Optimisation of spark erosion machining process parameters using hybrid grey relational analysis and artificial neural network model

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Abstract: Hastealloy C276 is hard to machine superalloy and extensively used in various engineering applications. It possess good strength and lower thermal conductivity which results in decreased tool life and poor machinability by conventional machining. Advanced machining processes have developed to overcome these difficulties and claimed as an alternative methods. Electrical Discharge Machining (EDM) is one of the advanced method used for machining of hard materials. This article details an investigation on EDM process and development of hybrid Grey ANN model. Taguchi method and ANOVA are used for designing the experiments and statistical analysis respectively. Grey Relational Analysis is adopted for determining the Grey Relational Grade (GRG) to represent the multi aspect optimization model and a

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neural network has been evolved to predict GRG by feeding the Grey Relational Co-efficient (GRC) values as input to developed neural network model. A comparison has been done between the experimental values and predicted values.

Keywords: electrical discharge machining; EDM; hard materials; haste alloy; Taguchi's methodology; form and orientation tolerances; grey relational analysis; GRA; artificial neural network; ANN.

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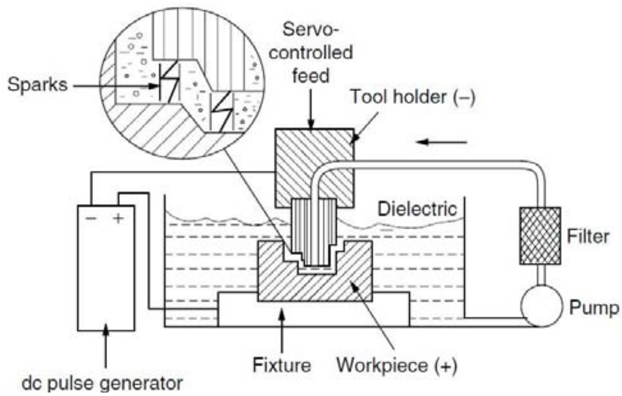
1 Introduction

Superalloys are heat resistant materials and the mechanical, chemical properties of the materials are remains unchanged during high temperature applications (Cai et al., 2014; Wu, 2007; Dave et al., 2013; Natarajan et al., 2013). The properties of superalloys such as high strength and hardness, low thermal diffusivity makes them as hard to machine materials (Qu et al., 2014). High strength and high hardness of these materials results in poor machining performance and more tool wear with the help of traditional machining processes. So there is a need to find a solution for machining of these superalloys with the help of unconventional material removal process. Electrical discharge machining (EDM) is one of the advanced method of material removal, extensively used for machining the various engineering components which are used in automobiles, aerospace and biomedical industries (Ho and Newman, 2003). A continuous and repeated electrical discharge between the tool (electrode) and the work materials, results in material removal from the work piece in the presence of dielectric fluid (Luis et al., 2005; Marafona and Chousal, 2006). The tool (electrode) moves towards the work piece until the gap between the tool and work piece is close enough to ionise the dielectric fluid by supplied voltage. Tool (electrode) and the work material are separated by the short duration discharges in dielectric gap. The removal of material takes place due to the erosive action. The material removal process takes place with irrespective of material hardness. The schematic of EDM process is shown in Figure 1 (El-Hofy, 2005). An exploration on EDM drilling of nickel alloy is detailed and the supplied current is the important process parameter for obtaining the better material removal rate (MRR) (Kuppan et al., 2008). The plan of experiment is most important to decide the significance of the process parameters. Taguchi's experimental design method is a powerful approach for planning the experiments and to solve the single objective optimisation problems. The machining performance and influence of process variables are detailed by various researchers on EDM process (Dhanabalan et al., 2013; Bharti et al., 2010; Caiazzo et al., 2015; Baraskar et al., 2013). Grey system theory has been suggested by Deng and it has been confirmed to be a successful approach for handling the deficient and uncertain information (Deng, 1989). Various multi criteria decision making (MCDM) tools such as grey relational analysis (GRA) have been used for conventional and unconventional machining process for determining the multi performance machining characteristics (Tripathy and Tripathy, 2016; Palanisamy and Senthil, 2016).

Figure 1 Schematic of electrical discharge machine



Regardless of various advantages, the output variables have some uncertainty and unclear data in GRA method. To overcome such kind of limitations, grey-based advanced optimisation method have been employed by various researchers. The use of grey-based fuzzy method will considerably improve the performance of machining. The grey fuzzy approach has momentous influence on the enhancement of machining performance and accuracy of outcomes (Ahilan et al., 2009; Das et al., 2014; Lin et al., 2000; Pandey and Panda, 2014; Suresh et al., 2014; Guo et al., 2017). So the adoption of the grey theory with any of the artificial intelligence decision making tools will help to improve the desired performance measures. The development of intelligent decision making tools for prediction of desired performance measure makes significant improvement in the manufacturing domain. Various intelligence decision making tools were developed for decision making in EDM process (Pradhan and Biswas, 2010). In present days the artificial neural network (ANN) have developed as most flexible tool for modelling which is used in numerous manufacturing applications to predict the various desired performance measures (Dimla et al., 1997; Dini, 1997). Various neural network models were developed for EDM process parameter prediction and the compatible results were attained with the help of developed models (Tsai and Wang, 2001). Among the number of existing algorithms in neural network models, the Levenberg-Marquardt algorithm (trainlm) has the greatest convergence (Kao and Tarng, 1997; Panda and Bhoi, 2005; Malinov et al., 2001; Demuth and Beale, 2000; Wang et al., 2003).

It is observed from the available literatures, that there are lack of investigation performed on multi-aspects optimisation of process variables using grey-based ANN approach by considering the performance measures namely MRR, surface roughness (SR), overcut (OC), circularity error and perpendicularity error for EDM process. In the present article, an attempt has been taken to conduct investigation on the process parameters and to develop the multi aspects optimisation model using grey-ANN method to predict the multi performance characteristics. Taguchi-based grey approach is employed to determine the grey coefficient values. The grey relational coefficient (GRC) values have been used as input values to develop the ANN model. The multi performance index, grey relational grade (GRG) is predicted with the help of developed neural network model.

2 Materials and methods

Haste alloy C276 is a nickel-based superalloy which has excellent corrosion and chemical resistance. Because of its exceptional properties, the material has wider applications especially in digesters and bleach plants in paper industries, heat exchangers, sulphuric acid reactors, and chemical environments. Haste alloy C-276 is selected as work material in this present investigation and it is clamped inside of the machining chamber. EDM machine (Model EMS 5030) has been used for the experimentation for making through holes. Copper electrode is used as a tool for machining of Haste alloy C276 and kerosene is used as a di-electric medium.

In traditional method of experimental design, more number of experimental runs are to be performed with selected process variables and levels. These kind of problems could be resolved by implementing Taguchi's experimental design approach. Taguchi proposed a unique layout for conducting experiments called as Orthogonal Array (OA) and also to analyse the process variables with minimum number of experimental runs. Current, pulse on time and pulse off time are selected as input variables and MRR, surface roughness, overcut, form and orientation tolerance errors are considered as performance measures. The input process variables are selected based upon the available literature. The selected input process variables, levels and range of values are specified in Table 1. Based on the selected parameters and levels, an L_{27} OA have been opted for EDM drilling of haste alloy.

Figure 2 Experimental setup for machining of haste alloy C-276 (see online version for colours)

Table 1 Input process parameters and levels

Symbols	*Process variables*	*Levels*		
		1	*2*	*3*
A	Current (A)	5	10	15
B	Pulse on Time (µs)	30	60	90
C	Pulse off time (µs)	3	6	9

Figure 3 Tool used for machining of haste alloy C-276 (see online version for colours)

Figure 4 Machined hole using EDM in haste alloy C-276

Weight loss method is used to compute the MRR. Mitutoyo SJ 410 model is used for measuring the surface roughness. Overcut, form and orientation tolerance are measured by Helmel make Co-ordinate Measuring Machine (CMM), model 216-142. The experimental setup and tool used for machining are shown in Figure 2 and Figure 3 respectively. The drilled hole using EDM is shown in Figure 4. The experiments were conducted as per L_{27} OA and the observations are presented in Table 2.

Table 2 Experimental Layout and measured responses

Order	*Current (A)*	*Pulse on (μs)*	*Pulse off (μs)*	*MRR (g/min)*	*Surface roughness (microns)*	*Overcut (mm)*	*Circularity error (mm)*	*Perpendicularity error (mm)*
1	5	30	3	0.0435	0.30	0.8842	0.3487	0.6440
2	5	30	6	0.0443	0.32	0.9029	0.3634	0.6821
3	5	30	9	0.0459	0.32	0.9280	0.3753	0.7444
4	5	60	3	0.0481	0.32	0.9404	0.3927	0.7546
5	5	60	6	0.0490	0.32	0.9427	0.4033	0.7590
6	5	60	9	0.0512	0.33	0.9449	0.4148	0.7961
7	5	90	3	0.0519	0.34	1.1043	0.4248	0.9427
8	5	90	6	0.0523	0.34	1.1956	0.4252	0.9948
9	5	90	9	0.0526	0.35	1.3080	0.5163	0.8050
10	10	30	3	0.0534	0.35	0.5389	0.2359	0.3740
11	10	30	6	0.0540	0.36	0.5878	0.2413	0.3928
12	10	30	9	0.0546	0.40	0.7334	0.2489	0.4039
13	10	60	3	0.0563	0.40	0.7695	0.2744	0.4252
14	10	60	6	0.0574	0.40	0.7829	0.2802	0.4354
15	10	60	9	0.0581	0.40	0.8089	0.2817	0.4895
16	10	90	3	0.0620	0.41	0.8398	0.2838	0.5104
17	10	90	6	0.0636	0.41	0.8402	0.2961	0.5163
18	10	90	9	0.0645	0.42	0.8681	0.3182	0.5922
19	15	30	3	0.0651	0.45	0.1611	0.0795	0.0230
20	15	30	6	0.0655	0.49	0.1884	0.1266	0.0457
21	15	30	9	0.0662	0.50	0.2597	0.1579	0.1468
22	15	60	3	0.0674	0.50	0.3311	0.1693	0.1935
23	15	60	6	0.0678	0.50	0.3647	0.1909	0.2433
24	15	60	9	0.0685	0.50	0.4549	0.1914	0.2628
25	15	90	3	0.0749	0.52	0.4617	0.1994	0.2917
26	15	90	6	0.0783	0.54	0.5029	0.2055	0.3150
27	15	90	9	0.0812	0.56	0.5368	0.2143	0.3490

2.1 Grey relational analysis

GRA is a multi-criteria decision making method which used to solve the multi aspect optimisation problems and it is an effective method for various machining processes (Ahilan et al., 2009).

Step 1 The preferred quality aspects for rate of material removal is maximum the better; for normalising this desired performance characteristic equation (1) has been employed.

$$Y_{pq} = \left(\frac{Z_{pq} - Min(X_{pq})}{Max(X_{pq}) - Min(X_{pq})} \right) \tag{1}$$

The preferred quality aspects for surface roughness, overcut, form and orientation tolerances (circularity error and perpendicularity error) are minimum the better; for normalising this desired performance characteristics equation (2) has been employed.

$$Y_{ij} = \left(\frac{Max(X_{pq}) - X_{pq}}{Max(X_{pq}) - Min(X_{pq})} \right) \tag{2}$$

where X_{pq} is the output variables, *min* (X_{pq}) is the least values of X_{pq} and *max* (X_{pq}) is the highest values of X_{pq}, p is the output variables and *'q'* is the experimental run number. Basically maximised normalised values are indicators of better the performance characteristics.

Step 2 The maximum values from the normalisation irrespective of response process variables, experimental runs are calculated by equation (3).

$$R = Max(Y_{pq}) \tag{3}$$

Step 3 The complete variance among the reference sequence value R and each value from normalisation is evaluated by equation (4):

$$\Delta_{pq} = |Y_{pq} - R| \tag{4}$$

where R is the expected sequence, Y_{pq} is the comparability sequence and 'Δ_{pq} is the deviation sequence of R and Y_{pq}.

Step 4 The grey relation coefficient (GRC) ξ_{pq} for each of the normalised values is computed using the equation (5) and the values are shown in Table 3.

$$\xi_{pq} = \left(\frac{Min(\Delta_{pq}) + \zeta Max(\Delta_{pq})}{\Delta_{pq} + \zeta Max(\Delta_{pq})} \right) \tag{5}$$

where ζ is the differentiating coefficient, $\zeta \in [0, 1]$ and 0.5 is the commonly accepted value. Larger the values of GRC means the relational degree will be influential.

Step 5 The GRG for each experimental run is calculated as follows in equation (6):

$$Y_{\gamma} = \frac{\sum_{i=1}^{n} \xi_{pq}}{n} \tag{6}$$

where n is the number of response variables.

Table 3 Calculated GRC and GRG values for EDM of haste alloy C276

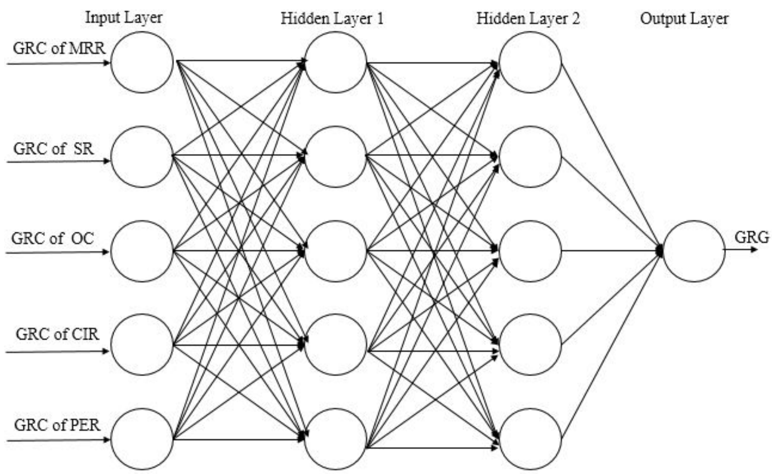
S. no	*GRC and GRG values*						
	MRR	*Surface roughness*	*Overcut*	*Circularity error*	*Perpendicularity error*	*GRG*	*Rank*
1	0.3333	1.0000	0.4423	0.5379	0.5005	0.5628	16
2	0.3381	0.8667	0.4360	0.4857	0.5000	0.5253	20
3	0.3481	0.8667	0.4278	0.4606	0.4985	0.5203	21
4	0.3628	0.8667	0.4239	0.4596	0.4402	0.5106	22
5	0.3692	0.8667	0.4232	0.4443	0.4366	0.5080	23
6	0.3859	0.8125	0.4225	0.4343	0.4333	0.4977	24
7	0.3915	0.7647	0.3781	0.4205	0.4326	0.4775	25
8	0.3948	0.7647	0.3566	0.3923	0.3443	0.4506	26
9	0.3973	0.7222	0.3333	0.3333	0.3333	0.4239	27
10	0.4041	0.7222	0.6028	0.7440	0.7871	0.6520	10
11	0.4093	0.6842	0.5734	0.7372	0.7483	0.6305	11
12	0.4147	0.5652	0.5005	0.7225	0.7456	0.5897	12
13	0.4309	0.5652	0.4852	0.7205	0.7325	0.5869	13
14	0.4420	0.5652	0.4798	0.7155	0.6974	0.5800	14
15	0.4493	0.5652	0.4696	0.6775	0.6771	0.5677	15
16	0.4954	0.5417	0.4580	0.6592	0.6097	0.5528	17
17	0.5171	0.5417	0.4578	0.6379	0.5803	0.5470	18
18	0.5302	0.5200	0.4479	0.6365	0.5379	0.5345	19
19	0.5393	0.4643	1.0000	1.0000	1.0000	0.8007	1
20	0.5456	0.4063	0.9546	0.9673	0.9942	0.7736	2
21	0.5569	0.3939	0.8533	0.9520	0.9711	0.7454	3
22	0.5773	0.3939	0.7713	0.9270	0.9127	0.7164	4
23	0.5845	0.3939	0.7380	0.9261	0.8904	0.7066	5
24	0.5975	0.3939	0.6612	0.9066	0.8356	0.6790	9
25	0.7495	0.3714	0.6561	0.8871	0.8187	0.6966	6
26	0.8667	0.3514	0.6266	0.8125	0.8162	0.6947	7
27	1.0000	0.3333	0.5492	0.7817	0.7932	0.6915	8

The GRG γ_j represents the closeness of correlation between the reference sequence or ideal sequence and the comparative sequence. If higher value of GRG is attained, then the corresponding set of process variable is closer to the most favourable combination for obtaining better multi performance characteristics.

2.2 *Evolution of proposed grey-based ANN model*

The use of artificial intelligence tool makes remarkable changes in most of engineering domains in recent years. Optimisation and modelling are essential to control and understanding of any process. Accurate control is a requirement to accomplish superior quality and increase in productivity. Several researchers made an effort with the help of statistical techniques to build a model from the data which were obtained from experiments. ANN has a significant part in learning the linear and nonlinear problems in various engineering fields. On the other hand, ease of creating network models is one of the advantages of employing ANN (Sapuan and Mujtaba, 2009; Dimla et al., 1997; Dini, 1997). The MATLAB toolbox is used for developing the neural network model. A network model having input layer with five numbers of neurons and an output layer with single neuron has been developed. The quantity of hidden layers in the network and the number of neurons in the layers were decided by trial and error approach. The developed ANN structure for prediction of GRG is shown in Figure 5.

Figure 5 Structure of developed neural network model



Training of performance measure (output) is a vital stage to predict the desired process parameter accurately. A model of feed forward back propagation (FFBP) with Levenberg-Marquardt algorithm-based network was trained (Kao and Tarng, 1997; Panda and Bhoi, 2005; Malinov et al., 2001; Demuth and Beale, 2000; Wang et al., 2003). Required data for testing and training are attained from the experiments. The learning function is gradient descent algorithm with momentum weight and bias learning function. The trials used for ANN prediction shown in Table 4.

Trials are performed to obtain the best mean correlation coefficient value. The structure with multi-layer network (5-20-18-1) produces best mean correlation coefficient and the values are shown in Figure 6. Therefore, this developed structure could be employed for the prediction of GRG.

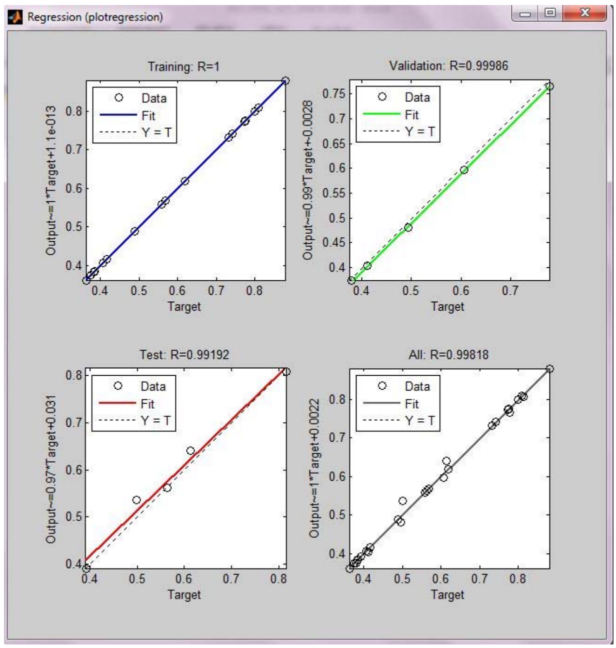
Table 4 Trials of ANN prediction for various network architectures

Trial no	*Network structure*	*R values*			
		Training	*Validation*	*Testing*	*All*
1	5-12-14-1	1	0.9997	0.9833	0.9961
2	5-14-16-1	1	0.9847	0.9731	0.9920
3	5-16-18-1	1	0.9963	0.9956	0.9973
4	5-18-20-1	1	0.9951	0.9235	0.9804
5	5-20-20-1	1	0.9852	0.9956	0.9980
6	5-12-16-1	1	0.9966	0.9950	0.9978
7	5-12-18-1	1	0.9751	0.8857	0.9774
8	5-12-20-1	1	0.9604	0.9540	0.9648
9	5-14-18-1	1	0.9771	0.9835	0.9882
10	5-14-12-1	1	0.9954	0.9782	0.9955
11	5-14-20-1	1	0.7508	0.9973	0.9575
12	5-16-12-1	1	0.9998	0.9960	0.9987
13	5-16-14-1	1	0.9825	0.9995	0.9946
14	5-16-16-1	1	0.8398	0.9051	0.9715
15	5-16-20-1	1	9.9819	0.9739	0.9724
16	5-18-12-1	1	0.9889	0.9980	0.9979
17	5-18-14-1	1	0.9959	0.9980	0.9985
18	5-18-16-1	1	0.6958	0.9549	0.9264
19	5-18-18-1	1	0.9972	0.9952	0.9986
20	5-18-20-1	1	0.9951	0.9235	0.9804
21	5-20-12-1	1	0.9963	0.9952	0.9989
22	5-20-14-1	1	0.4950	0.92997	0.8562
23	5-20-16-1	1	0.9953	0.9979	0.9972
24	5-20-18-1	1	0.9998	0.9919	0.9981
25	5-20-20-1	1	0.9858	0.9956	0.9980

3 Results and discussion

The exploration on EDM of haste alloy C-276 using Taguchi-based grey approach, analysis of variance (ANOVA) are discussed in this section. The influence of selected input process variables on multi performance machining characteristics and development of grey-based ANN model are detailed.

Figure 6 Regression plot for the developed network (see online version for colours)



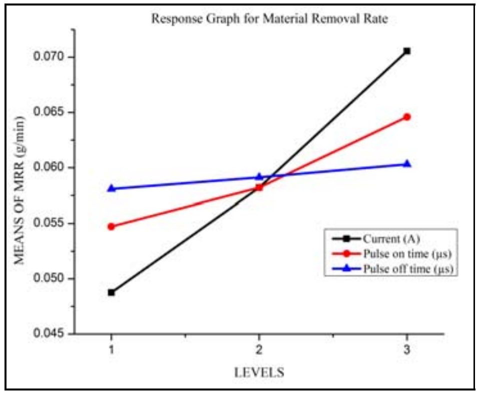
3.1 *Influence of process parameters on MRR*

The removal rate of material is categorised under higher the better criterion. The main effect plot is obtained for the MRR and it is shown in Figure 7. It is depicted from the illustration, that the MRR is increased by increase in level of current, pulse on time and pulse off time. The increase of applied current will have the possibility of increasing the discharge energy pulses and hence there is an improvement in the rate of material removal. The increase in levels of pulse on time results in applying the same amount of heat flux for a long time which causes an increment of heat. The increased heat is transferred to the work material as the plasma channel expands thus results in an improvement in the rate of material removal (Pradhan and Biswas, 2011).

Table 5 Response table for MRR – EDM of haste alloy

Levels	*Current (A)*	*Pulse on time (µs)*	*Pulse off time (µs)*
1	0.04876	0.05472	0.05807
2	0.05821	0.05820	0.05913
3	0.07055	0.06459	0.06031
Delta	0.02179	0.00987	0.00224
Rank	1	2	3

Figure 7 Main effect plot for MRR (see online version for colours)



Taguchi's analysis is performed and the results are presented in Table 5. The optimum machining condition for obtaining higher MRR is determined as $A_3B_3C_3$. It is make known from the investigation that the applied current is the important process variable which influences the MRR.

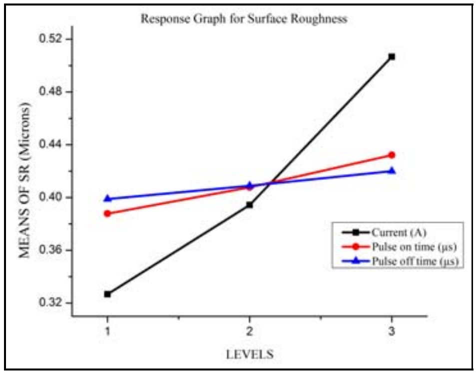
3.2 Influence of process parameters on surface roughness

In EDM, the surface roughness is categorised under smaller the better criterion. The main effect plot is obtained for the surface roughness and it is presented in Figure 8. It is perceived from the illustration, that the roughness of the machined surface is increased with increasing in applied current, pulse on time and pulse off time. It is observed from the experimental analysis that the increase of applied current results in the increase of heat energy discharge at the work zone. At this zone, there is a formation of molten metal pool and overheated. Continuous discharges result in craters thus increases the roughness of the machined surface. As the rate of material removal is achieved by the craters formation because of sparks, it is that the larger size in crater creates the rough surface during machining. So the size of the crater depends on the energy per spark has the ability of controlling the surface quality of work material. The roughness of electrically discharged machine surface increases with the increase of energy pulse which results in higher values of surface roughness (Pradhan and Biswas, 2011).

Table 6 Response table for surface roughness – EDM of haste alloy

Levels	*Current (A)*	*Pulse on time (µs)*	*Pulse off time (µs)*
1	0.3267	0.3878	0.3989
2	0.3944	0.4078	0.4089
3	0.5067	0.4322	0.4200
Delta	0.1800	0.0444	0.0211
Rank	1	2	3

Figure 8 Main effect plot for surface roughness (see online version for colours)



Taguchi's analysis is performed and the results are exhibited in Table 6. The optimum machining conditions for obtaining minimised surface roughness is determined as $A_1B_1C_1$. It is make known from the analysis that the current is the important parameter which has significant impact on surface roughness in EDM of haste alloy C276.

3.3 Influence of process parameters on overcut

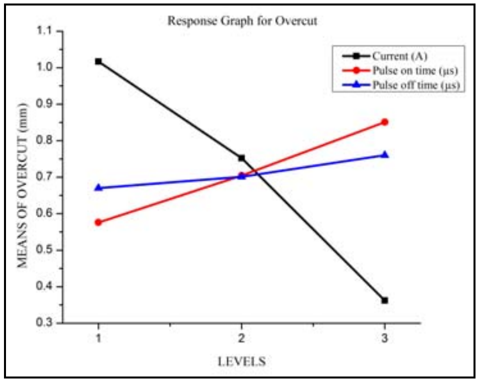
In EDM, the overcut is categorised under smaller the better criterion. The main effect plot is obtained for the overcut and it is presented in Figure 9. It is witnessed from the illustration, that the overcut value is getting decrease with increase of current and it is increased with escalation in pulse on and pulse off time. If the removal of debris not done properly, it results in secondary sparking in the machining zone and at the side walls of the machined hole. This phenomenon become predominant while the energy discharge is more and results in the deep craters and hence increases the overcut. When the pulse duration increases, the rate of material removal is more within the short period of time and there are some difficulties with debris to move out from the inter electrode gap which has the ability of causing secondary spark results in decreased dimensional accuracy.

Table 7 Response table for overcut – EDM of haste alloy

Levels	*Current (A)*	*Pulse on time (μs)*	*Pulse off time (μs)*
1	1.0168	0.5760	0.6701
2	0.7522	0.7044	0.7009
3	0.3624	0.8508	0.7603
Delta	0.6544	0.2748	0.0902
Rank	1	2	3

Taguchi's analysis is performed and the results are exhibited in Table 7. The optimum machining conditions for obtaining minimised overcut is determined as $A_3B_1C_1$. It is make known from the analysis that the current is the important parameter which influences the overcut in EDM of haste alloy C276.

Figure 9 Main effect plot for overcut (see online version for colours)



3.4 *Influence of process parameters on form and orientation tolerance errors*

Circularity and perpendicularity are known as the form and orientation tolerances. The errors of these form and orientation tolerance are the important performance measures in any unconventional machining processes. The form and orientation tolerance errors of machined surface plays a significant role in mechanical design and quality control of a geometrical product. The effective measurement and efficient evaluation of these tolerances as performance measure needs attention. The response graph for the form and orientation tolerance errors in EDM of haste alloy C-276 is shown in Figure 10. It is conspicuous from the illustration that the form and orientation tolerance error is decreased with applied current. However, it is increased with increase in pulse on time and pulse off time. The presence of dielectric fluid in the work spot should effectively remove the debris, otherwise secondary sparking will happen and hence there is the less possibility of obtaining the accurate circular hole. When the pulse duration increases the rate of material removal is more within the short period of time and there are some difficulties with debris to move out from the inter electrode gap which has the ability of causing secondary spark results in increased possibility of form and tolerance errors.

Table 8 Response table for form and orientation tolerance error – EDM of haste alloy

Levels	*Circularity error*			*Perpendicularity error*		
	Current (A)	*Pulse on time (µs)*	*Pulse off time (µs)*	*Current (A)*	*Pulse on time (µs)*	*Pulse off time (µs)*
1	0.5957	0.2557	0.2834	0.5418	0.2003	0.2503
2	0.2441	0.3009	0.3132	0.2196	0.2666	0.2869
3	0.1070	0.3902	0.3501	0.0811	0.3755	0.3053
Delta	0.4886	0.1344	0.0667	0.4606	0.1752	0.0549
Rank	1	2	3	1	2	3

Taguchi's analysis is performed and the results are exhibited in Table 8. The optimum machining conditions for obtaining minimised form and orientation tolerance error is determined as $A_3B_1C_1$. It is make known from the analysis that the current is the important parameter which influences form and orientation tolerances in EDM of haste alloy C276.

Figure 10 Main effect plot for form and orientation tolerance errors (see online version for colours)

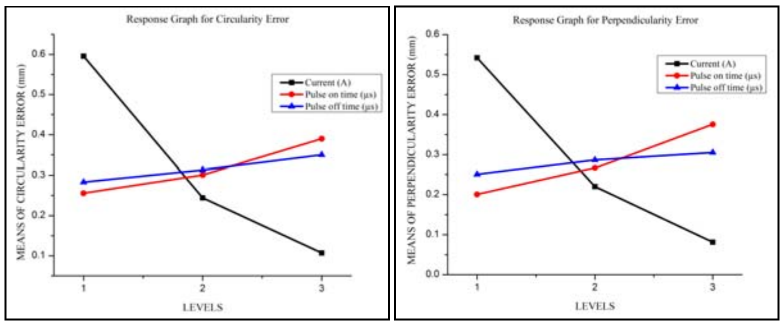
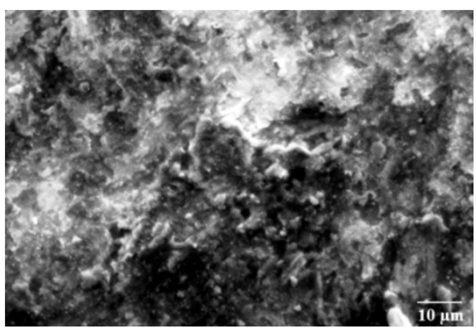


Figure 11 SEM image of the spark erosion machined haste alloy C-276 work surface



The SEM micrograph of the spark erosion machined haste alloy C-276 shown in Figure 11. The micrograph illustrates the machined surface didn't encountered with any adverse change.

3.5 *ANOVA for desired performance measures*

ANOVA is a statistical analysis tool used to determine the significance of process parameters on the performance measures at 95% confidence level which is used for various nontraditional machining process such EDM (Singh et al., 2012; Sivasankar et al., 2013) and it is computed using statistical software Minitab 16.0.

Table 9 ANOVA for EDM of haste alloy C276

Source	*DF*	*Seq SS*	*Adj SS*	*Adj MS*	*F*	*P*
MRR (g/min)						
Current (A)	2	0.002149	0.002149	0.001075	388.93	0
Pulse on (μs)	2	0.000451	0.000451	0.000226	81.6	0
Pulse off (μs)	2	2.27E-05	2.27E-05	1.13E-05	4.1	0.032
Error	20	5.53E-05	5.53E-05	2.8E-06	---	---
Total	26	0.002678	---	---	---	---
Surface roughness (Ra) (microns)						
Current (A)	2	0.148763	0.148763	0.074381	480.45	0
Pulse on (μs)	2	0.008919	0.008919	0.004459	28.8	0
Pulse off (μs)	2	0.002007	0.002007	0.001004	6.48	0.007
Error	20	0.003096	0.003096	0.000155	---	---
Total	26	0.162785	---	---	---	---
Overcut (mm)						
Current (A)	2	1.95065	1.95065	0.97533	334.18	0
Pulse on (μs)	2	0.34025	0.34025	0.17012	58.29	0
Pulse off (μs)	2	0.03783	0.03783	0.01892	6.48	0.007
Error	20	0.05837	0.05837	0.00292	---	---
Total	26	2.3871	---	---	---	---
Circularity error (mm)						
Current (A)	2	1.1434	1.1434	0.5717	195.3700	0
Pulse on (μs)	2	0.0842	0.0842	0.0421	14.3900	0
Pulse off (μs)	2	0.0201	0.0201	0.0101	3.4400	0.052
Error	20	0.0585	0.0585	0.0029	---	---
Total	26	1.3063	---	---	---	---
Perpendicularity error (mm)						
Current (A)	2	1.0056	1.0056	0.5028	159.5900	0
Pulse on (μs)	2	0.1409	0.1409	0.0705	22.3600	0
Pulse off (μs)	2	0.0141	0.0141	0.0071	2.2400	0.133
Error	20	0.0630	0.0630	0.0032	---	---
Total	26	1.2236	---	---	---	---

The ANOVA analysis for MRR, surface roughness, overcut, form and orientation tolerance errors in electrical discharge drilling of haste alloy C276 are presented in Table 9. From the 'P' values, it is observed from the analysis that the current is the significant process variable for MRR, surface roughness, overcut, form and orientation tolerances in electrical discharge drilling of haste alloy C276.

3.6 Performance analysis of developed neural network model

Numerical deviation among the experimental values and the predicted values from the developed model is known as error. The prediction capability of developed model is tested by calculating the prediction error using the following equation (7):

$$\text{Mean Absolute Percentage Error (\%)} = \frac{1}{n}\sum\nolimits_{i=1}^{n} \frac{E_V - P_V}{E_V} * 100 \tag{7}$$

The root mean square error (RMSE) and the correlation coefficient value for evaluating the prediction model is obtained by the equations (8), and (9):

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum\nolimits_{i=1}^{n}(E_V - P_V)^2} \tag{8}$$

$$\text{R}^2 = 1 - \frac{\sum\nolimits_{m=1}^{n}(P_V - E_V)^2}{\sum\nolimits_{m=1}^{n}(E_V)^2} \tag{9}$$

where E_V and P_V are the experimental values and predicted values respectively, 'n' is the number of observations. The performance analysis of developed model is presented in Table 10.

Table 10 Performance analysis of developed models for EDM of haste alloy C276

Performance measures	*Error values of the developed ANN model*
Mean absolute percentage error (MAPE)	0.6263
Root mean square error (RMSE)	0.0086
Mean absolute error (MAE)	0.006263
Correlation coefficient	0.9981

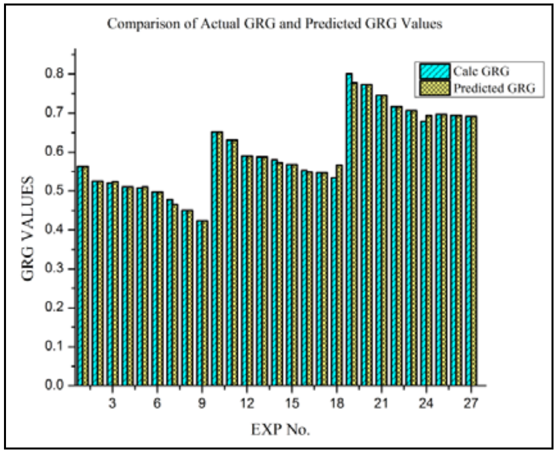
3.7 Comparison of calculated GRG values with predicted values by ANN model

The combination of grey method with any advanced decision making tool will improve the performance of determining the optimum multiple performance characteristics (Prabhu and Vinayagam, 2013). The major objective of the current investigation is to develop a neural network model for prediction of GRG. The GRA has been performed (Uyyala et al., 2014) and the calculated GRC values are given as input to the developed neural network model. Based on the correlation coefficient, the ability of performance of each network has been investigated. In order to establish the best possible configuration of neural network, the amount of error convergence was investigated by varying the quantity of hidden layers and neurons in the hidden layers. It is concluded from the result shown in Table 4 that the network having hidden layers of two numbers and (20–18) neurons generates the greatest performance for the each output parameters based on trial and error approach. Developed network was trained with Lavenberg-Marquardt algorithm (Sapuan and Mujtaba, 2009) and the mean correlation coefficient for the developed network is 0.9981. Thus, the network having two layers with (20–18) neurons has been preferred as the best possible network for prediction purpose. It is also monitored that the network performance can be considerably enhanced by enlarging the quantity of neurons in the hidden layer. Table 11 illustrates comparison among the experimental values and the values predicted by developed network model. It clearly depicts that the developed neural network predicts the parameters with very less amount of error. The comparison among calculated GRG values and the values predicted by ANN model are illustrated in Figure 12 and it is revealed that there is an extremely close relationship between the experimental values and predicted values.

Table 11 Comparison of calculated GRG and predicted GRG values

S. no	*GRGs*	
	Calculated	*Predicted by ANN*
1	0.5628	0.5628
2	0.5253	0.5253
3	0.5203	0.5240
4	0.5106	0.5106
5	0.5080	0.5108
6	0.4977	0.4977
7	0.4775	0.4660
8	0.4506	0.4506
9	0.4239	0.4239
10	0.6520	0.652
11	0.6305	0.6305
12	0.5897	0.5897
13	0.5869	0.5869
14	0.5800	0.5723
15	0.5677	0.5677
16	0.5528	0.5487
17	0.5470	0.5470
18	0.5345	0.5662
19	0.8007	0.7775
20	0.7736	0.7736
21	0.7454	0.7454
22	0.7164	0.7164
23	0.7066	0.7066
24	0.6790	0.6943
25	0.6966	0.6966
26	0.6947	0.6947
27	0.6915	0.6915

Figure 12 Comparison of calculated GRG values with predicted ANN GRG values (see online version for colours)



4 Conclusions

Investigations on EDM of haste alloy C-276 and developing a model with high precision for the prediction of GRG is most important for manufacturing domain. In this present investigation, an experimental investigation and grey-based ANN model is developed to predict the ANN-GRG.

- The desired performance measures are attained from the trials which are conducted on EDM process as per Taguchi's L_{27} orthogonal array.
- The best possible set of machining variables for the desired output variables are ascertained by Taguchi's approach.
- A statistical analysis has been employed to ascertain the significance of the independent variables on desired performance measures of EDM of haste alloy. It is conspicuous from the ANOVA that the applied current is the most influencing factor for all the desired performance measures.
- The grey relational co-efficient values are given as input to the developed neural network model and the ANN-GRG values are predicted from the developed neural network model.
- From the comparative analysis, it is observed that the developed grey-ANN model predicts the desired performance measure accurately. It is concluded from the investigation, that the proposed ANN-GRG model has been employed successfully and it has the capability of reducing the uncertainty among the data which results in better prediction of performance characteristics.

- The assessment outcomes prove that the proposed grey-based ANN approach is an effective tool and it can be employed for various machining processes with multi performance machining characteristics.

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