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ORIGINAL PAPER

Experimental investigation and optimization of process parameters during electric discharge machining of Inconel X-750

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Abstract

This article highlights the application of multiple criteria optimization using the Grey relation analysis (GRA) and Weightage principal component analysis (WPCA) method in EDM of Inconel X-750. Taguchi's based design of experiment L_9 orthogonal array (OA) was used to perform machining operations using a copper tool. When machining comes to accuracy, higher dimensional tolerances, extreme surface finish, cutting of hard materials, there is an extreme need for non-traditional techniques like EDM. The effects of process parameter namely, peak current (I_p), pulse on time (T_{on}), pulse off time (T_{off}) and voltage (V) on Material removal rate (MRR) and Surface roughness (R_a) has been studied. The optimal parametric setting obtained from WPCA and GRA approach are found as 15 amp, 74 µs, 8 µs, 40 voltage, and 18 amp, 63 µs, 9 µs, 60 voltages, respectively. Outcomes of confirmatory tests show that WPCA gives better agreement with actual results which is highly desired for an efficient machining environment. Also, a comparative study of both the developed hybrid modules was performed to evaluate the feasibility. Outcomes reveal that WPCA improved the preferred solution value by 12.67%. The result of ANOVA confirms the most influencing parameter on machining performances.

Keywords Inconel · GRA · WPCA · Taguchi · Optimization

Abbreviations

GRA	Grey relation analysis
GRC	Grey relation coefficient
GRG	Grey relation grade
MRR	Material removal rate
Ra	Surface roughness
ANOVA	Analysis of variance
MPI	Multi-performance index
OA	Orthogonal array
Min	Minute
mm	Milli meter
Nm	Newton meter
N	Newton
LB	Lower is better
HB	Higher is better
S/N	Single to noise
N	Normalize
PCA	Principal component analysis
TOPSIS	Techniques for order of preference by similarity to ideal solution
VIKOR	Vlse Kriterijumska Optimizacija Kompromisno Resenje
RSM	Response surface methodology
NSGA-II	Nondominated sorting genetic algorithm-II
AHP	Analytic hierarchy process

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1 Background and rationale

EDM is a primary manufacturing process that produces complex shapes, cavities, and intricate shapes which is not possible by other machining processes (shaper, miller, grinding, etc.); very hard material like Monel alloys, Inconel alloys, carbides, etc. can easily be machined. The removal of unwanted substances in EDM takes place by the production of continuous spark in the gap among the tool and workpiece placed into the dielectric medium. Due to melting and vaporization, the unwanted material in the form of fine particles are removed by flushing of dielectric pressure and new dielectric comes into action till achieving the desired shape. Due to the advancement in the lifestyle of the human being, it becomes mandatory to upgrade the quality of the prevailing materials or other options are the development of novel materials by a different process. The final manufacturing of these materials is not possible without the machining process. In this series, Inconel X-750 is widely used in high-performance applications such as jet engine and airframe components- lock wire, exhaust liners and turbine seals, automotive-ignition systems, sensors, safety devices, and electrical switchgear, etc. In this modern age, there is very fast competition among manufacturing industries and simultaneously, they have to make a compatible balance between the quality, productivity and cost-effectiveness for customer satisfaction. In machining science, quality directs the rate of surface finishing and productivity related to the rate of material removal. Hence, due to conflicting criteria of the manufacturing performance, it becomes unthinkable to obtain the optimum values of multiple conflicting responses. To tackle such types of complex issues, optimization engineering plays an important role in the selection of optimum condition of machine parameters.

Various eminent scholars performed different work by taking a variety of material, tools & different process parameters and explored the major performance procedures. From prior work, it is observed that very limited work is available on EDM performance optimization using a correlation study on multiple machining performance. In this study, the problem can be dealt with safely and a vast state of the art makes it easier to select the factors & performance parameters during the WPCA and GRA optimization modules. Satpathy et al. (2017) used Taguchi based L_9 orthogonal array to employ the EDM of Al-SiC-20% Si–C reinforced metal matrix composites using a copper tool. The machine parameters considered as gap voltage (V_g), duty cycle (DC), pulse-time (T_{on}) & peak current (I_p) and machining performances are taken as MRR, TWR, SR & diametric overcut (Z). The combined approach of PCA and TOPSIS was used as a hybrid optimization to achieve the optimal parametric setting. The outcomes of the machining show the optimal combination as Peak current (I_p) of 3 Amp., duty cycle (DC) at 80%, pulse-time (T_{on}) of 75μ-s, and gap voltage (V_g) of 40 v which has been validated by a confirmatory test. Kumar Mohanty et al. (2017)investigated machining (EDM) performances using the VIKOR method for multi-response optimization according to Taguchi based design of experiments consists of a total of nine number of balanced experiments. The machining performance was assumed as MRR, TWR, SR, and RO. The outcome of ANOVA demonstrates the feasible model adequacy and shows that prefer solution value is maximum affected by the current (74.82%). VIKOR method shows the higher application potential in real practice for multi-criteria decision making (MCDM) issues. Mishra and Routara (2017) investigated the EDM of EN-24 alloy steel according to the combined philosophy of GRA and Taguchi. The conflicting machining performances were aggregated into a single objective function known as Grey relation grade (GRG). ANOVA was used to detect the most significant factor affecting assessment value. It has been found that pulse-Time (T_{on}) and peak current (I_p) are the most significant factor with 46% and 34%, respectively, trailed by flushing pressure (F_P). T_{off}, T_{on} and I_p affecting the rate of tool wear with 31%, 31% and 45%, respectively. The proposed GRA based Taguchi method effectively optimized the EDM process parameters with satisfactory validated results. Bhosle and Sharma (2017) studied the machining behaviour of Inconel 600 alloy material during the micro-EDM drilling process using Tungsten Carbide (WC) tool. The optimization of the process parameter was done by the hybrid approach of GRA- Taguchi. The machining performances taken in this study are the rate of material removal, taper, overcut and diametric variation. The optimal setting obtained using the GRA method are found as, 175 v, 1000 pF, 20 μm/s, 15 μs, 50 μs. The result of the study demonstrates that capacitance is the most significant factor trailed by voltage, feed rate and taper angle. Prasanna et al. (2017) used AA7075-Si–C alloy work material, copper tool and kerosene oil as a dielectric medium for the electric discharge machining process. The EDM performance is considered as MRR and rate of tool wear. PCA was explored for assignment of priority weight of the particular response. The outcome of the machining shows that MRR is directly dependent upon the current values. The confirmatory test shows the satisfactory performance of the machining responses to achieve the optimal result. Khullar et al. (2017) applied the RSM methodology together with the NSGA-II. Central composite design under RSM methodology was applied to design experiments and ANOVA has performed over the input parameter. The prime settings show that MRR and SR have value 1.167 mm^3/min and 1.280 μm, respectively. The results show that MRR is mostly affected by the pulse on values which is 31.1% and pulse off value which is 30.49%. Anand et al. (2017) executed experiments over magnetic assisted EDM and compared the results with the conventional EDM using GRA based Taguchi approach and Copper as a tool material. The results show that MRR increased up to 41.42% & SR was reduced by 2.17% in the finest settings. Prime settings were 15 amps. Ton of 150 μs, the voltage of 85 volts and servo voltage of 30%. MRR and SR are significantly improved in the case of EDM. Kumar et al. (2017) applied the NSGA-II technique on wire EDM of Inconel 718 as work material. The MRR & Ra were the major performance measure, while the wire tension, wire-speed, discharge C & T_{on} were taken as process parameters. ANOVA reveals that the MRR and the kerfs are entirely dependent upon the V & T_{on}, whereas the current holds the minimum contribution. The optimality results from the Taguchi shows that the wire tension of 16 N, Current 20 A, Wire-speed of 205 mm/s & Pulse on time of 30 ms is the prime setting.

State of the art shows that sufficient work is available an EDM using TOPSIS, VIKOR, GRA, Utility concept, NSGA-II, etc. for multi-criteria optimization. Prior state of art shows that eminent scholars developed various optimization modules such as GRA, TOPSIS, AHP, NSGA, etc. The application of the PCA method has attempted in a very limited manner. It has been observed that work is not sufficiently flourished to check the response correlation & priority weight issues. Most of the studies assume the equal priority weight of the conflicting performances and negligible responses correlation, which precedes error, ambiguity, and imprecision in the outcomes of the machining performances. In this paper, the correlation between machining responses has been identified and fruitfully tackled by the exploration of PCA. Assignment of response priority weight and the correlation between the response deals with statistically verified techniques during machining of Inconel X-750. Machining performances considered as Material removal rate (MRR) & Surface roughness (Ra) using copper as a tool. The unified aim of the current work is to achieve the desired values of these conflicting machining performances according to the Taguchi design concept. An attempt has been made to overcome the limitation of traditional optimization modules.

2 Experimentation

Initially, the trial experiments were performed on the setup, as shown in Fig. 1. The work material Inconel X-750 which lies in a Ni–Cr dual grade alloy having superior properties like tensile creep resistance, good formability, high-temperature oxidation, etc. Inconel X-750 is used as work material and it is widely preferred over other alloys in gas turbine blades, aircraft assemblies, nuclear components, nuclear valves, pressure vessels, tooling, etc. The various constituents present in the alloys are like Ni, Cr, Fe, and Mn and the physical properties like density, melting point, Poisson's ratio, and resistivity, whereas value is 8.3 g/cm^3, 1391–1422 °C, 0.30 and 1.2×10^{-6} Ω, respectively. The machining was performed on EDM Model no. C-3822. The sample of Inconel X-750 was dipped into the dielectric medium and copper was used as a tool. During machining, the unwanted materials are removed in the form of fine particles that were cleaned by flushing pressure. The input current can be varied from 1 A to 20 amperes. The pulse on-time varies from 1 µs to 99 µs. The pulse off time varies from 1 µs to 9 µs. The voltage can be varied, starting from 5 to 60 v. The Inconel X-750 sheet has been taken for conducting the experiments possessing the dimension 50 × 100 × 5mm, as shown in Fig. 2. The copper was selected as a tool material due to erosion-resistant behaviour in the dielectric medium, as shown in Fig. 3.

Roughness Tester (Handy Surf Tokyo Seimitsu made by Japan and Model No E-MC-S24B used for computation of Ra and the rate of the MRR has been calculated using the expression:

$$\mathrm{MRR} = \frac{(\text{Initial Weight of the workpiece} - \text{Final Weight of the workpiece})}{\text{Density of the workpiece} \times \text{ machining time}}\ \mathrm{mm}^3/\mathrm{min}.$$

The domain of the experiment are depicted in Table 1 and Taguchi's based L_9 orthogonal array has been used to perform machining, as shown in Table 2. The images of the Machined workpiece by the Copper tool (Fig. 3) are shown in Fig. 4 and the value of the experimental outcome is depicted in Table 3.

3 Results and discussion

In this study, two-hybrid approaches (GRA and WPCA) are used for the combination of conflicting responses during the machining of Inconel X-750. After getting optimal settings from both the optimization modules, the confirmatory examination has been performed to verify the application potential of both the modules.

Fig. 1 Machining of workpiece

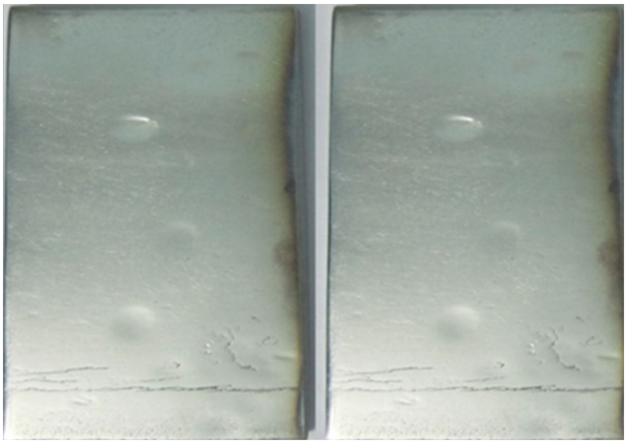

Fig. 2 Inconel X-750 sheet

Fig. 3 Copper tool

Table 1 Domain of experiment

Factor	Symbols	$Level_1$	$Level_2$	$Level_3$
Peak current	I_p	12	15	18
Pulse-on-time	T_{on}	63	74	85
Pulse-off-time	T_{off}	7	8	9
Voltage gap	V	40	50	60

3.1 Grey relation analysis (GRA)

GRA system is widely used for aggregation of multiple conflicting responses into a single objective function known as GRA (Gopalsamy et al. 2009; Durairaj et al. 2013; Ali et al. 2019). The Grey relational analysis deals with the GRG ranks and value (Jangra et al. 2011; Sathisha et al. 2012; Rajmohan 2019). These subsystems significantly influence the response variable, which has evaluated using the GRA method. Nowadays, GRA procedure is widely used in optimization problems of industrial engineering, statistical analysis, mathematical case studies, scheduling problems, management studies, banking and finance sectors, etc.

Table 2 L_9 orthogonal array

No.	I_p	T_{on}	T_{off}	V
1	12	63	7	40
2	12	74	8	50
3	12	85	9	60
4	15	63	8	60
5	15	74	9	40
6	15	85	7	50
7	18	63	9	50
8	18	74	7	60
9	18	85	8	40

Fig. 4 Machined workpiece by copper tool

GRA approach includes the following procedure:

1. Experiment conduction according to Taguchi's L_9 OA.
2. Normalization of the obtained data.
3. Determination of grey relation coefficient (GRC).
4. Calculating the grey relation grade (GRG).

Initially, the responses retrieved from the L_9 matrix have been normalized to the values between 0 & 1 using Eqs. 1 and 2. The machining characteristics have two different aspects, i.e., either higher will be the better or lower the better (Selvarajan et al. 2015). For the above trials and the performance values, the lower the better will be considered for Ra and MRR is considered as Higher the better (Yadav and Kumar Verma 2019). The normalization of experimental data was done using the expression.

Higher-the-better:

$$x_i^*(j) = \frac{x_i(j) - \min x_i(j)}{\max x_i(j) - \min x_i(j)}. \tag{1}$$

Table 3 Experimental data

No.	MRR mm^3/min.	Ra (µm)
1	73.94	4.14
2	67.01	3.64
3	31.00	4.66
4	59.25	5.54
5	96.57	4.16
6	65.98	4.86
7	39.31	6.08
8	66.26	4.96
9	105.44	3.34

Lower-the-better:

$$x_i^*(j) = \frac{\min\, x_i(j) - x_i(j)}{\max\, x_i(j) - \min\, x_i(j)}. \tag{2}$$

Afterward, data normalization is completed; GRC has been calculated. The ideal structure value for the variable is unknown in GRA analysis and the distinguishing coefficient is usually assumed. The GRC has been defined according to the equation:

$$\xi_i(k) = \frac{\Delta_{\min} + \xi\,\Delta_{\max}}{\Delta \mathrm{oi} + \xi\,\Delta_{\max}}, \tag{3}$$

where ξ is defined as an identification coefficient and Δoi denoted as the current value of the sequence. In this work all, the parameters have been given equal preference by considering $\xi = 0.25$, while $\Delta_{\max}$ and $\Delta_{\min}$ are the maximum and minimum absolute difference. The GRG of each trial was obtained using the average method, where the summation of the corresponding performance measures was added and divided. After Grey relational coefficient (GRC), the GRG has been calculated (Table 4) using the formula:

$$\mathrm{GRG} = \frac{1}{p}\sum \in (k), \tag{4}$$

where p is the number of machining performance variables.

The significance of individual variables was evaluated based on maximum and minimum differential values acquired. The following process mechanism is attributed to the optimum factor levels of the EDM strategy. The GRG alternatives mean analysis is described in Table 5. The voltage with the highest delta value of 0.2529 affects GRG noticeably. The second affecting variable is pulse on-time 0.2119, followed by pulse off time and current with delta values of 0.2111 and 0.0732, respectively.

ANOVA for GRG.

The ANOVA is an arithmetic system applied used in data to identify the significance of the major contributing factors towards any performance measure (Kumar et al. 2014; Panda et al. 2016 and Singh et al. 2016). The GRG values from GRA Approaches are closely related to each other in terms of results and optimum settings. The settings have been attained using the GRG. It has been noticed that the ANOVA is showed to regulate the significant level of each input parameter. From Table 6, input current, pulse on-time pulse off time, voltage and error are 89.57%, 0.15%, 3.74%, 2.90% and 3.65%, respectively. The contribution graphs (Fig. 5) has been plotted to examine the results more clearly. The model summary of GRG and main effects plot ($I_p3T_{on}1T_{off}3V3$) for the S/N ratio of GRG are shown in Table 6 and Fig. 6, respectively. The ANOVA analysis has been dealt with to know the various causal factors over the performance together with the percentage error.

Table 4 Normalized data and corresponding GRG

S. no.	N-MRR	N-Ra	GRC		GRG
			MRR	Ra	
1	0.5768	0.7080	0.4643	0.4138	0.4391
2	0.4837	0.8905	0.5082	0.3595	0.4339
3	0.0000	0.5182	1.0000	0.4910	0.7455
4	0.3795	0.1970	0.5685	0.7172	0.6428
5	0.8808	0.7007	0.3620	0.4164	0.3892
6	0.4699	0.4452	0.5155	0.5289	0.5222
7	0.1116	0.0000	0.8174	1.0000	0.9087
8	0.4736	0.4087	0.5135	0.5502	0.5318
9	1.0000	1.0000	0.3333	0.3333	0.3333

Table 5 Response table for means

Level	I_p	T_{on}	T_{off}	V
1	0.5395	0.6636	0.4977	0.3872
2	0.5181	0.4517	0.4700	0.6216
3	0.5913	0.5337	0.6812	0.6401
Delta	0.0732	0.2119	0.2111	0.2529
Rank	4	2	3	1

3.2 WPCA method

WPCA method are efficiently used to identify the correlation between the machining performance and assignment of response priority weight during the combination of various machining responses into a single objective function called as Multiple Performance Index (MPI) (Biswas et al. 2011; Bijeta Nayak et al. 2018; Pamuji et al. 2018). As aggregation of multi-response is not feasible by the traditional Taguchi method and exploration of WPCA based Taguchi method has been effectively achieved in this paper (Mishra et al. 2015; Das et al. 2018). The aggregation of PCs into a single objective function are known as Multi Performance Index (MPI)

Table 6 ANOVA for GRG

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-value	P value
Regression	4	2.8850	96.35%	2.8850	0.7212	33.02	0.001
I_p	1	2.6818	89.57%	0.0007	0.0007	0.03	0.864
T_{on}	1	0.0044	0.15%	0.0623	0.0623	2.86	0.152
T_{off}	1	0.1119	3.74%	0.0439	0.0439	2.01	0.215
V	1	0.0868	2.90%	0.0868	0.0868	3.98	0.103
Error	5	0.1092	3.65%	0.1092	0.0218		
Total	9	2.9942	100.00%				

S = 0.1477, R-sq = 96.35%, R-sq(adj) = 93.43% and R-sq(pred) = 84.21%

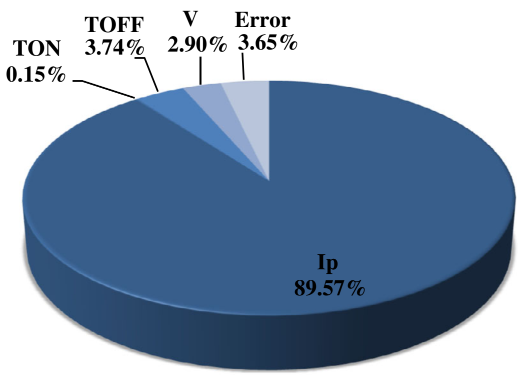

Fig. 5 Influence of EDM parameters on GRG

(Padhi et al. 2014; Das et al. 2014a, b). In this paper, the optimized multiple machining performances are MRR and Ra in EDM using the WPCA method (Lahane 2013).

The basic methodology of WPCA consists of the following procedure:

i. Normalization of data.

Initially, all the observed data is normalized (Table 7) from 0 to 1, because the data are in several ranges, units & other features (Padhi et al. 2014).

For Lower the Better Approach

$$I^*(k) = \frac{\min\ I_i(m)}{I_i(m)}. \tag{5}$$

For Higher the Better Approach

$$I_i^*(m) = \frac{I_i(m)}{\max\ I_i(m)}. \tag{6}$$

ii. Calculation of Correlation Coefficient.

The correlation coefficient (Table 8) is calculated by

$$S_{j1} = \frac{\mathrm{Cov}(I_i(j), I_i(1))}{\sigma_{Ii}(j) \times \sigma_{Ii}(1)}, \tag{7}$$

where $\mathrm{Cov}(I_i(j), I_i(1))$ is the covariance of sequences $I_i(j)$ and $I_i(1)$, $\sigma_{Ii}(j)$ is the standard deviation of sequence $I_i(j)$, $\sigma_{Ii}(j)$ is the standard deviation of sequence $I_i(j)$..

iii. Eigenvalue and eigenvector.

The eigenvalues and eigenvectors are coupled from the correlation coefficient array:

$$(S - \lambda_k J_m)B_{ik}, \tag{8}$$

where λ_k eigen values and $\sum_{k=1}^{n} \lambda_k$, $k = 1,2, \ldots, n$:

$$B_{ik} = [b_{k1}, b_{k2}, \ldots, b_{\mathrm{kn}}]^{\mathrm{T}}.$$

iv. Calculation of major principal coefficient:

$$\mathrm{PC}_{mk} = \sum_{k=1}^{n} I_m(i) \times B_i(k), \tag{9}$$

where PC_{mk} = principal component.

v. Calculation of MPI.

The accountability proportion (AP) are considered as the individual weight for each PC. MPI explained the weighted sum of all the PCs developed in the preceding step, considering the two responses, including MRR and Ra. WPCA, therefore, prevents such ambiguity and approximation by consolidating all components with the weights that are analytical and statistically verified. The Eigenvalues (Table 9) for the responses are obtained as 0.854 and 0.146. The main parts have weights of 0.499849 and each additional MPI value is calculated using Eq. (10) for the ith experiment. Table 10 shows the developed MPI values:

$$\mathrm{MPI} = \mathrm{AP}_1 \times \mathrm{PC}_1 + \mathrm{AP}_2 \times \mathrm{PC}_2, \tag{10}$$

Fig. 6 Optimal setting by GRA method

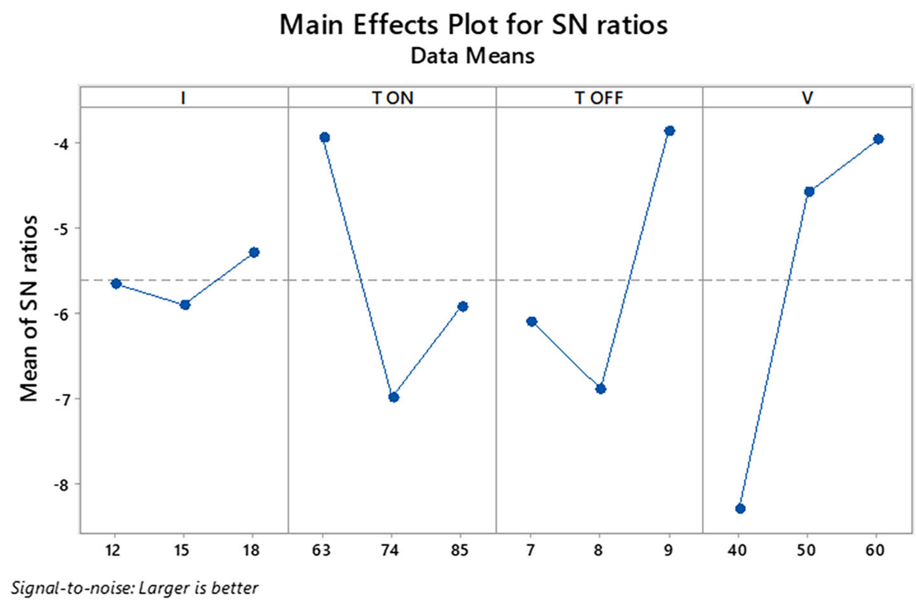

Table 7 Normalized data

S. no.	N-MRR	N-Ra
1	0.7012	0.8067
2	0.6355	0.9175
3	0.2940	0.7167
4	0.5619	0.6028
5	0.9158	0.8028
6	0.6257	0.6872
7	0.3728	0.5493
8	0.6284	0.6733
9	1	1

Table 8 Response correlation analysis

S. no.	Correlation parameter	P value	Correlations	Comment
1.	MRR and Ra	0.033	0.707	Both are correlated

Table 9 PCA calculation

Eigenvectors			The eigenvalue of the correlation matrix		
Source	PC_1	PC_2	Eigenvalue	1.7073	0.2927
N MRR	0.707	0.707	Proportion	0.8540	0.1460
N Ra	0.707	– 0.707	Cumulative	0.8540	1.0000

3.2.1 ANOVA for MPI

The ANOVA is an arithmetical procedure applied to the data to know the significance and the major contributing factors towards any performance measure (Goud and Sharma 2017).

Table 10 Computed MPI

S. no	PC1	PC2	MPI
1	1.0661	– 0.0746	0.8996
2	1.0980	– 0.1994	0.9086
3	0.7145	– 0.2988	0.5666
4	0.8235	– 0.0289	0.6990
5	1.2151	0.0798	1.0494
6	0.9282	– 0.0434	0.7864
7	0.6519	– 0.1248	0.5385
8	0.9203	– 0.0318	0.7813
9	1.4140	0.0000	1.2075

The MPI Approaches are closely related to each other in terms of results and optimum settings. The contribution of various process parameters such as input current (I_p), pulse on-time (T_{on}), pulse off time (T_{off}), voltage (V) and error is 92.52%, 2.14%, 0.03%, 2.02%, and 3.28%, respectively. The model summary of MPI and contribution of influencing parameters are mentioned to examine the results more clearly in Table 11 and Fig. 7, respectively.

Mean analysis of the MPI values achieved is conducted to analyze the effects of the distinct variables that influence the MPI. It develops the mean value of MPI and obtains the optimal values. The MPI prediction for the attained levels is made using Eq. (8):

$$\gamma_{pred} = \gamma_m + \sum_{i=1}^{q} (Y - \gamma_m), \quad (11)$$

where γ_{pred} predicted value of MPI, γ_m average value of MPI and Y mean value of MPI ith parameter at jth level.

Table 11 ANOVA for MPI

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	*F* value	*P* value
Regression	4	6.3090	96.72%	6.3090	1.5772	36.83	0.001
I_p	1	6.0354	92.52%	0.0393	0.0393	0.92	0.382
T_{on}	1	0.1398	2.14%	0.1557	0.1557	3.64	0.115
T_{off}	1	0.0022	0.03%	0.0068	0.0068	0.16	0.705
V	1	0.1314	2.02%	0.1314	0.1314	3.07	0.140
Error	5	0.2141	3.28%	0.2141	0.0428		
Total	9	6.5231	100.00%				

S = 0.2069, R-sq = 96.72%, R-sq(adj) = 94.09% and R-sq(pred) = 87.20%

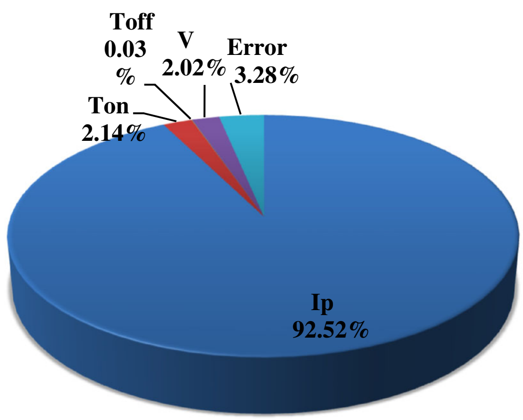

Fig. 7 Influence of EDM parameters on MPI

MPI values acquired for each experimental run in the L9 orthogonal array shows that experimental number 9 has the highest MPI value. The process constraints with experiment number 9 are found as best, resulting in optimum production and giving the least Ra and greater MRR. Figure 8 shows the MPI ranking on experimental runs The MPI means assessment is presented in Table 12. The MPI values and their corresponding means at each level in the orthogonal array lead to the response table. The Voltage with the highest delta value of 0.3698 affects MPI considerably. The second affecting variable is pulse off time, and the next one is a pulse on time and inputs current with delta values of 0.2202, 0.2007 and 0.0533. Variation of input current and pulse delta values on time is minimal and has the least influence on behavior.

To evaluate the impact of machining parameters, ANOVA has performed on the established index and Table 10 shows the outcomes acquired from MPI. It is revealed that the findings of the mean response table are competent. The most important variables are input voltage, pulse off moment, and input voltage. The four variables 'p' values are less than 0.05, thus demonstrating the significance. Input current contributes 92.52%, followed by a pulse-off moment with a 2.14% contribution. The most negligible parameter was the pulse off time. The optimum parameter level for the highest MPI is achieved at 15 amp input, 74 pulse on time, 8 pulse off time and 40. Observations indicate that the maximum MPI value

Fig. 8 Optimal setting by WPCA method

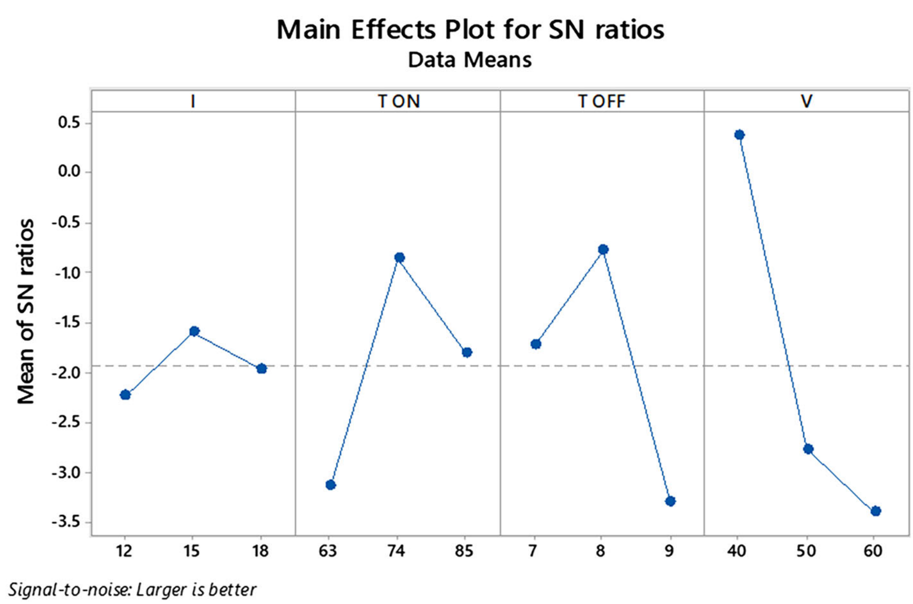

Table 12 Response table for means

Level	I	T_{on}	T_{off}	V
1	0.7916	0.7124	0.8225	1.0522
2	0.8450	0.9131	0.9384	0.7445
3	0.8425	0.8535	0.7182	0.6824
Delta	0.0533	0.2007	0.2202	0.3698
Rank	4	3	2	1

of 1.26963 is the predicted optimal ($I_p 2T_{on} 2T_{off} 2V1$) parameter level.

4 Confirmatory test

In this study, two multi-objective techniques were used for aggregation of multiple machining responses such as MRR & Ra. GRA method aggregates the multi responses into a single function, i.e., GRG. The confirmatory test was performed to validate the results of optimum techniques and select the finest method which can improve the EDM performance characteristics. The optimal setting obtained from S/N ratio GRG (Fig. 6) are found as $I_p 3T_{on} 1T_{off} 3V3$. From Table 4, it has been observed that the highest GRG has secured by run order no 7 which corresponds to the parametric setting as $I_p 1T_{on} 3T_{off} 3V2$. Similarly, in the case of the WPCA method, the aggregated single objective function is determined using weight obtained from PCA analysis, as shown in Table 9. Table 10 shows the MPI and corresponding S/N ratio plot is obtained. The optimal setting obtained from Fig. 8 are found as $I_p 3T_{on} 1T_{off} 3V3$ The predicted value of GRG is found as 0.9226 which corresponding to the optimal setting as $I_p 2T_{on} 2T_{off} 2V1$. The confirmatory test was performed on the optimal setting obtained from GRA. The result of confirmatory shows a satisfactory arrangement with the actual outcomes, as shown in Table 13. The prefer solution value is found as 1.1098. In the WPCA method, the confirmatory test was done an optimal setting obtained as $I_p 2T_{on} 2T_{off} 2V1$, and from Table 14, it is observed that high predicted value 1.2696 (corresponding the optimal setting as $I_p 2T_{on} 2T_{off} 2V1$) and good arrangement with the initial setting results which is highly desired for effecting machining environment. The prefer solution value in this case are found as 1.2709.

5 Comparative study

From Table 15, it has been noticed that the optimal setting of both modules is found different. The prefer solution value in WPCA is found higher than the GRG method which shows the robustness and higher application potential in the machining environment. Also, WPCA shows an improvement of 12.67% than the GRG method.

6 Conclusions

In this paper, the exploration of the PCA method are employed to identify the correlation among machining responses and priority weight assignment which has not considered in the traditional optimization modules. These works have examined the effects of process parameters on machining performance during (EDM) of InconelX-750 composite. Grey method and WPCA technique were used for optimizing the MRR and Ra. Based on the results, the following conclusions are made:

1. Both the optimization modules GRA and WPCA fruitfully aggregated the machining performance viz. MRR & Ra into a single objective function finally optimized by the Taguchi concept.
2. The favourable parametric setting obtained from WPCA and GRA are found as 15 amp, 74 µs, 8 µs, 40 voltage, and 18 amp, 63 µs, 9 µs, 60 v, respectively. The validation of the optimal setting has performed by the confirmatory test which shows satisfactory agreement.
3. ANOVA was used to identify the effects of process parameter viz. input current (I_p), pulse on time (T_{on}), pulse off time (T_{off}), Voltage (V) on MRR & Ra.
4. Prefer solution value for GRA & WPCA are found as 1.1098 & 1.2709. The higher value of WPCA shows the robustness & application potential for real practice.
5. Higher prefer solution values are highly desired for an efficient machining environment. As the proposed module was developed in a generalized way, and it can be customized for other machining process such as Drilling, Turning, milling, etc.

6.1 Future scope of work

The present study proposed a robust hybrid optimization approach in EDM of Inconel X-750. This material process a wide range of high-performance application hence machining performance optimization of InconelX-750 is potential of research for industry and academia. WPCA approach can be customized and endorsed in quality control & productivity improvement of the manufacturing process. The involvement of some other machining factors such as different type tools, fluid, the interaction effect of process parameters can be explored in the future for a better understanding of machining aspects.

Table 13 Predicted and experimental values of GRA

S. no.	Machining parameter	GRA-Taguchi	Optimal machining parameters GRA-Taguchi	
		Initial setting	Predicted	Confirmatory
1	Setting	$I_p 1 T_{on} 1 T_{off} 1 V 1$	$I_p 3 T_{on} 1 T_{off} 3 V 3$	$I_p 3 T_{on} 1 T_{off} 3 V 3$
2	MRR	73.94		86.5
3	Ra	4.14		3.67
4	Preferred solution value	0.4391	0.9226	1.1098

Table 14 Predicted and experimental values of WPCA

S. no.	Machining parameter	WPCA-Taguchi	Optimal machining parameters WPCA	
		Initial setting	Predicted	Confirmatory
1	Setting	$I_p 1 T_{on} 1 T_{off} 1 V 1$	$I_p 2 T_{on} 2 T_{off} 2 V 1$	$I_p 2 T_{on} 2 T_{off} 2 V 1$
2	MRR	73.94		107.37
3	Ra	4.14		2.56
4	Preferred solution value	0.8996	1.2696	1.2709

Table 15 Comparative value of GRA and WPCA

Selective parameter	Optimal setting GRA-Taguchi	Optimal setting WPCA-Taguchi	Optimal value GRA-Taguchi	Optimal value WPCA-Taguchi	Overall improvement (%)
Peak current	12	12	1.1098	1.2709	12.67%
Pulse-on-time	63	74			
Pulse-off-time	9	8			
Voltage gap	60	40			

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Compliance with ethical standards

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