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ORIGINAL PAPER

Experimental investigations on silicon carbide mixed electric discharge machining

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Abstract

In this study, silicon carbide mixed electrical discharge machining (SCMEDM) process has been developed and later on modelled also using an artificial neural network (ANN) based technique as well as response surface methodology (RSM). Experiments were conducted with Al LM-25/SiC metal matrix composites as per Box Behnken design (BBD). Discharge current, pulse-on-time, servo-voltage, powder concentration, tool material and varying reinforcement levels were considered as machining input parameters. Material removal rate, tool wear rate and surface roughness were taken to be the response parameters. Analysis of variance (ANOVA) method was used to investigate the significant effect of parameters on the response measures. The experimental data was trained using a back-propagation ANN technique. Research shows that the influence of current, pulse length and tool material on the machining characteristics of Al LM-25 MMCs is significant. Surrogated models were also developed for proposed process using RSM. However, the accuracy of ANN models was found to be better than that of RSM models.

Keywords Silicon carbide mixed electrical discharge machining (SCMEDM) · Artificial neural network (ANN) · Analysis of variance (ANOVA) · Response surface model (RSM)

Abbreviations

ANN	Artificial neural network
RBFNN	Radial Basics Function Neural Network
NSGA	Non sorting genetic algorithm
SCMEDM	Silicon carbide mixed electro discharge machining
WEDM	Wire electro discharge machining
FEM	Finite element method
DEM	Dimensional exponential model
TWR	Tool wear rate
SF	Surface finish
CR	Crater radius
ρ_w	Density of work piece material
K_w	Work piece thermal conductivity
Vg	Voltage GapT_{ON} Pulse-on-time
T_{OFF}	Pulse-off-time
Ra	Surface Roughness
R^2	Coefficient of determination
BPNN	Back propagation neural network
ANOVA	Analysis of variance
PCA	Principal Component Analysis
MMC	Metal matrix composites
SEM	Scanning electron microscopy
MRR	Metal removal rate
SR	Surface roughness
OC	Over cut
SEM	Scanning electron microscope
I_P	Input Current
α_w	Thermal expansion coefficient
Cp	Concentration of powder
WT	White layer thickness
PMEDM	Powder mixed electro discharge machining

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1 Introduction

Metal matrix composites (MMC) have rapidly penetrated into numerous industries including aerospace, defence, manufacturing, automobile, electronic and nuclear [1].Due to their favourable properties such as light in weight, better wear resistance, better specific strength and temperature resistance than conventional materials [2], they are extensively used in many industrial applications. In the realm of industrial production, conventional machining approaches generally are insufficient to machine MMC for achieving the required precision and intricate shapes, which are also time-consuming and sometimesdifficult to machine [3–5]. An advanced manufacturing process is the only way to achieve such features on a component. In the recent past, Electrical discharge machining (EDM) has been gaining attention as a significant technology for cutting several hard and difficult-to-machine materials due to the intense heating made by controlled, localized electric sparks and produces negligible stress (minimum surface tension) on the workpiece surface to remove material. Thus, by considering the most appropriate and optimal process parameters, which mostly consume precious time and effort, the EDM process becomes more effective in terms of cost, quality and productivity than traditional machining of difficult-to-cut materials. As a result of the effective utilization of experimental, modelling and optimization methodology, a new technological solution is able to meet and control multiple objectives simultaneously (multi-objective) in order to provide optimized machining of advanced MMCs. Many statistical and computational approaches have been used for predictive modelling, including RSM [6–11], ANN [12–17], Taguchi method [18–21], GRA [22–26], desirability function approach of RSM [27–30], PCA [31, 32], TOPSIS [33–35], GA [36–39] and PSO [40–43].The machinability of various materials has been extensively explored by employing various experimentaldesign, numerical modelling approaches and optimization techniques [44–47], The objective was to estimate the performance and to modify the inputfactors in cutting the materials likeStainless steel, A2 tool steel, Grey cast iron, Inconel 600, 601, 625, 825, 718,MDN 300, AISI D2, D3, D6, AISI 316 L,Ti6Al4V, Ti13Zr13Nb, nickel alloy, Al7075, Al6061, Al6063 alloy, Al-SiC MMC, Si_3.

2 Literature Review

Several publications applying one out of statistical or computationaltechnique rather than considering both to solve multi-objective problems, which are crucial in improving machining performance. Hence, appropriate technological guideline is required to be developedfor effective and optimum machining of LM-25/SiC MMC material by SCMEDM process. Because of its extreme strength at high temperatures, excellent corrosion resistance and exceptional wear resistance.

However, until now, no author has performed any economic analysis facilitating cost-effective manufacturing based on SCMEDM that can provide scope for further researches related to techno-economic aspect.The current investigation handles sustainability assessment of EDM processes so as to analyze the machining efficiency of silicon carbide mixed electrical discharge machining of LM-25/SiC MMC with respect to MRRs, TWRs andSRs by employing process parameters (discharge current, gap voltage, pulse-on-time, powder content, tool material and reinforcement percentage).Experimental investigations, prediction models and optimal design of multi-responses are investigated using Box-Behnken's (BBD) design, ANOVA and statistical techniques. Afterward, an artificial neural network (ANN) is employed as a computational model for multi-response optimization. In addition, a best-fit economic analysis is used to determine the suitability of PMEDM for difficult-to-cut materials [2, 48] as well as hard-to-cut materials [49, 50], with the purpose of raising manufacturing industry awareness.SEM observation helped interpret the results by investigating the impact of discharge current on machined surface morphology, recast layer thickness and crack width on the SCMEDMed work surface thickness and crack length. This study provides a method for assessing sustainability while considering the machining performancefrom the perspective of novelty; these results can help establish an economic advantage for SCMEDM in industries such as automotive, aerospace, military and electrical. Mentioned points make the present study unique and will lead to a significant contribution to advance sustainable manufacturing (Table 1).

Reviewing the literature reveals that ANN is frequently used in modelling and process optimization. It is able to build nonlinear relationships between a large variety of input and output parameters. An ANN can be trained on any number of data sets and it is capable of maintaining implicit relationships between inputs and outputs implicitly, unlike mathematical models which are data-driven, self-adaptive and rigid. Furthermore, artificial neural networks can be trained on a wide range of data sets and they can infer complex nonlinear functional relationships between inputs and outputs implicitly. Most research uses a single-hidden-layer ANN architecture, thus, the accuracy of the resulting model has received less attention. Further, the previous work did not consider composites, notably LM-25/SiC composites, as a work item. Despite the fact that tool material is a key parameter, it can affect the accuracy of SCMEDM [70].

Table 1 Research contribution on ANN modelling

Author(s)	Prediction approach	Work Piece	Process variable	Machine response	Result
Shrivastava et al. [51]	ANN and RSM	copper-iron graphite MMC	Ton, T_{off}, Ip, Grit no	MRR,SR	RSM and ANN are both more reliable and competent methods for estimating the average SR
Rajesh et al. [52]	RSM, Radial Basics Function Neural Network (RBFNN) and ANN	LM-25 Al composites	V_d, Ip, Ton, T_{off}, Sg,P_{oil}	MRR,SR	Prediction model RSM,RBFNN and ANN predict the error by RSM is 1.34655%,RBFNN is 1.5236% and the ANN model is 0.7878%
Surya et al. [53]	RSM and ANN	Wire EDM of Al7075-TiB_2 in-situ composites	Ton, T_{off}, Ip, S	MRR, CR, DE	70% of the training set correlated well with the observed values, according to an ANN
Dubey et al. [54]	RSM	Al7075–5% B_4Cp metal matrix composites	V_g, Ton, T_{off}, Ip,	TWR, SR	In Additive mixed electrical discharge machining Pulse off-time had a negligible effect on Ra
Phate et al. [55]	RSM,integrated PCA-ANN	Aluminium silicate composites with a silicate content of 15–20% (Al/SiCp)	P_{ON}, P_{OFF}, Ip, WFR,WT,FP,SiC (%)	MRR, Ra, KRF	Essential process parameters are the silicate percent composition, the pulse off time (POFF) and the current (IP)
Preetham et al. [56]	RSM	Aluminium metal matrix hybrid composites	Ton, T_{off},Wt, F,	Ra	Pulse length (pulse on time) had the biggest influence on the work piece's surface integrity
S. Singh et al.[57]	RSM and ANN	LM-25/SiC MMC	Ton, T_{off}, Ip,	MRR,TW,SR	SCMEDM is mostly influenced by current intensity and pulse duration
Singh et al. [58]	Back-propagation algorithm and RSM	D3 die steel using ANNs	Ton, Ip, duty cycle, Pg and electrode rotation	MRR, SR	Presented mathematical models for predicting MRR and SR during helium-assisted EDM machining of with a
Agrawal et al. [59]	ANN and GA	Copper-iron-carbide MMC	Ton, T_{off}, Ip, powder con. (g/l)	MRR, Ra	Ton significantly affect the MRR
Kumar and Chouhan [60]	RSM and ANN	Al7075/10/SiCp and Al 7075 hybrid composites	Cutting speed, feed rate, approach angle	Ra	Cutting speed has significant factor for Ra
Bhuyan et al. [61]	fuzzy logic and RSM	Al-SiCp MMC	T_{ON}, I_p andF_p	R_a,R_q and R_z	Ip has more impact of Ra
Kumar &Sreebalaj[62]	ANN	Al MMC with fly ash particles	T_{ON}, T_{OFF} and I_P	MRR, TWR and SR	T_{ON}, T_{OFF} has significantly effect on MRR
Unune et al. [63]	Fuzzy logic	Nimonic 80A	I_P, T_{OFF}	MRR, R_a	MRR increases with increase in both I_P& T_{OFF}
Sahu et al. [64]	RSM and ANN	Al-SiC MMC	I_P, V T_{ON}, T_{OFF} and flushing pressure	R_a and OC	V, T_{OFF} and flushing pressure are significant parameters in affecting Ra
Ubale et al. [65]	BPNN with one -hidden layer	70 wt% W- 30 wt% Cu MMC	I_P, T_{ON}, T_{OFF}, Wt and Gp	MRR	5–12-1 best model selected for modelling the MRR

Table 1 (continued)

Author(s)	Prediction approach	Work Piece	Process variable	Machine response	Result
Lalwani et al. [66]	RSM,ANN and NSGA- II	Inconel 718 super alloy	T_{ON}, T_{OFF}, SV, I_p and WT	Kf, R_a and MRR	ANN model predict better MSE value for ANN (1.49%) and RSM (5.71%)
Manikandan et al. [67]	ANFIS	LM6/SiC/ Dunite HMMC	T_{ON}, T_{OFF}, Wf, SV, and flushing pressure	MRR), Ra, overcut, circularity error	T_{ON} has most influencing parameter for machining of WEDM of LM6/ SiC/Dunite HMMC
Singh et al. [68]	RSM	hybrid aluminium MMC with SiC/ Gr	I, V, T_{on} and tool material,	MRR, Ra	MRR and the Ra significantly influenced by both Copper and Brass electrodes
Phate et al. [69]	DEM,,RSM and ANFIS	aluminium-based alloy	T_{ON}, T_{OFF} and I_p	Roughness (Ra)	'I_p' is most affecting parameter followed by the 'T_{ON}', 'T_{OFF}' and 'CP'

Earlier research did not take account of it while modelling this process.

3 Experimentation

3.1 Silicon Carbide Mixed Electrical Discharge Machining (SCMEDM)

Researchers have demonstrated that SCMEDM increases the speed of EDM based machining SCMEDM is an advanced machining technique that mixes a fine, abrasive, electrically conductive powder with the dielectric medium. Metallic powders suspended in a dielectric medium reduce the insulating strength of the material, resulting in a higher inter electrode gap. These results in improved EDM performance like higher MRR reduce TWR and SR than regular EDM. Figure 1 depicts the schematic of SCMEDM.

In PMEDM suitable powder SiC is chosen to mix with the dielectric liquid in a controlled set-up with pumping device. The powder is mixed using a stirrer for complete mixing in the dielectric liquid and pump ensures that it so not get settled in the tank. Similar to conventional EDM thermal energy is generated at the junction of electrode and job with the help of high voltage electrical sparks. Due to presence of powder the electrical density at the machining spot decreases which in turn forces the thermal energy produced to raise the local temperature to a higher value thereby melting and vaporising the job material. To avoid excessive heating short pulses are used. PMEDM involves adding conductive powders to achieve an increased MRR, SF and tool life by causing dielectric liquid to breakdown earlier [71]. Conduit powders such as copper [71], aluminium [70–72] of various sizes, chromium [73], silicon carbide [74], CNT [75], manganese[76], boron carbide [77], graphene nano powder [78], graphite [79] and others, when added to the dielectric liquid will results in higher MRR and reduced SR. By mixing powder with dielectric liquid, the MRR can be increased by 1% to 33% without compromising quality [80]. In one study [81], an increase in MRR due to non-uniform heat dissipation was identified, resulting in the dissipation of surplus residual heat.

Al powders in the appropriate proportion are mixed with dielectric liquid to enhance the responses [82].As per during machining of aluminium composite with copper electrodes, addition of aluminium powder in specified quantities to dielectric liquid leads to better MRR and SR [72]. The appropriate addition of CNTs to EDM's dielectric liquid increases its machining rate and reduces the SR [83]. Nano-almond powder significantly improved titanium alloy surface quality for biomedical applications by forming carbon-enriched surfaces for better osseointegration [70]. A CNT additive was found to reduce micro crack formation and improve the

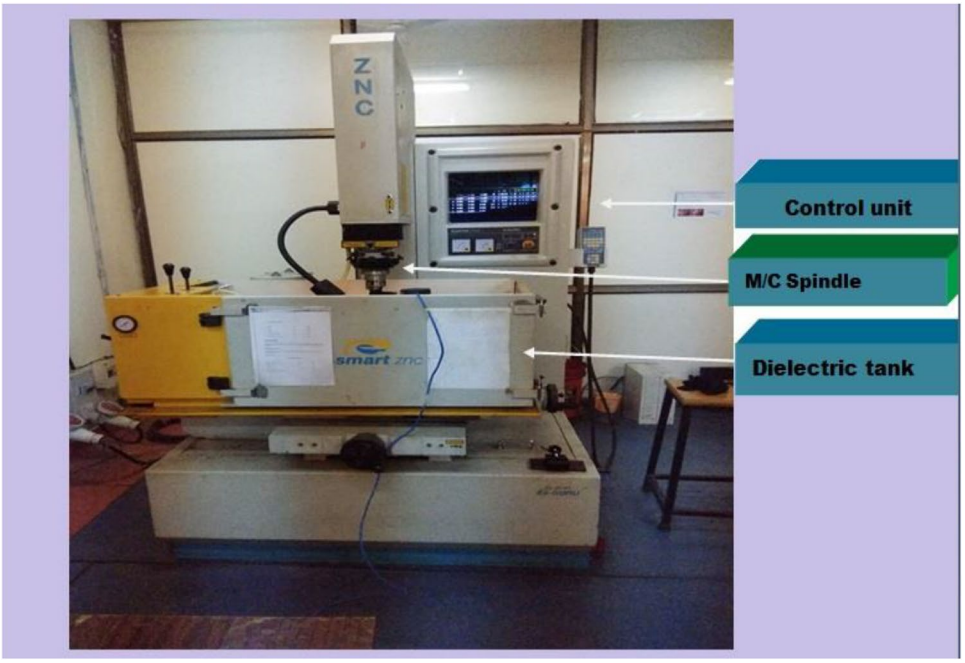

Fig. 1 ZNC EDM machine ELECTRA PLUS, (Model S-50 ZNC)

stability of machining [75]. Adding chromium to dielectric liquid produces a chromium-rich machined surface [84]. To improve the SR, the powder concentration needs to be controlled [77]. Depending on the workpiece and surface finish of the components, proper identification of powder size and concentration can yield a mirror finish [85]. Chromites powders in an appropriate size and concentration reduce SR and cracks and reduce crater size when machining H-11 die steel [73]. The micro hardness of the machined surface must also increase with an increase in powder concentration. A proper choice of powder concentration can yield better results [86]. Micro hardness is measured when manganese powder is mixed with dielectric liquid during machining of OHNS die steel. A maximum of 8% of the powder can be added in proportion to dielectric liquid [70]. Multi walls of CNT increased MRR until 8 gm/lit of powder concentration was reached [80]. When machining H11 die steel, the ability of materials to transfer current effectively increased MRR. SR reduced until SiC powder concentration of 4 gm/lit was achieved. Due to addition of SiC in the dielectric liquid, the transfer of material from electrode to job was of small quantity [87]. Dubey et al. [54] experimented on Al7075– 5%B_4Cp metal matrix composite by incorporating chromium powder in machining. Higher peak current and pulse on time increase the height of recast layers. Singh et al. [88] implemented RSM &ANN technique to estimate experimental inputs and modelling of measure response such as MRR, TW, and SR. It is observed that predicted results from ANN model are compared with experimental result are quite satisfactory. Naiket al. [89] Response surface methodology (RSM) and analysis of variance (ANOVA) are employed, respectively, for experimental analysis, predictive modelling in electrical discharge machining process for aluminium–silicon carbide metal matrix composite. Result reveal that discharge current have major influence on machined surface. Phate et al. [90] have employed the Artificial Neural Network (ANN)-Based PCA technique for analysing processes and enhancing the process performance. From the investigation. It is observed that the % composition of silicate, the pulse off time (POFF) and current (IP), are the most critical process parameters. Ming et al. [91] proposed a multi-variable regression model using back propagation neural network (BPNN) and a radial basis neural network (RBNN) to model and optimize die sinking EDM process of SiC/Al composites. Padhee et al. [92] A response surface methodology (RSM) has been used to analyze the effects of independent variables on the results and develop Non-sorted genetic algorithms (NSGA) for investigating the machining performance of power mix EDM using EN 31 steel.Tall et al. [93] observed MRR of the Al/Al_2O_3 composite with EDM can be improved by adding aluminium powder in the dielectric liquid. Kolli et al. [94] found that adding graphite powder (14 g/L) and surfactant (varying between 0.25 and 15.0 g/L) to a dielectric fluid when EDMing titanium alloy improved the MRR. Kansal et al. [95] observed that the machining rate of die steel has been improved by adding silicon powder (average particle size 30 mm) in the dielectric fluid, in particular an increase from 2.67 to 4.58 mm^3/min was reported at a 3 g/L concentration of Si powder. According to Singh et al. [96], the highest MRR was found when silicon powder was diluted by 8 g/L PMEDM. In Kumar et al. [97] studied that during PMEDM

of the Al-SiCP MMC, peak current, powder concentration and pulse duration are the influencing factors. The authors observed that reinforcement of 10% SiC particles (average size of 25 mm) with 4 g/L silicon powder concentration results in to a higher MRR of 2.93 mm^3/min. According to the PMEDM studies [98–103] a higher powder concentration in dielectric liquids improves machining performances. Tripathy et al. deployed TOPSIS and GRA techniques to assess the efficacy of chromium powder mixed EDM with copper electrode for machining H-11 die steel. Experimental results indicate that adding a proper concentration of particles of the proper size improves SF [104]. Kansal et al. [105] have demonstrated that a novel nano porous layer generated by PMEDM techniques can enhance the biomechanical anchorage of bone-implant structures. Tripathy and Tripathy [106] studied chromium powder mixed EDM to investigate the effect of process variables on micro hardness in H-11die steel and estimate the migrated material from workpiece to tool depending on peak current, powder concentration, duty cycle and pulse time employing SEM and EDS. Nanimina et. al. [107]. Experimental results showed that using nano aluminium powder as a matrix in EDM to machine Ti6Al4V workpieces with a copper-tungsten electrode improved SF by reducing micro cracks and crates. Surface restoration is improved due to uniform distribution of silver particles and a carbide-rich surface layer formed by alloying of transfer elements. Hamidullah et. al. [108] studied the effect of SiC powder concentration on particle deposition, subsurface structures and surface topography during PMEDM of Ti-6Al-4 V-ELI material and concluded that the material transfer mechanism improves with low pulse currents and higher suspended particle concentration. Kumar et. al. [109] investigated machining of Inconel 825 workpieces using Al_2O_3 micro PMEDM machining. It was determined that discharge current, pulse duration and voltage are the major parameters affecting MRR and SR. Rajavel et. al. [110] presented a comprehensive review of EDM of various composite materials. Saharia et. al. [111] studied Hybrid PMEDM with Multi-Walled Carbon Nano Tube (CNT) powders and kerosene for grinding EN19 alloy steel parts with brass electrodes. Surekha, et. al. [112] investigated experimentally the use of aluminium powder in EDM with brass electrodes for machining EN-19 alloy steel and concluded that gap voltage and peak current affect MRR significantly.

3.2 Material of the Work Piece

An abrasive tool was used to machine LM-25/SiC reinforced composite material and developed work piece specimens with dimensions of 150 × 15x10 mm (Length x Width x Thickness).Semi-automatic polishing equipment is used to polish the specimens to get a consistent surface quality on each one. The chemical composition of Al LM-25(Wt %) composite material includes: Al 92.3812, Cu 0.0944, Mn 0.2396, Ni 0. 662, Si 0.243, Fe 0.032, Zn 0.005, Pb 0.002, Sn 0.070 and C6. The mechanical properties are Density 2,680 kg/m^3, Ultimate tensile strength 282 MPa, Percent elongation 5, Brinell hardness number 92 BHN and Modulus of elasticity 71GPa.

3.3 Experimental Details

Figure 1 illustrates the schematic perspective in its entirety. ELEKTRA PLUS Model S-50 ZNC, Pune, India PMEDM is utilised to conduct experimentation. When a sample of the required size is prepared from an LM-25 reinforced composite alloy containing 0%, 5% and 10% by weight of silicon carbide reinforced material with a size of 30 microns (280 mesh), it exhibits superior wear resistance, high specific strength, low density and high stiffness while also exhibiting excellent thermal and shock resistance. A cylindrical electrode (ø12 mm) was employed as a negative-polarity electrode and EDM oil was used as the dielectric liquid in this experiment. During the tests, both electrodes were kept in a silicon carbide mix dielectric to keep them from corroding.

4 Experimental Method

4.1 Experimental Design with RSM

Regression analysis has been carried out using commercial statistical software (Minitab 19) to model the response variables. The impact of process parameters on performance factors are modelled and estimated using an ANOVA test [113, 114]. ANOVA is also used to investigate the significance of the developed models to estimate the significance level of input parameters; interaction and quadratic terms [115, 116]. To establish the adequacy and prediction capabilities of the developed empirical models, correlation coefficient R^2, adjusted R^2 and predicted R^2were used [117].

This research work is focused to evaluate the impact of six machining parameters (discharge current, servo power, pulse-on-time, tool material, % reinforcement and powder concentration) on machine performance, including the MRR, TWR and SR during silicon carbide mix EDM machining of LM-25/SiC composites. According to Box Behnken designs [118] a total of 54 experiments are required to estimate the impact of six machining parameters on machine response. Each experiment will be replicated once. Table 2 and 3 show the input parameters and experimental results for the TWR, MRR, and Ra, which are averages of values derived in both runs.The current set of input parameters was chosen after performing literature research, evaluating mechanism competence and taking machine constraints into account. In order to establish a mathematical relationship between

Table 2 Process variables and their levels

Process variables	Unit	Symbols	Optimum level		
			Min	Centre	Max
			–1	0	1
Discharge Current (Ip)	Ampere	A	2	3	4
Pulse on time (T_{on})	Micro second	B	30	50	75
Servo Voltage (Vs)	Volt	C	50	60	70
Con. of powder	gm/ltr	D	0	2	4
Tool Material	-	E	Brass	Copper	Graphite
% Reinforcement	-	F	LM-25	LM-25–5%SiC	LM-25–10%SiC

the dependent and independent variables, response surface methodology was applied [119]. Using RSM, the number of experimental trials can be reduced to some extent and hence, their interactions can be studied effectively.

Generally, the second-order regression model shown in Eq. 1 is used in response surface methodology.

$$Y = \beta_o + \sum \beta_i X_i + \beta_i X_{ii}^2 + \beta_{ij} X_i, X_j + € \quad (1)$$

Y represents the predicted response; X_i is the input variables, $X_{ii}{}^2$ and X_i, X_j is the square and constant term, respectively. The unknown regression coefficients are βo, βi, βii and βij and € is the error. Experimental work has been performed to examine the impact of different EDM input parameters such as discharge current, servo voltage, pulse on time, powder concentration, different types of tool material and different weight fraction of work material on machining performance viz. MRR, TWR, SR. The parametric level is coded using the equation.

$$Coded\ value\ (z) = \frac{X - \frac{Xmax+Xmin}{2}}{\frac{Xmax-Xmin}{2}} \quad (2)$$

As shown in Eq. 2, *Z* represents the coded value (-1, 0, 1), The values *Xmax* and *Xmin* are the maximum and minimum values of actual parameters and the actual value *X* is the value of the parameter.

5 Results and Discussion

5.1 Analysis of Variance

The accuracy of the developed models was evaluated with an ANOVA test using Minitab 19 Software. The results are presented in Tables 4, 5, and 6 using the response surface models of MRR, TWR, and SR, described in the following sections. In this study, the adequate criterion was R^2, adjusted R^2 and anticipated R^2, all of which were around one, suggesting that the models were appropriate and fit the data well. MRR has an R^2 of 86.83%, TWR has an R^2 of 84.43% and Ra has an R^2 of 80.34%.Through this backward elimination procedure, insignificant terms can be removed from fit quadratic models, and the lack of fit test will not appear significant. Following the backward elimination process, the final quadratic response based analysis was performed.

ANOVA Table 4 shows that the most significant influencing factor for MRR is the tool material with a contribution of 11.90%, followed by powder concentration, servo voltage, discharge current, pulse-on-time, and% reinforcement, with contributions of 7.15%, 5.02%, 4.04% and 3.24%, respectively. In addition, the coefficient of determination (R^2) and adjusted (R^2) values are 86.83%, and 83.38%respectively, which indicates close alignment between the coefficient of determination (R^2) and 77.13% significance level of the model. The lack of a fit test was deemed less significant than intended for MRR.

Further, Table 5 shows that the most influential parameter for TWR is pulse on time, which contributes 6.94%. Other important considerations include powder concentration, discharge current, servo voltage, % reinforcement and tool material, which contribute 5.55%, 4.61%, 4.09%, 3.80% and 3.22%, respectively. In general, the coefficients of determination (R^2) and adjusted (R^2) values of 84.43% and 80.35% are in agreement with the experimental results.

According to ANOVA Table 6, tool material is the most significant parameter for SR (11.90%). It is followed by servo voltage, powder concentration, pulse on time, discharge current and % reinforcement percentage contribution (6.07%, 5.15%, 2.46%, 2.02% and 1.49%).The value of the coefficient of determination (R^2) 80.34% is reasonable agreement with the adjusted (R^2) 76.24% respectively. This results in the not significant lack of fit being beneficial for SR.

According to this study, the anticipated R^2 and the modified R^2 were both in agreement with one another. The lack of fit was not statistically significant for each of the examples. A coefficient of variation (CV) number less than 0.41 indicates that the studies are more accurate and consistent.

Table 3 Experimental run with process parameters and machine response

Sr.No	Run no	Ip amp	Ton µs	V volt	Powder con gm/ltr	T tool	W work	MRR (mm^3/min)	TWR (mm^3/min)	SR (µm)
1	1	−1	−1	0	−1	0	0	1.86567	0.03348	5.104
2	2	1	−1	0	−1	0	0	2.25835	1.84642	9.723
3	3	−1	1	0	−1	0	0	2.89164	2.11116	8.535
4	4	1	1	0	−1	0	0	3.21343	3.50334	9.677
5	51	−1	−1	0	1	0	0	2.582	3.09062	9.967
6	52	1	−1	0	1	0	0	3.14328	3.59285	9.885
7	53	−1	1	0	1	0	0	3.71194	3.96696	9.456
8	54	1	1	0	1	0	0	4.24119	4.72232	10.64
9	13	0	−1	−1	0	−1	0	0.10925	1.54581	7.592
10	14	0	1	−1	0	−1	0	0.82119	2.9229	8.607
11	15	0	−1	1	0	−1	0	0.18462	2.5629	7.757
12	16	0	1	1	0	−1	0	0.61819	3.13436	8.839
13	17	0	−1	−1	0	1	0	2.46865	2.8584	6.394
14	18	0	1	−1	0	1	0	3.11925	3.6761	9.885
15	19	0	−1	1	0	1	0	3.4258	3.86991	9.044
16	20	0	1	1	0	1	0	3.8225	4.56991	9.742
17	9	0	0	−1	−1	0	−1	0.16656	2.63348	6.583
18	10	0	0	1	−1	0	−1	1.20894	2.92232	9.884
19	43	0	0	−1	1	0	−1	0.46776	3.04464	10.83
20	44	0	0	1	1	0	−1	1.42314	3.8558	9.847
21	11	0	0	−1	−1	0	1	0.1985	0.73348	6.499
22	12	0	0	1	−1	0	1	1.20297	1.51116	9.092
23	45	0	0	−1	1	0	1	1.32313	1.52232	9.432
24	46	0	0	1	1	0	1	2.55119	1.84464	8.661
25	5	−1	0	0	−1	−1	0	0.30144	1.0229	9.278
26	6	1	0	0	−1	−1	0	0.52388	2.53436	9.849
27	47	−1	0	0	1	−1	0	1.61731	1.378	7.142
28	48	1	0	0	1	−1	0	2.64328	1.9771	9.813
29	7	−1	0	0	−1	1	0	1.78656	0.63274	8.697
30	8	1	0	0	−1	1	0	2.20716	1.98973	9.831
31	49	−1	0	0	1	1	0	2.72895	1.37168	10.85
32	50	1	0	0	1	1	0	3.51462	2.88938	10.63
33	27	0	−1	0	0	−1	−1	0.03731	0.8229	10.33
34	28	0	1	0	0	−1	−1	0.07626	1.83348	10.93
35	29	0	−1	0	0	1	−1	0.05462	0.54424	8.457
36	30	0	1	0	0	1	−1	0.5231	1.80973	9.557
37	31	0	−1	0	0	−1	1	0.03231	0.0229	7.132
38	32	0	1	0	0	−1	1	0.16119	0.81145	7.782
39	33	0	−1	0	0	1	1	0.07462	0.04424	7.478
40	34	0	1	0	0	1	1	0.16925	0.74424	8.209
41	35	−1	0	1	0	0	−1	0.07731	0.01116	7.249
42	36	1	0	−1	0	0	−1	0.18119	0.22232	8.819
43	37	−1	0	1	0	0	−1	0.46831	0.07116	6.463
44	38	1	0	1	0	0	−1	1.48656	0.08116	9.192
45	39	−1	0	−1	0	0	1	0.13731	0.08232	5.394
46	40	1	0	−1	0	0	1	1.41656	0.01116	5.471
47	41	−1	0	1	0	0	1	1.96104	0.72232	7.946
48	42	1	0	1	0	0	1	2.38059	1.65089	9.996
49	21	0	0	0	0	0	0	0.22388	0.04464	8.153
50	22	0	0	0	0	0	0	0.21656	0.03348	4.788

Table 3 (continued)

Sr.No	Run no	Ip amp	Ton µs	V volt	Powder con gm/ltr	T tool	W work	MRR (mm^3/min)	TWR (mm^3/min)	SR (µm)
51	23	0	0	0	0	0	0	0.2485	0.01116	4.711
52	24	0	0	0	0	0	0	0.25626	0.03348	4.432
53	25	0	0	0	0	0	0	0.02631	0.01116	8.131
54	26	0	0	0	0	0	0	0.01274	0.01116	6.073

Table 4 Summary of ANOVA table for MRR

Source	DF	Adj SS	Adj MS	F-Value	*P*-Value
Model	11	75.7428	6.8857	25.17	0.000
Linear	6	36.1532	6.0255	22.03	0.000
A-Discharge Current	1	7.9162	7.9162	28.94	0.000
B-Pulse on Time	1	7.1460	7.1460	26.12	0.000
C-Servo Voltage	1	6.5938	6.5938	24.10	0.000
D-Con. of powder	1	4.9667	4.9667	18.16	0.000
E-Tool Material	1	13.0456	13.0456	47.69	0.000
F-% reinforcement	1	0.6530	0.6530	2.39	0.130
Square	5	46.5016	9.3003	34.00	0.000
A*A	1	8.9394	8.9394	32.68	0.000
B*B	1	8.7675	8.7675	32.05	0.000
C*C	1	7.2178	7.2178	26.38	0.000
D*D	1	10.0194	10.0194	36.63	0.000
F*F	1	7.6255	7.6255	27.87	0.000
Error	42	11.4897	0.2736		
Lack-of-Fit	36	11.3161	0.3143	10.87	0.003
Pure Error	6	0.1736	0.0289		
Total	53	87.2325			

Table 5 Summary of ANOVA table for TWR

Source	DF	Adj SS	Adj MS	F-Value	*P*-Value
Model	11	88.928	8.0844	20.70	0.000
Linear	6	48.556	8.0926	20.72	0.000
A-Discharge Current	1	1.365	1.3652	3.50	0.068
B-Pulse on Time	1	19.566	19.5656	50.10	0.000
C-Servo Voltage	1	18.338	18.3381	46.96	0.000
D-Con. of powder	1	17.668	17.6680	45.25	0.000
E-Tool Material	1	1.320	1.3199	3.38	0.073
F-% Reinforcement	1	3.676	3.6762	9.41	0.004
Square	5	62.776	12.5552	32.15	0.000
A*A	1	0.881	0.8812	2.26	0.141
B*B	1	23.632	23.6321	60.52	0.000
C*C	1	19.125	19.1249	48.98	0.000
D*D	1	27.271	27.2713	69.84	0.000
F *F	1	7.668	7.6681	19.64	0.000
Error	42	16.401	0.3905		
Lack-of-Fit	36	15.599	0.4333	3.24	0.072
Pure Error	6	0.802	0.1336		
Total	53	105.329			

Table 6 Summary of ANOVA table for SR

Source	DF	Adj SS	Adj MS	F-Value	*P*-Value
Model	13	112.778	8.6752	7.09	0.000
Linear	6	47.247	7.8745	6.43	0.000
A-Discharge Current	1	12.689	12.6891	10.37	0.003
B-Pulse on Time	1	4.257	4.2573	3.48	0.070
C- Servo Voltage	1	13.990	13.9904	11.43	0.002
D-Con. of powder	1	1.480	1.4798	1.21	0.278
E-Tool Material	1	1.308	1.3085	1.07	0.307
F-% Reinforcement	1	4.620	4.6196	3.78	0.059
Square	4	52.436	13.1091	10.71	0.000
B*B	1	6.070	6.0697	4.96	0.032
D*D	1	38.901	38.9012	31.79	0.000
E*E	1	14.324	14.3238	11.71	0.001
F *F	1	7.010	7.0099	5.73	0.021
2-Way Interaction	3	13.656	4.5519	3.72	0.019
C*D	1	7.311	7.3115	5.97	0.019
C*F	1	3.057	3.0573	2.50	0.122
D*E	1	3.287	3.2870	2.69	0.109
Error	40	48.949	1.2237		
Lack-of-Fit	34	33.591	0.9880	0.39	0.964
Pure Error	6	15.358	2.5597		
Total	53	161.727			

A degree of confidence of 95% was employed for identifying important machining factors, including the TWR and Ra. It was concluded that tool material, powder concentration, servo voltage, discharge current, and pulse on time had the greatest impact on MRR. The pulse time, the voltage, the quantity of powder all has great impact on TWR, while the tool material has a significant impact on Ra. The high discharge energy quickly breaks down the material, therefore increasing its resistance.

5.2 Prediction using ANN

Analogous neural networks can be used to forecast response parameters for a given set of process parameters. To obtain the most accurate predictions the neural network should be trained with some samples before testing. The weights and bias values have been calculated as 6–15-15–3 structure To perform the ANN prediction, the network received six input

variables—Ip, Ton, Vs, C, material, reinforced % and three output variables—MRR, TWR, and SR Matlab software ANN prediction module has been used to separate training data from test data. The literature has reported that training data of 70% can lead to more accurate results of prediction. The current study kept 70% of the training data for prediction, and the rest for training. ANN models produce six input parameters and three output parameters by varying the number of neurons in the hidden layer. For optimal regression values, not only the number of neurons in the hidden layer should be varied, but also the learning rate and the momentum coefficient. The learning rate should be varied between 0 and 1, while the momentum coefficient should be varied between 0 and 2.

An ANN system demonstrates the capability to handle complex functions. It has been successfully utilized in a variety of industries for multiple purposes, including defect detection, process identification, estimation of property values, smoothing of data and error detection. A neural network can also be effectively used for designing and developing products, optimizing processes and estimating activity coefficients [120, 121]. Based on the concept of biological neural networks, a neural network could be regarded as a massively parallel, highly distributed tool for processing large amount of data. It consists of a set of neurons capable of acquiring, learning and adjusting to new information to ensure that knowledge is retained [122]. A multi-layered neural network was used to simulate the SCMEDM process and predict the TWR, MRR and Ra response variables for the machining of aluminium and SiC MMC.

5.3 ANN Performance

A total of fifty-four unique input–output patterns were analysed using the NN package in MATLAB. The assumption X = N1-N2-Y is used for generalised ANN models. Where X, represents the input layer's number of neurons, N1 denotes the first hidden layer's number of neurons, N2 denotes the second hidden layer's number of neurons and Y denotes the output layer's number of neurons. In addition, noise was included in the weights to help keep the network structure stable whilst it was tuned for performance. The model was trained using a technique known as Levenberg–Marquardt (LM), which is a kind of optimization algorithm. The following Eq. (3) was used to evaluate the network's performance using the Mean Square Error (MSE).

$$\mathrm{MSE} = \frac{1}{M \times N} \sum_{j=1}^{N} \sum_{j=1}^{N} (Y'i - Yi)2 \tag{3}$$

Y_i signifies the ith neuron's experimental output, Y_i signifies the i_{th} neuron's projected output, N signifies the total number of training patterns and M signifies the total number of neurons in the output layer [123]. There have been numerous optimization efforts made by altering the number of neurons in the first layer of the 6-N1-15–3 NN. The number of neurons in the N_1 layer was fixed at fifteen while the number of neurons in the second hidden layer was varied between one and fifteen to improve the 6–15-N_2-3 algorithm. With this approach, the total number of neuron combinations in the hidden layers could be significantly reduced. The ANN model is trained using 38 of the 54 experimental values and the trained ANN model is tested using 16 of the 54 experimental values. Variation in the mean squared error during ANN model training for various epoch counts was investigated. At epoch 5, the best validation was seen with an MSE of 2.086 in the single hidden layer (Fig. 2). The regression coefficient acquired during the training of the ANN model is 0.99657, which is extremely close to one. The best validation performance value achieved using a double hidden layer is 2.9188 at epoch 3, as shown in Fig. 3 and the

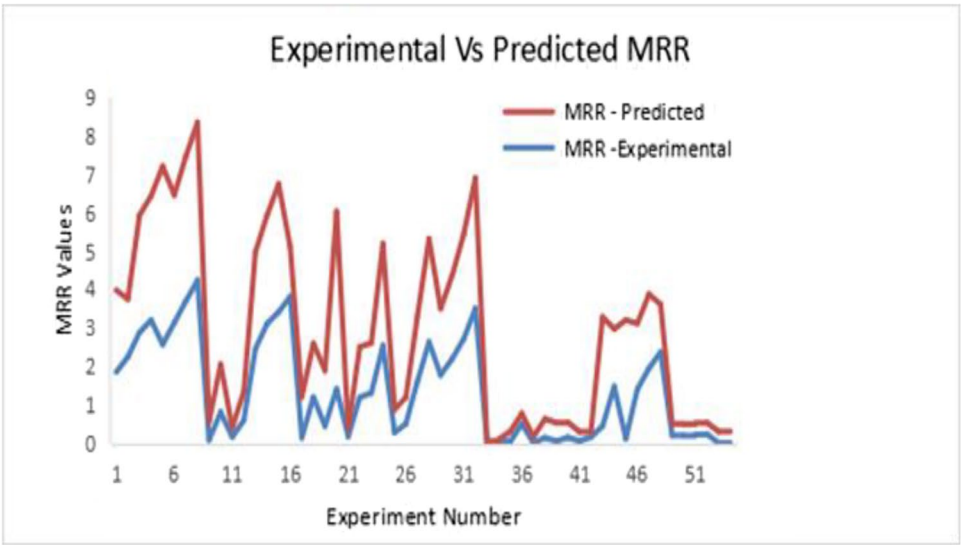

Fig. 2 Experimental and predicted MRR value

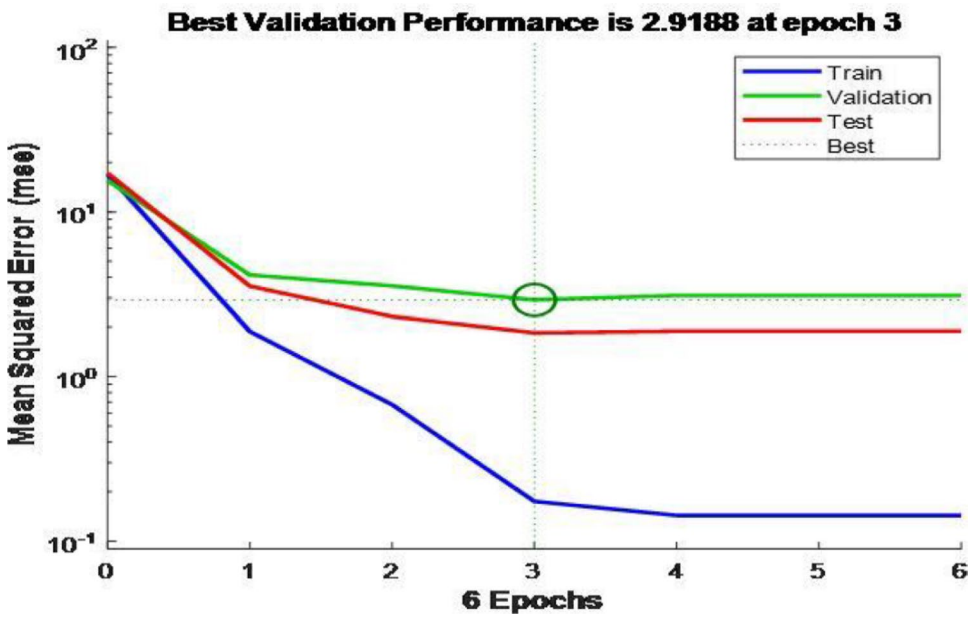

Fig. 3 Mean squared errors obtained during ANN training (double hidden layer)

corresponding experimental and predicted values for TWR as a sample are depicted in Fig. 2. The regression coefficient acquired during the training of the ANN model was 0.99308. To prevent local minima, the NN structure was trained several times with negligible weight variation throughout the training phase. Thus, in the study, the 6–15-15–3 (Double hidden layer) structure was used to evaluate the performance of SCMEDM processes (Table 7).

5.4 A Parametric Study on Machine Response Using the RSM Model

The new ANN model 6–15-15–3 (double hidden layer) was used to test the influence of input process parameters on response variables. While graphs for each parameter were constructed, the rest were left at their default values of 0.

5.4.1 Parametric effect on MRR

Based on their results in Table 4, the following parameters also have a significant effect on MRR: Ip, Ton, Vs, C, tool material, and % reinforcement. However, Ip is the most influencing parameter, showing a sharp spike in MRR by 2.4 mm3/min when it decreases initially before increasing from 3 to 4A.The reason for this is that an increase in peak current produces more heat energy and hence increases the melting and evaporation of material from the workpiece, resulting in an increased MRR.In addition, the MRR increases by 1.2 mm^3/min when Ton is raised from 30 to 75 s, and it increases by even more when the servo voltage is raised from 50 to 70 V. The voltage has become increasingly dominant in MRR because of a decrease in electrode gap between the workpiece and the tool. By adding large amounts of abrasive particles to dielectric liquid the dielectric strength of the fluid is enhanced as well, which raises the MRR..As a result of their high thermal conductivity, copper tools produce a higher MRR than brass and graphite tools and the addition of 1% reinforcement to a workpiece has the least impact on MRR (46%) (Fig. 4).

5.4.2 Parametric effect on TWR

Furthermore, the TWR was graphically analyzed with input parameters and Ip, Ton, Vs and C was found to have significant impacts on the TWR, as shown in Table 6. The most influential parameter, Ip, indicates significant increases in TWR when the current increases steeply from 2 to 4A, Also, the mean TWR increases directly proportional to the Ton when the Ton increases the time from 52.5 s to 75 s. In addition, TWR increases with an increase in servo voltage from 50 to 70 v. In fact, abrasive particles in the dielectric liquid appear to be the main factor affecting the TWR. This indicates that powder concentration is the most important factor for the TWR. The tool material also has a considerable impact on the tool wear rate. Despite the fact that 100% reinforcement was found insignificant in the current study, its effect cannot be ignored when compared to other parameters [124] (Fig. 5).

5.4.3 The Parametric Influence on SR

From the perspective of quality, surface quality is the most important factor. Hence, the impact of input parameters on the SR was analyzed graphically, and it was discovered that Ra was maximum at a higher value of Ip, Ton, Vs. and C, and minimum at a low value, as shown in Table 6.

Table 7 Testing the capability of ANN models using Double hidden layer for prediction of MRR, TWR and SR

	Process parameter						Target values			ANN Predicted values			ANN Absolute Error		
S.N	Ip	Ton	V	C	T	W	MRR	TWR	SR	MRR	TWR	SR	MRR	TWR	SR
	Amp	µs	volt	gm/ltr			(mm^3/min)	(mm^3/min)	(µm)	(mm^3/min)	(mm^3/min)	(µm)	(mm^3/min)	(mm^3/min)	(µm)
1	2	30	60	0	0	5	1.86567	0.0334	5.104	1.7399	3.0116	7.9758	0.1257	2.9781	2.8718
2	4	30	60	0	0	5	2.25835	1.8464	9.723	2.3304	1.71758	9.5503	0.0720	0.1288	0.1726
3	2	75	60	0	0	5	2.89164	2.1111	8.535	2.8058	2.1653	8.1780	0.0857	0.0541	0.3569
4	4	75	60	0	0	5	3.21343	3.5033	9.677	2.8771	3.2243	9.4535	0.3362	0.2789	0.2234
5	2	30	60	4	0	5	2.582	3.0906	9.967	1.9466	0.9014	6.2024	0.6353	2.1891	3.7645
6	4	30	60	4	0	5	3.14328	3.5928	9.885	3.2880	3.6716	9.8524	0.1447	0.0788	0.0325
7	2	75	60	4	0	5	3.71194	3.9669	9.456	3.6173	3.8431	9.5094	0.0946	0.1237	0.0534
8	4	75	60	4	0	5	4.24119	4.7223	10.646	3.4430	3.1944	11.318	0.7981	1.5278	0.6725
9	3	30	50	2	-1	5	0.10925	1.5458	7.592	0.7082	1.2536	7.0936	0.817451	0.2921	0.4983
10	3	75	50	2	-1	5	0.82119	2.9229	8.607	0.8564	2.8741	8.550	0.0352	0.0487	0.0564
11	3	30	70	2	-1	5	0.18462	2.5629	7.757	0.2842	2.6327	7.6472	0.0996	0.0698	0.1097
12	3	75	70	2	-1	5	0.61819	3.1343	8.839	1.2673	1.8115	10.092	0.6491	1.3227	1.2533
13	3	30	50	2	1	5	2.46865	2.8584	6.394	2.7390	3.0364	6.7010	0.2704	0.1780	0.3070
14	3	75	50	2	1	5	3.11925	3.6761	9.885	2.4138	0.8244	8.2218	0.705438	2.8516	1.6631
15	3	30	70	2	1	5	3.4258	3.8699	9.044	3.3744	3.8044	8.8657	0.0513	0.0654	0.1782
16	3	75	70	2	1	5	3.8225	4.5699	9.742	3.9893	4.4866	9.1413	0.1668	0.0832	0.6006
17	3	50	50	0	0	0	0.16656	2.6334	6.583	0.3141	2.2205	6.7696	0.1475	0.4129	0.1866
18	3	50	70	0	0	0	1.20894	2.9223	9.884	1.1904	2.9778	9.5585	0.0184	0.0555	0.3254
19	3	50	50	4	0	0	0.46776	3.0446	10.832	0.8355	1.3340	9.3629	0.3678	1.7105	1.4690
20	3	50	70	4	0	0	1.42314	3.8558	9.847	1.2937	3.6094	9.937	0.1293	0.2463	0.0901
21	3	50	50	0	0	10	0.1985	0.7334	6.499	0.6225	0.5410	6.6001	0.4240	0.1923	0.1011
22	3	50	70	0	0	10	1.20297	1.5111	9.09	1.0652	1.4142	8.7451	0.1377	0.0968	0.3448
23	3	50	50	4	0	10	1.32313	1.5223	9.432	1.3761	1.3994	9.2243	0.0529	0.1228	0.2076
24	3	50	70	4	0	10	2.55119	1.8446	8.661	2.7055	1.9121	8.5628	0.1543	0.0674	0.0981
25	2	50	60	0	-1	5	0.30144	1.0229	9.278	0.8882	0.9658	7.5153	0.5868	0.0570	1.7626
26	4	50	60	0	-1	5	0.52388	2.5436	9.849	0.5048	2.5747	9.6749	0.0190	0.0403	0.1741
27	2	50	60	4	-1	5	1.61731	1.378	7.142	1.6037	1.1876	7.2296	0.0135	0.1903	0.0876
28	4	50	60	4	-1	5	2.64328	1.9771	9.813	1.0564	2.8280	8.1873	1.5868	0.8509	1.6256
29	2	50	60	0	1	5	1.78656	0.6327	8.697	1.7234	0.7017	8.7143	0.0631	0.0690	0.0173
30	4	50	60	0	1	5	2.20716	1.9897	9.83	2.2380	1.6848	6.8361	0.0309	0.3048	2.9938
31	2	50	60	4	1	5	2.72895	1.3716	10.851	2.1895	0.3574	6.7496	0.5394	1.0142	4.1013
32	4	50	60	4	1	5	3.51462	2.8893	10.632	3.4028	2.8093	10.568	0.1117	0.0800	0.0639
33	3	30	60	2	-1	0	0.03731	0.8229	10.337	0.0991	0.8832	10.038	0.0618	0.0603	0.289
34	3	75	60	2	-1	0	0.07626	1.8334	10.937	1.7224	3.6281	11.468	1.6461	1.7946	0.5317
35	3	30	60	2	1	0	0.05462	0.5442	8.457	0.6378	1.3047	9.0700	0.5832	0.7605	0.6130
36	3	30	60	2	1	0	0.5231	1.8097	9.557	0.6378	1.3047	9.0700	0.1147	0.5049	0.4869
37	3	30	60	2	0	10	0.03231	0.0229	7.132	0.1805	0.0705	6.9075	0.1482	0.0476	0.2244
38	3	75	60	2	-1	10	0.16119	0.8114	7.782	0.0169	0.7425	7.9358	0.1442	0.0689	0.1538
39	3	30	60	2	1	10	0.07462	0.0442	7.478	0.8934	0.6766	5.8829	0.8188	0.7209	1.5950
40	3	75	60	2	1	10	0.16925	0.7442	8.209	0.4591	0.8344	8.2009	0.2899	0.0902	0.0080
41	2	50	50	2	0	0	0.07731	0.0111	7.249	0.3579	2.0334	6.2650	0.2806	2.0222	0.9839
42	4	50	50	2	0	0	0.18119	0.2223	8.819	0.4898	0.2970	8.7608	0.3087	0.0747	0.0581
43	2	50	70	2	0	0	0.46831	0.0711	6.463	0.4055	0.1453	6.3926	0.0627	0.0742	0.0703
44	4	50	70	2	0	0	1.48656	0.0811	9.192	1.4422	0.2603	8.7464	0.0442	0.1791	0.4455
45	2	50	50	2	0	10	0.13731	0.0823	5.394	0.0744	0.3868	6.4568	0.0628	0.3044	1.0628
46	4	50	50	2	0	10	1.41656	0.0111	5.471	1.6285	-0.05842	5.9198	0.2119	0.0695	0.4488
47	2	50	70	2	0	10	1.96104	0.7223	7.946	1.9845	0.6586	7.5425	0.0234	0.0637	0.4034

Table 7 (continued)

S.N	Process parameter						Target values			ANN Predicted values			ANN Absolute Error		
	Ip Amp	Ton µs	V volt	C gm/ltr	T	W	MRR (mm^3/min)	TWR (mm^3/min)	SR (µm)	MRR (mm^3/min)	TWR (mm^3/min)	SR (µm)	MRR (mm^3/min)	TWR (mm^3/min)	SR (µm)
48	4	50	70	2	0	10	2.38059	1.6508	9.996	2.2602	1.7261	9.8858	0.1203	0.0752	0.1101
49	3	50	60	2	0	5	0.22388	0.0446	8.153	0.2321	0.0484	5.8971	0.0082	0.0038	2.2558
50	3	50	60	2	0	5	0.21656	0.0334	4.788	0.2321	0.0484	5.8971	0.0155	0.0149	1.1091
51	3	50	60	2	0	5	0.24850	0.0111	4.711	0.2321	0.0484	5.8971	0.0163	0.0373	1.1861
52	3	50	60	2	0	5	0.25626	0.0334	4.432	0.2321	0.0484	5.8971	0.0241	0.0149	1.4651
53	3	50	60	2	0	5	0.02631	0.0111	8.13	0.2321	0.04846	5.8971	0.2058	0.0373	2.2328
54	3	50	60	2	0	5	0.01274	0.0111	6.073	0.2321	0.04846	5.8971	0.2193	0.0373	0.1758

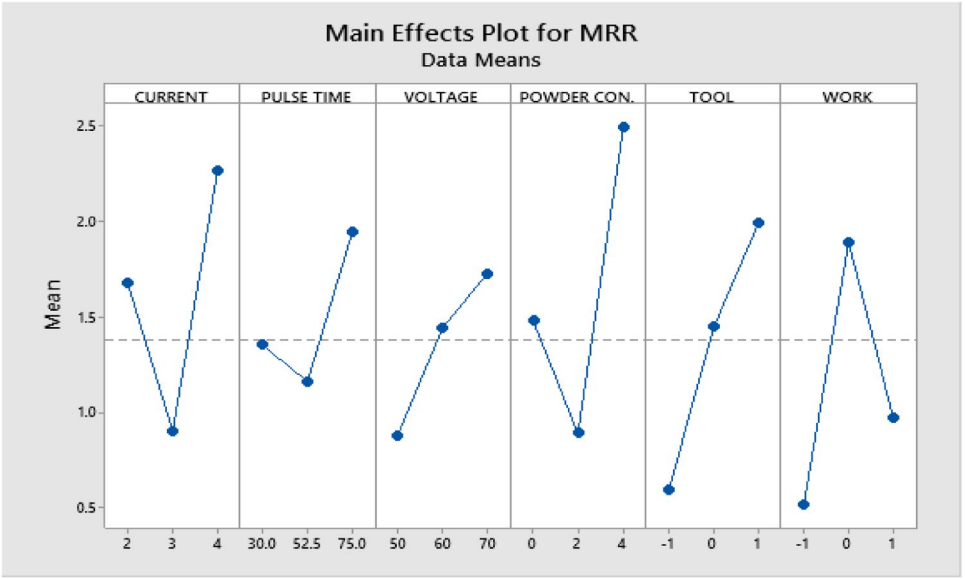

Fig. 4 Effect of input parameter on MRR

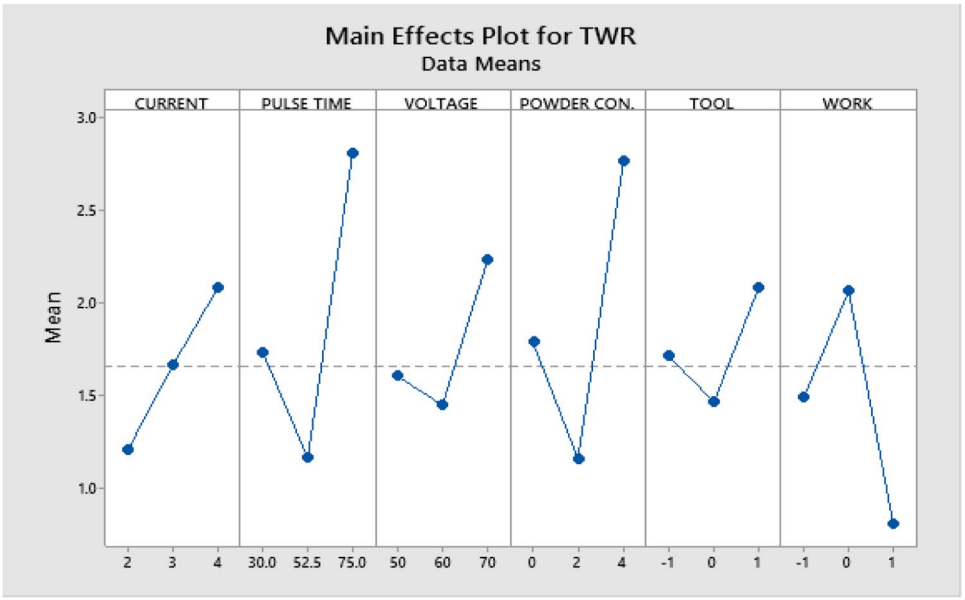

Fig. 5 Effect of input parameter on TWR

However Ip is the most important parameter that increases Ra value with an incremental current from 2 to 4A as a result, the SR is mainly affected by current. In addition, Ra increases by 9.5 µm when Ton increases from 52.5 s to 75.0 s, respectively. Additionally, Ra increased by 9.5 *m when Ton increased from 52.5 s to 75.0 s, and Ra is also directly proportional to voltage for the same range of IP and V. In the present study, surface quality was also affected by the addition of abrasive particles. These particles speed up the material removal process, resulting in a decline in SR. Tool material selection also affects surface quality, as tool reinforcement has a negative impact on Ra (Fig. 6).

5.5 Morphology of the SEM Image

As reported in the literature, the discharge energy is responsible for the bulk of the changes in surface texture throughout the SCMEDM process. As a result, a variety of parametric settings were tested to determine the surface quality of specimens machined using SCMEDM.A material characterization reveals uneven deposition, pockmarks, holes, debris globules, as well as an appearance of a white layer. The run order of 31 specimens is shown in Fig. 7;

Despite higher MRR being obtained from the high discharge energy strike on the surface, there were still deep pockets, lower debris and a recast layer with a poor SF in the machine [125]. The discharge energy is directly proportional to the size of the crater and the amount of metal removed. Increased discharge enlarges and multiplies globules, voids and pockmarks. White layer (also known as recast layer) also undergoes thermal and chemical reactions; which can result in changes to the chemical composition of the upper layers as well as phase shifts. The white layer is often harder than the bulk material due to its oxide content. It is important to note that the effects of SCMEDM parameters on the LM-25/SiC composite surface layers have not been examined in this study and more investigation is needed.

6 Conclusions

The purpose of this study is to develop a ANN model for the prediction of performance measures that include Metal Removal Rate (MRR), Tool Wear Rate (TWR) and Surface Roughness (Ra) for the SCMEDM process for machining LM-25/SiC composites and examining the significance of machining parameters such as discharge current (Ip), pulse on-time (T_{ON}), servo voltage, powder concentration, tool materials and percent reinforcement for performance measures.

Design of Experiments (DOE), Artificial Neural Networks (ANN) and Analysis of Variances (ANOVA) are used as models in this study. The designed ANN model accurately predicted MRR, TWR and Ra values as a result of the approach taken. As a result of the used approach, the developed ANN model was able to predict MRR, TWR and Ra values with excellent accuracy as a result of the approach adopted. During the training of the ANN model, the regression coefficient obtained is 0.99308; for validation is 0.89047 and for testing the trained ANN model is 0.94429. The overall regression coefficient is 0.96811,

This research may have both practical and theoretical ramifications. On the practical side, the results of the research can help practitioners develop an effective and efficient SCMEDM technique for machining LM-25/SiC

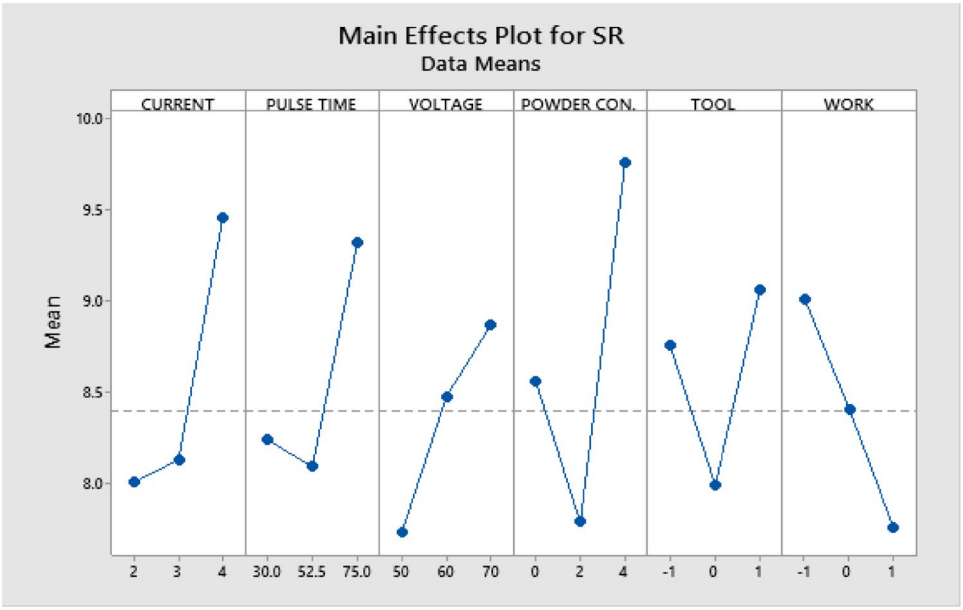

Fig. 6 Effect of input parameter for SR

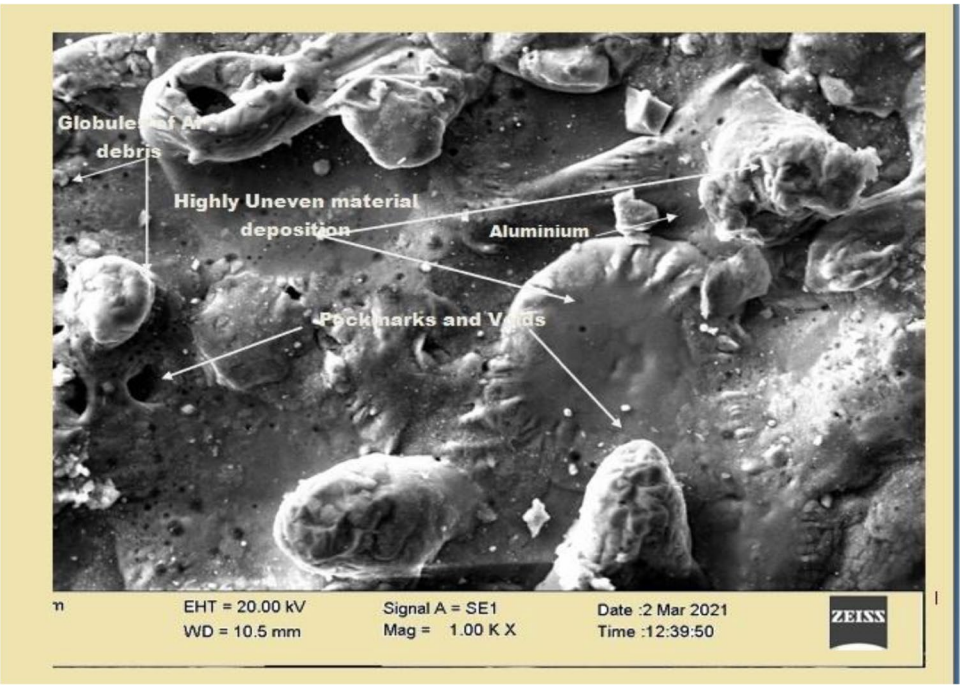

Fig. 7 Run order-31, SEM micrograph at A = 3A, B = 30 µs, C = 60 V, D = 2gm/ltr, E = Brass tool, F = LM-25/SiC (10%)

MMC. On the other side, theoretical implications include expanding knowledge of the SCMEDM process database and gaining a better grasp of the linkages between machining parameters and performance measurements. Future study could involve optimising the SCMEDM process for cutting different materials or the same material but with different sets of machining parameters and performance measurements. Another research strategy may be to optimise the SCMEDM process for cutting the same material but using different optimization tools and comparing the results to validate present research findings. The following conclusions have been reached as a result of this research:

1. As the results of the ANOVA analysis showed, the tool material had the largest effect on the SCMEDM machining of the LM-25/SiC composite. According to this research, the tool material is the most influential parameter for MRR, with the highest percentage of contribution of 11.90%, followed by powder concentration, servo voltage, discharge current, pulse-on-time and reinforcement, with contributions of 7.15%, 5.02%, 4.04% and 3.24%, respectively.
2. In ANOVA analysis, the predictive error for the RSM models for MRR, TWR and Ra is less than 6% on average for experimental values.
3. By employing a feed-forward back propagation neural network with a 6–15-15–3 structure, it was possible to generate an accurate process model. The best validation performance value was 2.9188 at epoch 3 when using a double hidden layer.
4. By comparing the results predicted by ANN models and RSM models, it was found that ANN generated more reliable and acceptable results for the study than RSM because of its higher modeling capability.
5. Compared to the RSM model, the neural network model forecasts MRR, TWR and Ra better. The decrease predicted value of the neural network model compares favorably to that of the RSM model.
6. In high discharge energy settings, SCMEDM-machined materials produced larger debris globules, more pockmarks and more uneven layer deposition.

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The authors declare that all procedures followed were in accordance with the ethical standards.

Declarations

Conflict of Interest The authors declare that there is no conflict of interest regarding the publication of this paper.

Consent to Participate All the authors declare their consent to participate in this research article.

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