

Optimizing machining parameters of wire-EDM process to cut Al7075/SiCp composites using an integrated statistical approach

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Abstract Metal matrix composites (MMCs) as advanced materials, while producing the components with high dimensional accuracy and intricate shapes, are more complex and cost effective for machining than conventional alloys. It is due to the presence of discontinuously distributed hard ceramic with the MMCs and involvement of a large number of machining control variables. However, determination of optimal machining conditions helps the process engineer to make the process efficient and effective. In the present investigation a novel hybrid multi-response optimization approach is proposed to derive the economic machining conditions for MMCs. This hybrid approach integrates the concepts of grey relational analysis (GRA), principal component analysis (PCA) and Taguchi method (TM) to derive the optimal machining conditions. The machining experiments are planned to machine Al7075/SiCp MMCs using wire-electrical discharge machining (WEDM) process. SiC particulate size and its weight percentage are explicitly considered here as the process variables along with the WEDM input variables. The derived optimal process responses are confirmed by the experimental validation tests and the results showed satisfactory. The practical possibility of the derived optimal machining conditions is also analyzed and presented using scanning electron microscope examinations. According to the growing industrial need of making high performance, low cost components, this investigation

provide a simple and sequential approach to enhance the WEDM performance while machining MMCs.

Keywords Al7075/SiC metal matrix composites (MMCs) · Wire-electrical discharge machining (WEDM) · Principal component analysis (PCA) · Gray relational analysis (GRA) · Taguchi method (TM)

1 Introduction

The material technologies in the present advanced manufacturing industries lead to the possible development of innovative materials that have properties and shape suitable for practical use. The particulate reinforced metal matrix composites (MMCs) in the class of advanced materials have been gaining importance due to their outstanding improved mechanical properties over conventional metallic alloys for diverse specialized applications in aerospace and automobile industries. However, due to the presence of hard ceramic particulate as the reinforcement made these materials as difficult-to-cut using traditional machining methods [1, 2]. As the result, these materials have limited their applications to only a few specialized components. On the other hand, the non-traditional machining methods have expanded their importance for machining MMCs. However, non-traditional machining methods involve expensive equipment and complex mechanisms while producing the components with high precision and intricate shapes.

Wire-electrical discharge machining (WEDM) in the class of non-traditional machining methods has been popularly known as an efficient and economical machining method used to machine difficult-to-cut materials regardless of their hardness into complex contours [3, 4]. WEDM

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is a widely accepted non-contact thermo-electrical machining process for metal removal in which material is removed by generating a series of discrete sparks between electrode and work piece immersed in a dielectric medium [5]. Therefore, WEDM is identified as an effective alternative for machining metal matrix composites for producing complex shapes with a high degree of accuracy. Discharge current, pulse duration, pulse frequency, wire speed, wire tension, and dielectric flow are significant control variables in WEDM [6] while the metal removal rate (MRR), surface roughness (R_a), kerf width (K_w) and white layer thickness (WLT) are considerable output parameters in evaluating the machinability. Apart from these WEDM control variables, while machining MMCs, the reinforced ceramic particulate size and percentage in the matrix also play a significant role in evaluating the machinability, as the ceramic content in MMCs as reinforcement alters the material hardness and electrical conductivity apparently [7]. Generally, the selection of the WEDM process variables is primarily based on the operator's experience and the data handbook provided by the machine tool manufacturer. However, such criteria may guarantee neither high production rate nor good surface quality of the machine component [5] because the process responses are highly correlated with each other. This made the process highly complicated in choosing the appropriate cutting conditions. Hence, the selection of optimal machining conditions became quite essential because the MMCs are relatively costlier than the conventional metals and alloys and the WEDM process also a cost expensive machining process.

Therefore, a significant amount of research has explored on different methodologies of achieving the ultimate WEDM goals of optimizing the numerous process parameters to enhance the overall machining reliability. Which include the evolutionary optimization techniques such as genetic algorithm (GA), simulated annealing (SA), particle swarm optimization (PSO), ant colony optimization (ACO) and artificial bee colony (ABC) algorithm [8] and the statistical based optimization techniques such as Taguchi method (TM), grey relational analysis (GRA), principal component analysis (PCA), etc. The evolutionary techniques require a huge number of experimental data so that they are treated as costlier and time consuming approaches while the statistical optimization approaches are limited with less number of process variables, their levels of variability and are suitable for the process with a single quality characteristic and to find its optimal process parameters at a time. However, practically the manufacturing processes involve multiple quality characteristics which are generally complex but essential. In case of WEDM process, while machining MMCs, the increased number of control variables made the process much

complex to derive its optimal process conditions due to the conflicting nature between the process responses at their process control parameters which in turn raised the difficulty in finding the optimal machining conditions. Therefore, the state of affairs raised the need of an effective optimization approach to handle multiple correlated responses simultaneously to succeed at the solutions to this problem.

In this paper, a novel hybrid multi-response optimization approach is proposed to derive the optimal machining conditions for machining MMCs under WEDM process. This hybrid approach integrates the concepts of GRA, PCA and TM to deal with the problem of simultaneous optimization of five correlated WEDM performance measure such as metal removal rate, surface roughness, kerf width, wire wear rate, and white later thickness while machining Al7075/SiCp MMCs.

2 Literature review

WEDM is an effective alternative for machining advanced materials like metal matrix composites [9]. To improve the performance of WEDM process, the experimental works in Ref. [9] have been well explored on various aspects of modelling, simulation and process optimization. Ramakrishnan and Karunamoorthy [10] proposed artificial neural network (ANN) models and multi-response signal-to-noise (MRSN) ratio in addition to Taguchi's parametric design approach to predict and optimize the performance characteristics of WEDM process namely material removal rate and surface roughness. Yuan et al. [11] developed a reliable multi-objective optimization technique based on Gaussian process regression (GPR) to optimize the high-speed wire-cut electrical discharge machining (WEDM-HS) process. The model performance of the GPR, back-propagation neural network (BPNN) was compared based on the experimental results and found that, the GPR models have the advantages over BPNN models in terms of model accuracy and feature scaling and probabilistic variable.

Mandal et al. [12] proposed artificial neural network (ANN) with back propagation algorithm was used to model the MRR and tool wear rate in EDM process and simultaneously the non-dominating sorting genetic algorithm-II (NSGA-II) was adopted for these models for optimization. Kuriakose and Shunmugam [13] considered the cutting velocity and surface finish as the process performance characteristics of WEDM. A multiple regression model was developed to represent the relationship between input and output variables and a non-dominated sorting genetic algorithm (NSGA) was used to optimize the process performance. Scott et al. [14] presented a factorial design model to predict the process responses via. MRR and

surface finish and consequently based on the concept of a non-dominated point the best control settings of WEDM process were determined. In Ref. [6], the relationship between control factors and responses were established by means of nonlinear regression models and then GA was employed to optimize the WEDM process.

In the aforesaid multi-objective optimization approaches for WEDM, modeling of process responses is vital and requires enormous experimental data for developing the best-fit model. This results in a rise of experimentation cost, time and expertise in process modeling. In addition, the values of resulted process variables in the optimal front may not be available with the parameter control panel of the WEDM machine.

Taguchi's utility concept is being used for a wide range of manufacturing applications to improve the production quality [15]. Ramakrishnan and Karunamoorthy [16] proposed the Taguchi's robust parametric design approach to optimize three WEDM responses via. MRR, R_a and WWR. These three responses were replaced by an MRSN ratio which represents the overall quality index and hence the optimal process settings were derived for the maximum MRSN. Tosun et al. [17] used Taguchi's analysis of S/N ratio to obtain the optimum machining parameter combination based on kerf and MRR as WEDM responses. The investigations presented in Refs. [16] and [17], in the former, the multi-response optimization problem was converted into a single objective of MRSN to maximize, while in the later, a weighting method was adopted to transform the normalized kerf and normalized MRR into a single objective format, and hence minimized the resultant weighted objective function. Owing to the increasing complexity of the present advanced manufacturing processes with simultaneous optimization of multiple responses, the original Taguchi approach failed to solve a multi-response optimization problem as it is designed to optimize a single response only.

To overcome these shortcomings in dealing with the problem of simultaneous optimization of multiple correlated responses, the Taguchi's utility concept has been integrated with the other suitable multivariate statistical methods such as desirability function approach, GRA and PCA. The idea of these coupled approaches was the derivation of an equivalent process quality index by accumulating the multiple responses to represent the overall quality of the process so that the problem of simultaneous optimization of multiple responses is substituted by the problem of maximizing the overall quality index of the process. Hence, Taguchi's utility theory can be effectively applied to maximize the overall quality of the process.

The results in GRA and PCA approaches are based on the original data and the calculations are simple and easy to understand [15]. In GRA coupled Taguchi technique, the

data are processed based on the assumption that the output responses are interrelated or independent. Therefore, the multiple output responses are weighted and aggregated into a single quality index to optimize. PCA based Taguchi approach aggregates the multiple process responses distributed in multiple dimensions by eliminating the correlation among them without much loss of information and expresses as a single quality index to optimize. However, the relative performance of these optimization methods is completely unknown as the optimal results of these approaches are different [18, 19]. The grey relational analysis eventually presents the comparative difference between the values in sequence based on the grey relational grade values. Therefore, GRA is useful to measure the approximate correlation among the members in the sequence [17]. While PCA highlights the similarity and dissimilarity among the data sequences by identifying the dimensions in which the data sequences are distributed. By accumulating these merits in GRA and PCA, Chiang et al. [20] proposed the Taguchi method combined with the grey relational analysis to find the robust parameters of thin-film sputtering process with multiple quality characteristics. In order to consider the correlation between quality characteristics, the principal component analysis was eventually used. The weights for quality characteristics were determined by employing the entropy measurement method to eliminate the multiple co-linearity between them. Sibalija and Majstorovic [21] also integrated GRA and PCA to uncorrelate and synthesize responses into a single performance measure. They used the grey relational grade as the synthetic multi-response performance index which adequately takes into account of all the possible correlated responses with respect to the customer specifications. Weights for the grey relational coefficients are derived based on the total variance of the original responses from PCA. However, the multiple responses in these coupled approaches were aggregated based on the allocation of individual priority weights for each response. The change in the value of priority weights changes the overall quality index value [22]. In addition, the process responses practically may not hold equal weights and are varied based on the functional requirement of the machined product specified by the manufacturing engineer. For a particular machining application: (i) the degree of the importance of the output response may vary based on the application criteria and the functional requirements which alters the weights for the response; (ii) the correlation between the responses should not be negligible as the change in one response causes to significant change in the rest of the responses. Therefore, the judgement of priority of weights in conjunction with the assumption of negligible response correlation may lead to imprecision, uncertainty as well as vagueness in the solution [23].

In contrast to the above multi-response optimization approaches, the specific objective of this paper is to develop a simple, sequential and efficient method to deal with the simultaneous optimization of multiple correlated performance measures of WEDM process for machining the metal matrix composites. Therefore, the concepts of GRA, PCA and TM are integrated to handle the correlated multiple responses with due consideration of the correlations among them, their individual importance and assumptions related to the type of process.

3 Methodology for multi-objective optimization

For simultaneous optimization of multiple WEDM quality characteristics in the present investigation, GRA, PCA and TM are integrated and applied sequentially. This section gives a brief idea about these three approaches.

3.1 GRA

GRA based on grey system theory was first proposed by Deng [24]. Grey theory deals with a system containing insufficient information or in which the model is unsure. GRA can be applied to complex multivariate systems to analyze the uncertain relations between multiple variables associated with the system [25]. In recent years, grey relational analysis has become a powerful tool to analyze the processes with multiple performance characteristics. Since, the present problem consists of five process quality measures which have correlation between them. Therefore finding the optimal settings of the process is a highly difficult task. Therefore, application of grey relational analysis is inevitable to handle these five responses for optimizing the production quality [26]. To bring all the responses of different dimensions at diverse ranges of the system, usually GRA uses the data pre-processing given as follows [27]:

Step 1: Array of measured multiple responses during machining

$$A = \begin{bmatrix} y_{11} & y_{12} & y_{13} & \cdots & y_{1n} \\ y_{21} & y_{22} & y_{23} & \cdots & y_{2n} \\ y_{31} & y_{32} & y_{33} & \cdots & y_{3n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ y_{i1} & y_{i2} & y_{i3} & \cdots & y_{in} \end{bmatrix}, \tag{1}$$

where A is the array of the original sequence of the measured responses, i the number of experimental run and n the number of the response.

Step 2: Normalization of array of original sequence of the measured responses

The responses are normalized using the following formulas.

The lower-the-better (LB) is the criterion:

$$x_i(k) = \frac{\max y_i(k) - y_i(k)}{\max y_i(k) - \min y_i(k)}. \tag{2}$$

The higher-the-better (HB) is the criterion:

$$x_i(k) = \frac{y_i(k) - \min y_i(k)}{\max y_i(k) - \min y_i(k)}, \tag{3}$$

where $x_i^*(n)$ is the normalised value of the i th corresponding to the n th response; the $\max y_i^o(n)$ is the largest value of $y_i(n)$ in the n th response and the $\min y_i^o(n)$ is the smallest value of $y_i(n)$ in the n th response. Therefore, the normalized array of the original sequence of the responses x is represented as

$$x = \begin{bmatrix} x_{11} & x_{12} & x_{13} & \cdots & x_{1n} \\ x_{21} & x_{22} & x_{23} & \cdots & x_{2n} \\ x_{31} & x_{32} & x_{33} & \cdots & x_{3n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{i1} & x_{i2} & x_{i3} & \cdots & x_{in} \end{bmatrix}. \tag{4}$$

Step 3: Calculation of grey relational coefficient and grey relational grade

In GRA, the grey relational grade represents the measure of relevance among the process responses. After the data processing, the grey relational coefficient $\xi_i(k)$ for the k th process response in the i th experiment can be expressed as

$$\xi_i(k) = \frac{\Delta_{\min} + \zeta \Delta_{\max}}{\Delta_{0i}(k) + \zeta \Delta_{\max}}, \tag{5}$$

where $\Delta_{0i} = \|x_0(k) - x_i(k)\|$ is the deviation of absolute value $x_0(k)$ and $x_i(k)$. ζ is the distinguishing coefficient $0 \leq \zeta \leq 1$.

$$\Delta_{\min} = \min_{\forall j \in i} \min_{\forall k} \|x_0(k) - x_j(k)\|, \tag{6}$$

$$\Delta_{\max} = \max_{\forall j \in i} \max_{\forall k} \|x_0(k) - x_j(k)\|. \tag{7}$$

Step 4: Determination of overall grey relational grade

The overall grey relational grade represents as the overall performance characteristic of multiple responses of the process. This is calculated as the average of individual grey relational grades of the responses at the i th experimental run

$$\gamma_i = \frac{1}{n} \sum_{k=1}^n \xi_i(k). \tag{8}$$

Therefore, the overall grey relational grade converts the multiple responses (multi-grey relational grades) into a single response (overall grey relational grade) with the objective to maximize. Finally the overall grey relational

grades rank the experimental runs and the set of variables corresponding to the experimental run having higher grey relational grade referred as closer to the optimal values.

3.2 PCA

PCA is a multivariate statistical approach introduced by Pearson [28] and was further developed by Hotelling [29]. To deal with multiple correlated performance responses, PCA converts the data of the multiple correlated responses into several uncorrelated quality indices called principal components and is then simultaneously accumulated to formulate a mathematical function called composite principal component (CPC). CPC represents the overall quality of the process. Thus, based on the maximization of the overall quality of the process, the composite principal component is maximized to find the optimal set of process variables. PCA uses the data pre-processing to bring all the responses of different dimensions at diverse ranges of the system. The procedural steps involved in PCA are given below [7, 18].

Step 1: Array of measured multiple responses during machining

$$A = \begin{bmatrix} y_{11} & y_{12} & y_{13} & \cdots & y_{1k} \\ y_{21} & y_{22} & y_{23} & \cdots & y_{2k} \\ y_{31} & y_{32} & y_{33} & \cdots & y_{3k} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ y_{i1} & y_{i2} & y_{i3} & \cdots & y_{ik} \end{bmatrix}, \tag{9}$$

where A is the S/N ratio of each response, i the number of experimental runs and k the number of the response.

Step 2: Normalization of array of multiple responses

The responses are normalized using the following formula.

The lower-the-better (LB) is the criterion

$$x_i(k) = \frac{\max y_i(k) - y_i(k)}{\max y_i(k) - \min y_i(k)}. \tag{10}$$

The higher-the-better (HB) is the criterion

$$x_i(k) = \frac{y_i(k) - \min y_i(k)}{\max y_i(k) - \min y_i(k)}, \tag{11}$$

where $x_i(k)$ is the normalised value of the k th response; $\min y_i(k)$ is the smallest value of $y_i(k)$ for the k th response; and $\max y_i(k)$ is the largest value of $y_i(k)$ for the k th response. The normalized array x is shown as

$$x = \begin{bmatrix} x_{11} & x_{12} & x_{13} & \cdots & x_{1k} \\ x_{21} & x_{22} & x_{23} & \cdots & x_{2k} \\ x_{31} & x_{32} & x_{33} & \cdots & x_{3k} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{i1} & x_{i2} & x_{i3} & \cdots & x_{ik} \end{bmatrix}. \tag{12}$$

Step 3: Calculation of variance-covariance matrix M from the normalized data

$$M = \begin{bmatrix} N_{11} & N_{12} & N_{13} & \cdots & N_{1k} \\ N_{21} & N_{22} & N_{23} & \cdots & N_{2k} \\ N_{31} & N_{32} & N_{33} & \cdots & N_{3k} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ N_{i1} & N_{i2} & N_{i3} & \cdots & N_{ik} \end{bmatrix}, \tag{13}$$

$$N_{k,l} = \frac{\text{Cov}[x_i(k), x_i(l)]}{\sqrt{\text{Var}[x_i(k)]\text{Var}[x_i(l)]}}, \tag{14}$$

where $l = 1, 2, 3, \dots, k$, and $\text{Cov}[x_i(k), x_i(l)]$ is covariance of sequences $x_i(k)$ and $x_i(l)$.

Step 4: Calculation of eigenvalues λ_j and eigenvectors V_j from the correlation coefficient array.

Step 5: Evaluation of the principal components ψ_j .

The eigenvector V_j represents the factor of the j th number of quality characteristics of the j th principal component. For example, if represents the j th quality characteristic, the j th principal component ψ_j can be treated as a quality indicator with the required quality characteristic.

$$\begin{aligned} \psi_j &= (V_{1j}Q_1 + V_{2j}Q_2 + \cdots + V_{ij}Q_i)^{1/j} \\ &= \sum_{j=1}^k (V_jQ_j)^{1/j}, \end{aligned} \tag{15}$$

where ψ_1 is the first principal component, and ψ_2 is the 2nd principal component, and so on. The principal components are aligned in descending order with respect to variance, and therefore the ψ_1 accounts for the most variance in the data.

Step 6: Evaluation of the composite principal component ψ .

The composite principal component ψ represents the index of multi-composite quality for multi-quality responses. It is defined as the combination of principal components with their individual eigenvalues.

3.3 TM

TM is an effective tool to deal with the optimization of multiple responses influenced by multiple variables simultaneously. It minimizes the number of experimental runs without considerable loss of data. Hence, it has become an extensively adopted method to solve the complex problems. In this method, the performance characteristic is represented by S/N ratio and the largest value of S/N ratio is desired. S/N ratios are logarithmic functions of desired output and served as objective function in the optimization process. There are three types of S/N ratios: the lower-the-better, the higher-the-better, and the nominal-the-better and these are expressed as [30]

(i) Lower-the-better

$$\frac{S}{N} = -10 \log \left(\frac{1}{n} \sum_{i=1}^n y_i^2 \right). \quad (16)$$

(ii) Higher-the-better

$$\frac{S}{N} = -10 \log \left(\frac{1}{n} \sum_{i=1}^n \frac{1}{y_i^2} \right). \quad (17)$$

(iii) Normal-the-better

$$\frac{S}{N} = -10 \log \left(\frac{1}{ns} \sum_{i=1}^n y_i^2 \right), \quad (18)$$

where y_i is the i th value of measured response, n the total number of runs and s the standard deviation.

4 PCA based GRA integrated TM

GRA is one of the successfully used multi-response optimization techniques for solving the problems with multiple correlated performance characteristics of distinct manufacturing processes. Some of these manufacturing processes are: CNC turning [31], high-speed end milling [32], drilling of Al/SiC metal matrix composite [33], electrical discharge machining (EDM) [34], Micro-EDM [35], Wire-EDM process of particle-reinforced material [36], and laser cutting process [37]. GRA defines the grey relational grade favourable as an indicator of overall performance of the process replacing the multiple performance characteristics. However, while data processing in GRA, most of the researchers determined the weighting values for the process responses based on their own subjective estimation, but this approach cannot objectively reveal the relative importance of various performance characteristics.

PCA converts the data of multiple responses into a set of principal components which are consequently converged and accumulated based on their eigenvalues into a composite principle component (CPC). The CPC is assumed to replace multiple quality characteristics into a single quality index representing the overall process quality. Hence, the optimal combination of the process variables is derived by maximizing the CPC. However, there are two shortcomings highlighted in the process of dealing with multiple correlated process responses in PCA [38] that: firstly if there exists one eigen value which is greater than 1, then based on Kaiser's criterion, the corresponding principal component is assumed to

represent the actual responses and the eigen vector corresponding to the largest Eigen value is used to replace the actual responses for further analysis. Stochastic manufacturing systems may result more than one principal component and may exist more than one eigenvalue which is greater than 1. In such case, determination of feasible solution corresponding to each response is not guaranteed. Secondly, the derived composite principal component based optimal values cannot be guaranteed in replacing the multiple responses as the chosen principal component with only fewer variations can be explained by the total variation [28].

In the present investigation, five WEDM process responses viz., surface roughness, metal removal rate, wire wear ratio, kerf and white layer thickness were taken into consideration to represent the WEDM performance quality characteristics during machining Al7075/SiCp MMCs with due consideration of particulate size, volume fraction, pulse-on time, pulse-off time and wire tension as the process variables to present the total performance compliance of the machining process. Since the chosen process responses highly correlate with the process control variables, they need to optimize simultaneously. Therefore, the problem is treated as the multi-response optimization problem to optimize five correlated responses simultaneously.

Therefore, with reference to the above discussions, the GRA or PCA alone cannot be applied to the present problem as they aggregates the process responses based on their individual priorities. Therefore, in the present investigation, initially to transfer the experimentally measured data into comparability sequences the GRA is adopted and then grey relational coefficients are calculated for each response. In the next step, to estimate the grey relational grade (GRG) in GRA, the PCA is applied to evaluate the weighting values corresponding to the performance characteristics so that their relative importance can be properly and objectively described. However, the derived GRG, based on optimal set of variable cannot be assured to replace the multiple responses because the chosen principal components, in which fewer variations can be explained by total variation. Therefore, the Taguchi's robust higher-the-best SNR criterion is employed to optimize the PCA weighted GRG to determine the optimal settings to make the methodology more practical and efficient [32]. Finally, the significance of the chosen process variables for the process performance is studied by employing the analysis of variance (ANOVA). The proposed methodology of PCA based GRA integrated Taguchi's approach for multi-response optimization approach is depicted in Fig.1.

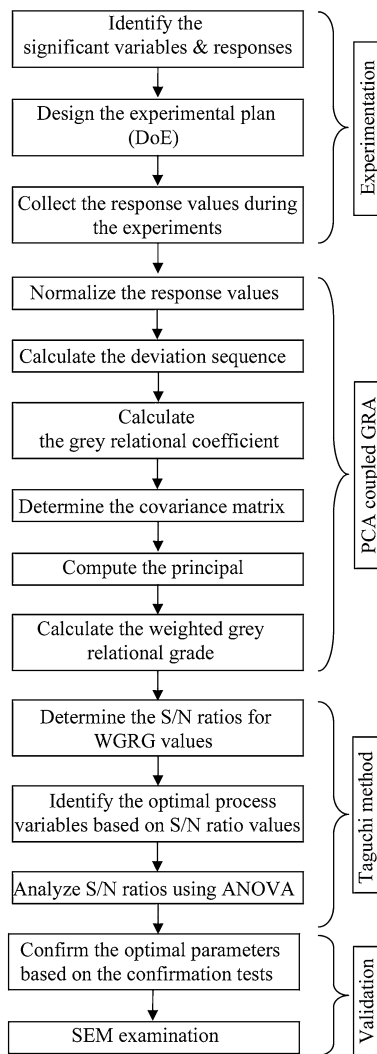


Fig. 1 Proposed methodology

5 Experimentation

5.1 Equipment, workpiece material and experimental procedure

Machining experiments were conducted on a five-axis CNC-Wire Electrical Discharge Machine, model number CT 520A, made by Joemars Machinery and Electric Industrial Co. Ltd., Taiwan. Details of work specimens, the electrode and the other machining conditions are listed in Table 1. Prior to machining, experiments were designed according to the design of experiments (DOE) to minimize the number of experimental runs and total 27 experiments were conducted based on Taguchi's L_{27} orthogonal array [39].

Work materials are the stir cast Al7075/SiCp MMCs. The cast specimens consist different sizes of silicon carbide particulate such as 25, 50 and 75 μm at different volumes

Table 1 Machining conditions

No.	Description
1	Work piece (anode): Al7075/SiC _p
2	Tool (cathode): brass wire of diameter 250 μm
3	Work piece height: 5 mm
4	Cutting length: 75 mm
5	Angle of cut: vertical
6	Location of work piece: centre to the table
7	Servo reference voltage: 35 V
8	Average voltage gap maintained: 40 V
9	Die-electric temperature: 25 °C
10	Die-electric fluid: distilled water

such as 5%, 10% and 15%. Based on the pilot experimental runs, the levels of WEDM control variables were selected as listed in Table 2. The experimental design matrix is presented in Table 3.

5.2 Measurement of responses

Surface roughness (R_a), MRR, wire wear ratio (WWR), kerf (K_w) and WLT are considered as the machining responses to measure, as these are more significant WEDM performance characteristics representing the machined component surface quality, dimensional accuracy and production rate. R_a was measured by using MITUTOYO surface tester with 0.8 mm cut-off value. Total six measurements were taken at six different locations in the direction perpendicular to the cutting and their average value was considered as the final R_a value. While calculating MRR, the work piece weight was measured before and after machining and MRR was estimated as the ratio of the weight difference of the work piece before and after machining to the machining time. For WWR measurement, the weight of the wire spool was measured before machining and after machining. Then WWR was calculated as the ratio of the weight loss of wire after machining to the weight of wire before machining. The weights of the wire before machining and after machining were measured

Table 2 Control factors and their levels

S. No.	Variable	Notation	Levels		
			-1	0	1
1	Particulate size / μm	X_1	25	50	75
2	Volume of SiC /%	X_2	5	10	15
3	Pulse-on time / μs	X_3	5	7	9
4	Pulse-off time / μs	X_4	25	35	45
5	Wire tension /g	X_5	1	5	9

Table 3 Design of experimental matrix: Taguchi’s L_{27} orthogonal array

Exp. No.	Coded control factor				
	X_1	X_2	X_3	X_4	X_5
1	-1	-1	-1	-1	-1
2	-1	-1	0	0	0
3	-1	-1	1	1	1
4	-1	0	-1	0	0
5	-1	0	0	1	1
6	-1	0	1	-1	-1
7	-1	1	-1	1	1
8	-1	1	0	-1	-1
9	-1	1	1	0	0
10	0	-1	-1	0	1
11	0	-1	0	1	-1
12	0	-1	1	-1	0
13	0	0	-1	1	-1
14	0	0	0	-1	0
15	0	0	1	0	1
16	0	1	-1	-1	0
17	0	1	0	0	1
18	0	1	1	1	-1
19	1	-1	-1	1	0
20	1	-1	0	-1	1
21	1	-1	1	0	-1
22	1	0	-1	-1	1
23	1	0	0	0	-1
24	1	0	1	1	0
25	1	1	-1	0	-1
26	1	1	0	1	0
27	1	1	1	-1	1

using an electronic balance with high accuracy and recorded as the response value of WWR.

In WEDM, the corner errors due to variation in Kerf are quite common and are limiting the internal corners to be produced in the WEDM components. This occurs because of the vibrations and deflections of the wire in the spark gap. Therefore Kerf greatly influences the dimensional accuracy of the finished part. In order to produce the WEDMed components with a high degree of dimensional accuracy, the study of process parameters on Kerf is important. The surface quality of the WEDM part is usually measured in terms of surface integrity, surface cracks, surface roughness, etc. and all of these are greatly affected by the white layer thickness. There are many WEDM process variables which are significant to the formation of white layer during machining. The study of the parameters in this investigation for white layer thickness helps to produce better surface quality of the machined product.

Hence, the K_w and WLT were taken into consideration as the process responses and were measured using computerized optical microscope, model GX51 inverted microscope made by OLYMPUS CORPORATION with the magnification range of 20 μm . The measurements were taken across the direction of machining at six different locations along the machined length and the averages of them were considered as the kerf and WLT values. The measured values of responses are listed in Table 4.

6 Optimization using GRA-PCA-TM technique

In the procedure of the proposed method, the experimentally measured data were normalized as the first step using Eqs. (2) and (3) to minimize the redundancy and the dependency between the responses. Typically, MRR is treated as a maximization response; Eq. (3) was used to normalize. While the rest of the responses, such as surface roughness, wire wear ratio, kerf and white layer thickness were considered to minimize, therefore Eq. (2) was used to normalize. The resulted normalized values are listed in Table 5. From Table 5, the larger values of the normalized results stand for better performance, and the maximum normalized results that are equal to 1 specify the best performance [24].

After normalization, the resulted normalized values were used to compute the grey relational coefficients for each response by using Eq. (5). Deviation sequence values in Eq. (5) were derived by substituting the normalized values in Eqs. (6) and (7). Table 6 presents the results of all deviation sequences (Δ_{0i}) for $i = 1-27$, and Table 7 presents the obtained grey relational coefficient values from the deviation sequence. Consequently to reflect the relative importance of process responses objectively while calculating the grey relational grade, the method of PCA is specifically introduced to derive the appropriate weight of each response [40]. The eigen values and the corresponding eigenvectors and the variance contribution of the responses are presented in Table 8. The weighted grey relational grade (WGRG) was calculated and listed in Table 9. Hence the multi-response optimization problem is converted into a single objective optimization problem with the objective to maximize the WGRG. Subsequently, Taguchi’s robust higher-the-best SNR criterion is employed to optimize WGRG listed in Table 9. The S/N ratio plot for the WGRG is represented graphically in Fig. 2. With the help of Fig. 2, the set of optimal WEDM process variables were determined. From Fig. 2, the predicted optimal levels of control variables refer to $X_1: -1, X_2: 0, X_3: -1, X_4: 1, X_5: -1$.

Table 4 Experimentally measured responses

Exp. No.	R_a / μm	MRR /(g·min ⁻¹)	WWR	K_w /mm	WLT / μm
1	0.75	0.064	0.003	0.314	3.568
2	1.07	0.069	0.018	0.368	3.573
3	1.46	0.073	0.057	0.398	3.627
4	1.00	0.057	0.005	0.320	3.511
5	1.23	0.037	0.024	0.350	3.541
6	1.30	0.089	0.054	0.356	3.593
7	1.34	0.019	0.015	0.310	3.523
8	1.25	0.061	0.023	0.333	3.565
9	1.78	0.079	0.070	0.350	3.533
10	1.17	0.046	0.011	0.340	3.550
11	0.96	0.035	0.016	0.347	3.539
12	1.55	0.104	0.056	0.371	3.690
13	0.88	0.017	0.006	0.291	3.521
14	1.31	0.063	0.023	0.340	3.567
15	1.81	0.082	0.074	0.352	3.586
16	1.43	0.040	0.014	0.320	3.544
17	1.77	0.044	0.042	0.327	3.548
18	1.67	0.048	0.059	0.327	3.552
19	1.20	0.019	0.017	0.313	3.623
20	1.64	0.069	0.034	0.340	3.573
21	1.57	0.083	0.065	0.343	3.637
22	1.57	0.045	0.022	0.321	3.549
23	1.33	0.047	0.033	0.323	3.551
24	1.83	0.052	0.051	0.332	3.506
25	1.45	0.028	0.025	0.294	3.532
26	1.79	0.018	0.042	0.309	3.522
27	2.49	0.078	0.091	0.334	3.582

7 Results and discussions

7.1 Statistical analysis of WGRG

Analysis of variance test (ANOVA) was conducted for WGRG values to understand the significance of each individual process variable on the WGRG. Table 10 shows the output of ANOVA. It is observed from Table 10 that the p -value less than 0.05 indicate that the variable is considered to be statistically significant at 95% confidence level. It is also observed from Table 10 that pulse-on time, wire tension and particulate size are the most significant process parameters on the overall performance of the process. The individual percentage contribution of each variable in the performance of the process is presented in Fig. 3. It is clear from Fig. 3 that pulse-on time is the major influencing factor contributing 67.87% to the overall quality of the machine component followed by wire tension contributing 20.09%, particulate size contributing 10.58%,

volume fraction contributing 1.12% and pulse-off time contributing 0.35%.

7.2 Confirmatory experiments

The derived set of optimal values for the process variables from the proposed approach is: 25 μm of particulate size, 10% volume of SiCp, 6 μs of pulse-on time, 45 μs of pulse-off time and 1 g of wire tension. Once the optimal level of the machining parameters was identified, the confirmation experiments were conducted to validate the derived optimal WEDM parameters to assess practical feasibility of the proposed novel methodology. The results of confirmation tests listed in Tables 11 and 12 show close correlation between the predicted and experimental values of the derived optimal control variables.

Figures 4, 5, 6 and 7 show the microscopic examinations of the machining responses of the obtained levels of variables. Figure 4 indicates the best possible surface finish

Table 5 Normalization of experimental data

S. No.	R_a / μm	MRR /($\text{g}\cdot\text{min}^{-1}$)	WWR	K_w /mm	WLT / μm
1	1.000	0.540	1.000	0.785	0.646
2	0.816	0.598	0.830	0.280	0.630
3	0.592	0.644	0.386	0.000	0.301
4	0.856	0.460	0.977	0.729	0.984
5	0.724	0.230	0.761	0.449	0.731
6	0.684	0.828	0.420	0.393	0.566
7	0.661	0.023	0.864	0.822	0.788
8	0.713	0.506	0.773	0.607	0.655
9	0.408	0.713	0.239	0.449	0.915
10	0.759	0.333	0.909	0.542	0.703
11	0.879	0.207	0.852	0.477	0.737
12	0.540	1.000	0.398	0.252	0.000
13	0.925	0.000	0.966	1.000	0.794
14	0.678	0.529	0.773	0.542	0.649
15	0.391	0.747	0.193	0.430	0.589
16	0.609	0.264	0.875	0.729	0.722
17	0.414	0.310	0.557	0.664	0.709
18	0.471	0.356	0.364	0.664	0.696
19	0.741	0.023	0.841	0.794	0.155
20	0.489	0.598	0.648	0.542	0.630
21	0.529	0.759	0.295	0.514	0.269
22	0.529	0.322	0.784	0.720	0.706
23	0.667	0.345	0.659	0.701	0.699
24	0.379	0.402	0.455	0.617	1.000
25	0.598	0.126	0.750	0.972	0.759
26	0.402	0.011	0.557	0.832	0.791
27	0.000	0.701	0.000	0.598	0.601

Table 6 Calculation of deviation sequences (Δ_{0i})

S. No.	R_a / μm	MRR /($\text{g}\cdot\text{min}^{-1}$)	WWR	K_w /mm	WLT / μm
1	0.000	0.460	0.000	0.215	0.354
2	0.184	0.402	0.170	0.720	0.370
3	0.408	0.356	0.614	1.000	0.699
4	0.144	0.540	0.023	0.271	0.016
5	0.276	0.770	0.239	0.551	0.269
6	0.316	0.172	0.580	0.607	0.434
7	0.339	0.977	0.136	0.178	0.212
8	0.287	0.494	0.227	0.393	0.345
9	0.592	0.287	0.761	0.551	0.085
10	0.241	0.667	0.091	0.458	0.297
11	0.121	0.793	0.148	0.523	0.263
12	0.460	0.000	0.602	0.748	1.000
13	0.075	1.000	0.034	0.000	0.206
14	0.322	0.471	0.227	0.458	0.351
15	0.609	0.253	0.807	0.570	0.411
16	0.391	0.736	0.125	0.271	0.278
17	0.586	0.690	0.443	0.336	0.291
18	0.529	0.644	0.636	0.336	0.304
19	0.259	0.977	0.159	0.206	0.845
20	0.511	0.402	0.352	0.458	0.370
21	0.471	0.241	0.705	0.486	0.731
22	0.471	0.678	0.216	0.280	0.294
23	0.333	0.655	0.341	0.299	0.301
24	0.621	0.598	0.545	0.383	0.000
25	0.402	0.874	0.250	0.028	0.241
26	0.598	0.989	0.443	0.168	0.209
27	1.000	0.299	1.000	0.402	0.399

with little damage. Figure 5 exhibits the continuous kerf with little localized irregularities due to the unsterilized spark and irregularly dropped SiC particle around the cutting path. Figure 6 shows the white layer over the machined surface and Fig. 7 shows the wire surface after machining at the obtained optimal machining variables. These figures show that the best possible output responses are obtained through the proposed methodology. Hence, the feasible result of validation experiment highlighting the enrichment in quality characteristic at the optimal parameter setting.

8 Conclusions

In this article, a hybrid, integrated approach of PCA weighted GRA based TM has been proposed to optimize the multiple quality characteristics for machining Al7075/SiCp MMCs in WEDM process. Five WEDM responses were considered to represent the process performance. To

solve the problem of simultaneous optimization of five process responses, grey relational analysis was employed to transform into optimization of a single response problem, the GRG. The concept of PCA was introduced to derive the appropriate weight of each response while calculating the GRG. WGRG was derived by accumulating the values of PCA weighted GRG values. Consequently the WGRG was optimized based on the Taguchi's signal-to-noise, higher-the-better criterion.

The concluding remarks of this article can be summarized as follows:

- (i) Derived values of optimal WEDM combinations from the proposed methodology are: 25 μm of particulate size, 10% volume of SiCp, 6 μs of pulse-on time, 45 μs of pulse-off time and 1 g of wire tension for overall quality of the process.
- (ii) The resulted values of the process responses for optimum variables are R_a 0.75 μm , MRR 0.026 $\text{g}\cdot\text{min}^{-1}$, WRR 0.006, K_w 0.290 mm and WLT 3.468 μm .

Table 7 Calculation of grey relational coefficients of individual responses

S. No.	R_a / μm	MRR /($\text{g}\cdot\text{min}^{-1}$)	WWR	K_w /mm	WLT / μm
1	1.000	0.521	1.000	0.699	0.585
2	0.731	0.554	0.746	0.410	0.575
3	0.551	0.584	0.449	0.333	0.417
4	0.776	0.481	0.956	0.649	0.969
5	0.644	0.394	0.677	0.476	0.650
6	0.613	0.744	0.463	0.452	0.535
7	0.596	0.339	0.786	0.737	0.702
8	0.635	0.503	0.688	0.560	0.592
9	0.458	0.635	0.397	0.476	0.855
10	0.675	0.428	0.846	0.522	0.627
11	0.805	0.387	0.772	0.489	0.655
12	0.521	1.000	0.454	0.401	0.333
13	0.870	0.333	0.936	1.000	0.708
14	0.608	0.515	0.688	0.522	0.588
15	0.451	0.664	0.383	0.467	0.549
16	0.561	0.405	0.800	0.649	0.643
17	0.460	0.420	0.530	0.598	0.632
18	0.486	0.437	0.440	0.598	0.622
19	0.659	0.339	0.759	0.708	0.372
20	0.495	0.554	0.587	0.522	0.575
21	0.515	0.675	0.415	0.507	0.406
22	0.515	0.424	0.698	0.641	0.630
23	0.600	0.433	0.595	0.626	0.624
24	0.446	0.455	0.478	0.566	1.000
25	0.554	0.364	0.667	0.947	0.675
26	0.455	0.336	0.530	0.749	0.705
27	0.333	0.626	0.333	0.554	0.556

Table 9 Calculation of weight grey relational grade (overall quality index) and corresponding S/N ratios

S. No.	WGRG	S/N ratio (higher-the-better)
1	0.620	-4.152
2	0.379	-8.427
3	0.226	-12.918
4	0.622	-4.124
5	0.336	-9.473
6	0.327	-9.709
7	0.425	-7.432
8	0.359	-8.898
9	0.346	-9.218
10	0.404	-7.872
11	0.412	-7.702
12	0.350	-9.119
13	0.649	-3.755
14	0.345	-9.244
15	0.262	-11.634
16	0.391	-8.156
17	0.285	-10.903
18	0.273	-11.277
19	0.353	-9.045
20	0.300	-10.458
21	0.263	-11.601
22	0.348	-9.168
23	0.337	-9.447
24	0.391	-8.156
25	0.447	-6.994
26	0.332	-9.577
27	0.246	-12.181

Table 8 Analysis of (covariance matrix) eigen values, eigenvectors, accountability proportion (AP) and cumulative accountability proportion (CAP) computed for the five major quality indicators

	ψ_1	ψ_2	ψ_3	ψ_4	ψ_5
Eigenvectors	0.998	-0.031	0.02	0.017	-0.044
	0.019	0.368	-0.509	-0.704	-0.331
	0.054	0.181	-0.219	-0.187	0.939
	0.009	0.362	-0.629	0.683	-0.081
	0.013	0.837	0.544	0.055	-0.024
Eigenvalues	0.1349	0.00233	0.00044	0.00015	0.00008
AP	0.978	0.017	0.003	0.001	0.001
CAP	0.978	0.995	0.998	0.999	1

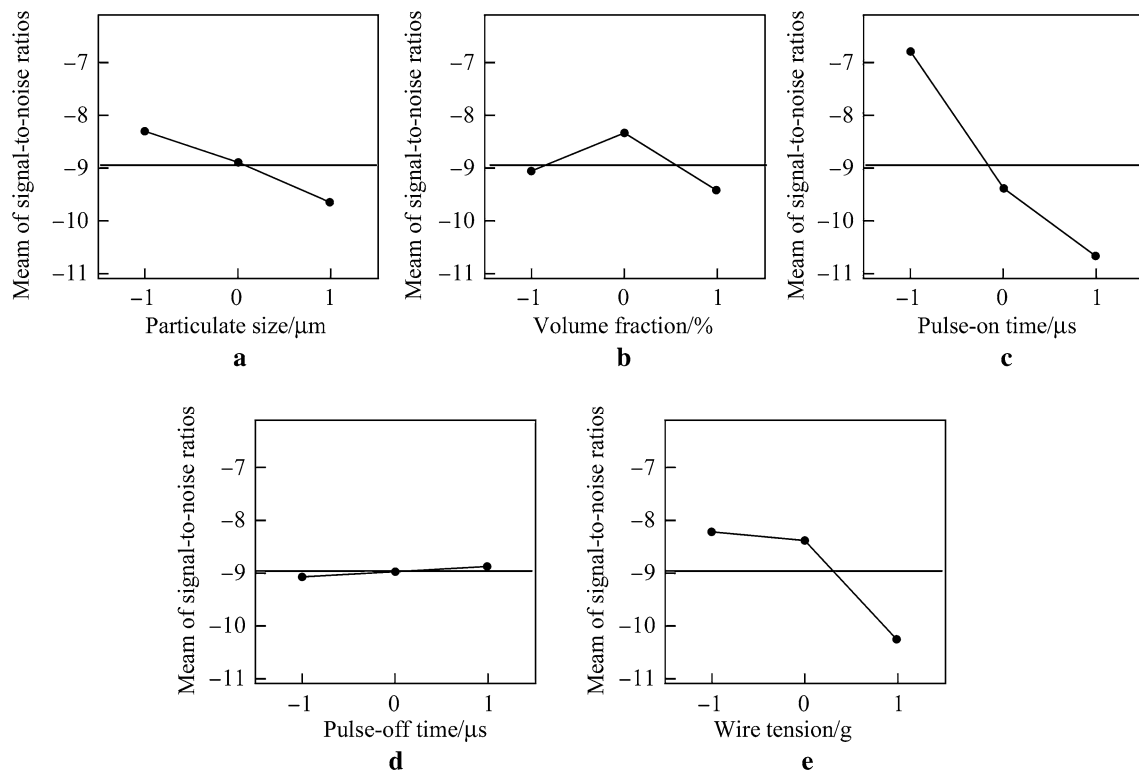


Fig. 2 S/N ratio plot of weighted grey relational grade

Table 10 ANOVA analysis for the composite quality indicator WGRG

Source	DF	Seq SS	Adj SS	Adj MS	F	P	Rank
Regression	5	0.201241	0.201241	0.040248	8.290400	0.000187	
Particulate size	1	0.021287	0.021287	0.021287	4.3847	0.048577	3
Volume fraction	1	0.002245	0.002245	0.002245	0.4623	0.503967	4
Pulse-on time	1	0.136590	0.136590	0.13659	28.135	0.000029	1
Pulse-off time	1	0.000697	0.000697	0.000697	0.1435	0.708585	5
Wire tension	1	0.040423	0.040423	0.040423	8.3263	0.008850	2
Error	21	0.101951	0.101951	0.004855			
Total	26	0.303192					

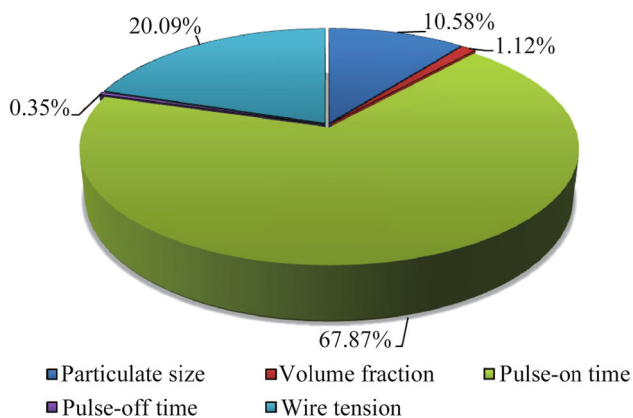


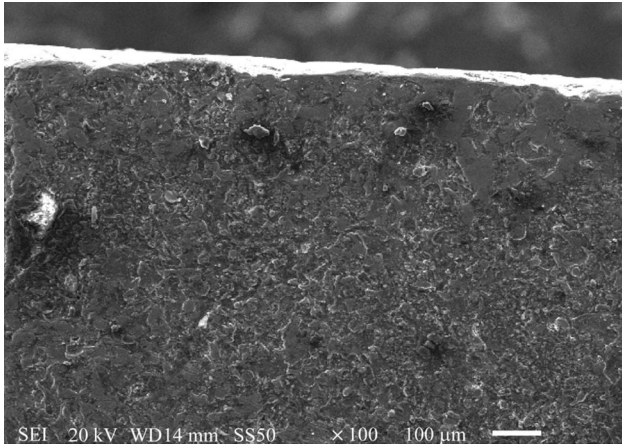
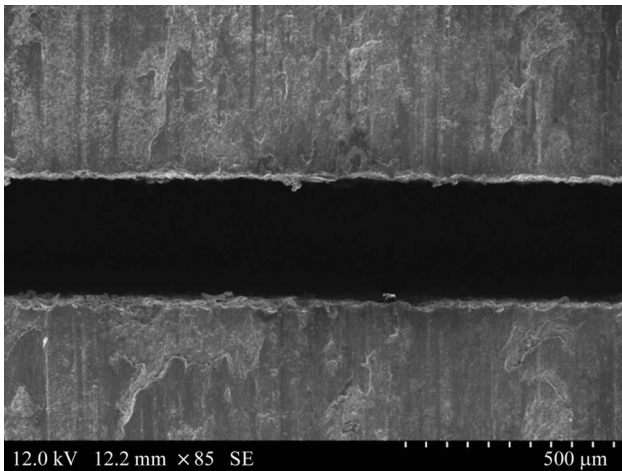
Fig. 3 Percentage contribution of variables on WGRG

Table 11 Results of confirmatory experiment

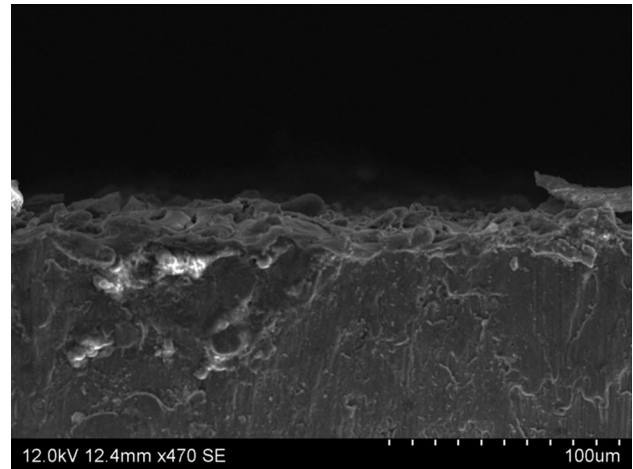
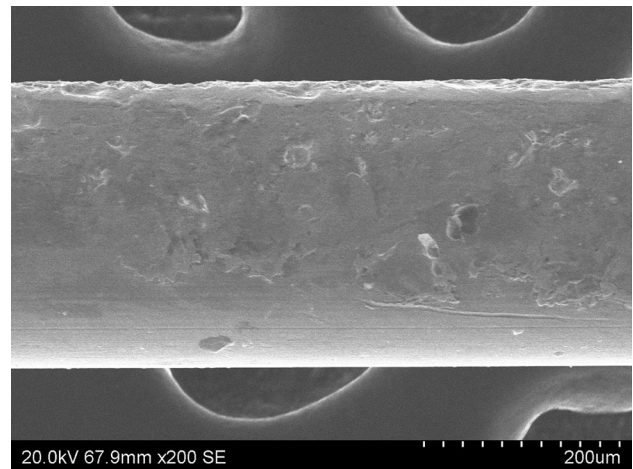
Process variable	Level	Optimal settings	
		Prediction	Experimental
Particulate size/ μm	-1	25	25
Volume fraction of SiC _p /%	0	10	10
Pulse-on time/ μs	-1	6	6
Pulse-off time/ μs	1	45	45
Wire tension/g	-1	1	1
S/N ratio of WGRG		-5.209	-5.211
Value of WGRG		0.543	0.540

Table 12 Optimal process responses of confirmatory experiment

$R_a/\mu\text{m}$	$\text{MRR}/(\text{g}\cdot\text{min}^{-1})$	WWR	K_w/mm	$\text{WLT}/\mu\text{m}$
0.75	0.026	0.006	0.290	3.468

**Fig. 4** SEM micro-graph of the machined MMC surface at 25 μm of particulate size, 10% volume of SiCp, 6 μs of pulse-on time, 45 μs of pulse-off time and 1 g of wire tension**Fig. 5** Kerf of the machined MMC at 25 μm of particulate size, 10% volume of SiCp, 6 μs of pulse-on time, 45 μs of pulse-off time and 1 g of wire tension

- (iii) The results of ANOVA reveal that particulate size, pulse-on time and wire tension has significant on the overall quality WGRG of the process. The percentage contribution of the process variables on the overall performance is observed as particulate size: 10.58%, volume fraction of SiCp: 1.12%, pulse-on time: 67.87%, pulse-off time: 0.35% and wire tension: 20.09%.

**Fig. 6** White layer thickness of the machined MMC at 25 μm of particulate size, 10% volume of SiCp, 6 μs of pulse-on time, 45 μs of pulse-off time and 1 g of wire tension**Fig. 7** SEM micro-graph of the wire used to machine the MMC at 25 μm of particulate size, 10% volume of SiCp, 6 μs of pulse-on time, 25 μs of pulse-off time and 1 g of wire tension

- (iv) The experimental validation test is conducted and the results are found with good agreement based on the obtained process conditions.
- (v) In the determined optimal process response, the analysis of SEM graphs of the machined MMCs and wire is also presented to present the practical possibility of the proposed approach and the derived optimal results. On the whole, the SEM examination results are also convincing the predicted results from the proposed method.

Hence the proposed methodology will help in deriving the optimal process conditions to increase the quality and productivity of the wire electrical discharge machined components made of Al7075/SiCp MMCs. This study can also be effectively applied to optimize the

problem of simultaneous optimization of multiple correlated performance characteristics in other manufacturing processes to promote manufacturing efficiency and to automate the machining process based on the chosen optimal values.

References

- Mali HS, Manna A (2012) Simulation of surface generated during abrasive flow finishing of Al/SiCp-MMC using neural networks. *Int J Adv Manuf Technol* 61(9–12):1263–1268
- Senthilkumar C, Ganesan G, Karthikeyan R (2008) Study of electrochemical machining characteristics of Al/SiCp composites. *Int J Adv Manuf Technol* 43(3–4):256–263
- Hamatani G, Ramulu M (1990) Machinability of high temperature composites by abrasive waterjet. *J Eng Mater Technol* 112(4):381
- Grabowski A, Nowak M (2008) Laser beam interactions with metal matrix AlSi alloy/SiCp composites. *J Achiev Mater Manuf Eng* 31(2):233–240
- Prasad DVSSSV, Gopala Krishna A (2008) Empirical modeling and optimization of wire electrical discharge machining. *Int J Adv Manuf Technol* 43(9–10):914–925
- Mahapatra SS, Patnaik A (2006) Optimization of wire electrical discharge machining (WEDM) process parameters using Taguchi method. *Int J Adv Manuf Technol* 34(9–10):911–925
- Thella BR, Gopala KA (2013) Simultaneous optimization of multiple performance characteristics in WEDM for machining ZC63/SiCp MMC. *Adv Manuf* 1(3):265–275
- Yusup N, Zain AM, Hashim SZM (2012) Evolutionary techniques in optimizing machining parameters: review and recent applications (2007–2011). *Expert Syst Appl* 39(10):9909–9927
- Rao TB, Krishna AG (2014) Selection of optimal process parameters in WEDM while machining Al7075/SiCp metal matrix composites. *Int J Adv Manuf Technol* 73(1–4):299–314
- Ramakrishnan R, Karunamoorthy L (2008) Modeling and multi-response optimization of Inconel 718 on machining of CNC WEDM process. *J Mater Process Technol* 207(1–3):343–349
- Yuan J, Wang K, Yu T et al (2008) Reliable multi-objective optimization of high-speed WEDM process based on Gaussian process regression. *Int J Mach Tools Manuf* 48(1):47–60
- Mandal D, Pal SK, Saha P (2007) Modeling of electrical discharge machining process using back propagation neural network and multi-objective optimization using non-dominating sorting genetic algorithm-II. *J Mater Process Technol* 186(1–3):154–162
- Kuriakose S, Shunmugam MS (2005) Multi-objective optimization of wire-electro discharge machining process by non-dominating sorting genetic algorithm. *J Mater Process Technol* 170(1–2):133–141
- Scott D, Boyina S, Rajurkar KP (1991) Analysis and optimization of parameter combinations in wire electrical discharge machining. *Int J Prod Res* 29(11):2189–2207
- Tarng YS, Juang SC, Chang CH (2002) The use of grey-based Taguchi methods to determine submerged arc welding process parameters in hardfacing. *J Mater Process Technol* 128(1–3):1–6
- Ramakrishnan R, Karunamoorthy L (2005) Multi response optimization of wire EDM operations using robust design of experiments. *Int J Adv Manuf Technol* 29(1–2):105–112
- Tosun N, Cogun C, Tosun G (2004) A study on kerf and material removal rate in wire electrical discharge machining based on Taguchi method. *J Mater Process Technol* 152(3):316–322
- Datta S, Nandi G, Bandyopadhyay A et al (2009) Application of PCA-based hybrid Taguchi method for correlated multicriteria optimization of submerged arc weld: a case study. *Int J Adv Manuf Technol* 45(3–4):276–286
- Pradhan MK (2013) Estimating the effect of process parameters on MRR, TWR and radial overcut of EDMed AISI D2 tool steel by RSM and GRA coupled with PCA. *Int J Adv Manuf Technol* 68(1–4):591–605
- Chiang YM, Hsieh HH (2009) The use of the Taguchi method with grey relational analysis to optimize the thin-film sputtering process with multiple quality characteristic in color filter manufacturing. *Comput Ind Eng* 56(2):648–661
- Sibalija TV, Majstorovic VD (2010) An integrated approach to optimise parameter design of multi-response processes based on Taguchi method and artificial intelligence. *J Intell Manuf* 23(5):1511–1528
- Singh A, Datta S, Mahapatra SS et al (2011) Optimization of bead geometry of submerged arc weld using fuzzy based desirability function approach. *J Intell Manuf* 24(1):35–44
- Shen DH, Du JC (2005) Application of gray relational analysis to evaluate HMA with reclaimed building materials. *J Mater Civ Eng* 17(4):400–406
- Deng JL (1989) Introduction to grey system theory. *J Grey Syst* 1(1):1–24
- Singh PN, Raghukandan K, Pai BC (2004) Optimization by grey relational analysis of EDM parameters on machining Al–10%SiCp composites. *J Mater Process Technol* 155–156:1658–1661
- Huang MS, Li CJ, Yu JC et al (2009) Robust parameter design of micro-injection molded gears using a LIGA-like fabricated mold insert. *J Mater Process Technol* 209(15–16):5690–5701
- Tosun N, Pihitili H (2009) Gray relational analysis of performance characteristics in MQL milling of 7075 Al alloy. *Int J Adv Manuf Technol* 46(5–8):509–515
- Pearson K (1901) On lines and planes of closest fit to systems of points in space. *Philos Mag* II:559–572
- Hotelling H (1933) Analysis of a complex of statistical variables into principal components. *J Educ Psychol* 24:417–441
- Ross PJ (1996) Taguchi techniques for quality engineering: loss function, orthogonal experiments, parameter and tolerance design. McGraw-Hill, New York
- Tzeng CJ, Lin YH, Yang YK et al (2009) Optimization of turning operations with multiple performance characteristics using the Taguchi method and Grey relational analysis. *J Mater Process Technol* 209(6):2753–2759
- Lu HS, Chang CK, Hwang NC et al (2009) Grey relational analysis coupled with principal component analysis for optimization design of the cutting parameters in high-speed end milling. *J Mater Process Technol* 209(8):3808–3817
- Haq AN, Marimuthu P, Jeyapaul R (2007) Multi response optimization of machining parameters of drilling Al/SiC metal matrix composite using grey relational analysis in the Taguchi method. *Int J Adv Manuf Technol* 37(3–4):250–255
- Lin J, Lin C (2002) The use of the orthogonal array with grey relational analysis to optimize the electrical discharge machining process with multiple performance characteristics. *Int J Mach Tools Manuf* 42(2):237–244
- Meena VK, Azad MS (2012) Grey relational analysis of micro-EDM machining of Ti-6Al-4V alloy. *Mater Manuf Processes* 27(9):973–977
- Chiang KT, Chang FP (2006) Optimization of the WEDM process of particle-reinforced material with multiple performance characteristics using grey relational analysis. *J Mater Process Technol* 180(1–3):96–101
- Çaydaş U, Hasçalık A (2008) Use of the grey relational analysis to determine optimum laser cutting parameters with multi-performance characteristics. *Opt Laser Technol* 40(7):987–994
- Su CT, Tong LI (1997) Multi-response robust design by principal component analysis. *Total Qual Manag* 8(6):409–416

39. Palanikumar K, Karthikeyan R (2007) Optimal machining conditions for turning of particulate metal matrix composites using Taguchi and response surface methodologies. *Mach Sci Technol* 10:417–433
40. Fu T, Zhao J, Liu W (2012) Multi-objective optimization of cutting parameters in high-speed milling based on grey relational analysis coupled with principal component analysis. *Front Mech Eng* 7(4):445–452