Engineering Science and Technology, an International Journal 18 (2015) 171–177

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Contents lists available at ScienceDirect

Engineering Science and Technology, an International Journal

journal homepage: http://www.elsevier.com/locate/jestch

JESTECH

Full length article

WEDM process variables investigation for HSLA by response surface methodology and genetic algorithm

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ARTICLE INFO

Article history:
Received 6 September 2014
Received in revised form
5 November 2014
Accepted 5 November 2014
Available online 23 December 2014

Keywords:
Genetic algorithm
HSLA
Overcut
Response surface methodology
WEDM

ABSTRACT

Wire electric discharge machining (WEDM) is a thermo-electric spark erosion non-traditional type manufacturing process. The applications of WEDM have been found in aerospace and die manufacturing industries, where precise dimensions were the prime objective. This process is applied in case of processing difficult to machine material. Brass wire is used as an electrode and High strength low alloy (HSLA) steel as a work-piece during experimentation. The present research deals with the effect of process parameters on the overcut while machining the HSLA steel on WEDM. The mathematical model has been developed with the help of Response Surface Methodology (RSM). Further this model is processed with help of Genetic Algorithm (GA) to find out the optimum machining parameters. The percentage error between the predicted and experimental values lies in the range of ±10%, which indicates that the developed model can be utilized to predict the overcut values. The experimental plan was executed according to central composite design. The optimal setting of process parameters is pulse on-time-117 μs; pulse off-time-50 μs; spark gap voltage-49 V; peak current-180 A and wire tension-6 g; for minimum overcut, whereas at the optimal setting overcut is 9.9922 μm.

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1. Introduction

Wire electrical discharge machining (WEDM) is a non-conventional machining process used for hard to cut conductive material. Wire EDM finds many applications; for instance, in the manufacturing of various press tools, dies and even electrodes used in other areas of EDM. Wire EDM is now widely used in the aerospace, automobile and medical industries, as well as in virtually all areas of conductive material machining. The mechanism of metal removal in WEDM constitutes the erosion of material due to spark discharge between tool electrode and workpiece, immersed in a liquid dielectric medium. The microprocessor also constantly maintains the gap between the wire and the workpiece, which varies from 0.025 to 0.05 mm. Some of the attempts [8–10] have been discussed by various authors. Pandey and Jilani [14] worked on the machining characteristics using distilled water, tap water and a mixture of both. They observed that the best machining rate was achieved by tap water. William and Rajurkar [22] reported that wire electrical discharge machine (WEDM) manufacturers and users aims to achieve higher machining rate with desired accuracy and minimum surface damage. The complex and random nature of the erosion process in WEDM requires the application of deterministic as well as stochastic techniques. Surface roughness profiles were studied with a stochastic modelling and analysis methodology to better understand the process mechanism. With the application of scanning electron microscopic (SEM) important features of WED machined surfaces are found out. Bhatti and Hashmi [2] found a manipulator for obtaining the intricate and complex shape with WEDM.

Scott et al. [16] investigated the effects of WEDM process parameters, particularly the spark cycle time and spark on-time on thin cross-section cutting of Nd–Fe–B magnetic material, carbon bipolar plate, and titanium. In addition, Garg et al. [6] studied the main effects of pulse on time and pulse off time; the quadratic effects of pulse on time, peak current, and servo voltage; and the interaction effect of pulse on time and servo voltage, as well as pulse on time and pulse off time, have significant effects on dimensional deviation during the machining of Ti 6–2–4–2 alloy on WEDM. Takahata and Gianchandani [21] studied the use of electrode arrays for batch EDM generation of micro-features. Scott

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Peer review under responsibility of Karabuk University.

http://dx.doi.org/10.1016/j.jestch.2014.11.004
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et al. [15] used a factorial design requiring a number of experiments to determine the most favourable combination of the WEDM parameters. They investigated that the discharge current, pulse duration and pulse frequency is the noteworthy process parameters affecting the metal removal rate and surface finish, while the wire speed, wire tension and dielectric flow rate have the least. Khanna and Singh [19] optimized the process parameters for cryogenic treated D-3 material for WEDM. They found that cutting rate decreases with increase in pulse width, time between two pulses and servo reference mean voltage. Cutting rate first decreases and then increases in wire mechanical tension. Sharma et al. [18] made the mathematical models for cutting speed and dimensional deviation using response surface methodology. Analysis of variance (ANOVA) has been utilized for the analysis of significant process parameters. Pulse on-time found to be the most significant factor for both response variables. Goswami and Kumar [7] investigated the surface integrity, material removal rate and wire wear ratio of Nimonic 80A using WEDM process. Taguchi Technique has been adopted for the planning of experiments, while for multi-response optimization, Grey Relational theory was utilized. Higher value of pulse off-time and lower value of pulse-on time is beneficial for a good surface quality.

Most of the researchers have worked on cutting rate, metal removal rate, surface finish, electrode wear and dimensional accuracy etc. But a comparatively less work has been reported on the modelling and analysis of overcut, which is the basic reason of dimensional deviations. There are three product quality issues like surface finish, overcut and radial cut. Out of these issues overcut is considered for the present research work, because overcut cannot be eliminated as it is inherent to WEDM process, but can be minimized by a proper selection of process parameters. In the present work, high strength low alloys steel is considered for machining on WEDM. The mathematical model has been developed using RSM and optimization has been carried using Genetic Algorithm.

2. Experimental set-up

The experiments were performed on Electronica Make Elektra Sprintcut 734 wire electric discharge machine tool as shown in Fig. 1. The fixed process parameters are as during experimentation:

- Workpiece: High strength low alloy steel
- Electrode (tool): 250 μm Diameter Brass wire
- Conductivity: 20 mho
- Cutting voltage (V): 80 V
- Die-electric temperature: 35 °C
- Injection pressure set point was at 7 kg/cm^2
- Peak voltage (VP): setting 2
- Servo feed: 2050 units

The investigation of significant control factors for WEDM process based on the quality of the machining are grouped in various categories. The control factors, their designated symbols and range are given in Table 1. The range of all the control factors is selected for the present study based on the results obtained from preliminary experiments [17]. The material used for experimentation is High Strength low alloy steel. The chemical composition of material is given in Table 2. The overcut (V) is shown as in Fig. 2 and is calculated as.

$$\text{Overcut}(V) = \frac{\text{Width of cut} - D}{2} \tag{1}$$

Fig. 1. WEDM machine tool.

3. Experimental methodology

In this optimization of control factors two methodologies are used, one is Response Surface Methodology and other is Genetic Algorithm. These two methodologies are explained below.

3.1. Response surface methodology

Response Surface Methodology is a collection of mathematical and statistical techniques useful for the modelling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize this response [3]. RSM has been applied for developing the mathematical models in the form of multiple regression equations for the quality characteristics of WEDM process. In applying the response surface methodology, the dependent parameter was viewed as a surface to which a mathematical model is fitted. For the development of regression equations related to various quality characteristics of WEDM process, the second order response surface has been assumed as:

$$Y = b_0 + \sum_{i=1}^{k} b_i x_i + \sum_{i=1}^{k} b_{ii} x_i^2 + \sum_{i<j=2}^{k} b_{ij} x_i x_j + e_r \tag{2}$$

This assumed surface Y contains linear, squared and cross product terms of parameters x_i's. In order to estimate the regression coefficients, a number of experimental design techniques are available. Also no replication is needed to find error mean square.

Table 1
Control factors, symbols and their ranges.

Control factors	Symbol	Range (machine units)
Pulse on time	T_{on} (μs)	111–117
Pulse off time	T_{off} (μs)	36–50
Spark gap voltage	SV (V)	30–50
Peak current	IP (A)	120–180
Wire tension	WT (grams)	6–10

Table 2
Chemical composition of HSLA.

Element	C	P	S	Si	Ni	Cr	Mo	Cu	Al	Cb	V	Ti	Sn	Sb	Fe
Weight (%)	0.06	0.8	0.06	0.4	1.6	0.62	0.37	1.13	0.01	0.03	0.03	0.02	0.03	0.025	Balance

The error mean square can be found out by replicating the centre points. Box and Hunter [4] have proposed that the scheme based on central composite rotatable design fits the second order response surface quite accurately. The procedure of methodology is as given below:

- Pilot experiments are performed.
- Design the input parameters according to preliminary experiments and output quality characteristics according to requirement.
- *S*elect the experimental design.
- Regression analysis is to be carried out.
- Analysis of variance is to be found out.
- If the model is significant.
- Use the model for optimization in Genetic Algorithm.
- If model is not significant then input parameters screening are to be carried out and repeat the process from step 3.

3.2. Genetic algorithm

A genetic algorithm (GA) is a procedure used to find the solutions to search problems through application of the principles of evolutionary biology. Genetic algorithms use biologically inspired techniques such as genetic inheritance, natural selection, mutation, and sexual reproduction (recombination, or crossover). Along with genetic programming (GP), they are one of the main classes of genetic and evolutionary computation (GEC) methodologies [5].

Genetic algorithms are typically implemented using computer simulations in which an optimization problem is specified. For this problem, members of a space of candidate solutions, called individuals, are represented using abstract representations called chromosomes. The GA consists of an iterative process that evolves a working set of individuals called a population toward an objective function, or fitness function [11]. Traditionally, solutions are represented using fixed length strings, especially binary strings, but alternative encodings have been developed. The evolutionary process of a GA is a highly simplified and stylized simulation of the biological version. It starts from a population of individuals randomly generated according to some probability distribution, usually uniform and updates this population in steps called generations. Each generation, multiple individuals are randomly selected from the current population based upon some application of fitness, bred using crossover, and modified through mutation to form a new population.

Crossover – exchange of genetic material (substrings) denoting rules, structural components, features of a machine learning, search, or optimization problem.

Selection – the application of the fitness criterion to choose which individuals from a population will go on to reproduce.

Replication – the propagation of individuals from one generation to the next.

Mutation – the modification of chromosomes for single individuals.

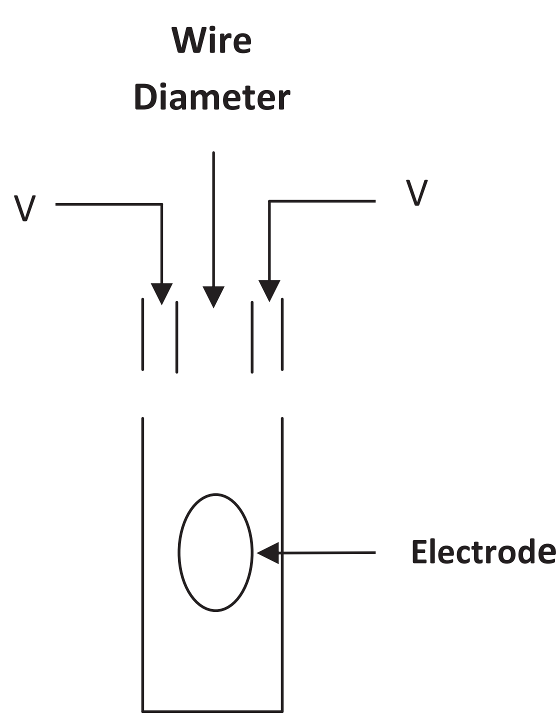

Fig. 2. Overcut (*V*).

4. Results and discussion

Experiments were planned according to central composite design [12] of half fraction. 32 experiments (Table 3) were performed for investigation of overcut. The experiments are/were performed according to run order given in Table 3 of design matrix. This run order minimizes the experimental error, as the experiments are performed randomly.

After performing analysis in design expert 6.0, the fit summary suggests that the model is quadratic, which further defines the Analysis of Variance (ANOVA). The insignificant terms (i.e. *p*-value < 0.05) are removed and after pooling the insignificant term, pooled version of ANOVA given in Table 4. From the pooled version of ANOVA, the value of R^2 and adjusted R^2 is above 95%. This means that regression model provides an excellent explanation of the relationship between the independent variables and the response variable (overcut). The model *F*-value is 113.87 and *p*-value is less than 0.05, which make the model significant. Lack of fit is non-significant as the *p*-value observed for lack of fit is 0.5012. R^2 define that, how well the future outcomes can be explained by this model due to all control factors while adjusted R^2 explains the future outcomes only due to significant terms only.

If the difference between predicted R^2 and adjusted R^2 is greater than 0.2, it shows that the model is insignificant or the values are wrongly interpreted. In this research, this difference comes out to be less than 0.2, which verifies that model is significant. Adequate precision gives the signal to noise ratio and a value greater than 4 is desirable [12]. The final equation in terms of actual factors:

$$\begin{aligned}\textbf{Overcut} = {} & 2652.29 - 40.92 \times T_{on} - 8.72 \times T_{off} - 3.71 \times SV + 0.83 \\ & \times IP + 2.59 \times \mathrm{WT} + 0.16 \times T_{on}^2 + 0.02 \times SV^2 + 0.067 \\ & \times T_{on} \times T_{off} - 0.011 \times T_{on} \times IP + 0.017 \times T_{off} \\ & \times SV + 7.395\mathrm{E}\text{-}003 \times \mathrm{SV} \times \mathrm{IP} - 0.043 \times SV \times WT \qquad (3)\end{aligned}$$

Table 3
Design matrix.

Std	Run	A: T_{on} (μs)	B: T_{off} (μs)	C: *SV* (V)	D: *IP* (A)	E: *WT* (g)	Overcut (μm)
24	1	114	43	40	210	8	15
3	2	111	50	30	120	6	31
12	3	117	50	30	180	6	17
19	4	114	29	40	150	8	25.5
29	5	114	43	40	150	8	21
6	6	117	36	50	120	10	16
8	7	117	50	50	120	6	12
23	8	114	43	40	90	8	28
20	9	114	57	40	150	8	18
31	10	114	43	40	150	8	21.5
7	11	111	50	50	120	10	19.5
14	12	117	36	50	180	6	11
27	13	114	43	40	150	8	19.5
5	14	111	36	50	120	6	24.5
1	15	111	36	30	120	10	49.5
16	16	117	50	50	180	10	11.5
13	17	111	36	50	180	10	26
28	18	114	43	40	150	8	23.5
26	19	114	43	40	150	12	27
9	20	111	36	30	180	6	35.5
11	21	111	50	30	180	10	29.5
30	22	114	43	40	150	8	22
22	23	114	43	60	150	8	14
21	24	114	43	20	150	8	44.5
10	25	117	36	30	180	10	26
25	26	114	43	40	150	4	18.5
4	27	117	50	30	120	10	33
18	28	120	43	40	150	8	20.5
2	29	117	36	30	120	6	34.5
15	30	111	50	50	180	6	19
17	31	108	43	40	150	8	35.5
32	32	114	43	40	150	8	21

Fig. 3 shows the normal plot of residuals, which gives that all the residuals fall on a straight line. The first test of a good model is verified by this, which is known as Normality test or Normal probability plot of residual. Fig. 4 gives the residual vs predicted plot, which means that residuals are randomly distributed and make no structure. For a good test the residuals must be structureless. This shows that the models proposed are adequate and there is no reason to suspect any violation of the independence or constant variance assumption [1,13].

Table 4
Pooled ANOVA after pooling insignificant terms.

Analysis of variance table [partial sum of squares]						
Source	SS	DF	MS	*F*-value	Prob > *F*	
Model	10,164.88	12	847.07	113.87	<0.0001	Significant
A-T_{on}	1785.38	1	1785.38	240.01	<0.0001	Significant
B-T_{off}	715.04	1	715.04	96.12	<0.0001	Significant
C-*SV*	5251.04	1	5251.04	705.9	<0.0001	Significant
D-*IP*	828.38	1	828.38	111.36	<0.0001	Significant
E-*WT*	315.38	1	315.38	42.4	<0.0001	Significant
T_{on}^2	272.01	1	272.01	36.57	<0.0001	Significant
SV^2	396.34	1	396.34	53.28	<0.0001	Significant
$T_{on} \times T_{off}$	126.56	1	126.56	17.01	0.0006	Significant
$T_{on} \times IP$	60.06	1	60.06	8.07	0.0104	Significant
$T_{off} \times SV$	95.06	1	95.06	12.78	0.002	Significant
$SV \times IP$	315.06	1	315.06	42.35	<0.0001	Significant
$SV \times WT$	45.56	1	45.56	6.13	0.0229	Significant
Residual	141.34	19	7.44			Significant
Lack of fit	106.5	14	7.61	1.09	0.5012	Not significant
Pure error	34.83	5	6.97			
Cor total	10,306.22	31				
Std. dev.	2.73		*R*-squared		0.9863	
Mean	298.16		Adj *R*-squared		0.9776	
C.V.	0.91		Pred *R*-squared		0.957	
PRESS	443.17		Adeq precision		43.91	

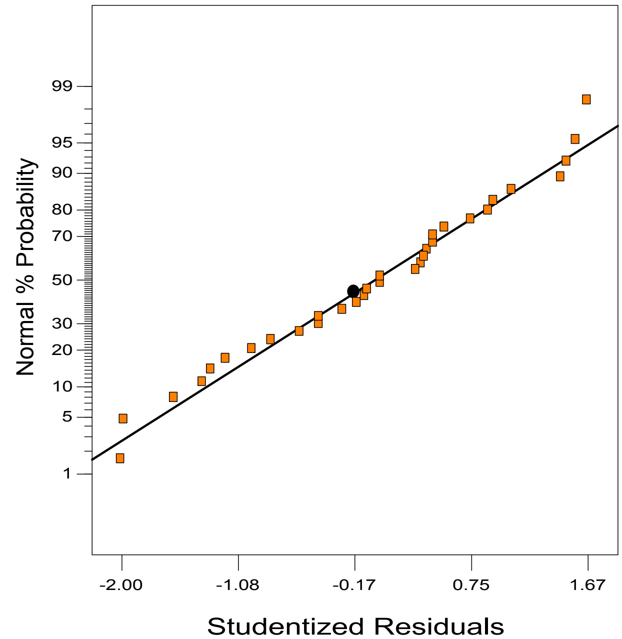

Fig. 3. Normal plot of residual.

Fig. 5(a)–(e) gives the interaction plot of process parameters. Fig. 5(a) shows the interaction plot of T_{on} and T_{off}. Overcut observed to be decreased with increase of T_{off}. This is due to the fact that overcut depends on the discharge energy, when T_{off} increases the time for which current is off increases which decreases the discharge energy and hence the overcut decreases. With the increase of T_{on}, overcut decreases. The probable reason for decrease in overcut may be evenly distribution of the spark. Fig. 5(b) shows the interaction plot of T_{on} and *IP*. The variation of T_{on} is already cited in the previous text. With the increase of *IP*, overcut observed to be

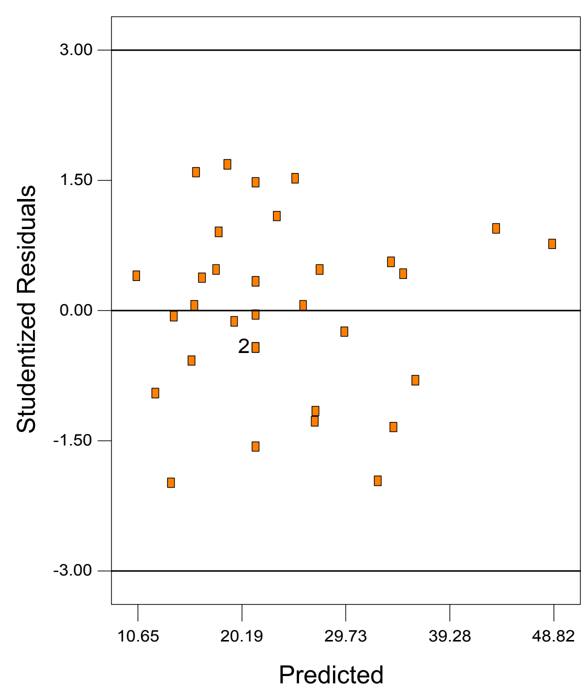

Fig. 4. Residual vs predicted plot.

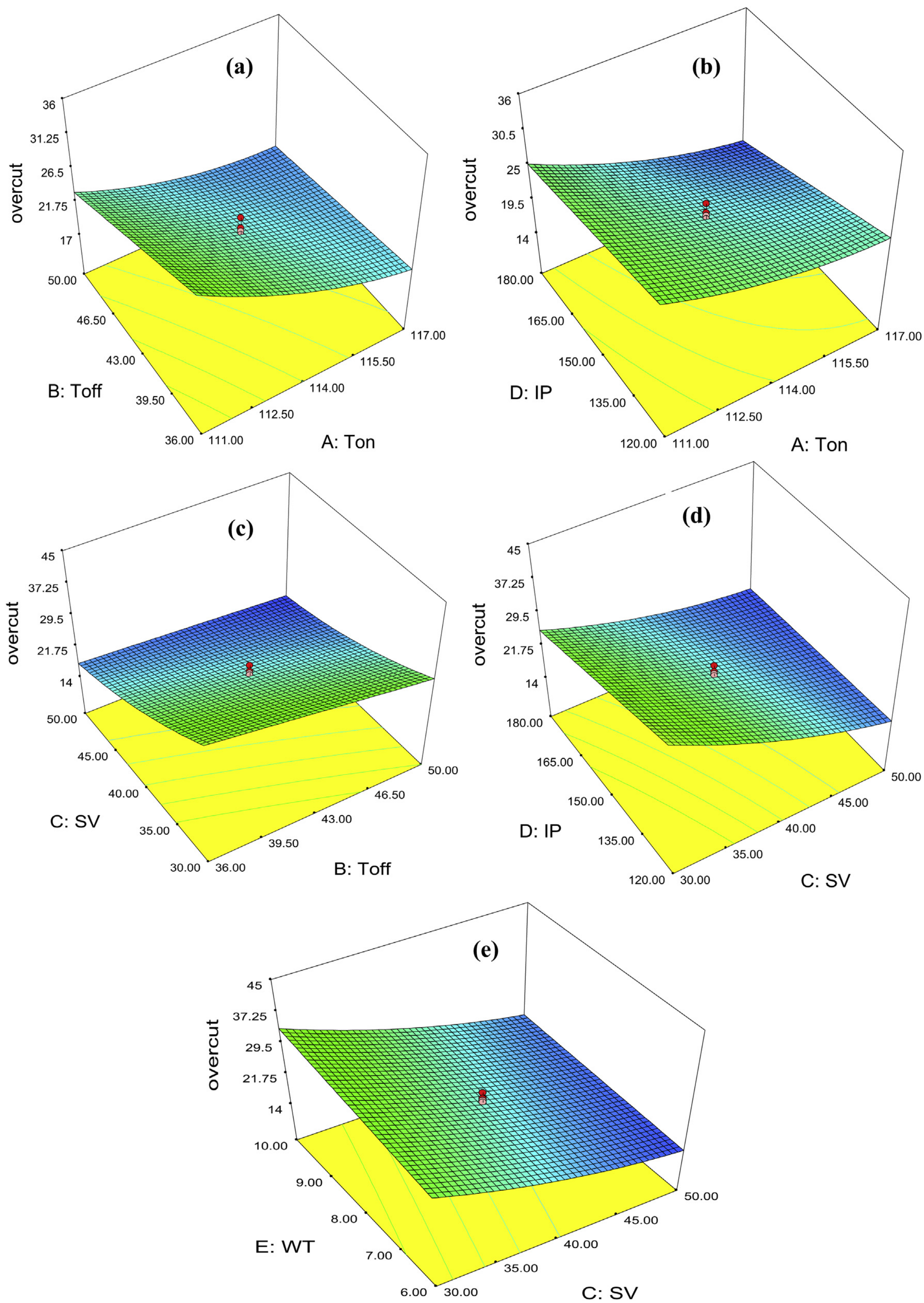

Fig. 5. Interaction plots (a) T_{on} and T_{off} (b) T_{on} and *IP* (c) *SV* and T_{off} (d) *IP* and SV (e) *WT* and *SV*.

slightly decreased. The main reason behind this is that with the increase in peak current the discharge will be more, which results into the higher debris. These debris deposited on to the work-piece and result unwanted spark. This causes the tool material erosion, which result into less material removal and hence overcut decreases [20]. Fig. 5(c) gives the variation of T_{off} and *SV* along with the overcut. With the increase of *SV*, the overcut decreases due to decrease in the discharge energy. Fig. 5(d) shows the three

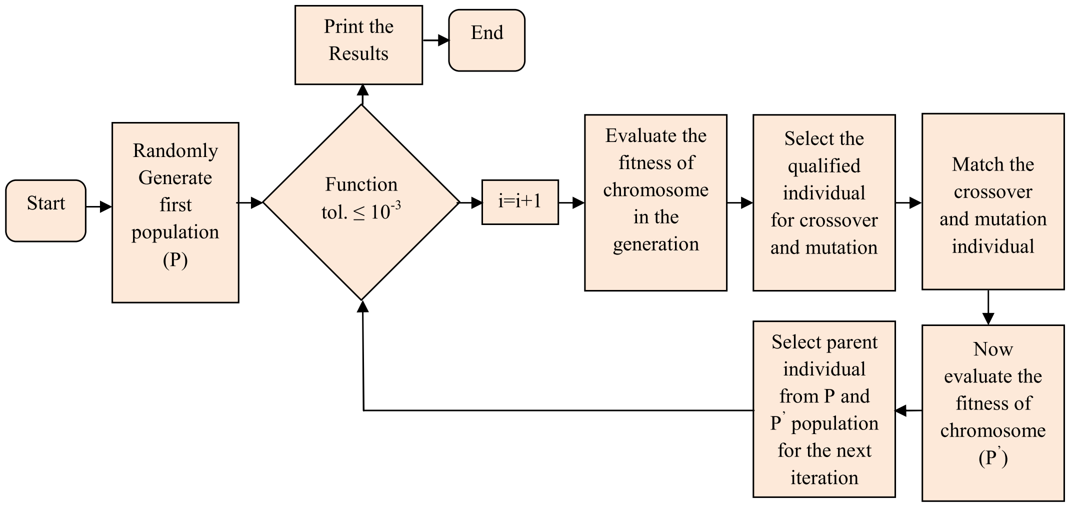

Fig. 6. Flow-chart of genetic algorithm.

dimensional interaction plots of *SV* and *IP* with overcut. The explanation of both parameters in lieu of overcut is given in the previous text. In Fig. 5(e) Overcut increases with increase in the WT. This is due to the fact that with increase in WT, the deflections of wire removed and it become straight. Due to which generated sparks removes the material and increases the overcut.

5. Optimization of overcut through genetic algorithm

The final equation (2) further utilized in genetic programming. The procedure of optimization through genetic algorithm (GA) is shown by a flow chart in Fig. 6. The lower and upper bound of control factors are given in Equations (4)–(8) and when the objective function is optimized for the best value of overcut then there are different values of selection, mutation and crossover.

$$111 \leq T_{on} \leq 117 \quad (4)$$

$$36 \leq T_{off} \leq 50 \quad (5)$$

$$30 \leq SV \leq 50 \quad (6)$$

$$120 \leq IP \leq 180 \quad (7)$$

$$6 \leq WT \leq 10 \quad (8)$$

After a thorough investigation of selection, cross-over fraction, mutation, cross-over and migration. It is envisaged that the optimized setting of genetic tool is that the Selection is remainder. Cross-over fraction is 0.8. Mutation is uniform and ratio is 0.2. Cross-over is heuristic and ratio is 1.4. Migration is forward. At this optimized setting the best fitness and best range between individual plot are shown in Figs. 7 and 8. As seen in the Fig. 7, value of the mean fitness decreases with increasing number of iteration. Function tolerance was found after 51 iteration number. The ranges of these 51 iterations are given in Fig. 8.

6. Conclusion

The different experiments were conducted on WED-machine tool using brass wire as electrode. Experiments were performed at different settings of control factors. The best individual settings are given in Table 5. Main contribution of the study is to the

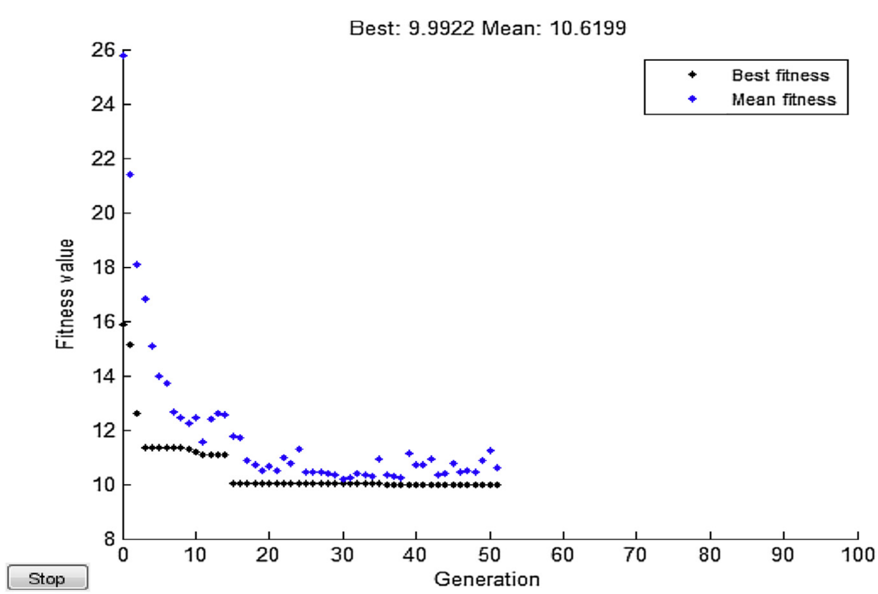

Fig. 7. Best fittest plot.

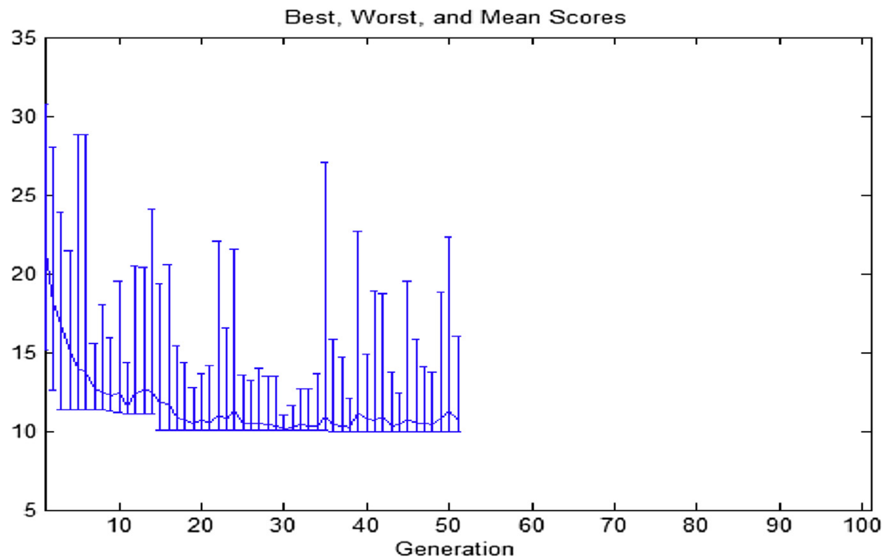

Fig. 8. Ranges of individuals.

Table 5
Best individual for minimum overcut.

Control factors	Symbol	Value
Pulse on time	T_{on} (μs)	117
Pulse off time	T_{off} (μs)	50
Spark gap voltage	*SV* (V)	49
Peak current	*IP* (A)	180
Wire tension	*WT* (grams)	6

minimum overcut (i.e. 9.9922 μm) and to find out optimizing setting using an amalgamation of RSM and GA. RSM and GA approach provide a systematic and effective methodology for the modelling and the optimization. The RSM based overcut model can be optimized using a genetic algorithm in order to find the optimum values of control factors. The given model can be utilized to select the level of control factors. Further multi quality characteristics can be optimized by artificial intelligence technique like genetic algorithm. It is also concluded from the ANOVA that the model is significant and reproducibility of the results are good with the value of R^2 as 0.9863.

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