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A novel optimization algorithm on surface roughness of WEDM on titanium hybrid composite

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Abstract. Titanium based alloys and composites have excellent strength and stability in high thermal condition, excellent resistance to creep, wear and corrosion, light weight and bio-compatible properties and are extensively used in defence, aerospace, spacecrafts, marine, automobile, sports and bio-medical applications. This paper presents an investigation based on a novel optimization algorithm called desirable grey relational analysis (DGRA) where experimental analysis is done on wire electro-discharge machining (WEDM) of a developed novel titanium hybrid composite having enhanced corrosion resistance, wear resistance, improved tribological and biocompatible properties than pure titanium, fabricated by laser engineered net shaping (LENS) process varying peak current (Ip) and pulse duration (PD) as main input process parameters. A mathematical model is proposed based on 2 factors 4 levels design of experiments on output response like surface roughness (SR) and satisfactory results are obtained and authenticated by the confirmatory test. Deionized water is used as dielectric medium. Diffused zinc-coated brass wire is used as tool electrode. SR enhances with the enhancement of Ip but reduces with PD. The process model is prepared and the optimum process parameters are hence determined. The best SR obtained experimentally is 1.31 μm (Ip, 3A, PD, 4 μs). One optimized solution is obtained where Ip is 4.666 A, PD is 17.092 μs, SR is 1.742 μm, standard error (StdErr) of Design is 0.049 and Desirability is 0.900. The novelty lies in the combination of desirability function and grey relational analysis where experimental SR measured at optimized condition gets improved by 2.78% by desirability approach and further improves to 7.29% when predicted with DGRA.

Keywords. WEDM; titanium hybrid composite; process parameters; surface roughness; optimization; desirable grey relational analysis.

1. Introduction

Titanium hybrid composites (THCs) are light, strong and durable with excellent strength and stability in high thermal condition, excellent resistance to creep, wear and corrosion. They are highly used in various industries like defence, biomedical applications, automobile, aerospace, chemical, food industries, etc. by Gu *et al* [1]. Nowadays, titanium is widely used for manufacturing different medical equipments for its excellent bio-compatibility with bone growth and other tissues. Titanium is used in diverse medical purpose like, bones, hips, dental problems and knees replacement enucleation and has an assortment of various other surgical instruments by Elias *et al* [2]. There are also few limitations like high initial cost, availability and ease of manufacturability by Kumar *et al* [3]. The authors used response surface methodology (RSM) in Box–Behnken design (BBD) with desirability function on WEDM on pure titanium and obtained pulse-on time, pulse-off time and peak current to be the major factors affecting the output responses like material removal rate (MRR), wire wear (WW) ratio and dimensional deviation. The authors then obtained enhanced dependency of these process parameters affecting the surface integrity, SR and wire rupture [4, 5]. The researchers again studied the thickness of recast layer and surface crack density [6] and examined the dependency of the same contributing factors by multi-objective optimization using Taguchi method and RSM. Machining these composites by conventional machining methods is extremely difficult because of occurrence of rough surface finish at elevated temperature causing excessive wear. The microstructure, corrosion and fatigue behavior of titanium varying different environmental conditions was deliberated by Saji *et al* [7] and Fleck *et al* [8]. In biomedical research

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machining titanium with maximum precision but in minimum time is an important issue. WEDM uses electrical as well as thermal responses for precision machining of conductive materials. Manjaiah *et al* [13] provided combined information in the application of electric-discharge machining (EDM) and WEDM on titanium based alloys and composites and identified the research gaps. The review also provided knowledge on different optimization processes and highlighted on the analysis of surface integrity like SR, surface topography, surface metallurgy, layer formation and residual stress generation in WEDM on titanium based composites. Various researchers studied about the developments of THC using induction skull melting (ISM) like Niu *et al* [9], powder metallurgy (PM) like Lin *et al* [10], and other powder sintering process [11, 12] but failed to obtain better hybrid composites. But here lies the limitation of fabrication of complex shapes by ISM, PM and other powder sintering methods. Therefore, LENS process is proposed for better feasibility of the development of THC which is socially viable which has feasibility and acceptance in social environment.

LENS [16–20] occupies powdered ceramics or metals for manufacturing precision functional parts. It creates complex, net-shape components in an exceedingly superior approach unswervingly from powders with negligible post processing, boosting up the manufacturing process. In LENS, a "layer by layer" or a "line by line" mechanism is employed for the fabrication of the components by the geometry obtained from computer aided design. The powdered metal is provided just at the focus of the laser beam with the help of the nozzle-deposition technique. Hence, powder feed rate is the most vital deposition parameter during LENS as obtained by Attar *et al* [16]. The most important advantage of using LENS is to produce intricate and graded hollow components combining different supplies using multiple powder feeders. LENS is used for recommissioning of damaged components previously considered unrepairable. THCs have a wide range of applications in industrial and manufacturing world; therefore LENS usage for such novel hybrid composite fabrication is mandatory. Better developments of microstructure formation of THCs during LENS were obtained [17–19]. Qiu *et al* [20] stated that optimization is very indispensable to obtain parametric optimal solution for successful fabrication of THCs by LENS. Padhee *et al* [21] used powder mixed EDM and conducted experiments on EZNC fuzzy logic die sinking EDM where the authors used copper electrode for machining. RSM was used in multi objective parametric optimization and obtained optimal process parameters. The authors used non-dominated sorting genetic algorithm (NSGA) for optimization, but since the output responses like MRR and SR were conflicting, hence a large research gap was created in the optimality process. Garg *et al* [22] used RSM technique on WEDM analysis on machining parameters of Inconel 625 which is vastly used in automobile and aerospace industries. Multi-objective optimization was used using desirability approach to obtain best machining conditions. The authors obtained greater significance of pulse-on and pulse-off time while spark gap voltage and wire feed were of lesser significance on the output responses like SR, gap current and cutting speed. Though the experimental results proved to be satisfactory but the research gap lies on the WEDM machining on LENS process of THC. Ghodsiyeh *et al* [23] investigated experimentally on the surface integrity after WEDM on Ti–6Al–4V and obtained increased MRR with fine surface finish. Taguchi method was implemented for design of experiments (DOE) and optimal condition was obtained using RSM. Kavimani *et al* [24] investigated the impacts of MRR and SR for novel magnesium composite and obtained the optimal solution using Taguchi method coupled with Grey relation analysis.

Numerous researchers have endeavored for the improvement of the performance of WEDM of titanium and its hybrid composites but have not yet concluded the optimal process parameters when developed by LENS. From the literature it is identified that various input process parameters are used for determining the optimal output responses, but very few have examined the dependency of Ip with PD on the SR. Hence, in this paper, the optimal process parameters for better surface finish using WEDM on THC are determined experimentally and compared with the past works. There is an increment of temperature throughout the machining of titanium as it is highly reactive to chemical agents influencing the wire breakage at the interface of tool and workpiece region. The major scope here is to analyze the WEDM performance parameters of THC with the input process parameters by optimization of machining parameters to acquire excellent machining condition in stipulations with SR. Therefore, 2 factors 4 levels DOE is premeditated using RSM design matrix. RSM is used because it reduces the trivial experimental runs and minimizes the error by considering more than one central point. RSM is the most flourishing statistical approach for the expansion of interactive and quadratic effects among the variables which maximizes the production by optimization. RSM facilitates in decision making under uncertainty circumstances plummeting ambiguity by maintaining a towering efficiency with respect to economical cost, time and other practical limitations. A 2^4 arrangement of run-orders is used in full quadratic mathematical model depending on the experimental results and optimization is done based on RSM. The novelty lies in the proposed algorithm of the optimization technique called desirable grey relational analysis (DGRA) which is a combination of desirability function and grey relational analysis where machining is carried on a new THC developed by LENS process which minimizes the error and validates with the experimental results. This developed novel hybrid composite possesses enhanced corrosion resistance, wear resistance, improved tribological and biocompatible properties when compared to pure titanium

[3–6] to make complex shapes for various industrial applications.

2. Experimental methodology

A developed novel TiNiCu THC is developed as the experimental sample whose main components by wt% is C(0.008), Fe(0.25), Al(2.5), Cu(5.0), Zr(1.5), Cr(0.5), V(0.5), H(0.1), Ni(39.5), and rest is Ti. The composite is developed by using a 500 W fiber laser doped by ytterbium in LENS (MR7, Optomec, United States of America) with continuous wave. The sample powders are kept in a box containing argon (Ar) and oxygen (O_2) lesser than 10 ppm by using laser power from 150 to 400 W, with a scan speed ranging in between 10 and 15 mm/s and the powder feed rate is kept constant at 2.4 g/min. The developed novel cylindrical specimen of diameter 11 mm and height 16 mm is used before and after the experiments is shown in figure 1.

Diffused zinc-coated brass wire whose wire diameter is 0.25 mm is used here. Figure 2 represents the schematic diagram of WEDM. The run orders of the experiments are carried out using CNC WEDM (model: AF 35/ONA; capacity: 1060 mm $\times$ 750 mm $\times$ 400 mm and UV axes: 120 $\times$ 120 with 1500 kg; accuracy achievable: $\pm$ 0.005) which is depicted in figure 3.

WEDM employs a wire as the tool electrode with electro-thermal mechanism for precision manufacturing. Both the tool electrode and the workpiece are inundated in dielectrics. The dielectric acts as an electrical insulator and then machining occurs with the occurrence of the electrical discharge. A gap is created on the wire advancement towards the workpiece and higher voltage is generated breaking the dielectric and generating the electrical discharge initiating a spark between the wire and workpiece interfaces. The dielectric becomes an ionized gas and turns into plasma bubble. The plasma bubble collapses, vigouring the cutting material to disperse into the dielectric, creating small craters leading to wire failure and rupture. This process continues approximately around 2,40,000 times per second removing the metal and a precision cut is formed. A flushing flow of dielectric acts as a coolant of the wire removing the scattered particles. As the wire erodes, a WEDM machine continuously supplies un-sullied wire from a reel and dumps the used eroded wire to trash bin for recycling. Two input process parameters taken in the DOE are Peak Current (A) of four levels 3, 6, 9 and 12 denoted by the factor A and Pulse duration (μs) of 4, 24, 50 and 100 denoted by the factor B. Both of these two input process parameters and SR as output response are considered as there is no available literature of WEDM on this developed THC from LENS process.

3. Results and discussions

3.1 *Material Removal Rate (MRR)*

MRR involves in the productivity of all manufacturing industries. It is the rate of removed quantity of the workpiece material when machining time is considered (mm^3/min); hence the characteristic efficiency of the machine is determined. From figure 4, it is observed that higher MRR is obtained with deionized water than with kerosene. It is primarily because of the adherence of carbon to the tool surface which defends the tool electrode's erosion in case of deionized water. But with kerosene, dense abrasives get accrued in the inter-electrode gap causing instability in the discharge. The increment of MRR in case of deionized water is due to the increment of the discharge current (power) as the removal of the material is easily obtained by increasing the density of the current [11]. The MRR increases and reaches a threshold value with increase in pulse on time duration but then decreases. For higher MRR, Ip, pulse-on time and PD are the main input process parameters and the other factors are less significant according to past literature [3–6]. This is mainly due to the increment of plasma channel and sufficient current density for proper stable discharge to the threshold value and decreases beyond due to occurrence of large carbon content forming large amount of recast layer. At high PD, increase

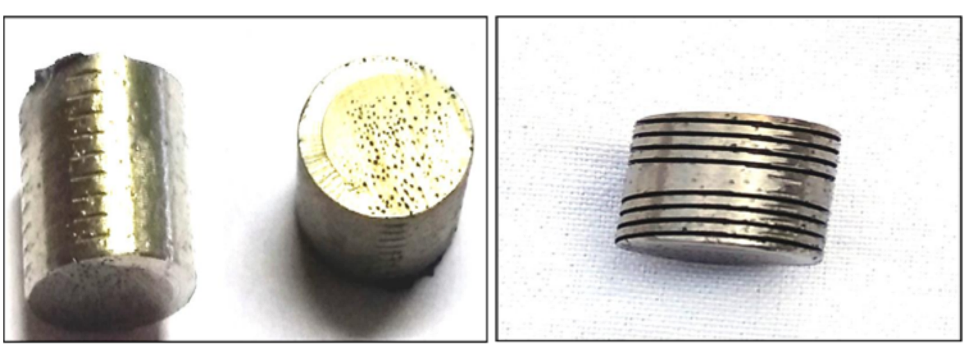

Figure 1. Titanium hybrid composite sample before and after WEDM.

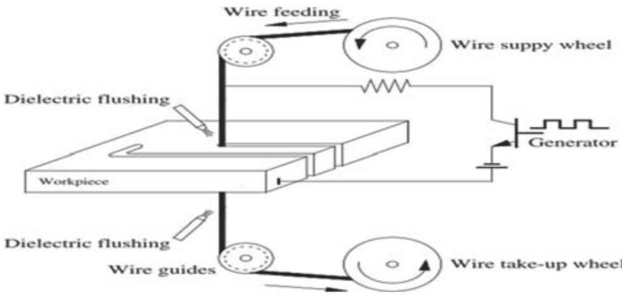

Figure 2. Schematic diagram of WEDM.

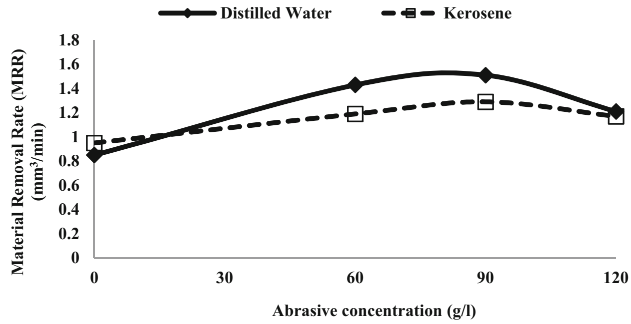

Figure 4. MRR obtained in different dielectrics.

in the localized temperature decomposes the carbon leading to lower the MRR value. It is also unswervingly proportional to the discharge pulse energy which is again dependent upon the servo voltage and capacitance. Thus, at elevated voltage wider gap is formed, leading to high discharge. The capacitance establishes the frequency, larger crater forms at the lower frequency. MRR is also affected largely by hardness. Lower hardness and melting temperature cause higher MRR which is determined by Niu *et al* [9]. According to Lin *et al* [10], higher MRR is obtained with the increment in PD. MRR also augments with the amplification in Ip. The MRR enhances linearly with the PD with deionized water, but enhances non-linearly up to the optimum zone and then reduces when kerosene is used. Electrode wear ratio (EWR) amplifies with PD with kerosene rather than deionized water as obtained by Chen *et al* [11]. This paper also provides a comparative correlation using kerosene and deionized water with silicon carbide (SiC) abrasive concentration as dielectrics. It is observed from figure 4, the maximum value of MRR is obtained after using 90 g/l SiC concentration in the dielectric fluid. MRR decreases beyond this value due the occurrence of greater amount of abrasive particles and large carbon content which forms large amount of recast layer on further increment of SiC concentration. But, the optimization on MRR is not obtained in this paper because the kerf width is not yet considered by varying the given process parameters.

3.2 *Surface Roughness (SR)*

SR is another important parameter which has a great impact on the performance characteristics of the machined components. It mainly varies with the discharge current followed by PD. Low discharge current and PD results in better SR. Proper selection of tool material is essential as SR depends on it. PD highly affects SR. From figure 5, it is evident that the experimental SR directly depends on

Figure 3. Experimental set-up of WEDM.

PD, higher the PD more is the SR, and it has been validated by the past research works [4–6, 13]. Increasing PD enhances the feed rate thus allowing greater discharge energy penetrating into the surface of work-piece material forming deep crater wear. SR augments with the discharge current for any material of the WEDM electrode. SR hence enhances with the discharge current. The best 'Ra' value obtained experimentally is 1.31 µm (Ip, 3A, PD, 4 µs).

Improved surface finish can be accomplished at elevated values of servo speed because of rapid erosion of particles. An augmentation in servo voltage amplifies SR because of more number of collisions between ions and electrons resulting in higher MRR. Therefore, for the sake of better surface finish, low standard value of servo voltage is required. Higher the pulse-off time, lower is the value of SR. The higher pulse-off time supplies better cooling effect and sufficient time to flush the unwanted debris. High dielectric pressure results in total removal of particles resulting in better surface finish. Low wire speed causes more melting of material due to higher energy and hence high MRR is obtained causing high SR. High wire speed causes instability in machining as less energy density occurs resulting in lower melting of material causing irregularities in the surface. Therefore, to obtain better surface finish, optimum wire speed is necessary [13]. Low wire tension is the root cause of amplified vibration during the machining, and high wire tension may result in breakage. The wire feed rate is another important dependant parameter affecting SR. Improved surface finish can be attained with the inferior machine feed by Alias *et al* [12].

3.3 *Optimization*

Optimization is done on input process parameters like peak current (A) and pulse duration (B) to obtain the best machining condition depending on the response of SR. A 2^4 combination of run-orders in a full quadratic mathematical model based on RSM is employed for optimization [14, 15]

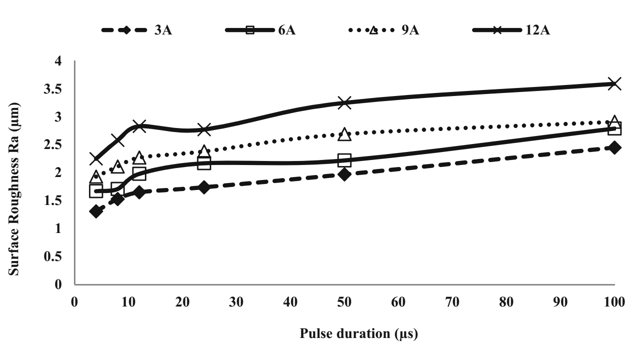

Figure 5. Experimental SR with variation of peak current and pulse duration on WEDM.

in Design Expert 11 software of DOE. In this paper, RSM is applied to develop the mathematical model in multiple regression form of equation for linear, quadratic and interactive effects of performance measures on WEDM. The response is dependent on the quantitative variables (process parameters) and is interpreted as a surface where the mathematical model is fitted. 16 runs/ set of experiments are performed as per RSM on titanium composite where straight slots are cut on the sample to measure the SR by Mitutoyo SJ 210. The second order response surface can be expressed by the Eq. (1):

$$Z = a_o + \sum_{i=1}^{m} a_i x_i + \sum_{i=1}^{m} a_{ii} x_i^2 + \sum_{i=1, j>1}^{m} a_{ij} x_i x_j + e \tag{1}$$

where Z is the output response (SR), a_o, a_i, a_{ii}, a_{ij} are the regression coefficients, m is the number of experimental factors, i represents the linear effect, j represents the quadratic effect, $x_i \& x_j$ represents the interactive effects on the variables and e is the random error which is randomly distributed with normal distribution with expected value as zero.

3.3a *Desirability (D)*: The desirability method [3–5, 22] is highly recommended as it is the simplest form of algorithm and highly flexible in weightage and importance for individual response. This approach transforms each response into utility bounded by the domain $0 < d_i < 1$; where d_i is the individual desirability of the response where higher this value represents more desirable. Only minor assumptions about utility is required related to criteria weights and partial value functions like preference related to independence of criteria, interval scale property and criteria weights as scaling constants [25]. The shape of the desirability function is dependent on the weight fieldw_i. Weights greater than 1 represent more emphasis on a goal and less than 1 represents less emphasis. In this paper, weightage factors are assigned to 1 which signifies the desirability under the domain of 0 to 1 of the single output response SR. In the overall desirability function D, each response can be allotted as importance r which is relative to the other responses as indicated in the Eq. (3). Importance greater than 3 represents a higher importance, 3 being neutral and 1 signifies lower importance. In this paper SR is considered to be of maximum importance assigned to 5. For maximum goal, desirability is defined as per Eq. (2):

$$d_i = \begin{cases} 0; & Z_i < \mathrm{Low}_i \\ \left(\dfrac{Z_i - \mathrm{Low}_i}{\mathrm{High}_i - \mathrm{Low}_i} \right)^{w_i}; & \mathrm{Low}_i < Z_i < \mathrm{High}_i \\ 1; & Z_i > \mathrm{High} \end{cases} \tag{2}$$

For minimum goal, only the boundary 0 and 1 replaces the position in the same boundary conditions. The overall desirability function is expressed as:

$$D = \left(\prod_{i=1}^{n} d_i^{r_i} \right)^{\frac{1}{\sum r_i}} \tag{3}$$

where Z is the output response, n is the number of responses and r_i is the target value in the i^{th} response. The importance is same; therefore D is the geometric mean of d_i [22, 25] as given in Eq. (3) and it can obtain one or more than one point for numerical optimization. The contour plots and 3-D response surface of SR have been plotted depending on the fitted mathematical model as shown in Eq. (4):

$$SR = +2.55 + 0.5397\mathrm{A} + 0.5542\mathrm{B} + 0.0387\mathrm{AB} + 0.0802\mathrm{A}^2 - 0.2258\mathrm{B}^2 \tag{4}$$

Equation (4) is used for prediction purpose of the output responses at specified levels of the factors, which helps in recognizing the relative impact of the factors. Table 1 represents the Analysis of variance (ANOVA) table for SR. Main focus is given on maximizing R^2 value and minimizing the difference of the model's Adj R^2 and the Pred R^2. The F-value obtained is 76.81 and corresponding P-value is <0.0001 that entails the significance of the model as P-values less than 0.05 indicates the model's significance. Only a 0.01% chance lies for the occurrence of noise. Here, A, B, B^2 are significant model terms as the P-values of these factors are less than 0.05. P-values larger than 0.1 signify the model terms and are not significant like AB (0.479) and A^2 (0.253) [23]. The Pred R^2 of 0.9319 is in reasonable agreement with the Adj R^2 of 0.9619 where the variation is only 0.03 which has to be under 0.2. R^2 is 0.9746 and Adeq Precision is 30.4102. Adeq Precision computes the signal to noise ratio. A ratio superior than 4 is desirable. 30.410 ratio designates a sufficient signal. This model can be developed and employed to navigate the design space.

Figure 6 indicates a close conformity of the actual and predicted values which clearly endows that the results obtained after the experimentation are in mitigation with the predicted values. Figure 7 represents the Box-Cox plot for power transforms which portrays the best lambda to be 0.44, current lambda to be 1.0 and CI for lambda is (-0.71, 1.91) which is inside the domain space signifying that the model is appropriately fitted in the design space and needs no transformation. Figure 8 depicts the contour plot of SR which indicates that there is an increment of SR with the augmentation of Ip and PD which has to be minimized by optimization. Figure 9 represents the decrement of std error of design whose lower limit is 0.0494867 and upper limit is 0.097679 which is very nominal.

3.3b *Desirable Grey Relational Analysis (DGRA)*: Grey relational analysis (GRA) is based on grey system theory invented by Prof. Deng (1982) in which the information quality and quantity form a continuum from nil to complete information like from black through grey to white. For such complex multi parametric optimization, various multi-criteria decision making techniques are used in statistical analysis for obtaining best and optimal set of results with least cost and maximum productivity. In the present investigation, a novel optimization algorithm named as desirable grey relational analysis (DGRA) is proposed for the improvement of the optimal results found from the desirability approach. The prime novelty lies in its dual optimization technique where the predicted response obtained from desirability function is coupled with GRA, something that has not been done by past researchers. Therefore, Taguchi method coupled with DGRA is espoused in this paper to identify the most important and influencing process parameter with the output response. The main advantage of DGRA is that it considers the predicted response obtained from desirability method with the actual experimental responses and all are coupled with GRA, hence the number of responses can be increased even in single objective optimization problem. Therefore more accuracy is obtained in this method with enhanced percentage of improvement. The steps of DGRA are as follows:

Step 1: Normalization: The normalization for the output response is calculated on the basis of the requirement and rated within 0 to 1. Here, both the experimental SR and

Table 1. Analysis of variance (ANOVA) results for the responses.

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	5.3	5	1.06	76.81	< 0.0001	*
A-Peak Current	2.48	1	2.48	179.74	< 0.0001	*
B-Pulse Duration	2.71	1	2.71	196.45	< 0.0001	*
AB	0.0075	1	0.0075	0.5408	0.479	
A^2	0.0203	1	0.0203	1.47	0.253	
B^2	0.1493	1	0.1493	10.81	0.0082	*
Residual	0.138	10	0.0138			
Cor Total	5.44	15				
R^2 = 0.9746	Adj R^2 = 0.9619		Pred R^2 = 0.9319	Adeq Precision 30.4102	PRESS = 0.3702	*Significant

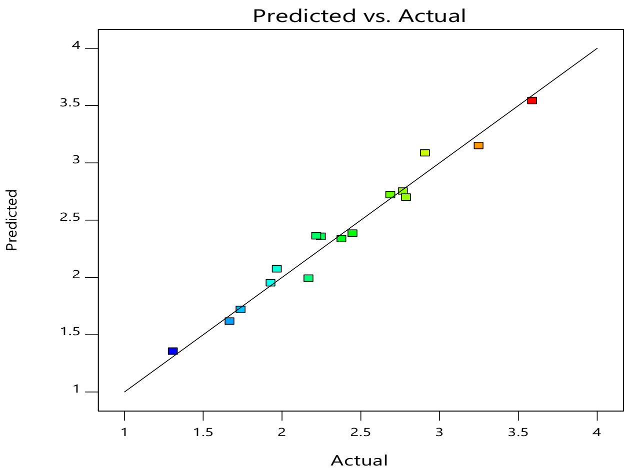

Figure 6. Predicted vs. Actual graph for SR.

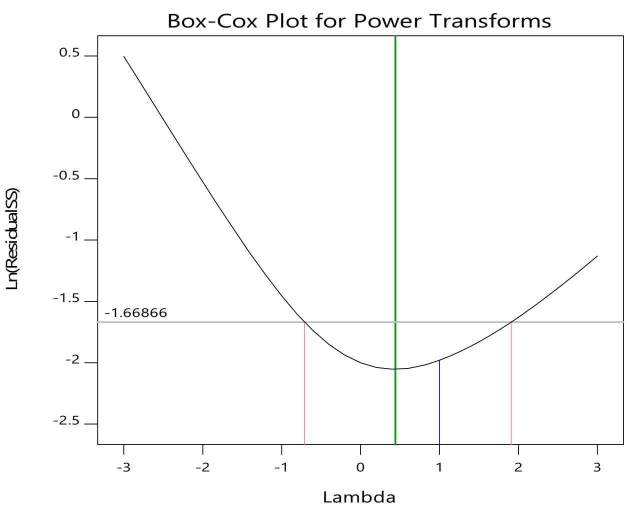

Figure 7. Box-Cox plot for SR.

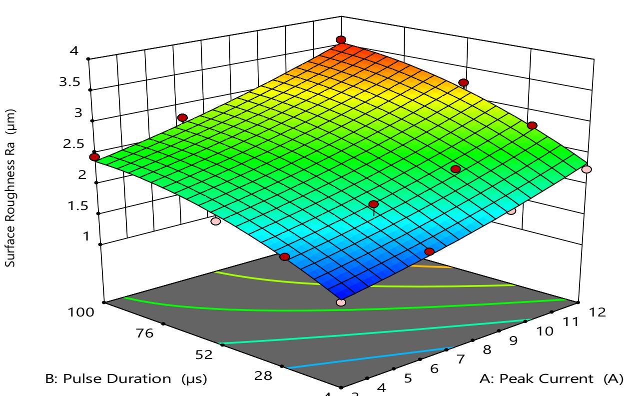

Figure 8. Response surface of SR.

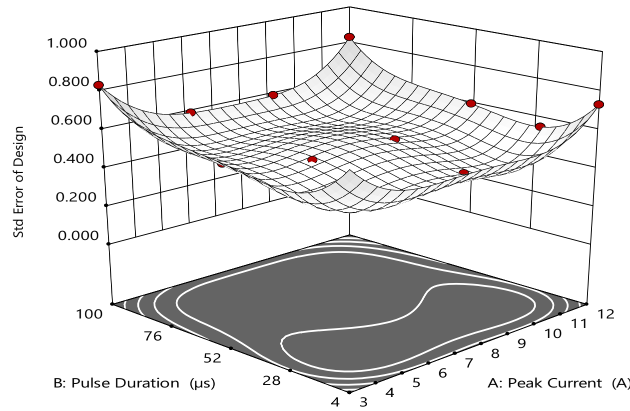

Figure 9. Std Error of Design.

predicted SR from desirability function are considered. Smaller the better for SR and larger the better for MRR and shown in Eq. (5):

$$X_i(k) = \begin{Bmatrix} \dfrac{Y_i(k) - \min Y_i(k)}{\max Y_i(k) - \min Y_i(k)}; & \text{Larger the better} \\ \dfrac{\max Y_i(k) - Y_i(k)}{\max Y_i(k) - \min Y_i(k)}; & \text{Smaller the better} \end{Bmatrix} \tag{5}$$

where $X_i(k)$ is the value obtained after the desirable grey relational generation, $Y_i(k)$ is the value obtained from the experimental runs, $\min Y_i(k)$, $\max Y_i(k)$ are the minimum and maximum values of $Y_i(k)$ and i represents the experimental number for the k^{th} response.

Step 2: Calculation of Desirable Grey Relational Coefficient (DGRC): It is calculated by Eq. (6):

$$\zeta_i(k) = \frac{\Delta_{\min} + \xi\Delta_{\max}}{\Delta_{oi}(k) + \xi\Delta_{\max}} \tag{6}$$

where ζ_i is the DGRC, $\Delta_{oi}(k)$is the offset of the absolute values flanked by the reference (considered to be 1.000), ξ is the characteristic coefficient (selected at 0.5) according to Kavimani *et al* [24], $\Delta_{\min}$ is the least value and $\Delta_{\max}$ is the highest value of $\Delta_{oi}(k)$.

Step 3: Calculation of Desirable Grey Relational Grade (DGRG): Here, the multi-objective values are converted to equivalent single objective value by using the Eq. (7):

$$\delta_i = \frac{1}{n}\sum_{k=1}^{n}\zeta_i(k) \tag{7}$$

where δ_i is the DGRG ranging between 0 to 1, n is the number of experimental runs, where highest value of DGRG represents the best possible parameters and response and ranking is done in descending order. The significance of Eq. (7) is that multi-objective values are transformed to single objective value. Table 2 represents the desirable grey relation response with the experimental runs and process parameters. The mean of DGRG ($DGRG_m$) is 0.557 which represent the better trial above this value. Therefore, rank 1 to 6 of run orders 1, 5, 7, 11, 8, 6 represent the better response.

Table 3 represents the response table of the DGRG means of the input process parameters. The highlighted bold denotes the optimal parametric condition for the best output response. It can hence be interpreted that both the input process parameters contribute in a similar fashion as depicted by their main effect. In this hypothetical research, a target of 0.62 is set based on the abridgment of the main effects of both the input process parameters. The mean value of the experimental and the predicted SR from DGRG above this target is the predicted value from DGRG (1.66125 μm) which is much better than the experimental value and the predicted value of SR from desirability function.

3.4 *Confirmatory test and validation*

After the confirmatory test, SR predicted mean obtained at 2.46277 μm, which is 95% two-sided confidence with a 95% PI low of 2.16804 and 95% PI high of 2.7575 with a nominal error of only 0.29473, where PI is prediction interval. Figure 10 represents the ramp diagram of the optimized result. One optimized solution is obtained from desirability approach where Ip is 4.666 A, PD is 17.092 μs, SR (Ra value) is 1.742 μm, StdErr of Design is 0.049 and Desirability is 0.900. Table 4 represents the validation test

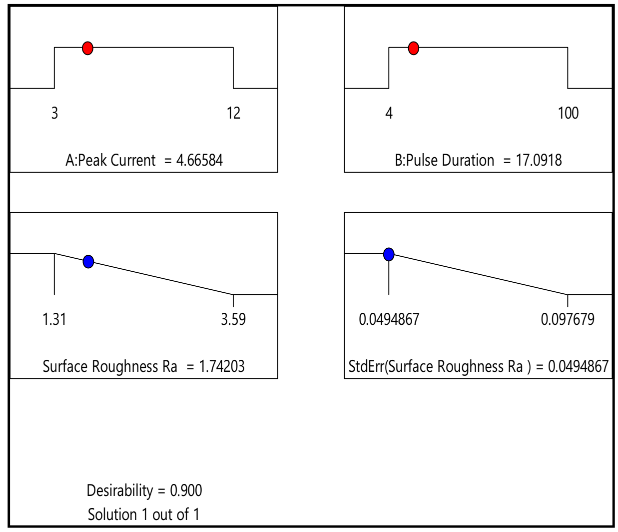

Figure 10. Optimized result.

Table 2. Desirable grey relation response.

Run order	Peak current (A)	Pulse duration (μs)	Actual SR (μm)	Pred. SR (μm)	X_1	X_2	$\Delta_{oi}(1)$	$\Delta_{oi}(2)$	ζ_1	ζ_2	δ_i	RANK
1	3	4	1.31	1.35	1.000	1.000	0.000	0.000	1.000	1.000	**1.000**	1
2	12	100	3.59	3.54	0.000	0.000	1.000	1.000	0.333	0.333	0.333	16
3	9	100	2.91	3.09	0.298	0.205	0.702	0.795	0.416	0.386	0.401	14
4	6	50	2.22	2.36	0.601	0.539	0.399	0.461	0.556	0.520	0.538	7
5	6	4	1.67	1.62	0.842	0.877	0.158	0.123	0.760	0.802	0.781	2
6	6	24	2.17	1.99	0.623	0.708	0.377	0.292	0.570	0.631	0.601	6
7	3	24	1.74	1.72	0.811	0.831	0.189	0.169	0.726	0.747	0.737	3
8	3	50	1.97	2.07	0.711	0.671	0.289	0.329	0.633	0.603	0.618	5
9	12	50	3.25	3.15	0.149	0.178	0.851	0.822	0.370	0.378	0.374	15
10	3	100	2.45	2.39	0.500	0.525	0.500	0.475	0.500	0.513	0.506	10
11	9	4	1.93	1.95	0.728	0.726	0.272	0.274	0.648	0.646	0.647	4
12	9	24	2.38	2.34	0.531	0.548	0.469	0.452	0.516	0.525	0.521	9
13	9	50	2.69	2.72	0.395	0.374	0.605	0.626	0.452	0.444	0.448	11
14	6	100	2.79	2.7	0.351	0.384	0.649	0.616	0.435	0.448	0.441	12
15	12	4	2.25	2.36	0.588	0.539	0.412	0.461	0.548	0.520	0.534	8
16	12	24	2.77	2.75	0.360	0.361	0.640	0.639	0.438	0.439	0.439	13

$DGRG_m = 0.557498626$

Table 3. Response table for DGRG means.

Symbol	Machining parameters	Level 1	Level 2	Level 3	Level 4	Main effect (max–min)	RANK
A	Peak current (A)	**0.7153843**	0.590322071	0.504207966	0.42008	0.29530419	2
B	Pulse duration (μs)	**0.7405262**	0.574129387	0.494736867	0.4206	0.31992418	1

Table 4. Validation test.

Machining parameters		Responses and results		
Peak current (A)	Pulse duration (μs)	Responses	SR (μm)	% improvement
5	17	Measured	1.7918	2.78
		Predicted by desirability	1.74203	4.64
		Predicted by DGRA	1.66125	7.29

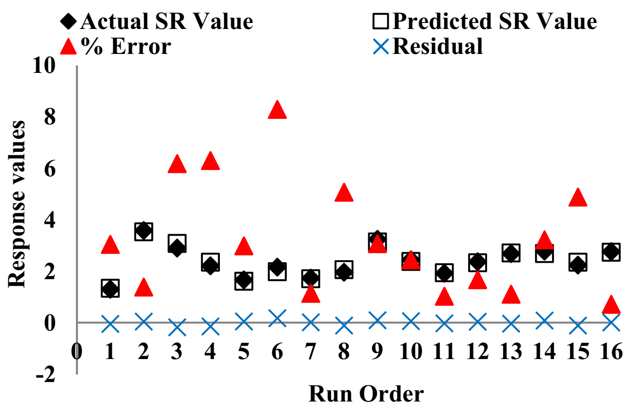

Figure 11. All-in-one graph.

of the optimized condition where the % improvement is 2.78% when compared with experimental and predicted value obtained from desirability.

It increases to 4.64% when compared with the predicted results obtained from desirability and DGRA. And it further gets incremented to 7.29% when compared with the experimental and predicted result from DGRA. Figure 11 represents the all-in-one graph of the output response of SR with the experimental run orders where the actual and predicted SR values are in close agreement with each other resulting nominal % error. Only run order 6 has maximum % error that is 8.3 %, the rest are lower than this value owing to close proximity between predicted and experimental results. All the residuals are very negligible, tending to zero which validates the experiment with the predicted SR values with nominal error.

4. Conclusions

In this paper, optimization on desirability approach and desirable grey relation analysis has been investigated on a developed novel TiNiCu composite based on the experimental runs of WEDM. Diffused zinc-coated brass wire of 0.25 mm wire diameter is used in deionized dielectric. A mathematical model is hence developed using RSM and optimal solution is determined and validated after confirmatory tests. Following conclusions are obtained from the result and analysis:

1. SR enhances with the increment in Ip and PD. The best SR obtained experimentally is 1.31 μm (Ip, 3A, PD, 4 μs). One optimized solution is obtained from the desirability function where Ip is 4.666 A, PD is 17.092 μs, SR (Ra value) is 1.742 μm, StdErr of Design is 0.049 and Desirability is 0.900.
2. The actual vs. predicted graph of the output response of SR depicts an excellent conformity which convinces this research to be on the accurate path. SR predicted mean is 2.46277 μm after the confirmatory test which is 95% two-sided confidence with a 95% PI low of 2.16804 and 95% PI high of 2.7575 with a nominal error of only 0.29473.
3. The percentage of improvement of experimental SR measured at optimized condition is 2.78% and it gets further improved to 7.29% when predicted with DGRA method.

Therefore, the developed composite is very much favorable for machining with the most efficient non-traditional machining process WEDM. Results infer that the approach of DGRA has superiority in obtaining the optimal solution rather than desirability function in single and multi-objective optimization problems. Padhee *et al* [21] obtained higher MRR at the cost of higher SR, but according to DGRA it can be improved. Garg *et al* [22] used Inconel 625 but here TiNiCu composite is used for investigation. Ghodsiyeh *et al* [23] investigated on WEDM of Ti–6Al–4V and obtained increased MRR with fine surface finish but the desirability is very less which may be improved if DGRA is used. In future, multi-response optimization on the output responses like material removal rate, surface roughness, kerf width and over cut can be considered varying other process parameters like power, time-off, servo voltage, wire tension, wire feed, etc. Metallographic testing and microstructural analysis may be done for analysis of surface topography.

Nomenclature

THC	Titanium hybrid composite
DGRA	Desirable grey relational analysis
WEDM	Wire electro-discharge machining
LENS	Laser engineered net shaping
Ip	Peak current

PD	Pulse duration
SR	Surface roughness
RSM	Response surface methodology
BBD	Box–Behnken design
MRR	Material removal rate
WW	Wire wear
DOE	Design of experiments
D	Overall desirability function
ANOVA	Analysis of variance
DGRC	Desirable grey relational coefficient
DGRG	Desirable grey relational grade
$DGRG_m$	Mean of DGRG

References

[1] Gu L, Li L, Zhao W and Rajurkar K P 2012 Electrical discharge machining of Ti6Al4V with a bundled electrode. *Int. J. Mach. Tool Manuf.* 53: 100–106

[2] Elias C N, Lima J H C, Valiev R and Meyers M A 2008 Biomedical applications of titanium and its alloys. *Bio Mater. Sci.* 60: 46–49

[3] Kumar A, Kumar V and Kumar J 2013 Multi-response optimization of process parameters based on response surface methodology for pure titanium using WEDM process. *Int. J. Adv. Manuf. Technol.* 68: 2645–2668

[4] Kumar A, Kumar V and Kumar J 2014 Surface integrity and material transfer investigation of pure titanium for rough cut surface after wire electro discharge machining. *Proc. IMechE Part B: J. Eng. Manuf.* 228: 880–901

[5] Kumar A, Kumar V and Kumar J 2013 Investigation of machining parameters and surface integrity in wire electric discharge machining of pure titanium. *Proc. IMechE Part B: J. Eng. Manuf.* 227: 972–992

[6] Kumar A, Kumar V and Kumar J 2016 Surface crack density and recast layer thickness analysis in WEDM process through response surface methodology. *Mach. Sci. Technol. Int. J.* 20: 201–230

[7] Saji V S, Jeong Y H, Yu J W and Choe H C 2010 Corrosion behavior of Ti-13Nb-13Zr and Ti-6Al-4V alloys for biomaterial application. *Corros. Sci. Technol.* 9: 12–15

[8] Fleck C and Eifler D 2010 Corrosion, fatigue and corrosion fatigue behavior of metal implant materials, especially titanium alloys. *Int. J. Fatigue* 32: 929–935

[9] Niu H Z, Xiao S L, Kong F T, Zhang C J and Chen Y Y 2012 Microstructure characterization and mechanical properties of TiB_2/TiAl in situ composite by induction skull melting process. *Mater. Sci. Eng. A.* 532: 522–527

[10] Lin H C, Lin K M and Chen Y C 2000 A study on the machining characteristics of TiNi shape memory alloys. *J. Mater. Process. Technol.* 105: 327–332

[11] Chen S L, Yan B H and Huang F Y 1999 Influence of kerosene and distilled water as dielectrics on the electric discharge machining characteristics of Ti–6A1–4V. *J. Mater. Process. Technol.* 87: 107–111

[12] Alias A, Abdullah B and Abbas N M 2012 Influence of machine feed rate in WEDM of titanium Ti-6Al-4V with constant current (6A) using brass wire. *Proc. Eng.* 41: 1806–1811

[13] Manjaiah M, Narendranath S and Basavarajappa S 2014 A review on machining of titanium based alloys using EDM and WEDM. *Rev. Adv. Mater. Sci.* 36: 89–111

[14] Nourbakhsh F, Rajurkar K P, Malshe A P and Cao J 2013 Wire electro-discharge machining of titanium alloy. *Proc. CIRP.* 5: 13–18

[15] Hsieh S F, Chen S L, Lin H C, Lin M H and Chiou S Y 2009 The machining characteristics and shape recovery ability of Ti–Ni–X (X=Zr,Cr) ternary shape memory alloys using the wire electro-discharge machining. *Int. J. Mach. Tool Manuf.* 49: 509–514

[16] Attar H, Ehtemam-Haghighi S, Kent D, Wu X and Dargusch M S 2017 Comparative study of commercially pure titanium produced by laser engineered net shaping, selective laser melting and casting processes. *Mater. Sci. Eng. A.* 705: 385–393

[17] Wu X, Liang J, Mei J, Mitchell C, Goodwin P S and Voice W 2004 Microstructures of laser-deposited Ti–6Al–4V. *Mater. Des.* 25: 137–144

[18] Marshall G J, Young W J, Thompson S M, Shamsaei N, Daniewicz S R and Shao S 2016 Understanding the microstructure formation of Ti-6Al-4V during direct laser deposition via in-situ thermal monitoring. *J. Occup. Med.* 68: 778–790

[19] Bandyopadhyay A, Espana F, Balla V K, Bose S, Ohgami Y and Davies N M 2010 Influence of porosity on mechanical properties and in vivo response of Ti6Al4V implants. *Acta Biomater.* 6: 1640–1648

[20] Qiu C, Ravi G A, Dance C, Ranson A, Dilworth S and Attallah M M 2015 Fabrication of large Ti–6Al–4V structures by direct laser deposition. *J. Alloy. Comp*. 629: 351–361

[21] Padhee S, Nayak N, Panda S K, Dhal P R and Mahapatra S S 2012 Multi-objective parametric optimization of powder mixed electro-discharge machining using response surface methodology and non-dominated sorting genetic algorithm. *Sādhanā* 37: 223–240

[22] Garg M P, Kumar A and Sahu C K 2017 Mathematical modeling and analysis of WEDM machining parameters of nickel-based super alloy using response surface methodology. *Sādhanā* 42: 981–1005

[23] Ghodsiyeh D, Akbarzadeh S, Izman S and Moradi M 2019 Experimental investigation of surface integrity after wire electro-discharge machining of Ti–6Al–4V. *Sādhanā* 44: 1–15

[24] Kavimani V, Prakash K S and Thankachan T 2019 Multi-objective optimization in WEDM process of graphene-SiC-magnesium composite through hybrid techniques. *Measurement.* 145: 335–349

[25] Montgomery D C 2012 *Design and analysis of experiments*, 8th ed. New York: John Wiley & Sons, Inc. pp. 478–544