Multi Response optimization of characteristics of AISI D2 steel using utility concept and harmonic search method machined with different tool materials

Thesis Submitted in Partial Fulfillment of the Requirements for the Award of

> Master of Technology In Production Engineering

> > By

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National Institute Of Technology, Rourkela

CERTIFICATE

This is to certify that the thesis entitled, "Multi Response optimization of characteristics of AISI D2 steel using utility concept and harmonic search method machined with different tool materials" submitted by Ms. Priyanka in partial fulfillment of requirements for the award of Degree of Master of Technology in Mechanical Engineering with specialization in "Production Engineering" at National Institute of Technology, Rourkela is an authentic work carried out by her under my guidance and supervision. To the best of my knowledge the matter embodied in the thesis has not been submitted to any other University or Institute for the award of any Degree or Diploma.

Date: 01-06-2014

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Abstract

Electrochemical machining (ECM) is widely used in manufacturing industry due to its many superior properties like no tool wear, good surface finish. Any conducting material can be machined with high dimensional accuracy and intricate designs can be easily carved on difficult to machine materials irrespective of their hardness. The magnetic properties and hardness etc. of the substrate material remain unchanged after machining with ECM due to lesser temperature generation during machining. The main challenge for using this method is that the specific energy requirement for the process is very large (about 150 times that required for conventional processes). Hence optimization techniques are necessary to get the best set of parameters in order to enhance the quality of machining. In the present work AISI D2 steel is machined with three different types of tools, copper, brass and graphite. Comparative study of the output responses obtained by machining with different tools was done to examine the advantage provided by individual tool material on the performance characteristics. Design of experiments was carried out using Response surface methodology combined with utility concept to convert the multi response system into an equivalent single response objective function by giving equal weightage to all the responses. Finally the responses were optimized by the nature inspired optimization technique Harmonic search algorithm as it takes lesser time and fewer calculations to optimize the responses. It was found that graphite tool gives the highest value of MRR and lowest value of overcut as compared to copper and brass tool while surface roughness obtained by machining with brass tool was found to be minimum.

Keywords: Electrochemical machining; Copper; Brass; Graphite; Response surface method; AISI D2 steel; Utility concept; Harmonic search algorithm.

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Chapter 1

1.1 Introduction

Electrochemical machining (ECM) is a non-conventional anodic dissolution process in which material removal takes place at atomic level by electrochemical action. The material removal rate depends only on the atomic weight and valence of the work material and not on the mechanical or physical properties of it. So any electrically conductive material can be easily machined irrespective of their hardness, strength or even thermal properties. ECM propounds many advantages over other machining processes however there are several disadvantages also.

Advantages: there is no hydrogen embrittlement of the products because hydrogen evolves at cathode while metal removal takes place due to anodic dissolution at the anode; no effect on ductility, yield strength, ultimate strength and micro hardness of the machined components.

Limitations: specific energy requirement for the process is very large (about 150 times that required for conventional processes). Not suitable for electrically non-conducting materials and jobs with very small dimensions; expensive machines; difficulty in handling and containing of the electrolyte.

Applications: Owing to its innovative nature and numerous material and machining benefits it has very wide cross industry applications. In aerospace industry, ECM is used in the manufacturing of turbine blades and blisks in jet engines and gas turbines, gears, nozzles, manifolds, diffusers etc., in automotive industry, turbochargers, gears, fuel systems, break systems, oil flow features, pistons, shafts, vehicle logos etc., in biomedical industry artificial implants (e.g. hip implants), surgical blades, saws etc., in chemical industry micro reactors, micro heat exchangers etc.

1.2 Fundamental Principle

During ECM, reactions occur at the electrodes i.e. at the anode or work piece and at the cathode or tool when kept in the electrolyte. For Electrochemical machining of steel, generally neutral solution of sodium chloride (NaCl) is taken as electrolyte. When potential difference is applied NaCl and water undergoes ionic dissociation.

NaCl \leftrightarrow Na⁺ + Cl H₂O \leftrightarrow H⁺ + (OH)

Due to potential difference b/w work piece (anode) and tool (cathode), positive ions move towards tool and negative ions move towards work piece. Iron atoms will come out of the anode (work piece) as:

$$Fe = Fe^{++} + 2e^{-}$$
 at anode

Similarly, the hydrogen gas will evolve as,

$$2H^+ + 2e^- \longrightarrow H_2 \uparrow at cathode$$

Within the electrolyte, iron ions would combine with chlorine ions to form iron chloride and with hydroxyl ions to form sodium hydroxide.

$$Fe^{++} + Cl \longrightarrow FeCl_2$$

Na⁺ + OH \longrightarrow NaOH

Chapter 2

2.1 Literature Review

Rajurkar et al. (1997) focused their study on the minimization of MRR such that exact amount of localized machining can be obtained to minimize the machining allowance. They found that the use of passivation electrolyte and pulse current minimizes generation of sludge hence improves the accuracy. Kumar et al. (2000) discussed a case study on Al-Si alloy employing an approach which is based on Taguchi combined with utility based method. The authors developed a model to predict the optimal settings of the process parameters such that optimal quality characteristics can be obtained. For obtaining different sets of optimal parameters, different weights can be assigned to different responses. Bhattacharyya and Munda (2003) developed an electrochemical micro-machining (EMM) experimental set-up to carry out research so that EMM process parameters can be adequately controlled. He found that value of voltage in between 6-10 V provides a significant amount of MRR with reasonable accuracy. He also found that lesser value of electrolytic concentration with moderate pulse on time and high voltage gives good dimensional accuracy lesser overcut and moderate MRR. Micro sparks are undesirable as it results in inaccuracy. Datta and Mahapatra (2003) applied Taguchi, Principal Component Analysis (PCA) and utility theory to optimize various correlated surface quality features of a mild steel product manufactured by straight turning operation. PCA is applied to convert correlated responses into independent quality indices and utility concept is used to convert multi responses into single response such that the problem is solved by Taguchi method. They explored the comprehensive procedure and mathematical expressions for the

above optimization methods and concluded the robustness and flexibility of the proposed optimization techniques. Erdal and Saka (2007) utilized Harmonic search method for the optimization of design of grillage system. Rao et al. (2008) presented a new method particle swarm optimization (PSO) to find out best combination of process parameters of ECM process. They formulated expressions for three objective functions to be maximized namely dimensional accuracy, MRR and tool life under the constraints of passivity of electrolyte, choking and maximum temperature to be allowed. The responses obtained from single objective and multiobjective are compared and it was found that those obtained from the multi-objective optimization are better. They also compared the performance of PSO with other nonconventional optimization methods and found that less no of trails are required to predict the optimum operating parameters. Routara et al. (2010) studied utility concept and combined it with Taguchi method for a case study in CNC end milling of leaded brass and found out the optimum process parameters which fulfils the multi objective and simultaneously satisfy multiple requirements of surface quality. A multi-objective optimization problem cannot be solved by conventional Taguchi method so utility theory is coupled with it to convert it into single-objective optimization problem. Ayachi et al. (2010) determined the arrangement of containers such that due delivery dates to customers can met and handling cost of containers can be reduced. To overcome with the problem they applied harmonic search method. This method was compared with the previously applied genetic algorithms and found good results. Chakradhar and Gopal (2011) Considered the effect of process parameters such as applied voltage, tool feed rate, electrolyte concentration for ECM on EN-31 steel and optimized them using grey relational analysis. Multi objective optimization is applied to consider surface roughness, MRR, overcut, cylindricity error simultaneously and it was observed that the most

significant process parameter was feed rate. Grey relation analysis was used to convert the above four responses into single Grey relational grade as the response to simplify the procedure. Samanta and Chakraborty (2011) applied artificial bee colony (ABC) algorithm to find out the optimal combinations of different operating parameters for three nontraditional machining processes, i.e. ECM, EDM, and ECMM. Both the single and multi-objective optimization problems for the considered NTM processes are solved using this algorithm. The results obtained while applying the ABC algorithm for parametric optimization of these three NTM processes are compared with those derived by the past researchers, which prove the applicability and suitability of the ABC algorithm in enhancing the performance measures of the considered NTM processes. Wu et al. (2011) proposed a method to apply computational fluid dynamics analysis to design the flow field arrangement of parameters for ECM and to design cathode adequately. They developed a numerical model for 3-D flow region and numerical simulation was done. The influence of cathode design as well as initial electrolytic pressure on the flow field was analyzed from the results of simulation. The presented method can be used to attain high efficiency in cathode design and low cost for the selection of initial electrolytic pressure as several "trial and error" cycles is reduced. Tajdari and Chavoshi (2013) developed different models based on artificial neural network (ANN), multiple regression analysis and co-active neuro fuzzy inference system (CANFIS) to envisage overcut in electrochemical drilling. They investigated that voltage and electrolyte concentration had increasing effect on radial overcut while feed rate has a decreasing effect. They further compared the models and found that ANN and CANFIS models are more accurate than regression analysis with an average error of almost 5 % in predicting radial overcut. Senthilkumar et al. (2013) have done experiments on aluminium silicon based composite in ECM to determine various important characteristics of machining by developing

empirical relation between responses and process parameters in ECM process using Response Surface Methodology and significance of different individual parameters and their combined effect are indicated in the ANOVA table. They found that tool feed rate and voltage influence MRR most while electrolyte concentration has greatest effect on surface roughness. Uttarwar and Chopde (2013) presented the results obtained from the Electrochemical Machining of AISI 202 stainless steel in which input parameters were taken as voltage, current, electrolytic concentration and time of electrolysis, feed rate and pressure while response variables were MRR and SR. The experiment was designed based on L32 orthogonal array. They explained the effect of variation of each input parameter on material removal rate and surface roughness using theoretical and computation based models. They found that MRR increases with increasing each of the input variables while surface roughness was mainly affected by time of machining. Bist et al. (2013) focused on optimizing two important characteristics of ECM i.e. MRR and surface roughness. The experiment was designed according to the Taguchi L₉ orthogonal array to calculate the responses on the basis of which the cutting performance was decided. They studied signal-to-noise ratio to minimize the variation in quality characteristic resulted from uncontrollable parameters. Yong and Ruigin (2013) presented the electrochemical shaping of tapered hole which is already drilled through electro-discharge machining and observed that surface roughness can be improved by controlling tool feed rate and machining voltage. They investigated experimentally the effect of various input parameters on hole diameters. Wale and Wakchaure (2013) studied the effects of cryotreatment on mechanical properties of cold worked tool steel such as AISI D2 and D3 at several combinations of heat treatment cycle. They found that the treatment improves the properties like hardness, microstructure, dimensional stability and decreases residual stress of the metal.

2.2 Research Objectives

From the thorough examination of past literature it has been observed that many works have been reported on the parametric effect of electro chemical machining on different output responses using a single tool material, but no systematic work has been done to study the comparative effect of different tool materials on the performance characteristics obtained under ECM machining so as to establish the advantages provided by individual tool material on the output responses. The aim of the present work can be summarized as given below:

- Comparative study of the output responses obtained by machining with different tools to examine the advantage provided by individual tool material on the performance characteristics.
- Effect of feed rate, electrolytic concentration and voltage on MRR, surface roughness and overcut of AISI D2 steel.
- To combine utility method with Response surface method.
- According to Harmonic search method to find which set of process parameters will give the optimal result for response variables.

Chapter – 3

Experimental setup

This chapter deals with experimental work in which experimental setup, work piece material selection, design of tool and the process of experimentation is discussed. All these information are used for the calculation of material removal rate and surface roughness and overcut.

3.1 Experimental setup:

All the experimental work was done on electrochemical machine purchased from METATECH-industry, Pune. The machining setup consists of three main parts:

- 1. Machining Cell
- 2. Control Panel
- 3. Electrolyte Circulation system

3.1.1 Machining Cell

In this component the main machining work is being carried out. This is made by assembling various precision machined component parts. There is arrangement for up and down movement of tool which is servo motorized, a glass window through which machining process can be seen from outside, vice for fixing the job which can move in horizontal and vertical direction, arrangement for incoming and outgoing of electrolyte. All the parts which is inside the machining chamber are exposed to electrolyte which is generally salt and acids so proper selection of material, coating etc. are necessary to make it corrosion resistant. The setup is shown in figure 3.1 the technical data are as follows:

- \circ Tool area- 122.72mm²
- o Cross head stroke- 150mm
- Tool feed motor- DC servo type



Fig. 3.1: Representative images showing (a) ECM Setup (b) Control panel

3.1.2 Control Panel

Control panel is used to control all the process parameters of machining. Voltage (V), current (I), feed rate (F), duration of time, all are adjusted through the switch buttons provided in the control panel. Technical specification of the control panel is as follows:

- Electrical Out Put Rating 0-300 A. DC at any voltage from 0 20 V.
- Efficiency Better than 80% at partial & full load condition.
- Protections Over load, Short circuit, single phasing.
- Operation Modes Manual/Automatic.
- Timer 0 99.9 min.
- \circ Tool Feed 0.2 to 2 mm / min.
- Z Axis motion Control Manual Forward and reverse , auto forward /reverse through micro controller

3.1.3 Electrolyte tank and Circulation system

The electrolyte tank consists of three chambers separated through filtering meshes; the capacity of the tank is 90 liters. Filtered electrolyte is pumped to the machining zone and used electrolyte goes to the chamber which is farthest away from the pump and after two filtrations it is again circulated for machining.



Fig: 3.2 Electrolyte tank



Fig: 3.4 Schematic diagrams of electrochemical machining [5]

3.2 Tool design

Tool is generally made by a non-reacting material. In the present work three types of tool materials are taken which are copper, brass and graphite. The shape of the tool is tapered cylinder in which the smaller diameter is 9.0 mm and larger diameter is 15mm in which a thorough hole of 3 mm is drilled for the passage of electrolyte. Total length of the tool is 50 mm in which M12 external thread is made in the upper part of to hold it in the tool holder. The length of the thread is 16 mm. Angle of taper is 6.84°.



Figure 3.5 representative images showing (a) Brass tool (b) Graphite tool (c) Copper tool

3.3 calculations of different responses

There are three different responses which are MRR, surface roughness and overcut. The calculations of these are as given below.

3.3.1 Calculation of MRR

MRR is calculated from the formula

 $MRR = \frac{initial weight-final weight}{time}$

3.3.2 Calculation of overcut diameter

Overcut diameter should be measured as

 $Overcut = \frac{Final \ diameter - initial \ diameter}{2}$

3.3.3 Calculation of surface roughness

After each run surface roughness of the drilled hole was measured using Talysurf (make: Taylor Hobson: Surtronic 3+).

Chapter 4

Experimental work and optimization techniques

In the current chapter the whole process of experimentation is discussed which is about the formation of design of experiment, application of RSM, utility based method and harmonic search optimization method. Design of experiment is face-centered central composite design. Total 60 experimental runs have been carried out in which 20 runs for each type of tool are there. Responses measured were MRR, surface roughness and overcut for each type of tool.

4.1 specification of work piece material

The material of work piece is AISI D2 tool steel. It is a high carbon, high chromium tool steel alloyed with vanadium, molybdenum, cobalt. It has high compressive strength, good thorough hardening properties, highly stable after hardening and shows resistance when tempered back. The work piece is in the shape of semi-circular disk of 100 millimeter diameter and 10 mm thickness.

Table 4.1.1: Chemical composition of AISI D2 Steel (wt. %)

ELEMENTS	С	Si	Mn	Mo	Cr	Ni	V	Co	Fe
Wt. %	1.5	0.3	0.3	1.0	15	0.3	0.8	1.0	79.8

Table 4.1.2: Mechanical and thermal properties of AISI D2 tool steel at room temperature (25°C)

Properties	
Density	7700 kg/m ³
Poisson's ratio	0.27- 0.3
Elastic modulus	1.9- 2.1 GPa
Tensile strength	1736 MPa
0.2 % offset yield strength	1532 MPa
Hardness (HRN)	57
Thermal expansion (At 20°C - 100°C)	10.4×10^{-6} /°C

AISI D2 tool steel is generally suggested for tools which requires high wear resistance combined with shock resistance properties and it can be supplied in numerous finishes, including premachined, fined machined and the hot rolled condition.

4.2 Response Surface Methodology (RSM)

RSM is a statistical technique which discovers the relationship between several explanatory variables and one or more response variables. G.E.P. Box and K.B. Wilson introduced this methodology in 1951. A series of designed experiments are performed to obtain the best set of parameters from the available range of parameters to optimize response variables. Box and Wilson have suggested a second-degree-polynomial to do this work. RSM is studied to understand the structure of the response surface i.e. to understand where the maximum, minimum and ridge lines occur and to find the region of occurrence of optimal response value. The response variable z is a function of process parameters (x, y) and it can be expressed by

$$z = f(x, y) + e$$

Where 'e' denotes the experimental error term. This may be due to environmental effect or error in the measurement of response variables. If response variable is linearly dependent upon the input variables then it can be expressed by a first order model but if there is any curvature in the response surface then second order model should be used. The approximating function with two variables is expressed as

$$z = a_0 + a_1 x + a_2 y + a_3 x^2 + a_4 y^2 + a_5 xy + e_4 y^2 + a_5 xy + e_5 xy$$

In the above model, the level of one factor does not depend upon the level of any other factor. To achieve an effective result, data are collected properly and method of least square is used to estimate the polynomial.

4.3 Concept of utility theory

The utility based theory is applied when a problem is of multi objective nature. The idea behind this theory in the mathematical from may be uttered as

$$U(Z_1, Z_2, \dots, Z_n) = f(U_1(Z_1), U_2(Z_2), \dots, U_n(Z_n))$$
(4.3.1)

Where $U_i(Z_i)$ represents the utility function of the ith attribute. The total utility value of any attribute should be calculated as the summation of each utility value for all the responses and can be written as

$$U(Z_1, Z_2, \dots, Z_n) = \sum_{i=1}^n U_i(Z_i).$$
(4.3.2)

Some value of weight is assigned to each attribute according to their importance so that the summation of all the weights is equal to 1.

$$U(Z_{1}, Z_{2}, \dots, Z_{n}) = \sum_{i=1}^{n} Wi \cdot U_{i}(Z_{i})$$
(4.3.3)

Here W_i represents the weight assigned to the ith response. A preference no. is set for each response to determine the utility value for each response. Two random preference numbers 0 and 9 are allotted to just acceptable and the best value of the response respectively. The preference no. for the ith response can be written on a logarithmic scale as follows:

$$P_i = A \times \log(\frac{Z_i}{Z'_i})$$
(4.3.4)

Where Z_i represents ith response and Z'_i is the just acceptable value of the response. Just acceptable value is the minimum or maximum value of the response depending upon we want to maximize or minimize it respectively. Where the value of the constant A is calculated by the equation as

$$A = \frac{9}{\log(\frac{Z^*}{Z_i'})}$$
(4.3.5)

Here Z^* is the best value. When $Z_i=Z^*$, $P_i=9$.

4.4 harmonic search algorithms

It is one of the nature inspired algorithm which is inspired from the making of new music from the old or existing music. This algorithm is based on the random search and hence a random no is used for the initialization of the search process. Compared to other optimization techniques it takes fewer mathematical expressions to solve the problem and lesser time. The flow chart diagram is given below for explaining the harmonic search algorithm.

Initiation of optimization problem and parameters

To maximize the objective function; f(z)

To give the possible range of values for each of the decision variables,

Harmony memory size (HMS), Harmonic memory consideration rate

With the use of constant random no. harmony memory is initialized and initial solutions are generated and sorted by the value of the objective function, better solutions are stored in the harmony memory and worst are rejected.

To create a new value of objective function based on value already in the memory by adjusting it with HMRC and PAR or by randomization



4.1 Flow chart for harmonic search algorithm

The optimization process makes use of some randomly generated parameters to solve the problem.

- Harmony memory size (HMS): it is the no. of solution vectors usually varies from 1 to 100.
- Harmony memory consideration rate (HMCR): it is the rate of choosing a value from the harmony memory and its typical range is 0.7 to 0.99.
- Pitch adjusting rate (PAR): it is the rate of choosing a value in the neighborhood. It normally varies from 0.1 to 0.5.
- Band width: it is the extent of maximum change in pitch adjustment rate and generally varies from 0.0001 to 1.0.

To optimize the set of vectors by harmonic search method, we have to define an objective function and equality and inequality constrains equation. The objective function will be maximized or minimized satisfying constrains.

A constraint can be defined as a restriction which must be fulfilled for the acceptance of the solution variables. It is a form of limitation on the variables which can be direct or indirect. Generally the constraints are stated in the form of a set of inequalities functions. The constraints come from the limitation of resources or condition of processes. For example, in the machining process we have to limit the value of speed to keep temperature in the allowed range. There are many techniques to handle the constraint.

- Penalty Functions
- Special representations and operators
- Separation of constraints and objectives
- Hybrid Methods

Penalty Functions: The idea of penalty functions is to convert a constrained optimization problem into an unconstrained problem by addition (or subtraction) of a certain quantity from the objective function which is based on the amount of constraint violation present in the solution.

In mathematical programming, two kinds of penalty functions are considered: exterior and interior. In the example of exterior methods, we start with an infeasible solution and from there we move towards the feasible area. In the case of interior methods, the penalty term is chosen such that its value will be small at points away from the constraint boundaries and will tend to

infinity as the constraint boundaries are approached. Then, if we start from a feasible point, the subsequent points generated will always lie within the feasible region since the constraint boundaries act as barriers during the optimization process. Types of penalty functions given are given below:

- 1. Death Penalty
- 2. Static Penalty: In this category, the approaches are considered in which the penalty factors will not depend on the current iteration number in any case, and so it remain the same during the entire process.
- 3. Dynamic Penalty
- 4. Adaptive Penalty
- 5. Recent Approaches
- 6. Self-Adaptive Fitness Formulation

The coding of the above optimization process is done on Matlab7.0 software.

4.5 Procedure of the experimentation

Prior to the start of the machining process, initial weight of the work piece is measured. All the parameters are set from the control panel, the work piece is set in the machining chamber and tool is fixed in the tool holder. Time for one run is set as 10 minutes. We should observe the machining area carefully so that there should not be any contact of tool with work piece as it will produce spark and the surface roughness will be ruined. The process parameters and their levels are given in the table 4.5.1. Three different materials of tools of same shape are taken and 20 runs are conducted for each type of tool. The experiment was designed according to second order face-centered central composite design. 20 numbers of runs were conducted and corresponding responses, MRR, overcut and surface roughness were measured and recorded. Three process parameters are taken up to three levels as shown in the table 4.5.1. The responses were measured and tabulated. In table 4.5.2, 4.5.3 and 4.5.4 design of experiment and experimental results for copper, brass and graphite tools are tabulated respectively.

Parameter	Level 1	Level 2	Level 3
Concentration	15	30	45
Feed	0.1	0.2	0.3
Voltage	10	12	14

Table 4.5.1: Domain of experiment

std	run	conc	eed	vol
1	20	15	0.1	10
3	19	15	0.3	10
9	3	15	0.2	12
5	11	15	0.1	14
7	7	15	0.3	14
13	13	30	0.2	10
11	17	30	0.1	12
16	14	30	0.2	12
20	6	30	0.2	12
18	12	30	0.2	12
17	16	30	0.2	12
19	8	30	0.2	12
15	1	30	0.2	12
12	2	30	0.3	12
14	5	30	0.2	14
2	15	45	0.1	10
4	4	45	0.3	10
10	9	45	0.2	12
6	10	45	0.1	14
8	18	45	0.3	14

Table 4.5.2: Design of experiment

Run	Concentration	Feed	Voltage	MRR		Surface
no	(g/l)	(mm/min)	(V)	(g/l)	Overcut(mm)	roughness (μm)
1	30	0.2	12	0.0879	0.634	9.61832
2	30	0.3	12	0.1552	0.501	10.374
3	15	0.2	12	0.0608	0.404	12.0817
4	45	0.3	10	0.1618	0.542	8.2173
5	30	0.2	14	0.0841	0.631	8.9437
6	30	0.2	12	0.0812	0.554	9.7233
7	15	0.3	14	0.1428	0.423	12.4963
8	30	0.2	12	0.0874	0.591	9.15731
9	45	0.2	12	0.0856	0.731	6.884
10	45	0.1	14	0.0941	0.894	5.10266
11	15	0.1	14	0.0591	0.581	11.6483
12	30	0.2	12	0.0829	0.587	9.7034
13	30	0.2	10	0.0797	0.432	8.0133
14	30	0.2	12	0.0805	0.582	9.3163
15	45	0.1	10	0.0718	0.655	7.3253
16	30	0.2	12	0.083	0.523	9.879
17	30	0.1	12	0.0615	0.615	9.3791
18	45	0.3	14	0.1684	0.751	6.1913
19	15	0.3	10	0.1421	0.224	13.4017
20	15	0.1	10	0.0583	0.381	12.7627

Table 4.5.3: Response table for copper tool

Run no	Concentration (g/l)	Feed (mm/min)	Voltage (V)	surface roughness (µm)	overcut (mm)	MRR (g/min)
1	15	0.1	10	7.4523	0.341	0.0507
2	45	0.1	10	7.7583	0.605	0.0632
3	30	0.2	10	4.2887	0.412	0.0661
4	15	0.3	10	8.35733	0.198	0.0896
5	45	0.3	10	10.9203	0.512	0.0945
6	30	0.1	12	5.5143	0.585	0.0608
7	15	0.2	12	10.822	0.314	0.065
8	30	0.2	12	6.302	0.534	0.0753
9	30	0.2	12	5.79533	0.524	0.0744
10	30	0.2	12	6.898	0.591	0.0646
11	30	0.2	12	6.053	0.547	0.067
12	30	0.2	12	6.4323	0.592	0.0657
13	30	0.2	12	6.099	0.503	0.0682
14	45	0.2	12	8.468	0.691	0.0767
15	30	0.3	12	7.1993	0.481	0.0979
16	15	0.1	14	10.9513	0.551	0.0558
17	45	0.1	14	6.0093	0.854	0.0642
18	30	0.2	14	4.8717	0.591	0.06831
19	15	0.3	14	10.3017	0.403	0.0981
20	45	0.3	14	6.9006	0.701	0.0993

Table 4.5.4: Design of experiment and experimental results of brass tool

Run no	Concentration (g/l)	Feed (mm/min)	Voltage (V)	Surface roughness (µm)	MRR (g/min)	Overcut (mm)
1	15	0.2	12	14.845	0.0931	0.202
2	30	0.2	12	11.446	0.0851	0.272
3	30	0.2	14	10.21267	0.0855	0.332
4	15	0.3	14	14.426	0.1622	0.213
5	45	0.3	14	7.4357	0.1891	0.409
6	30	0.2	12	11.55467	0.0854	0.278
7	15	0.1	10	15.62867	0.0651	0.221
8	30	0.2	12	10.0233	0.0858	0.291
9	15	0.3	10	14.1787	0.1512	0.214
10	45	0.3	10	8.198	0.1852	0.271
11	30	0.2	10	9.15067	0.0849	0.222
12	45	0.1	14	6.2341	0.0835	0.451
13	30	0.1	12	10.979	0.0767	0.317
14	15	0.1	14	13.2283	0.0701	0.311
15	45	0.1	10	8.5627	0.0807	0.367
16	30	0.2	12	11.968	0.0864	0.298
17	30	0.2	12	10.80167	0.0886	0.302
18	30	0.2	12	10.787	0.0891	0.321
19	45	0.2	12	8.267	0.0956	0.321
20	30	0.3	12	8.21267	0.1705	0.251

Table 4.5.5: Design of experiment and experimental results of graphite tool

Chapter- 5

Results and discussion

5.1 Data analysis for copper tool

All the responses, MRR, SR and O.C calculated from the observation table for the copper tool were analyzed one by one through ANOVA. The variations of responses can be seen through 3-D surface plots. Finally the responses were converted in to a single response using utility concept and optimized through harmonic search method.

5.1.1 *Material removal rate:* For clear understanding of the effect of different parameters 3-D surface plots are used.





Figure 5.1.1 surface plots for MRR with respect to (a) feed rate and concentration, (b) Voltage and concentration and (c) Voltage and feed rate

The effect of various machining parameters on MRR is shown in table 5.1.1. MRR increases with increase in feed rate, voltage and electrolytic concentration for the given range of variables; however the effect is highest for feed rate then concentration and is least influenced by voltage.

Source	Sum of	df	Mean	F	p- value	
	Squares		Square	Value	Prob > F	
Model	0.024	9	2.711E-003	108.90	< 0.0001	significant
A-	1.407E-003	1	1.407E-003	56.51	< 0.0001	
concentration						
B-feed rate	0.018	1	0.018	727.41	< 0.0001	
C-voltage	1.211E-004	1	1.211E-004	4.87	0.0519	
AB	1.280E-006	1	1.280E-006	0.051	0.8252	

Table 5.1.1: ANOVA for MRR (g/l)

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AC	9.384E-005	1	9.384E-005	3.77	0.0808	
BC	3.120E-005	1	3.120E-005	1.25	0.2890	
A^2	5.877E-005	1	5.877E-005	2.36	0.1554	
B^2	2.563E-003	1	2.563E-003	102.96	< 0.0001	
C^2	4.572E-005	1	4.572E-005	1.84	0.2052	
Residual	2.489E-004	10	2.489E-005			
Lack of Fit	2.000E-004	5	4.001E-005	4.09	0.0740	not
						significant
Pure Error	4.887E-005	5	9.774E-006			
Cor Total	0.025	19				

From the above table it is clear that the model is significant as its F-value is 108.90. In this case A, B, B^2 are significant model terms. Here the value of Predicted R-Squared of 0.9324 is in reasonable agreement with the Adjusted R-Squared of 0.9808 and close to 1.0 which suggests that the variation in the observed value can be explained by the chosen model satisfactorily. The value of Adequate precision is 32.82 is good as it measures the S/N ratio.





Fig 5.1.2 Residuals plot for MRR showing (a) Normal plots for residuals (b) Residuals vs predicted (c) Residuals vs run no. (d) Predicted vs actual

Figure 5.1.2 represents the various residual plots for MRR. The normal probability indicates that the residuals follow the normal curve. Residuals versus predicted plot should be a random scatter as it tests the assumption of constant variance. Residuals versus run plot should be randomly scattered as trends indicate a time related variable that might be lurking in the background. The plot between actual and predicted values helps to detect a response which is not easily predicted by the model itself.

5.1.2 Overcut: Overcut increases with increase in voltage and electrolytic concentration whereas it decreases with increase in feed rate for the given range of variables; however the effect is highest for concentration then voltage and then by feed rate. The variation is clearly depicted in the surface plots given below:


Figure 5.1.3: Surface plots for overcut with respect to (a) feed rate and concentration, (b) Voltage and concentration and (c) Voltage and feed rate

The effect of various machining parameters on overcut is shown in table 5.1.2. From the above table it is clear the model is significant as its F-value is 49.59. In this case A, B and C are significant model terms. Here the value of Predicted R-Squared of 0.948 is in reasonable agreement with the Adjusted R-Squared of 0.9584 and close to 1.0 which suggests that the

variation in the observed value can be explained by the chosen model satisfactorily. The value of Adequate precision is 30.977 is good as it measures the S/N ratio.

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	0.40	9	0.045	49.59	< 0.0001	Significant
A- concentration	0.24	1	0.24	269.51	< 0.0001	
B-feed rate	0.047	1	0.047	51.96	< 0.0001	
C-voltage	0.11	1	0.11	121.17	< 0.0001	
AB	4.351E-004	1	4.351E-004	0.48	0.5034	
AC	3.001E-004	1	3.001E-004	0.33	0.5770	
BC	1.201E-004	1	1.201E-004	0.13	0.7229	
A^2	2.482E-004	1	2.482E-004	0.27	0.6115	
B^2	5.551E-017	1	5.551E-017	6.148E- 014	1.0000	
C^2	1.931E-003	1	1.931E-003	2.14	0.1743	
Residual	9.030E-003	10	9.030E-004			
Lack of Fit	2.028E-003	5	4.056E-004	0.29	0.9000	not significant
Pure Error	7.001E-003	5	1.400E-003			
Cor Total	0.41	19				

Table 5.1.2: ANOVA for overcut

Figure 5.1.4 shows the residuals plot for overcut as given below. The normal probability of residuals indicates that the residuals follow almost normal curve. Residual versus predicted plot is a random scatter. Residuals versus run is randomly scattered and no trend is observed. Hence all the graphs are satisfactory.

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Fig 5.1.4 Residuals plot for overcut showing (a) Normal plots for residuals (b) Residuals vs predicted (c) Residuals vs run no. (d) Predicted vs actual

5.1.3 Surface roughness: Overcut decreases with increase in electrolytic concentration. It first decreases then increases with increase in voltage for the given range. With feed rate it first increases and then decreases; however the effect is highest for concentration then voltage followed by feed rate. The variation is clearly depicted in the surface plots (figure 5.1.5).



Figure 5.1.5: Surface plots for surface roughness with respect to (a) feed rate and concentration, (b) Voltage and concentration and (c) Voltage and feed rate

The effect of various machining parameters on overcut is shown in table 5.1.3. From the above table it is clear the model is significant as its F-value is 29.04. In this case A, B and C are significant model terms. Here Lack of Fit is also significant which decreases the model accuracy. However the value of Predicted R-Squared of 0.7546 is in reasonable agreement with the Adjusted R-Squared of 0.93 and the difference is less than 0.2 which suggests that the variation

in the observed value can be explained by the chosen model. The value of Adequate precision is 18.555 is good as it measures the S/N ratio.

	Sum of		Mean	F	p-value Prob >	
Source	Squares	df	Square	Value	F	
Model	89.89	9	9.99	29.04	< 0.0001	Significant
A- concentration	82.20	1	82.20	239.02	< 0.0001	
B-feed rate	1.99	1	1.99	5.79	0.0369	
C-voltage	2.85	1	2.85	8.29	0.0164	
AB	0.030	1	0.030	0.089	0.7721	
AC	0.62	1	0.62	1.81	0.2087	
BC	0.021	1	0.021	0.060	0.8117	
A^2	0.18	1	0.18	0.53	0.4830	
B^2	1.17	1	1.17	3.39	0.0953	
C^2	1.53	1	1.53	4.46	0.0609	
Residual	3.44	10	0.34			
Lack of Fit	3.07	5	0.61	8.20	0.0187	Significant
Pure Error	0.37	5	0.075			
Cor Total	93.32	19				

Table 5.1.3: ANOV	A for surface	roughness of	copper tool
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Figure 5.1.6 represents Residuals plot for surface roughness. The normal probability indicates that the residuals do not follow the normal curve. Residual versus predicted plot is a random scatter. Residuals versus run is not randomly scattered but a slightly increasing and a trend is observed. This may be due to some lurking background variable. Predicted versus actual graph is good enough to predict a value.





Fig 5.1.6: Residuals plot for surface roughness showing (a) Normal plots for residuals (b) Residuals vs predicted (c) Residuals vs run no. (d) Predicted vs actual

5.1.4 Exploration of utility concept: Utility values for each response was calculated using equation 4.3.1 by providing equal weightage (1/3) to each of them. Finally overall utility value was calculated using equation 4.3.3 and tabulated in Table 5.4.

	MRR	Overcut	Surface roughness	Overall
Run no	(g/l)	(mm)	(um)	ntility
1	2 492775		(µIII)	2.02(712
1	3.483775	2.234664	3.0917	2.936/13
2	8.307419	3.765656	2.386767	4.819947
3	0.356251	5.164959	0.966433	2.162548
4	8.660774	3.254162	4.558998	5.491311
5	3.108811	2.265507	3.769485	3.047934
6	2.811073	3.111763	2.990523	2.97112
7	7.600907	4.866117	0.651955	4.372993
8	3.435374	2.691361	3.549494	3.22541
9	3.258808	1.308924	6.209105	3.592279
10	4.062073	0	8.999997	4.354023
11	0.115636	2.80233	1.306924	1.408297
12	2.986874	2.735522	3.009618	2.910671
13	2.652872	4.729215	4.793304	4.058464
14	2.737613	2.791148	3.38906	2.972607
15	1.767201	2.022769	5.629986	3.139986
16	2.997102	3.486204	2.842456	3.108588
17	0.453378	2.432517	3.326443	2.070779
18	8.999999	1.133405	7.197582	5.776995
19	7.559213	8.999993	0	5.519735
20	0	5.546113	0.455347	2.000487

Table 5.1.4: Overall utility values for responses

From the above table it is clearly visible that run number 18 is getting the highest overall utility value. Using the above overall utility values as the final response values a regression equation is obtained in terms of actual factors to form the objective function for finding the optimum design points using harmony search method. The equation is as follows:

Overall utility = 23.2197 - 0.070835 * concentration + 12.6003 * feed rate - 3.67442 * voltage - 0.225804 * concentration * feed rate + 0.0134944 * concentration * voltage - 0.926816 * feed rate * voltage + 45.7575 * feed rate^2 + 0.141353 * voltage^2.

5.1.5 Optimization of process parameter using harmonic search method: To obtain the optimal set of process parameters, the parameters are set as given below:

Objective function = 23.2197 - 0.070835 * concentration + 12.6003 * feed rate - 3.67442 * voltage - 0.225804 * concentration * feed rate + 0.0134944 * concentration * voltage - 0.926816 * feed rate * voltage + 45.7575 * feed rate^2 + 0.141353 * voltage^2- eg(sol).

Where eg(sol) is the penalty function. Static penalty function is used to handle the constraints. Following are the constraints used in the algorithm. All the constraints are of greater than and equal type. Here sol (1) represents feed rate and sol (3) represents voltage.

Temperature constraint:

gx(1)=1-sol(1)^2.133007*0.0383054*sol(3)^-0.351436*1.37984062 Passivity constraint:

gx(2)=sol(1)^-0.844369*0.000517010*sol(3)^1.546257*289806.8658-1 Choking constraint:

gx(3)=1-sol(1)^0.075213*0.00057885048*sol(3)^0.240542*127581.4164

Maximum no of iterations is = 1000; No. of inequality constraints = 3; No. of equality constraints = 0; Harmonic memory size = 6; Harmony consideration rate = 0.9; Minimum pitch adjusting rate = 0.45; Maximum pitch adjusting rate = 0.9; Minimum band width = 0.0001;

Maximum band width = 1.0

The optimal set of variables satisfying the given constraints was as follows:

Electrolytic concentration = 15 g/l; applied voltage = 14 V; tool feed rate = 0.3.

The value of responses; MRR = 0.1428 g/min, overcut = 0.423 mm, surface roughness = 12.4963 are obtained.

5.2 Data analysis for brass tool

All the responses, MRR, SR and O.C which were calculated from the observation table for the brass tool are analyzed one by one through ANOVA. The variations of responses were observed through 3-D surface plots. Finally the responses were converted in to a single response using utility concept and optimized through harmonic search method.

5.2.1 Material removal rate: The effect of various machining parameters on MRR is shown in table 5.2.1. MRR increases with increase in feed rate, voltage and electrolytic concentration for the given range of variables; however the effect is highest for feed rate then concentration and is least influenced by voltage which is obvious from the given surface plots in figure 5.2.1.

From the above table it is clear that the model is significant as its F-value is 52.34. In this case A, B, B^2 are significant model terms. Here the value of Predicted R-Squared of 0.9421 is in

reasonable agreement with the Adjusted R-Squared of 0.9457 and close to 1.0 which suggests that the variation in the observed value can be explained by the chosen model satisfactorily. The value of Adequate precision is 20.173 is good as it measures the S/N ratio.



Figure 5.2.1: Surface plots for MRR with respect to (a) feed rate and concentration, (b) Voltage and concentration and (c) Voltage and feed rate

Table 5.2.1: ANOVA for MRR (g/l) of brass tool

	Sum of		Mean	F	p-value Prob	
Source	Squares	df	Square	Value	> F	
Model	0.39	6	0.065	52.34	< 0.0001	significant
A- concentration	0.24	1	0.24	194.68	< 0.0001	
B-feed rate	0.041	1	0.041	33.04	< 0.0001	
C-voltage	0.11	1	0.11	85.64	< 0.0001	
AB	2.531E-004	1	2.531E-004	0.20	0.6593	
AC	6.613E-005	1	6.613E-005	0.053	0.8212	
BC	5.281E-004	1	5.281E-004	0.42	0.5260	
Residual	0.016	13	1.244E-003			
Lack of Fit	9.586E-003	8	1.198E-003	0.91	0.5697	not significant
Pure Error	6.581E-003	5	1.316E-003			
Cor Total	0.41	19				





Fig 5.2.2: Residuals plot for surface roughness showing (a) Normal plots for residuals (b) Residuals vs predicted (c) Residuals vs run no. (d) Predicted vs actual

Figure 5.2.2 represents the various residual plots for MRR. The normal probability indicates that the residuals follow the normal curve. Residuals versus predicted plot should be a random scatter as it tests the assumption of constant variance. Residuals versus run plot should be randomly scattered as trends indicate a time related variable that might be lurking in the background. The plot between actual and predicted values helps to detect a response which is not easily predicted by the model itself.

5.1.2 Overcut: Overcut increases with increase in voltage and electrolytic concentration whereas it decreases with increase in feed rate for the given range of variables; however the effect is highest for concentration then voltage and then feed rate. The variation is clearly depicted in the surface plots.

The effect of various machining parameters on overcut is shown in table 5.1.2. From the above table it is clear that the model is significant as its F-value is 52.34. In this case A, B and C

are significant model terms. Here the value of Predicted R-Squared of 0.9118 is in reasonable agreement with the Adjusted R-Squared of 0.9419 and close to 1.0 which suggests that the variation in the observed value can be explained by the chosen model satisfactorily. The value of Adequate precision is 30.954 is good as it measures the S/N ratio.



Figure 5.2.3: Surface plots for overcut with respect to (a) feed rate and concentration, (b) Voltage and concentration and (c) Voltage and feed rate

~	Sum of		Mean	F	p-value Prob	
Source	Squares	df	Square	Value	> F	
Model	0.39	6	0.065	52.34	< 0.0001	significant
A- concentration	0.24	1	0.24	194.68	< 0.0001	
B-feed rate	0.041	1	0.041	33.04	< 0.0001	
C-voltage	0.11	1	0.11	85.64	< 0.0001	
AB	2.531E-004	1	2.531E-004	0.20	0.6593	
AC	6.613E-005	1	6.613E-005	0.053	0.8212	
BC	5.281E-004	1	5.281E-004	0.42	0.5260	
Residual	0.016	13	1.244E-003			
Lack of Fit	9.586E-003	8	1.198E-003	0.91	0.5697	not significant
Pure Error	6.581E-003	5	1.316E-003			
Cor Total	0.41	19				

Table 5.2.2: ANOVA for overcut for the brass tool

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Fig 5.2.4: Residuals plot for overcut showing (a) Normal plots for residuals (b) Residuals vs predicted (c) Residuals vs run no. (d) Predicted vs actual

Figure 5.2.4 shows the residuals plot for overcut as given below. The normal probability of residuals indicates that the residuals follow almost normal curve. Residual versus predicted plot is a random scatter. Residuals versus run is randomly scattered and no trend is observed. Hence all the graphs are satisfactory.

5.1.3 Surface roughness: Overcut decreases with increase in electrolytic concentration. It first decreases then increases with increase in voltage for the given range. With feed rate it first increases and then decreases; however the effect is highest for concentration then voltage followed by feed rate. The variation is clearly depicted in the surface plots (figure 5.1.5).

The effect of various machining parameters on overcut is shown in table 5.1.3. From the above table it is clear the model is significant as its F-value is 52.11. In this case A, B, AB, AC, BC, A^2 and C^2 are significant model terms. Here Lack of Fit is also significant which decreases the model accuracy. However the value of Predicted R-Squared of 0.8910 is in reasonable agreement with the Adjusted R-Squared of 0.9603 and the difference is less than 0.2 which suggests that the variation in the observed value can be explained by the chosen model. The value of Adequate precision is 22.648 is good as it measures the S/N ratio.





Figure 5.2.5: Surface plots for surface roughness with respect to (a) feed rate and concentration, (b) Voltage and concentration and (c) Voltage and feed rate

Source	Sum of	đf	Mean	F	p- value (Prob	
Source	Squares	ui	Square	Value	> F)	
Model	76.01	9	8.45	52.11	< 0.0001	significant
A- concentration	6.13	1	6.13	37.81	0.0001	
B-feed rate	3.59	1	3.59	22.17	0.0008	
C-voltage	6.639E-003	1	6.639E-003	0.041	0.8437	
AB	1.80	1	1.80	11.12	0.0075	
AC	15.71	1	15.71	96.96	< 0.0001	

Table 5.2.3: ANOVA	for surface	roughness	of brass tool
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BC	1.83	1	1.83	11.29	0.0072	
A^2	35.11	1	35.11	216.62	< 0.0001	
B^2	0.22	1	0.22	1.38	0.2680	
C^2	6.12	1	6.12	37.76	0.0001	
Residual	1.62	10	0.16			
Lack of Fit	0.90	5	0.18	1.24	0.4092	not significant
Pure Error	0.72	5	0.14			
Cor Total	77.63	19				



(a)

(b)

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Fig 5.2.6: Residuals plot for Surface roughness showing (a) Normal plots for residuals (b) Residuals vs predicted (c) Residuals vs run no. (d) Predicted vs actual

Figure 5.2.6 represents Residuals plot for surface roughness. The normal probability indicates that the residuals follow the normal curve. Residual versus predicted plot is a random scatter. Residuals versus run is not randomly scattered but a slightly increasing and a trend is observed. This may be due to some lurking background variable. Predicted versus actual graph is good enough to predict a value.

5.1.4 Exploration of utility concept: Utility values for each response was calculated using equation 4.3.1 by providing equal weightage (1/3) to each of them. Finally overall utility value was calculated using equation 4.3.3 and tabulated in Table 5.4.

Run no	Surface roughness (µm)	Overcut (mm)	Mrr (g/l)	Overall utility values
1	3.695478	5.652778	0	3.116085
2	3.309159	2.122467	2.950532	2.794053
3	8.999993	4.488165	3.551199	5.679786
4	2.595133	9.000027	7.623796	6.406318
5	0.027214	3.150158	8.336659	3.83801
6	6.586863	2.329457	2.432204	3.782841
7	0.114023	6.160698	3.326521	3.200414
8	5.305015	2.891109	5.295871	4.497332
9	6.109656	3.007509	5.134885	4.750684
10	4.437493	2.266626	3.243875	3.315998
11	5.69203	2.743006	3.732263	4.055766
12	5.108544	2.256217	3.469933	3.611565
13	5.619348	3.259356	3.969935	4.28288
14	2.468838	1.304081	5.542508	3.105142
15	4.02706	3.534732	8.809898	5.45723

Table 5.2.4: Overall utility response for brass tool

16	0	2.698143	1.283259	1.327134
17	5.761591	0	3.160717	2.974103
18	7.776351	2.266626	3.991512	4.678163
19	0.587048	4.624162	8.837221	4.682811
20	4.433875	1.215611	9.000001	4.883162

From the above table it is clearly visible that run number 4 is getting the highest overall utility value. Using the above overall utility values as the final response values a regression equation is obtained in terms of actual factors to form the objective function for finding the optimum design points using harmony search method. The equation is as follows:

Overall utility = 33.94505 + 0.149446 * concentration + 13.5265 * feed rate - 5.55183 * voltage - 0.307741 * concentration * feed rate + 0.0197403 * concentration * voltage + 0.581591 * feed rate * voltage - 0.0055395 * concentration^2 + 0.194952 * voltage^2

5.2.5 Optimization of process parameters obtained from harmonic search method: To obtain the optimal set of process parameters, the parameters are set as given below:

The objective function which is to be maximize is

Objective function = 33.94505 + 0.149446 * concentration + 13.5265 * feed rate - 5.55183 * voltage - 0.307741 * concentration * feed rate + 0.0197403 * concentration * voltage + 0.581591 * feed rate * voltage - 0.0055395 * concentration^2 + 0.194952 * voltage^2- eg (sol)

Where eg(sol) is the penalty function. Static penalty function is used to handle the constraints. Following are the constraints used in the algorithm. All the constraints are of greater than and equal type. Here sol (1) represents feed rate and sol (3) represents voltage.

Temperature constraint:

gx(1)=1-sol(1)^2.133007*0.0383054*sol(3)^-0.351436*1.37984062

Passivity constraint:

gx(2)=sol(1)^-0.844369*0.000517010*sol(3)^1.546257*289806.8658-1

Choking constraint:

gx(3)=1-sol(1)^0.075213*0.00057885048*sol(3)^0.240542*127581.4164

Maximum no of iterations is = 1000; No. of inequality constraints = 3; No. of equality constraints = 0; Harmonic memory size = 6; Harmony consideration rate = 0.9; Minimum pitch adjusting rate = 0.45; Maximum pitch adjusting rate = 0.9; Minimum band width = 0.0001;

Maximum band width = 1.0

The optimal set of variables satisfying the given constraints was as follows:

Electrolytic concentration = 15 g/l; applied voltage = 14 V; tool feed rate = 0.3.

The value of responses; MRR = 0.0981 g/min, overcut = 0.403 mm, surface roughness = 10.3017μ m are obtained.

5.3 Data analysis for graphite tool

All the responses, MRR, SR and O.C which were calculated from the observation tables for the brass tool were analyzed one by one through ANOVA. The variations of responses with process

parameters were observed through 3-D surface plots. Finally the responses were converted in to an equivalent response using utility concept and optimized through harmonic search method.

5.3.1 Material removal rate: The effect of various machining parameters on MRR is shown in figure 5.3.1. MRR increases with increase in feed rate, voltage and electrolytic concentration for the given range of variables; however the effect is highest for feed rate then concentration and is least influenced by voltage which is obvious from the given surface plots in figure 5.3.1.



(c)

Figure 5.3.1: Surface plots for MRR with respect to (a) feed rate and concentration, (b) Voltage and concentration and (c) Voltage and feed rate

Table 5.3.1: ANOVA for MRR (g/l) of graphite tool

	Sum of	10	Mean	F	p-value Prob >	
Source	Squares	df	Square	Value	F	
Model	0.031	11	2.804E-003	573.75	< 0.0001	significant
A- concentration	3.125E-006	1	3.125E-006	0.64	0.4470	
B-feed rate	0.023	1	0.023	4755.26	< 0.0001	
C-voltage	1.800E-007	1	1.800E-007	0.037	0.8526	
AB	1.272E-004	1	1.272E-004	26.03	0.0009	
AC	1.081E-005	1	1.081E-005	2.21	0.1753	
BC	6.301E-006	1	6.301E-006	1.29	0.2891	
A^2	7.804E-005	1	7.804E-005	15.97	0.0040	
B^2	3.288E-003	1	3.288E-003	672.69	< 0.0001	

C^2	4.019E-005	1	4.019E-005	8.22	0.0209	
A^2C	1.030E-005	1	1.030E-005	2.11	0.1846	
AB^2	1.596E-004	1	1.596E-004	32.65	0.0004	
Residual	3.910E-005	8	4.888E-006			

From the above table it is clear the model is significant as its F-value is 163.09. In this case A, B, AB, and B^2 are significant model terms. Here the value of Predicted R-Squared of 0.9510 is in reasonable agreement with the Adjusted R-Squared of 0.9871 and close to 1.0 which suggests that the variation in the observed value can be explained by the chosen model satisfactorily. The value of Adequate precision is 36.985 is good as it measures the S/N ratio.



(a)

(b)

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Fig 5.3.2: Residuals plot for MRR showing (a) Normal plots for residuals (b) Residuals vs predicted (c) Residuals vs run no. (d) Predicted vs actual

Figure 5.3.2 represents the various residual plots for MRR. The normal probability indicates that the residuals follow the normal curve. Residuals versus predicted plot should be a random scatter as it tests the assumption of constant variance. Residuals versus run plot should be randomly scattered as trends indicate a time related variable that might be lurking in the background. The plot between actual and predicted values helps to detect a response which is not easily predicted by the model itself.

5.3.2 Overcut: Overcut increases with increase in voltage and electrolytic concentration whereas it decreases with increase in feed rate for the given range of variables; however the effect is highest for concentration then voltage and then by feed rate. The variation is clearly depicted in the surface plots.

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Figure 5.3.3: Surface plots for overcut with respect to (a) feed rate and concentration, (b) Voltage and concentration and (c) Voltage and feed rate

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Fig 5.3.4: Residuals plot for overcut showing (a) Normal plots for residuals (b) Residuals vs predicted (c) Residuals vs run no. (d) Predicted vs actual

Figure 5.3.4 shows the residuals plot for overcut as given below. The normal probability of residuals indicates that the residuals follow almost normal curve. Residual versus predicted plot is a random scatter. Residuals versus run is randomly scattered and no trend is observed. Hence all the graphs are satisfactory.

The effect of various machining parameters on overcut is shown in table 5.3.2. From the above table it is clear the model is significant as its F-value is 17.66. In this case A, B and C are

significant model terms. Here the value of Predicted R-Squared of 0.8907 is in reasonable agreement with the Adjusted R-Squared of 0.8403 and the difference is less than 0.2 which suggests that the variation in the observed value can be explained by the chosen model satisfactorily. The value of Adequate precision is 17.865 is good as it measures the S/N ratio.

G	Sum of	16	Mean	F	p-value (Prob	
Source	Squares	đi	Square	Value	> F)	
Model	0.071	3	0.024	32.77	< 0.0001	significant
A- concentration	0.043	1	0.043	60.31	< 0.0001	
B-feed rate	9.548E-003	1	9.548E-003	13.30	0.0022	
C-voltage	0.018	1	0.018	24.69	0.0001	
Residual	0.011	16	7.179E-004			
Lack of Fit	9.929E-003	11	9.027E-004	2.90	0.1250	not significant

Table 5.3.2: ANOVA for over cut of graphite tool

Pure Error	1.557E-003	5	3.115E-004		
Cor Total	0.082	19			

5.3.3 Surface roughness: Overcut decreases with increase in electrolytic concentration. It first decreases then increases with increase in voltage for the given range. With feed rate it first increases and then decreases; however the effect is highest for concentration then voltage followed by feed rate. The variation is clearly depicted in the surface plots (figure 5.1.5).



Figure 5.3.5: Surface plots for surface roughness with respect to (a) feed rate and concentration, (b) Voltage and concentration and (c) Voltage and feed rate

The effect of various machining parameters on overcut is shown in table 5.3.3. From the above table it is clear the model is significant as its F-value is 29.04. In this case A, B and C are significant model terms. Here Lack of Fit is also significant which decreases the model accuracy.





(b)



Fig 5.3.6: Residuals plot for surface roughness showing (a) Normal plots for residuals (b) Residuals vs predicted (c) Residuals vs run no. (d) Predicted vs actual

However the value of Predicted R-Squared of 0.7546 is in reasonable agreement with the Adjusted R-Squared of 0.93 and the difference is less than 0.2 which suggests that the variation in the observed value can be explained by the chosen model. The value of Adequate precision is 18.555 is good as it measures the S/N ratio.

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	119.38	7	17.05	14.77	< 0.0001	significant
A- concentration	112.96	1	112.96	97.81	< 0.0001	
B-feed rate	0.48	1	0.48	0.41	0.5330	
C-voltage	1.75	1	1.75	1.51	0.2421	
AB	0.15	1	0.15	0.13	0.7263	
AC	0.11	1	0.11	0.095	0.7630	
BC	2.22	1	2.22	1.92	0.1909	
A^2	1.72	1	1.72	1.49	0.2455	
Residual	13.86	12	1.15			
Lack of Fit	11.43	7	1.63	3.37	0.1001	not significant
Pure Error	2.43	5	0.49			
Cor Total	133.24	19				

Table 5.3.3: ANOVA for surface roughness of graphite tool

Figure 5.1.6 represents Residuals plot for surface roughness. The normal probability indicates that the residuals do not follow the normal curve. Residual versus predicted plot is a random

scatter. Residuals versus run is not randomly scattered but a slightly increasing and a trend is observed. This may be due to some lurking background variable. Predicted versus actual graph is good enough to predict a value.

5.3.4 Exploration of utility concept: Utility values for each response was calculated using equation 4.3.1 by providing equal weightage (1/3) to each of them. Finally overall utility value was calculated using equation 4.3.3 and tabulated in Table 5.4.

	Surface			Overall
Run no	roughness	Mrr (g/l)	Overcut(mm)	utility
	(µm)			values
1	0.503761	3.019406	3.734766	2.419311
2	3.050027	2.261096	2.351273	2.554132
3	4.166479	2.300674	1.424403	2.630519
4	0.784129	7.70492	3.48821	3.99242
5	7.273987	9.000002	0.454534	5.576174
6	2.957497	2.290797	2.249818	2.499371
7	0	0	3.316767	1.105589
8	4.349762	2.330236	2.037309	2.905769
9	0.953454	7.112207	3.466431	3.844031
10	6.318266	8.824116	2.3684	5.836927
11	5.241712	2.241237	3.295775	3.592908
12	8.999993	2.100901	0	3.700298
13	3.457942	1.383967	1.639381	2.16043
14	1.632879	0.624545	1.728234	1.328553
15	5.892045	1.81303	0.958362	2.887812
16	2.613321	2.389052	1.926781	2.309718
17	3.617399	2.601269	1.864782	2.694483
18	3.630707	2.648764	1.581075	2.620182
19	6.236191	3.243054	1.581075	3.686773
20	6.300758	8.126119	2.724885	5.717254

Table: 5.3.4 overall utility response for graphite tool

From the above table it is clearly visible that run number 10 is getting the highest overall utility value. Using the above overall utility values as the final response values a regression equation is

obtained in terms of actual factors to form the objective function for finding the optimum design points using harmony search method. The equation is as follows:

Overall utility = -0.186822 + 0.0605902 * concentration - 9.10927 * feed rate + 0.118964 * voltage - 0.0481098 * concentration * feed rate + 0.000751585 * concentration * voltage - 0.717383 * feed rate * voltage + 82.3632 * feed rate^2

5.2.5 Optimization of process parameters using harmonic search method: To obtain the optimal set of process parameters, the parameters are set as given below:

The objective function, which is to be maximize satisfying the constraints

-0.186822 + 0.0605902 * concentration - 9.10927 * feed rate + 0.118964 * voltage - 0.0481098 * concentration * feed rate + 0.000751585 * concentration * voltage - 0.717383 * feed rate * voltage + 82.3632 * feed rate^2-eg(sol).

Where eg(sol) is the penalty function. Static penalty function is used to handle the constraints. Following are the constraints used in the algorithm. All the constraints are of greater than and equal type. Here sol (1) represents feed rate and sol (3) represents voltage.

Temperature constraint:

gx(1)=1-sol(1)^2.133007*0.0383054*sol(3)^-0.351436*1.37984062 Passivity constraint:

gx(2)=sol(1)^-0.844369*0.000517010*sol(3)^1.546257*289806.8658-1 Choking constraint:

gx(3)=1-sol(1)^0.075213*0.00057885048*sol(3)^0.240542*127581.4164

Maximum no of iterations is = 1000; No. of inequality constraints = 3; No. of equality constraints = 0; Harmonic memory size = 6; Harmony consideration rate = 0.9; Minimum pitch adjusting rate = 0.45; Maximum pitch adjusting rate = 0.9; Minimum band width = 0.0001;

Maximum band width = 1.0

The optimal set of variables satisfying the given constraints was as follows:

Electrolytic concentration = 15 g/l; applied voltage = 14 V; tool feed rate = 0.3.

The value of responses; MRR = 0.1622 g/min, overcut = 0.213 mm, surface roughness = 14.426µm are obtained.

5.4 Comparison of the effect of different tool materials on the output responses



Figure 5.4.1 Graph representing the effect of different tool materials on MRR

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Figure 5.4.2Graph representing the effect of different tool materials on overcut



Figure 5.4.3: Graph representing the effect of different tool materials on surface roughness.

From the above figures it is clear that with graphite tool, MRR comes out to be maximum and overcut value comes out to be minimum while surface roughness comes out to be minimum with brass tool.
Chapter 6

6.1Conclusions

- Maximum material removal rate and minimum radial overcut was obtained by using graphite as the tool material.
- Best surface finish of the machined surface was obtained by using brass tool.
- Optimization of the output responses obtained by machining with graphite tool using Harmonic search method yielded the optimal parametric combination as f=0.3mm/min, V=14V, C=15g/l. The output responses obtained under this combination was found to be MRR= 0.1428 g/min, Surface roughness = 12.4963µm, Radial overcut= 0.423mm.
- The optimal parametric combination obtained for brass tool by applying Harmonic search method was f=0.3mm/min, V=14V, C=15g/l. The output responses corresponding to the optimal set of combination is MRR= 0.0981 g/min, Surface roughness = 10.3017µm, Radial overcut= 0.403mm.
- The same technique of optimization was applied to the output responses obtained for copper tool and the optimal parametric combination was found to be f=0.3mm/min, V=14V, C=15g/l. The corresponding responses were MRR = 0.1622 g/min, overcut = 0.213 mm, surface roughness = 14.426µm.

6.2 Recommendation and future scope

The present work indicated that highest MRR and least overcut were obtained with graphite tool whereas machining with brass tool resulted in best surface finish. Therefore, graphite tool is recommended in those practical applications where material removal rate needs to be high and dimensional accuracy of the final product is a vital requirement. Similarly, electrochemical machining with brass tool is recommended in the applications where the machined surface needs to have a good surface finish.

The current research work was carried out using different tool materials, brine solution as electrolyte and AISI D2 tool steel to study the effect of each tool material during the machining process. Still there is a need to study the effect of more variations in the machining conditions to enhance the performance characteristics. Therefore, future works can be carried out in the following directions:

- 1. The effect of variation of tool materials on different work piece materials during electrochemical machining process must be studied.
- More research works must be carried out by performing electrochemical machining using different electrolytes and tool combinations such that decisions can be made on the compatibility of tool materials with different electrolytes.

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