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ORIGINAL ARTICLE

Optimization of electrical discharge machining characteristics of WC/Co composites using non-dominated sorting genetic algorithm (NSGA-II)

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Abstract Electrical discharge machining (EDM) is a process for shaping hard metals and forming deep and complex shaped holes by arc erosion in all types of electro conductive materials. In the present work, the effectiveness of the EDM process with tungsten carbide and cobalt composites is evaluated in terms of the material removal rate and the surface finish quality of the workpiece produced. The objective of this research is to study the influence of operating parameters of EDM such as pulse current, pulse on time, electrode rotation and flushing pressure on material removal rate and surface roughness. The experimental results are used to develop the statistical models based on second order polynomial equations for the different process characteristics. The non-dominated sorting genetic algorithm (NSGA-II) has been used to optimize the processing conditions. A non-dominated solution set has been obtained and reported.

Keywords WC/Co composite · Electrical discharge machining (EDM) · Non-dominated sorting genetic algorithm (NSGA-II) · Modeling

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1 Introduction

Electrical discharge machining is used for material removal through the action of an electrical discharge of short duration and high current density between the tool and workpiece. EDM has proved valuable in the machining of super-tough, electrically conductive materials such as new space-age materials. These materials would have been difficult to machine by conventional methods, but EDM has made it relatively simple to machine intricate shapes that would be impossible to produce with conventional cutting tools. This machining process is continuously finding further applications in the machining industry [1].

Tungsten carbide is an important tool and die material mostly because of high hardness, strength and wear resistance over a wide range of temperatures. It has high specific strength and cannot be processed easily by conventional machining techniques. The literature available on electric discharge machining of tungsten carbide and cobalt carbide is very limited [2]. Electro-discharge machine manufacturers and users are always interested in acquiring better stability and higher productivity in the machining process. The higher rate of material removal with desired accuracy and minimal surface damage make the EDM operation less costly and the process more economically viable and affordable. However, due to a great number of variables and a variety of products, optimal machining performance is rarely achieved. It is necessary to investigate how the erosion parameters affect the machining process. The results will provide significant information to achieve optimal performance in the process [3].

Often optimization problems have multiple objectives. Most of the time these objectives are conflicting (i.e., optimizing one objective causes the other objectives to be poor). The genetic algorithm (GA) is an evolutionary algorithm that uses genetic operators to obtain optimal solutions without any assumptions about the search space. GA works with a population of feasible solutions and, therefore, it can be used in multi-objective optimization problems to capture a number of solutions simultaneously [4]. GA based multi-objective optimization methodologies have been amply applied to find a representative set of Pareto-optimal solutions in the past decade and beyond. For the past 15 years or so, evolutionary multi-objective optimization (EMO) methodologies have adequately demonstrated their usefulness in finding a well-converged and well-distributed set of near Pareto-optimal solutions [5, 6]. Due to these extensive studies and available source codes both commercially and freely, the EMO procedures have been popularly applied in various problem-solving tasks and have received a great deal of attention even by the classical multicriterion optimization and decision-making communities [7]. Non-dominating sorting GA (NSGA-II) is one of the most widely used methods for generating the Pareto frontier. The NSGA-II algorithm ranks the individuals based on dominance. NSGA-II uses elitism and a phenotype crowd comparison operator that keeps diversity without specifying any additional parameters [8].

In this work, a study focused on the die-sinking EDM of cobalt-bonded tungsten carbide (WC/Co), whose field of applications is in constant growth, is carried out. Consequently, an analysis on the influence of current intensity, pulse time, electrode rotational speed and flushing pressure over technological variables such as surface roughness and metal removal rate (*MRR*) is performed using design of experiments (DOE) and regression analysis. The use of these techniques has enabled creation of second order polynomial models, which make it possible to explain the variability associated with each of the technological variables studied. In addition, these models can be used for optimization by which the optimum parameter settings can be obtained with minimization of surface roughness and maximization of *MRR* as objectives [9]. The NSGA-II algorithm has been used for optimization of EDM characteristics of WC/Co composites.

2 Experimental study

The experiments were conducted in an Electronica die sinking EDM (M100 model, Electronica, India) machine, which has been equipped with a transistor switched power supply. The electrode has been fed downwards under servo control into the workpiece. Copper cylindrical electrodes of 12 mm diameter were used as tool. Kerosene was used as a dielectric fluid. The dielectric fluid was circulated by jet flushing. The machining conditions are provided in Table 1. Parameter ranges are selected on the basis of preliminary experiments conducted by using a one variable at a time approach. There are a large number of factors to consider within the EDM process, but in this work the level of the current, pulse on time, electrode rotation and dielectric flushing pressure have only been taken into account as design factors. The factors and setting levels are presented in Table 2 [10]. Experiments have been conducted according to L27 orthogonal array covering the full range of current settings, with pulse on time settings to collect more data for modeling. For each experiment, a new set of tool and workpiece has been used. The experiments were conducted on 70%WC/30%Co composites. The density of WC and Co are 15.7 g/cc and 13.55 g/cc while the grain sizes of WC and Co are 6 μm and 3 μm, respectively.

Table 1 Machining conditions

Descriptions	
Electrode	Material: copper (electrolytic grade)
	Size: cylindrical with a diameter of 13 mm
Workpiece	Material: tungsten carbide with 30%Co
	Size: cylindrical rod of diameter 13 mm
	Dielectric fluid: kerosene
Flushing	Jet flushing
	Flushing pressure: 0.5–1.5 kg/cm^2
Rotational speed	250, 500, 1000 rpm
Discharge current	5, 10, 15 A
Pulse on time	200, 500, 1000 μs

The response variables selected for this study are metal removal rate (*MRR*) and surface roughness (*Ra*), the metal removal rate has been calculated using the following expression:

$$MRR(\mathrm{mg/min}) = \frac{\mathit{Volume\ of\ material\ removed\ from\ part}}{\mathit{Time\ of\ machining}} \tag{1}$$

The surface roughness has been measured on a Surfcoder SE1200 surface testing analyser (Kosaka, Japan). For each sample, five readings of surface roughness were taken and an average value of the five was considered as the final reading. The results are presented in Table 3.

Table 2 Process parameters and their levels

Parameters	Level 1	Level 2	Level 3
Rotational speed, rpm	250	500	1,000
Pulse current, A	5	10	15
Pulse on time, μs	200	500	1,000
Flushing pressure, kg/cm^2	0.5	1.0	1.5

Table 3 Experimental results

S. no.	Electrode rotation, rpm	Current, A	Pulse on time, μs	Flushing pressure, kg/ cm2	*MRR*, mg/ min	*Ra*, μm
1	250	5	200	0.5	38.19	3.94
2	250	5	200	1.0	46.05	2.84
3	250	5	200	1.5	51.37	2.35
4	250	10	500	0.5	46.50	8.83
5	250	10	500	1.0	56.07	6.37
6	250	10	500	1.5	62.56	5.27
7	250	15	1,000	0.5	49.31	14.74
8	250	15	1,000	1.0	59.45	10.64
9	250	15	1,000	1.5	66.33	8.80
10	500	5	500	0.5	37.77	3.89
11	500	5	500	1.0	45.54	2.81
12	500	5	500	1.5	50.81	2.39
13	500	10	1,000	0.5	49.84	8.24
14	500	10	1,000	1.0	60.09	5.94
15	500	10	1,000	1.5	67.05	4.91
16	500	15	200	0.5	121.07	7.56
17	500	15	200	1.0	145.98	5.45
18	500	15	200	1.5	162.87	4.51
19	1,000	5	1,000	0.5	40.48	3.63
20	1,000	5	1,000	1.0	48.81	2.62
21	1,000	5	1,000	1.5	54.46	2.37
22	1,000	10	200	0.5	122.37	4.22
23	1,000	10	200	1.0	147.55	3.05
24	1,000	10	200	1.5	164.62	2.52
25	1,000	15	500	0.5	119.74	7.47
26	1,000	15	500	1.0	144.38	5.39
27	1,000	15	500	1.5	161.09	4.46

3 Statistical modeling

Statistical models based on second order polynomial equations are developed for the different process characteristics using the experimental results.

$$\begin{aligned} &\textit{Material removal rate } (MRR) = -30.3660 + 0.1589R \\ &+9.5259I - 0.1241T + 20.8585P - 0.0001R^2 - 0.2318I^2 \\ &+0.0001T^2 - 9.2131P^2 - 0.0002RI - 0.0000RT \\ &+0.0220RP + 1.9991IP - 0.0199TP \end{aligned} \quad (2)$$

$$\begin{aligned} &\textit{Surface roughness } (Ra) = 4.2307 - 0.0116R + 0.5816I \\ &+0.0099T - 4.7481P + 0.0000R^2 + 0.0085I^2 - 0.0000T^2 \\ &+2.1239P^2 - 0.0002RI - 0.0000RT - 0.0020RP \\ &-0.2462IP - 0.0018TP \end{aligned} \quad (3)$$

Here, electrode rotation (R) is in rpm, current (I) in A, pulse on time (T) in μs and flushing pressure (P) in kg/cm^2.

4 Optimization

The objectives of the present study for optimization are as follows:

1. Maximization of the *MRR*
2. Minimization of surface roughness

A set of non-dominated solutions has been obtained using NSGA-II and the best solution has been taken.

4.1 General procedure of evolutionary multi-objective optimization

As stated before, dual goals in a multi objective optimization are to find a set of solutions as close as possible to the Pareto optimal front and simultaneously as diverse as possible. Except for the fitness assignment method for multiple objectives the basic structure of a Pareto based evolutionary multi-objective optimization is similar to that of GA. The procedure is given in ref. [11]. The two-objective genetic algorithm optimization method investigated here is an elitist non-dominated sorting genetic algorithm (NSGA-II) developed by Deb in 2001. 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. After two offspring's are created using the crossover and mutation operators, they are compared with both of their parents to select the two best solutions among the four parent-offspring solutions [12].

The flow chart of the NSGA II program is shown in Fig. 1. It starts with a random initial generation. First, the parents and offspring are combined to form a string. When the objective functions of all strings in a generation are calculated, the solutions are classified into various non-dominated fronts. The crowded tournament selection operator, also developed by Deb in 2001, is used to compare two solutions and returns the winner of the tournament according to two attributes: (1) a non-dominated front in the population and (2) a local large crowding distance. The first condition makes sure that the chosen solution lies on a better non-dominated front, and the second condition ensures a better spread among the solutions. The simulated binary crossover (SBX) is used here to create two offspring from two-parent solutions. The random simplest mutation operator is applied randomly to create a solution from the entire search space [13].

Multi objective optimization problems give rise to a set of Pareto optimal solutions, none of which can be said to be

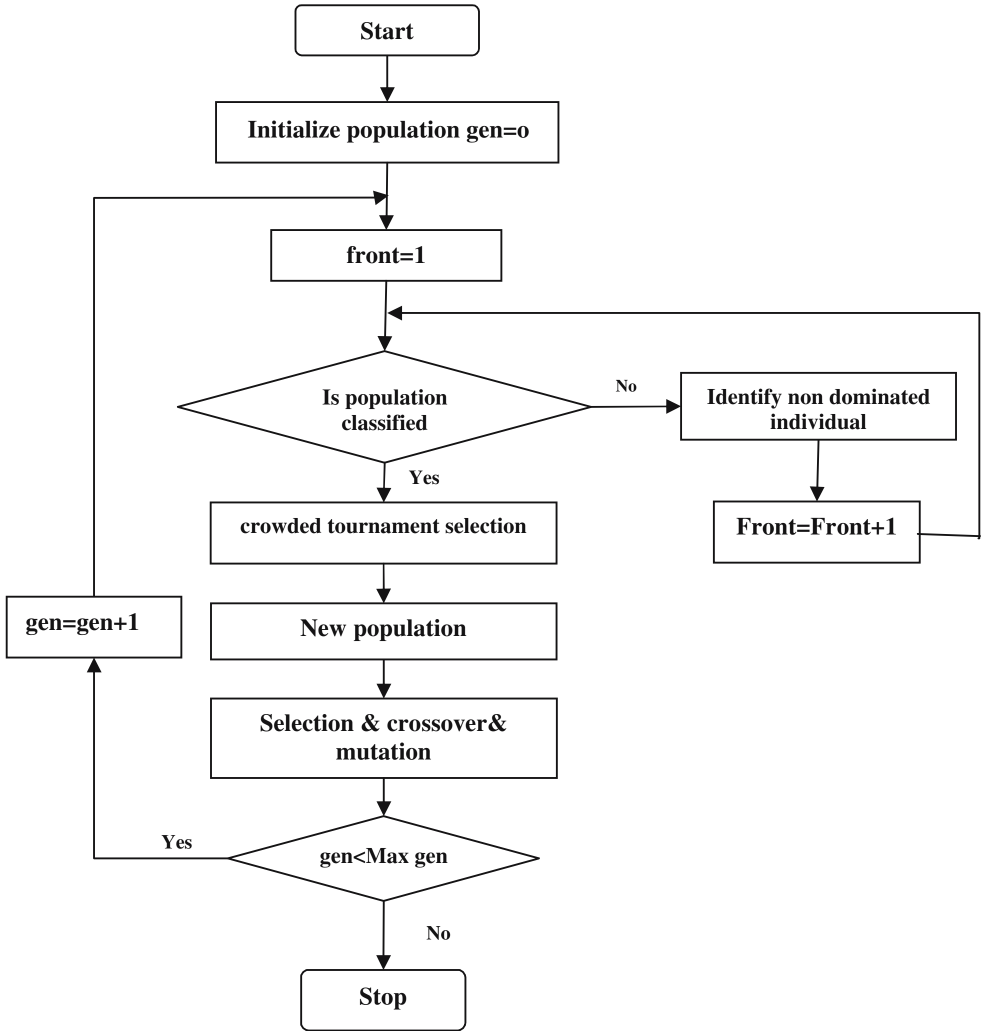

Fig. 1 Flow chart of NSGA II program [12]

better than any other in all objectives. In any interesting multi objective optimization problem, there exist a number of such solutions, which are of interest to designers and practitioners. Since no one solution is better than any other solution in the Pareto optimal set, it is also a goal in a multi objective optimization to find as many such Pareto optimal solutions as possible. Unlike most classical search and optimization problems, GAs work with a population of solutions and thus are likely candidates for finding multiple Pareto optimal solutions simultaneously [13].

4.2 NSGA-II algorithm [5, 13, 14]

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

1. Population initialization

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

2. Non-dominated sort

The initialized population is sorted based on non-domination. The fast sort algorithm [4] is described as below.

- For each individual p in main population P:
- Initialize $S_p = 0$. This set would contain all the individuals that are 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 1, 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 nonempty, i.e., $F_i \neq 0$
- $Q = 0$. The set for storing the individuals for $(i+1)^{\text{th}}$ 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 $q_{\text{rank}} = i+1$. Update the set Q with individual q, i.e., $Q = Q \text{ U } q$.
- 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 [6] since it utilizes the information about the set that an individual dominates (S_p) and the number of individuals that dominate the individual (n_p).

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 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 fronts is meaningless [6]. 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., $I = sort(F_i, m)$.
- Assign infinite distance to boundary values for each individual in F_i, i.e., $I(d_1) = \infty$ and $I(d_{\text{n}}) = \infty$
- For $k = 2$ to $(n-1)$

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

- $I(k)m$ is the value of the m^{th} objective function of the k^{th} individual in I.

The basic idea behind the crowding 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.

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 ($\prec_{\text{n}}$) [15]. The comparison is carried out as below based on

(a) Non-domination rank p_{rank}, i.e., individuals in front F_i will have their ranks $p_{\text{rank}} = i$.
(b) Crowding distance $F_i(d_j)$

$p \prec_n q$ if

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

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

5. Genetic operators

Real-coded GAs use a simulated binary crossover (SBX) [16] operator for crossover and polynomial mutation [6].

(a) Simulated binary crossover

Simulated binary crossover simulates the binary crossover observed in nature and is give 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,

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

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

(b) Polynomial mutation

$$c_k = p_k + \left(p_k^{\mu} - p_k^{l}\right)\delta_k$$

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^1 is the lower bound and δ_k is small variation which is calculated from a polynomial distribution by using

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

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

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

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 crossover p_c=0.9 with distribution index η_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 1,000 generations are quite enough to find the true optimal solutions.

5 Discussion

Electro discharge machining characteristics of WC/Co composites produced through the powder metallurgy route are studied. Second order polynomial models were developed for metal removal rate (*MRR*) and surface roughness (*Ra*) using MINITAB software. The fit summary recommended that the quadratic model is statistically significant for analysis of *MRR*. The value of R^2 is over 95%, which means that the regression model provides an excellent explanation of the relationship between the independent variables (factors) and the response (*MRR*). The associated *p*-value for the model is lower than 0.05 (i.e., p=0.05, or 95% confidence) indicates that the model is considered to be statistically significant [17]. The ANOVA table for the quadratic model for *MRR* is shown in Table 4. Figure 2 displays the normal probability plot of the residuals for *MRR*. It can be seen that the residuals are located on a straight line, which means that the errors are normally distributed and the regression model is fairly well fitted with the observed values.

Table 4 Analysis of variance for *MRR*, mg/min

Source	*DF*	*SS*	*MS*	*F*	*P*
Regression	13	54320.64	4178.511	1949.81	0.02
Linear	4	2239.77	559.942	261.28	<0.001
Square	4	1191.71	297.928	139.02	0.03
Interaction	5	706.58	141.315	65.94	0.002
Residual error	13				<0.001
Total	26				

Similarly the value of R^2 for surface roughness is 96%, which means that the regression model provides an excellent explanation of the relationship between the independent variables (factors) and the response (*Ra*). The associated *p*-value for the model is lower than 0.05 (i.e., p= 0.05, or 95% confidence), which indicates that the model is considered statistically significant. The result proves that the electrode rotation and flushing pressure enhance the surface finish. The ANOVA table for the quadratic model for *Ra* is shown in Table 5. The model results indicate that the model is significant and the lack of fit is insignificant. Figure 3 displays the normal probability plot of the residuals for *Ra*. It is observed that the residuals are located on a straight line, which means that the errors are normally distributed and the regression model is fairly adequate.

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 solution, none of the solutions is absolutely better than any other solution and hence this solution is called as non-dominated solution [3].

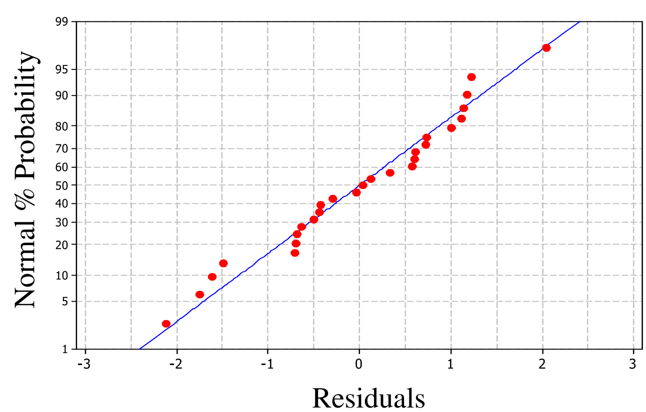

Fig. 2 Normal plot of residuals for *MRR*, mg/min

Table 5 Analysis of variance for *Ra*, μm

Source	*DF*	*SS*	*MS*	*F*	*P*
Regression	13	230.4143	17.72418	278.66	0.03
Linear	4	8.6240	2.15600	33.90	<0.001
Square	4	4.5041	1.12601	17.70	<0.001
Interaction	5	11.6750	2.33501	36.71	0.02
Residual Error	13	0.8269	0.06360		0.002
Total	26				

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) developed by Deb and Goel in 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 ($\prec_n$) is used by the GA to sort the population for selection purposes [18].

The procedure was repeated ten times to get a greater number of points in the Pareto solution set. The non dominated solution set obtained over the entire optimization process is shown in Fig. 4. 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

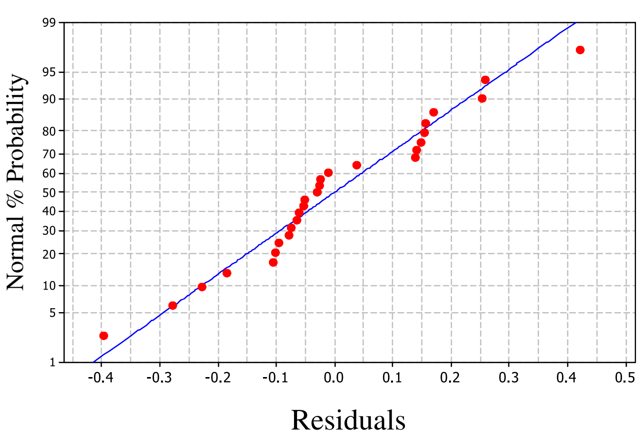

Fig. 3 Normal plot of residuals for *Ra*, μm

Table 6. The 26 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 6.

From the experimental results presented in Table 3, the parameters for trial number 12 (S. no.12) resulted in a *Ra* value of 2.39 μm and a *MRR* of 50.81 mg/min. By optimization using NSGA-II It can be seen that the *MRR* can be increased about three times to 165 mg/min for the same surface finish (trial no. 25, Table 6). In the experimental results the maximum *MRR* obtained is 164.62 mg/min (trial no. 24) with a surface roughness value of 2.52 μm *Ra*. Also from the optimization results there are five different cases in which the *MRR* is greater than the highest value of *MRR* obtained by experiment.

From the experimental results presented in Table 3, the parameters for trial number 3 resulted in the minimum *Ra* value of 2.35 μm and a corresponding *MRR* of 51.37 mg/min; by optimization using NSGA-II the observed *Ra* values were comparatively less than the experimental values.

By using the non-dominated sorting genetic algorithm (NSGA-II), the non-dominated solution set is obtained. None of the solutions in the Pareto optimal set is better than any other solution in the set. The process engineer can select optimal combinations of parameters from the Pareto optimal solution set, depending on the requirements.

The increase in electrode rotation increases the *MRR* and decreases the surface roughness. The increase in *MRR* is due to the effective flushing of the rotary electrode. When the cylindrical electrode rotates, due to the centrifugal action, a new layer of dielectric fluid was thrown into the machining gap [19]. This induces a conductive atmosphere for effective discharge and encourages process stability. The enhanced discharge increased the *MRR* and efficiency. With increased peripheral speed of the electrode, the ignition time delay increases, thus bringing down the energy transferred through the individual discharges for material removal. This diminishes the crater dimensions to give a better roughness value. From Table 6 it is seen that the optimum values of electrode rotational speed range from 808 rpm to 892 rpm. Increase in speed beyond 892 rpm may not have much impact on the EDM characteristics.

As the pulse current increases, the *MRR* as well as the surface roughness increase. The increase in current intensity increases the pulse energy and hence the *MRR* increases with current intensity [20]. The increase in discharge current resulted in an increase in *Ra* value irrespective of

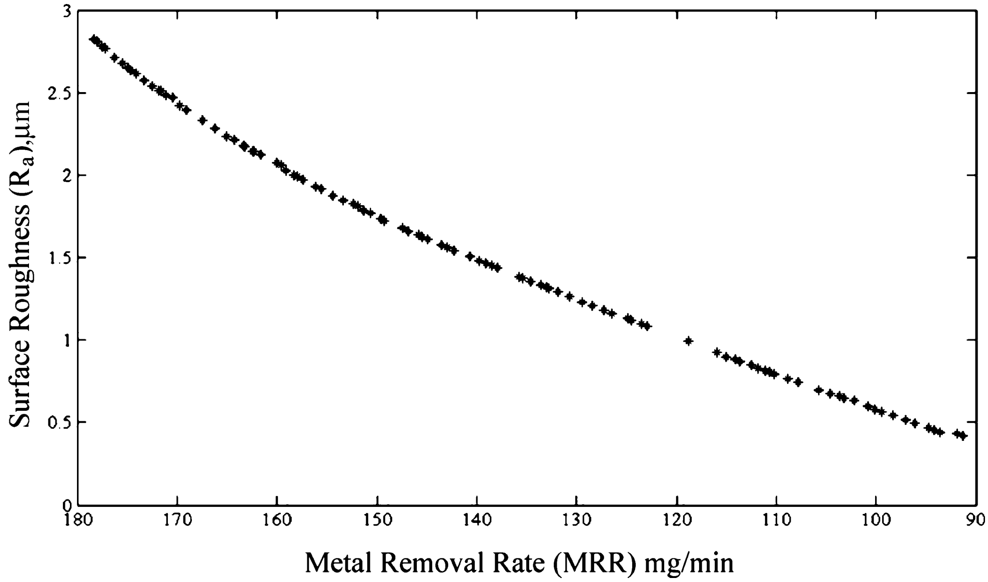

Fig. 4 Optimal chart obtained through NSGA II

the electrode. This event is due to the increase in discharge energy, which subsequently causes a larger crater on the surface of the body. It can be seen that the increase in current has opposing effects on *MRR* and surface finish. For better *MRR* higher current is required whereas the surface roughness is less at lower current. Hence, a wide range of optimum current values can be seen in Table 6.

The *MRR* decreased with the increase in the pulse duration. Short pulse duration caused less surface vaporization, whereas long pulse duration may cause the plasma channel to expand and decrease the energy density for the workpiece. Consequently, the resulting craters will be broader and deeper and thus the surface finish will be rougher [21]. Obviously with shorter duration of sparks the surface finish will be better. Hence an optimum value of pulse on time is 200 µs as observed from Table 6.

A flushing pressure increase helps to evacuate the debris of the workpiece that was removed by the spark discharges. The machining performance has been improved with better surface quality since the removed particles in the machining gap are evacuated more efficiently, so the *MRR* increases [22]. It can be seen that when flushing pressure is less than a certain pressure, it is impossible to do any machining. Hence the optimum flushing pressure values are between 1.1 kg/cm^2 and 1.5 kg/cm^2, as observed from Table 6.

6 Conclusion

The EDM process parameters for WC/Co composites 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 metal removal rate and surface roughness have been used for optimization. The choice of one solution over the other depends on the requirement of the process engineer. If the requirement is a better surface finish or higher material removal rate, a suitable combination of variables can be selected. Optimization will help to increase production rate considerably by reducing machining time.

Table 6 Optimal combinations of parameters for the EDM process

S. no.	Rotational speed, rpm	Current, A	Pulse time, µs	Flushing pressure, kg/ cm^2	*MRR*, mg/ min	*Ra*, µm
1	814	15.0	200	1.5	176.0	2.95
2	844	5.4	200	1.2	99.5	0.56
3	839	7.9	200	1.3	124.0	1.13
4	839	5.3	200	1.1	96.8	0.51
5	808	10.0	200	1.5	146.0	1.74
6	843	8.5	200	1.4	131.0	1.29
7	813	14.0	200	1.4	171.0	2.71
8	892	9.0	200	1.4	136.0	1.44
9	816	14.0	200	1.5	175.0	2.87
10	842	6.7	200	1.3	112.0	0.85
11	843	6.4	200	1.2	109.0	0.77
12	810	10.0	200	1.5	149.0	1.82
13	813	14.0	200	1.5	172.0	2.74
14	819	8.9	200	1.4	135.0	1.42
15	841	6.2	200	1.2	107.0	0.75
16	843	8.2	200	1.4	129.0	1.24
17	839	5.0	200	1.2	94.9	0.47
18	816	13.0	200	1.4	170.0	2.65
19	888	7.6	200	1.3	122.0	1.08
20	814	11.0	200	1.4	152.0	1.90
21	840	6.6	200	1.3	111.0	0.84
22	812	14.0	200	1.5	171.0	2.68
23	842	6.2	200	1.2	107.0	0.74
24	816	13.0	200	1.5	166.0	2.43
25	814	13.0	200	1.4	165.0	2.39
26	811	11.0	200	1.4	154.0	1.98

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