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INTEGRATED STATISTICAL METHODOLOGY FOR OPTIMIZING THE MACHINING PARAMETERS IN SiC POWDER MIXED – EDDSG PROCESS TO MACHINE Ti6Al4V

INTEGRIRANA STATISTIČNA METODOLOGIJA ZA OPTIMIZIRANJE PARAMETROV BRUŠENJA POVRŠINE Ti6Al4V ZLITINE Z EDDSG PROCESOM V MEŠANICI S SiC PRAHOM

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The objective of this research work was targeted to investigate the hybrid-statistical methodology to deduce the economical-machining-condition through multi-output optimization in silicon carbide powder mixed-Electro Discharge Diamond Surface Grinding of Ti6Al4V. In this work, Grey-Fuzzy based principal component analysis along with Taguchi's orthogonal array is utilised for the multi-output optimization of hybrid-machining process parameters for minimal surface roughness, minimal wheel-wear rate, and maximal material removal rate. Eighteen experiments have been conducted according to Taguchi's L_{18} orthogonal array on in-house-designed and fabricated powder mixed-Electro Discharge Diamond Surface Grinding set-up. The single Multi-Output Performance Index is calculated by the aggregation of all multi-responses by using Grey-Fuzzy-Taguchi method based principal component analysis function. The optimum combination of process parameters and the effect of these parameters on the Multi-Output Performance Index are determined by the use of ANOVA analysis and response table. For the validation test, one additional confirmation experiment is conducted on this set-up according to the derived optimal condition and the outcomes of the results showed satisfactory matching between the predicted and experimented result. The specific contribution of this research work is to develop and describe the procedure of integrated statistical methodology for multi-output optimization of machining parameters in powder mixed-Electro Discharge Diamond Surface Grinding of Ti6Al4V. This integrated statistical approach hybridizes the concepts of Grey Relational Analysis, Fuzzy, principal component analysis and Taguchi approach to find the optimum combination of machining parameters for economical machining. This optimum combination of process parameters supports engineers to establish an economical and effective process.

Keywords: analysis of variance (ANOVA), powder mixed-electro discharge diamond surface grinding (PM-EDDSG), hybrid process, grey relational analysis, fuzzy, principal component analysis (PCA), Taguchi's method (TM), Ti-6Al-4V

Pričujoč članek opisuje raziskavo hibridne statistične metodologije za določitev ekonomičnih pogojev mehanske obdelave z večkomponentno analizo optimizacije izhodnih podatkov brušenja površine Ti6Al4V zlitine s tako imenovanim postopkom PM-EDDSG (diamantno brušenje površine z elektro erozijo v mešanici prahu). V tem delu je uporabljena osnovna komponentna analiza, ki temelji na tako imenovani sivo-zabrisani logiki (angl.: Grey-Fuzzy) v kombinaciji s Taguchijevo ortogonalno matriko, s katero naj bi napovedali izhodne pogoje za doseganje minimalne površinske hrapavosti, minimalne obrabe brusilnega koluta in maksimalno hitrost odstranjevanja materiala pri hibridni mehanski obdelavi s PM-EDDSG postopkom. Avtorji so izvedli osemnajst eksperimentov v skladu s Taguchijevo L_{18} ortogonalno matriko na doma dizajniranem in izdelanem stroju za PM-EDDSG postopek. Posamezen večizhodni indeks učinkovitosti (MOPI; angl.: Multi-Output Performance Index) so izračunali z združitvijo vseh večkratnih odzivov in z uporabo G-F-T metode (angl.: Grey-Fuzzy-Taguchi method), ki temelji na komponentni funkcijski analizi. Optimalno kombinacijo procesnih parametrov in vpliv teh parametrov na MOPI so določili z uporabo ANOVA analize in tabele odzivov. Kot validacijski test so izvedli še en dodatni eksperiment na pričujoči napravi pri dobljenih optimalnih pogojih. Rezultati preizkusa so pokazali zadovoljivo ujemanje med napovedanimi in z eksperimentom dobljenimi rezultati. Specifični prispevek tega raziskovalnega dela je razvoj in opis postopka integrirane statistične metodologije za več izhodno optimizacijo parametrov mehanske obdelave površine Ti6Al4V zlitine s PM-EDDSG postopkom. Ta integrirani statistični pristop združuje koncepte sivo-zabrisane relacijske analize (angl.: Grey-Fuzzy Relational Analysis), osnovne komponentne analize in Taguchijeve metode za določitev optimalne kombinacije procesnih parametrov ekonomične mehanske obdelave. Ta optimalna kombinacija procesnih parametrov omogoča procesnim inženirjem uvajanje novega ekonomičnega in učinkovitega procesa.

Ključne besede: analiza variance (ANOVA), diamantno brušenje površine z elektroerozijo v mešanici prahu (PM-EDDSG), hibridni proces, siva relacijska analiza, zabrisanost, osnovna komponentna analiza (PCA), Taguchijeva metoda (TM), Ti-6Al-4V

1 INTRODUCTION

Powder Mixed-Electro Discharge Diamond Surface Grinding is an emerging hybrid process for the machining of hard materials like Ti6Al4V. This material is widely utilized in various applications, including bio-medical, automotive, etc. Lin et al.[1] did experimentation on the Electrical Discharge Machining of SKD11 steel and reported that the material removal rate and electrode wear ratio are improved together by using a Taguchi-Fuzzy logic approach for solving the multi-output optimization problem. Kung et al.[2] conducted experimentation on Powder Mixed Electrical Discharge Machining of 94WC-6Co and developed the models for material

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removal rate and electrode wear ratio by Response Surface Methodology. Further, they studied the influence of input variables on the responses. Singh et al.[3] conducted experimentation on the Electro Discharge Face Grinding of WC-Co and studied the influence of process variables over the responses. Lin et al.[4] carried out experimentation on the Electrical Discharge Machining of SKD11 steel and showed that a combined Grey Relational Analysis-orthogonal array approach enhances the machining performance in multi-output optimization. This combined methodology improves the process outputs, i.e., electrode wear ratio, material removal rate and surface roughness in the Electrical Discharge Machining process. Tarng et al.[5] carried out experiments and reported the use of the Taguchi approach to find the optimum combination of welding variables in the submerged arc-welding of mild steel plates. Ko et al.[6] applied a Grey Relational Analysis and the Fuzzy-orthogonal array method on Electrical Discharge Machining, Tzeng et al.[7] applied the Fuzzy-Taguchi method on Electrical Discharge Machining and Lin et al.[8] applied Grey-Fuzzy method on Electrical Discharge Machining for the multi-output optimization of process variables. George et al.[9] applied the Taguchi method to find the optimum combination of process variables on Electrical Discharge Machining of C-C composites. Fung et al.[10] performed experimental work and presented the use of the principal component analysis-Taguchi approach for the optimization of multi-output in, fiber-reinforced polybutylene terephthalate composites. Alagumurthi et al.[11] have conducted experimental work on the grinding of mild steel and compared the factorial design of experiment with the Taguchi design of experiment approach, used to find the optimal grinding conditions. They reported that depth of cut, wheel speed and work speed were important grinding parameters that affect the grinding quality. Jean et al.[12] conducted experimental work and reported the use of a principal component analysis-Taguchi approach to develop a robust Electron Beam Welding Treatment process with high efficiency multiple-performance characteristics (MPCs). Dutta et al.[13] conducted experimentation on Wire Electrical Discharge Machining of D2 tool steel. They applied Response Surface Methodology to develop the models for each response and these models were used to predict the behaviour of process variables on the responses. They applied Grey Relational Analysis-Taguchi methodology to find the optimal variables setting in multi-response optimization. Lahane et al.[14] did experimental work and proposed a Weighted Principal Component method for multi-outputs optimization of the process factors in the wire Electrical Discharge Machining of HSS steel. V. K. Jain[15] reported that Hybrid Machining Process performance is more effective as compared to separate performance of component process with similar input variables.

Based on the above literature review, there is the necessity for efficient optimization methodology to take care of the problems related to the co-occurring optimization of multi-correlated responses and their solutions. Taguchi's methodology has been broadly utilized for process parameters optimization. This technique is beneficial for single response optimization, however, ineffective to optimize the multi-responses. In this research work, Taguchi's method is integrated with Grey-fuzzy based principal component analysis to beat the drawback in managing the difficulty of the simultaneous optimization of multi-correlate responses.

This integrated statistical methodology is utilized to derive an identical equivalent process-quality index by combining the multi-responses to depict the overall quality of the process so that the difficulty of concurrent optimization of multi-responses is substituted by the problem of maximizing the process - Overall Quality Index. That is why Taguchi's Utility-Theory can be efficiently utilized to maximize the process overall quality.

In this research work, a unique integrated multi-output optimization methodology is planned to deduce the optimum combination of machining variables in the Powder Mixed-Electro Discharge Diamond Surface Grinding of Ti6Al4V. This integrated methodology hybridizes the concepts of Grey, Fuzzy, Principal Component-Analysis and Taguchi to take care of the problem of co-occurring optimization of three correlative Powder Mixed-Electro Discharge Diamond Surface Grinding process performance measures like material removal rate, surface roughness, and wheel wear rate in machining of Ti6Al4V.

2 METHOD FOR MULTI-OUTPUT-OPTIMIZATION

2.1 Grey Relational Analysis Method

In Grey Relational Analysis, the initial step is to normalize the experimental data between zero-to-one by using Equations (1) and (2). For material removal rate, the higher is the better criterion is selected. Similarly, for surface roughness and wheel wear rate, the lower is the better criterion has been selected.[16]

For higher is the better criterion (H-T-B),

$$x_i^*(t) = \frac{x_i^{(0)}(t) - \min x_i^{(0)}(t)}{\max x_i^{(0)}(t) - \min x_i^{(0)}(t)} \tag{1}$$

For lower is the better criterion (L-T-B),

$$x_i^*(t) = \frac{\max x_i^{(0)}(t) - x_i^{(0)}(t)}{\max x_i^{(0)}(t) - \min x_i^{(0)}(t)} \tag{2}$$

where, $x_i^{(0)}(t)$ = original sequence, $x_i^{(*)}(t)$ = value after the Grey Relational normalization, $\min x_i^{(0)}(t)$ = lowest value of $x_i^{(0)}(t)$, $\max x_i^{(0)}(t)$ = maximum value of $x_i^{(0)}(t)$, $i = 1, 2, ..., p$; $t = 1, 2, ..., q$, p = total experiment and q =

total observation data. The next step is to determine the deviation sequence [$\Delta_{oi}(t)$] for every output (ζ = 0.5) and then the Grey Relational Coefficient is determined by using Equation (3).

$$\gamma\left(x_o^*(t), x_i^*(t)\right) = \frac{\Delta_{\min} + \zeta\Delta_{\max}}{\Delta_{oi}(t) + \zeta\Delta_{\max}} \tag{3}$$

$$0 < \gamma\left(x_o^*(t), x_i^*(t)\right) \leq 1, \quad \Delta_{oi}(t) = \left|x_o^*(t), x_i^*(t)\right|,$$

$$\Delta_{\max} = \max_{\forall j \in i} \max_{\forall t} \left|x_o^*(t), x_j^*(t)\right|, \; \Delta_{\min} = \min_{\forall j \in i} \min_{\forall t} \left|x_o^*(t), x_j^*(t)\right|.$$

ζ is the distinguishing coefficient, $\zeta \in [0,1]$. Where, $x_o^*(t)$ = Reference sequence and $x_i^*(t)$ = Comparability sequence.

In the final step, the Grey Relational Grade is determined by using Equations (4) and (5) and its log S value is calculated for the higher is the better (H-T-B) concept.

$$\gamma(x_o^{(*)}, x_i^{(*)}) = \frac{1}{q}\sum_{t=1}^{q} \beta_t \gamma\left(x_o^{(*)}(t), x_i^{(*)}(t)\right) \tag{4}$$

$$\sum_{t=1}^{q} \beta_t = 1 \tag{5}$$

where q is the number of process responses. The Grey Relational Grade shows the interrelation between $x_o^{(*)}(t)$ and $x_i^{(*)}(t)$.

2.2 Taguchi's Method

Taguchi's Method is a technique usually used to frame-up the orthogonal array of experiments, with less variance between the experiment outcomes. This methodology not only helps to develop the orthogonal array but also minimize the numbers of experimental runs, enough to optimize and analyze the process. There are three kinds of signal-to-noise ratios: lower is the better (L-T-B), higher is the better (H-T-B), and nominal is the better (N-T-B), which is expressed in mathematical forms by Equations (6), (7) and (8). An ANOVA analysis is utilized for data-analysis to investigate the effect of main machining variables on the output responses.

Lower is the better (L-T-B),

$$l_i = -10 \log\left[\frac{1}{n}\sum_{i=1}^{n} y_i^2\right] \tag{6}$$

Higher is the better (H-T-B),

$$l_i = -10 \log\left[\frac{1}{n}\sum_{i=1}^{n} \frac{1}{y_i^2}\right] \tag{7}$$

Nominal is the better (N-T-B),

$$l_i = -10 \log\left[\frac{1}{ns}\sum_{i=1}^{n} y_i^2\right] \tag{8}$$

where y_i is the measured output response at the i^{th} trial, n is the total number of experimental-runs, l_i is the loss-quality function at the i^{th} trial and s denotes the standard deviation.

2.3 Principal Component Analysis

Principal Component Analysis was introduced by Pearson and Hotelling (1933). This methodology is utilized to define the variance and covariance relation with the help of linear composition of original parameters. The PC_1 describes the maximal variance in the collected data and the PC_2 describes the remaining variance that was left by the PC_1 and so on. Suppose, the system-variability is depicted by the p-components. The system variability may be described by a smaller number, m ($m \leq p$), of the PCs, i.e., m PCs can account for the majority of variance within the original p parameters.

For the response variables, Z_1, Z_2 … Z_p, there is the following PCs Y_i (i =1, 2, 3, ..., p).

$$Y_1 = a_{11}Z_1 + a_{12}Z_2 + \ldots + a_{ip}Z_p$$

$$Y_2 = a_{21}Z_1 + a_{22}Z_2 + \ldots + a_{2p}Z_p$$

$$Y_m = a_{m1}Z_1 + a_{m2}Z_2 + \ldots + a_{mp}Z_p$$

where $a_{m1}^2 + a_{m2}^2 + \ldots + a_{mp}^2 = 1$

Here, Y_1 is known as first principal component, Y_2 is known as the second principal component and so on. The m^{th} component coefficient is the parts of the eigenvector matching to the m^{th} biggest eigenvalues. The principal component analysis can be done on MINITAB software.

Principal Component Analysis is an effective methodology to describe the slight number of components that is responsible for the principal sources of variation in a set of correlated-quality characteristics.

The procedure of Principal Component Analysis is as follows:

a) Calculate the signal-to-noise ratio for every output-response by Equations (6) to (8).
b) Normalize the signal-to-noise ratio of every output responses into 0 to 1 by the use of Equations (1) and (2).
c) Carry out principal component analysis on the normalized data.
d) Determine the eigen-values, and eigen-vectors.
e) Calculate the numbers of PCs, m, and compute.

2.4 Fuzzy Method

In this methodology, the fuzzy reasoning grade (FRG_0) is calculated by the use of the max-min fuzzy interface and the centroid defuzzification methods. The system of Fuzzy Logic contains 5 components; Fuzzifier, Membership Function, Rules, Inference System, and Defuzzifier.

The fuzzy-logic-interface system for this research work is developed using MathWorks TM MATLAB® 8.1.0.604 (Release 2013a), Fuzzy Logic Toolbox. Here, the basic structure of the fuzzy logic unit for two fuzzy inputs with one fuzzy output is displayed in **Figure 1**.

Fuzzy linguistic description is the formal presentation of systems made through fuzzy IF-THEN rules.

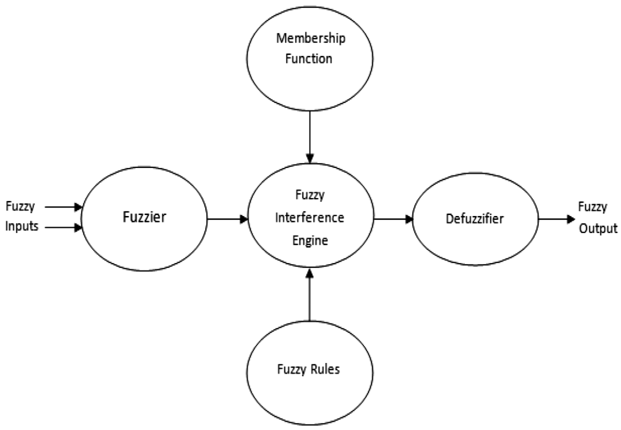

Figure 1: Basic structure of fuzzy logic unit

Rule one: IF (Y_1 is E_1) and (Y_2 is G_1) then (Z is F_1) else

Rule two: IF (Y_1 is E_2) and (Y_2 is G_2) then (Z is F_2) else

Rule twenty five: IF (Y_1 is E_{25}) and (Y_2 is G_{25}) then (Z is F_{25}) else

μ_{Ei}, μ_{Gi} and μ_{Fi} are the membership functions corresponding to the E_i, G_i and F_i fuzzy subsets. In this research work, five fuzzy-subsets are allotted to two inputs and nine fuzzy subsets are allotted to the output as displayed in **Figure 4**. The total possible number of fuzzy rules used here is twenty-five. These fuzzy rules are obtained with the evidence that a bigger log S value corresponds to the major benefit to the process output. Suppose, Y_1 and Y_2 are the values of the inputs, the membership function of the multi-output Z can be displayed by Equation (9).

$$\mu_{F_0}(Z) = \left(\mu_{E_1}(Y_1) \wedge \mu_{G_1}(Y_2) \wedge \mu_{F_1}(Z)\right) \ldots \vee \vee\left(\mu_{E_n}(Y_1) \wedge \mu_{G_n}(Y_2) \wedge \mu_{F_n}(Z)\right) \tag{9}$$

Here, $\wedge$ is related to minimal and $\vee$ is related to maximal operation. For the defuzzification, centre-of-gravity methodology is used, which convert multi-output μ_{C_0} (Z) into crisp fuzzy reasoning grade (FRG_0) using Equation (10).

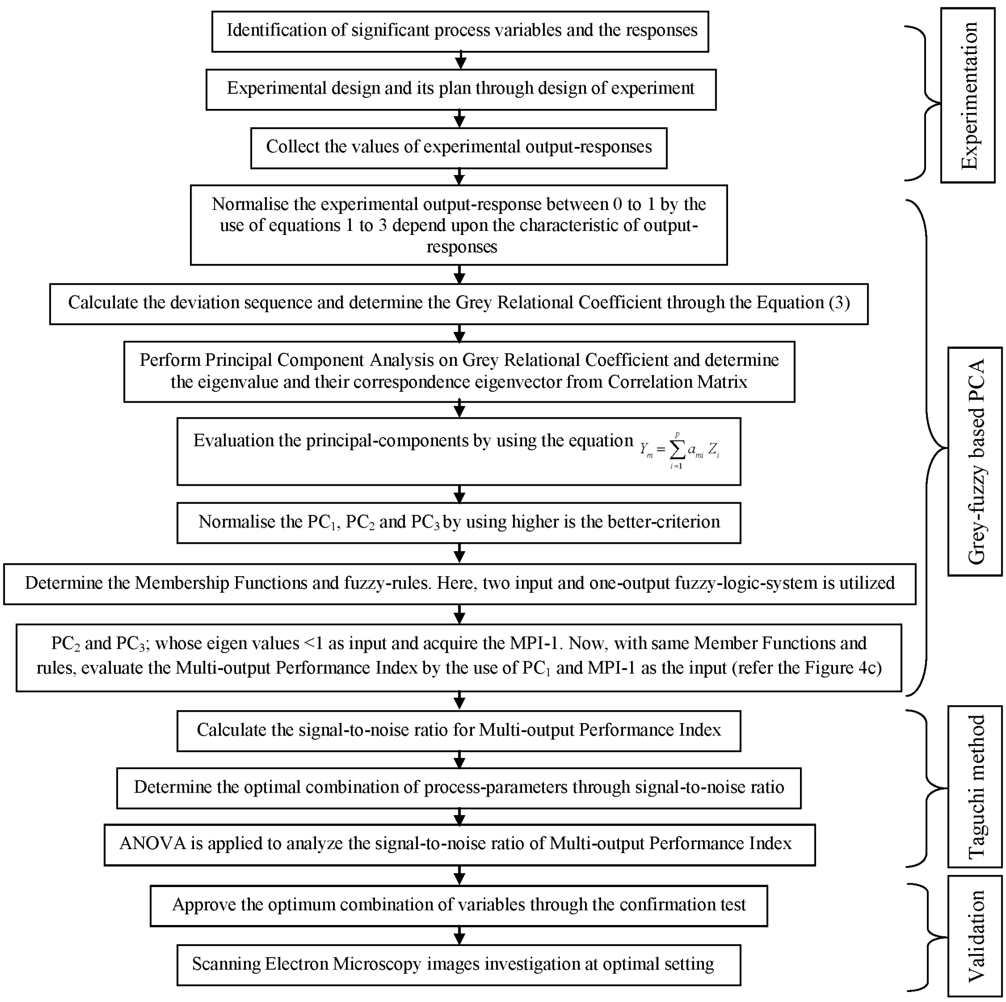

Figure 2: Methodology of Integrated Statistical Grey-Fuzzy-TM based PCA Approach

$$FRG_0 = \frac{\sum Z\mu_{F_0}(Z)}{\sum \mu_{F_0}(Z)} \tag{10}$$

3 METHODOLOGY FOR AN INTEGRATED GREY-FUZZY-TAGUCHI-BASED PCA APPROACH

The detail procedure for an integrated Grey-Fuzzy-Taguchi-based PCA method is shown in **Figure 2**.

4 EXPERIMENTAL PART

Eighteen experiments were conducted according to Taguchi's L_{18} orthogonal array on in-house-designed and fabricated silicon carbide Powder Mixed-Electro Discharge Diamond Surface Grinding set-up. All the details of the Powder Mixed-Electro Discharge Diamond Surface Grinding set-up are available at Modi et al.[17] The schematic-photographic diagram of Powder Mixed-Electro Discharge Diamond Surface Grinding frame-up is displayed in **Figure 3**.

The various input parameters like powder concentration (gm/L), current (A), pulse-on-time (μs), wheel-speed (min^{-1}) and duty cycle (DC) were selected for the experimental investigation. Depending upon the initial experimental results and Electrical Discharge Machining capacity, the variables range was selected as displayed in **Table 1**.

Table 1: Various input variables and their levels

Symbol	Control Factor	Level 1	Level 2	Level 3
P-C	SiC Powder Concentration (gm/L)	2	4	–
I	Current (A)	1	5	9
T_{on}	Pulse-on-time (μs)	100	150	200
S	Wheel Speed (min^{-1})	350	550	750
DC	Duty Cycle	0.61	0.69	0.77

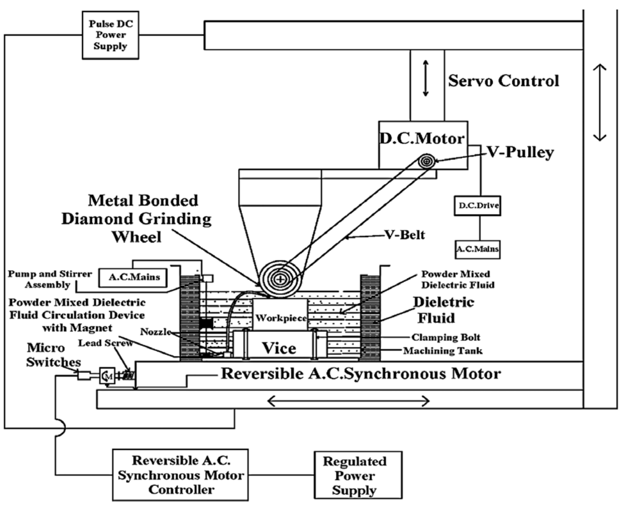

Figure 3: Schematic diagram of in-house-designed and fabricated Powder Mixed-Electro discharge diamond surface grinding set-up

The detailed description of the bronze-diamond wheel is displayed in **Table 2**.

Table 2: Detail description of bronze-diamond grinding wheel

Abrasive	Diameter	Thickness	Bond material	Concentration	Bore	Depth of abrasive	Grit size
Diamond	100 mm	10 mm	Bronze	75 %	32 mm	5 mm	80/100

In this experimentation, the work-piece material was Ti6Al4V. The work-piece is flat and rectangular in shape. The composition of Ti-6Al-4V (grade-5) is Carbon = 0.02 %, Al = 6.05 %, Ti = 90.1 %, V = 3.7 % and Fe = 0.13 %. The silicon carbide powder is added into the dielectric fluid of the EDDSG set-up. The powder particle size is approximately #30 μm and the concentration range is from 2 gm/litre to 4 gm/litre.

Equation (11) was used to calculate the material removal rate and wheel wear rate for each machining process.

$$\frac{MRR}{WWR}(\mathrm{mg/min}) = \frac{DWW \times 100}{t} \tag{11}$$

DWW is the difference in the work-piece/wheel weight before and after the machining time equal to 30 min. The material removal rate and wheel wear rate were measured by using the High Precision Electronic Balance, WENSAR, HPB-310 Model. The surface roughness of the machined work-piece was measured by the Surtronic-25 surface roughness tester at the cut-off value of 0.8 mm. The digital tachometer was used for the grinding wheel speed measurement.

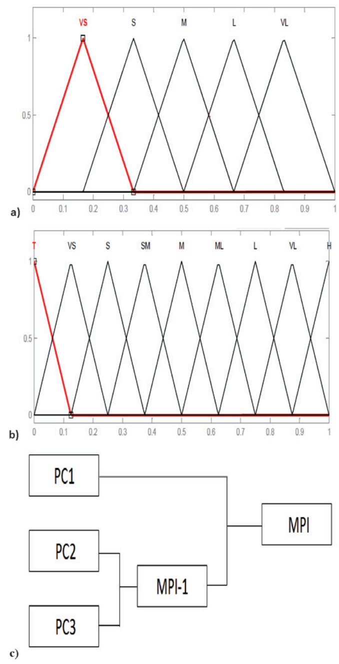

Figure 4: a) Membership function of inputs, b) Membership function of output, c) Fuzzy-Interface system at 2-level

Table 3: L_{18} orthogonal array, output responses, log S value, and normalised log S value

Exp. No	Control Factor					Responses			log S value			Normalized log S value		
	P-C	I	T_{on}	S	DC	MRR (mg/min)	R_a (μm)	WWR (gm/min)	MRR	R_a	WWR	MRR	R_a	WWR
1	1	1	1	1	1	1.50	1.54	0.0078	3.52	–3.75	42.16	0.44	0.21	0.000
2	1	1	2	2	2	1.60	1.33	0.0162	4.08	–2.48	35.81	0.53	0.14	0.387
3	1	1	3	3	3	1.52	1.01	0.0421	3.64	–0.09	27.51	0.46	0.00	0.893
4	1	2	1	1	2	1.66	3.34	0.0083	4.40	–10.47	41.62	0.59	0.59	0.033
5	1	2	2	2	3	1.84	4.61	0.0198	5.30	–13.27	34.07	0.74	0.75	0.493
6	1	2	3	3	1	1.55	3.52	0.0515	3.81	–10.93	25.76	0.49	0.62	1.000
7	1	3	1	2	1	2.20	5.98	0.0289	6.85	–15.53	30.78	1.00	0.88	0.694
8	1	3	2	3	2	1.65	5.37	0.0169	4.35	–14.60	35.44	0.58	0.83	0.410
9	1	3	3	1	3	1.75	6.94	0.0281	4.86	–16.83	31.03	0.67	0.95	0.679
10	2	1	1	3	3	1.59	1.40	0.0137	4.03	–2.92	37.27	0.52	0.16	0.298
11	2	1	2	1	1	1.11	1.05	0.0172	0.91	–0.42	35.29	0.00	0.02	0.419
12	2	1	3	2	2	1.23	1.40	0.0443	1.80	–2.92	27.07	0.15	0.16	0.920
13	2	2	1	2	3	1.86	5.86	0.0110	5.39	–15.36	39.17	0.75	0.87	0.182
14	2	2	2	3	1	1.52	4.07	0.0327	3.64	–12.19	29.71	0.46	0.69	0.759
15	2	2	3	1	2	1.45	2.33	0.0280	3.23	–7.35	31.06	0.39	0.41	0.677
16	2	3	1	3	2	1.60	5.76	0.0104	4.08	–15.21	39.66	0.53	0.86	0.152
17	2	3	2	1	3	1.42	6.63	0.0088	3.05	–16.43	41.11	0.36	0.93	0.064
18	2	3	3	2	1	1.88	7.65	0.0146	5.48	–17.67	36.71	0.77	1.00	0.332

5 PROCESSING OF EXPERIMENTAL DATA

Here, **Table 3** displays the L_{18} orthogonal array, output responses, log S value, and normalised log S value. **Table 4** displays the deviation sequence and Grey Relational Coefficient. **Table 5** displays the eigenvalues, eigenvector. **Table 6** displays the fuzzy rules. **Table 7** displays the principal components and multi-output performance index and **Table 8** displays the response and ANOVA for multi-output performance index.

Figure 5 displays the fuzzy logic reasoning procedure for the test result 8; **Figure 6** displays the surface plot of multi-output performance index with inputs; **Figure 7** displays the % contribution of machining process-parameters on multi-output performance index, and **Figure 8** displays the signal to noise-ratio plot of multi-output performance index.

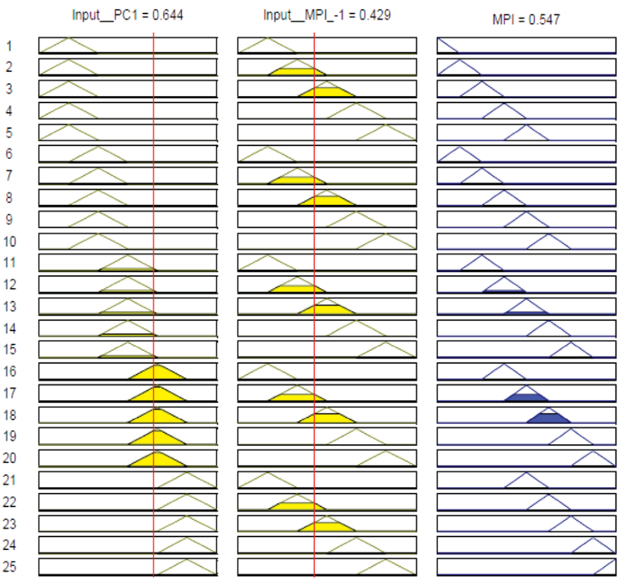

Figure 5: Fuzzy logic reasoning procedure for the test result 8

Calculation of the deviation sequence and Grey Relational Coefficient (GRC).

Table 4: Displays the deviation sequence and GRC

Exp. No.	Deviation sequence			GRC		
	MRR	R_a	WWR	MRR	R_a	WWR
1	0.560	0.792	1.000	0.472	0.387	0.333
2	0.466	0.864	0.613	0.518	0.367	0.449
3	0.541	1.000	0.107	0.480	0.333	0.824
4	0.412	0.409	0.967	0.548	0.550	0.341
5	0.262	0.250	0.507	0.657	0.667	0.497
6	0.512	0.383	0.000	0.494	0.566	1.000
7	0.000	0.122	0.306	0.999	0.805	0.620
8	0.421	0.175	0.590	0.543	0.741	0.459
9	0.335	0.048	0.321	0.599	0.913	0.609
10	0.475	0.839	0.702	0.513	0.373	0.416
11	1.001	0.981	0.581	0.333	0.338	0.463
12	0.850	0.839	0.080	0.370	0.373	0.862
13	0.246	0.132	0.818	0.670	0.792	0.379
14	0.541	0.312	0.241	0.480	0.616	0.675
15	0.610	0.587	0.323	0.451	0.460	0.608
16	0.466	0.140	0.848	0.518	0.781	0.371
17	0.640	0.071	0.936	0.438	0.876	0.348
18	0.230	0.000	0.668	0.685	1.000	0.428

Principal Component Analysis for eigenvalue and eigenvector.

Table 5: Displays the eigenvalues, and eigenvector

	PC_1	PC_2	PC_3
Eigenvalue	1.6666	0.9246	0.4089
Eigenvector	[0.640, 0.681, –0.354]	[–0.383, 0.117, 0.916]	[–0.666, 0.722, 0.186]
Proportion	0.556	0.308	0.136
Cumulative	0.556	0.864	1.000

Primarily, the principal components (PCs) are divided into two categories with eigenvalue > 1 and eigenvalue < 1. MPI-1 is calculated through PC_2 and PC_3 as input with eigenvalue < 1. Final multi-output performance index is calculated through PC_1 and MPI-1 as the input by using the similar membership functions and rules.

Table 6: Twenty-five fuzzy rules in tabular form

MPI	Input 1					
	VS	S	M	L	VL	
Input 2	VS	T	VS	S	SM	M
	S	VS	S	SM	M	ML
	M	S	SM	M	ML	L
	L	SM	M	ML	L	VL
	VL	M	ML	L	VL	H

The Fuzzy logic reasoning procedure for the test result 8 is displayed in **Figure 5**. The surface plot of the multi-output performance index is displayed in **Figure 6**.

Calculation of multi-output performance index (MPI).

Table 7: Principal Components and multi-output performance index (MPI)

Exp. no.	Principal components			Normalise PCs			MPI-1	MPI
	PC_1	PC_2	PC_3	PC_1	PC_2	PC_3		
1	0.448	0.531	0.027	0.335	0.000	0.059	0.500	0.379
2	0.423	0.653	0.003	0.302	0.190	0.000	0.500	0.348
3	0.242	0.978	0.073	0.072	0.698	0.175	0.417	0.188
4	0.605	0.587	0.095	0.535	0.087	0.230	0.103	0.285
5	0.699	0.785	0.136	0.656	0.397	0.332	0.300	0.458
6	0.348	1.171	0.265	0.207	1.001	0.652	0.500	0.287
7	0.968	1.045	0.031	1.000	0.803	0.069	0.464	0.500
8	0.690	0.715	0.258	0.644	0.288	0.637	0.429	0.547
9	0.790	0.894	0.373	0.772	0.567	0.922	0.809	0.875
10	0.435	0.621	0.005	0.319	0.141	0.004	0.060	0.124
11	0.279	0.591	0.108	0.119	0.094	0.262	0.112	0.042
12	0.186	0.975	0.182	0.000	0.694	0.447	0.609	0.500
13	0.834	0.696	0.196	0.829	0.258	0.481	0.298	0.591
14	0.488	0.874	0.250	0.386	0.536	0.616	0.617	0.503
15	0.387	0.783	0.144	0.257	0.395	0.352	0.322	0.191
16	0.732	0.630	0.288	0.698	0.154	0.710	0.414	0.594
17	0.754	0.589	0.405	0.726	0.091	1.003	0.500	0.675
18	0.968	0.771	0.345	1.000	0.376	0.853	0.662	0.500

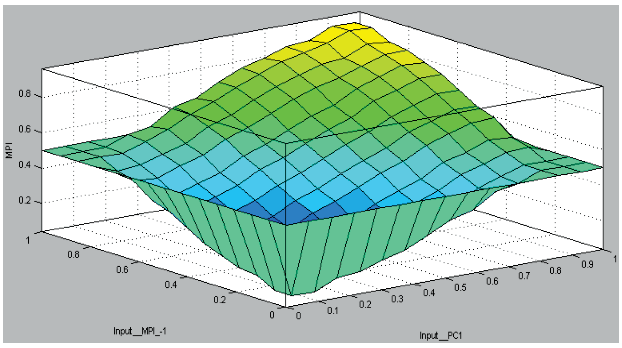

Figure 6: Surface Plot of MPI with inputs

6 RESULTS AND DISCUSSION

The ANOVA test was performed on the multi-output performance index. The influence of various machining process parameters on the multi-output performance index and the ANOVA analysis result is displayed in **Table 8**. The optimum combination of various process parameters obtained through the integrated statistical optimization method for the multi-output optimization in Powder Mixed-Electro Discharge Diamond Surface Grinding of Ti6Al4V, is powder concentration with level one; current with level three; pulse-on-time with level three; the speed with level two and duty cycle with level three. For the validation test, one additional confirmation experiment was performed on this set-up according to the derived optimal condition and the outcomes of the result showed satisfactory matching between predicted and experimented results. The confirmation test result is listed in **Table 9**, which displays the closure correlation between the experimental and predicted values.

A Scanning Electron Microscopy investigation has been conducted on the produced machine surface through silicon carbide powder mixed-Electro Discharge Diamond Surface Grinding process under optimal condi-

Table 8: Response and ANOVA for multi-output performance index (MPI)

Response table				Symbol	ANOVA table					
Level 1	Level 2	Level 3	Max-Min		DF	SS	MS	F	P	C (%)
–8.118^{p}	–10.062		1.945	P-C	1	0.001200	0.001200	0.03	0.860	0.258
–13.967	–8.907	–4.397^{p}	9.570	I	2	0.382457	0.191229	5.26	0.035	82.47
–8.763	–9.685	–8.823^{p}	0.922	T_{ON}	2	0.000869	0.000435	0.01	0.988	0.187
–10.970	–6.430^{p}	–9.871	4.540	S	2	0.037324	0.018662	0.51	0.617	8.049
–10.802	–8.373	–8.096^{p}	2.707	DC	2	0.041857	0.020929	0.58	0.584	9.026
				Error	8	0.291024	0.036378			
				Total	17	0.754733				

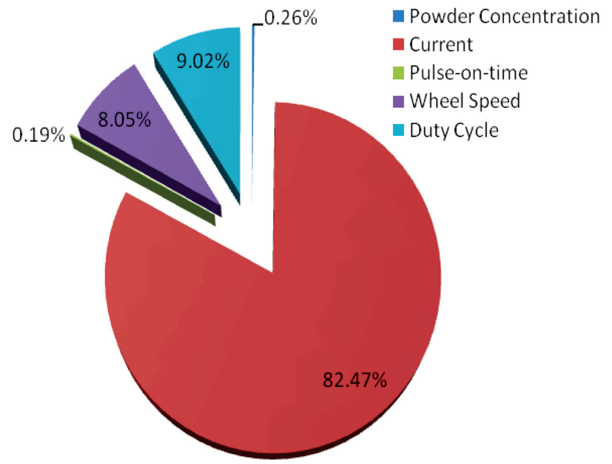

Figure 7: Percentage contribution of machining process parameters on MPI

Table 9: Result of confirmation test

Factor Level	Initial Process Parameters	Optimal Process parameter	
		Prediction	Experiment
	$PC_1I_1T_{on_1}S_1D_1$	$PC_1I_3T_{on_3}S_2D_3$	$PC_1I_3T_{on_3}S_2D_3$
MRR (mg/min)	1.50	-	1.86
R_a (µm)	1.54	-	6.00
WWR (gm/min)	0.0078	-	0.024
MPI	0.379	0.739	0.754
Improvement in MPI is 0.375			

tions. **Figure 9** displays the SEM image of the: a) produced machined surface at optimum condition (I = 9 A, T_{on} = 200 µs, DC = 0.77, S = 550 min^{-1}, P-C = 2 gm of powder/L); b) White recast layer thickness at optimum condition (I = 9 A, T_{on} = 200 µs, DC = 0.77, S = 550 RPM, P-C = 2 gm of powder/L). These images revealed that satisfactory output-responses are acquired through the suggested integrated statistical methodology.

6.1 Confirmation test

The estimated grade

$$\hat{\gamma}=\gamma_m+\sum_{i=1}^{n}(\bar{\gamma}_i-\gamma_m) \quad (12)$$

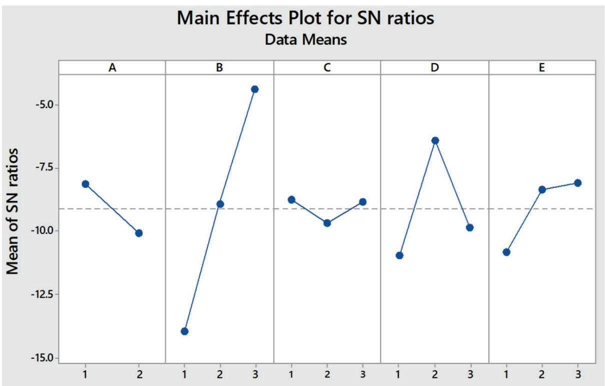

Figure 8: S/N-ratio plot of MPI

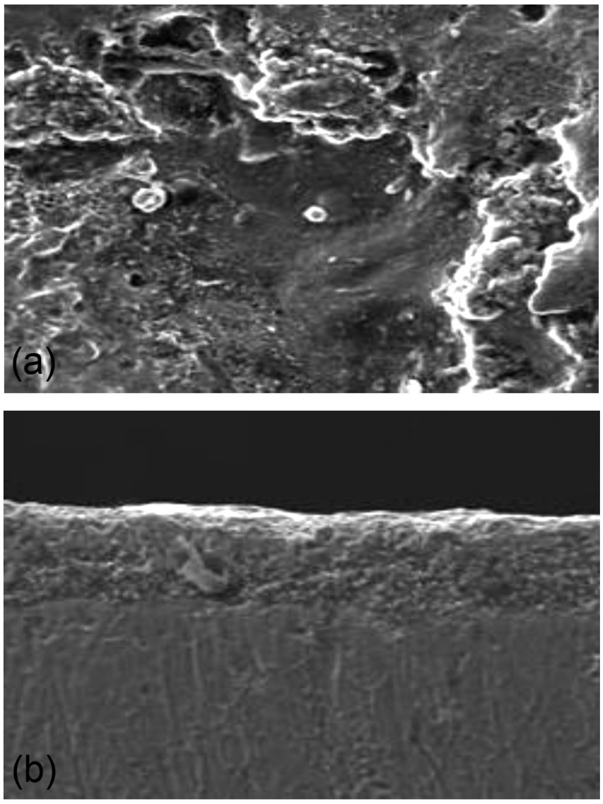

Figure 9: a) SEM image of the produced machined surface in Powder Mixed - EDDSG process with SiC powder under optimum conditions (I = 9 A, T_{on} = 200 µs, DC = 0.77, S = 550 min^{-1}, P-C = 2 gm of powder/L), b) SEM image of wrlt thickness with SiC powder under optimum conditions (I = 9 A, T_{on} = 200 µs, DC = 0.77, S = 550 min^{-1}, P-C = 2 gm of powder/L).

where γ_m is the average grade, $\bar{\gamma}_i$ is the optimum level average grade and 'n' is the total significant design variables that affect the multi-output response. To ensure the enhancement in quality performance, a confirmation test is performed. The outcome of this test is displayed in **Table 9**.

7 CONCLUSIONS

In this research paper, an integrated statistical methodology of Grey-Fuzzy-Taguchi's Method based principal component analysis has been utilized for multi-output optimization of the machining parameters in silicon carbide powder mixed-Electro Discharge Diamond Surface Grinding processes of Ti6Al4V. The single multi-output performance index is calculated by the aggregation of all multi-responses through Grey-Fuzzy-Taguchi's Method-based principal component analysis function. Hence, ANOVA is applied on multi-output performance index to calculate the signal-to-noise ratio with Higher is the Better criterion.

The following conclusions could be drawn based on the analysis of outcomes obtained through the suggested approach and SEM image investigations:

1. The optimal level of machining process parameters derived from the integrated statistical methodology of Grey-Fuzzy-Taguchi's Method-based principal component analysis approach are: 2 gm/L of powder concentration; 9 A of current; 200 µs of pulse-on-time; 550 revolution per min (min^{-1}) of wheel speed and 0.77 of duty cycle.

2. The experimental results of output responses under optimal condition are material removal rate equal to 1.86 mg/min; R_a equal to 6.00 µm; and wheel wear rate equal to 0.024 gm/min.

3. It is observed through ANOVA results that the percentage contribution of various process parameters on the process performance is powder concentration (0.26 %); current (82.47 %); pulse-on-time (0.19 %); wheel speed (8.05 %); and duty cycle (9.02 %). The current is the most significant parameter that affects the process performance.

4. The Multi-output Performance Index has been improved by 0.375.

5. The SEM outcomes also equally satisfy the predicted outcomes from the suggested integrated statistical methodology.

The suggested integrated statistical method may also be utilized to optimize the problem of the co-occurring optimization of multi-correlated responses in some other production machining processes to improve the production efficiency and also automate the production machining process based on the calculated optimum values.

Nomenclature

ANOVA	Analysis of variance
PM-EDDSG	Powder Mixed-Electro Discharge Diamond Surface Grinding
HM	Hybrid Machining
EDG	Electro Discharge Grinding
EDM	Electrical Discharge Machining
HMP	Hybrid Machining Process
RSM	Response Surface Methodology
DC	Duty Cycle (%)
DWW	Difference in work-piece/wheel weight before and after the machining
WEDM	Wire Electrical Discharge Machining
I	Current (A)
MRR	Material Removal Rate (mg/min)
WWR	Wheel Wear Rate
R_a	Average Roughness of Surface (µm)
MIN^{-1}	Revolution per minute
S	Wheel Speed (MIN^{-1})
T_{on}	Pulse on-time (µs)
t	Time in min
ρ	Density of work-piece material (gm/cm^3)
P-C	Powder Concentration
OA	Orthogonal Array
CM	Correlation Matrix
GRA	Grey Relational Analysis
PCA	Principal Component Analysis
a_{mp}	m_{th} element in the p_{th} eigen vector
TU-Theory	Taguchi's Utility Theory
OQI	Overall Quality Index
H-T-B	Higher is the better Criterion
L-T-B	Lower is the better Criterion
N-T-B	Nominal is the better Criterion
GRC	Grey Relational Coefficient
GRG	Grey Relational Grade
TM	Taguchi's Method
PC/PC$_S$	Principal Component / Principal Components
MF/MF$_S$	Membership Function/Membership Functions
MPI	Multi-output Performance Index

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