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# Modeling of Electrical Discharge Machining Process Using Conventional Regression Analysis and Genetic Algorithms

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**An attempt was made to model input-output relationships of an electrical discharge machining process based on the experimental data (collected according to a central composite design) using multiple regression analysis. Three input parameters, such as peak current, pulse-on-time and pulse-duty-factor, and two outputs, namely, material removal rate (MRR) and surface roughness (SR) had been considered for the said modeling. The value of regression coefficient was determined for each model. The performances of the developed models were tested with the help of some test cases collected through the real experiments and were found to be satisfactory. It had been posed as an optimization problem and solved using a genetic algorithm to determine the set(s) of optimal parameters for ensuring the maximum MRR and minimum SR. It was also formulated as a multi-objective optimization problem and a Pareto-optimal front of solutions had been obtained.**

**Keywords** analysis of variance, central composite design, electrical discharge machining, genetic algorithm, multi-objective optimization, regression analysis

## 1. Introduction

Electrical discharge machining (EDM) is one of the most widely used non-conventional machining processes. It is an electro-thermal process that uses thermal energy to machine any electrically conductive parts regardless of hardness. It has a wide application in the manufacture of mold, die, and automotive, aerospace and surgical components (Ref 1). The performance of this process is influenced by many factors, such as discharge current, voltage, pulse-on time, pulse-off time, die-electric flushing pressure, electrode polarity, electrode's discharging area and processing depth, and others. They have significant influences on the outputs, namely, material removal rate (MRR), electrode wear rate (EWR), and surface roughness (SR).

Optimal selection of process parameters is very much essential, as it is a costly process to increase MRR considerably and at the same time, to achieve desired surface finish. Traditionally, this is carried out by relying heavily on the operator's experience or using conservative technological data provided by the EDM equipment manufacturers, which may produce inconsistent machining performance. This study aimed to develop input-output relationships of EDM process using conventional regression analysis and optimize the process parameters using a genetic algorithm (GA) (Ref 2, 3).

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## 2. Literature Review

Petropoulos et al. (Ref 4) used statistical multi-parameter analysis to model surface finish in EDM process. Multiple statistical regression models were developed and close correlation was observed between SR and EDM input variables. A SR model was designed by Her and Weng (Ref 5) using regression analysis of the experimental data. Taguchi's orthogonal array was used for the experimental design. A GA was used to determine the machining parameters responsible for optimum surface finish. Puertas and Luis (Ref 6) developed model of SR of EDM process using a factorial design of experiments and regression analysis. The most important input variables were identified and interactions among them were explained. Modeling of die-sinking EDM process for MRR, EWR, and SR was carried out by Puertas et al. (Ref 7) using a factorial design of experiments and multiple regression analysis. Significant variables were identified for each of the responses. A mathematical model of the wire-EDM process for SR was obtained by Kanlayasiri and Boonmung (Ref 8) using multiple regression analysis. The model was validated using a new set of experimental data and the maximum prediction error of the model was found to be $<7\%$. Kanagarajan et al. (Ref 9) developed statistical models of EDM process based on second order polynomial equations. Non-dominated sorting genetic algorithm (NSGA-II) (Ref 10) had been used to optimize the processing conditions and a set of non-dominated solutions was reported. The modeling and optimization of the electrical discharge turning process was carried out by Matoorian et al. (Ref 11) using statistical analysis and Taguchi's robust design method. Mohammadi et al. (Ref 12) derived the model of MRR for wire-electrical discharge turning process based on statistical analysis. Taguchi's orthogonal array was used for design of experiments and both regression analysis as well as analysis of variance (ANOVA) was performed on the experimental data. Signal-to-noise (S/N) ratio analysis was employed to find the optimal condition. Haddad and Tehrani (Ref 13) obtained the regression model of MRR and SR for cylindrical wire electrical discharge turning of AISI D3 tool steel using the response surface methodology. Modeling of wire-EDM in trim cutting operation was done by Sarkar et al. (Ref 14) using a central composite design (CCD) (Ref 15) and response surface methodology. Optimization of the trim cutting operation had been carried out using desirability function approach and Pareto-optimization algorithm, and the later was found to be the superior.

In this article, nonlinear regression analysis had been conducted using the experimental data collected as per CCD to establish input-output relationships of an EDM process. As it is a complex and stochastic process, it might be difficult to determine the optimal input parameters for the best machining performance, i.e., productivity and quality, MRR and SR. In this study, MRR and SR had been considered, as the MRR reflects productivity and surface finish indicates the quality of the product. It is to be noted that the higher the MRR is, the more will be the SR. However, the aim of the machining could be to obtain the maximum MRR after maintaining a good surface finish. Thus, there exists a conflict. The said problem had been solved by treating it as both single objective (by putting both the objective functions in the form of a single objective) as well as multi-objective optimization problems, separately. An attempt was also made to obtain Pareto-optimal front of solutions.

The rest of the text has been organized as follows: Section 3 describes the experimental setup, explains the experimental procedure and method of data collection. Results are stated and discussed in Section 4. Concluding remarks are made in Section 5 and the scope for future work has been indicated in Section 6.

## 3. Experimental Data Collection

This section describes the experimental setup, explains the method of conducting experiments and data collection.

### 3.1 Experimental Setup

Experiments were conducted on Elektra Eznc Die Sinking EDM machine (refer to Fig. 1). The machine had a maximum current capacity of 50 A. According to the convention of normal polarity, the work-piece is connected to the positive terminal and the tool is attached to the negative terminal of the source, whereas for reverse polarity, it is done just the reverse. The machine had 28 pulse-on time settings and 12 pulse-off time settings. Experiments were conducted in the reverse polarity. Experimental data based on the CCD were collected to study the effects of various machining parameters on EDM process. These studies had been undertaken to investigate the effects of peak current, pulse-on-time, and pulse-duty factor on MRR and SR. Mild steel work-piece had been machined using a copper tool and paraffin oil was used as the dielectric medium. It is important to mention that it is also possible to interchange this job-tool combination in the EDM. Both paraffin oil as well as de-ionized water can be used as the dielectric medium to strengthen the flow of electrons. In this study, paraffin oil was used, as it is the most commonly used one.

### 3.2 Experimental Procedure

Cylindrical work-pieces of 30.0 mm diameter and 6.0 mm thickness were used for the experiments. Each sample had been machined for 1 min. Machining times were measured using a stop watch. Weights of the work-pieces had been determined using a digital balance of Afcoset make before and after the commencement of machining to calculate the MRR. SR values were measured using a Taylor-Hobson machine.

### 3.3 Data Collection

Three input variables, namely, peak current, pulse-on-time, and pulse-duty-factor were identified and their ranges had been decided through some trial experiments (refer to Table 1). For the said three input variables, experiments were carried out for $2^3 + 2 \times 3 + 3 = 17$ combinations of them, according to the CCD (Ref 15). For each combination of input variables, experiments were conducted for three times, so that the ANOVA could be carried out. Experimental data to be used for developing the model and those for testing the same are shown in Appendices A and B, respectively. Figure 2 displays the picture of some machined test samples (i.e., test cases bearing serial numbers 2, 5, and 8 of Appendix B).


**Fig. 1** Die-sinking EDM machine

## 4. Results and Discussion

Input-output relationships of most of the manufacturing processes (for example, in EDM) are, in general, complex and nonlinear in nature. Results of nonlinear regression analysis to establish input-output relationships of this process are stated and discussed below. Moreover, it had been posed as an optimization problem and solved using the GA.

### 4.1 Results of Statistical Regression Analysis

Conventional nonlinear regression analysis was carried out to ensure a least squared fitting to error surface using a software named Minitab 14 (Ref 16). The following expression had been obtained for MRR in coded units:

**Table 1 Input variables and their ranges**

| S. no. | Input variables | Uncoded symbol | Coded symbol | Minimum value | Mid-value | Maximum value |
|---|---|---|---|---|---|---|
| 1 | Peak current, A | $I_p$ | $X_1$ | 6 | 12 | 18 |
| 2 | Pulse-on-time, µs | $T_{on}$ | $X_2$ | 50 | 400 | 750 |
| 3 | Pulse-duty-factor | $t$ | $X_3$ | 4 | 8 | 12 |

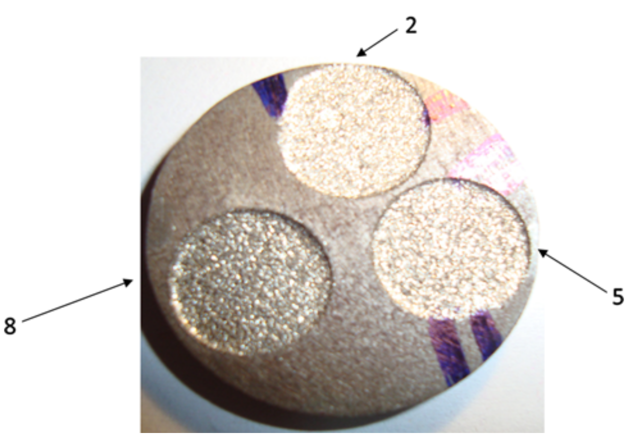


**Fig. 2** EDM machined test samples bearing serial numbers 2, 5, and 8 of Appendix B

$$\begin{aligned}\mathrm{MRR} = {} & 0.355540 + 0.201057x_1 - 0.034810x_2 + 0.064493x_3 \\ & - 0.002604x_1^2 - 0.029771x_2^2 - 0.004854x_3^2 \\ & + 0.033242x_1x_2 + 0.035600x_1x_3 - 0.055483x_2x_3\end{aligned} \quad \text{(Eq 1)}$$

Regression coefficient of the developed model was found to be equal to 0.978 (which is near to the ideal value of 1.0). It indicates that the model was adequate enough to make further predictions. Results of the ANOVA are shown in Table 2. The model was built for 95% confidence level. As the probability values ($p$) for the combined linear, square and interaction terms were found to be $<0.05$, they had significant contributions toward the output: MRR. The terms used in the ANOVA table are explained in the following paragraphs.

"Degrees of freedom" (DF) is the rank of a quadratic form. If there are $n$ observations and one parameter (the mean) that needs to be estimated then it needs $n-1$ DF for estimating variability. As there were 51 observations, DF was 50. The sequential (sometimes called type I) sums of squares (Seq SS) measure the reduction in the residual sums of squares provided by each additional term in the model. The adjusted (sometimes called type III) sums of squares (Adj SS) measure the reduction in the residual sums of squares provided by each term relative to a model containing all the other terms. The sequential and adjusted sums of squares will be the same for all terms, if the design matrix is orthogonal. The most common case where this occurs is with factorial and fractional factorial designs (with no covariates), when analyzed in coded units. For 95% confidence level, if the $p$ value (probability) for one or more coefficients is $<0.05$, then these coefficients can be called statistically significant.

The adjusted mean square (Adj MS) values are adjusted sums of squares (Adj SS) divided by the corresponding DF. The $F$ value or $F$ ratio is the test statistic used to decide whether the model as a whole has statistically significant predictive capability, i.e., whether the regression SS is big enough, considering the number of variables needed to achieve it. $F$ is the ratio of the model mean square to the error mean square. If for a particular type of terms (say linear/square/interaction), the calculated $F$ value is found to be more than the table-calculated value, it will have significant contribution toward the response. The $p$ values tell whether a variable has statistically significant predictive capability in the presence of the other variables, i.e., whether it adds something to the equation. In some circumstances, a non-significant $p$ value might be used to determine whether to remove a variable from a model without significantly reducing the model's predictive capability.

**Table 2 Results of ANOVA for MRR**

| Source | DF | Seq SS | Adj SS | Adj MS | $F$ | $p$ |
|---|---|---|---|---|---|---|
| Regression | 9 | 1.51897 | 1.51897 | 0.168775 | 250.20 | 0.000 |
| Linear | 3 | 1.37385 | 1.37385 | 0.457949 | 678.88 | 0.000 |
| Square | 3 | 0.01430 | 0.01430 | 0.004768 | 7.07 | 0.001 |
| Interaction | 3 | 0.13082 | 0.13082 | 0.043606 | 64.64 | 0.000 |
| Residual error | 41 | 0.02766 | 0.02766 | 0.000675 | | |
| Lack-of-fit | 5 | 0.02415 | 0.02415 | 0.004831 | 49.62 | 0.000 |
| Pure error | 36 | 0.00350 | 0.00350 | 0.000097 | | |
| Total | 50 | 1.54663 | | | | |

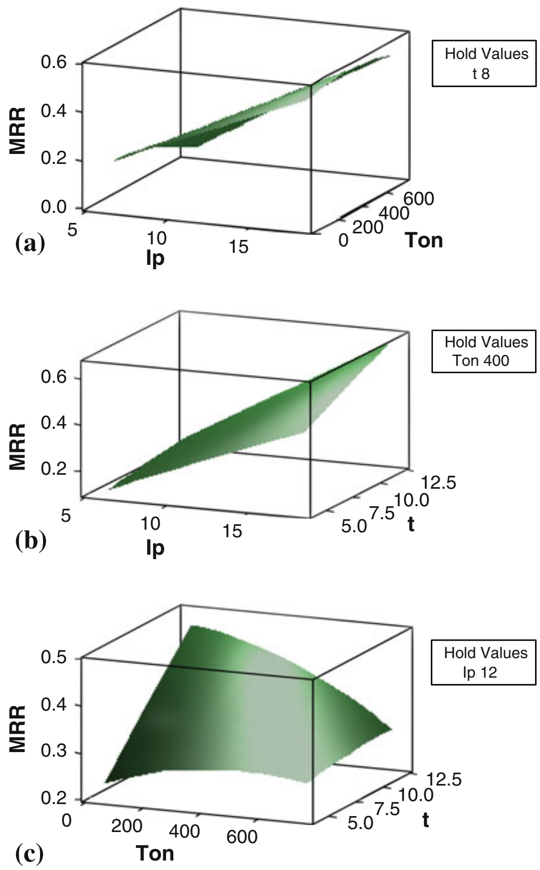


**Fig. 3** Surface plots for MRR: (a) MRR vs. $I_p$ and $T_{on}$, (b) MRR vs. $I_p$ and $t$, and (c) MRR vs. $T_{on}$ and $t$

The said response had been expressed in terms of un-coded units of input variables as given below.

$$\begin{aligned}\mathrm{MRR} = & -0.112931 + 0.0170470 I_p + 0.000222059 T_{on} \\ & + 0.0190297 t - 7.23331 \times 10^{-5} I_p^2 - 2.43026 \times 10^{-7} T_{on}^2 \\ & - 3.03374 \times 10^{-4} t^2 + 1.58294 \times 10^{-5} I_p T_{on} \\ & + 0.00148333 I_p t - 3.96310 \times 10^{-5} T_{on} t \end{aligned} \qquad \text{(Eq 2)}$$

Figure 3(a) shows that MRR increased with peak current $I_p$. Moreover, it increased initially with pulse-on-time $T_{on}$ and then decreased with a further increase of pulse-on-time. The relationship between MRR and $I_p$ was found to be more or less linear, whereas that between MRR and $T_{on}$ was seen to be nonlinear. Figure 3(b) displays the similar relationship between MRR and $I_p$ as explained above, whereas MRR was seen to increase with the pulse-duty-factor $t$. Figure 3(c) shows the relationship between MRR and $T_{on}$ and that between MRR and $t$, which exactly matched with those mentioned above. MRR increased with $I_p$ because energy input per pulse increased as the peak current increases. MRR was found to increase with $t$ also, as pulse frequency increased with the pulse duty factor for the same $T_{on}$. However, MRR initially increased with $T_{on}$ because pulse energy increased but decreased after a certain value of the same. For the larger $T_{on}$ or discharge duration, a very large plasma diameter was formed which led to global expansion of the plasma channel. Due to this reason, pressure and energy of the plasma channel diminished over the molten metal of the electrodes. As a consequence, this phenomenon brought instability into the process lowering the MRR. Thus, to summarize, MRR increased more or less linearly with $I_p$ and $t$, and it increased initially and then decreased nonlinearly with $T_{on.}$

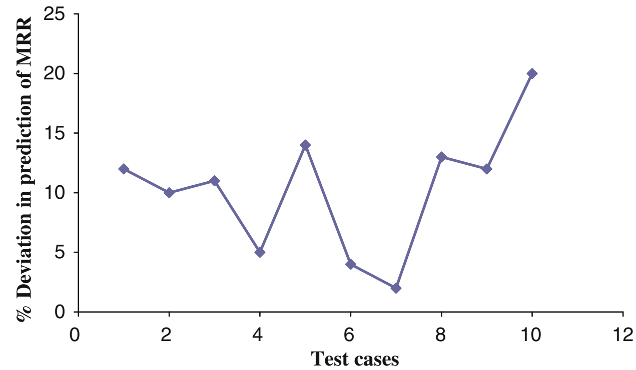


**Fig. 4** Percent deviations in predictions of MRR

**Table 3 Results of ANOVA for SR**

| Source | DF | Seq SS | Adj SS | Adj MS | *F* | *p* |
|---|---|---|---|---|---|---|
| Regression | 9 | 204.034 | 204.034 | 22.6704 | 34.12 | 0.000 |
| Linear | 3 | 119.171 | 119.171 | 39.7236 | 59.78 | 0.000 |
| Square | 3 | 51.222 | 51.222 | 17.0739 | 25.70 | 0.000 |
| Interaction | 3 | 33.641 | 33.641 | 11.2138 | 16.88 | 0.000 |
| Residual error | 41 | 27.243 | 27.243 | 0.6645 | | |
| Lack-of-fit | 5 | 17.261 | 17.261 | 3.4521 | 12.45 | 0.000 |
| Pure error | 36 | 9.982 | 9.982 | 0.2773 | | |
| Total | 50 | 231.276 | | | | |

The performance of the developed model had been tested on 10 experimentally observed cases, which had not been considered in developing the same. Some of the machined test samples are shown in Fig. 2. Figure 4 displays the values of % deviation in prediction of MRR for the said 10 test cases. The average absolute % deviation in predictions was found to be equal to 10.3.

Similarly, nonlinear regression model had been developed for the other response: SR. The regression coefficient was seen to be equal to 0.856. Table 3 shows the results of the ANOVA. All the linear, square, and interaction terms were found to have significant contributions toward the response: SR.

Regression equation for SR (expressed in uncoded units) was found to be as follows:

$$\begin{aligned}\mathrm{SR} = & 1.76966 + 0.882071 I_p + 0.00686577 T_{on} - 0.447132 t \\ & - 0.0373631 I_p^2 - 9.89173 \times 10^{-6} T_{on}^2 \\ & + 0.0221831 t^2 + 0.000517857 I_p T_{on} + 0.0109375 I_p t \\ & - 2.76786 \times 10^{-4} T_{on} t \end{aligned} \qquad \text{(Eq 3)}$$

Figure 5 displays the surface plots of SR, expressed as the functions of input factors. SR was found to have nonlinear relationships with $I_p$ and $T_{on}$. Initially, SR increased with both $I_p$ and $T_{on}$ and then it was seen to decrease with them at the

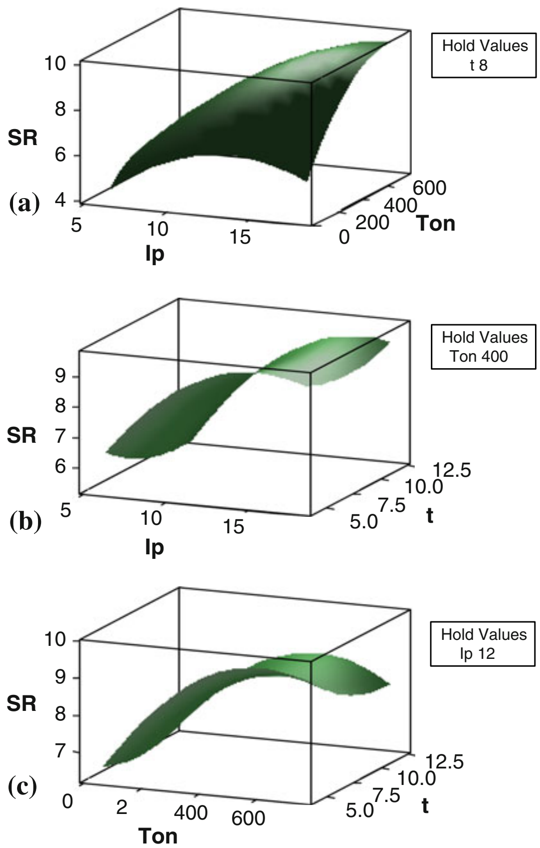


**Fig. 5** Surface plots for SR: (a) SR vs. $I_p$ and $T_{on}$, (b) SR vs. $I_p$ and $t$, and (c) SR vs. $T_{on}$ and $t$

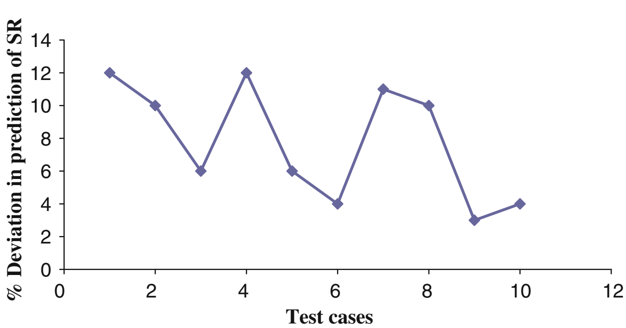


**Fig. 6** Prediction of SR

end (refer to Fig. 5a). Pulse energy increased with $I_p$ and $T_{on}$, and resulted an increase in volume of material removal per pulse or crater size. As a consequence, SR also increased. However, very high values of $I_p$ and $T_{on}$ made the process unstable and reduced MRR and SR. Moreover, a close watch on Fig. 5(b) and (c) reveals that almost a linear relationship could exist between SR and $t$.

The test cases had been passed through the said developed model on SR. The values of % deviation in predictions of SR are shown in Fig. 6. The value of average absolute % deviation in predictions of SR was found to be equal to 7.8.

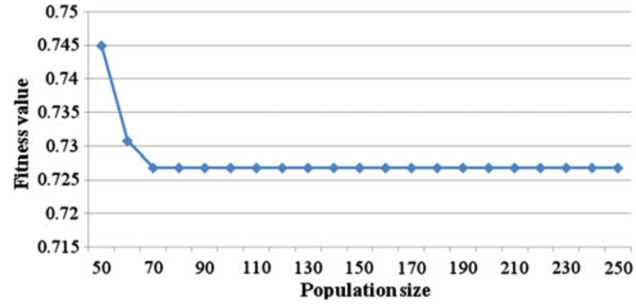


**Fig. 7** GA-parametric study

### 4.2 Single Objective Optimization

Both MRR as well as SR had been expressed separately, as the nonlinear functions of input variables, such as $I_p$, $T_{on}$, and $t$. Now, our aim was to maximize the MRR and minimize the SR simultaneously, in EDM process. To determine the set of input variables in order to satisfy both the above criteria, it had been solved using a GA. The problem had been formulated as a maximization problem considering both the objective functions as given below:

$$\begin{aligned} \text{Maximize} \quad & Y = \text{MRR} + 1/\text{SR}, \\ \text{subject to} \quad & 6.0 \leq I_p \leq 18.0, \\ & 50.0 \leq T_{on} \leq 750.0, \\ & 4.0 \leq t \leq 12.0. \end{aligned}$$

Thus, a problem having two objective functions had been formulated as a single objective optimization problem. A binary-coded GA had been used to solve the said problem. Ten bits (i.e., binary numbers: 1, 0) were assigned to represent each variable. Thus, the GA-string was found to be 30-bits long. Tournament selection scheme had been adopted in this study, in which a few strings (whose number is kept equal to the tournament size) are taken at random from the population and the best one is selected for the mating pool. The process continues, until the size of mating pool becomes equal to the population size. A single-point crossover and bit-wise mutation had been used in this study. As the performance of a GA depends on its parameters, a systematic thorough study (Ref 3) had been conducted to determine the set of optimal parameters. Results of a part of the said study are shown in Fig. 7.

The GA through its exhaustive search had determined the following set of optimal input parameters: $I_p = 17$ A, $T_{on} = 138$ µs, and $t = 11$. The corresponding outputs: MRR and SR were found to be equal to 0.6089 g/min and 7.3 µm, respectively. Experiments had been conducted for the said set of optimal input parameters and the responses: MRR and SR had been measured. As the machine used for this experiment did not have the provision to set $T_{on}$ at 138 µs, machining had been done at the nearest available $T_{on}$, i.e., 150 µs. Thus, the input parameters had been set at $I_p = 17$ A, $T_{on} = 150$ µs, and $t = 11$. Experimental values of the outputs: MRR and SR had been found to be equal to 0.4798 g/min and 7.7 µm, respectively. It is interesting to note that the experimentally found MRR was seen to be slightly less than that obtained by the GA. It might have happened due to the fact that $T_{on}$ had been set at 150 µs in place of 138 µs, while conducting the real experiment. The said reason had been verified through a trivial calculation of MRR using the regression equation. It is also

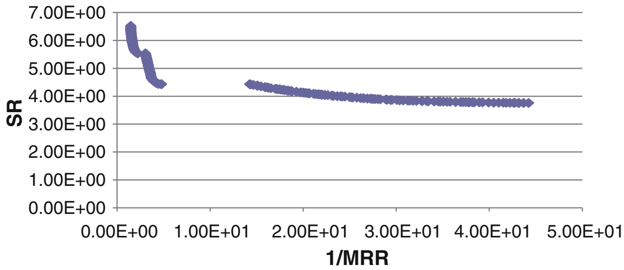


**Fig. 8** Pareto-optimal front of solutions

important to note that the experimentally observed SR value (i.e., 7.7 μm) was found to be almost the same with that determined by the GA (i.e., 7.3 μm).

### 4.3 Multi-Objective Optimization

Our aim was to maximize the MRR after maintaining a minimum value for SR. It is difficult to obtain the same, as both MRR as well as SR increase simultaneously. Thus, there is a conflict and consequently, it became an ideal problem to be tackled using a multi-objective GA. A non-dominated sorting GA (i.e., NSGA-II) (Ref 10) had been used to obtain the Pareto-optimal front of solutions (refer to Fig. 8). The Pareto-optimal front is defined as the locus of all optimal solutions obtained after putting different weights on 1/MRR and SR artificially. The working cycle of NSGA-II is explained through a few steps given below.

1. The initial population is generated randomly based on the ranges of variables of the problem.
2. The initialized population is then sorted based on non-domination into a few fronts.
3. Each individual of every front is assigned a rank (fitness) and a crowding distance value. Individuals in the first front are given a fitness value of 1 and individuals in second front are assigned fitness value of 2, and so on. Crowding distance is calculated for each individual as a measure of how close an individual is to its neighbors.
4. Parents are selected from the population using binary tournament selection based on rank and crowding distance.
5. The selected population generates offspring's through crossover and mutation operations.
6. The solutions in current population and current offsprings are sorted again based on non-domination and only the best individuals are selected. The selection is based on the rank and crowding distance on the last front.

It is important to notice that a continuous Pareto-optimal front of solutions could not be achieved for this problem. It could have happened due to the fact that no optimal solution could exist in some portions of the range of input variables, in order to satisfy both the objective functions simultaneously. It is also interesting to note that a large number of optimal solutions lying on the obtained Pareto front are available to the user. He/She could choose a particular optimal solution lying on the Pareto front and determine the corresponding set of input variables as shown in Table 4.

**Table 4 A few points lying on the Pareto-optimal front and their corresponding inputs**

| S. no. | MRR, g/min | SR, μm | $I_p$, A | $T_{on}$, μs | $t$ |
|---|---|---|---|---|---|
| 1 | 0.2090 | 4.4 | 6 | 50 | 10 |
| 2 | 0.3030 | 5.2 | 7 | 50 | 12 |
| 3 | 0.4910 | 5.6 | 18 | 50 | 7 |
| 4 | 0.6720 | 6.5 | 18 | 618 | 12 |
| 5 | 0.0480 | 4.1 | 6 | 718 | 11 |

## 5. Concluding Remarks

Nonlinear regression analysis had been conducted to establish the relationships of MRR and SR separately with the input variables $I_p$, $T_{on}$, and $t$. MRR was found to increase more or less linearly with $I_p$ and $t$, and it increased initially and then decreased nonlinearly with $T_{on}$. Moreover, SR was seen to have nonlinear relationships with $I_p$ and $T_{on}$, but a more or less linear relationship with $t$. Both the regression models had performed well in predicting the results of some test cases. More or less 10% deviations in prediction of the responses had been reported for both of them on the test cases. An attempt had also been made to obtain a set of input variables corresponding to the simultaneous maximum and minimum values of MRR and SR, respectively. The obtained optimal results had also been tested through a real experiment and found to be satisfactory. It had also been treated as a multi-objective optimization problem and solved using a multi-objective GA, named NSGA-II. An interesting Pareto-optimal front of solutions had been obtained consequently, which might be used to select an optimal solution depending on the requirement.

## 6. Scope for Future Work

In future, an attempt will be made to understand the microstructures through microscopic analysis. To automate a process, input-output relationships are to be known before-hand in both forward as well as reverse directions. The authors are working, at present, on these issues.

### Acknowledgments

The authors gratefully acknowledge the help and cooperation of Mr. S. Bag and Mr. S. Patra of IIT Kharagpur, India, in carrying out the real experiments.

## Appendices

### Appendix A Experimental data collected as per CCD

| | Inputs | | | Outputs | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | MRR, g/min | | | | SR, µm | | | |
| S. no. | $I_p$, A | $T_{on}$, µs | $t$ | First | Second | Third | Avg. | First | Second | Third | Avg. |
| 1 | 6 | 50 | 4 | 0.1334 | 0.1204 | 0.1157 | 0.1180 | 4.5 | 4.4 | 4.9 | 4.6 |
| 2 | 18 | 50 | 4 | 0.3411 | 0.3322 | 0.3318 | 0.3320 | 6.5 | 6.6 | 6.3 | 6.5 |
| 3 | 6 | 750 | 4 | 0.0749 | 0.0761 | 0.0738 | 0.0749 | 6.2 | 6.4 | 6.0 | 6.2 |
| 4 | 18 | 750 | 4 | 0.4887 | 0.5022 | 0.4954 | 0.4954 | 10.0 | 9.3 | 10.8 | 10.0 |
| 5 | 6 | 50 | 12 | 0.2457 | 0.2524 | 0.2390 | 0.2457 | 5.5 | 5.3 | 5.6 | 5.5 |
| 6 | 18 | 50 | 12 | 0.6585 | 0.6756 | 0.6928 | 0.6756 | 6.0 | 5.8 | 6.2 | 6.0 |
| 7 | 6 | 750 | 12 | 0.0513 | 0.0582 | 0.0441 | 0.0547 | 3.1 | 3.1 | 3.2 | 3.1 |
| 8 | 18 | 750 | 12 | 0.5307 | 0.5374 | 0.5472 | 0.5340 | 10.4 | 10.6 | 10.2 | 10.4 |
| 9 | 6 | 400 | 8 | 0.1342 | 0.1237 | 0.1198 | 0.1217 | 5.1 | 5.0 | 5.5 | 5.2 |
| 10 | 18 | 400 | 8 | 0.5869 | 0.5673 | 0.6066 | 0.5869 | 8.7 | 8.5 | 8.3 | 8.5 |
| 11 | 12 | 50 | 8 | 0.3935 | 0.3774 | 0.4097 | 0.3935 | 5.4 | 5.2 | 5.7 | 5.4 |
| 12 | 12 | 750 | 8 | 0.2609 | 0.2638 | 0.2702 | 0.2623 | 8.5 | 8.5 | 8.6 | 8.5 |
| 13 | 12 | 400 | 4 | 0.2684 | 0.2774 | 0.2729 | 0.2729 | 8.8 | 9.2 | 8.5 | 8.8 |
| 14 | 12 | 400 | 12 | 0.4354 | 0.4331 | 0.4378 | 0.4354 | 8.1 | 8.3 | 8.4 | 8.3 |
| 15 | 12 | 400 | 8 | 0.3307 | 0.3402 | 0.3572 | 0.3354 | 9.0 | 7.7 | 10.4 | 9.0 |
| 16 | 12 | 400 | 8 | 0.3564 | 0.3582 | 0.3577 | 0.3574 | 10.1 | 10.0 | 10.2 | 10.1 |
| 17 | 12 | 400 | 8 | 0.3588 | 0.3470 | 0.3519 | 0.3553 | 8.5 | 8.7 | 8.3 | 8.5 |

### Appendix B Data collected for testing the models of MRR and SR

| | Inputs | | | Outputs | |
|---|---|---|---|---|---|
| S. no. | $I_p$, A | $T_{on}$, µs | $t$ | MRR, g/min | SR, µm |
| 1 | 7 | 150 | 11 | 0.2389 | 6.5 |
| 2 | 8 | 200 | 11 | 0.2660 | 7.1 |
| 3 | 9 | 300 | 10 | 0.2649 | 6.7 |
| 4 | 10 | 300 | 10 | 0.3164 | 8.6 |
| 5 | 11 | 400 | 9 | 0.3472 | 8.8 |
| 6 | 13 | 500 | 9 | 0.4073 | 8.7 |
| 7 | 14 | 500 | 7 | 0.3903 | 10.6 |
| 8 | 15 | 750 | 9 | 0.3641 | 8.5 |
| 9 | 16 | 750 | 10 | 0.4090 | 9.8 |
| 10 | 17 | 750 | 11 | 0.4255 | 9.3 |

## References


1. G.F. Benedict, *Nontraditional Manufacturing Process*, Marcel Dekker, New York, 1987
2. J.H. Holland, *Adaptation in Natural and Artificial Systems*, The University of Michigan Press, Ann Arbor, MI, 1975
3. D.K. Pratihar, *Soft Computing*, Narosa Publishing House, New Delhi, 2008
4. G. Petropoulos, N.M. Vaxevanidis, and C. Pandazaras, Modeling of Surface Finish in Electro-Discharge Machining Based Upon Statistical Multi-Parameter Analysis, *J. Mater. Process. Technol.*, 2004, **155–156**, p 1247–1251
5. M.G. Her and F.T. Weng, A Study of the Electrical Discharge Machining of Semi-Conductor $BaTiO_3$, *J. Mater. Process. Technol.*, 2002, **122**, p 1–5
6. I. Puertas and C.J. Luis, A Study on the Machining Parameters Optimization of Electrical Discharge Machining, *J. Mater. Process. Technol.*, 2003, **143–144**, p 521–526
7. I. Puertas, C.J. Luis, and L. Alvarez, Analysis of the Influence of EDM Parameters on Surface Quality. MRR and EW of WC-Co, *J. Mater. Process. Technol.*, 2004, **153–154**, p 1026–1032
8. K. Kanlayasiri and S. Boonmung, Effects of Wire-EDM Machining Variables on Surface Roughness of Newly Developed DC 53 Die Steel: Design of Experiments and Regression Model, *J. Mater. Process. Technol.*, 2007, **192–193**, p 459–464
9. D. Kanagarajan, R. Karthikeyan, K. Palanikumar, and J. Davim, Optimization of Electrical Discharge Machining Characteristics of WC-Co Composites Using Non-Dominated Sorting Genetic Algorithm (NSGA-II), *Int. J. Adv. Manuf. Technol.*, 2008, **36**, p 1124–1132
10. K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, A Fast and Elitist Multi-Objective Genetic Algorithm: NSGA-II, *IEEE Trans. Evol. Comput.*, 2002, **6**, p 182–197
11. P. Matoorian, S. Sulaiman, and M.M.H.M. Ahmad, An Experimental Study for Optimization of Electrical Discharge Turning (EDT) Process, *J. Mater. Process. Technol.*, 2008, **204**, p 350–356
12. A. Mohammadi, A.F. Teharani, E. Emanian, and D. Karimi, Statistical Analysis of Wire Electrical Discharge Turning on Material Removal Rate, *J. Mater. Process. Technol.*, 2008, **205**, p 283–289
13. M.J. Haddad and A.F. Tehrani, Investigation of Cylindrical Wire Electrical Discharge Turning (CWEDT) of AISI, D3 Tool Steel Based on Statistical Analysis, *J. Mater. Process. Technol.*, 2008, **198**, p 77–85
14. S. Sarkar, M. Sekh, S. Mitra, and B. Bhattacharya, Modeling and Optimization of Wire Electrical Discharge Machining of γ-TiAl in Trim Cutting Operation, *J. Mater. Process. Technol.*, 2008, **205**, p 376–378
15. D.C. Montgomery, *Design and Analysis of Experiments*, Wiley, New York, 2001
16. Minitab 14, Statistical Software, www.minitab.com