ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645
Indian Journal of Science and Technology, *Vol 11(23), DOI: 10.17485/ijst/2018/v11i23/114377, June 2018*

Optimization of WEDM Process using Taguchi Utility Analysis

G. Rajyalakshmi*

School of Mechanical Engineering, VIT University, Vellore – 632014, Tamil Nadu, India; rajyalakshmi@vit.ac.in

Abstract

This research paper focused on development of a multi response optimization technique, using traditional utility – Taguchi method in conjunction with the principal component analysis for weight assignment concept in Wire Electrical Discharge Machining (WEDM). Inconel-825 super alloy has been selected as work material for experimentation. The effect of process parameters such pulse on time (TON), pulse off time (TOFF), Corner Servo voltage (CS), flushing pressure (WP), Wire Feed (WF), Wire Tension (WT), Spark Gap Voltage (SV) and Servo Feed (SV) were investigated on Material Removal Rate (MRR), Surface Roughness (SR) and Spark Gap (SG) in WEDM operation. Further, the responses such as MRR, SR and SG were modelled empirically through regression analysis. The optimization of multiple responses has been done for satisfying the requirements of industrial users, in contrast to the traditional multi-response techniques. Finally, confirmation experiment was performed to validate the effectiveness of the proposed optimal condition.

Keywords: Multi Response Optimization, Principal Component Analysis, Super Alloys, Utility Concept, WEDM

1. Introduction

Wire Electrical Discharge Machining (WEDM) has become one of the most extensively used non-traditional material removal processes. Researchers have successfully applied WEDM process to machine super alloys, composite materials, High-Speed Steel (HSS), conductive ceramics etc. Its unique feature of using thermal energy to machine electrically conductive materials regardless of hardness is a distinctive advantage in the manufacture of mold, die and automotive, aerospace and surgical components. WEDM is a process for eroding and removing material by transient action of electric sparks on electrically conductive materials, one being the work piece electrode and the other being the tool electrode, immersed in a dielectric fluid and separated by a small gap. The main mode of erosion is caused due to local thermal effect of an electric discharge. The work piece material is removed by a local high temperature associated with a very high energy density caused by ionization within the discharge column between the work piece and electrode. Hence, the material removal mechanism of EDM process is thermal erosion caused by melting and vaporization. The schematic view of wire EDM process is shown in Figure 1.

In recent years, wire-EDM has become an important non-traditional machining process, widely used in the aerospace and automotive industries. However, selection of cutting parameters for obtaining higher cutting efficiency or accuracy in wire-EDM is still not fully solved, even with the most up-to-date CNC wire-EDM machine. This is mainly due to the complicated stochastic process mechanisms in wire-EDM. As a result, the relationships

*Author for correspondence

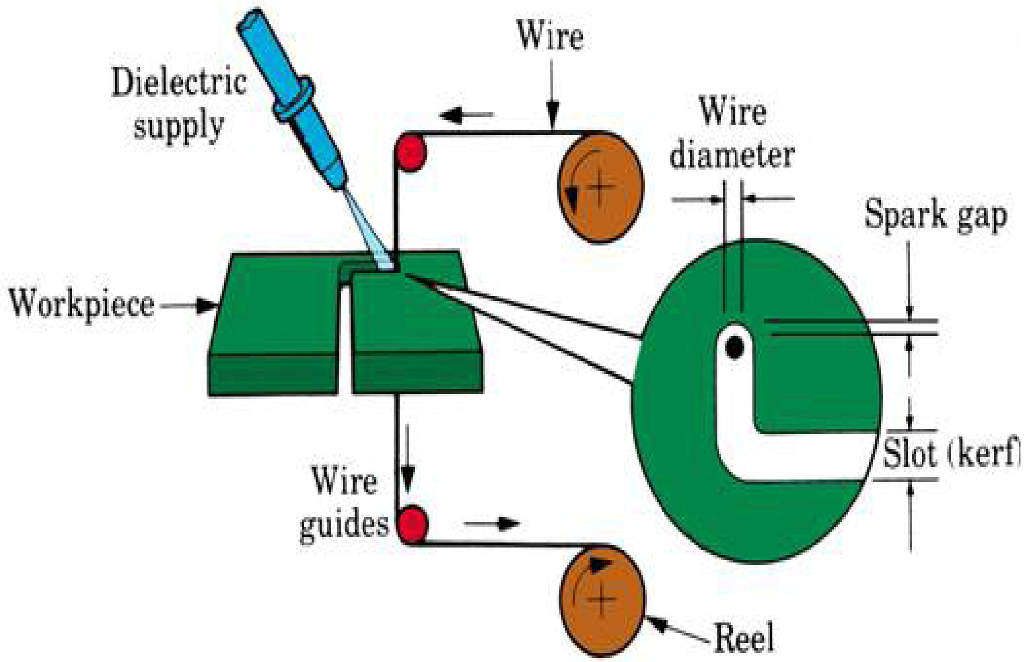

Figure 1. Schematic diagram of the basic principle of WEDM process.

between the cutting parameters and cutting performance are hard to model accurately.

Some of the most important performance measures (responses) of WEDM process are Material Removal Rate (MRR), Speak Gap (SG) and Surface Roughness (SR), which are affected by several process parameters, e.g. pulse-on-time, pulse off time, corner servo voltage, flushing pressure, wire feed, wire tension, Spark Gap Voltage, servo feed etc. Improved performance of WEDM process can only be achieved by setting the optimal levels for those process parameters.

2. Literature Review

WEDM is a complex machining process controlled by a large number of process parameters such as the pulse duration, discharge frequency and discharge current density. Any slight variations in the process parameters can affect the machining performance measures such as surface roughness and cutting ratio. In Electrical Discharge Machining (EDM), it is important to select machining parameters for achieving optimal machining performance. Usually, the desired machining parameters are determined based on experience or on handbook values. However, this does not ensure that the selected machining parameters result in optimal or near optimal machining performance for that particular electrical discharge machine and environment.

In[1] developed a theoretical model to estimate the MRR and surface quality of work piece. Experiments with different values of discharge current, pulse duration time and interval time were conducted to investigate their effects on the surface finish of the work piece and material removal rates. The theoretical prediction and experimental results are in agreement when compared. In[2] explained the method of optimization of Wire Electrical Discharge Machining (WEDM) process parameters using Taguchi method. It has been shown that the grey-based Taguchi method can optimize the multi-response processes through the settings of the process parameters[3] but, in this paper, Lin proposed that the grey relational analysis is not used for calculating the S/N ratio. This is because grey relational analysis based on the grey system theory[4] is used for solving the complicated inter-relationships among the multiple responses. A grey relational grade is then obtained for analyzing the relational degree of the multiple responses. The fuzzy-based Taguchi method can also be used to optimize the multi-response process through the settings of process parameters stated by[5]. In[6] examined multiple quality optimization of the injection molding for Polyether Ether Ketone (PEEK). This study looked into the dimensional deviation and strength of screws produced by the injection molding. This study applied the Taguchi method to cut down on the number of experiments and combined grey relational analysis to determine the optimal processing parameters for multiple quality characteristics.

In[7] used the grey relational analysis for the determination of optimal drilling parameters with the objective of minimization of surface roughness and burr height. In[8] used the grey relational analysis method for optimization of the EDM process. Most of the applications of Taguchi method concentrate on the optimization of single response problems[9]. The grey relational analysis based on grey system theory can be used for solving the complicated interrelationships among the multi responses explained by[9]. A grey relational grade is obtained to evaluate the multiple responses. As a result, optimization of the multiple responses can be converted into optimization of a single relational grade. In short, there is an ample scope of applying the proposed methodology of grey relational analysis and Taguchi method with the multiple responses for the optimization. In[10] The analysis of surface characteristics like surface roughness, micro cracks of Inconel-825 is carried out and an excellent machined nano finish can be obtained by setting the machining parameters at optimum level. The Taguchi design of experimental technique is used to optimize the machining parameters and an L9 orthogonal array is selected. In[11] reported on Inconel 718 that MRR and SR increases when pulse on time is increased and delay time is decreased. In[12] investigated the effect of electrode material, such as Sn, Zn and Mg, on machinability of annealed non alloyed steel in WEDM process. It was reported that material used for fabrication of wire electrode must be characterized by a small work function and high melting and evaporation temperature. It was found that coating of copper, brass, steel and molybdenum wires by a layer of a material possessing a small work function such as Mg, alkaline metals may increase the cutting efficiency during WEDM. It was also concluded that the machinability during WEDM is improved significantly with the proper combination of electrical, mechanical, physical and geometrical properties of wire electrode. In[13] demonstrated a systematic procedure of using Taguchi parameter design in process control of individual milling machines. The Taguchi parameter design had been done in order to identify the optimum surface roughness performance with a particular combination of cutting parameters in an end-milling operation. In[14] applied Taguchi optimization methodology to optimize cutting parameters in end milling while machining hardened steel with TiN coated carbide insert tool under semi-finishing and finishing conditions of high speed cutting considering the milling parameters - cutting speed, feed rate and depth of cut. With the aim to alleviate the problems of using experience and engineering knowledge, some other researchers have been motivated to apply different techniques of multi-response optimization for determining the optimal process conditions for EDM processes. In[15] used Taguchi method with fuzzy logic; In[16] employed grey-fuzzy logic; In[17] adopted Taguchi method with utility concept; In[18] used non-linear goal programming based on genetic algorithm; In[19], In[20], In[21] utilized desirability function approach; In[22–24] applied Grey Relational Analysis (GRA) and in[25] developed an inverse model for simultaneous optimization of multiple responses of EDM processes. But none of these methods take care of the possible correlation between the response variables that may exist, whereas, correlation analysis reveals that some of the responses of EDM process are usually correlated. For example, the correlation coefficient between MRR and EWR in the experimental data of[26] is found as -0.87, which is statistically significant at 5% level. So, ideally, a principal component analysis (PCA)-based method that can take into account the possible correlation between the responses should be used for multi-response optimization of EDM processes. In[27] studied for the prediction of surface roughness in Electrical Discharge Machining (EDM). Training of the models was performed with data from series of EDM experiments on SKD 11 (AISI D2) Tool steel; in the development of predictive models, machining parameters of discharge current, pulse duration and duty cycle were considered as model variables with a constant voltage 50 volt. For this reason, extensive experiments were carried out in order to collect surface roughness dataset. The developed model is validated with a new set of experimental data, and predictive behavior of models is analyzed. The reported results indicate that the proposed model can satisfactorily predict the surface roughness in EDM. In[28] presented a paper is to obtain the optimal parameters of turning process (cutting speed, spindle speed, feed rate and depth of cut) which results in an optimal of surface roughness for machining aluminum alloy ENAC43400 shaft (46 × 150 mm) in a CNC turning machine type StarChip 450 by using a carbide cutting tool type DNMG 332; surface roughness was measured using the POCKET SURF EMD-1500 tester. In[29] studied the effects of process parameters of ECM as well as their interactions are investigated and the process parameters are optimized through the desirability function of the response surface methodology. The microstructure of the Monel 400 alloys specimen, machined with ECM, is studied to understand the effect of electrolyte and other parameters during the machining. However, none of the above methods for multi-response optimization takes into account the possible correlations between the responses that may exist. In order to take care of the possible correlations between the response variables, many researchers[30–32] proposed to make use of PCA[33]. The PCA technique can transform several related variables into a smaller number of uncorrelated principal components, which are linear combinations of the original variables. The past researchers suggested optimizing the process settings with respect to principal components instead of the original response variables. Recently[32], proposed the PCA-based UT approach to optimize multiple responses that may be correlated. The PCA-based UT approach seems to be very appealing. But one apparent problem in it is that it does not make use of Taguchi's SN ratio concept appropriately. From observations it was shown that if Taguchi's SN ratio concept is integrated into the PCA-based UT approach, it can be the most systematic and practical approach for optimization of correlated responses.

3. Optimization Techniques

3.1 Taguchi's Design of Experimentation

Taguchi proposed the robust design based on design of experimentation. This method provides a best tool for parameter design of performance characteristics. Design of experiments includes selection of appropriate orthogonal array and assignment of factors and interaction in appropriate column. Taguchi method reduces the number of experiments by using orthogonal array thus reducing the efforts of large experimentation. Taguchi's robust design method aims at achieving a target value and minimizing variability around the target value. Taguchi used a quadratic function for modeling quality loss whenever the characteristic deviates from its target value and considered SN ratio as a measure of performance. The most notable aspect of SN ratio is that it combines location and dispersion of a response variable in a single performance measure, whereas, other methods examine mean and variance as separate performance measures. Taguchi (Phadke, 1989) categorized the response variables mainly into three different classes, e.g. smaller-the-better (STB), Larger-the-better (LTB) and Nominal-the-best (NTB). The formulae for computation of SN ratio (ηij) for *jth* response corresponding to *ith* trial ($i = 1,2,\ldots,m$; $j = 1,2,\ldots,p$) are different for different types of response variables, and these are given as follows:

For HTB response variable,

$$\text{S/N Ratio } = -10\log_{10}(1/n)\sum_{i=1}^{n}\frac{1}{\mathrm{y}_{\mathrm{ij}}^{2}} \tag{1}$$

For STB response variable,

$$\text{S/N Ratio } = -10\log_{10}(1/n)\sum_{i=1}^{n}y_{ij}^{2} \tag{2}$$

For NTB response variable,

$$\text{S/N Ratio} = -10\log_{10}\left(\frac{\bar{y}_{ij}^{2}}{s_{ij}^{2}}\right) \quad (3)$$

The Analysis of Variance (ANOVA) is applied to outcome of experiments which helps to determine percentage contribution of individual parameter on output parameter against predefined level of confidence. In this research work, the effects of eight input factors, such as pulse on time (Ton), pulse off time (Toff), corner servo voltage (CS), flushing pressure of dielectric fluid (WP), wire feed (WF), wire tension (WT), Spark Gap Voltage (SV) and servo feed(SF), have been investigated on three response characteristics such as material removal rate (MRR), Spark Gap (SG) and surface roughness (SR) using L36 orthogonal array. ANOVA and mean effect plot were determined using Minitab16 Software.

3.2 Utility Concept

Utility can be defined as the usefulness of a product or a process in reference to the levels of expectations to the consumers. The performance evaluation of any machining process depends on number of output characteristic. Therefore, a combined measure is necessary to gauge its overall performance, which must take into account the relative contribution of all the quality characteristics. Such a composite index represents the overall utility of a product/process. It provides a methodological framework for the evaluation of alternative attributes made by individuals, firms and organizations. Utility refers to the satisfaction that each attributes provides to the decision maker. Thus, utility theory assumes that any decision is made on the basis of the utility maximization principle, according to which the best choice is the one that provides the highest satisfaction to the decision maker[8].

According to the utility theory[9,10] if X_i is the measure of effectiveness of an attribute (or quality characteristics) *i* and there are *n* attributes evaluating the outcome space, then the joint utility function can be expressed as:

$$U(X_1, X_2,.......X_n) = f(U_1(X_1) U_2(X_2),.....,U_n(X_n) \quad (4)$$

Here, *Ui (Xi)* is the utility of the i^{th} attribute.

The overall utility function is the sum of individual utilities if the attributes are independent, and is given as follows:

$$U(X_1, X_2,....X_n = \sum_{i=1}^{n} U_i(X_i). \quad (5)$$

The overall utility function after assigning weights to the attributes can be expressed as:

$$U(X_1, X_2,....X_n) = \sum_{i=1}^{n} W_i.U_i(X_i) \quad (6)$$

The preference number can be expressed on a logarithmic scale as follows:

$$P_i = A \times \log\left(\frac{X_i}{X_i^{'}}\right) \quad (7)$$

Here, X_i is the value of any quality characteristic or attribute *i*, $X_i^{'}$ is just acceptable value of quality characteristic or attribute i and A is a constant. The value A can be found by the condition that if $X_i = X^*$ (where X^* is the optimal or best value), then $P_i = 9$ .Therefore,

$$A = \frac{9}{\log \frac{X^*}{X_i^{'}}} \quad (8)$$

The overall utility can be expressed as follows:

$$U = \sum_{i=1}^{n} W_i P_i \quad (9)$$

Subject to the condition:

$$\sum_{i=1}^{n} W_i = 1$$

Overall utility index that has been computed treated as a single objective function for optimization. Among various quality characteristics types, viz. Lower-the-Better (LB), Higher-the-Better (HB), and Nominal-the-Best (NB) suggested by Taguchi, the utility function would be higher. In the proposed approach utility values of individual responses are accumulated to calculate overall utility index. Overall utility index servers as the single objective function for optimization.

4. Experimental Details

4.1 Work Material

Due to their high temperature mechanical strength and high corrosion resistance properties, super alloys are nowadays used in Marine, Space and other applications. Their ability to maintain their mechanical properties at high temperatures severely hinders the machinability of these alloys[26,27]. Its poor thermal diffusivity generates high temperature at the tool tip as well as high thermal gradients in the cutting tool, affecting the tool life adversely. Inconel 825 is very chemically reactive and therefore, has a tendency to weld to the cutting tool during machining thus, leading to premature tool failure. Owing to all these problems, it is very difficult to machine Inconel 825 by conventional machining processes and moreover, by conventionally used tool materials.

4.2 Experimental Procedure

The experiments were carried out on Ultra Cut 843/ ULTRA CUT f2 CNC WEDM machine. In this machine, all the axes are servo controlled and can be programmed to follow a CNC code which is fed through the control panel. All three axes have an accuracy of 1 μm. The electrode material used was a 0.25 mm diameter brass wire. A small gap of 0.025 mm to 0.05 mm is maintained in between the wire and work-piece. The high energy density erodes material from both the wire and work piece by local melting and vaporizing. The di-electric fluid (deionized water) is continuously flashed through the gap along the wire, to the sparking area to remove the debris produced during the erosion. A collection tank is located at the bottom to collect the used wire erosions and then is discarded. The wires once used cannot be reused again, due to the variation in dimensional accuracy. Through an NC code, machining can be programmed. Wire-cut electrical discharge machining of Inconel 825 alloy has been considered in the present set of research work. The size of the work piece considered for experimentation on the wire-cut EDM is 10 mm width, 10 mm length and 15 mm depth of cut. According to the Taguchi method based on robust design a L36 (21 X 37) mixed orthogonal array is employed for the experimentation.

In setting the machining parameters, particularly in rough cutting operation, the goal is threefold - the maximization of MRR, minimization of SR and minimization of gap width. Generally, the machine tool builder provides machining parameter table to be used for setting machining parameter. This process relies heavily on the experience of the operators. In practice, it is very difficult to utilize the optimal functions of a machine owing to there being too many adjustable machining parameters. With a view to alleviate this difficulty, a simple but reliable method based on statistically designed experiments is suggested for investigating the effects of various process parameters on MRR, SR and Gap width and determines optimal process settings. In the present work, data have been collected from few experimental runs with randomly chosen factor combinations. A quadratic model has been fitted for identification of the process to establish approximate interrelation among various process parameters as well as response variables. These mathematical models have been utilized to generate data as per Taguchi design. Finally, grey-based Taguchi technique has been adopted to evaluate the optimal process environment. Among the eight WEDM parameters two levels for one control factor (Pulse on time) and three levels for remaining seven control factors, are considered for optimality analysis during machining of Inconel 825 alloy.

4.3 Machining Parameter Selection and Performance Evaluation

The selection of optimum machining parameters in WEDM is an important step. Improperly selected param-

Table 1. Experimental factors and their levels for Wire Electrical Discharge Machining process

Parameter	Symbol	Level-1	Level-2	Level-3
Pulse On Time (A)	T ON (µs)	105	115	-
Pulse Off Time (B)	T OFF (µs)	50	55	60
Corner servo©	CS (volts)	50	60	70
Flushing pressure (D)	WP (Kg/cm^2)	8	10	15
Wire feed rate€	WF (m/min)	2	5	6
Wire tension (F)	WT (Kg-f)	9	10	11
Spark Gap Voltage (G)	SV (volts)	20	25	30
Servo Feed (H)	SF (mm/min)	1050	1100	1150

eters may result in serious problems like short-circuiting of wire, wire breakage and work surface damage which is imposing certain limits on the production schedule and also reducing productivity. As Material Removal Rate (MRR), Surface Roughness (Ra) and Spark Gap (SG) are most important responses in WEDM; various investigations have been carried out by several researchers for improving the MRR, Surface Finish and kerf width. However, the problem of selection of machining parameters is not fully depending on machine controls rather material dependent. To perform the experimental design, the levels of machining parameters are selected as in Table 1.

4.4 Analysis of Experimental Results

The multiple responses from the experiment were calculated as follows and presented in Table 2.

Material removal rate is calculated as:

MRR = V_c * b* h mm^3/min.

Where: V= Cutting speed in mm/min.

b = Width of cut in mm.

h = Height of the work piece in mm and Surface roughness is measured with surfcorderSE3500 in µm and Spark Gap is measured with micrometer in mm.

Table 2. Experimental results

Exp. No.	T ON	T OFF	CS	WP	WF	WT	SV	SF	MRR	SR	SG
1	1	1	1	1	1	1	1	1	120.3	1.54	0.02
2	1	2	2	2	2	2	2	2	143.2	1.86	0.03
3	1	3	3	3	3	3	3	3	182.2	1.41	0.03
4	1	1	1	1	1	2	2	2	119.6	1.68	0.01
5	1	2	2	2	2	3	3	3	139.5	1.66	0.04
6	1	3	3	3	3	1	1	1	183.7	1.75	0.01
7	1	1	1	2	3	1	2	3	112.8	1.47	0.04
8	1	2	2	3	1	2	3	1	142.5	1.17	0.05
9	1	3	3	1	2	3	1	2	195.7	1.99	0.04
10	1	1	1	3	2	1	3	2	114.7	1.86	0.04
11	1	2	2	1	3	2	1	3	147.7	1.54	0.04
12	1	3	3	2	1	3	2	1	202.1	1.94	0.04
13	1	1	2	3	1	3	2	1	115.8	1.86	0.03
14	1	2	3	1	2	1	3	2	127.1	1.85	0.01
15	1	3	1	2	3	2	1	3	144.3	1.61	0.04
16	1	1	2	3	2	1	1	3	123.3	1.94	0.04
17	1	2	3	1	3	2	2	1	131.6	1.38	0.04
18	1	3	1	2	1	3	3	2	187.1	1.47	0.04
19	2	1	2	1	3	3	3	1	371.2	1.91	0.05
20	2	2	3	2	1	1	1	2	315.3	1.88	0.01
21	2	3	1	3	2	2	2	3	325.5	2.58	0.04

Table 2 Continued

22	2	1	2	2	3	3	1	2	277.8	2.03	0.04
23	2	2	3	3	1	1	2	3	294.3	2.30	0.01
24	2	3	1	1	2	2	3	1	309.3	1.91	0.03
25	2	1	3	2	1	2	3	3	267.3	1.94	0.01
26	2	2	1	3	2	3	1	1	329.2	1.95	0.03
27	2	3	2	1	3	1	2	2	325.8	2.25	0.03
28	2	1	3	2	2	2	1	1	264.7	2.23	0.05
29	2	2	1	3	3	3	2	2	247.8	2.04	0.04
30	2	3	2	1	1	1	3	3	352.2	2.44	0.01
31	2	1	3	3	3	2	3	2	401.2	2.05	0.01
32	2	2	1	1	1	3	1	3	348.7	2.94	0.03
33	2	3	2	2	2	1	2	1	360.0	2.32	0.03
34	2	1	3	1	2	3	2	3	322.5	1.90	0.04
35	2	2	1	2	3	1	3	1	352.5	1.82	0.03
36	2	3	2	3	1	2	1	2	274.8	2.30	0.04

Statistical analysis was carried out on the experimental data obtained through Taguchi experimental design using statistical software MINITAB 16. Analysis of Variance (ANOVA) was performed to determine the influence of input parameters on the output response variables.

4.5 Single Objective Optimization using Taguchi Method

4.5.1 Effect on MRR

To determine the effect of process parameters on MRR, response values are calculated and presented in Table 2. Figure 2 represents the mean effect plot of material removal rate as pulse on time (Ton), pulse off time (Toff), corner servo voltage (CS), flushing pressure of dielectric fluid (WP), wire feed (WF), wire tension (WT), Spark Gap Voltage (SV) and servo feed (SF) on MRR at the selected machining conditions. The average values of material removal rate for each parameter at levels 1, 2 and 3 for raw data plotted in Figure 2. It shows that the material removal rate increases with the increase in pulse on time. Pulse of time and corner servo voltage has very slight effect on material removal rate. MRR is increased negligibly for short duration after that it is increased slightly with increase in pulse off time and corner servo voltage.

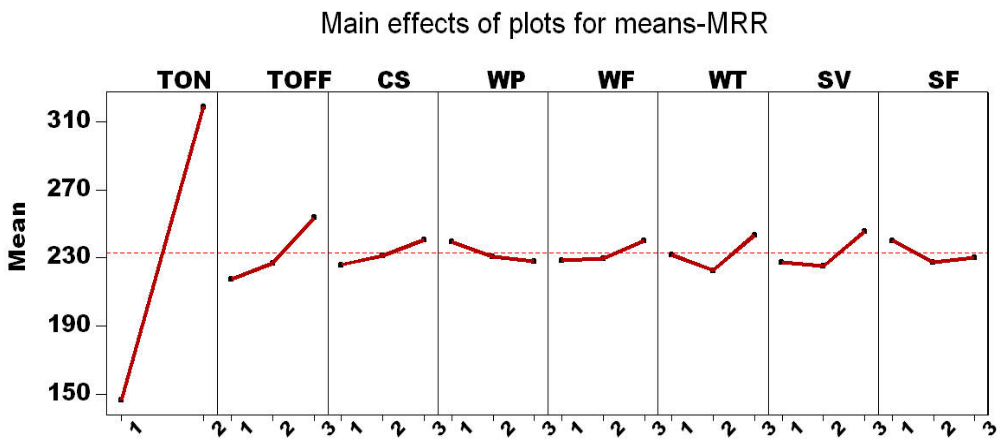

Figure 2. Response graph for MRR.

Flushing pressure is showing negligible effect on MRR. Material removal rate is slightly increased with increase in wire feed.

4.5.2 Effect on Surface Roughness

To determine the effect of process parameters on MRR, response values are calculated and presented in Table 2. Figure 3 represents the mean effect plot of surface roughness against process parameters on surface roughness. It is seen from the Figure 3 that surface roughness increases with the increase of pulse on time and zero feed. Pulse off time showing no effect on surface roughness for shorter duration after that surface roughness is increasing with pulse off time. Wire feed and Spark Gap Voltage affecting on surface roughness in the negligible manner. Surface roughness is increasing with increase in wire feed and Spark Gap Voltage for short period after that it is decreasing. Flushing pressure and wire tension are responding similarly with respect to surface roughness. Corner servo voltage has negligible effect on surface roughness.

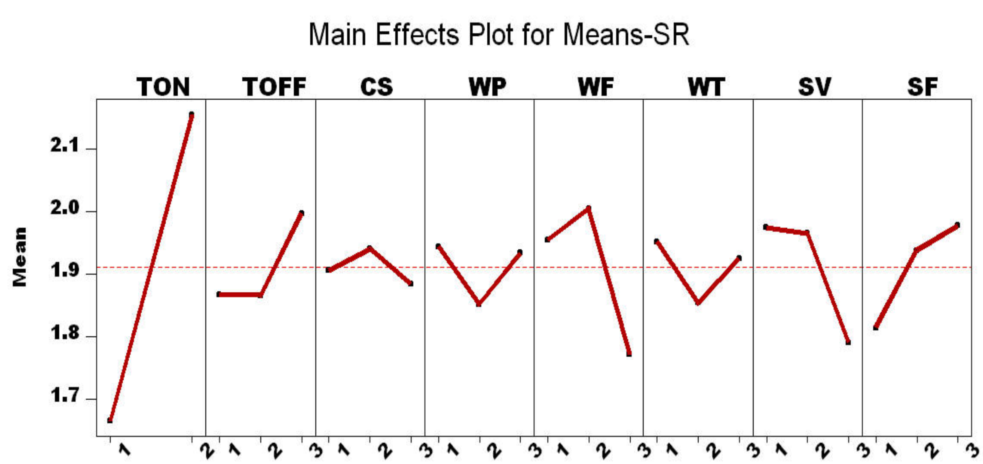

Figure 3. Response graph for SR.

Table 3. Response table for Mrr, Sr, Sg.

Response Table for MRR			
Parameter	**Level1**	**Level 2**	**Level 3**
T ON	146.333	318.944	
T OFF	217.656	226.656	253.604
CS	226.031	231.198	240.688
WP	239.354	230.594	227.969
WF	228.385	229.594	239.938
WT	231.885	222.688	243.344
SV	227.188	225.125	245.604
SF	240.281	227.563	230.073
Response Table for SR			
Parameter	Level1	Level 2	Level 3
T ON	1.66556	2.15500	
T OFF	1.86750	1.86583	1.99750
CS	1.90583	1.94000	1.88500
WP	1.94417	1.85250	1.93417
WF	1.95500	2.00417	1.77167
WT	1.95167	1.85417	1.92500
SV	1.97500	1.96500	1.79083
SF	1.81500	1.93833	1.97750
Response Table for SG			
Parameter	Level1	Level 2	Level 3
T ON	0.036527	0.031666	
T OFF	0.034166	0.032500	0.035625
CS	0.034583	0.039583	0.028125
WP	0.032916	0.035833	0.033541
WF	0.027916	0.038333	0.036041
WT	0.027500	0.038333	0.040208
SV	0.035000	0.035416	0.031870
SF	0.037083	0.030833	0.034375

4.5.3 Effect on Spark Gap

To determine the effect of process parameters on MRR, response values are calculated and presented in Table 2. The mean effect plot of surface roughness against process parameters on Spark Gap was given in Figure 4. It is seen from the Figure 4, Spark Gap increases with the increase of pulse on time and servo feed. Pulse off time showing slight effect on Spark Gap for shorter duration after that Spark Gap is decreasing with pulse off time. Corner servo voltage, wire feed and wire tension showing greater influence on Spark Gap. It is increasing with increase in wire feed. Spark Gap voltage and servo feed are affecting significantly.

4.5.4 Confirmation Experiments for Taguchi Results

The confirmation test for the optimal parameter combination with its selected levels is conducted to evaluate the quality characteristics for WEDM of Inconel-825. Once the optimum parameters are selected for response characteristics individually, confirmation experiments are conducted for validation of that optimum values. The Table 6 gives the comparison of predicted values with confirmation experimental values. The response values obtained from the confirmation experiment are MRR = 365.915 mm^3/min, SR = 2.08 μm and SG = 0.0409 mm.

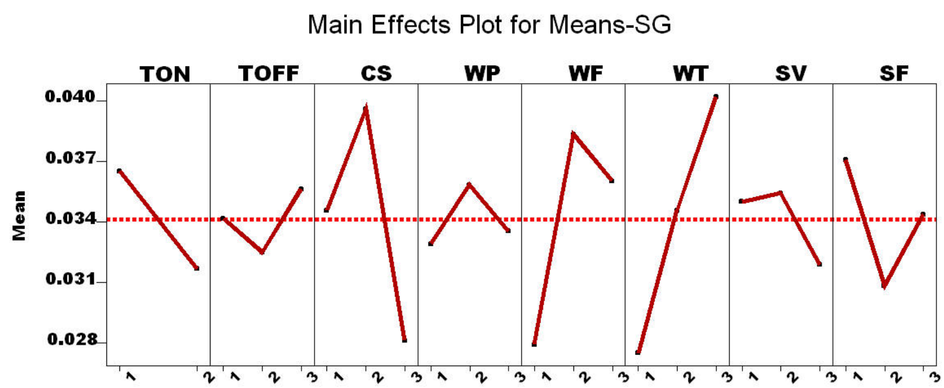

Figure 4. Response graph for SG.

Table 4. Optimal process parameters combination obtain from Taguchi method

S. No.	Response characteristics	Optimal Parameter Combination								Response characteristics values	
		TON	TOFF	CS	WP	WF	WT	SV	SF	OA	Confirmation experiment
1	MRR (mm^3/min)	2	3	3	2	3	3	3	1	328.175	365.915
2	SR (μm)	1	1	1	3	2	1	2	3	2.25	2.08
3	SG (mm)	1	3	2	2	2	3	2	1	0.0450	0.0409

After performing single objective optimization of process, scaled s/n ratio values for all response characteristics are calculated using equation 10 for performing PCA analysis.

The scaled S/N ratio values of multiple responses are calculated. The normalized SN ratios values of the response variables are then subjected to PCA in STATISTICA software.

4.6 Multi Response Optimization

The preference scales for calculating overall utility was constructed using Equation 7. For construction of preference scale for material removal rate, the smallest value of material removal rate was considered from the experiments (Table 2) as the minimum acceptable value because this characteristic is "higher-the-better" type. As indicated in Equation 8, optimal value of selected characteristics is desired for calculation of value of A under determination of preference scale. Single response optimization was performed for material removal rate using Taguchi's design. The graph was plotted and best optimal combination (TON- 2 TOFF- 3 CS- 3 WP- 2 WF- 3 WT- 3 SV- 3 SF- 1) was determined using Minitab 16 software (Figure 4). The predicted optimal value of material removal rate (3365. mm^3/min) was calculated using Taguchi approach.

Preference scale construction material removal rate

X^*= optimum value of MRR= 365.915(mm^3/min)

X^1= minimum acceptable value of MRR=112.875 (mm^3/min) (assumed, as all the observed values of MRR in Table 4 are in between 112.875 and 401.25 (mm^3/min))

Using these values and the equations (4) and (5), the preference scale for MRR was constructed as

$$P_{MRR}=17.62 \log [X_{MRR}/112.875] \quad (8)$$

4.6.1 *Surface Roughness*

For construction of preference scale for surface roughness, the largest value of for surface roughness was considered from the experiments (Table 3) as the minimum acceptable value because this characteristic is "lower-the-better" type. As indicated in Equation 8, optimal value of selected characteristics is desired for calculation of value of 'A' under determination of preference scale. Single response optimization was performed for surface roughness using Taguchi's design. The graph was plotted and best optimal combination (TON- 1 TOFF- 1 CS- 1 WP- 3 WF- 2 WT- 1 SV-2 SF- 3) was determined using Minitab 16 software (Figure 3).

The predicted optimal value of for surface roughness (2.08 μm) was calculated using Taguchi approach.

X^* = optimum value of SR = 2.08 μm.

X^1 = minimum acceptable value of CS = 2.94 μm (assumed, as all the observed values of CS in Table 2 are in between 1.17 to 2.94 μm)

Using these values and the Equations (4) and (5), the preference scale for SR was constructed as:]

$$P_{SR}= -59.88 \log [X_{SR}/2.94] \quad (9)$$

4.6.2 *Spark Gap*

For construction of preference scale for Spark Gap, the largest value of for Spark Gap was considered from the experiments (Table 2) as the minimum acceptable value because this characteristic is "lower-the-better" type. As indicated in Equation 8, optimal value of selected characteristics is desired for calculation of value of 'A' under determination of preference scale. Single response optimization was performed for Spark Gap using Taguchi's design. The graph was plotted and best optimal combination (TON- 1 TOFF- 3 CS- 2 WP-2 WF- 2 WT- 3 SV-2 SF-1) was determined using Minitab 16 software (Figure 4).

X^* = optimum value of SG = 0.0409 mm.

X^1 = minimum acceptable value of SG = 0.05 mm.

Using these values and the Equations (7) and (8), the preference scale for SG was constructed as:

$$P_{SG} = -103.155 \log [X_{SG}/0.05] \quad (10)$$

Based on the contribution obtained from PCA analysis of each response characteristics the weights have been assigned. However, there is no constraint on the weights and it can be any value between 0 and 1 subject to the condition specified in Equation (9).

The customers' requirements and priorities should be taken into consideration while deciding the weights of response characteristics.

4.6.3 Utility Value Calculation

The utility value of each turned part was calculated using the following relation (overall utility function):

$$U\ (n, R) = P_{MRR} * W_{MRR} + P_{SR} * W_{SR} + P_{SG} * W_{SG} \quad (11)$$

Where, n = trial number,
n =1, 2. . . 27;
R = replication number, R = 1, 2, 3.

Table 5. Overall utility values and ranks

Experiment Number	Overall Utility value	Rank	S/N ratios of utility value
1	11.2437	26	21.0182
2	7.93326	11	17.9890
3	11.6165	29	21.3015
4	12.7905	32	22.1378
5	7.8942	10	17.9462
6	13.7597	33	22.7722
7	8.5986	16	18.6886
8	11.505	28	21.2177
9	6.9203	7	16.8025
10	6.5171	6	16.2811
11	8.9602	18	19.0464
12	7.2343	9	17.1879
13	7.0967	8	17.0211
14	11.4976	27	21.2121
15	8.9585	17	19.0447
16	5.6690	1	15.0701
17	10.4377	22	20.3721
18	10.8914	23	20.7417
19	9.0230	19	19.1070
20	16.7917	36	24.5019

Table 5 Continued

21	6.2089	3	15.8603
22	8.4673	14	18.5549
23	12.1628	31	21.7007
24	10.2086	21	20.1793
25	15.8706	34	24.0119
26	10.9560	24	20.7930
27	8.4772	15	18.5650
28	6.0785	2	15.6759
29	8.0236	12	18.0874
30	12.0926	30	21.6504
31	16.5939	35	24.3990
32	6.3750	4	16.0896
33	8.4581	13	18.5455
34	9.1429	20	19.2217
35	11.2124	25	20.9940
36	6.3822	5	16.0994

The utility values thus calculated are reported in Table 5.

4.6.4 Analysis of the Data and Determination of Optimal Settings of Process Parameters

The data (utility values) were analyzed for Signal-to-noise (S/N) ratio. Since utility is a "higher the better" (HB) type of characteristic, (S/N) HB has been used (Ross, 1996):

The S/N ratios for overall utility values are given in Table 9. The mean responses and main effects in terms of S/N ratios of utility values are calculated and reported in Figure 7.

It is clear from the Figure 7 that the second level of Pulse on time (T ON-2), the second level of pulse off time (T OFF -2), third level of corner servo voltage (CS-3), first level of flushing pressure (WP-1), first level of wire feed (WF-1), first level of wire tension (WT-1), third level of Spark Gap voltage (SV-3) and second level of servo feed (SF-2) would yield best performance in terms of utility value and S/N ratio within the selected range of parameters.

The ANOVA for S/N ratios of utility values are given in Table 6. It is clear from the Table 6 that wire feed is showing maximum contribution on responses followed by corner servo voltage, Spark Gap voltage and pulse off time. Pulse on time and flushing pressure is showing negligible effect on responses.

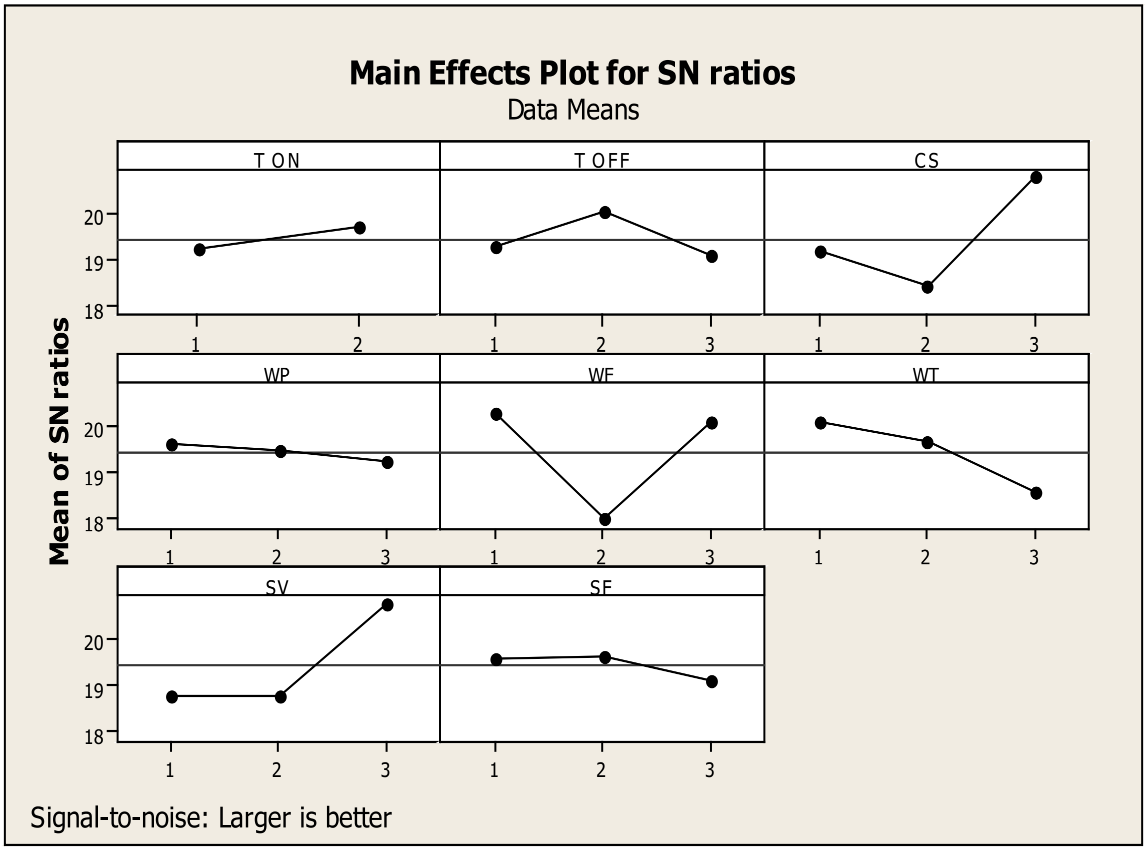

Figure 5. Response graph of S/N ratios utility values.

Table 6. ANOVA for S/N ratios of overall utility value

ANOVA for S/N ratios of overall utility value					
Source	**DF**	**SS**	**MS**	**F**	**%**
TON	1	1.861	1.86140	0.27	0.8271
T OFF	2	5.782	2.89109	0.43	2.57
CS	2	34.909	17.4544	3.20	15.516
WP	2	1.002	0.5012	0.09	0.44537
WF	2	39.495	19.7476	3.92	17.555
WT	2	14.655	7.3277	1.46	6.5139
SV	2	30.992	15.4961	2.39	13.775
SF	2	1.688	0.8440	0.13	0.7503
Error	20	94.593	4.72965		
Total	35	224.977			

4.6.5 Confirmation Experiments

The confirmation test for the optimal parameter setting with its selected levels was conducted to evaluate the response characteristics for WEDM of Inconel825. Experiment 16 (Table 6) shows the highest utility value, indicating the optimal process parameter set of T ON-1;TOFF-1; CS-2; WP-3; WF-2; WT-1; SV-1; SF-3 has the best multiple performance characteristics among the thirty six experiments, which can be compared with results of confirmation experiment for validation of results. Table 11 shows the comparison of the experimental results using the orthogonal array (T ON-1;TOFF-1; CS-2; WP-3; WF-2; WT-1; SV-1; SF-3) and utility theory design optimal (T ON-2;TOFF-2; CS-3; WP-1; WF-1; WT-1; SV-3; SF-2) WEDM parameters on Inconel-825. The response values obtained from the confirmation experiment are MRR = 139.257 mm^3/min, SR = 1.78 µm and SG = 0.041 mm. The material; removal rate shows an increased value of 123.375 mm^3/min to 139.257 mm^3/min, the surface roughness shows a reduced value of 1.97 µm to 1.78 µm and the Spark Gap shows a reduced value of 0.045 to 0.041 mm respectively. The corresponding improvement in material removal rate is 12.875%, surface roughness and Spark Gap were 9.64%, and 8.89% respectively.

Table 7. Results of confirmation experiment

Response parameters	Optimal process parameters	
	Predicted value	Actual value through Confirmation Experiment
MRR (mm^3/min)	123.375	139.257
SR (µm)	1.97	1.78
SG (mm)	0.0450	0.041

5. Conclusions

This paper presented multi-objective optimization process parameters of WEDM of Inconel-825 super alloy using Taguchi technique and traditional utility analysis in conjunction with principal component analysis for weightage assignment. The statistical analysis (ANOVA) highlighted that the major influencing machining parameter considered in this study improves machining performance of WEDM process. The mathematical modelling was presented for predicting optimal condition of material removal rate, Spark Gap and surface roughness and statistically validated by ANOVA.ANOVA test results show that two machining parameters pulse on time (T ON), Wire Tension (WT) have significant influence on material removal rate of WEDM process. The pulse on time, wire feed and Spark Gap have significant effect on surface roughness. The three machining parameters Corner Servo voltage (CS), Wire Feed rate (WF) and Wire Tension (WT) showing greatest influence on Spark Gap. The multi-objective optimization of all three responses namely MRR, SR and SG are presented using utility concept with PCA. The optimal machining performance of Inconel-825 super alloy cloud be achieved at T ON-2;TOFF-2; CS-3; WP-1; WF-1; WT-1; SV-3; SF-2. This parameter combination in higher material removal rate could equal to 139.27 mm^3/min, lower Kerf width of 0.041 mm and minimum surface roughness of 1.78 µm.

6. References

1. Tarng YS, Ma SC, Chung LK. Determination of optimal cutting parameters in Wire Electrical Discharge Machining. International Journal of Machine Tools and Manufacture. 1995; 35(12):1693–701. Crossref.
2. Mahapatra SS, Patnaik A. Optimization of Wire Electrical Discharge Machining (WEDM) process parameters using Taguchi method. International Journal of Advanced Manufacturing Technology. 2006; 34:911–25. Crossref.
3. Lin JL, Tarng YS. Optimization of the multi-response process by the Taguchi method with grey relational analysis. Journal of Grey System. 1998; 10(4):355–70.
4. Deng J. Introduction to grey system. Journal of Grey System. 1989; 1:1–24.

5. Lin JL, Wang KS, Yan BH, Tarng YS. Optimization of the electrical discharge machining process based on the Taguchi method with fuzzy logics. Journal of Materials Processing Technology. 2000; 102:48–55. Crossref.
6. Chung F, Kuo J, Te-Li S. Optimization of multiple quality characteristics for polyether ether Ketone injection molding process. Fibers and Polymer. 2006; 7(4):404–13.
7. Tosun N. Determination of optimum parameters for multi performance characteristics in drilling by using grey relational analysis. International Journal of Advanced Manufacturing Technology. 2006; 28:450–5. Crossref.
8. Lin CL, Lin JL, Ko TC. Optimization of the EDM process based on the orthogonal array with fuzzy logic and Grey relational analysis method. International Journal of Advanced Manufacturing Technology. 2002; 19:271–7. Crossref.
9. Jeyapaul R, Shahabudeen P, Krishnaiah K. Quality management research by considering multi-response problems in the Taguchi method - a review. International Journal of Advanced Manufacturing Technology. 2005; 26:1331–7. Crossref.
10. Prabhu S, Vinayagam BK. AFM surface investigation of Inconel 825 with multi wall carbon nano tube in electrical discharge machining process using Taguchi analysis. Achieves of Civil and Mechanical Engineering. 2011; 11(1):149–70.
11. Ramakrishnan R, Karunamoorthy L. Modeling and multi-response optimization of Inconel 718 on machining of CNC WEDM process. Journal of Materials Processing Technology. 2008; 207(1–3):343–9.
12. Prohaszka J, Mamalis AG, Vaxevanidis NM. The effect of electrode material on machinability in wire electro-discharge machining. Journal of Materials Processing Technology. 2007; 69(1–3):233–7.
13. Yang LJ, Chen CJ. A systematic approach for identifying optimum surface roughness performance in end-milling operations. Journal of Industrial Technology. 2001; 17:1–8.
14. Ghani JA, Choudhury IA, Hassan HH. Application of Taguchi method in the optimization of end milling parameters. Journal of Material Processing Technology. 2004; 145(1):84–92.
15. Lin JL, Wang KS, Yan BH, Tarng YS. Optimization of the electrical discharge machining process based on the Taguchi method with fuzzy logics. Journal of Materials Processing Technology. 2000; 102:48–55. Crossref.
16. Lin JL, Lin CL. The use of grey-fuzzy logic for the optimization of the manufacturing process. Journal of Materials Processing Technology. 2005; 160:9–14. Crossref.
17. Kansal HK, Singh S, Kumar P. Performance parameters optimization (multi-characteristics) of Powder Mixed Electric Discharge Machining (PMEDM) through Taguchi's method and utility concept. Indian Journal of Engineering and Materials Sciences. 2006; 13:209–16.
18. Kanagarajan D, Karthikeyan R, Palanikumar K, Davim,JP. Application of goal programming technique for Electro Discharge Machining (EDM) characteristics of cemented carbide (WC/Co). International Journal of Materials and Product Technology. 2009; 35:216–27. Crossref.
19. El-Taweel TA. Multi-response optimization of EDM with Al-Cu-Si-TiC P/M composite electrode. International Journal of Advanced Manufacturing Technology. 2009; 44(1-2):100–13. Crossref.
20. Pradhan MK, Biswas C. Multi-response optimization of EDM of ALSI D2 tool steel using response surface methodology. International Journal of Machining and Machinability of Materials. 2011; 9:66–85. Crossref.
21. Baraskar SS, Banwait SS, Laroiya SC. Multi-objective optimization of Electrical Discharge Machining process using Derringer's desirability function approach. International Journal of Materials Engineering Innovation. 2011; 2:203–21. Crossref.
22. Jung JH, Kwon WT. Optimization of EDM process for multiple performance characteristics using Taguchi method and grey relational analysis. Journal of Mechanical Science and Technology. 2010; 24:1083–90. Crossref.
23. Natarajan N, Arunachalam RM. Experimental investigations and optimization of process parameters in micro-EDM with multiple performance characteristics. International Journal of Experimental Design and Process Optimization. 2011; 2:336–56. Crossref.
24. Singh S. Optimization of machining characteristics in electric discharge machining of 6061Al/Al2O3p/20P composites by grey relational analysis. International Journal of Advanced Manufacturing Technology. 2012; 63(9-12):1191–202. DOI: 10.1007/s00170-012-3984-8, 2012. Crossref.
25. Sanchez HT, Estrems M, Faura F. Development of an inversion model for establishing EDM input parameters to satisfy material removal rate, electrode wear ratio and surface roughness. International Journal of Advanced Manufacturing Technology. 2011; 57:189–201. Crossref.
26. Lin YC, Wang AC, Wang DA, Chen CC. Machining performance and optimizing machining parameters of Al2O3-TiC ceramics using EDM based on the Taguchi method. Materials and Manufacturing Processes. 2009; 24:667–74. Crossref.
27. Das R, Pradhan MK, Das C. Prediction of surface roughness in Electrical Discharge Machining of SKD 11 tool steel using Recurrent Elman Networks. Jordan Journal of Mechanical and Industrial Engineering. 2013; 7(1):67–71.

28. Aghdeab SH, Mohammed LA, Ubaid AM. Optimization of CNC turning for aluminum alloy using simulated annealing method. Jordan Journal of Mechanical and Industrial Engineering. 2015; 9(1):39–44.
29. Kalaimathi M, Venkatachalam G, Sivakumar M. Experimental investigations on the electrochemical machining characteristics of Monel 400 alloys and optimization of process parameters. Jordan Journal of Mechanical and Industrial Engineering. 2014; 8(3):143–51.
30. Tong LI, Wang CH. Multi-response optimization using principal component analysis and grey relational analysis. International Journal of Industrial Engineering. 2002; 9:343–50.
31. Tong LI, Wang CH, Chen HC. Optimization of multiple responses using principal component analysis and technique for order preference by similarity to ideal solution. International Journal of Advanced Manufacturing Technology. 2005; 27:407–14. Crossref.
32. Datta S, Mahapatra SS. Simultaneous optimization of correlated multiple surface quality characteristics of mild steel turned product. Intelligent Information Management. 2010; 2:26–39. Crossref.
33. Johnson RA, Wichern DW. Applied multivariate statistical analysis. New Delhi: Prentice Hall of India Pvt. Ltd; 1996.