject. It is one of the most existing of all the area of tool design. Stamping presses and stamping dies are tools used to produce high volume sheet metal parts. These parts achieve their shapes through the effect of the die. Sheet metal stampings have now replaced many components, which were cast or machined. material economy and the resultant reduction in weight and cost, high productivity, use of unskilled labor, and a high degree of possible precision have rendered press work indispensable for many mass produced goods.

For the manufacturing of the die, the selection of appropriate material selection of manufacturing process and highly precise mating of the upper and lower half of the die is significant. The proper heat treatment of die blocks, and prevents warping. Also, manufacturing within the tolerances limits provided is important for proper functioning of the die and obtaining dimensional accuracy in the product. Also while designing and manufacturing of die the factor of economy is also kept in mind. [3]

Press working may be defined as a chip less manufacturing process by which various components are made from sheet metal. The machine used for press working is called a press. The main features of a press are: a frame which supports a ram or a slide and a bed, a source of mechanism for operating the ram in line with and normal to the bed. The ram is equipped with a suitable punch and a die block is attached to the bed. A stamping is produced by downward stroke of ram when the punch moves towards and into the die block.

II. COMPONENTS OF THE DIE AND THE PRESS

A simple cutting die used for punching and blanking operation is shown in fig. Below the definition of main components of the press are given;

Bed:-

The bed is the lower part of press frames that serves as a table to which bolster plate mounted.

Bolster plate:-

This is a thick plate secured to the press bed, which is used for locating and supporting the die assembly. It is usually 5 to 12.5 mm thick.

Die-set:

It is unit assembly, which incorporates lower and upper shoe, two or more guideposts and guideposts bushings.

Die: The die may be defined as a female portion to complete tool for producing work in a press. It is also referred to a complete tool consisting of a pair of members for producing work in a press.

Lower shoe:-

The lower shoe of die set is generally mounted on the bolster plate of the press. The die block is mounted on the lower; also the guide post is mounted in it.

Punch:-

This is the male components of the assemblies, which is directly or indirectly moved by and fastens to the press ram or slide.

Punch plate:-

The punch plate or the punch plate retainer fits closely over the body of the punch and holds in proper relative position.

Upper shoe:-

This is the upper part of the die, which contains guidepost bushing and guidepost assembly.

Back up plate:-

Back up plate or pressure plate is placed so that the intensity of pressure does not become excessive on punch holder. The plate distributes the pressure over a wide area and the intensity of pressure on the punch holder is reduced to avoid crushing.

Stripper:-

It is the plate which used to strip the metal strip from a cutting punch or die it may also guide the strip.

Knock-out:-

It is mechanism usually connected to and operated by the press ram for pressing a work piece from die.

III. MATERIAL AND METHOD USED

3.1 Details of Work piece Material

Selected material is Aluminium 6061-T651 Thickness 0.2 , 0.3 & 0.4 mm

3.2 Details of Die

Die hole is of 10mm diameter. Hence
Blanking perimeter = $\pi D = 3.14 \times 10 = 31.4$mm
Strip thickness is taken as 2 mm

3.3 Details of Punch

Stock Thickness(mm)	Die block Thickness, (mm)
Up to 1.5	20 to 25
1.5 to 3	25 to 30
3.0 to 4.5	30 to 35
4.5 to 6.0	35 to 40
Over 6.0	40 to 50

Table 3.1 Die block

Punch Numbers	Final Manufacturing Values
1	Ø9.96
2	Ø9.95
3	Ø9.94
4	Ø9.85
5	Ø9.84
6	Ø9.83
7	Ø9.89
8	Ø9.88
9	Ø9.87

Table 3.2 Punch Size

3.4 Details of Machine

Sr. No.	Item	Specification
1	Video Measuring Machine (VMM)	Model VMM 2515,Glass Table Sie-350 x 280, Metal Table Size-480 x 280mm X, Y Travel 250 x 150, Net Wt. 120kg, Z Axis Travel-150mm, Resolution X,Y,Z Scales:1um, Work Distance-108mm, X, Y Axis Accuracy-(3+L/200)um, Optical Magnification 0.7-4.5X, Digital Magnification 10-300X, Power AC 110V/60Hz;220v/50Hz, Software-Quick Measuring 3.0
2	Fly Press Machine	Frame Height-48-60", work Height-15-20",Screw Diameter-3.5", Screw Lead-3 start, Maximum Wt.-800kg, Fly Wheel Mass-322lbs, Application- Two Operator Floor (Standing)Work
3	Press Tool/Blanking Die	L x W x H-150x100x120, Blank Size-Ø10,Punch Length 75mm, Die Plate size-80x80x25, Tool Wt.8.61kg

IV. EXPERIMENTATION DETAILS

4.1 Selection of blanking parameters

The methodology that is followed to attain the research objectives is divided into the following work phases: Classify the blanking parameters into controllable and uncountable. The identified controllable parameters are clearance, blank holder force, sheet metal thickness, and material type. While, the uncountable parameters are material prosperities inconsistency and conditions (shape, defects and internal stresses), friction and wear state of the tool, stroke rate or blanking speed, and punch-die alignment.

Choose the controllable factors that influence the blanking process.

Select an appropriate working range for each potential factor. It is found that the working range of clearance fall within the range (0-15%) of the sheet metal thickness and the working range of the thickness of their used material fall within the range (0.25-0.6) mm.

Prepare to use of Design of Experiments (DOE) technique by selecting the experimental levels for each selected factor, i.e. the clearance to be in three levels (5, 10, 15 %) of the sheet metal thickness sheet metal thickness to be in three levels (0.2, 0.3, 0.4) mm.

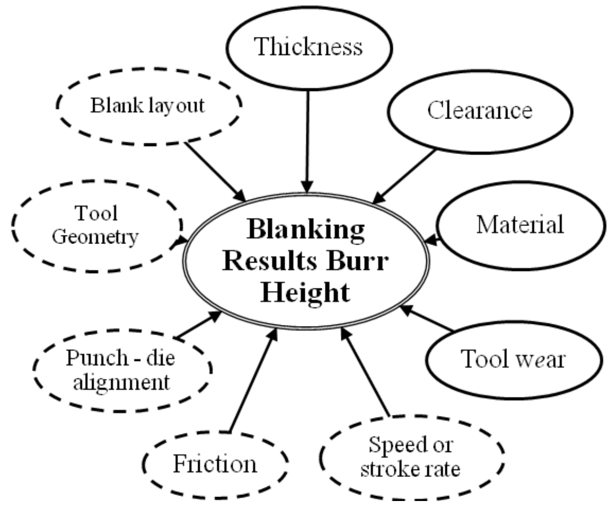


Figure:4.1 Blanking Process Parameters

4.1.1 Influence of Blanking Clearance

In blanking processes, the clearance expressed as a percentage of the sheet thickness, is defined by:

$$C=100\frac{Dm-Dp}{2t}\ (\%)$$

Dm, Dp, and t are, respectively, the die diameter, the punch diameter, and the sheet thickness.

In order to study the influence of this design parameter, four tools have been designed corresponding to four different clearances, 5%, 10%, 15%, and 20%. These values correspond to the most used clearances in industry.

4.1.2 Influence of the Sheet Thickness

For a given material, the energy requirement in blanking is influenced by the sheet thickness. It has been observed that:

1. The blanking energy decreases with increasing clearance to sheet thickness ratio c/t and increases with increasing sheet thickness.
2. The proportions of the different depth characteristics of the sheared profile are affected by the thickness.
3. To study the effects of the interactions between the clearances and the sheet thickness, a series of

experiments have been carried out with Three thickness values of 0.25, 0.5, and 0.6 mm`.

4.1.3 Influence of the Tool Wear / Wear Radius

The design of the tool is one of the main features in the industrial process. Therefore it is necessary to study the effects of tool wear on the blanking force and the sheared profile variations. The quality of the work piece is governed by the state of the tool wear.

Wear is defined as a slow degradation of the blanking tool caused by the friction involved between tool and sheet metal. The rate of wear is affected by parameters such as tool material, blanked part material, punch–die clearance, punch velocity, lubrication, and material thickness. Generally, wear takes place on the external surface of the tool. It causes the cutting edges to be rounded. Therefore, the influence of the tool wear can be accounted for by changing the values of the edge radii Rwp and Rwd.

Experimental investigation into the blanking process was carried out using punches with different wear states. The aim was to define the relationship between the sheared profile of the component and the forces applied to the tool evolutions versus the tool wear evolution.

Three wear states of the tool were chosen corresponding to:

A new die with: Rwd= 0.01 mm.
A new punch with: Rwp= 0.01 mm.
Two “worn out” punches with different edge radii Rwp= {0.15, 0.3} mm.

4.2 Optimum Clearance

Various experimental studies showed that the mechanical and geometrical aspect of the sheared edge during the blanking operation for a given material are affected by some parameters such as the blanking clearance, the wear state of the tool, and the thickness of the sheet. In blanking processes, the clearance is expressed in percentage of the sheet thickness and is defined by:

$$C=100\frac{Dm-Dp}{2t}\ (\%)$$

Where,
Dm, Dp and t are the die diameter, the punch diameter and the sheet thickness, respectively.

4.3 Die Design & Manufacturing

The following factors influence the design of the die.

1. Piece part size.
2. Stock thickness.
3. Profile of piece part contour.
4. Type of tool.
5. Machinery available for manufacturing of tool.

Design of Press Tool involves the following steps.

1. Drawing strip layout and comparing material utilization.
2. Determination of forces (press tonnage) required for the operation.
3. Design of die block.
4. Determination of die opening size and punch size.
5. Design of punch assembly and calculating maximum allowable length of punch.
6. Design of stripper plate.
7. Design of back up plate.
8. Selection of die set.

The die block size essentially depends on the work piece size and stock thickness. Sometimes the type of blank contour and the type of die may also influence the choice of die block size.

Die hole is of 10mm diameter. Hence
Blanking perimeter = πD = 3.14×10 =31.4mm
Strip thickness is taken as 2 mm.
Total shear area =31.4×2 = 62.8 mm2
Shear strength of material is taken as 350 MPa.
Hence shear force (load) = 350×62.8 = 21.980KN
From table no. 3.1,
Die thickness = 25 mm
Hence we take thickness of die block = 25 mm.
(As strip thickness 2mm & perimeter 32mm)
The minimum distance between the die opening & the outside edge of the die
Block should be from 30mm to 1.25 times the die block thickness.
Hence die opening to edge = 1.25×die thickness
= 1.25×25 =32 mm =35mm
Hence die block is to be 80×80×25 mm.
Required press capacity:
Shear force = 22KN.
Plus add 30% additional force =22×1.3 = 28.6KN
Required press capacity = 29 KN i. e. 3Ton.
Punching force:

The force required to be exerted by the punch in order to shear out the blank from the stock can be estimated from the actual shear area & the shear strength of the material.

Punching force = L×t×shear strength

$= \pi \times 10 \times 2 \times 350$

$= 21.98$ K N

Stripping force = 0.024×L×t

$= 0.024 \times \pi \times 10 \times 2 = 1.5$ KN

Clearance / side-

1.C = C x S x √Tmax / 10 (S=Sheet thickness, Ss= Shear stress in N/mm²).

0.05x0.025 x√335/10=0.022/side.............................(1)

10% of Clearance value=0.025/side.............................(2)

15% of Clearance value=0.027/side.............................(3)

2.C=0.05x0.5x√480/10=0.054/side...............................(1)

10% of Clearance value=0.060/side.............................(2)

15% of Clearance value=0.063/side.............................(3)

3.C=0.05x0.4x√550/10=0.072/side...............................(1)

10% of Clearance value=0.080/side.............................(2)

15% of Clearance value=0.085/side.............................(3)

4.4 Introduction (Grey Relational Analysis)

In a blanking operation, many factors simultaneously influence on blanking process to determine the state of development of the system Usually, we want to know which factors influences the system more and which factor influences the system little. However, the relationship between various factors is usually grey where the information is unclear, incomplete and uncertain. Moreover, practical and experimental data was difficult to obtain and too much scatter to analyze. Two conventional statistical methods frequently used on the relationship between independent and dependent factors were factor analysis and regression analysis methods. However, this analysis prescribes that there must be relationship of mutual influence between variables, and the function relationship will only be worked out under the condition of large quantities of data, which should conform to the typical distribution, like the normal distribution. To overcome the shortage of regression analysis and factor analysis, multi-attribute method, Grey relational analysis (GRA) has been proposed to solve the problem. GRA is a kind of effective tool to make system analysis, and also lays a foundation for modeling, forecasting, clustering of grey systems. Comparing to regression analysis and factor analysis in mathematic statistics, grey relational has some merits such as small sample, having no use for typical distribution, no requirement for independency and small amount of calculation. Additionally, GRA analysis is already proved to be simple and accurate method for selecting factors especially for those problems with unique characteristic. Grey relational grade (GRG) can be used to describe the relationships among the factors and to determine the important factors that significantly influence some defined objectives. GRA can provide a ranking scheme that rank the order of the grey relationship among dependent and independent factors and this allow us to decide which input factors need to be considered more precisely. In the case when experiments are ambiguous or when the experimental method cannot be carried out exactly, grey analysis helps to compensate for the shortcoming in statistical regression .Grey relation analysis is an effective means of analyzing the relationship between sequences with less data and can analyze many factors that can overcome the disadvantages of statistical method.

Taguchi method or Taguchi approach is a DOE technique with new experimental strategy where the quality is defined in general terms. The method could be used not only to improve quality, but also to quantify the improvements made in terms of saving money. The experimental design and analyze of the results can be done with less effort and expenses by using the Taguchi approach. Since the method enormously reduces the number of experiments, quality loss of results must be taken into account.

4.5 Design of Experiment

Taguchi approach provides a new experimental strategy in which a modified and standardized form of design of experiment (DOE) is used. This technique helps to study effect of many factors (variables) on the desired quality characteristic most economically. By studying the effect of individual factors on the results, the best factor combination can be determined. Taguchi designs experiments using specially constructed tables known as "ORTHOGONAL ARRAY" (OA). The use of these tables makes the design of experiments very easy and consistent and it requires relatively lesser number of experimental trials to study the entire parameter space. As a result, time, cost, and labor saving can be achieved. The experimental results are then transformed into a signal-to-noise (S/N) ratio. Taguchi recommends the use of the S/N ratio to measure the quality characteristics deviating from the desired values. Usually, there are three categories of quality characteristic in the analysis of the S/N ratio, i.e. the-lower-the-better, the-higher-the-better, and the nominal-the-better. The S/N ratio for each level of process parameters is computed based on the S/N analysis. Regardless of the category of the quality characteristic, a greater S/N ratio corresponds to better quality characteristics.

4.5.1 Blanking Process Variables & Their Levels

Problem studied here consists of a blanking operation of Medium carbon steel sheet. Experiment is carried out on press machine. For these a simple blanking die is manufactured to obtained 10mm diameter blank. Different punches of appropriate diameters are used to obtained different clearances. The different parameters and their levels that are selected for experimentation are sheet metal thickness (0.2, 0.3, 0.4mm), clearance (5%, 10%, 15%), and Tool wear radius (0.01, 0.15, 0.30mm) . The most of these ranges are selected in the light of the data available in the literature. The parameters & their levels are shown in Table.

For selecting appropriate orthogonal arrays, degree of freedom (number of fair and independent comparisons needed for optimization of process parameters and is one less than the number of levels of parameters) of array is calculated. There is six degree of freedom owing to three blanking input parameters. Accordingly, full factorial, 9 experiments were carried out to study the effect of input parameters. Each experiment was repeated five times in order to reduce experimental errors. The readings are taken of each blank at five different positions by rotating the blank & average of that is taken as the burr height reading of that blank. In all tests, the burr height was reading of that blank. In all tests, the burr height was measured on video measuring machine (VMM).

Table .4.1 Process Parameters and their Levels.

Level	Sheet Thickness(mm)	Clearance (%)	Tool Wear Radius (mm)
	(A)	(B)	(C)
1	0.2	5	0.01
2	0.3	10	0.15
3	0.4	15	0.30

The Taguchi arrays can be derived or looked up. Small arrays can be drawn out manually; large arrays can be derived from deterministic algorithms. While there are many standard orthogonal arrays available, each of the arrays is meant for the specific number of independent design variables & levels. For example, if one wants to conduct an experiment to understand the influence of 3 different independent variables with each variable having 3 levels then an L-9 orthogonal array might be a right choice. L-9 orthogonal array is meant for understanding the effect of 3 independent factors each having 3 factor level values. This array assumes that there is no interaction between two factors. While in many cases, no interaction model assumption is valid, there are some cases where there is a clear evidence of interaction. The arrays are selected by the number of parameters (variables) and the number of levels (states). From Taguchi array selector we conclude that L-9 Array is convenient but results obtained are only relative not exact for exact result L-27 Array is used.

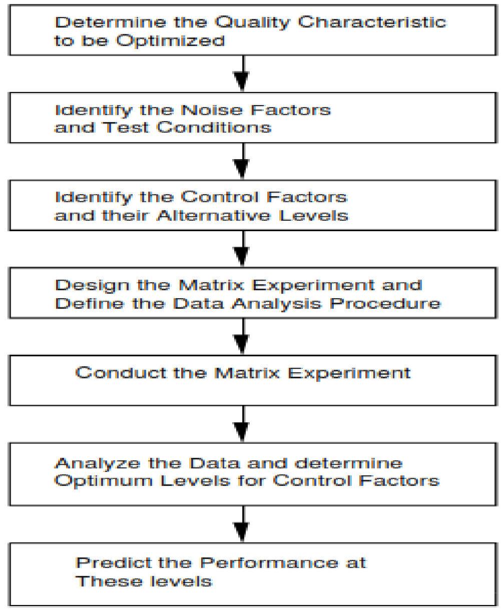


Figure.4.2 Flow chart of the Taguchi Method

The first step of Taguchi method requires the knowledge about the domain that is examined, since the main function, side effects and failure modes have to be identified. A wrong decision in this step makes all other steps useless. The second step is to find control factors and their levels. To reduce the number of experiments, only the most important factors should be considered. Two or three factor levels can be chosen. In the latter case, the levels should be evenly distributed. The factor levels should be placed very carefully, since the Taguchi method defines the significant and optimal parameters only within the levels. The orthogonal array that defines the experiments is selected in the third step. The fourth step is to perform the experiments. Optimal factors are predicted in the fifth step. And in the last step of Taguchi method optimal parameters should be tested to confirm or reject optimal parameters found by Taguchi method.

4.6 Gray Relational Analysis

In Grey relational analysis, experimental data i.e., measured features of quality characteristics are first normalized ranking from zero to one. This process is known as Grey relational generation. Next, based on normalized experimental data, Grey relational coefficient is calculated to represent the correlation between the desired and actual experimental data. Then overall Grey relational grade is determined by averaging the Grey relational coefficient corresponding to selected responses. The overall performance characteristic of the multiple response process depends on the calculated Grey relational grade. This approach converts a multiple response process optimization problem into a single response optimization situation with the objective function is higher Grey relational grade. The optimal parametric combination is then evaluated which would result highest Grey relational grade. The optimal factor setting for maximizing overall Grey relational grade can be performed by Taguchi method

4.6.1 Grey-based Taguchi Method

The Grey theory established by Dr. Deng includes Grey relational analysis, Grey modeling, prediction and decision making of a system in which the model is unsure or the information is incomplete [16]. It provides an efficient solution to the uncertainty, multi-input and discrete data problem. The relation between machining parameters and machining performance can be found out using the Grey relational analysis. And this kind of interaction is mainly through the connection among parameters and some conditions that are already known. Also, it will indicate the relational degree between two sequences with the help of Grey relational analysis. Moreover, the Grey relational grade will utilize the discrete measurement method to measure the distance [11].

In grey relational analysis, black represents having no information and white represents having all information. A grey system has a level of information between black and white. This analysis can be used to represent the grade of correlation between two sequences so that the distance of two factors can be measured discretely. In the case when experiments are ambiguous or when the experimental method cannot be carried out exactly, grey analysis helps to compensate for the shortcoming in statistical regression. Grey relation analysis is an effective means of analyzing the relationship between sequences with less data and can analyze many factors that can overcome the disadvantages of statistical method. Grey relational analysis is widely used for measuring the degree of relationship between sequences by grey relational grade. Grey relational analysis is applied by several researchers to optimize control parameters having multi-responses through grey relational grade. In the grey relational analysis, the grey relational grade is used to show the relationship among the sequences. If the two sequences are identical, then the value of grey relational grade is equal to 1. The grey relational grade also indicates the degree of influence that the comparability sequence could exert over the reference sequence. Therefore, if a particular comparability sequence is more important than the other comparability sequences to the reference, then the grey relational grade for that comparability sequence and reference sequence will be higher than other grey relational grades.

The Grey theory can provide a solution of a system in which the model is unsure or the information is incomplete. Besides, it provides an efficient solution to the uncertainty, multi-input and discrete data problem .

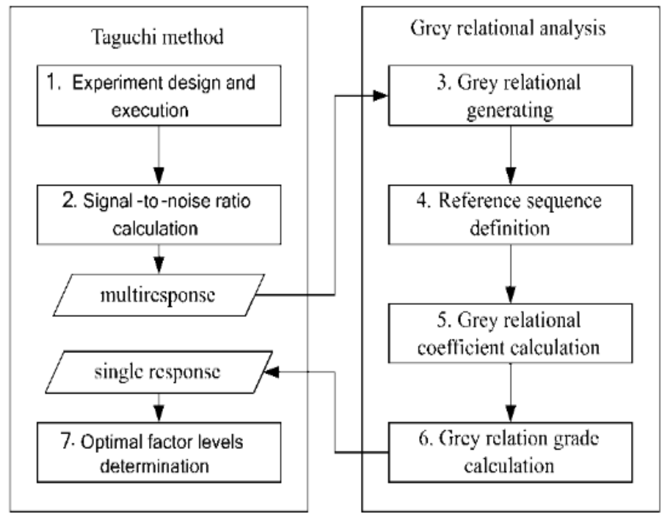


Figure:4.3 Procedure of the grey-based Taguchi method

Higher Grey relational grade means that the corresponding parameter combination is closer to the optimal. The mean response for the Grey relational grade with its grand mean and the main effect plot of Grey relational grade are very important because optimal process condition can be evaluated from this plot [10].

Consider that the Blanking process to be investigated corresponds to 9 different experiments. For the GRA, these 9 experiments become 9 subsystems. The influence of these subsystems on the response variable is to be analyzed using GRA technique. Hence, the process (system) is assessed by conducting 9 experiments (subsystems) where each experiment is termed as comparability sequences were obtained. The parametric conditions corresponding to the highest grey relational grade give minimum values of the burr height. In this manner, the multi-objective problem has been converted into single objective optimization using GRA technique. The problem has eight performance characteristics that need to be minimized by choosing appropriate processing conditions. They are: clearance, thickness and tool nose radius. In such cases, the problem is converted into a single objective problem using grey relational analysis, see Fig. 1. The grey relational analysis deals with the ranks, and not with the real value of the grey relational grade .

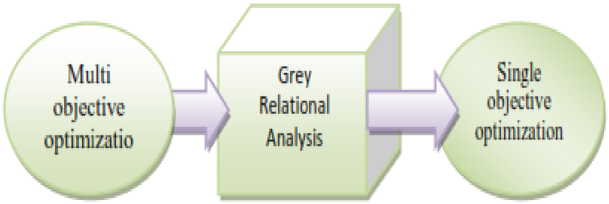


Figure: 4.4 Purpose of gray relational analysis

The Grey Relational Analysis (GRA) associated with the Taguchi method represents a rather new approach to optimization. The grey theory is based on the random uncertainty of small samples which developed into an evaluation technique to solve certain problems of system that are complex and having incomplete information. While only one outcome is optimized in the Taguchi method, multiple outcomes can be optimized in a Grey Relational Analysis. For this reason, the Grey Relational Analysis method, allowing optimization of multiple outcomes, was chosen in the study.

V. RESULT ANALYSIS AND DISCUSSIONS

The Grey Relational Analysis (GRA) associated with the Taguchi method represents a rather new approach to optimization. While only one outcome is optimized in the Taguchi method, multiple outcomes can be optimized in a Grey Relational Analysis.

5.1 Optimization process is carried out in the following steps.

- **Experimental Results**
- **Optimization using GRA**

Step 1: Taguchi Method for S/N ratio
Step 2: Normalization of S/N ratio
Step 3: Determination of deviation sequences,
Step 4: Calculation of grey relational coefficient (GRC)
Step 5: Determination of grey relational grade (GRG)
Step 6: Determination of optimum parameters

- **Confirming Result**

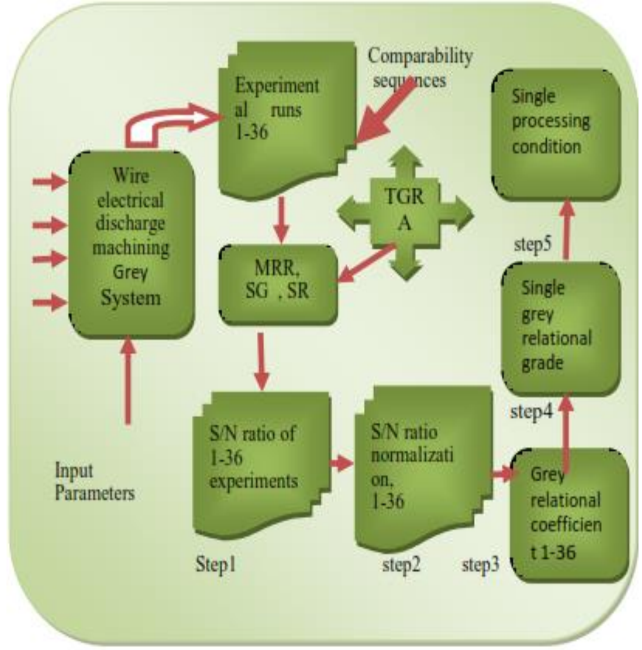


Figure: 5.1 Stepwise procedure of GRA optimization

5.1.1 Taguchi Method to S/N Ratio

Taguchi Method is developed by Dr. Genichi Taguchi, a Japanese quality management consultant. The Taguchi method utilizes orthogonal arrays from design of experiments theory to study a large number of variables with a small number of experiments. Using orthogonal arrays significantly reduces the number of experimental configurations to be studied. Furthermore, the conclusions drawn from small scale experiments are valid over the entire experimental region spanned by the control factors and their settings. [10]

The method explores the concept of quadratic quality loss function and uses a statistical measure of performance called Signal-to-Noise (S/N) ratio. The S/N ratio takes both the mean and the variability into account. The S/N ratio is the ratio of the mean (Signal) to the standard deviation (Noise). The ratio depends on the quality characteristics of the product/process to be optimized.

The standard S/N ratios generally used are as follows: -

1) Nominal is Best (NB)
2) Lower the Better (LB)
3) Higher the Better (HB)

The optimal setting is the parameter combination, which has the highest S/N ratio.

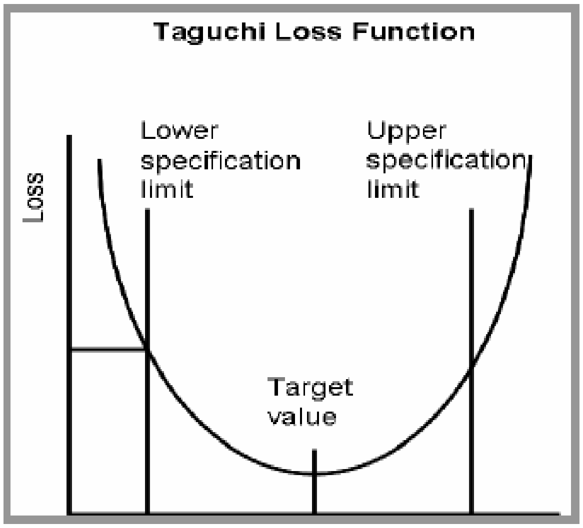


Figure: 5.2 Taguchi's quadratic loss function

- **Taguchi's S/N Ratio for (HB) Higher-the-better**

(Quality characteristics is usually a nominal output, say *Current)*

$$\eta = -10\ log_{10}\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}.$$

- **Taguchi's S/N Ratio for (LB) Lower-the-better**

(Quality characteristics is usually a nominal output, say *Defects)*

$$\eta = -10\ log_{10}\frac{1}{n}\sum_{i=1}^{n}y_i^2$$

- **Taguchi's S/N Ratio for (NB) Nominal-the-best**

(Quality characteristics is usually a nominal output, say *Diameter)*

$$\eta = 10\ log_{10}\frac{1}{n}\sum_{i=1}^{n}s2$$

5.1.2 Normalization of S/N Ratio

It is the first step in the grey relational analysis; a normalization of the S/N ratio is performed to prepare raw data for the analysis where the original sequence is transferred to a comparable sequence. Linear normalization is usually required since the range and unit in one data sequence may differ from the others. A linear normalization of the S/N ratio in the range between zero and unity is also called as the grey relational generation [13]. Further analysis is carried out based on these S/N ratio values. The transformation of S-N Ratio values from the original response values was the initial step. For that the equations of "larger the better", "smaller the better" and "nominal the best" were used. Subsequent analysis was carried out on the basis of these S/N ratio values [19].

When the range of the series is too large or the optimal value of a quality characteristic is too enormous, it will cause the influence of some factors to be ignored. The original experimental data must be normalized to eliminate such effect. There are three different types of data normalization according to whether we require the LB (lower-the-better), the HB (higher-the-better) and NB (nominal-the-best). The normalization is taken by the following equations.

(a) HB (higher-the-better)

$$x_i(k) = \frac{y_i - min\ y_i\ (k)}{\max y_i(k) - min\ y_i\ (k)}$$

(b) LB (lower-the-better)

$$x_i(k) = \frac{\max y_i(k) - y_i\ (k)}{\max y_i(k) - min\ y_i\ (k)}$$

(c) NB (nominal-the-best)

$$X_i^*\ (k) = \frac{y_i\ (k) - y_i}{\max y_i(k) - y_i\ (k)}.$$

Here, i= 1, 2… m; k=1, 2… n

Where $x_i(k)$ is the value after the grey relational generation, min $y_i(k)$ is the smallest value of $y_i(k)$for the k^{th}response, and max $y_i(k)$ is the largest value of $y_i(k)$for thek^{th}response. An ideal sequence is $x_0(k)$ for the responses. The purpose of grey relational grade is to reveal the degrees of relation between the sequences say, [$x_0\ (k)$ *and* $x_i\ (k)$, *i*= 1, 2,3.......,9].

5.1.3 Determination of Deviation Sequences, Δ_{0i}

The deviation sequence $\Delta_{0i}$is the absolute the reference sequence x_0(k) and the comparability sequence x_i(k) after normalization. It is determined using

$$\Delta_{0i} = |x_0\ (k)\ \text{-}\ x_i\ (k)|$$

5.1.4 Calculation of Grey Relational Coefficient (GRC)

GRC for all the sequences expresses the relationship between the ideal (best) and actual normalized S/N ratio. If the two sequences agree at all points, then their grey relational coefficient is 1.

$$\xi_i(k) = \frac{\Delta_{min} + \theta\ \Delta_{max}}{\Delta_{0i}(k) + \theta\ \Delta_{max}}.$$

Where,

$\Delta_{0i} = \|x_o(k) - x_i(k)\| =$ Difference of the absolute value $x_o(k)$ *and* $x_i(k)$; θ is the distinguishing coefficient $0 \le \theta \le 1$; $\Delta_{min} = \forall j^{min} \in i \forall k^{min} \|x_o(k) - x_j(k)\|$ = the smallest value of Δ_{0i}; and $\Delta_{max} = \forall j^{max} \in i \forall k^{max} \|x_o(k) - x_j(k)\|$ = largest value of Δ_{0i}.Comparability sequence and ζ is the distinguishing coefficient. The value of θ can be adjusted with the systematic actual need and defined in the range between 0 and 1, $\theta \in [0, 1]$. It will be 0.5 generally.

5.1.5 Determination of Grey Relational Grade (GRG)

The overall evaluation of the multiple performance characteristics is based on the grey relational grade. After averaging the grey relational coefficients, the grey relational grade γ_i can be computed as:

$$\gamma_i = \frac{1}{n} \sum_{k=1}^{n} \xi_i(k).$$

Where,
n = number of process responses.

If the two sequences agree at all points, then their grey relational coefficient is 1 everywhere and therefore, their grey relational grade is equal to 1. In view of this, the relational grade of two comparing sequences can be quantified by the mean value of their grey relational coefficients and the grey relational grade. The grey relational grade also indicates the degree of influence that a comparability sequence could exert over the reference sequence. Therefore, if a particular comparability sequence is more important than the other comparability sequences to the reference sequence, then the grey relational grade for that comparability sequence and reference sequence will be higher than other grey relational grades.

The higher value of grey relational grade corresponds to intense relational degree between the reference sequence $x_0(k)$ and the given sequence x_i (k). The reference sequence $x_0(k)$ represents the best process sequence. Therefore, higher grey relational grade means that the corresponding parameter combination is closer to the optimal.

5.1.6 Determination of Optimum Parameters

The grey relational grade calculated for each sequence is taken as a response for the further analysis. The larger-the better quality characteristic was used for analyzing the GRG, since a larger value indicates the better performance of the process. The quality characteristics used is given by Eq. 1. The number of repeated test is one, since only one relational grade was acquired in each group for this particular calculation of S/N.

5.2 Optimization of process parameters using Taguchi based Grey Relational Analysis

The control parameters at three different levels and three different response parameters considered for multiple performance characteristics in report.

Table 5.1:- Response parameters and control parameters with their levels

Level	Sheet Thickness(mm)	Clearance (%)	Tool Wear Radius (mm)
	(A)	(B)	(C)
1	0.2	5	0.01
2	0.3	10	0.15
3	0.4	15	0.30

In this work, L-9 Orthogonal Array design matrix is used to set the control parameters to evaluate the process performance. The Table shows the design matrix used in Experimentation.

Run No.	L-9 Array (Half factorial)			Parameters		
				Thickness	Clearance	
	A	B	C	in MM	%	Redius
1	1	1	1	0.25	5	0.01
2	1	2	2	0.25	10	0.15
3	1	3	3	0.25	15	0.3
4	2	1	2	0.5	5	0.15
5	2	2	3	0.5	10	0.3
6	2	3	1	0.5	15	0.01
7	3	1	3	0.6	5	0.3
8	3	2	1	0.6	10	0.01
9	3	3	2	0.6	15	0.15

Table 5.2 Design Matrix of L-9 Orthogonal Array

Run No.	L-9 Array (Half factorial)			Parameters		
				Thickness	Clearance	
	A	B	C	in MM	%	Redius
1	1	1	1	0.25	5	0.01
2	1	2	2	0.25	10	0.15
3	1	3	3	0.25	15	0.3
4	2	1	2	0.5	5	0.15
5	2	2	3	0.5	10	0.3
6	2	3	1	0.5	15	0.01
7	3	1	3	0.6	5	0.3
8	3	2	1	0.6	10	0.01
9	3	3	2	0.6	15	0.15

Experiments were conducted as per L-9 orthogonal array, assigning various values of the levels to the process parameters. [30] After individual experiments for each set of values were conducted on medium carbon steel sheet for Ø10mm Blank, burr height, Accuracy & Circularity are calculated using video measuring machine (VMM) and the final results. Table

Table 5.3 Experimental results

							RESPONSE VALUE		
Run No.	L-9 Array (Half factorial)			Parameters			Average	Average	Average
				Thickness	Clearance		Burr Height	Accuracy	Circularity
	A	B	C	in MM	%	Redius	in µ	(Ø in mm)	(Ø in mm)
1	1	1	1	0.25	5	0.01	**0.013**	**10.036**	**0.048**
2	1	2	2	0.25	10	0.15	**0.023**	**10.082**	**0.045**
3	1	3	3	0.25	15	0.3	**0.034**	**10.014**	**0.08**
4	2	1	2	0.5	5	0.15	**0.024**	**10.065**	**0.07**
5	2	2	3	0.5	10	0.3	**0.038**	**10.045**	**0.038**
6	2	3	1	0.5	15	0.01	**0.067**	**10.033**	**0.039**
7	3	1	3	0.6	5	0.3	**0.049**	**10.01**	**0.008**
8	3	2	1	0.6	10	0.01	**0.082**	**10.043**	**0.042**
9	3	3	2	0.6	15	0.15	**0.106**	**10.064**	**0.053**

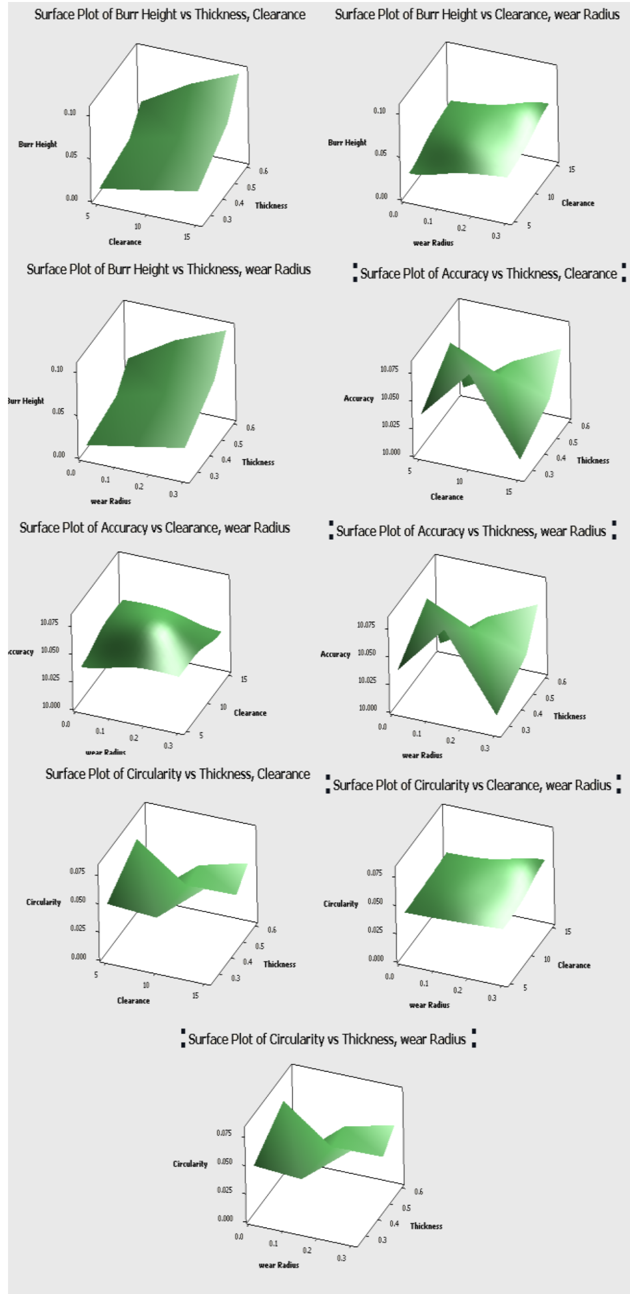


Figure: 5.3 Experimental results

` The transformation of S-N Ratio values from the original response values was the initial step. For that the equations of "larger the better", "smaller the better" were used. Subsequent analysis was carried out on the basis of these S/N ratio values are given in the Table.

Table 5.4Signal-to-Noise ratios

Run No.	RESPONSE VALUE			S/N RATIO		
	Average Burr Height in µ	Average Accuracy (Ø in mm)	Average Circularity (Ø in mm)	Average Burr Height(LB)	Average Accuracy(HB)	Average Circularity(HB)
1	0.013	10.036	0.048	-37.72	-20.03	-26.38
2	0.023	10.082	0.045	-32.77	-20.07	-26.94
3	0.034	10.014	0.08	-29.37	-20.01	-21.94
4	0.024	10.065	0.07	-32.40	-20.06	-23.10
5	0.038	10.045	0.038	-28.40	-20.04	-28.40
6	0.067	10.033	0.039	-23.48	-20.03	-28.18
7	0.049	10.01	0.008	-26.20	-20.01	-41.94
8	0.082	10.043	0.042	-21.72	-20.04	-27.54
9	0.106	10.064	0.053	-19.49	-20.06	-25.51

In the 2nd step of the grey relational analysis, pre-processing of the data was first performed for normalizing the raw data for analysis. This is shown in Table 5. Yij is normalized as Zij (0 = Z= 1) by the following formula to avoid the effect of adopting different units and to reduce the variability.

Table 5.5 Normalized Signal-to-Noise ratios

Run No.	Parameters			NORMALISED S/N RATIO		
	Thickness in MM	Clearance %	Redius	Average Burr Height(LB)	Average Accuracy(HB)	Average Circularity(HB)
1	0.25	5	0.01	1.00	0.6	0.8
2	0.25	10	0.15	0.73	0.0	0.8
3	0.25	15	0.3	0.54	1.0	1.0
4	0.5	5	0.15	0.71	0.2	0.9
5	0.5	10	0.3	0.49	0.5	0.7
6	0.5	15	0.01	0.22	0.7	0.7
7	0.6	5	0.3	0.37	1.0	0.0
8	0.6	10	0.01	0.12	0.5	0.7
9	0.6	15	0.15	0.00	0.2	0.8

The grey relational coefficient is calculated to express the relationship between the ideal (best) and actual normalized experimental results. Before that the deviation sequence for the reference and comparability sequence were found out. These are given in Table.

Table 5.6 Deviation sequences

Run No.	Parameters			DEVIATION SEQUENCE		
	Thickness in MM	Clearance %	Redius	Average Burr Height(LB)	Average Accuracy(HB)	Average Circularity(HB)
1	0.25	5	0.01	0.00	0.4	0.2
2	0.25	10	0.15	0.27	1.0	0.2
3	0.25	15	0.3	0.46	0.0	0.0
4	0.5	5	0.15	0.29	0.8	0.1
5	0.5	10	0.3	0.51	0.5	0.3
6	0.5	15	0.01	0.78	0.3	0.3
7	0.6	5	0.3	0.63	0.0	1.0
8	0.6	10	0.01	0.88	0.5	0.3
9	0.6	15	0.15	1.00	0.8	0.2

The grey relational grade was determined by averaging the grey relational coefficient corresponding to each performance characteristic. It is given in the Table 8. The overall performance characteristic of the multiple response process depends on the calculated grey relational grade. [23]

Table 5.7 Grey Relational Co-efficient& Grade

Run No.	Parameters			GREY RELATIONAL COEFFICIENT			GREY RELATIONAL GRADE	RANK
	Thickness in MM	Clearance %	Redius	Average Burr Height(LB)	Average Accuracy(HB)	Average Circularity(HB)		
1	0.25	5	0.01	1.00	0.6	0.7	1.82	1
2	0.25	10	0.15	0.65	0.3	0.7	1.20	7
3	0.25	15	0.3	0.52	0.9	1.0	1.79	2
4	0.5	5	0.15	0.63	0.4	0.9	1.32	4
5	0.5	10	0.3	0.49	0.5	0.6	1.21	5
6	0.5	15	0.01	0.39	0.6	0.6	1.21	6
7	0.6	5	0.3	0.44	1.0	0.3	1.60	3
8	0.6	10	0.01	0.36	0.5	0.6	1.10	8
9	0.6	15	0.15	0.33	0.4	0.7	0.98	9

It is last step to determine the Optimal Factor and its Level Combination. The fig 6 shows the Grey relational grades for Burr Height, Accuracy & Circularity. Since the experimental design is orthogonal, it is possible to separate out the effect of each parameter on the grey relational grade at different levels. For example, the mean of the grey relational grade for the thickness at levels 1, 2 and 3 can be calculated by averaging the grey relational. The mean of the grey relational grade for each level of the Blanking parameters is summarized and shown in Table.

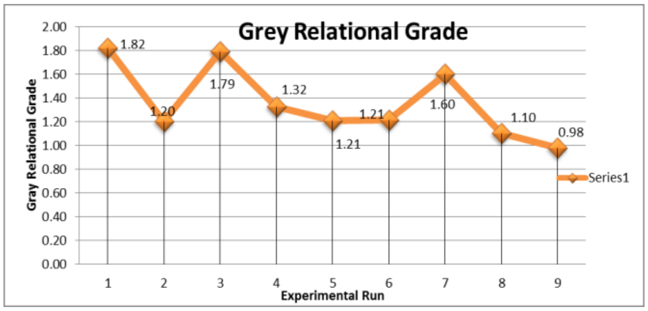
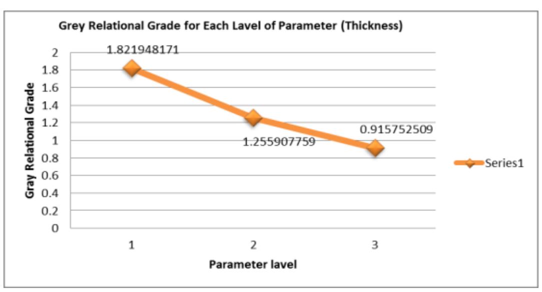


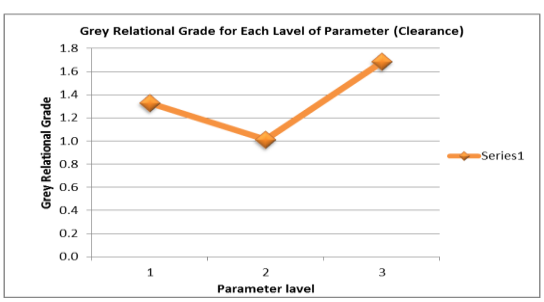
Figure: 5.4Grey Relational Grades

The larger the grey relational grade, the better is the multiple performance characteristics.[13] However, the relative importance among the machining parameters for the multiple performance characteristics still needs to be known, so that the optimal combinations of parameter levels can be determined more accurately. With the help of fig 7 and Table 10, the optimal parameter combination was determined as A1 (Sheet thickness, 0.25mm), B1 (Clearance 5%) and C1 (Wear radius, 0.01).

Table: 5.8 Individual Effects of input parameters on the Grey Relational Grade.

Parameters	Lavel 1	Lavel 2	Lavel 3	Max-Min	Rank
Thickness	1.821948171	1.255907759	0.915752509	0.906195662	1
Clearance	1.3	1.013008601	1.682757026	0.669748425	2
Wear Redius	1.522308312	1.808629209	1.718671492	0.286320897	3





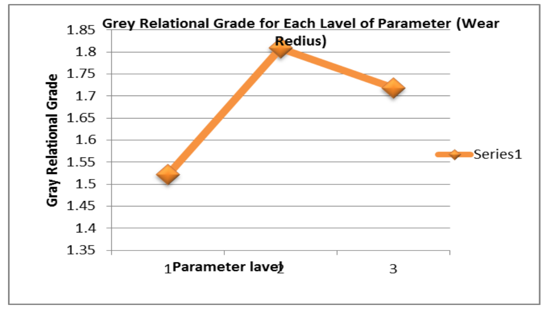


Figure: 5.5Grey relational grades for each level of parameters

5.3 Confirming Results

The Confirmation for the optimal process parameters with its level has conduct to evaluate quality characteristics for Blanking of medium carbon steel sheet. Table 12 shows highest grey relational grade, indicating the initial process parameters set of A1B1C1 for the best multiple performance characteristics among the nine experiments. Table 14 shows the comparison of the experimental results for the conditions (A1B1C1) with predicted result for optimal (A1B1C1) Blanking process parameters.

The predicted Values were obtained by

Predicted Response=Average of A1 + Average of B1 + Average of C1 – 2 x Mean of response (Yij)

The response value obtained from the experiment are Minimum Burr height = 0.013mm, Accuracy of Blank = 10.036mm, and Circularity of Blank = 0.048mm. The comparison is shows the good agreement between the predicted and experimental values.

Table 5.9 Confirmation Result

	Optimal Process Parameters	
	Predicted	**Experimented**
Level	**A1B1C1**	**A1B1C1**
Burr Height	0.013	0.012
Accuracy of Blank	10.036	10.081
Circularity of Blank	0.048	0.043

VI. CONCLUSION

The developed experimental investigation of the sheet metal blanking process makes it possible to study the effects of process parameters such as the material type, the punch-die clearance, the thickness of the sheet and the blank holder force and their interactions on the geometry of the sheared edge especially the burrs height. In general, clearance plays a key role in both product quality and the service life of dies. A good clearance design not only increases the quality of product manufactured, but also reduces product's burr. As a result, the wear of punches and dies can be greatly reduced and the life expectancy of punching dies increased. More punching times is positively related to bigger wear, while less punching times is related to smaller wear.

The quality of a product is the main factor for showing growth of a company. The quality of the product mainly depends upon the material and process parameters. Optimization technique plays a vital role to increase the quality of the product. To overcome the shortage of regression analysis and factor analysis, multi-attribute method, Grey relational analysis (GRA) has been proposed to solve the problem. The Grey Relational Analysis (GRA) associated with the Taguchi method represents a rather new approach to optimization. While only one outcome is optimized in the Taguchi method, multiple outcomes can be optimized in a Grey Relational Analysis. Grey relation analysis is an effective means of analyzing the relationship between sequences with less data and can analyze many factors that can overcome the disadvantages of statistical method.

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