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Simultaneous optimization of multiple performance characteristics in WEDM for machining ZC63/SiC_p MMC

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Abstract The compliance of an integrated approach, 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 SiC_P reinforced ZC63 metal matrix composites (MMCs) is investigated in this work. The WEDM is proven better for its efficiency to machine MMCs among others, while the particulate size and volume percentage of SiC_p with the composite are the utmost important factors. These improve the mechanical properties enormously, however reduce the machining performance. Hence the WEDM experiments are conducted by varying the particulate size, volume fraction, pulse-on time, pulse-off time and wire tension. In the view of quality cut, the most important performance indicators of WEDM as surface roughness (R_a), metal removal rate (MRR), wire wear ratio (WWR), kerf (K_w) and white layer thickness (WLT) are measured as responses. PCA is used as multi-response optimization technique to derive the composite principal component (CPC) which acts as the overall quality index in the process. Consequently, Taguchi's S/N ratio analysis is applied to optimize the CPC. The derived optimal process responses are confirmed by the experimental validation tests results. The analysis of variance is conducted to find the effects of choosing process variables on the overall quality of the machined component. The practical possibility of the derived optimal process conditions is also presented using SEM.

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1 Introduction

Ceramic reinforced metal matrix composites (MMCs) as advanced materials strike the aerospace and automobile industries with their enhanced mechanical properties. The magnesium based MMCs possess the superior physical and mechanical properties, such as excellent specific strength, wear resistance, hardness, higher corrosion resistance, low thermal expansion, excellent strength to weight ratio, etc. [1–3] However, the presence of discontinuously distributed hard ceramic particulate in the matrix made them highly difficult-to-cut using conventional machining methods like turning, milling, drilling, etc. Hence the applications of these composites have been limited in the regular commercial applications. Müller et al. [4] also noticed some reasons lowering the applications of ceramic reinforced MMCs when using conventional machining processes, which are the higher production costs, the complexity of the machining.

The parameters such as chemical compositions, properties of the reinforcement and matrix, dispersion, fabrication methods and conditions, etc. have significant influence on the mechanical properties and its machinability. Many investigations have been successfully conducted and reported on the variations of the mechanical properties under several aforesaid conditions. However, controlling the machining variables to achieve the best production has been considered as a highly difficult task for the manufacturing industries today. The presence of hard particles in the matrix intermittently hides cutting edge, for example, an abrasive in grinding wheel on the tool surface causes the relentless abrasion of cutting tool in due course resulting in poor surface quality of the machined component. Narahari et al. [5] highlighted some issues during machining Al-SiC_P composites cast with conventional high speed steel and tungsten carbide tools as 25 % reduced tool life than that of unreinforced alloy and further reduction in tool life for the further increase in SiC_P content beyond 20 % due to the abrasion of the tool. Manna et al. [6, 7] investigated the optimal combination of process parameters for better surface roughness (R_a) during Al/SiC-MMC turning. It shows that it is a challenging aspect to produce good surface quality for Al/SiC-MMC components in turning due to the adhesion of these particles when cutting tool edge. However, the non-conventional machining methods, such as laser beam machining [8], electrochemical machining [9], water jet machining [10], electric discharge machining [11], are proven effective with the capability to cut the materials regardless of their hardness and machine these composites. Usually the machine tool manufacturer provides the machine tool operational details along with the tooling information and other machining parameters corresponding to the generally used materials in the industries. However these details are still not adequate for machining the advanced materials like MMCs. It became complicated to select the suitable conditions for efficient machining due to the stochastic process mechanisms in the non-traditional machining processes [12].

Many research works have been reported focusing on the electric discharge machining (EDM) of MMCs. Karthikeyan et al. [13] developed mathematical models for optimizing EDM LM25/SiC MMCs process. Recently, the pulse duration and the percent volume fraction of SiC are considered as process variables to find the optimal values of metal removal rate (MRR), the tool wear rate (TWR) and R_a. The optimal cutting conditions are determined in order to determine the economical machining of this process in this investigation. Ramulu et al. [14] reported the surface integrity of SiC_P/Al composite in EDM. George et al. [15] considered the EDM process parameter including pulse current, gap voltage and pulse-on-time to optimize the responses of electrode wear rate (EWR) and MRR while machining carbon–carbon composite. It was found that the lower values of parameters substantially reduced the EWR, while the higher values resulted in higher MRR within this experimentation region. Sameh et al. [16] reported the effect of pulse on time, peak current, average gap voltage and the percent volume fraction of SiC present in the aluminium matrix on R_a, MRR and EWR while machining Al/SiC_P in EDM. R_a was increased with increasing pulse on time, SiC percentage, peak current and gap voltage, while the increased MMR was observed for the increased value of pulse on time, peak current and gap voltage. The higher values of both pulse time and peak current levels resulted in the increase of the EWR. Roux et al. [17] investigated the surface integrity of the EDMed Al/SiC/15 % MMC. It was found that the pulse energy is highly significant on R_a while for reinforcement is negligible. Hung et al. [18] presented a report on the EDM of Al/SiC_p that the R_a was considerably affected by the current, and the effect of voltage and on-time was negligible. Senthilkumar et al. [9] reported the influence of some predominant electrochemical machining (ECM) process parameters, such as the applied voltage, electrolyte concentration, electrolyte flow rate and tool feed rate on the MRR and R_a during machining cast LM25 Al/10 %SiC composites. In this investigation the increased MMR was reported for the increased levels of any of the considered machining parameters. However, the higher R_a is reported for the higher level of machining parameters except applied voltage. This is due to the excessive heating of electrolyte for the higher voltages that increase R_a. Some non-traditional methods such as EDM and ECM have certain limitations in the linear cutting and elaborate preparation of pre-shaped electrode (tool), and huge and costly equipments are needed to make the complex contours during machining.

On the other hand, the wire electrical discharge machining (WEDM) is proven as an effective and economical method for machining MMCs into complex contours [19, 20]. It is a thermo-electrical process where the metal removal takes place in a series of electric sparks discharges at the interface of continuously supplied wire (electrode) and the workpiece in the presence of dielectric medium in its working principle. The presence of abrasive deteriorates the electrical and thermal conductivity of MMCs, decreasing the MRR during machining [21]. Discharge current, pulse-on time, pulse-off time, and voltage are the most commonly used control parameters that are significant for high speed machining of alloys [22]. However the parameters including volume fraction, particulate size distribution also have considerable influence on the machining performance while machining MMCs. Yan et al. [23] observed the increased trend of R_a with the increased volume fraction of the reinforcement. They also noted that the increased volume fraction of reinforcement resulted in wire breakage. Meanwhile the ceramic reinforcement improves the mechanical properties greatly.

According to Ref. [24], the R_a of MMCs machined using WEDM was found to be significantly different from that of unreinforced alloy. Manna et al. [25] determined the optimal WEDM process parameter settings during Al/SiC-MMC machining. Pulse peak voltage, pulse on-time, pulse off-time, peak current, wire feed rate, wire tension, spark gap set voltage are considered as process control parameters while the MMR, R_a, gap current and spark gap are deemed as process responses. The optimum process parameters were determined for effective machining using the Gauss elimination method. Rozenek et al. [26] thought the current, voltage and pulse-on time as significant parameters for cutting rate and surface finish during machining SiC and Al_2O_3 particulate-reinforced aluminium matrix composites using WEDM. Huang et al. [27] proposed a strategy to find the optimal multi-cut WEDM process planning including the number of machining operations and their corresponding machining-parameters setting for each operation.

These investigations on WEDM present the detailed variability of the performance measures including R_a, MRR, wire wear ratio (WWR) and kerf (K_w) while machining MMCs. Some works also suggest the optimal machining conditions for minimum R_a, maximum MRR and minimum WWR. Very few were focused on K_w as WEDM responses while machining MMCs. However, the white layer thickness (WLT) is still not completely understood while machining MMCs in WEDM. The particulate size of SiC and its percentage as the process variables of WEDM have not been considered up to now. The aim of present work was to investigate five process responses including R_a, MRR, WWR, K_w and WLT toward optimization of WEDM of ZC63/SiC$_P$ with due consideration of particulate size, volume fraction, pulse-on time, pulse-off time and wire tension as process variables. Hence, the work presents the total performance compliance of the machining process to improve the machinability.

2 Principal component analysis (PCA)

PCA is a multivariate statistical approach introduced by Pearsion [28] and further developed by Hotelling [29]. The present problem consists of five process quality measure and is found with correlation between them. As a result, the analysis of all these multiple quality characteristics for the optimal settings of the process is found to be a highly difficult task [30]. However, PCA can convert these multiple correlated responses data into several uncorrelated quality indices. A mathematical function is then formulated by gathering all or some quality indices called composite principal component (CPC) which stands for the overall quality of the process. Finally, the CPC can be used to determine the optimal conditions. In order to make all the responses with different dimensions at diverse ranges of the system unique, PCA is usually used in the data pre-processing. The procedural steps involved in PCA are given as follows [31].

Step 1 Array the measured multiple responses during machining

$$\boldsymbol{A} = \begin{bmatrix} y_{11} & y_{12} & y_{13} & \cdots & y_{1k} \\ y_{21} & y_{22} & y_{23} & \cdots & y_{2k} \\ y_{31} & y_{32} & y_{33} & \cdots & y_{3k} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ y_{i1} & y_{i1} & y_{i1} & \cdots & y_{i1} \end{bmatrix}, \quad (1)$$

where i is the number of experimental runs, k the number of the response, $\boldsymbol{A}$ the S/N ratio of each response.

Step 2 Normalize the multiple responses array

The responses are normalized using the following formulae:

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

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

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

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

where $x_i(k)$ is the normalised value of kth response, min $y_i(k)$ the smallest value of $y_i(k)$ for kth response, and max $y_i(k)$ the largest value of min $y_i(k)$ for kth response. $\boldsymbol{x}$ is the normalized array.

$$\boldsymbol{x} = \begin{bmatrix} x_{11} & x_{12} & x_{13} & \cdots & x_{1k} \\ x_{21} & x_{22} & x_{23} & \cdots & x_{2k} \\ x_{31} & x_{32} & x_{33} & \cdots & x_{3k} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{i1} & x_{i2} & x_{i3} & \cdots & x_{ik} \end{bmatrix}. \quad (4)$$

Step 3 Calculate the variance–covariance matrix $\boldsymbol{M}$ from the normalized data

$$\boldsymbol{M} = \begin{bmatrix} N_{11} & N_{12} & N_{13} & \cdots & N_{1k} \\ N_{21} & N_{22} & N_{23} & \cdots & N_{2k} \\ N_{31} & N_{32} & N_{33} & \cdots & N_{3k} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ N_{i1} & N_{i2} & N_{i3} & \cdots & N_{ik} \end{bmatrix}, \quad (5)$$

$$N_{k,l} = \frac{\mathrm{Cov}(x_i(k), x_i(l))}{\sqrt{\mathrm{Var}(x_i(k)) \times \mathrm{Var}(x_i(l))}}, \quad (6)$$

where $l = 1, 2, 3, \cdots, k$, and $\mathrm{Cov}(x_i(k), x_i(l))$ is the covariance of sequences $x_i(k)$ and $x_i(l)$.

Step 4 Calculate the eigen values and eigen vectors from the correlation coefficient array and denoted by λ_j and $\boldsymbol{V}_j$ respectively.

Step 5 Evaluate the principal components ψ_j.

The eigen vector $\boldsymbol{V}_j$ represents the weighting factor of j number quality characteristics of the jth principal component. For example, if Q_j represents the jth quality characteristic, the jth principal component ψ_j will be treated as a quality indicator with the required quality characteristic.

$$\psi_j = \left(V_{1j}Q_1 + V_{2j}Q_2 + \cdots + V_{jj}Q_j\right)^{1/j} = \sum_{j=1}^{k}\left(V_j \times Q_j\right)^{1/j}, \tag{7}$$

where ψ_1 is the first principal component, ψ_2 the second 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 Evaluate the CPC ψ.

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

3 Taguchi method (TM)

TM is an effective tool to simultaneously deal with the optimization of multiple responses influenced by multiple variables. It can minimize the number of experimental runs without considerable data loss and become an extensively adopted method to solve some complex problems in manufacturing. In this method, the performance characteristic is represented by S/N ratio and the largest value of S/N ratio is required. These are the logarithmic functions of desired output and served as objective function in the optimization process. There are three types of S/N ratio as the LB, the HB, and the normal-the-better. The S/N ratio with a LB characteristic can be expressed as [32]:

(i) LB

$$\frac{S}{N} = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right). \tag{8}$$

(ii) HB

$$\frac{S}{N} = -10\log\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right). \tag{9}$$

(iii) Normal-the-better

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

In Eqs. (8)–(10), y_i is the ith value of measured response, n the total number of runs, and s the standard deviation.

4 Proposed methodology: PCA integrated TM

The experimentally measured response data are converted into a set of individual components to find the optimal combination of variables by using PCA. However, there are still two obvious shortcomings for the PCA method [33]. Firstly, if there exists one eigen value that is greater than 1, the corresponding principal component will be selected to represent the actual responses [34] based on Kasier's criterion. The eigen vector corresponding to the largest eigen value can be used to replace the actual responses for further analysis. However, now the stochastic manufacturing systems may result in more than one principal component and may have more than one eigenvalue greater than 1, and the determination of feasible solution corresponding to the each response is not guaranteed in such cases. Secondly, the derived CPC based on optimal set of variable cannot be assured to replace multi-response as the chosen principal component, in which fewer variations can be explained by total variation [30]. However, the PCA integrated with TM makes the methodology more practical and efficient for solving multi-response optimization problems [35]. Many researchers have been using this integrated methodology to find the optimal set of process variables in their work. Fung et al. [36] used PCA-TM to optimize the injection-molding conditions of fiber-reinforced PBT and Gauri et al. [37] used it to determine the optimal set of WEDM variables.

In this paper, PCA-TA method is used to determine the optimum levels of WEDM process parameters for machining ZC63/SiC_P MMC and L_{27} orthogonal array is used in the experimentation design. Five process responses viz., R_a, MRR, WRR, K_w and WLT are considered as the WEDM performance measures. Thus, the multi-response case, PCA was implemented to convert the correlated responses to a set of interrelated components and then to evaluate the principal components. Therefore, the CPC was derived as the combination of principal components with their individual eigen values. Then the Taguchi's robust HB S/N criterion is employed to optimize the CPC to determine the optimal settings of the process variables. Finally, the analysis of variance (ANOVA) was used to study the significance of the chosen process variable parameter for multiple responses problem.

5 Experimental procedures

5.1 Materials

ZC63 magnesium alloy (Zn—5.5–6.5, Cu—2.4–3.0, Mn—0.25–075, Si_{max}—0.2, Ni_{max}—0.01, other—0.30, Mg—balance) is selected as matrix in this investigation as it has be

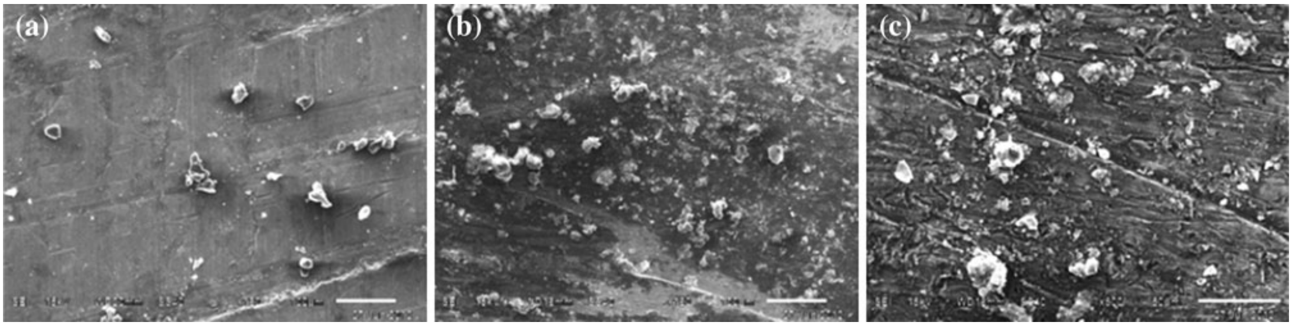

Fig. 1 Distribution of SiC_P in ZC63 alloy matrix **a** 25 μm in size and 5 % in volume fraction, **b** 50 μm in size and 10 % in volume fraction, **c** 75 μm in size and 15 % in volume fraction

found a wide variety of applications in aerospace and automobile industries [38]. Particulate silicon carbide of sizes 25, 50 and 75 μm is considered as reinforcement at its different volumes such as 5 %, 10 % and 15 % respectively.

5.2 Stir casting

The samples of ZC63/SiC_P were prepared using stir casting technique developed by Golmakaniyoon et al. [39], which has been proven as the simple, cost effective and the most suitable method to produce bulk MMCs. The required quantities of SiC_P (in 5 %, 10 %, 15 % Vol.) of each size were taken in powder containers heated to about 200 °C and maintained for about 30 min. Then ZC63 cast alloy was melted in a steel crucible about 675–700 °C which is above the liquidus state of the matrix alloy for 30 min. The molten metal was stirred to create a vortex, and the preheated SiC particles were quickly added into the molten alloy while stirring. Then stirring was continued for 30 min at the hold temperature. Castings were produced using tilt-casting technique for minimizing the melt turbulence and the quick emergence of entrapped air. The whole experiments were carried out with the protection of 0.5 % $SF_6 + N_2$. Total 27 castings were prepared in 9 varieties each with 3 numbers varying the particulate size and volume fraction of reinforcement. Figure 1 shows the SEM of all levels SiC_P in ZC36 matrix alloy.

Table 1 Machining conditions

No.	Description
1	Work piece (anode): ZC63/SiC_p
2	Tool (cathode): brass wire of diameter 250 μm
3	Work piece height: 6 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

5.3 WEDM experimental parameters and procedures

Initially the robust Taguchi's design of experiments (DOE) is employed to minimize the number of experimental runs and the experiments are designed for an L_{27} orthogonal array consisting of 27 experimental runs [40]. Then the machining was conducted on a five-axis CNC-WEDM (CT 520A). The details of work specimens, the electrode and the other machining conditions are listed in Table 1. The levels of process variables are selected based on the literature and the pilot experiment, as shown in Table 2. The design of experimental matrix is presented in Table 3.

5.4 Machining of ZC63/SiC_P MMCs and responses measurement

R_a, MRR, WWR, K_w and WLT are considered as machining responses since these are responsible factors indicating the efficiency, quality and quantity of the WEDM process. MITUTOYO surface roughness tester was used to measure R_a with 0.8 mm cut-off value. Six measurements were taken at six different locations in the direction perpendicular to the cutting, and their average value was considered. The weight of the work piece was measured before and after machining, and MRR was

Table 2 Control factors and their levels

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	6	8	10
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

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

estimated as the ratio of the weight difference of the work piece before and after machining to the machining time. The machining time is taken from the continuously updated CNC system for each cut. For WWR measurement, the weight of the wire spool was measured before the machining, and the weight of discarded wire after machining for each experiment in the design matrix was measured. 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 using an electronic balance with high accuracy and recorded as the response value of WWR. K_w and WLT were measured by using Computerized Optical Microscope (model GX51 inverted microscope) with the magnification range of 20 μm. These were measured at six different locations along the machined length in the perpendicular direction and the averages of them were considered as the K_w and WLT. The measured responses are listed in Table 4.

Table 4 Experimentally measured responses

No.	R_a/μm	MRR/(g·min^{-1})	WWR	K_w/mm	WLT/μm
1	0.67	0.074	0.002	0.322	3.556
2	0.99	0.079	0.017	0.376	3.561
3	1.38	0.083	0.056	0.406	3.665
4	0.92	0.067	0.004	0.328	3.449
5	1.15	0.047	0.023	0.358	3.529
6	1.22	0.099	0.053	0.364	3.581
7	1.26	0.029	0.014	0.318	3.511
8	1.17	0.071	0.022	0.341	3.553
9	1.70	0.089	0.069	0.358	3.471
10	1.09	0.056	0.010	0.348	3.538
11	0.88	0.045	0.015	0.355	3.527
12	1.47	0.114	0.055	0.379	3.760
13	0.80	0.027	0.005	0.299	3.509
14	1.23	0.073	0.022	0.348	3.555
15	1.73	0.092	0.073	0.360	3.574
16	1.35	0.050	0.013	0.328	3.532
17	1.69	0.054	0.041	0.335	3.536
18	1.59	0.058	0.058	0.335	3.540
19	1.12	0.029	0.016	0.321	3.711
20	1.56	0.079	0.033	0.348	3.561
21	1.49	0.093	0.064	0.351	3.675
22	1.49	0.055	0.021	0.329	3.537
23	1.25	0.057	0.032	0.331	3.539
24	1.75	0.062	0.050	0.340	3.444
25	1.37	0.038	0.024	0.302	3.520
26	1.71	0.028	0.041	0.317	3.510
27	2.41	0.088	0.090	0.342	3.570

6 Simultaneous optimization of correlated multiple responses

The experimentally measured data are normalized using the Eqs. (1) and (2) to minimize the redundancy and dependency between the responses. Equation (2) is used to normalize the minimization responses of R_a, WWR, K_w and WLT while Eq. (3) is used to normalize the maximization MRR responses. The normalized values results are listed in Table 5. Then the variance–covariance factors for normalized matrix is calculated as listed in Table 6. The accountability proportion (AP) in Table 6 represents the account degree of the respective response on the process generally called principal components. It is clear from the Table 6 that the values of ψ_1, ψ_2, ψ_3, ψ_4 and ψ_5 are 58 %, 23 %, 11 %, 5 % and 1 % represents the principal component values of R_a, MRR, WWR, K_w and WLT respectively. The individual principal components ψ_j are calculated using Eq. (7) and listed in Table 7. Therefore, by accumulating these CPCs, ψ is then derived for each experimental run as listed in Table 8.

Table 5 Normalization of experimental data

No.	R_a/μm	MRR/(g·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 Analysis of (covariance matrix) eigen values, eigen vectors, AP and cumulative accountability proportion (CAP) computed for the five major quality indicators

	ψ_1	ψ_2	ψ_3	ψ_4	ψ_5
Eigen vectors	0.317	−0.587	−0.175	0.073	−0.720
	−0.573	−0.293	−0.437	0.609	0.155
	0.577	−0.457	−0.120	0.067	0.663
	0.400	0.378	0.269	0.782	−0.118
	0.281	0.466	−0.831	−0.092	−0.064
Eigen values	0.16997	0.06810	0.03447	0.01557	0.00516
AP	0.58	0.232	0.118	0.053	0.018
CAP	0.58	0.812	0.929	0.982	1.000

Hence, the values of ψ serve as an overall quality index for each individual run which represents all the multiple responses measures of the WEDM process. Thus, the problem is converted into single objective optimization problem with minimization of the CPC.

Table 7 Principal component analysis for experimental observations

No.	ψ_1	ψ_2	ψ_3	ψ_4	ψ_5
1	1.080	−0.604	−0.857	1.023	−0.107
2	0.684	−0.634	−0.952	0.640	−0.018
3	0.126	−0.572	−0.681	0.434	−0.090
4	1.140	−0.350	−1.090	0.888	−0.046
5	0.922	−0.330	−0.805	0.528	−0.081
6	0.301	−0.424	−0.897	0.838	−0.168
7	1.245	−0.112	−0.663	0.690	−0.047
8	0.809	−0.385	−0.820	0.826	−0.036
9	0.295	0.038	−1.051	0.747	−0.136
10	0.989	−0.426	−0.826	0.678	−0.001
11	1.050	−0.442	−0.831	0.553	−0.139
12	−0.071	−0.697	−0.511	0.872	0.000
13	1.474	−0.236	−0.669	0.841	−0.194
14	0.757	−0.399	−0.836	0.788	0.001
15	0.145	−0.100	−0.792	0.778	−0.126
16	1.041	−0.223	−0.731	0.768	0.050
17	0.740	−0.007	−0.685	0.710	−0.004
18	0.617	0.028	−0.681	0.731	−0.166
19	1.068	−0.454	−0.156	0.731	−0.076
20	0.580	−0.260	−0.802	0.809	0.066
21	0.184	−0.348	−0.545	0.898	−0.146
22	0.922	−0.162	−0.720	0.785	0.059
23	0.871	−0.203	−0.739	0.787	−0.117
24	0.680	0.151	−0.962	0.693	−0.046
25	1.152	−0.010	−0.619	0.861	−0.077
26	0.998	0.189	−0.576	0.651	−0.067
27	0.006	0.301	−0.645	0.839	0.000

7 Results and discussions

The identified levels of optimal control variables become X_1-1, X_2-0, X_3-1, X_4-1, X_5-1. In the next step, these optimal process conditions are predicted and conformed by conducting the experimental runs to the optimal levels of the variables. The same experimental setup is used to conduct the validation experiments. The confirmation tests results were compared with those of the proposed method, as listed in Table 9.

ANOVA is conducted for the CPC values to understand the significance of each individual process variables on the responses. Table 10 shows the result of ANOVA. From Table 10 it can be observed that the p value is less than 0.05, which indicates that the variable is considered to be statistically significant at 95 % confidence level. It is also

Table 8 Calculation of CPC (overall quality index) and corresponding S/N ratios

No.	CPC ψ	S/N ratio (HB)
1	1.272	2.090
2	1.169	1.356
3	1.001	0.009
4	1.277	2.124
5	1.136	1.108
6	1.125	1.023
7	1.199	1.576
8	1.166	1.334
9	1.121	0.992
10	1.181	1.445
11	1.183	1.460
12	1.086	0.717
13	**1.279**	**2.137**
14	1.155	1.252
15	1.051	0.432
16	1.177	1.416
17	1.087	0.725
18	1.071	0.596
19	1.138	1.123
20	1.113	0.930
21	1.051	0.432
22	1.150	1.214
23	1.146	1.184
24	1.136	1.108
25	1.197	1.562
26	1.124	1.015
27	1.039	0.332

Table 9 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	25	25
Wire tension/g	−1	1	1
S/N ratio of ψ		2.243	2.444
Value of ψ		1.290	1.325

Optimal process responses

R_a/μm	MRR/(g·min^{-1})	WWR	K_w/mm	WLT/μm
0.691	0.068	0.020	0.307	3.276

observed that from the chosen process variables, particulate size, pulse-on time and wire tension are significant process parameters on the overall performance of the process. The individual percentage contribution of each variable in the process performance is presented in Fig. 2.

Table 10 ANOVA for the composite quality indicator ψ

Source	DF	Seq. SS	Adj. SS	Adj. MS	F	P	Rank
X_1	2	0.007729	0.007729	0.003865	3.61	0.050	3
X_2	2	0.005334	0.005334	0.002667	2.49	0.114	4
X_3	2	0.07882	0.07882	0.03941	36.83	0.001	1
X_4	2	0.000019	0.000019	0.000009	0.01	0.991	5
X_5	2	0.017626	0.017626	0.008813	8.24	0.003	2
Error	16	0.017119	0.017119	0.00107			
Total	26	0.126646					

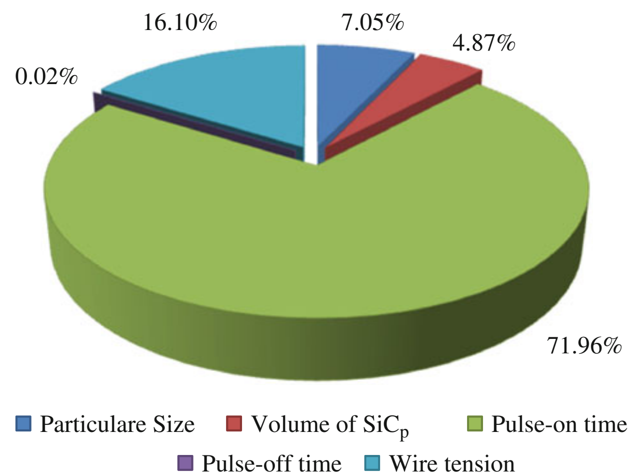

Fig. 2 Percentage contribution of variables on CPC

Figure 3 reveals the optimal combination set of process variables, namely, particulate size 25 μm, volume fraction of reinforcement 10 %, pulse-on time 6 μs, pulse-off time 25 μs and wire tension 1 gms.

Figure 4 reveals the best surface finish with little damage, which is due to pits resulted by the removal of SiC particles and their residuals. Figure 5 shows the continuous K_w with little localized irregularities due to the unsterilized spark and the irregularly dropped SiC particle around the cutting path. Figure 6 shows the unremitted recast layer (white layer) over the machined surface for the optimum values of control variables. Figure 7 presents the un-considerably worn wire surface after machining at the obtained optimal machining variables during confirmation test. On the whole, the microscopic examination results are convinced the predicted results from the proposed method.

8 Conclusions

(i) The resulted values of the optimization variables are observed as 25 μm of particulate size, 10 % volume of

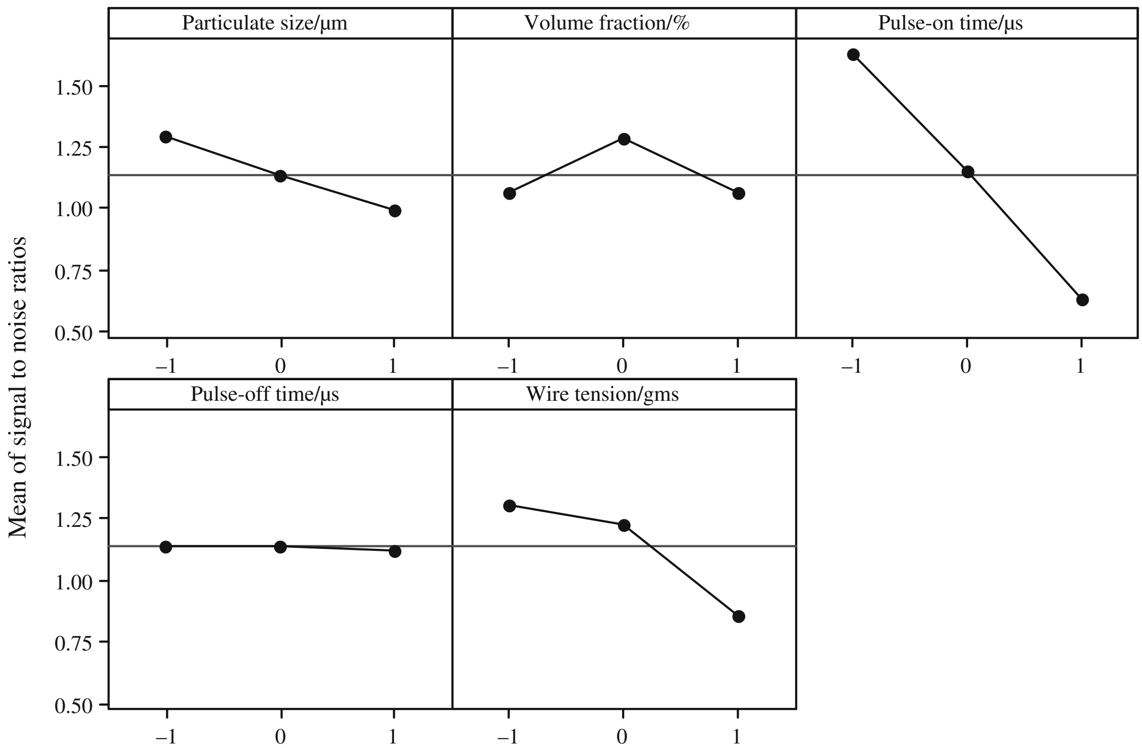

Fig. 3 S/N ratio plot of CPC

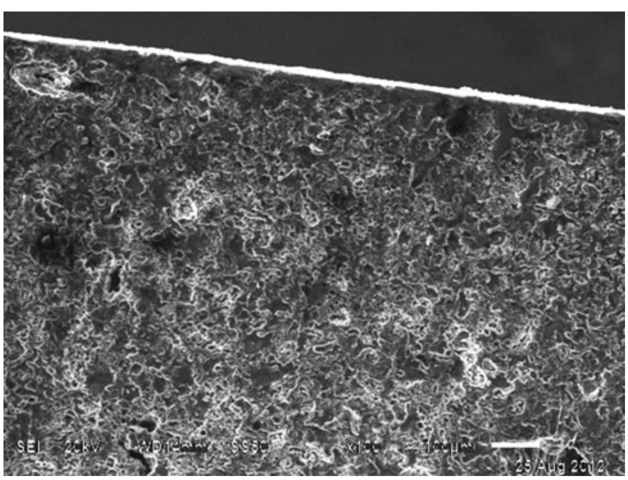

Fig. 4 SEM of the machined MMC surface at 25 µm of particulate size, 10 % volume of SiC_P, 6 µs of pulse-on time, 25 µs of pulse-off time and 1 gms of wire tension

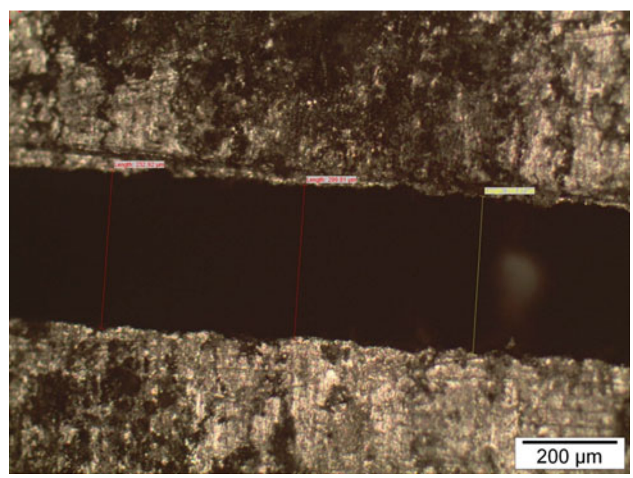

Fig. 5 SEM of K_w for the machined MMC at 25 µm of particulate size, 10 % volume of SiC_P, 6 µs of pulse-on time, 25 µs of pulse-off time and 1 gms of wire tension

SiC_P, 6 µs of pulse-on time, 25 µs of pulse-off time and 1 gms of wire tension for overall quality of the process.

(ii) The resulted values of the process responses for optimum variables are: R_a of 0.691 µm, MRR of 0.068 g/min, WRR of 0.020, K_w of 0.307 mm and 3.276 µm of WLT.

(iii) The results of ANOVA reveal that particulate size, pulse-on time and wire tension has physical significant on the overall quality of the process and pulse-off time and volume fraction of SiC_P are not important.

(iv) The process variables of particulate size (7.05 %), volume fraction of SiC_P (4.87 %), pulse-on time (71.96 %), pulse-off time (0.02 %) and wire tension (16.10 %) are vital to the overall performance of the process (on CPC). Particularly pulse-on time has greater significance than the rest of the process variables.

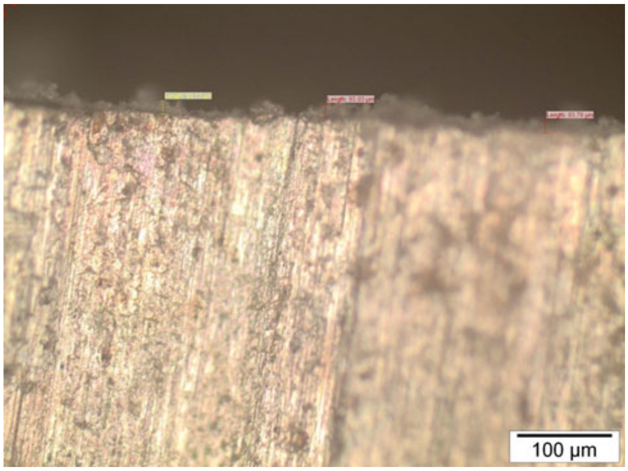

Fig. 6 SEM of WLT for the machined MMC at 25 µm of particulate size, 10 % volume of SiC_P, 6 µs of pulse-on time, 25 µs of pulse-off time and 1 gms of wire tension

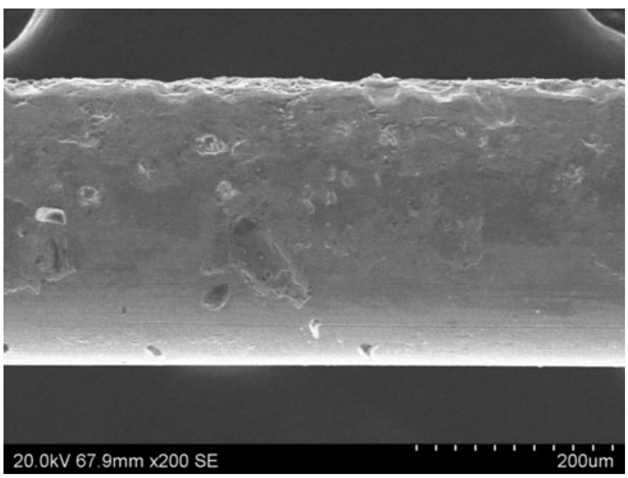

Fig. 7 SEM of the wire used to machine the MMC at 25 µm of particulate size, 10 % volume of SiC_P, 6 µs of pulse-on time, 25 µs of pulse-off time and 1 gms of wire tension

(v) The experimental validation test is conducted and the results are found with good agreement based on the obtained process conditions.

(vi) In the determined optimal process response, the analysis of the micrographs of the machined MMCs and wire are also presented to test the practical possibility of the obtained optimal results and the proposed method. On the whole, the microscopic examination results also convince the predicted results from the proposed method.

Hence, the proposed methodology is proven effectively for the simultaneous optimization of multiple correlated performance characteristics of WEDM process for machining ZC63/SiC_P MMCs. Further, the proposed integrated methodology could be also applied for different machining process on different materials in different machining conditions so as to automate the machining process based on the chosen optimal values.

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