CHAPTER 3

EXPERIMENTAL DESIGN

3.1 INTRODUCTION

The experimental design methodology is very important in maintaining the reliability of entire research work. It is useful for conducting experiments, recording the experimental results, and analysis of the results. The methodology for the present research work has been designed effectively to conduct least number of experiments to study the entire spectrum of levels of ECMM process parameters for Maximum MRR on Nickel and its alloys. The reduction in number of experiments greatly reduces the time and the cost.

In order to understand the effect of each ECMM process parameter on MRR and to identify the significant parameters, experiments need to be conducted by varying the level of each parameter one at a time. This proves very cumbersome as the number of experiments to be conducted increases exponentially with the number of process parameters. Hence, it’s highly difficult to draw any conclusion with minimum number of experiments in this approach. Hence, well planned set of experiments, in which all parameters of interest are varied over a specified range, is a much better approach to obtain systematic data.

Performing the experiments on the sub set of complete set of experiments makes the experimentation process quick and cost effective. The
Taguchi method using the orthogonal array is highly effective in identifying the sub set of experiments to be done to study the complete range and combination of process parameters in minimal number of experiments. Hence, Taguchi methodology is used to for selecting optimum levels of process parameters and number of experiments required to ensure the quality of experimentation. Employing this statistical method to design the experiments and analyze the result sets enables the researcher to find the optimal levels of process parameters qualitatively. Estimation of the experimental error greatly helps to improve the quality of experiments conducted.

The result of analysis using ANOVA is highly effective in deriving inferences regarding the optimum combination of process parameters for maximum MRR. The use of GA helps to optimize the set of process parameters under the process constraints. In this research work Taguchi and ANOVA are utilized to design, experiment, analyze and confirm the results. The GA is used to optimize the process parameters.

The different phases of experiments and the techniques used for the experimentation are given in the following paragraphs.

Phase -I

- Development of experimental setup providing varying range of input parameters in ECMM and measuring the various responses.
- Investigation of the working ranges and the levels of the ECMM process parameters (pilot experiments) affecting the selected quality characteristics, by using one factor at a time approach.
Phase -II
➤ Investigation of the effects of ECMM process parameters on Material Removal Rate (MRR).
➤ Prediction of optimal combinations of ECMM process parameters.
➤ Experimental verification of optimized characteristics using Taguchi’s parameter design approach.

Phase -III
➤ The Taguchi L₁₈ orthogonal array has been used to plan the experiments and to find the effects of process parameters on MRR.

Phase -IV
➤ Development of ANOVA optimization model.
➤ Determination of optimal combination of ECMM process parameters for maximum MRR.

Phase -V
➤ Development of optimization model for optimization using Genetic Algorithms.
➤ Determination of optimal sets of ECMM process parameters.
➤ Verification of coherences between the experimental, ANOVA and GA results.
3.2 TAGUCHI EXPERIMENTAL DESIGN AND ANALYSIS

3.2.1 Taguchi’s Philosophy

Taguchi’s comprehensive system of quality engineering is one of the greatest engineering achievements of the 20th century. His methods mainly focus on the effective application of engineering strategies. It includes both upstream and shop-floor quality engineering. Upstream methods efficiently use small-scale experiments to reduce variability and remain cost-effective, and robust designs for large-scale production. Shop-floor techniques provide cost-based, real time methods for monitoring and maintaining quality in production. The farther upstream a quality method is applied, the greater leverages it produces on the improvement.

Taguchi’s philosophy is founded on the following three very simple and fundamental concepts (Phillip J. Ross 1988):

- Quality should be designed into the product and not inspected into it.
- Quality is best achieved by minimizing the deviations from the target. The product or process should be so designed that it is immune to uncontrollable environmental variables.
- The cost of quality should be measured as a function of deviation from the standard and the losses should be measured system-wide.

Taguchi proposes an “off-line” strategy for quality improvement as an alternative to an attempt to inspect quality into a product on the production line. Taguchi observes that poor quality cannot be improved by the process of inspection, screening and salvaging since no amount of inspection can put
quality back into the product. Taguchi recommends a three-stage process: System Design, Parameter Design and Tolerance Design (Phillip J. Ross 1988). In the present work Taguchi’s Parameter Design approach is used to study the effect of process parameters on the various responses of the ECMM process.

3.2.2 Experimental Design Strategy

Taguchi recommends orthogonal array (OA) for layout of experiments. These OA’s are generalized Graeco-Latin squares. To design an experiment, suitable OA is to be selected. Then the parameters and interactions of interest are to be assigned to appropriate columns. Use of linear graphs and triangular tables suggested by Taguchi makes the assignment of parameters simple. The array forces all experimenters to design almost identical experiments (Roy R.K 1990).

In the Taguchi method the results of the experiments are analyzed to achieve one or more of the following objectives (Phillip J. Ross 1988):

- To establish the best or the optimum condition for a product or process
- To estimate the contribution of individual parameters and interactions
- To estimate the response under the optimum condition

The optimum condition is identified by studying the main effects of each of the process parameters. The main effects indicate the general trends of influence of each parameter. The knowledge about individual parameters and its contributions is a key in deciding the nature of control to be established on
a production process. The analysis of variance (ANOVA) is a statistical treatment most commonly applied to the results of the experiments in determining the percent contribution of each parameter against a stated level of confidence. Study of ANOVA table for a given analysis helps to determine which of the parameters need control (Phillip J. Ross 1988).

Taguchi suggests (Roy R.K 1990) two different routes to carry out the complete analysis. First, as a standard approach, the results of a single run or the average of repetitive runs are processed through main effect and ANOVA analysis. In the second approach, as per Taguchi’s recommendations, multiple runs are used to analyze Signal-to-Noise ratio (S/N). The S/N ratio is a concurrent quality metric linked to the loss function (Barker T.B 2005). By maximizing the S/N ratio, the loss associated can be minimized. It is sufficient to generate repetitions at each experimental condition of the controllable parameters and analyze them using an appropriate S/N ratio.

In the present investigation, the S/N data analysis has been performed. The effects of the selected ECMM process parameters for maximum MRR have been investigated through the plots of the main effects. The optimum condition for maximum MRR has been established through S/N data. No outer array has been used and instead, experiments have been conducted two times at each experimental condition.

**Loss Function**

The heart of Taguchi method is his definition of the nebulous and elusive term quality as the characteristic that avoids loss to the society from the time the product is shipped. Loss is measured in terms of monetary units and
is related to quantifiable product characteristic. Taguchi defines quality loss via his loss function. He unites the financial loss with the functional specification through a quadratic relationship that comes from a Taylor series expansion. The quadratic function takes the form of a parabola. Taguchi defines the loss function as a quantity proportional to the deviation from the nominal quality characteristic. He has found the following quadratic form to be a workable function (Roy R.K 1990):

\[ L(y) = k (y-m)^2 \]  \hspace{1cm} (3.1)

Where,
\[ L = \text{Loss in monetary units} \]
\[ m = \text{value at which the characteristic should be set} \]
\[ y = \text{actual value of the characteristic} \]
\[ k = \text{constant depending on the magnitude of the characteristic and the monetary unit involved} \]

![Figure 3.1: Taguchi Loss Function](image)

The characteristics of the loss function are (Roy R.K 1990):
- The farther the product’s characteristic varies from the target value, the greater is the loss. The loss must be zero when the quality characteristic of a product meets its target value.

- The loss is a continuous function and not a sudden step as in the case of traditional goal post approach. This characteristic of the continuous loss function illustrates the point that merely making a product within the specification limits does not necessarily mean that product is of good quality.

The loss-function can also be applied to product characteristics other than the situation where the nominal value is the best value (m). The loss-function for a smaller is better type of product characteristic (LB) is shown in figure 3.2. The loss function is identical to the “nominal is the best” type of situation when m=0, which is the best value for “smaller the better” characteristic (no negative value). The loss function for a “larger the better” type of product characteristic (HB) is also shown in figure 3.2, where m = 0.

### 3.2.3 Signal to Noise Ratio

The loss-function discussed above is an effective figure of merit for making engineering design decisions. However, to establish an appropriate loss function with its $k$ value to use as a figure of merit is not always cost effective and easy. In order to address this issue, Taguchi created a transform function for the loss-function which is named as signal-to-noise (S/N) ratio (Barker T.B 2005).
The S/N ratio, as stated earlier, is a concurrent statistic. A concurrent statistic is able to look at two characteristics of a distribution and combine these characteristics into a single figure of merit. The S/N ratio combines both the parameters (the mean level of the quality characteristic and variance around this mean) into a single metric (Barker T.B 2005).

A high value of S/N ratio implies that signal is much higher than the random effects of noise factors. Process operation consistent with highest S/N ratio always yields optimum quality with minimum variation (Barker T.B 2005). The S/N ratio consolidates several repetitions (at least two data points are required) into one value.

The mean squared deviation (MSD) is a statistical quantity that reflects the deviation from the target value. The quality characteristics are different for MSD expressions. The standard definition of MSD is used for the “nominal is best” characteristic. The unstated target value is zero for “Lower the better”. The inverse of each large value becomes a small value and the unstated target value is zero for “Higher the better”. Hence, the smallest magnitude of MSD is being sought for all the three expressions.

The equation for calculating S/N ratios for “Lower the better” (LB), “Higher the better” (HB) and “Nominal is best” (NB) types of characteristics are as follows (Phillip J. Ross 1988):
Figure 3.2: The Taguchi Loss-Function for HB and LB Characteristics

a. Higher the Better:

\[(S/N)_{HB} = -10\log(MSD_{HB})\]  \hspace{1cm} (3.2)

Where

\[
MSD_{HB} = \frac{1}{R} \sum_{j=1}^{R} \left( \frac{1}{y_j^2} \right)
\]
b. Lower the Better:

\[(S/N)_{LB} = -10 \log(\text{MSD}_{LB}) \]

(3.3)

Where

\[\text{MSD}_{LB} = \frac{1}{R} \sum_{j=1}^{R} (y_j^2)\]


c. Nominal the Best

\[(S/N)_{NB} = -10 \log(\text{MSD}_{NB}) \]

(3.4)

Where

\[\text{MSD}_{NB} = \frac{1}{R} \sum_{j=1}^{R} (y_j - y_o)^2\]

R = Number of repetitions

Relation between S/N Ratio and Loss Function

Single sided quadratic loss function with minimum loss at the zero value of the desired characteristic is shown in figure 3.2. As the value of y increases, the loss grows. Since, loss is to be minimized the target in this situation for y is zero. The basic loss function (Eq. 3.1) is:

\[L(y) = k (y-m)^2\]

If m = 0

\[L(y) = k (y^2)\]

The loss may be generalized by using k=1 and the expected value of loss may be found by summing all the losses for a population and dividing by the number of samples R taken from this population. This in turn gives the following expression (Barker T.B 2005).

\[E_L = \text{Expected loss} = (\Sigma y^2/R)\]

(3.5)

The above expression is a figure of demerit. The negative of this demerit expression produces a positive quality function. Taguchi adds the
final touch to this transformed loss-function by taking the log (base 10) of the negative expected loss and then he multiplies by 10 to put the metric into the decibel terminology (Barker T.B 2005). The final expression for “Lower the better” S/N ratio takes the form of Equation 3.3. The same thought pattern follows in creation of other S/N ratios.

3.2.4 Selection of orthogonal array (OA)

In selecting an appropriate OA, the pre-requisites are (Roy .R.K 1990):

- Selection of process parameters and/or interactions to be evaluated
- Selection of number of levels for the selected parameters

Several methods are suggested by Taguchi to determine the required parameters for inclusion in an experiment (Phillip J. Ross 1988). They are:

a) Brainstorming
b) Flow charting
c) Cause-Effect diagrams

The total Degrees of Freedom (DOF) of an experiment is a direct function of total number of trials. If the number of levels of a parameter increases, the DOF of the parameter also increases since DOF calculated as the number of levels minus one. Thus, increasing the number of levels for a parameter increases the total degrees of freedom in the experiment which in turn increases the total number of trials. Thus, two levels for each parameter are recommended to minimize the number of experiment (Phillip J. Ross 1988). If curved or higher order polynomial relationship between the parameters under study and the response is expected, at least three levels for each parameter
should be considered (Barker T.B 2005). The DOF selected for the process parameters are given in table 3.1.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>EC</th>
<th>V</th>
<th>C</th>
<th>DC</th>
<th>F</th>
<th>Error</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>DOF</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>7</td>
<td>17</td>
</tr>
</tbody>
</table>

The standard two level and three level arrays (Taguchi 1979) are:

- Two level arrays: L_4, L_8, L_{12}, L_{16}, L_{32}
- Three level arrays: L_9, L_{18}, L_{27}

The number as subscript in the array designation indicates the number of trials in that array. The total degrees of freedom (DOF) available in an orthogonal array are equal to the number of trials minus one (Phillip J. Ross 1988):

\[ f_{L_N} = N - 1 \]  \hspace{1cm} (3.6)

Where,
- \( f_{L_N} \) = Total degrees of freedom of an OA
- \( L_N \) = OA designation
- \( N \) = Number of trials

When a particular OA is selected for an experiment, the inequality \( f_{L_N} \geq \) Total degrees of freedom required for parameters and interactions must be satisfied.

In accordance to the total degree of freedom (17), the \( L_{18} \) orthogonal array has been selected for this experiment. The \( L_{18} \) orthogonal array has 8 columns and 18 rows and it can handle one two-level parameter and seven three-level process parameters at most. Since, our experiment needs only five three-level process parameters \( L_{18} \) orthogonal array is most suitable. The array
selected has 5 columns and 18 rows and hence 18 experiments are needed to study the effects of all the five process parameters.

**Figure 3.3: TaguchiExperimental Design and Analysis Flow Diagram**

```
Selection of Orthogonal Array (OA)

<table>
<thead>
<tr>
<th>Decide</th>
<th>Number of parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number of Levels</td>
</tr>
<tr>
<td></td>
<td>Interactions of interest</td>
</tr>
<tr>
<td></td>
<td>Degrees of freedom (DOF) required</td>
</tr>
</tbody>
</table>

Selection of Orthogonal Array (OA)

Assign parameters and interactions to columns of OA using linear graph and / or Triangular tables

Noise ?

Consider noise factors and use appropriate outer array

Decide the number of repetitions (at least two repetitions)

- Run the experiment in random order
- Record the responses
- Determine the S/N ratio

Conduct ANOVA on data

Identify control parameters which affect mean of quality characteristics

Classify the factors and select proper levels

- Predict the mean at the selected levels
- Determine confidence intervals
- Determine optimal range
- Conduct confirmation experiments
- Draw conclusions
```
3.2.5 Assignment of parameters and interaction to the OA

The OA’s have several columns available for assignment of parameters and some columns subsequently can estimate the effect of interactions of these parameters. Taguchi has provided two tools to aid in the assignment of parameters and interactions to arrays (Phillip J. Ross 1988):

1. Linear graphs
2. Triangular tables

Each OA has a particular set of linear graphs and a triangular table associated with it. The linear graphs indicate various columns to which parameters may be assigned and the columns subsequently evaluate the interaction of these parameters. The triangular tables contain all the possible interactions between parameters (columns). Using the linear graphs and / or the triangular table of the selected OA, the parameters and interactions are assigned to the columns of the OA.

3.2.6 Experimentation and data collection

The experiment is performed against each trial condition. Each experiment at a trial condition is repeated. Randomization has been carried to reduce bias in the experiment. The data are recorded against each trial condition and S/N ratios of the repeated data points are calculated and recorded against each trial condition.
3.2.7 Data analysis

A number of methods have been suggested by Taguchi for analyzing the data: observation method, ranking method, column effect method, ANOVA, S/N ANOVA, plot of average response curves, interaction graphs etc. (Phillip J. Ross 1988). However, in the present investigation the following methods have been used:

- Plot of mean response curves
- ANOVA for data
- S/N response graphs

The plot of average responses at each level of a parameter indicates the trend. It is a pictorial representation of the effect of parameter on the response. The change in the response characteristic with the change in levels of a parameter can easily be visualized from these curves. Typically, ANOVA for OA’s are conducted in the same manner as other structured experiments (Phillip J. Ross 1988). The S/N ratio is treated as a response of the experiment, which is a measure of the variation within a trial when noise factors are present. A standard ANOVA can be conducted on S/N ratio which will identify the significant parameters (mean and variation).

3.2.8 Parameter classification and selection of optimal levels

When the ANOVA on the data (identifies control parameters which affect average) and S/N data (identifies control parameters which affect variation) are completed, the control parameters may be put into four classes (Phillip J. Ross 1988):
Class I : Parameters which affect both average and variation  
(Significant in ANOVA)

Class II : Parameters which affect variation only  
(Significant in S/N ANOVA only)

Class III : Parameters which affect average only  
(Significant in data ANOVA only)

Class IV : Parameters which affect nothing,  
(Not significant in both ANOVAs)

The parameters design strategy is to select the proper levels of class I and class II parameters to reduce variation and class III parameters to adjust the average to the target value. Class IV parameters may be set at the most economical levels since nothing is affected.

3.2.9 Prediction of the mean

After determination of the optimum condition, the mean of the response ($\mu$) at the optimum condition is predicted. The mean is estimated only from the significant parameters. The ANOVA identifies the significant parameters. Suppose, parameters A and B are significant and $A_2B_2$ (second level of $A=A_2$, second level of $B=B_2$) is the optimal treatment condition. Then, the mean at the optimal condition (optimal value of the response characteristic) is estimated as (Phillip J. Ross 1988):

$$T = \bar{A}_2, \bar{B}_2$$

Where,

$T$ = Overall mean of the response

$A_2, B_2$ = Average values of response at the second levels of parameters A and B respectively

It may also happen that the prescribed combination of
parameter levels (optimal treatment condition) is identical to one of those in the experiment. If this situation exists, then the most direct way to estimate the mean for that treatment condition is to average out all the results for the trials which are set at those particular levels (Phillip J. Ross 1988).

### 3.2.10 Determination of confidence interval

The estimate of the mean ($\mu$) is only a point estimate based on the average of results obtained from the experiment. Statistically this provides a 50% chance of the true average being greater than $\mu$. It is therefore customary to represent the values of a statistical parameter as a range within which it is likely to fall, for a given level of confidence (Phillip J. Ross 1988). This range is termed as the confidence interval (CI). In other words, the confidence interval is a maximum and minimum value between which the true average should fall at some stated percentage of confidence.

The following two types of confidence interval are suggested by Taguchi in regards to the estimated mean of the optimal treatment condition.

1. Around the estimated average of a treatment condition predicted from the experiment. This type of confidence interval is designated as $\text{CI}_{\text{POP}}$ (confidence interval for the population).

2. Around the estimated average of a treatment condition used in a confirmation experiment to verify predictions. This type of confidence interval is designated as $\text{CI}_{\text{CE}}$ (confidence interval for a sample group).
The difference between $CI_{\text{POP}}$ and $CI_{\text{CE}}$ is that $CI_{\text{POP}}$ is for the entire population i.e., all parts made under the specified conditions, and $CI_{\text{CE}}$ is for only a sample group made under the specified conditions. Because of the smaller size (in confirmation experiments) relative to entire population, $CI_{\text{CE}}$ must slightly be wider. The expressions for computing the confidence intervals are given below (Roy R.K 1990)

3.3 Machining Performance Evaluation

The machining performance is evaluated by material removal rate (MRR) and Dimensional Deviation. MRR is defined as amount of material removed per unit machining time. Dimensional deviation of the machined micro hole has been considered as machining accuracy criteria. It is the difference between the radius of the machined hole and the radius of the tool electrode. The diameters of holes drilled were measured with the help of an optical microscope. Machining time is noted for each experiment. The lower the dimensional deviation is better the machining performance. The higher the MRR, is better the machining performance. Therefore, the dimensional deviation is the “lower the better” and the MRR is the “Higher the better” performance characteristic respectively.

3.3.1. Material Removal Rate (MRR)

Material removal rate is expressed as the amount of material removed under a period of machining time (T) in minutes and calculated using the following equation.

$$MRR (\text{mm}^3/\text{min}) = \frac{\text{Area of the hole (mm}^2\text{)} \times \text{depth of the hole (mm)}}{\text{Machining Time (min)}}$$

(3.7)
3.3.2 Signal-to-Noise Ratio (S/N Ratio)

In Taguchi design methodology, basically the experimental results are converted into a single quality characteristics evaluation index i.e. S/N ratio. The least variation and the optimal design are obtained by means of the S/N ratio. The benefits of S/N ratio includes increasing the factor weighting effect, decreasing mutual action, simultaneously processing the average and variation, and improving engineering quality. The higher the S/N ratio, the more stable the achievable quality. Depending on the required objective characteristics, different calculation methods can be applied as follows:

The smaller the better (SB) where the objective optimal value is the smaller the better, dimensional deviation.

\[ \eta = -10 \log \left[ \sum_{i=1}^{n} y_i^{-2} \right] \]  \hspace{1cm} (3.8)

The larger the better (LB) where the objective optimal value is larger the better, such as material removal rate.

\[ \eta = -10 \log \left[ \sum_{i=1}^{n} y_i^{-2} \right] \]  \hspace{1cm} (3.9)

where \( \eta = \) S/N ratio and \( y = \) result of experiment (MRR).

3.3.3 Analysis of variance (ANOVA)

The S/N ratio determined from the experimental values were statistically studied by ANOVA to explore the effects of each machining parameter on the observed values and to elucidate which machining parameter significantly affected the MRR. Different software are available to perform ANOVA such as “DESIGN EXPERT”, “Minitab 15” etc. In this work
“Minitab 15” has been used for the analysis purpose. The related equations are as follows:

\[ S_m = \frac{\left( \sum \eta_i \right)^2}{18} \]  \hspace{2cm} (3.10)

\[ S_T = \sum \eta_i^2 - S_m \]  \hspace{2cm} (3.11)

\[ S_A = \frac{\left( \sum \eta_{Ai} \right)^2}{N - S_m} \]  \hspace{2cm} (3.12)

\[ S_E = S_T - \sum S_A \]  \hspace{2cm} (3.13)

\[ V_A = S_A / f_A \]  \hspace{2cm} (3.14)

\[ F_{AO} = V_A / V_E \]  \hspace{2cm} (3.15)

Where,

- \( S_m \) = sum of squares based on the mean
- \( S_T \) = sum of squares based on the total variation
- \( S_A \) = sum of squares based on the parameter A (like electrolyte concentration, voltage, current, duty cycle or frequency)
- \( S_E \) = sum of squares based on the error
- \( \eta_i \) = value of \( \eta \) in the \( i \)th experiment (\( i = 1 \) to 18)
- \( \sum \eta_{Ai} \) = sum of the \( i \)th level parameter A (\( i = 1, 2 \) or \( i = 1–3 \))
- \( N \) = number of repetition at each level parameter A,
- \( f_A \) = number of degrees of freedom of parameter A
- \( V_A \) = variance of parameter A
- \( F_{AO} \) = F–test parameter for A

F-test can be used to determine which process parameters have significant effect on the performance characteristics. P-test is designed to know whether factor is significant or not depending on its value. If P value is less than alpha value which is generally taken as 0.05, then factor have significant effect on performance characteristics.
The experimentations are conducted after setting the desired values of process parameters like voltage, current, duty cycle, and frequency with the microcontroller based pulsed power supply system. Hence, the calculation of duty cycle has to be done in advance. In a pulsed power supply, current and voltage switches between 0 and peak values in a set frequency.

Duty cycle is the ratio between the pulse ON time in relation to the total experiment time i.e. sum of ON and OFF time. The ON time and OFF time are calculated using following equations.

\[
\text{Duty Cycle} = \frac{T_{\text{on}}(\text{ms})}{T_{\text{total}}(\text{ms})} \quad (3.16)
\]
\[
T_{\text{total}} = T_{\text{on}} + T_{\text{off}} \quad (3.17)
\]
\[
T_{\text{on}} = \text{Duty cycle} \times T_{\text{total}} \quad (3.18)
\]
\[
\text{Frequency} = \frac{1}{T_{\text{total}}} \quad (3.19)
\]

Table 3.2 and table 3.3 shows ON time and OFF time values required to set for a particular frequency and duty cycles.

<table>
<thead>
<tr>
<th>Frequency (Hz)</th>
<th>Total Time (ms)</th>
<th>Duty cycle</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>33.3%</td>
</tr>
<tr>
<td></td>
<td>On time (ms)</td>
<td>Off Time (ms)</td>
</tr>
<tr>
<td>30</td>
<td>33.33</td>
<td>11.90</td>
</tr>
<tr>
<td>40</td>
<td>25</td>
<td>8.33</td>
</tr>
<tr>
<td>50</td>
<td>20</td>
<td>6.66</td>
</tr>
<tr>
<td>60</td>
<td>33.33</td>
<td>5.55</td>
</tr>
</tbody>
</table>
Table 3.3: Calculated ON time and OFF time - SDSS and Inconel 600

<table>
<thead>
<tr>
<th>Frequency (Hz)</th>
<th>Total Time (ms)</th>
<th>Duty cycle</th>
<th>On time (ms)</th>
<th>Off Time (ms)</th>
<th>On time (ms)</th>
<th>Off Time (ms)</th>
<th>On time (ms)</th>
<th>Off Time (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>33.3%</td>
<td>50.00%</td>
<td>66.66%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>30</td>
<td>33.33</td>
<td>11.11</td>
<td>22.22</td>
<td>16.67</td>
<td>16.66</td>
<td>22.22</td>
<td>11.11</td>
<td></td>
</tr>
<tr>
<td>40</td>
<td>25</td>
<td>8.33</td>
<td>16.67</td>
<td>12.5</td>
<td>12.5</td>
<td>16.67</td>
<td>8.33</td>
<td></td>
</tr>
<tr>
<td>50</td>
<td>20</td>
<td>6.67</td>
<td>13.33</td>
<td>10</td>
<td>10</td>
<td>13.33</td>
<td>6.67</td>
<td></td>
</tr>
</tbody>
</table>

The amplitude of the pulse (ON TIME) is called the peak current. The level of energy which is equal to D.C. level when time (duty cycle) is considered, is called as average current or machining current. The relationship between average and peak current is given by:

\[
\text{Average current} = \text{Peak current} \times \text{Duty cycle} \quad (3.20)
\]

Peak current values are to be set accordingly for getting required machining current i.e. average current. The calculated average current for Nickel, SDSS, and Inconel 600 are tabulated in table 3.4 and table 3.5 respectively.

Table 3.4: Average Current - NICKEL

<table>
<thead>
<tr>
<th>Average current (amp)</th>
<th>Peak current (amp)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DC 33.33%</td>
</tr>
<tr>
<td>0.1</td>
<td>0.30</td>
</tr>
<tr>
<td>0.3</td>
<td>0.90</td>
</tr>
<tr>
<td>0.5</td>
<td>1.50</td>
</tr>
</tbody>
</table>
Table 3.5: Average Current - SDSS and Inconel 600

<table>
<thead>
<tr>
<th>Average current (amp)</th>
<th>Peak current (amp)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DC 33.33%</td>
</tr>
<tr>
<td>0.6</td>
<td>1.8</td>
</tr>
<tr>
<td>0.8</td>
<td>2.4</td>
</tr>
<tr>
<td>1.0</td>
<td>3.0</td>
</tr>
</tbody>
</table>

Similarly calculation is made for average voltage using equation

\[
\text{Average voltage} = \text{Peak voltage} \times \text{Duty cycle.} \tag{3.21}
\]

The required machining voltage (average voltage) can be obtained by setting appropriate Peak voltage. The calculated machining voltage for Nickel, SDSS, and Inconel 600 are given in table 3.6 and table 3.7 respectively.

Table 3.6: Average Voltage - NICKEL

<table>
<thead>
<tr>
<th>Average voltage (volts)</th>
<th>Peak voltage (volts)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DC 33.33%</td>
</tr>
<tr>
<td>3.5</td>
<td>10.50</td>
</tr>
<tr>
<td>5.0</td>
<td>7.00</td>
</tr>
<tr>
<td>6.5</td>
<td>5.25</td>
</tr>
</tbody>
</table>

Table 3.7: Average voltage - SDSS and Inconel 600

<table>
<thead>
<tr>
<th>Average voltage (volts)</th>
<th>Peak voltage (volts)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DC 33.33%</td>
</tr>
<tr>
<td>8</td>
<td>24</td>
</tr>
<tr>
<td>9</td>
<td>27</td>
</tr>
<tr>
<td>10</td>
<td>30</td>
</tr>
</tbody>
</table>
During machining, a bubble coming from the bottom side of the work piece indicates that the hole reached the bottom. It should be observed carefully to get accurate results. Machining to be continued till a circular hole at the exit side is machined. For each experiment machining time is noted. With the help of optical microscope, the diameter of the holes drilled is recorded.

Material Removal Rate (MRR) is calculated by using machining time, area of hole and sheet thickness for each experimental combination. Using calculated MRR values S/N ratio for each experiment were calculated. ANOVA is performed to determine, factor affects the MRR significantly. Finally the experimental values are validated with Genetic Algorithms.

3.3.4 Confirmation Test

The optimum level of process parameters has been determined by using S/N ratio values. Once the optimal level of the process parameters has been selected, the final step is to predict and verify the improvement of the performance characteristic using the optimal level of the process parameters. The purpose of conformation test is to validate the conclusions drawn during analysis phase.

The predicted or estimated S/N ratio $\eta$ using optimal levels of process parameters can be calculated as;

$$\eta = \eta_m + \sum_{i=1}^{q} (\eta_i - \eta_m)$$  \hspace{1cm} (3.22)

where,

$\eta_m = \text{total mean of S/N ratio}$
\[ q = \text{number of significant parameters} \]
\[ \eta_i = \text{mean of S/N ratio at optimum level} \]

After predicting the response (S/N ratio), a confirmation experiment is designed and conducted with the optimal levels of the machining parameters to verify the improvement of performance characteristic.

### 3.4. GENETIC ALGORITHMS (GA)

#### 3.4.1 Introduction

Genetic algorithms belong to the larger class of evolutionary algorithms (EA), which generate solutions to optimization problems using techniques inspired by natural evolution, such as inheritance, mutation, selection, and crossover. Decision making situation occurs in all fields like science, technology and management, etc. where GA is applied with an objective to maximize or minimize a task. In order to solve the problems related to inventory, transportation, queuing, scheduling etc., many optimization procedures have been developed over the past six decades.

Most of the traditional optimization procedures end its search in the “local optima” rather than finding the “global optima”. To overcome this, many number of non traditional search and optimization algorithms were developed over the past four decades. They are,

1. Genetic Algorithm (GA)
2. Simulated Annealing (SA)
3. Tabu Search (TS)
4. Ant Colony Optimization (ACO)
5. Particle Swarm Optimization (PSO)
6. Scatter Search (SS), etc.

Genetic algorithms (GA) is computerized search and optimization algorithm based on the mechanics of natural genetics and natural selection (Goldberg D. 2000). It was inspired by Darwin’s theory about evolution. Prof. Holland of University of Michigan envisaged the concept of GA. Number of students and researchers have contributed for the development of this field.

The optimization model for the ECMM process is multi-variable non-linear objective function with non-linear constraints and is highly complicated to solve using the traditional optimization methodologies. The Genetic Algorithm (GA) in particular have proven to be a powerful tool to solve such complex optimization problems without any approximation. Genetic Algorithms are computerized search and optimization algorithms belonging to the class of evolutionary algorithms (EA) and works with a set of solutions.

The operation of GA begins with generation of a set of random solution. The fitness value of each solution has to be evaluated. The higher the fitness value, the better the solution. The generated population is then operated by the reproduction, crossover and mutation operators to create the new population which is evaluated and tested for the termination criterion. One cycle of population evaluation and subsequent three GA operations constitute a generation in the GA terminology. The GA operations are continued until the termination criterion is met for a specified number of generations (Deb Kalyanmoy 1995).
Figure 3.4: Structure of Genetic Algorithm
A simple genetic algorithm starts with a set of randomly generated initial population. The basic steps involved in the genetic algorithm are given below.


2. [Fitness] Evaluate the fitness $F(X)$ of each chromosome $X$ in the population.

3. [New Population] Create a new population by repeating following steps until new population is complete.

4. [Selection] Select two parent chromosomes from a population according to their fitness (the better fitness, the bigger chance to be selected).

5. [Crossover] With a crossover probability cross over the parents to form new offspring (children). If no crossover was performed, offspring is the exact copy of parents.


7. [Accepting] Place new offspring in the new population.

8. [Replace] Use new generated population for a further run of the algorithm.

9. [Test] If the end condition is satisfied, stop, and return the best solution in current population.


### 3.4.2 Implementation of GA

The principle of natural genetics is that ‘Fit parents would yield fit offspring’. GA has wide variety of applications in engineering problems because of simplicity and ease of operation. The minimum or maximum of a function is found based on the variation of $X_1, X_2, X_3 \ldots X_n$ beginning with one or more starting point. GA evaluates a set of points, and the basic element of GA consists of a chromosome and fitness value. The fitness value describes
how well an individual can adapt to survival and mating. In this study, the basic elements of GA consists of a value of electrolyte concentration, machining current, machining voltage, duty cycle and frequency.

GA works on the basis of binary code in the form of 0 and 1. An individual in GA is denoted by $I = \{EC, C, V, DC, F, f(EC, C, V, DC, F)\}$. A set of search individual is called a population and general structure of GA and convergence GA result depicting. The parameters used in GA are; population size = 100, length of chromosome = 20, selection operator = stochastic uniform, crossover probability = 0.8, mutation probability = 0.2, fitness parameter = MRR. The objective function is given by $MRR = f(EC,C,V,DC,F)$.

Genetic algorithms can be used to solve the constrained optimization problems as well as unconstrained optimization problems. GA can be used to solve maximization problems as well as minimization problems. In the chapter, a constrained optimization problem is considered to explain the implementation of genetic algorithm. Let us consider the following maximization problem.

Subject to the constraints maximize $f(x)$.

$$X_i^L \leq X_i \leq X_i^U \text{ for } i = 1, 2, 3 \ldots \ldots N \quad (3.23)$$

The operation of GA begins with a population of encoded solution. Each string is evaluated to find the fitness value. Then the population is operated by the three important genetic operators to create a new population. The performance of GA is mainly influenced by these three operators.
1. Selection of Reproduction
2. Crossover
3. Mutation

**Fitness Function**

GA mimics the survival of the fittest principle of nature to make a search process. Therefore, GA is naturally suitable for solving maximization problems. Minimization problems are transformed into maximization problems by some suitable transformation. Fitness function $F(x)$ is derived from the objective function and used in successive genetic operations. Certain genetic operators require that fitness function be non-negative, although certain operators do not have this requirement. Following are the fitness function for different objective functions.

$$F(X) = f(X) \quad \text{for maximization problems} \quad (3.24)$$

$$F(X) = \frac{1}{f(X)} \quad \text{for minimization problems, if } f(X) \neq 0 \quad (3.25)$$

$$F(X) = \frac{1}{(1+f(X))} \quad \text{for minimization problems, if } f(X) = 0 \quad (3.26)$$

**Selection or Reproduction**

Selection or reproduction is usually the first operator applied on population. Reproduction operator selects the best chromosomes from the population to form a matting pool for next operation. Many number of selection operators were used in the genetic algorithm literature. The essential ideas in all of them is, the above average strings are picked from the current population and their multiple copies are inserted in the matting pool in
a probabilistic manner. In genetic algorithm, the probability of selection $P_s$ of each string depends on the fitness of individual string. The probability of selection is calculated using the following equation:

$$\text{Probability of selection of } i^{\text{th}} \text{ string } p_s = \frac{F_i}{\sum_{j=1}^{n} F_j} \quad (3.27)$$

Where $F_i$ - Fitness value of $i^{\text{th}}$ string, $n$ - Population size

The string has more probability of selection will get more chance for selection.

**Crossover or Recombination**

Crossover operator produces new offspring in combining the information contained in two parents. The crossover operation is performed with a probability of crossover $P_c$, crossover occurs only if the random number generated is less than the crossover probability $P_c$ (like flipping of a coin with a probability) otherwise the two strings repeated without any change. Depending on the representation of the variables, the offspring will be subjected to crossover.

**Mutation**

After crossover operation is performed, the string is subjected to mutation operation. This is to prevent falling all solutions of the population into a local optimum of solved problem. Mutation operator alters a chromosome locally to hopefully create a better string. The bit wise mutation is performed with a probability of mutation of mutation $P_m$. Mutation occurs only if the random number generated is less than the mutation probability $P_m$ (like flipping of a coin with a probability) otherwise the bit kept unchanged.
A simple genetic algorithm treats the mutation only as a secondary operator with roll of restoring lost genetic materials. The mutation is also used to maintain diversity in the population. For example, consider the following strings.

\[
\begin{align*}
1 & 1 & 1 & 0 \\
1 & 0 & 0 & 1 \\
1 & 1 & 0 & 0 \\
1 & 0 & 0 & 0
\end{align*}
\]

Notice that all four strings have a ‘1’ in the leftmost bit position. If the true optimum solution requires a ‘0’ in the position, the selection or cross operators will not change the value of the bit. The mutation operator will change its value. Following are the mutation methods available for different coded string.

1. Binary Valued Mutation
2. Real Valued Mutation

### 3.4.3 Experimental Validation (GA)

The optimized parameters obtained for the maximum MRR shows that as the generation progresses the solutions are approaching optimum. A validation of experiment is conducted using the optimum process parameters. It is observed that MRR obtained from validation experiments is closer to the optimized MRR obtained using GAs. It infers the practical applicability of the combined use of Taguchi methodology, ANOVA and GAs for optimizing the ECMM process parameters to obtain maximum MRR.