PARAMETRIC OPTIMIZATION OF DIE SINKING EDM USING RSM-GRA-TLBO APPROACH FOR M2 DIE STEEL

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Abstract

Modern machining processes are become excessive dependent to meet with common needs of modernization in civilization. In this attempt EDM is taken up in to primary consideration as it is sharing prominent role in the entity of modern machining processes. It was observed that the salient feature like high energy generation for highly sophisticated surface generations. In order to highlight the role of EDM, simulation was developed to inter relate process parameters to extend the range of applications. In this paper experiments are carried out with respect to process parameters pulse on-duration (Ton) and peak current (I_p) with the help of Response Surface Methodology (RSM). By make use of Grey Relational Analysis (GRA) various responses like Surface roughness (SR), White layer thickness (WLT), and Material Removal Rate (MRR) have been transformed into an unique response. Simultaneously the empirical model was executed by TLBO (Teaching Learning Based Optimization). Ultimately Multicriteria decision making (MCDM) based on RSM-GRA-TLBO is used to investigate optimum parameter values. The MCDM approach based on RSM-GRA-TLBO indicates the optimal configuration for MRR, SR, and WLT will be Ip:3A, Ton:42µs. In SR, WLT and MRR, respectively, the percentage errors for the expected and experimental tests are 5.5%, 4.4% and 7.3%.

Keywords – Ip, Ton, MRR, SR, WLT, RSM, GRA and TLBO.

1. Introduction

Electro discharging machine (EDM) is becoming increasingly an integral part of the tool space. It is increasingly becoming an important manufacturing method for the production of hard materials and alloys used in the industries of aerospace, machinery and die. Continuous advances in the efficiency of metal removal and the introduction of numerical control have significantly improved the feasibility of the process, both in terms of the product form and the content. Nevertheless, there are a variety of problems related to using EDM, the key one being surface integrity after machining. To order to prevent future failures resulting from surface defects, an accurate understanding of the type and degree of surface damage incurred under various machining conditions is important. It was observed during EDming of M2 that the machined surface is characterized by too many unwanted features such as white layer formation, development of cracks that eventually cause material failure [6]. During cooling, the white layer on the machined surface is formed by re-solidifying the molten metal, which is not flushed away by the dielectric fluid. White layers are strong, brittle and usually associated with tensile stress, thus reducing the fatigue life of machined components, and also having negative effects on surface finishing [1]. The formation of cracks may be attributed to the presence of thermal and tensile stresses within the component being machined. When the electrode discharges bombard the sample surface during the machining process, thermal stress is produced. Tensile stress inside the sample is created because the dielectric does not fully sweep the material that melts during the machining process away from the machined surface. It is noticed that cracks are created when the tension in the surface exceeds the ultimate resistance of the material. This further leads to reduction in fatigue as well as corrosion resistance. In order to minimize probability of failures related to surface defects it would be better to emphasize on adequate understanding of the nature and degree of surface damage under different machining conditions. It is evident that setting the optimum machining parameters is essential to improve the quality of the EDM_{ed} product. A proper modelling technique, correlating the input process parameters with that of the EDM_{ed} job surface integrity will help to obtain optimal machining parameters to get machined surface as good as possible. Due to the complicated stochastic process mechanism of the EDM method, it is very difficult to compare the input parameters such as pulse duration and peak current through specific mathematical model focused on the device dynamics to the surface integrity over the length. Since the MCDM method focused on RSM-GRA-TLBO is a highly scalable modelling device with the potential to learn the mapping between input and output without having a previous connection between them, it may be a reasonable option for modelling such a random and complicated process when M2 die steel is being machined[2]. The present research emphasizes the creation of a soft computing model focused on an MCDM method based on RSM-GRA-TLBO to compare the higher-order effects of major electro-discharge machining (EDM) process parameters like pulse on-duration (Ton) and peak current (Ip) with different aspects of surface integrity such as material MRR, SR and WLT,

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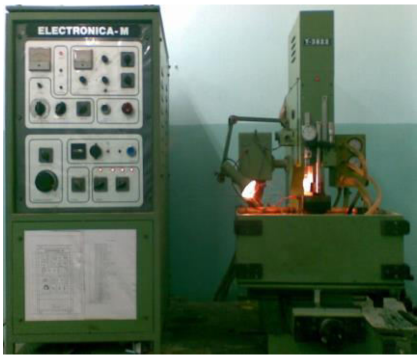
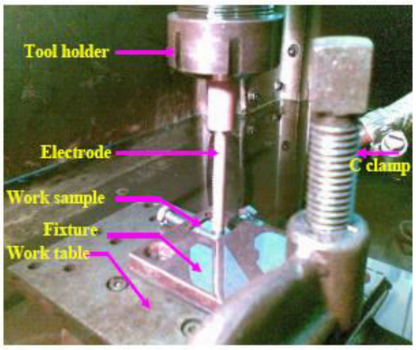
when M2 die steel is being machined. Furthermore, the confirmation tests are undertaken to test the approval of expected and experimental effects.

2. Experimentation

To achieve a positive parametric combination, experimental examination and review are conducted in different parametric combinations, taking into consideration the existing study priorities. The research was conceptualized to fulfil the objectives of the analysis. The workpiece material used in this work is M2 Die Steel with 10mm×10mm×10mm measurements. The 6 mm-diameter cylindrical brass electrode is used for drilling a 2 mm-depth blind hole on a workpiece. As seen in Figure 1 the machine tool used to perform the blind hole is EDM, ELECTRONICA-M, India. In the EDM phase Castrol oil has been picked as dielectric. In the present work, the pulse-on duration and peak current of the response surface methodology (RSM) vary as per the central-composite-second order rotatable design (CCRD). Experiments were carried out at fixed gap voltage of 135V, and dielectric flushing pressure. Before and after machining clean the work sample with acetone, measure the weight of the sample at dry condition and finally calculate the MRR. Using a surface texture measuring device at various positions, it was possible to measure SR in terms of the Centreline average values (Ra) of samples, and then to evaluate average SR. Per sample the average white layer thickness measurement is carried out using optical micrographs taken at a magnification of 500x from the machined surface. Figure 2 shows the process diagrams that were deployed for the present research. The design array according to the CCRD with performance measures is shown in Table 1.

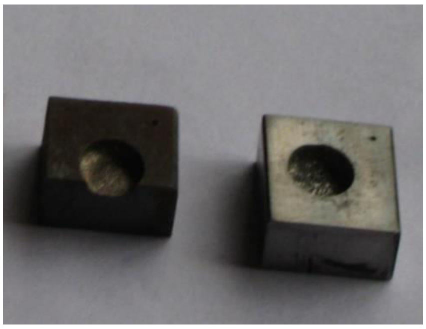


EDM machine



Experimental setup of EDM machine

Copper electrode



Work sample after machining with EDM

Figure 1. Photographs of experimental setup, electrode and work samples

Expt no.	Coded variables		Original values of machining parameters		Experimental Results		
	X_1	X_2	T_{on} µs	I_p A	Surface roughness (Ra) µm	WLT µm	MRR mm3/min
1	1	-1	400	3.5	3.978	16.6	10.15
2	1	1	400	6.5	4.41	20.6	14.072
3	0	0	252	5	3.574	13.98	13.5

4	1.414	0	462	5	4.314	20.39	11.49
5	-1	-1	104	3.5	2.576	7.41	10.881
6	0	0	252	5	3.624	9.51	12.26
7	0	1.414	252	7	3.844	17.91	17.84
8	0	0	252	5	3.37	12.47	9.957
9	-1	1	104	6.5	2.804	9.13	14.63
10	0	0	252	5	3.356	11.21	13.156
11	0	0	252	5	3.376	10.6	9.893
12	0	-1.414	252	3	3.056	10.1	13.248
13	-1.414	0	42	5	2.66	5.95	11.2

Table 1. Experimental results

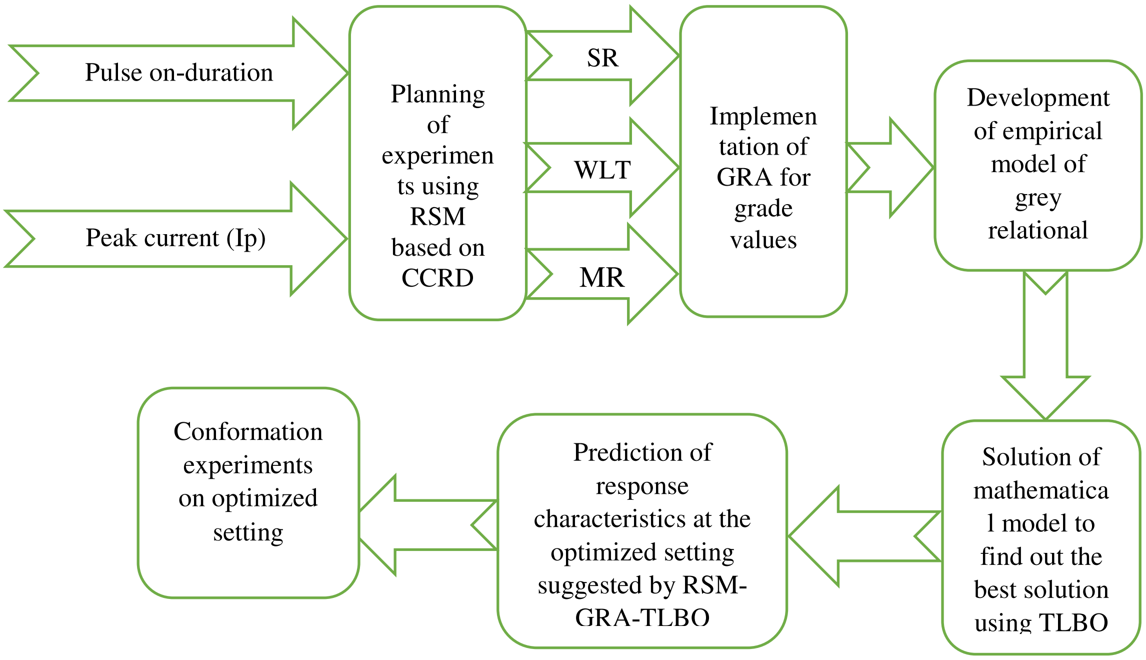


Figure 2. Process flow diagram

3. Results and discussions

The Die sinking EDM is a very complicated phenomena which in its existence is very stochastic and depends on a set of attributes. A minor adjustment in one variable will alter the performance unexpectedly.

3.1 Formulation of RSM models

3.1.1 SR, WLT, and MRR Models

The methodology-based response surface study is performed to build the mathematical model by establishing the mathematical relationship between responses and essential process parameters, like pulse on-duration (X1) and peak current (X2) [3]. The results achieved from the experiments planned, as shown in Table 1. The coefficients of Eq. 3.1,3.2 and 3.3 are obtained for different RSM models of SR, WLT, and MRR. The mathematical relationship for correlating the process parameters and EDM responses (SR, WLT, and MRR) as mentioned below:

$$Y_u\,(SR) = 3.461 + 0.947X_1 + 0.302X_2 + 0.014X_1^2 - 0.024X_2^2 + 0.096X_1X_2 \quad (3.1)$$

$$Y_u\,(WLT) = 11.561 + 7.274X_1 + 2.847X_2 + 1.469X_1^2 + 2.286X_2^2 + 1.078X_1X_2 \quad (3.2)$$

$$Y_u\,(MRR) = 11.781 - 0.155X_1 + 2.434X_2 - 1.019X_1^2 + 3.103X_2^2 + 0.082X_1X_2 \quad (3.3)$$

These mathematical models have been obtained to reflect the independent, quadratic and interactive effects of the various machining parameters on the responses in EDM process. The surface regression values for SR, WLT, and MRR are shown in table 2,3, and 4. The response values (Y_u) for SR, WLT, and MRR are determined based on regression equations as shown in Table 5.

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Table 2. Response surface regression: SR versus Ton, Ip:

Coded Coefficients:

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	3.4606	0.0668	51.77	0.000	
Ton	0.9466	0.0749	12.64	0.000	1.00
Ip	0.3019	0.0726	4.16	0.004	1.00
Ton*Ton	0.014	0.113	0.13	0.902	1.01
Ip*Ip	-0.024	0.110	-0.22	0.832	1.01
Ton*Ip	0.096	0.141	0.68	0.517	1.00

Model Summary:

S	R-sq	R-sq(adj)	R-sq(pred)
0.149567	96.21%	93.50%	81.50%

ANOVA for SR:

Source	DF	Adj SS	Adj MS	F-Value	P-Value	
Model	5	3.97177	0.79435	35.51	0.000	significant
Linear	2	3.95977	1.97988	88.51	0.000	
Ton	1	3.57245	3.57245	159.70	0.000	
Ip	1	0.38732	0.38732	17.31	0.004	
Square	2	0.00159	0.00080	0.04	0.965	
Ton*Ton	1	0.00036	0.00036	0.02	0.902	
Ip*Ip	1	0.00109	0.00109	0.05	0.832	
2-Way Interaction	1	0.01040	0.01040	0.47	0.517	
Ton*Ip	1	0.01040	0.01040	0.47	0.517	
Error	7	0.15659	0.02237			
Lack-of-Fit	3	0.09073	0.03024	1.84	0.281	insignificant
Pure Error	4	0.06586	0.01647			
Total	12	4.12836				

Table 3. Response surface regression: WLT versus Ton, Ip:

Coded Coefficients:

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	11.561	0.683	16.93	0.000	
Ton	7.274	0.765	9.51	0.000	1.00
Ip	2.847	0.741	3.84	0.006	1.00
Ton*Ton	1.47	1.16	1.27	0.244	1.01
Ip*Ip	2.29	1.12	2.04	0.081	1.01
Ton*Ip	1.08	1.45	0.75	0.480	1.00

Model Summary:

S	R-sq	R-sq(adj)	R-sq(pred)
1.52786	94.07%	89.83%	82.45%

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ANOVA for WLT:

Source	DF	Adj SS	Adj MS	F-Value	P-Value	
Model	5	259.064	51.813	22.20	0.000	significant
Linear	2	245.403	122.702	52.56	0.000	
Ton	1	210.954	210.954	90.37	0.000	
Ip	1	34.449	34.449	14.76	0.006	
Square	2	12.361	6.181	2.65	0.139	
Ton*Ton	1	3.768	3.768	1.61	0.244	
Ip*Ip	1	9.699	9.699	4.15	0.081	
2-Way Interaction	1	1.300	1.300	0.56	0.480	
Ton*Ip	1	1.300	1.300	0.56	0.480	
Error	7	16.340	2.334			
Lack-of-Fit	3	4.409	1.470	0.49	0.706	insignificant
Pure Error	4	11.931	2.983			
Total	12	275.405				

Table 4. Response surface regression: MRR versus Ton, Ip:

Coded Coefficients:

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	11.781	0.661	17.81	0.000	
Ton	-0.155	0.741	-0.21	0.840	1.00
Ip	2.434	0.718	3.39	0.012	1.00
Ton*Ton	-1.02	1.12	-0.91	0.393	1.01
Ip*Ip	3.10	1.09	2.86	0.024	1.01
Ton*Ip	0.08	1.40	0.06	0.955	1.00

Model Summary:

S	R-sq	R-sq(adj)	R-sq(pred)
1.47985	75.15%	57.40%	30.74%

ANOVA for MRR:

Source	DF	Adj SS	Adj MS	F-Value	P-Value	
Model	5	46.3546	9.2709	4.23	0.043	significant
Linear	2	25.2781	12.6390	5.77	0.033	
Ton	1	0.0959	0.0959	0.04	0.840	
Ip	1	25.1822	25.1822	11.50	0.012	
Square	2	21.0691	10.5345	4.81	0.048	
Ton*Ton	1	1.8128	1.8128	0.83	0.393	
Ip*Ip	1	17.8738	17.8738	8.16	0.024	
2-Way Interaction	1	0.0075	0.0075	0.00	0.955	
Ton*Ip	1	0.0075	0.0075	0.00	0.955	
Error	7	15.3297	2.1900			
Lack-of-Fit	3	3.3670	1.1223	0.38	0.777	insignificant
Pure Error	4	11.9627	2.9907			
Total	12	61.6844				

Expt no.	Parameters				Y_u		
	Coded		Un coded				
	X_1	X_2	Ton (µs)	Ip (A)	Surface roughness (Ra) µm	WLT µm	MRR mm^3/min
1	1	-1	400	3.5	3.999	18.665	11.194
2	1	1	400	6.5	4.795	26.515	16.226
3	0	0	252	5	3.46	11.561	11.781
4	1.414	0	462	5	4.827	24.783	9.524
5	-1	-1	104	3.5	2.298	6.273	11.668
6	0	0	252	5	3.46	11.561	11.781
7	0	1.414	252	7	3.839	20.157	21.426
8	0	0	252	5	3.46	11.561	11.781
9	-1	1	104	6.5	2.709	9.811	16.372
10	0	0	252	5	3.46	11.561	11.781
11	0	0	252	5	3.46	11.561	11.781
12	0	-1.414	252	3	2.985	12.105	14.543
13	-1.414	0	42	5	2.15	4.212	9.962

Table 5. Response results

3.1.2. Acceptability examination for SR, WLT, and MRR models:

For lack of fit $F_O < F_\alpha$, degree of freedom of lack of fit, degree of freedom of error where

F_O= mean square$_{treatment}$ / mean square$_{error}$ and α is known as confidence level which is taken as 95% in our case.

The $F_{regression}$ = adjacent mean square$_{regression}$ / adjacent mean square$_{residual\ error}$ and

$F_{lack\ of\ fit}$ = adjacent mean square$_{lack\ of\ fit}$ / adjacent mean square$_{pure\ error}$

To validate the mathematical models created, variance analysis and F-ratio test were conducted. It is evident that the determined F-ratio values are smaller than the F-ratio normal values. The machining parameters obtained through RSM are in line with the mathematical models developed.

3.1.3. R^2 (R- squared)

It is the determination coefficient or multiple determinations. R^2 is the percentage of total response variation which is explained by predictors of the model. Generally speaking, the higher the R^2, the better that model fits the data. Thus, the R2 values were measured to assess if data is fitting in the developed models and these values are 96.2% for SR, 94.07% for WLT and 75.1% for MRR which indicates that data is fitting in the developed models for each of the responses.

4. Grey Relational Analysis (GRA)

In this approach the experimental data was fit in the range between 0 and 1. The Grey Relational coefficient is determined by correlating expected and real experimental data. The grey Relational grade is determined by multiplying with the coefficient obtained earlier at each and every response. The value of GRG is higher; the resulting mixture of factors is considered to be similar to the optimum [4]. The overall assessment of the multiple process responses is dependent on the Gray relational grade. As a consequence, optimisation of multiple responses can be transformed into unique grey relational grade optimization. The method parameter optimum level is the point with the largest Gray relational grade [11].

Table 9., shows all the data such as normalization, deviational sequence, GRC and grade. After the mean data has been solved, it was observed that Run order 13 offers the optimal environment according to the maximum GRG value (0.76349).

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Run order	NORMALIZING			DEVIATION SEQUENCES			GREY RELATION COEFFICIENT			Grey Relation Grade
	SR	WLT	MRR	SR	WLT	MRR	SR	WLT	MRR	
1	0.236	0.273	0.032	0.764	0.727	0.968	0.395	0.408	0.341	0.3812
2	0.000	0.000	0.526	1.000	1.000	0.474	0.333	0.333	0.513	0.3933
3	0.456	0.452	0.454	0.544	0.548	0.546	0.479	0.477	0.478	0.4780
4	0.052	0.014	0.201	0.948	0.986	0.799	0.345	0.337	0.385	0.3556
5	1.000	0.900	0.124	0.000	0.100	0.876	1.000	0.834	0.363	0.7324
6	0.429	0.757	0.298	0.571	0.243	0.702	0.467	0.673	0.416	0.5185
7	0.309	0.184	1.000	0.691	0.816	0.000	0.420	0.380	1.000	0.5998
8	0.567	0.555	0.008	0.433	0.445	0.992	0.536	0.529	0.335	0.4667
9	0.876	0.783	0.596	0.124	0.217	0.404	0.801	0.697	0.553	0.6838
10	0.575	0.641	0.411	0.425	0.359	0.589	0.540	0.582	0.459	0.5271
11	0.564	0.683	0.000	0.436	0.317	1.000	0.534	0.612	0.333	0.4930
12	0.738	0.717	0.422	0.262	0.283	0.578	0.656	0.638	0.464	0.5862
13	0.954	1.000	0.164	0.046	0.000	0.836	0.916	1.000	0.374	0.7635

Table 9. Grey Relational Analysis results

4.1. Development of RSM Model for GRG

The RSM analysis has been done to establish the relationship between GRG values and the parameters (Ton and Ip). Based on the GRG values obtained from the Grey relational analysis, as shown in Table 9., the values of different constants of the Eq. (4.1) are obtained for GRA model has been established as follows:

$$GRG = 1.401 - 0.001896\ Ton - 0.2124\ Ip + 0.000001\ Ton*Ton + 0.01935\ Ip*Ip + 0.000068\ Ton*Ip \tag{4.1}$$

Table 10. Response surface regression: GRG versus Ton, Ip

Coded Coefficients:

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	0.4974	0.0129	38.56	0.000	
Ton	-0.2157	0.0145	-14.92	0.000	1.00
Ip	-0.0032	0.0140	-0.23	0.823	1.00
Ton*Ton	0.0461	0.0218	2.11	0.073	1.01
Ip*Ip	0.0774	0.0212	3.65	0.008	1.01
Ton*Ip	0.0287	0.0273	1.05	0.328	1.00

Model Summary:

S	R-sq	R-sq(adj)	R-sq(pred)
0.0288662	97.17%	95.15%	87.00%

ANOVA for GRG:

Source	DF	Adj SS	Adj MS	F-Value	P-Value	
Model	5	0.200184	0.040037	48.05	0.000	significant
Linear	2	0.185603	0.092801	111.37	0.000	
Ton	1	0.185558	0.185558	222.69	0.000	
Ip	1	0.000045	0.000045	0.05	0.823	
Square	2	0.013658	0.006829	8.20	0.015	
Ton*Ton	1	0.003703	0.003703	4.44	0.073	
Ip*Ip	1	0.011123	0.011123	13.35	0.008	
2-Way Interaction	1	0.000923	0.000923	1.11	0.328	
Ton*Ip	1	0.000923	0.000923	1.11	0.328	
Error	7	0.005833	0.000833			
Lack-of-Fit	3	0.003167	0.001056	1.58	0.326	insignificant
Pure Error	4	0.002665	0.000666			
Total	12	0.206017				

With reference to the above, it is noticed that the p value of the regression model is less than 0.05, hence the responses are in line with the liner, square and interaction terms considered under review. However, the lack of fit is marginal with corresponding p value of 0.326 which is more than 0.05. The quadratic model has lower R^2 than the complete quadratic model (97.17%), and the adj value of R^2 is 95.15%, reflecting the significance of the solution relationship with the variables. Moreover, the regression model's p value is zero, and the model is statistically relevant at 95 percent conviction and, therefore, the model reflects the experimental results accurately.

5. Hybridization of RSM Model for GRG with TLBO

After solving the empirical model, which is established by integrating GRG value against the series of experiments given by CCRD, the solution of TLBO can be obtained. There are two stages, namely the process of teacher and the process of learner [5,8]. The best grade value can be achieved when the teacher and the learner interact. The learners should understand the new subject and do well in this direction. In present study, population size and iterations are set at 50 and 100, respectively.

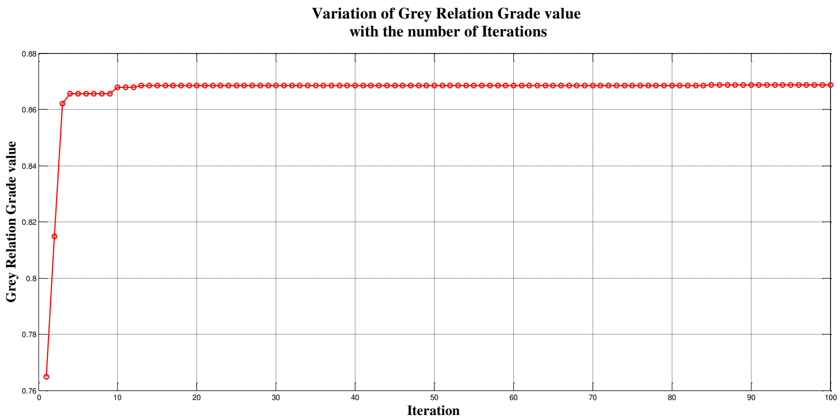

Figure 3. GRG verses Iteration

From the above figure it is evident that the optimum value is attained in the first thirteen iterations and the value remains constant thereafter. Under same operating conditions the computation time to resolve the algorithm is approximately 11 seconds, which is one tenth of the other algorithms. In this way TLBO saves lot of time in overcome the complexity to solve the algorithm. With respect to cost point of view minimal cost is obtained at a particular position [Ip:3A; Ton: 42 µs] with a Gray Relational Grade of 0.8686. Finally, a distinction was given correlate statistical procedure and MCDM approach. The validation tests have been carried out and it is observed that the optimum environment proposed by TLBO provides the expected SR, WLT and MRR values. The study results of the validation indicate a strong replication in the region of ±7.3% as shown in Table 11.

Responses	Optimal settings		Experimental values	Predicted values	Percentage error
	GRA	MCDM			
SR	Ton: 42 μs, Ip: 5A	Ton: 42μs, Ip: 3A	2.168 μm	2.054 μm	5.5
WLT			4.51 μm	4.32 μm	4.4
MRR			6.154 mm^3/min	5.734 mm^3/min	7.3

Table 11. Validation tests proposed by TLBO at suitable settings

6. Conclusions

The EDM process is stochastic and complex with so many input and output parameters which are very difficult to express with mathematical expressions. In the present work, as indicated by CCRD, M2 Die steel was machined at various EDM settings. The response properties were optimized using MCDM approach focused on RSM-GRA-TLBO. The results derived from this study shall be as follows:

(1) The optimum parametric combination in the experimental portion of this work is based on experimental findings for achieving minimal surface roughness at 3A/42μs, white layer thickness at 3A/42μs and maximum material removal rate at 5A/252μs.

(2) The recommended optimization results for Grey relational analysis and RSM-GRA-TLBO approach are 42μs/5A and 42μs/3A respectively.

(3) The range of % error between experiments and predicted values is ±7.3%. Therefore, the accuracy of TLBO based approach to MCDM tests is quite strong. The iteration time (11 seconds) for converge the solution is minimum in TLBO as compared with other optimization techniques.

7. References

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