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Optimization of ECM Process Parameters Using NSGA-II

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ABSTRACT

Electrochemical machining (ECM) could be used as one of the best non-traditional machining technique for machining electrically conducting, tough and difficult to machine material with appropriate machining parameters combination. This paper attempts to establish a comprehensive mathematical model for correlating the interactive and higher-order influences of various machining parameters on the predominant machining criteria, *i.e.* metal removal rate and surface roughness through response surface methodology (RSM). The adequacy of the developed mathematical models has also been tested by the analysis of variance (ANOVA) test. The process parameters are optimized through Nondominated Sorting Genetic Algorithm-II (NSGA-II) approach to maximize metal removal rate and minimize surface roughness. A non-dominated solution set has been obtained and reported.

Keywords: Electro Chemical Machining; Metal Removal Rate; Response Surface Methodology; Surface Roughness; NSGA-II

1. Introduction

Electrochemical machining (ECM) is one of the non-traditional machining techniques; it can achieve a wanted shape of a surface using metal dissolution by electrochemical reaction and can be applied to metals such as high-strength, heat-resistant and hardened steel. ECM has been used in industry for cutting, deburring, drilling and shaping [1]. In ECM electrical current passes between the cathode tool and the anode workpiece through an electrolyte solution. The workpiece is eroded in a way that can be described by Faraday's law of electrolysis. ECM is suitable for the machining of components of complex shape and high strength alloys, as typically found in the semiconductors industries [2]. Metal Matrix Composites (MMC's) are relatively new class of materials characterized by lighter weight and greater wear resistance than those of conventional materials. These materials have been considered for use in automobile brake rotors and various components in internal combustion engines. The machining of MMCs is very difficult due to the highly abrasive nature of the reinforcement [3]. Traditional edged cutting tool machining processes are uneconomical for such materials as the attainable degree of accuracy and surface finish are quite poor. Machining of complex shapes in such materials by traditional processes is still more difficult. To meet these demands, ECM processes has now emerged [4]. The present paper, therefore, emphasizes features of the development of comprehensive mathematical models for correlating the interactive and higher-order influences of the various machining parameters on the most dominant machining criteria, *i.e.* the metal removal rate and surface roughness phenomena, for achieving controlled ECM. The investigation into controlled ECM has been carried out through response surface methodology (RSM), utilizing the relevant experimental data as obtained through experimentation. The adequacy of thedeveloped mathematical models has also been tested by the analysis of variance test. The process parameters were optimized using Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) to maximize MRR and minimize Ra.

2. Experimental Planning

Experiments were conducted on METATECH ECM equipment. The dimensions of the specimens were 30 mm in diameter and 6 mm in height. The tool was made up of copper with a square cross section. Electrolyte was axially fed to the cutting zone through a central hole of the tool. The electrolyte used for experiment was fresh NaCl solution, because of the fact that NaCl electrolyte has no passivation effect on the surface of the job. The test specimens of LM25 Al/10%SiCp composites were produced through stir casting. The machining has been carried out for fixed time interval. The observations were made by varying predominant process parameters such as

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applied voltage, electrolyte concentration, electrolyte flow rate, and tool feed rate. MRR was measured from the weight loss. The surface roughness of the machined test specimens was measured using a Talysurf tester with a sampling length of 10 mm.

3. Response Surface Methodology

Response surface methodology (RSM) is the procedure for determining the relationship various between process parameters with the various machining criteria and exploring the effect of these process parameters on the coupled responses [5], *i.e.* the material removal rate and surface roughness phenomena. In order to study the effects of the ECM parameters on the above-mentioned two most important machining criteria, the metal removal rate (MRR) and surface roughness phenomenon (Ra), a second-order polynomial response surface mathematical model can be developed as follows to evaluate the parametric effects on the various machining criteria

$$Y_u = a_o + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n} a_{ii} x_i^2 + \sum_{i<j}^{n} a_{ij} x_i x_j + \varepsilon \qquad (1)$$

where Y_u is the corresponding response, e.g. the MRR and Ra created by the various process variables of ECM parameters. a_i represents the linear effect of x_i, a_{ii} represents the quadratic effect of x_i and a_{ij} reveals the linear-by-linear interaction between x_i and x_j. The second term under the summation sign of the polynomial equation *i.e.* Equation (1) attributes to linear effects, where as the third term of the above equation represents the higher order effects and lastly the fourth term of the above equation includes the interactive effects of the process parameters. In the response surface methodology each variable is coded in a manner so that the upper level is taken as +2 and lower level as −2 for designing the experiment and the test observations in an optimized way. The actual and coded parametric values for each parameter are listed in **Table 1**.

A well-designed experimental plan can substantially reduce the number of experiments. For determining the equation of the surface integrity, experimental designs have been developed with an attempt to formulate the mathematical relations using the smallest number of experiments possible. Keeping in view of the present research objectives, response surface methodology has been utilized in order to develop the mathematical relationship between the response, Y_u *i.e.* MRR and surface roughness and the predominant machining parameters are electrolyte flow rate, electrolyte concentration, applied voltage and tool feed rate according to the experimental plan based on central composite rotatable second order design as shown in **Table 2**.

Table 1. Actual and corresponding coded values for each parameter.

Parameters	Levels				
	−2	−1	0	1	2
Electrolyte concentration, X_1 (g/lit)	10	15	20	25	30
Electrolyte flow rate, X_2 (lit/min)	5	6	7	8	9
Applied voltage, X_3 (Volts)	12	13	14	15	16
Tool feed rate, X_4 (mm/min)	0.2	0.4	0.6	0.8	1

Table 2. Different controlling parametric combinations and test results.

Ex.No.	X_1	X_2	X_3	X_4	MRR (g/min)	Ra (µm)
1	−1	−1	−1	−1	0.124	10.274
2	1	−1	−1	−1	0.098	9.952
3	−1	1	−1	−1	0.245	8.752
4	1	1	−1	−1	0.278	8.196
5	−1	−1	1	−1	0.197	8.851
6	1	−1	1	−1	0.219	8.248
7	−1	1	1	−1	0.197	9.324
8	1	1	1	−1	0.342	7.724
9	−1	−1	−1	1	0.194	9.247
10	1	−1	−1	1	0.299	9.987
11	−1	1	−1	1	0.249	7.972
12	1	1	−1	1	0.389	8.131
13	−1	−1	1	1	0.482	6.386
14	1	−1	1	1	0.472	6.265
15	−1	1	1	1	0.529	6.729
16	1	1	1	1	0.656	6.583
17	−2	0	0	0	0.173	10.925
18	2	0	0	0	0.324	9.647
19	0	−2	0	0	0.214	8.689
20	0	2	0	0	0.299	7.854
21	0	0	−2	0	0.099	9.548
22	0	0	2	0	0.286	7.136
23	0	0	0	−2	0.299	9.597
24	0	0	0	2	0.721	6.845
25	0	0	0	0	0.227	6.389
26	0	0	0	0	0.287	6.253
27	0	0	0	0	0.295	6.054
28	0	0	0	0	0.245	6.921
29	0	0	0	0	0.268	6.824
30	0	0	0	0	0.226	6.354
31	0	0	0	0	0.289	6.542

4. Development of Empirical Models Based on RSM

After knowing the values of the observed response, the values of the different regression coefficients of second order polynomial mathematical equation *i.e*. Equation (1) have been evaluated and the mathematical models based on the response surface methodology have been developed by utilizing test results of different responses obtained through the entire set of experiments by using a computer software, MINITAB.14.

On Equation (1), the effects of various machining process variables on MRR and Ra has been evaluated by computing the values of different constants of Equation (1) utilising the relevant experimental data from **Table 2**. The mathematical relationship for correlating the MRR and Ra the considered machining process parameters is obtained as follows:

$$\begin{aligned}\mathrm{MRR}\\ &= -1.6538-(0.0334\,X_1)+(0.0417X_2)\\ &+(0.3976X_3)-(5.0188X_4)-(0.00008X_1^2)\\ &-(0.00002X_2^2)-(0.01602X_3^2)+(1.5837X_4^2)\\ &+(0.00442\,X_1X_2)+(0.0004\,X_1X_3)+(0.01175\,X_1X_4)\\ &-(0.00575\,X_2X_3)-(0.015\,X_2X_4)+(0.2493\,X_3X_4),\end{aligned} \quad (2)$$

$R^2 = 95.77\ \%$

$$\begin{aligned}\mathrm{Ra} &= 150.225-(0.977X_1)-(11.29X_2)\\ &-(12.74X_3)+(7.388X_4)+(0.035X_1^2)\\ &-(0.367X_2^2)+(0.384X_4^2)+(8.855X_4^2)\\ &-(0.0023X_1X_2)-(0.031X_1X_3)+(0.232X_1X_4)\\ &+(0.439X_2X_3)+(0.268X_2X_4)-(1.983X_3X_4)\end{aligned} \quad (3)$$

$R^2 = 96.05\%$

5. Optimization

To optimize cutting parameters in the machining of Al/SiCp composites, a non-dominated sorting genetic algorithm was used. The objectives set for the present study were as follows:

1. Maximization of the metal removal rate (MRR)
2. Minimization of average surface roughness (Ra)

The two-objective genetic algorithm optimization method used is a fast, elitist non-dominated sorting genetic algorithm (NSGA-II) developed by Deb [6]. This algorithm uses the elite-preserving operator, which favors the elites of a population by giving them an opportunity to be directly carried over to the next generation [7]. The NSGA-II is a modified version, which has a better sorting algorithm, incorporates elitism and does not require the choosing of a sharing parameter a priority. The flow chart of the NSGA-II is shown in **Figure 1**.

5.1. Description of NSGA-II Algorithm

The steps involved in the solution of optimization problem using NSGA-II are as follows.

5.1.1. Population Initialization

The population is initialized based on the problem range and constraints if any.

5.1.2. Non-Dominated Sort

The initialized population is sorted based on non-domination. The fast sort algorithm is described as below

- For each individual p in main population P
- Initialize $S_p = 0$. This set would contain all the individuals that is being dominated by p.
- Initialize $n_p = 0$. This would be the number of individuals that dominate p.
- For each individual q in P
- If p dominates q then. add q to the set S_p *i.e.* $S_p = S_P \mathrm{U}\{q\}$
- Else if q dominates p then increment the domination counter for p *i.e.* $n_p = n_p + 1$
- If $n_p = 0$ *i.e.* no individuals dominate p then p belongs to the first front; Set rank of individual p to one *i.e* $P_{\mathrm{rank}} = 1$. Update the first front set by adding p to front one, *i.e.*, $F_1 = F_1 \mathrm{U}\{q\}$
- This is carried out for all the individuals in main population P.
- Initialize the front counter to one, $i = 1$
- The following is carried out while the i^{th} front is non-empty *i.e.* $F_i \neq 0$
- $Q = 0$. The set for storing the individuals for $(i + 1)^{th}$ front.
- For each individual p in front F_i
- For each individual q in S_p (S_p is the set of individuals dominated by p)
- If $n_q = n_q - 1$, decrement the domination count for individual q.
- If $n_q = 0$ then none of the individuals in the subsequent fronts would dominate q.
- Hence set $q_{\mathrm{rank}} = i + 1$. Update the set Q with individual q *i.e.* $Q = Q\mathrm{U}q$.
- Increment the front counter by one.
- Now the set Q is the next front and hence $F_i = Q$.

This algorithm is better than the original NSGA [8] since it utilize the information about the set that an individual dominate (S_p) and number of individuals that dominate the individual (n_p).

5.1.3. Crowding Distance

Once the non-dominated sort is complete the crowding distance is assigned. Since the individuals are selected based on rank and crowding distance all the individuals

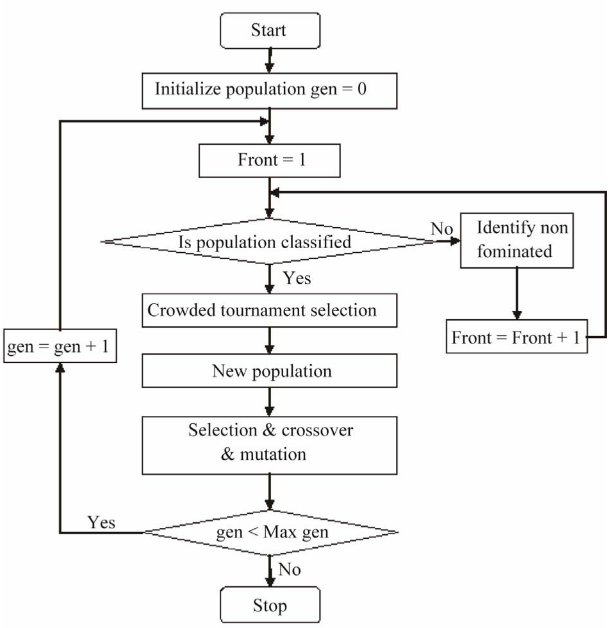

Figure 1. Flow chart of NSGA-II program.

in the population are assigned a crowding distance value. Crowding distance is assigned front wise and comparing the crowding distance between two individuals in different front is meaningless (Raghuwanshi *et al*., 2004). The crowing distance is calculated as below

- For each front F_i, n is the number of individuals.
- Initialize the distance to be zero for all the individuals *i.e.* $F_i(d_j) = 0$,where j corresponds to the j^{th} individual in front F_i.
- For each objective function m
- Sort the individuals in front F_i based on objective m *i.e.* $I = \text{sort}(F_i, m)$.
- Assign infinite distance to boundary values for each individual in F_i *i.e.* $I(d_1) = \infty$ and $I(d_n) = \infty$
- For $k = 2$ to $(n - 1)$

$$I(d_k) = I(d_k) + \frac{I(k+1)\cdot m - I(k-1)\cdot m}{f_m^{\max} - f_m^{\min}}$$

- $I(k)\cdot$m is the value of the m^{th} objective function of the k^{th} individual in I
- The basic idea behind the crowing distance is finding the Euclidian distance between each individual in a front based on their m objectives in the m dimensional hyper space. The individuals in the boundary are always selected since they have infinite distance assignment.

5.1.4. Selection

Once the individuals are sorted based on non-domination and with crowding distance assigned, the selection is carried out using a *crowded-comparison-operator* (α_n). The comparison is carried out as below based on

(1) Non-domination rank p_{rank} *i.e.* individuals in front F_i will have their rank as $p_{\text{rank}} = i$.

(2) Crowding distance $F_i(d_j)$

$p <_n q$ if

- $p_{rank} < q_{rank}$
- Or if p and q belong to the same front F_i then $F_i(d_p) > Fi(d_q)$ *i.e.* the crowing distance should be more.

The individuals are selected by using a binary tournament selection with crowed- comparison-operator.

5.1.5. Genetic Operators.

Real-coded GA's use Simulated Binary Crossover (SBX) operator for crossover and polynomial mutation [8].

1) Simulated Binary Crossover.

Simulated binary crossover simulates the binary crossover observed in nature and is given as below.

$$c_{1,k} = \frac{1}{2}\left[(1-\beta_k)\,p_{1,k} + (1+\beta_k)\,p_{2,k}\right]$$

$$c_{2,k} = \frac{1}{2}\left[(1+\beta_k)\,p_{1,k} + (1-\beta_k)\,p_{2,k}\right]$$

where $c_{i,k}$ is the i^{th} child with k^{th} component, $p_{i,k}$ is the selected parent and β_k (≥ 0) is a sample from a random number generated having the density

$$p(\beta) = \frac{1}{2}(\eta_c + 1)\beta^{\eta_c}, \text{ if } 0 \leq \beta \leq 1$$

$$p(\beta) = \frac{1}{2}(\eta_c + 1)\frac{1}{\beta^{\eta_c+2}}, \text{ if } \beta > 1$$

This distribution can be obtained from a uniformly sampled random number u between (0,1). η_c is the distribution index for crossover. That is

$$\beta(u) = (2u)^{\frac{1}{(\eta+1)}}$$

$$\beta(u) = \frac{1}{\left[2(1-u)\right]^{\frac{1}{(\eta+1)}}}$$

2) Polynomial Mutation:

The polynomial mutation is performed by

$$c_k = p_k + \left(p_k^u - p_k^l\right)\delta_k$$

where c_k is the child and p_k is the parent with p_k^u being the upper bound on the parent component, p_k^l is the lower bound and δ_k is small variation which is calculated from a polynomial distribution by using

$$\delta_k = (2r_k)^{\frac{1}{\eta_m+1}} - 1, \text{ if } r_k < 0.5$$

$$\delta_k = 1 - \left[2(1-r_k)\right]^{\frac{1}{\eta_m+1}}, \text{ if } r_k \geq 0.5$$

r_k is an uniformly sampled random number between (0,1) and η_m is mutation distribution index.

5.1.6. Recombination and Selection

The offspring population is combined with the current generation population and selection is performed to set the individuals of the next generation. Since all the previous and current best individuals are added in the population, elitism is ensured. Population is now sorted based on non-domination. The new generation is filled by each front subsequently until the population size exceeds the current population size. If by adding all the individuals in front F_j the population exceeds N then individuals in front F_j are selected based on their crowding distance in the descending order until the population size is N. And hence the process repeats to generate the subsequent generations.

The control parameters of NSGA–II must be adjusted to give the best performance. The parameters are: Probability of gross over $P_c = 0.9$ with distribution index $\eta_c = 20$, mutation probability $P_m = 0.25$ and population size $P_z = 100$. It was found that the NSGA-II with those control parameters produces better convergence and distribution of optimal solutions located along the Pareto optimal solutions. The 1000 generations are quite enough to find the true optimal solutions.

6. Discussion

The analysis of variance (ANOVA) and the F-ratio test have been performed to justify the goodness of fit of the developed mathematical models. The results of the analysis of variance are presented in **Table 3**. The calculated values of F-ratio for the lack of fit are found to be lesser than the standard percentage point of F distribution for 99% confidence limit is 7.87 for MRR and Ra. Also, values of R^2 of regression analysis have been calculated to test whether data is fitted in the developed model and these values show that data for each response are fitted in the developed models. The P-value for the model MRR and surface roughness is lower than 0.05 (*i.e.* $p= 0.05$, or 95% confidence) indicates that the model is considered to be statistically significant.

A single objective optimization algorithm will normally be terminated upon obtaining an optimal solution. However, for most of the multi-objective problems, there could be a number of optimal solutions .Suitability of one solution depends on a number of factors including user's choice and problem environment, and hence finding the entire set of optimal solutions may be desired. Among the Pareto optimal solutions, none of the solutions is absolutely better than any other solution and hence this solution is called as non-dominated solution [9]. GAs can find good solutions to linear and nonlinear problems by simultaneously exploring multiple regions of the solution space and exponentially exploiting promising areas through mutation, crossover and selection operations. In general, the fittest individuals of any population are more likely to reproduce and survive to the next generation, therefore improving successive generations. Non dominating Sorting GA (NSGA-II) by Deb and Goel (2002) is of the best methods for generating the Pareto frontier and is used in this study. The NSGA-II algorithm ranks the individuals based on dominance. The fast non dominated sorting procedure allows us to find the non domination frontiers where individuals of the frontier set are not dominated by any solution. The crowding distance is calculated for each individual of the new population. Crowding factor gives the GA the ability to distinguish individuals that have the same rank. This forces the GA to uniformly cover the frontier rather than bunching up at several good points by trying to keep population diversity. The comparison operator ($<n$) is used by the GA to sort the population for selection purposes [10].

The procedure was repeated ten times to get greater number of points in the pareto solution set. The non-dominated solution set obtained over the entire optimization process is shown in **Figure 2**.

This shows the formation of the pareto front leading to the final set of solutions. The corresponding objective function values and decision variables of this non-dominated solution set are given in **Table 4**. The 31 out of 100 sets were presented since none of the solutions in the non-dominated set is absolutely better than any other; any one of them is an acceptable solution. The choice of one solution over the other depends on the requirement of the process engineer. If a better surface finish or a higher production rate is required, a suitable combination of variables can be selected from **Table 4**. From the experimental results presented in **Table 2**, the parameters listed in the experiment number 25 leads to minimum Ra of 5.021 µm and the corresponding MRR of 0.358 gm/min, where the electrolyte concentration, electrolyte

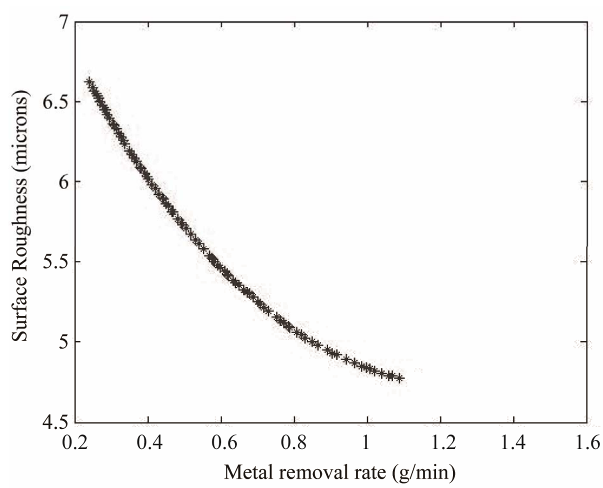

Figure 2. Optimal chart obtained through NSGA-II for composite Al/10%SiCp composite using NaCl.

Table 3. Analysis of variance test results for the developed models.

Source	D.f	Sum of squares		Mean sum of squares		F-value		*p*-value	
		MRR	Ra	MRR	Ra	MRR	Ra	MRR	Ra
Linear	4	0.4168	25.773	0.0175	2.4213	10.6	15.68	0.000	0.000
Square	4	0.1314	7.1034	0.0328	6.8048	19.88	44.07	0.000	0.000
Interaction	6	0.0505	2.4704	0.0084	1.1839	5.10	7.67	0.004	0.001
Lack of fit	10	0.0211	1.8967	0.0021	0.1896	2.4	1.98		
Error	6	0.0052	0.5737	0.0008	0.0956				
Total	30	0.6253	62.566						

Table 4. Optimal combinations of parameters for ECM of Al/10%SiCp composite using NaCl.

Sl No.	X_1	X_2	X_3	X_4	MRR (g/min)	Ra (µm)
1	10	5	16	1.0	0.248	6.589
2	10	5	16	1.0	0.240	6.624
3	21	5	16	1.0	1.178	4.733
4	18	5	15	0.9	0.312	6.333
5	13	5	15	1.0	0.517	5.670
6	18	5	15	1.0	1.041	4.805
7	**16**	**5**	**15**	**1.0**	**0.831**	**5.020**
8	15	5	15	1.0	0.764	5.131
9	14	5	15	0.9	0.592	5.478
10	15	5	15	1.0	0.751	5.152
11	11	5	15	0.9	0.391	6.052
12	19	5	15	1.0	1.070	4.785
13	17	5	15	1.0	0.916	4.918
14	16	5	15	1.0	0.786	5.093
15	12	5	15	1.0	0.439	5.897
16	16	5	15	1.0	0.822	5.047
17	13	5	15	1.0	0.553	5.576
18	16	5	15	1.0	0.865	4.979
19	10	5	16	1.0	0.270	6.498
20	15	5	15	1.0	0.732	5.187
21	10	5	16	1.0	0.290	6.420
22	13	5	16	1.0	0.568	5.537
23	14	5	15	0.9	0.618	5.418
24	11	5	16	0.9	0.379	6.092
25	13	5	15	1.0	0.578	5.512
26	12	5	15	1.0	0.421	5.955
27	14	5	15	1.0	0.678	5.292
28	15	5	15	0.9	0.578	5.512
29	19	5	15	1.0	1.143	4.749
30	11	5	15	1.0	0.719	5.152
31	18	5	16	1.0	0.998	4.838

Table 5. Validation test results for Al/10%SiCp composite using NaCl.

#	Electrolyte concentration, gm/lit	Electrolyte flow rate, Lit/min	Applied voltage, Volts	Tool feed rate, mm/min	MRR (gm/min)			Ra (μm)		
					Predicted	Actual	%Error	Predicted	Actual	%Error
1	16	5	15	1.0	0.831	0.810	2	5.020	5.131	3

flow rate, applied voltage and tool feed rate are 20 gm/lit, 7 lit/min, 14 volts and 0.6 mm/min respectively. By optimizing using NSGA-II, the Ra value is very close to the experimental value has been selected from the **Table 4**, trail no: 7. The Ra value is 5.020 μm and the corresponding MRR is 0.831 gm/min and the pertinent parameters are electrolyte concentration, electrolyte flow rate, applied voltage and tool feed rate are MRR is 0.831 gm/min and the pertinent parameters are electrolyte concentration, electrolyte flow rate, applied voltage and tool feed rate are 16 gm/lit, 5 lit/min, 15 volts and 1.0 mm/min respectively. This indicates that values obtained from the NSGA-II optimization technique are in close agreement with the experimental values and more or less the same parameter settings. In this study, after determining the optimum conditions and predicting the response under these conditions, a new experiment was designed and conducted with the optimum values of the machining parameters. Verification of the test results at the selected optimum conditions for MRR and Ra are shown in **Table 5**.

The predicted machining performance was compared with the actual machining performance and a good agreement was obtained between these performances. From the analysis of **Table 5**, it can be observed that the calculated error is small. The error between experimental and predicted values for MRR and Ra lie within 2% and 3%, respectively. Obviously, this confirms excellent reproducibility of the experimental conclusions.

7. Conclusion

The ECM process parameters have been optimized by using non dominated sorting genetic algorithm (NSGA II), and a non dominated solution set is obtained. The second order polynomial models developed for MRR and Ra have been used for optimization. The choice of one solution over the other depends on the process the engineer. If the requirement is a better Ra or higher MRR, a suitable combination of variables can be selected. Optimized value obtained through NSGA-II, is 5.020 μm and the corresponding MRR is 0.831 gm/min and the pertinent parameters are electrolyte concentration, electrolyte flow rate, applied voltage and tool feed rate are 16 gm/lit, 5 lit/min, 15 volts and 1.0 mm/min respectively. Optimization will help to increase production rate considerably by reducing machining time. The objectives such as MRR and Ra have been optimized using a multi-objective optimization method, non-dominating sorting genetic algorithm-II. A pareto-optimal set of 100 solutions is obtained.

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