EXPERIMENTAL STUDY AND DEVELOPMENT OF AN EMPIRICAL MODEL FOR SR AND MRR IN CNC WEDM OF AZ31B MAGNESIUM ALLOY BASED MMNC

Received: 15 November 2017 / Accepted: 10 December 2017

Abstract: Magnesium and its alloys reinforced with nano-size reinforcements have attracted the interest of the researchers because of its high strength to weight ratio, high damping capacity and displays improved mechanical property without affecting the ductility. The light weight nature of this structural material makes them a right choice to be used in the automobile and aerospace sector where weight reduction is a primary concern. This work determines optimum process parameters such as pulse on time, pulse off time, peak current, servo voltage and volume of silicon carbide (SiC_p) percentage which influence the wire electro discharge machining (WEDM) process during machining of AZ31B magnesium alloy based metal matrix nano-composite (MMNC) using combined methods of response surface methodology (RSM) and Taguchi-GRA-PCA hybrid method. Taguchi L27 experimental design is used in the experimental investigation, and a predictive model is developed to identify the optimum process parameters in the micro EDM process, which influence two main machining criteria such as surface roughness (SR) and material removal rate (MRR). Further analysis of variance (ANOVA) is carried out to determine the adequacy of the model and to identify which parameters has most influence on the responses. The proposed method can be used to select optimal process parameters from various sets of combinations of process parameters in a WEDM process.

Key words: WEDM, MMNC, RSM, GRA-PCA, SR, MRR

Eksperimentalna studija i razvoj empirijskog modela hrapavost površine i količine skinute strugotine kod CNC elektroerozione obrade sa žicom AZ31B magnezijumske legure na bazi metalnog nano kompozita. Magnezijum i njegove legure ojačane nano-armiranim ojačanjima privukle su interes istraživača zbog svog odnosa visoke snage i težine, visokog kapaciteta prigušivanja i prikaza poboljšane mehaničke osobine bez uticaja na duktilnost. Priroda ovog konstrukcijskog materijala lakog materijala je pravi izbor za korišćenje u automobilskom i vazduhoplovnom sektoru gde je smanjenje težine primarna briga. Ovaj rad određuje optimalne parametre procesa, kao što su impuls u vremenu, vreme impulsa, maksimalna struja, servo napon i volumen protoka silicijum karbida (SiC_p) koji utiču na proces obrade kompozita sa metalnom nano osnovom magnezijumske legure AZ31B koristeći kombinovane metode metodologije površine odziva (RSM) i Taguchi-GRA-PCA hibridne metode. U eksperimentalnom istraživanju koristi se Taguchi L27 eksperimentalni model, a razvijen je prediktivni model za identifikaciju optimalnih parametara procesa u mikro EDM procesu koji utiču na dva osnovna kriterijuma obrade, kao što su površinska hrapavost (SR) i količina skinutog materijala (MRR). Dalje analize varijanse (ANOVA) se sprovede kako bi se odredila adekvatnost modela i identifikovali koji parametri najviše utiču na izlazne veličine. Predloženi metod se može koristiti za odabir optimalnih parametara procesa iz različitih skupova kombinacija parametara procesa u EDM procesu.

Ključne reči: EDM sa žicom, nanokompozit sa metalnom osnovom, površina odziva, Tagucijeva GRA-PCA metoda, hrapavost površine, količina skinutog materijala

1. INTRODUCTION

There is need for high-performance and energy efficient materials with light-weight for some demanding applications in the aerospace, automobile, sports and electronics industries. The demand has led to the development of advanced materials like metal matrix composites. Magnesium is lightest of all structural materials. It is about 33% lighter than aluminium, 61% lighter than titanium and 77% lighter than stainless steel. Magnesium and its alloys possesses several good properties like excellent cast-ability suitable for pressure die castings, high damping capacity, good electromagnetic shielding, good machinability compared to other structural metals, less energy requirement in the production of magnesium compared to aluminium and is readily available [1, 2].

This good property of the magnesium and its alloys makes it a preferable candidate to be used in the industries where high strength to weight ratio is required. There is potential application of magnesium based metal matrix composite in automobile industries such as disk rotors, gears, piston ring grooves, gearbox bearings, connecting rods and shift forks [1].

In the recent years the field of research has shifted from conventional metal matrix composites to metal matrix nano composites. It is due to the fact that on addition of micron-size reinforcements, it generally leads to substantial reduction in the ductility of the magnesium matrix due to particle cracking and void formation at particle-matrix interface leading to accelerated failure but on the other hand addition of small volume fraction of nano-size reinforcements

produce results comparable or even superior to that of MMCs reinforced with similar or higher volume fraction of micron size reinforcements [2]. There are number of literatures available on method to develop the mechanical properties of magnesium and magnesium based alloys by reinforcing them with hard ceramic particles to form magnesium metal matrix composites (Mg-MMCs). Cao et al., [3] found that addition of Si-C nano particles on Mg-(2,4)Al-1Si magnesium alloys enhanced the tensile strength and yield strength while the ductility of magnesium alloy matrix castings was retained. They also postulates that Si-C nano particles bonds well with the Mg-alloy without forming any intermediate phase. Guo et al., [4] revealed that post process treatment like cyclic extrusion compression on as-extruded Mg-SiC nano composite prepared by ultrasonic cavitation based solidification process improved the hardness and grain refinement in the matrix and significantly improving the uniformity of nano particles distributions. Srikanth and Gupta., [5] proposed that the damping capability of the magnesium based composites reinforced with SiC particulates was improved due to the presence of SiC particulates. Ugandhar et al., [6] studied the effects of sub-micron size silicon carbide (SiC) particulate reinforcements used in magnesium matrix composites and found that SiC in sub-micron length scale are more effective in lowering coefficient of thermal expansion, and enhancing hardness when compared to SiC particulates in micron length scale. Since the nano particles reinforced Mg-metal matrix composites (MMC) exhibit promising mechanical properties and can be used for many applications, it is valuable to develop suitable machining methods, to facilitate their industrial applications. However, due to the presence of discontinuously distributed hard ceramic particulate in the matrix makes them highly difficult to machine using conventional machining process like turning, milling, drilling, etc. which may results in poor surface finish and excessive tool wear. With the conventional machining process it hard to machine complex shape geometry. These materials can be machined by many non-traditional methods like water jet and laser cutting etc. but these processes are limited to linear cutting only. On the other hand Wire Electrical Discharge Machining (WEDM) shows higher capability for cutting complex shapes and difficult to cut electrically conductive materials with high precision. Hence the wire electrical discharge machining (WEDM) becomes viable method to these composite materials [3,4]. There are several machining method used against MMCs with particulate reinforcement are reported in the literature. Chalisgaonkar & Kumar [7] investigated the effects of WEDM parameters such as wire type (zinc coated and uncoated brass wire), pulse on time (T_{ON}), pulse off time (T_{OFF}), peak current (IP), wire feed (WF), servo voltage (SV) and wire offset (W_{OFF}) on the responses viz., material removal rate (MRR), surface roughness and wire weight consumption (eroded weight of wire after machining) in machining of pure titanium and developed a model using dimensional analysis and optimizing using utility concept. Gopalakannan and Senthilvelan [8] studied the effect of EDM parameters

on metal matrix nanocomposite (MMNC) of Al-7075 reinforced with 1.5 wt% SiC nano particles using copper electrode. Babu and Venkataramaiah [9] applied Analytic hierarchy process (AHP)- combine with TOPSIS to optimize the process parameters in WEDM of Al6061/SiCp composite. The Wire Type (WT), Pulse ON Time (T_{ON}), Pulse OFF Time (T_{OFF}), Wire Feed rate (WF) and Sensitivity (S) is considered as the process parameters. Taguchi L_{18} orthogonal array is used to design the experiments for conducting the WEDM experiments and cutting speed (CS), material removal rate (MRR), surface roughness (SR) and dimensional deviation (DD) is considered as response. They found that sensitivity is the most significant WEDM process parameter among all other parameters. Lu et al., [10] investigated the optimization design of the cutting parameters for rough cutting processes in high speed end milling of SKD61 tool steel. Mehat et al., [11] tried to optimized the process parameters in the plastic injection moulding process through hybrid optimization approach by integrating the Taguchi parameter design, grey relational analysis (GRA), and principal component analysis (PCA). Patil and Brahmanekar [12] attempted to determine the metal removal rate (MRR) in WEDM of Al-SiC composites by trying to develop a semi empirical model of MRR by using dimensional analysis technique and compared the model developed by response surface methodology (RSM) and result shows that there is significant agreement in the predictions. Li et al., [13] investigated the machinability of magnesium metal matrix composites (Mg-MMCs) reinforced with high volume percentage of SiC (5%, 10%, 15%) using micro milling process and compared with the pure magnesium through response surface methodology (RSM) of design. Rao and Krishna [14] applied principal component analysis (PCA), coupled with Taguchi's robust theory for simultaneous optimization of correlated multiple responses of wire electrical discharge machining (WEDM) process for machining SiCp reinforced ZC63 metal matrix composites (MMC). Aggarwal et al., [15] formulated an empirical model for predicting cutting rate and surface roughness of Inconel 718 material machined by wire-EDM process with the help of response surface methodology (RSM).

In this paper an attempt has been made to investigate the physics in the machining Mg-SiC using WEDM process. Simultaneous optimization of multiple performance characteristics using Taguchi-GRA-PCA hybrid method and also experimental validation has been attempted.

2. EXPERIMENTAL DETAILS

In this study, the series of machining experiments was performed on SPRINTCUT CNC wire electrode discharge machine (Fig. 1). Zinc coated brass wire of 0.25 mm diameter was selected as the tool material. The length of cut selected on AZ31B magnesium alloy based metal matrix nano-composites was 10 mm. De-ionized water was used as the dielectric fluid which was continuously flushed from upper and lower

nozzles through the gap between the work-piece and the wire. The chemical composition of AZ31B magnesium alloy are Al-2.72%, Si-0.28%, Ti-0.011%, Mn-0.29, Zn-1.11 and Mg is balance. In the present work an experimental investigation was carried out in WEDM on AZ31B magnesium alloy based metal matrix nano-composites. Pulse on time (108–112–116 μ s), pulse of time (45–50–55 μ s), servo voltage (20–30–40 V), peak current (140–160–180 A), and volume percentage of SiC (5–10–15 %) were considered as process parameters. The surface roughness (*SR*) and material removal rate (*MRR*) were measured in different combination of cutting conditions employed during the experimental work based on Taguchi L_{27} (3^5) experimental design. The kerf width of the specimens was measured using LIECA DMI3000M inverted optical microscope using Q-win software and the *MRR* was computed using the empirical relationship given in equation (1).

$$MRR = \frac{K_f \times t \times l}{T}, mm^3/min \quad (1)$$

Where, K_f is the kerf width (mm), t thickness of the work piece (mm), l length of cut of the work-piece (mm) and T time taken to machine (min).

In order to measure the surface roughness, TAYLOR HOBSON Form Talysurf 2D profilometer was used as shown in figure 2. The stylus is placed over the cut surface and a data length of 5 mm is set and then the stylus is allowed to run over the specimen at the speed of 0.25 mm/sec. In order to reduce the errors in the measurements three readings were taken for each specimen at different locations and the average *SR* value of each was calculated.

Fig. 1. Experimental setup of WEDM process

Fig. 2. Taylor Hobson-form talysurf

Sl. No	A (T_{on})	B(T_{off})	C(SV)	D(I_p)	E (V_f)	SR (μ m)	MRR (mm^3/min)
1	108	45	20	140	5	2.81	6.81
2	108	45	20	140	10	2.65	6.43
3	108	45	20	140	15	2.52	6.52
4	108	50	30	160	5	3.02	6.79
5	108	50	30	160	10	2.83	6.73
6	108	50	30	160	15	2.31	6.76
7	108	55	40	180	5	2.76	6.99
8	108	55	40	180	10	2.77	6.59
9	108	55	40	180	15	2.54	6.75
10	112	45	30	180	5	3.18	7.22
11	112	45	30	180	10	3.23	6.86
12	112	45	30	180	15	2.49	7.03
13	112	50	40	140	5	3.73	7.11
14	112	50	40	140	10	2.80	6.81
15	112	50	40	140	15	2.67	7.01
16	112	55	20	160	5	3.23	7.07
17	112	55	20	160	10	3.53	6.90
18	112	55	20	160	15	2.60	6.99
19	116	45	40	160	5	3.27	7.24
20	116	45	40	160	10	3.25	7.08
21	116	45	40	160	15	2.73	7.02
22	116	50	20	180	5	3.13	7.18
23	116	50	20	180	10	3.07	6.94
24	116	50	20	180	15	2.40	7.06
25	116	55	30	140	5	3.23	7.17
26	116	55	30	140	10	3.08	6.88
27	116	55	30	140	15	2.85	6.94

Table 1. Experimental results of the responses with the set of process parameters

3. DEVELOPMENT OF MULTIPLE REGRESSION MODEL

A mathematical based multiple regression analysis(MRA) have been attempted to express the complex relationship between process parameters and responses during WEDM process. The developed quadratic model is in the following form.

$$y = \beta_0 + \sum_{i=1}^k \beta_i x_i + \sum_{i=1}^k \beta_{ii} x_i^2 + \sum_{i,j} \beta_{ij} x_i x_j + \varepsilon, (2)$$

Where, y is the performance output terms, $\beta_0, \beta_i, \beta_{ii}, \beta_{ij}$ is the regression coefficients and ε is the machining error.

$$\begin{aligned} SR = & -205 + 3.692 \times A - 0.194 \times B + 0.000 \times C + 0.0533 \times D + 0.204 \times E - 0.0163 \times A^2 + 0.00193 \times B^2 \\ & + 0.000006 \times C^2 - 0.000185 \times D^2 - 0.0094 \times E^2 - 0.00131 \times A \times E + 0.00066 \times B \times E + 0.000064 \times C \times E \\ & + 0.000247 \times D \times E \end{aligned} \quad (3)$$

$$\begin{aligned} MRR = & -93.7 + 1.668 \times A + 0.077 \times B + 0.0153 \times C + 0.0418 \times D - 0.171 \times E - 0.00724 \times A^2 - 0.00081 \times B^2 \\ & - 0.000166 \times C^2 - 0.000124 \times D^2 + 0.00721 \times E^2 - 0.00013 \times A \times E + 0.000469 \times B \times E - 0.000144 \times C \times E \\ & + 0.000037 \times D \times E \end{aligned} \quad (4)$$

Fig. 3 Predictive performance of both the responses

3.1 Analysis of variance

The ANOVA is a computational technique, which is used to estimate the relative significance of each factor in terms of percent contribution on the overall response. The factors with higher percentage contribution are ranked higher in terms of importance in the experiment and also have significant effects in controlling the overall response. This analysis was carried out for a

level of confidence of 95% (i.e., level of significance as 5%). The result shows that SiC vol. % has major contribution (52.72%) followed by T_{on} (21.46%) for SR and T_{on} (56.67%) followed by SiC vol. % (28.47) for MRR respectively. However, T_{off} , SV and I_p has minor effect on both the responses. Fig.4 (a) & (b) show the percentage contribution for SR and MRR .

Fig. 4 Bar graph of ANOVA

3.2 Interactive effect of process parameters on *SR* and *MRR*

Figure 5 (a) & (b) depict that with the increase in volume of Silicon Carbide percentage, the surface roughness decreases and with increase in pulse-on time the surface roughness increases. The reason can be attributed that with higher T_{on} , bigger craters might be generated on the surface of the work piece due to increase in the melting and evaporation rate, and for increase in volume percentage of silicon carbide, it may be due to the grain refinement and uniform mixing of the silicon carbide particle with the magnesium alloy.

Fig. 5. Showing the variation of *SR* in surface plot and contour plot

Figure 6 (a) & (b) shows that with the low volume of Silicon Carbide percentage, results in higher *MRR*, but as the volume of Silicon Carbide percentage increases the *MRR* relatively decreases.

Fig. 6. Showing the variation of *MRR* in surface plot and contour plot

4. MULTI-RESPONSE OPTIMIZATION TAGUCHI-GRA-PCA HYBRID METHODOLOGY

4.1 Taguchi method

The Taguchi method [11] is used to design experiments based on the orthogonal arrays (OA). Taguchi OA designs minimizes the number of experiments can be used to study the whole parameter space with a small number of experiments and it saves time and experimental cost. In analysing the results, the Taguchi method uses a statistical measure of performance known as signal-to-noise (S/N) ratio. The higher the S/N ratio value better is the setting of process parameters. The S/N ratio is a measure of performance to develop products or processes that are insensitive to noise factors in a controlled manner. Noise factors are uncontrollable factors that influence product or process uncertainty. These factors include humidity and weather. Depending on the objective, three different methods can be used to calculate the S/N ratio in the Taguchi method:

(i) Lower the better quality characteristics

$$n_{ij} = -10 \log \left(\frac{1}{n} \sum_{j=1}^n y_{ij}^2 \right) \quad (5)$$

(ii) Higher the better quality characteristics

$$n_{ij} = -10 \log \left(\frac{1}{n} \sum_{j=1}^n \frac{1}{y_{ij}^2} \right) \quad (6)$$

(iii) Nominal the better quality characteristics

$$n_{ij} = -10 \log \left(\frac{1}{n\sigma} \sum_{j=1}^n y_{ij}^2 \right) \quad (7)$$

Where, y_{ij} is the i^{th} experimental at the j^{th} test, n is the total number of the test, and σ is the standard deviation.

4.2 Grey relational analysis (GRA)

GRA is a method [10, 11] that measures the correlation degree among factors based on the similarity or difference among factors. Grey relational generation involves data pre-processing and calculation according to the quality characteristics. The steps involved in the grey relational generation is as follows.

Normalize the measured results according to the aim of the quality characteristics.

(i) Lower the better normalization method

$$y_i^*(k) = \frac{\max x_i^0(k) - x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)} \quad (8)$$

(ii) Higher the better normalization

$$y_i^*(k) = \frac{x_i^0(k) - \min x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)} \quad (9)$$

Where $x_i^0(k)$ is the measured results, $\max x_i^0(k)$ is the maximum value of $x_i^0(k)$ and $\min x_i^0(k)$ is the minimum value of $x_i^0(k)$, i is the number of experiments, and k means the quality characteristics.

We determine the difference sequence $\Delta_{0i}(k)$ and the minimum value $\Delta_{\min}$ and maximum value $\Delta_{\max}$ in the difference sequence. Where $\Delta_{0i}(k)$ is the offset in the absolute values of between the reference sequence $y_0^*(k)$ and the comparability sequence $y_i^*(k)$.

After the data processing, grey relational coefficient is calculated by the following equation,

$$\xi_i(k) = \frac{\Delta_{\min} + \zeta \Delta_{\max}}{\Delta_{0i}(k) + \zeta \Delta_{\max}} \quad (10)$$

Where ζ is the distinguishing coefficient which is normally set as 0.5 in this study, it ranges from 0 to 1. The grey relational grade is calculated by the following equation

$$\gamma_i = \frac{1}{n} \sum_{k=1}^n \beta_k \xi_i(k) \quad (11)$$

Where β_k represents the weighting value of the k th performance characteristics and it is calculated by principal component analysis and $\sum_{k=1}^n \beta_k = 1$.

The grey relational grade γ represents the level of correlation between the reference sequence and the comparability sequence. If the two sequences are identically coincidence, then the value of grey relational grade is equal to 1.

4.3 Principal component analysis (PCA)

PCA was developed by Pearson and Hotelling. This approach explains the structure of variance-covariance by the linear combinations of each quality characteristic.

1. The original multiple quality characteristics array

$X_i(j), i = 1, 2, \dots, m, j = 1, 2, \dots, n$

$$X = \begin{pmatrix} x_1(1) & x_2(2) & \dots & x_1(n) \\ x_2(1) & x_2(2) & \dots & x_2(n) \\ \vdots & \vdots & \ddots & \vdots \\ x_m(1) & x_m(2) & \dots & x_m(n) \end{pmatrix} \quad (12)$$

Where m is the number of experiment and n is the number of quality characteristics and x is the grey relational coefficient of each quality characteristics. In the present work $m=27$ and $n=2$.

2. Correlation coefficient array is evaluated as follows:

$$R_{ij} = \left(\frac{\text{cov}(x_i(j), x_i(l))}{\sigma_{x_i(j)} \times \sigma_{x_i(l)}} \right) \quad (13)$$

Where $\text{cov}(x_i(j), x_i(l))$ are the covariance of sequences $x_i(j)$ and $x_i(l)$ respectively; $\sigma_{x_i(j)}$ is the standard deviation of sequence $x_i(j)$ and $\sigma_{x_i(l)}$ is the standard deviation of sequence $x_i(l)$.

3. Determining the eigen values and eigen vector.

The eigen values and the eigen vector is determined from the correlation coefficient array,

$$(R - \lambda_k I_m) V_{ik} = 0 \quad (14)$$

Where λ_k is an eigen value, $\sum_{k=1}^n \lambda_k = n$, $k = 1, 2, 3, 4, \dots, n$;

$V_{ik} = [a_{k1} a_{k2} \dots a_{kn}]^T$ correspond to the eigen vector.

4. Principal components:

The uncorrelated principal component is formulated

$$Y_{mk} = \sum_{i=1}^n x_m(i) \cdot V_{ik} \quad (15)$$

Where y_{m1} is called the first principal components, y_{m2} is called the second principal component and so on.

4.4 Determination of optimal combination

The algorithm of Taguchi-GRA-PCA hybrid optimisation technique to determine the optimal combination of process parameters for WEDM machining process is described step by step in figure 7.

Fig. 7. Flowchart of hybrid Taguchi-GRA-PCA technique

Sl. No	Seq. S/N ratio		Data pre-processing		Deviation sequence		Grey relational coefficient	
	SR	MRR	SR	MRR	$\Delta_{0i}(1), SR$	$\Delta_{0i}(2), MRR$	SR	MRR
1	-9.59	16.65	0.54	0.47	0.45	0.52	0.52	0.48
2	-9.39	16.16	0.47	0	0.52	1	0.48	0.33
3	-8.02	16.28	0.02	0.12	0.97	0.87	0.33	0.36
4	-9.59	16.63	0.54	0.45	0.45	0.54	0.52	0.47
5	-9.40	16.55	0.48	0.38	0.52	0.61	0.49	0.45
6	-7.96	16.63	0	0.45	1	0.55	0.33	0.47
7	-9.12	16.89	0.38	0.71	0.62	0.28	0.44	0.63
8	-9.28	16.37	0.44	0.20	0.55	0.79	0.47	0.38
9	-8.08	16.58	0.04	0.41	0.95	0.59	0.34	0.45
10	-10.38	17.17	0.80	0.98	0.19	0.02	0.72	0.96
11	-10.17	16.72	0.73	0.53	0.26	0.46	0.65	0.52
12	-8.63	16.93	0.22	0.75	0.77	0.24	0.39	0.66
13	-10.96	17.03	1	0.84	0	0.15	1	0.76
14	-10.64	16.66	0.89	0.48	0.10	0.51	0.82	0.49
15	-8.52	16.91	0.18	0.73	0.81	0.26	0.38	0.65
16	-10.77	16.98	0.94	0.79	0.06	0.20	0.88	0.71
17	-10.95	16.78	0.99	0.59	0.01	0.40	0.99	0.55
18	-8.95	16.88	0.32	0.69	0.67	0.30	0.43	0.63
19	-10.29	17.19	0.77	1	0.22	0	0.69	1.00
20	-10.23	17.00	0.75	0.81	0.24	0.18	0.67	0.73
21	-8.70	16.93	0.24	0.74	0.75	0.25	0.39	0.65
22	-9.89	17.13	0.64	0.93	0.35	0.06	0.58	0.88
23	-9.73	16.83	0.59	0.64	0.41	0.35	0.55	0.58
24	-7.97	16.98	0.01	0.79	0.99	0.21	0.33	0.71
25	-10.44	17.10	0.82	0.91	0.17	0.08	0.74	0.85
26	-10.05	16.75	0.69	0.57	0.30	0.42	0.62	0.54
27	-9.09	16.83	0.37	0.64	0.62	0.35	0.44	0.58

Table 2. The sequences of S/N ratio and data processing

The deviation sequence from the results shown in the Table 2 can be calculated as follows

For SR

$$\Delta_{01}(1) = x_0^*(1) - x_1^*(1) = (1.000 - 0.541993961) = 0.4580$$

$$\Delta_{01}(2) = x_0^*(1) - x_1^*(2) = (1.000 - 0.4758433) = 0.52416,$$

and so on for the other remaining combinations. The same procedure can be repeated for MRR for all 27 runs. The grey relational coefficient can be calculated by using the Eq.10. The result of deviation sequence and the grey relational coefficient is given in Table 2. For the calculation of the grey relational grade Eq.11 is employed. But for these the weighting value is required, which is calculated by applying principal component analysis. The elements of the array for the multiple performance characteristics are the grey relational coefficients, which are listed in Table 2 which is used for evaluating the correlation coefficient matrix and then the eigen values is determined by using Eq.14 as shown in the Table 3.

Principal component	Eigen value	Explained variation (%)
First	1.376	68.8 %
Second	0.624	31.2 %

Table 3. The eigen vectors and explained variation for principal components

The eigen vector for principal components corresponding to each eigen values are computed and are listed in Table 4 and square of eigenvector can represent the contribution (weight) of the corresponding performance characteristics to the principal component. The contribution of SR and MRR on the first principal component is shown in Table 5 the weights for both the responses as 0.4999 and 0.4999 for SR and MRR respectively. The variance contribution for the first principal component characterizing the two quality characteristics is as high as 68.8%. Therefore, for this study, the squares of the respective eigenvectors are selected as the weighting values of the related quality characteristic.

Coefficients β_1 and β_2 in Eq.13 are set as 0.4999 and 0.4999 respectively.

Quality characteristics	Eigen vector	
	First principal component	Second principal component
Surface roughness	0.707	0.707
Metal removal rate	0.707	-0.707

Table 4. The Eigen vector for principal components

Quality characteristics	Contribution
Surface roughness	0.4999
Metal removal rate	0.4999

Table 5. The contribution of individual quality characteristics for the first principal component

Based on Eq.11 the grey relational grade γ has been calculated as follows:

$$\gamma_1 = 0.4999 \times 0.5219 + 0.4999 \times 0.4892 = 0.5054$$

Using the same procedure, the grey relational grade for all the comparability sequence for $i = 1 - 27$ can be calculated, as shown in the figure 8.

Fig. 8. Grey relational grade

To determine the optimal combination of wire EDM process parameters in machining Mg-SiC MMNC for minimum surface roughness and metal removal rate is done by sorting the average grey relational grade for each cutting parameter level. It is calculated by employing the main effect analysis of the Taguchi method. This process is performed by sorting the grey relational grades corresponding to the levels of the cutting parameters in each column of the orthogonal array and then taking the average of parameters with the same levels.

Generally, a larger grey relational grade indicates that the comparability sequence exhibits a stronger correlation with the reference sequence. A larger grey relational grade results in better multiple quality characteristics. Fig. 9 clearly shows that the multiple quality characteristics of the WEDM process which are significantly affected by the process parameters, selecting the level which have the largest average responses, and thus we get the optimal combination. From the above fig. 9 the optimal combination is A2B3C3D2E1.

Fig. 9. Effects of process parameters on the quality responses

5. CONFIRMATION TEST

After the optimal level of the parameters is identified by the grey relational analysis, the confirmation test is carried out, that is done by comparing the predicted results with the help of a confirmation experiment. The grey relational grade of the optimal combination can be estimated by the following equation.

$$\sigma = \sigma_t + \sum_{i=1}^n (\sigma_m - \sigma_t) \quad (16)$$

Where σ_t is the total mean of the grey relational grade, σ_m is the mean of the grey relational grade at the optimum level, and n is the number of the machining parameters.

As mentioned before, the optimal combination of process parameters was A2B3C3D2E1 and the estimated grey relational grade is 0.861, and it is calculated by using Eq.16. The grade of the confirmation experiment and prediction grade is shown in the Table 5. The confirmation experiment shows that the multiple quality characteristics was substantially promoted and the prediction error is within 1% for SR and MRR respectively which shows the effectiveness of the algorithm.

Optimal WEDM parameters			
	Prediction	Experiment	Error (%)
Level	A2B3C3D2E1	A2B3C3D2E1	
Surface Roughness (SR)	3.421	3.4426	0.66
Metal Removal Rate (MRR)	7.207	7.1832	0.33
Grey relational grade	0.861	0.8737	

6. CONCLUSIONS

In this study, parametric modelling and application of hybrid Taguchi-GRA-PCA for optimizing the cutting parameters of WEDM of machining

magnesium based nano composite was studied. Based on all this work, the following conclusions are summarized:

1. The empirical models for metal removal rate and surface roughness of Mg-SiC metal matrix composites machined by WEDM process have been developed using response surface methodology. The models developed are considered reliable representatives of the experimental results with prediction errors less than $\pm 5\%$.
2. The pulse-on time is the most influencing factor for material removal rate and volume percentage content of SiC for surface roughness of the magnesium based composite.
3. The principal component analysis, used to determine the corresponding weighting values of each performance characteristics while applying grey relational analysis to a problem with multiple-performance characteristics, is found to be capable of objectively reflecting the relative importance for each performance characteristic.
4. Based on analysis of variance, the major controllable factor significantly affecting the multiple-performance characteristics is pulse-on time and volume of silicon carbide percentage with a desired total contribution of 88 %.
5. The optimal combination of the cutting parameters obtained from the proposed method is the set with A1, B3, C3, D2, and E1. The confirmation experiment shows that the multiple quality characteristics was substantially promoted and the prediction error is within 1% for *SR* and *MRR* respectively which shows the effectiveness of the algorithm
6. The proposed algorithm greatly simplifies the optimization design of cutting parameters with multiple performance characteristics. Thus, the solutions from this method can be an useful reference for industries and operators who are willing to search for an optimal solution of cutting conditions.

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