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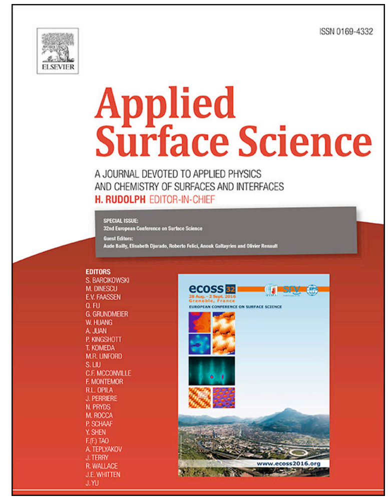

Full Length Article

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Abstract

In this research, a novel aluminum alloy and metal matrix composite was designed and developed for self healing purpose. Tin at varying weight percentages (5, 10, 15 & 20 wt %) was alloyed into aluminum along with other alloying elements to form a new set of metal alloy and 5 wt% of SiC particles was dispersed to the above said combinations to develop new sets of composite materials. Optical microscope of the developed set of samples reveals a modification in the grain structure with dispersion of tin element and with respect to increment of tin content the hardness value tends to decrease. Investigated the effect of wire electric discharge machining (WEDM) process parameters such as Pulse On time (PON), Pulse Off time (POFF), wire feed rate (WFR) along with the material elemental composition parameters Sn wt% and SiC wt% using Taguchi coupled Grey Relational Analysis. On behalf of the above said parameters a L32 orthogonal array based experimental design was finalized and based on the experimental studies single and multi criteria based optimization was conceded. Significance of each processing parameters over the output responses Material Removal Rate (MRR) and surface roughness (Ra) was examined through ANOVA method. Machine learning techniques was used and Neural Network models was developed to predict the MRR and Ra values and the experimental confirmations identified the effectiveness of the developed models.

Keywords: Surface Roughness; Machine Learning; Artificial Neural Network; Aluminum alloys; Metal matrix composites; wire electric discharge machining; Parametric optimization;

1. INTRODUCTION

Aluminum and its alloys are considered to be a widely accepted material after iron and its alloy; apart from the structural applications, the former is considered to be a replacement for the latter based on its enhanced properties. Aluminum posse's low density thereby reducing the weight of the component and henceforth can be considered as a well suitable material in the field of civil, food processing, aerospace and automobile industries as weight is considered to be a major constrain during the design process [1-3]. Aluminum and alloys poses superior malleability, formability easing for the secondary processes such as hot rolling, forming etc., corrosion resistance and workability but its hardness and reduced wear resistance restricts its use to a large level in the field of transport industries [4-6]. In order to overcome such distinct, dispersion of certain ceramic particles into aluminum matrix will be carried out thereby increasing the overall hardness of the material [7]. It has been stated from literatures that the proper selection of processing techniques, reinforcements along with its characteristics has to be properly monitored so as to achieve aluminum MMC with better mechanical properties and the interfacial bonding between the matrix material and reinforcement plays majorly in governing the acquired property of the aluminum MMC [8]. Alloying of the material also has been carried out so as to achieve the required properties for the material as per requirements. Certain researches over the addition of small quantities of tin to the aluminum matrix have found to increase the corrosion resistance of the developed alloy [9-12]. Apart from this, the addition of tin in aluminum has showcased a reduction in grain leading to an increment in strength based on researches. Aluminum alloys are found to be easily machined but it has to notice that with the introduction of hard ceramic particles into the matrix will reduce the machinability of the material increasing the tool wear rate [13]. Machining the Metal Matrix Composites through traditional schemes gets bottleneck due to the enhanced hardness, strength, resistance and melting point offered by the developed composites material thereby tempting the researchers to focus on the nontraditional machining methods.

Wirecut electrical discharge machining (WEDM) is a vital process mostly used in machining hard and brittle material and most often used in automotive, aviation, defense, medical instrument manufacturing, die and tool industry [14-18]. During WEDM operation, electrically charged electrode wire initiates rapid and cyclic spark discharges amid the gaps of tool electrode and work piece. Due to this practice a spark envelope is created covering the wire electrode producing a temperature of 12,000^{o}C approx. This high temperature attained, melts and evaporates away the work piece material [19-21]. The functioning of WEDM is non contact base and henceforth the residual stress related problem emerging due to cutting pressure will be negligible [22,23]. Against to these boons of WEDM operations, one of the main constraints of this machining operation is selection of the correct machining parameters and its combinations so as to achieve the maximum surface integrity, maximum material removal rate or else the combination of both for the profit of the company. Based on the materials, the processing parameters that have to be considered changes and the information provided by the supplier won't satisfy the machinist to select the correct parameter combination keeping different output responses such as surface roughness, material removal rate, heat affected zone etc. Certain WEDM process parameters that has to be monitored by the machinist in accordance to his output response requirements includes discharge current, voltage, pulse on time (PON), pulse off time (POFF), wire material, wire tension, wire feed rate (WFR), dielectric fluid and its flushing pressure [24,25].

The output responses of WEDM such as Material Removal Rate and surface roughness play a major role in industries and work piece applications. Literature has stated that higher surface integrity with balanced MRR is always recommended so as to achieve better results such as corrosion resistance, fatigue strength, wear resistance etc for the finished parts [26]. So as to achieve proportionate MRR with minimal Ra values, an optimal combination of WEDM machining parameters has to be considered and this vary based on the material which has propelled the researchers to narrow down their research in the field of optimization. Bobbili et al, machined armor steel employing WEDM and investigated the effect of process parameters on MRR and Ra values and concludes that PON, POFF and spark voltage are the significant factors for MRR and Ra values [27]. Baraskar et al, investigated the effect of input control factors on MRR and Ra values during Electrical Discharge Machining of EN8 Steel work piece and the multiobjective optimization of the output responses were carried out so as to achieve the better combination employing Non-dominated Sorting Genetic Algorithm (NSGA-II) [28]. Rajalakshmi and Ramaiah optimized the process parameters of WEDM process for machining Inconel 825 employing Taguchi Grey Relational Analysis (GRA) so as to achieve an improved MRR, Ra and spark gap and the optimal parameter was confirmed based on a L36 Orthogonal Array (OA) [29]. Varun and Venkaiah optimized the response parameters of a WEDM process for machining EN 353 so as to attain preeminent MRR, Ra and kerf width exploiting an optimization strategy that coupled GRA and genetic algorithm. An optimal solution from global space was concluded from the selected range of control factors [30]. Muthukrishnan and Davim studied the effect and optimized the process parameters for machining Al-SiC MMC and based on the experimental data a back propagation ANN model having the ability to predict the behavior of the operating system within the range was developed [31]. Panda put forward a hybrid optimization technique namely Neuro–Grey Modeling which carries out the parameter design and optimization of multi-machining characteristics of WEDM process and concluded that the model was reliable and can be implemented fast when compared with genetic algorithm [32]. It has been reported that the localized microstructural parameters such as phase distribution, grain size, distribution & grain structure also plays an important role on the effect of process parameters [35-42]. It also has been reported that the machine learning based ANN model has been used to predict the mechanical properties of metals & alloys [33, 34, 43].

Based on a detailed survey over literatures it was proved that development of Al-Sn alloys with higher quantities of Sn element has not been carried out by researchers and hence for a new composition of alloys and composites was developed in this study with varying weight percentage of Sn elements. Aluminum and its alloys has been considered as the metal with good machinability and numerous works proving this has been overviewed but the behavior of the newly developed set of alloys and composites are unknown and thereby a detailed study of the same has to be carried out. WEDM processing is considered in this research to study the machinability of the material, study the effect of each parameter over the MRR and Ra values and optimize the machine parameter so as to achieve a maximum MRR value with minimal Ra value through GRA. Based on the developed set of experimental design, ANN models will be developed to predict the MRR and Ra values so as to study the performance characteristics.

1. MATERIALS AND METHODS

2.1. Materials

In this research pure Aluminum is considered as the base material into which a set of alloying elements were added so as to enhance the strength, workability and corrosion resistance. Alloying element tin (Sn) of 99 percentage purity is considered in this research for varying proportions (5 wt%, 10wt%, 15wt% and 20wt %) and the ceramic particle that has to be dispersed into the attained aluminum alloy is Silicon Carbide (SiC) particles of 20 microns at 5 wt%. SiC particles are selected as the reinforcement particles owing to its enhanced mechanical properties and its ability to get dispersed into the matrix material. Chemical composition of the developed set of Al alloys and its composites are provided in table 1.

Table 1. Chemical Composition of the developed set of alloys and composites

Element (Wt.%)	Mg	Si	Fe	Sn	Mn	Cu	Cr	Zn	Ni	Ti	SiC	Al

S1	0.95	0.54	0.22	5	0.13	0.17	0.09	0.08	0.02	0.01	0	Bal
S2	0.95	0.54	0.22	10	0.13	0.17	0.09	0.08	0.02	0.01	0	Bal
S3	0.95	0.54	0.22	15	0.13	0.17	0.09	0.08	0.02	0.01	0	Bal
S4	0.95	0.54	0.22	20	0.13	0.17	0.09	0.08	0.02	0.01	0	Bal
S5	0.95	0.54	0.22	5	0.13	0.17	0.09	0.08	0.02	0.01	5	Bal
S6	0.95	0.54	0.22	10	0.13	0.17	0.09	0.08	0.02	0.01	5	Bal
S7	0.95	0.54	0.22	15	0.13	0.17	0.09	0.08	0.02	0.01	5	Bal
S8	0.95	0.54	0.22	20	0.13	0.17	0.09	0.08	0.02	0.01	5	Bal

1.2. Alloy and Composite Preparation

The development of Al-Sn alloy and Al-Sn-SiC composites was developed using stir casting techniques in which aluminum rods were cut into small pieces and melted in a graphite crucible. Once the melt is prepared, refining and skimming of the same is carried out and a mechanical stirrer is introduced into the melt for mechanical agitating. Once a vortex is created due to rotating motion of the mechanical stirrer, the alloying element viz. tin is gradually introduced into the vortex and then continuously stirred for an optimized time period maintained at 600 r.p.m of stirrer rotating speed so as to achieve a homogenous inclusion of the alloying element. The prepared aluminum alloy with tin (Sn) element alloyed into it at varying weight percentage (5, 10, 15, 20 wt %) is poured down into a preheated hot cast iron die. In order to achieve Al-Sn-SiC composites; into the prepared above said Al-Sn alloy a second phase ceramic particles SiC is introduced at a constant weight percentage of 5% through the vortex created due to continuous stirring. With the complete addition of SiC particles into the matrix, the stirrer speed is brought down to 300 rpm and stirred for 3 minutes thereby providing a homogenous dispersion of particles which is poured down to a preheated hot cast iron die for a defined shape.

The developed Aluminum based alloys and composites specimens were prepared and polished according to the standard metallographic technique to carry out the microstructural characterization. The polished specimens were etched using Keller's reagent and observed through an optical microscope (OM). The microhardness for the developed set of alloys and composites was measured using Vickers hardness tester at a load of 500 gm applied for a time period of 15 seconds.

1.3. Machining Studies

Aluminum based self healing alloys and composites with varying weight percentage of tin (5, 10, 15, 20 wt%) in the case of alloys and composites and a constant 5 wt% of SiC in the case composites has to be machined by WEDM. Based on literature survey over the WEDM of aluminum based alloys and composites, the various process parameters has been considered in which the material characteristics that may influence the output response in this research were considered to be the weight fraction of the reinforcement particles and alloying element respectively. The machining parameters considered in this study based on the expertise knowledge and literature survey are the pulse discharge ON and OFF time along with the wire feed rate. It is a known fact that an industry tries to attain the best results with minimal period of time and in this scenario an engineer tries to attain the minimal surface roughness value for the machined surface with maximum material removal rate and hence the above mentioned two factors were considered as the output response in this study.

Selection of levels for the considered set of control factors was optimized to a smaller range of working parameters through a detailed survey over literatures, expertise knowledge and through pilot experiments in which one factor at a time approach was considered. Based on the above said methodology, the operating parameters for machining the Aluminum based Sn alloy and Sn-SiC composites were finalized and set of processing parameters along with its levels are as provided in table 2.

Table 2. Levels of Control Factors

Sl. No	Control Factors	Symbol	Unit	Level I	Level I	Level III	Level IV
1	SiC Weight Percentage	SiC wt%	%	0	5		
2	Sn Weight Percentage	Sn wt%	%	5	10	15	20
3	Pulse ON Time	PON	µs	110	115	120	125
4	Pulse OFF Time	POFF	µs	40	45	50	55
5	Wire Feed Rate	WFR	m/min	4	5	6	7

Figure 1. WEDM machine and its parts

The machining of the alloy and composite specimens were carried out by a CNC WEDM machine of make AgieCharmilles CUT 20P as shown in figure 1 along with which a set of machined pieces are also portrayed. A brass wire of diameter 0.25 mm was considered in this study as the wire electrode material and de-ionised water was considered as the dielectric medium. Certain important parameters of WEDM was kept constant in this study which includes peak current gap voltage etc., and all the operating paremeters of the WEDM machine considered in this study is reported in table 3. The output responses considered in this research includes Material Removal Rate (MRR) and surface roughness (Ra) in which MRR was evaluated by the formulae as given in equation 1.

$$MRR = \frac{W}{\rho \times t} \qquad (1)$$

in which 'W' represents the weight loss during machinining, 'ρ' the density of the specimen and 't' for time taken per cut respectively. Ra values of the machined surface was evaluated from a set of 5 Ra values analysed employing a Mitutoyo made SJ 201P model surface tester.

Table 3. Experimental parameters

Sl. No	Experimental Facility and Machining Parameters	Specifications
1	Peak Current	10 A
2	Gap Voltage	20 V

3	PulseON (PON)	120, 125, 130 µs
4	PulseOFF(POFF)	40, 45, 50 µs
5	Wire Electrode Material	Brass
6	Wire Electrode Diameter	0.25 mm
7	Wire Tension	8 N
8	Wire Feed Rate (W*FR*)	5,6,7 m/min
9	Dielectric Fluid	De-ionized water
10	Work Piece Height	6 mm

1.4.Planning Experimental Design through Taguchi's Method

Based on the considered set of factors and levels in this research going forward with a full factorial design for experiments prompt to be expensive and time consuming. In this scenario, so as to reduce the number of experimental trials and at the same time analyzing the effect of each factor over the output response, an experimental design put forward by Taguchi was initiated. Considering each control factor to be independent to each other, based on Taguchi's method an L32 Orthogonal Array (OA) was concluded by employing Statistical Software R programming. The L32 OA was concluded as per the factors and levels of parameters as shown in table 2 and comes under the mixture technique of Taguchi's method.

Analyzing the results through Taguchi's method is carried out by changing the obtained results in the form of Signal to Noise ratio (SN ratio) and the based on the objective of the results, the SN ratio can be classified into three criteria which includes higher the better, nominal the better and smaller the better. In this research, MRR of the machine and Ra of the machined surface is considered as the output response and in which maximum MRR and minimum Ra value has to be attained, henceforth higher the better is considered for MRR and smaller the better for Ra value respectively. The equations used to obtain the SN ratios for higher and smaller the better are provided below as equation 2 and 3 respectively.

$$(S/N)_{HB} = -10log_{10}\frac{1}{n}\sum_{m=1}^{n}(1/r_m^2) \tag{2}$$

$$(S/N)_{SB} = -10log_{10}\frac{1}{n}\sum_{m=1}^{n}r_m^2 \tag{3}$$

in which 'y' represents the response value at a trial number of 'm', and 'n' denotes the total number of trials. The maximum value from the obtained set of SN ratio is considered as the best process parameter and based on this the best values for each control parameter was chosen to attain the optimal combination of parameters and thereby achieve an efficient output response. Analysis of Variance (ANOVA) was carried out for the validated experimental results to evaluate the conformity of the Taguchi analysis, figure out the sum of square, F values, P values and at the same time to authenticate the significance of each control factors over the output response along with its percentage contribution. The desired level of contribution considered in this research was 95%.

1.5. Empirical Model for the MRR and R_a

An empirical model adapted based on a mathematical linear multivariable regression model to predict the MRR and Ra value based on the control factors was carried out in this research and the format of the empirical model is as shown in equation 4. The developed model can also be used to investigate the effect of each control factor over the output response.

$$Y = C_0 + C_1 \times A + C_2 \times B + C_3 \times C + C_4 \times D \quad (4)$$

Where C_0, C_1, C2, C_3, C_4 stands for constants, Y dependent variable relatively for response variables viz. MRR, Ra in this research and the independent variables A, B, C, D stands for the control factors.

1.6. Grey Relational Analysis based Multi-Objective Optimization.

Taguchi's method of Analysis has been prompt to be an efficient method to study the behavior and to finalize optimal combinations of the control factors so as to achieve the efficient output response. But the major limitations that has to be taken into account for Taguchi's method in this research is that it can be able to evaluate only single-response problems whereas in this study regarding WEDM of samples, the machinist has to attain maximum MRR values with minimal Ra values as both are correlated to each other. Based on the Taguchi's method of single response optimization it is easy to attain the maximum MRR value by changing the process parameters but it may affect the Ra value negatively. Hence to resolve this problem to an extent Multi-Objective Optimization technique is considered and in this research effective use of Grey Relational Analysis (GRA) was carried out.

GRA comprises of mainly three steps which includes of the grey relational normalization of the output responses based on the response characteristics, computing the Grey Relational

Coefficients (GRC) for the output response based on which the Grey Relational Grade (GRG) is evaluated. Grey relational normalization of SN ratio for the output responses based on its performance characteristics is the initial step in GRA analysis. In this step SN ratio for MRR and Ra are obtained based on equation 2 and 3 based on its characteristics higher the better and lower the better respectively. This step converts the value of SN ratio within the range of zero to one and thereby reduces the chances for prioritizing one parameter over another during the analysis. Based on the output characteristics, the grey relational normalization equations also vary and are provided in equations 5 and 6.

In the case of MRR values, SN ratio values are obtained based on the objective higher the better and the normalization equation for the same is as shown in equation 5. While SN ratio values for Ra are based upon the performance characteristics lower the better and the grey relational normalizing equation for the same is as given in equation 6.

$$x_i^*(k) = \frac{x_i(k) - \min x_i(k)}{\max x_i(k) - \min x_i(k)} \quad (5)$$

$$x_i^*(k) = \frac{\max x_i(k) - x_i(k)}{\max x_i(k) - \min x_i(k)} \quad (6)$$

Where $x_i^*(k)$ and $x_i(k)$ represents the evaluated normalized value and the output response value respectively for the k^{th} response obtained from an i^{th} experimental trial. From the obtained normalized output response values, the GRC values are evaluated based on equation 7.

$$\xi_i(k) = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta_i(k) + \zeta\Delta_{max}} \quad (7)$$

in which $\Delta_i(k)$ can be defined as the absolute difference value between $x_i^*(k)$ and $x_i^0(k)$, Δ_{max}, Δ_{min} defines the global maximum and minimum value of the normalized data set respectively. The distinguishing coefficient of GRA (ζ) is used to expand or compress the GRG range and most often the value of the same is considered as 0.5 and the same is repeated in this research also. Based on the computed set of GRC values of the output response, the GRG value is evaluated by taking the average value of the GRC values and is done accordingly based on equation 8.

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

where γ_i stands for the GRG values and ‘n’ the number of output responses respectively. Based on the larger values, ranking of GRG values is carried out and the combination of process parameters with maximum GRG value in the OA considered is considered as the optimum combination. ANOVA for GRG values is carried out to study the contribution percent and statistical importance of each input parameters over GRG values.

2. Results and Discussion

3.1. Microstructural and Mechanical Characterization

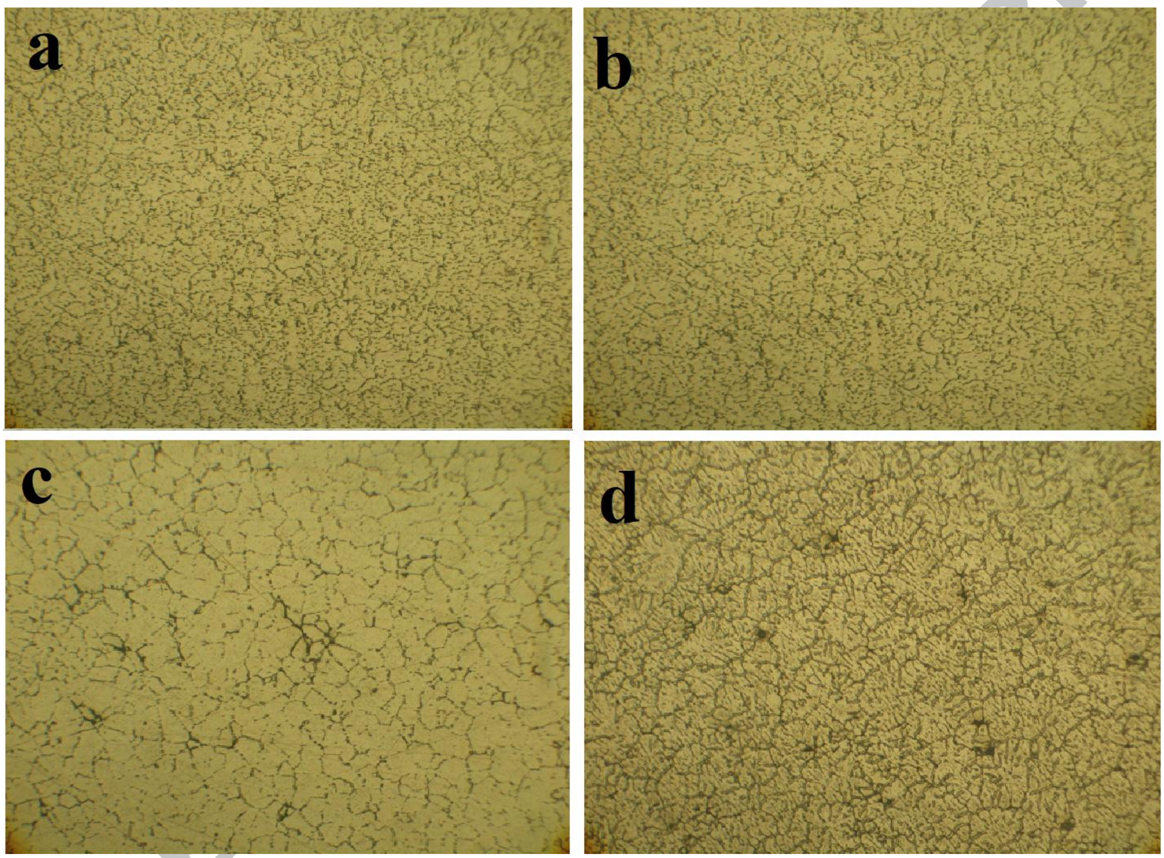


Figure 2. Optical micrographs of (a) S1, (b) S4, (c) S5, (d) S8

Optical micrographs of the developed alloys and its components are shown in figure 2(a-d) in which 2(a) and (b) portrays the optical image of aluminum alloys with 5 and 20 wt% of tin alloyed to it, while (c) and (d) demonstrates the image of aluminum composites with Sn and SiC particles dispersed into it. Comparing the optical micrographs of the developed alloys and composites with varying tin weight percentage, it can be stated that tin influences in defining the microstructural images of the developed alloys and composites, and it can also be stated that the introduction of tin particles into aluminum alloy has made grain structure coarser and thereby more eutectic phase. It has been previous report that manufacturing process affects the grain structure, grain size and microstructures which plays a vital role in the properties and performance of metals and alloys [46-49].

The hardness of the material governs the MRR and Ra value to a great extent and hence hardness and density evaluation was carried out in this research and the results thus obtained are provided in figure 3. It can be observed from figure that density values of the developed composites tends to increase with increase in tin weight percentage in both the scenario of alloys and composites and it has to be noticed that alloys showcased minimal density when compared with composites. The hardness value of the alloys tends to decrease with increase in the weight percentage of tin particles while the dispersion of SiC particles into the aluminum matrix enhanced the hardness of the developed composites when compared with the alloys.

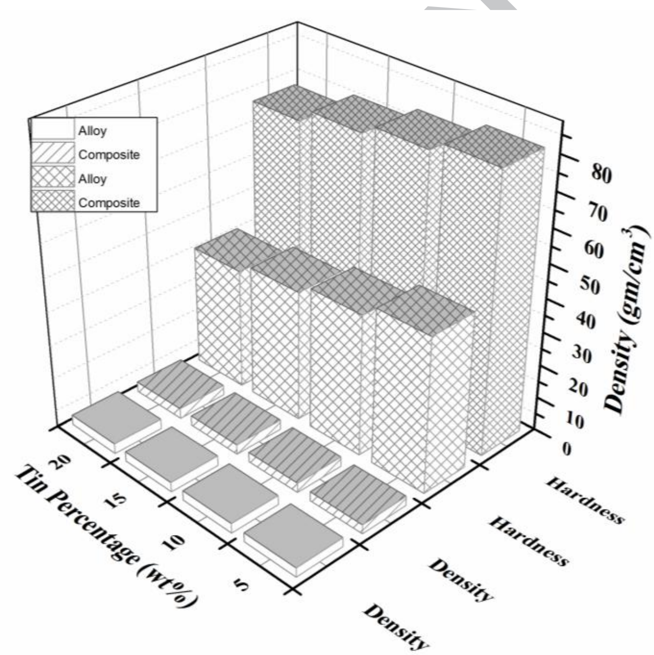


Figure 3. Hardness and Density plots of the developed alloys and composites.

2.2. Single Objective Optimization

The analysis of process parameters through Taguchi method to establish the optimal conditions so as to achieve the better results were carried out in this research. The analysis was done and the parametric influence over each response is discussed in this section. Experimental design has been carried out using L32 orthogonal array. L32 orthogonal array dataset has the material elemental composition parameters (i.e. Sn wt% and SiC wt %) data, WEDM process parameters data and output responses such as Material Removal Rate and surface roughness data. Figure 4 shows the visualization of L32 orthogonal array dataset in matrix scatter plot. R programming has been employed for data visualization.

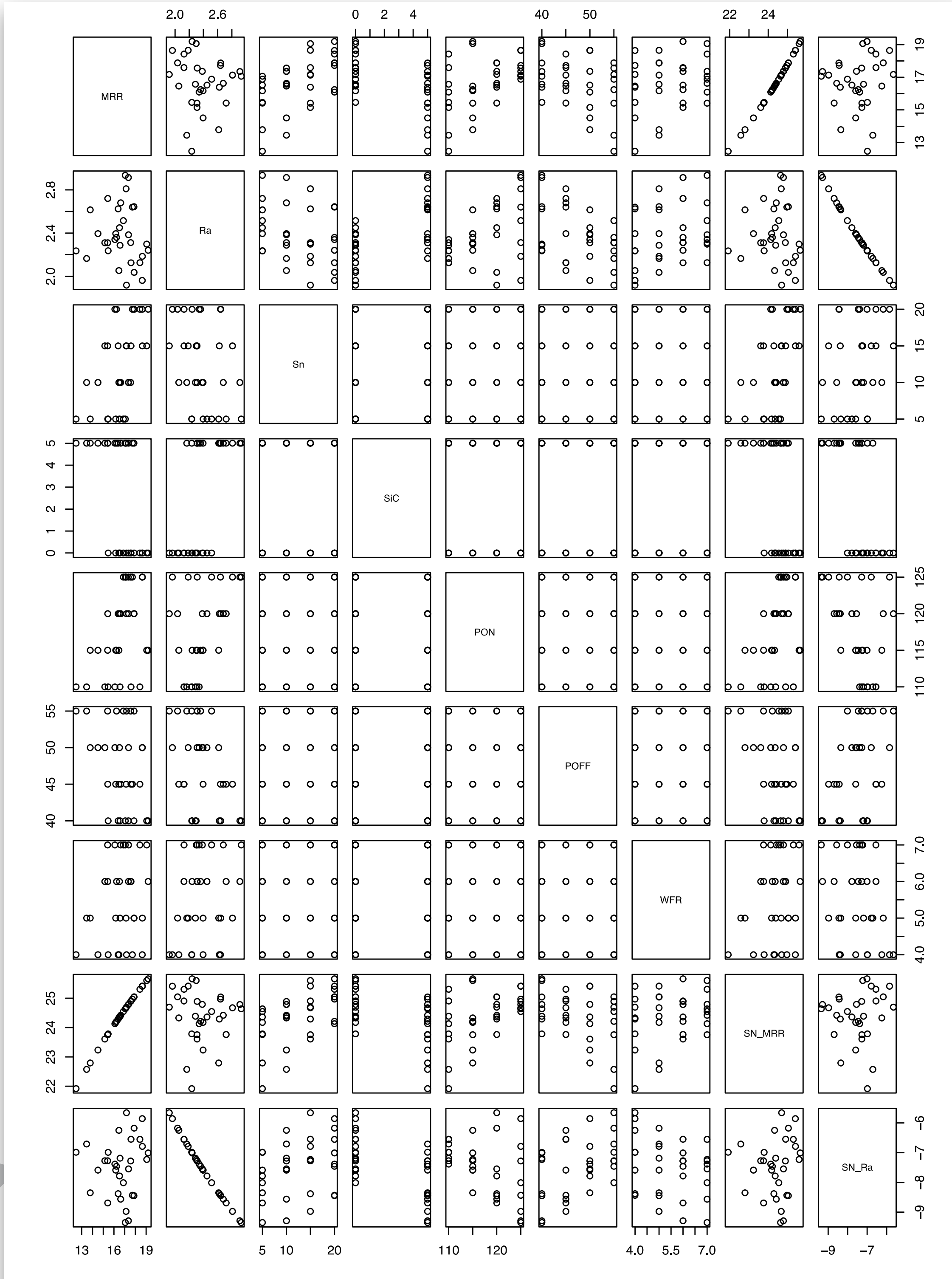


Figure4. Visualization of L32 orthogonal array dataset in matrix scatterplot.

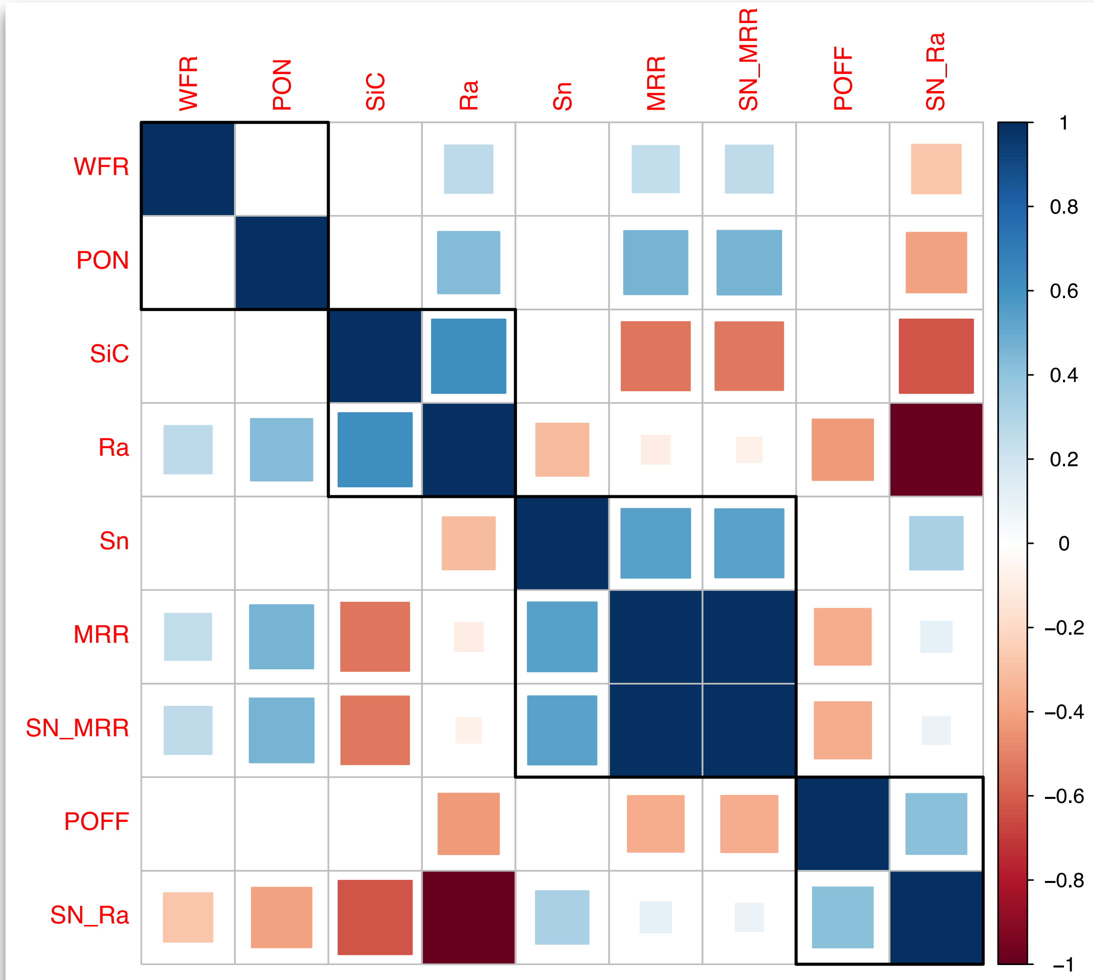


Figure.5 Hierarchical clustering of correlation coefficient matrix of input variables (i.e. both material elemental composition parameters and WEDM process parameters) and response variables (i.e. Material removal rate and Surface roughness).

Figure 5 shows the visualization of correlation matrix of input variables such as material elemental composition parameters, WEDM process parameters and response variables such as Material Removal Rate and surface roughness. The correlation matrix was reordered based on hierarchical clustering order according to the correlation coefficient to identify the structure and pattern in the matrix. The color intensity and size of square are proportional to the correlation co-efficient and then the positive and negative correlations are displayed in red and blue color respectively. The four black rectangles boundaries drawn inside the correlation matrix are shows the results of hierarchical clusters.

Analysis of the acquired MRR value based on the designed set of parameter combinations were carried out by converting the MRR response value to its SN ratio based on larger the better criteria. The attained MRR values along with its SN ratio values are provided in figure6. Based on the Taguchi analysis of the L32 OA, a SN ratio response graph was attained which briefs the effect of each control parameters over the output response MRR and the same is plotted as figure 6. Figure 6 demonstrates the effect of both material and machining parameters and aids to conclude the optimal set of processing parameters so as to achieve the maximum MRR value by the machinist.

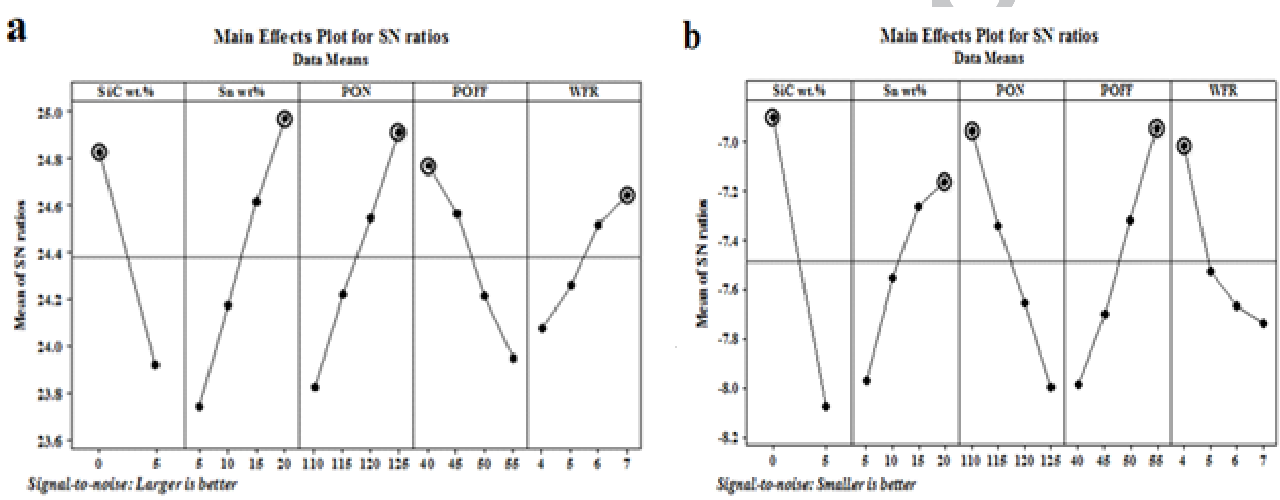
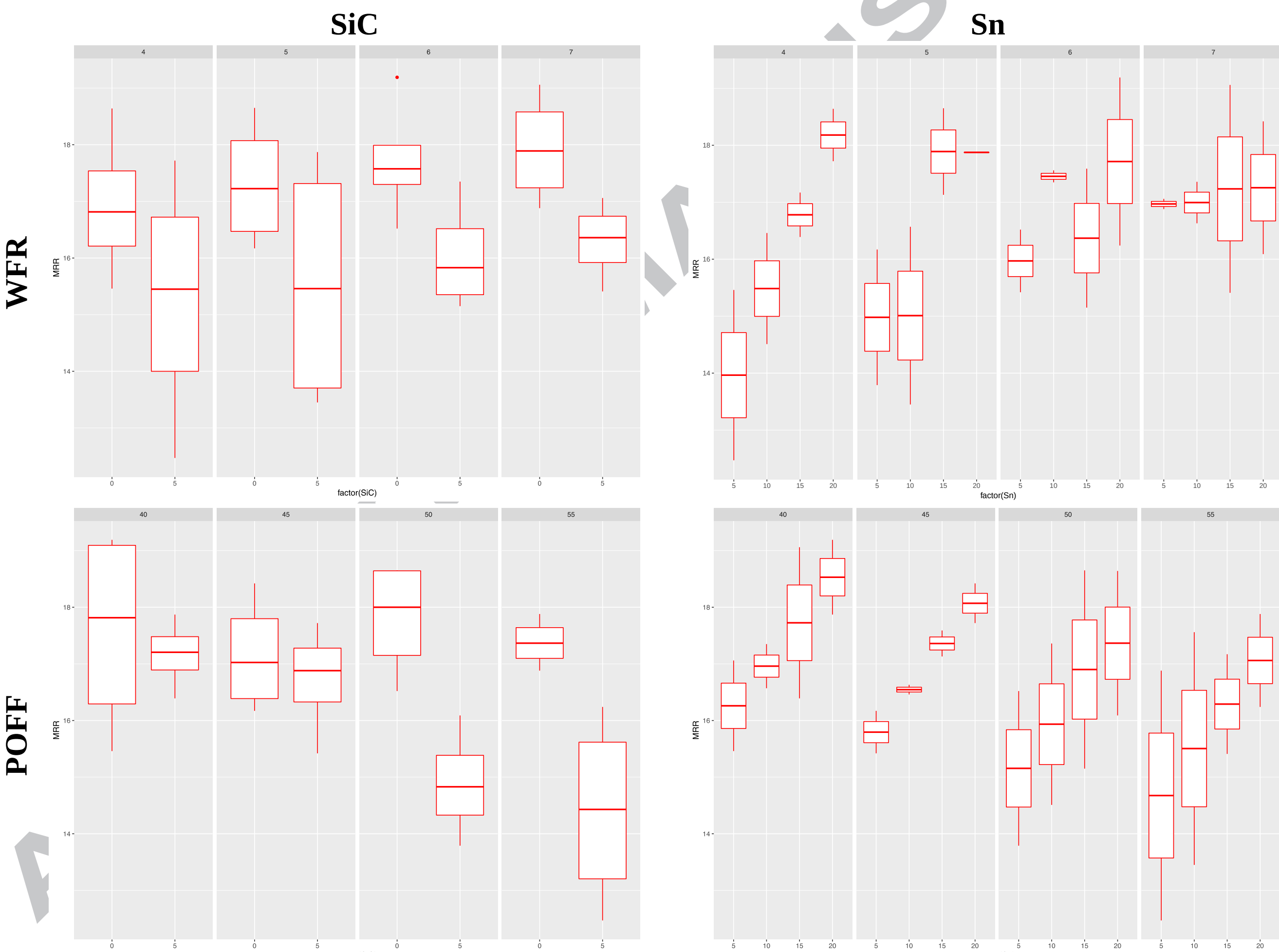


Figure 6. SN ratio response graph for (a) MRR (b) Ra

The results of analysis of variance between of MRR with SiC and Sn for various WDEM process parameter are shown in box plot. The analysis of variance and its visualization plots modeled using R programming in R Studio. From figure 6(a) and 7 it can be surveyed that the material parameters have made a great impact in governing the MRR value and it can be observed that with increase in the weight fractions of SiC particles, the MRR values tends to decrease. The increment in the hardness values of the developed composites when compared to the developed alloys with introduction of SiC particles can be stated as the major hitch causing the reduction of MRR values. The insulating nature of SiC particles dispersed into the matrix of aluminum alloys limits the generation of electric sparks, which can also be attributed, for the reduction of the MRR values. It can be viewed from figure 6(a) and figure 7 that with introduction of the alloying Sn element, the MRR values tends to increase. Tin being a soft material when alloyed with the matrix aluminum alloy showcase a tendency to decrease hardness of the developed alloy and composite specimens, thus enabling the easy passage of the wire through the material boosting the WFR thereby increasing the MRR value. Again to this, it can be added that Sn element with a melting point of 231°C even though alloyed with the aluminum metal showcases a tendency to melt down once the temperature surpasses the melting point. It is a known fact that during WEDM, electric sparks are produced creating a high temperature between the interface of work piece and wire electrode leading to crater formation due to the melting and vaporizing of the minute part of the cutting specimen [44]. In this scenario, the electric sparks produced during the machining tends to melt the alloyed tin element due to the increased temperature which gets vaporized and flushed away leading to the increment of MRR values.



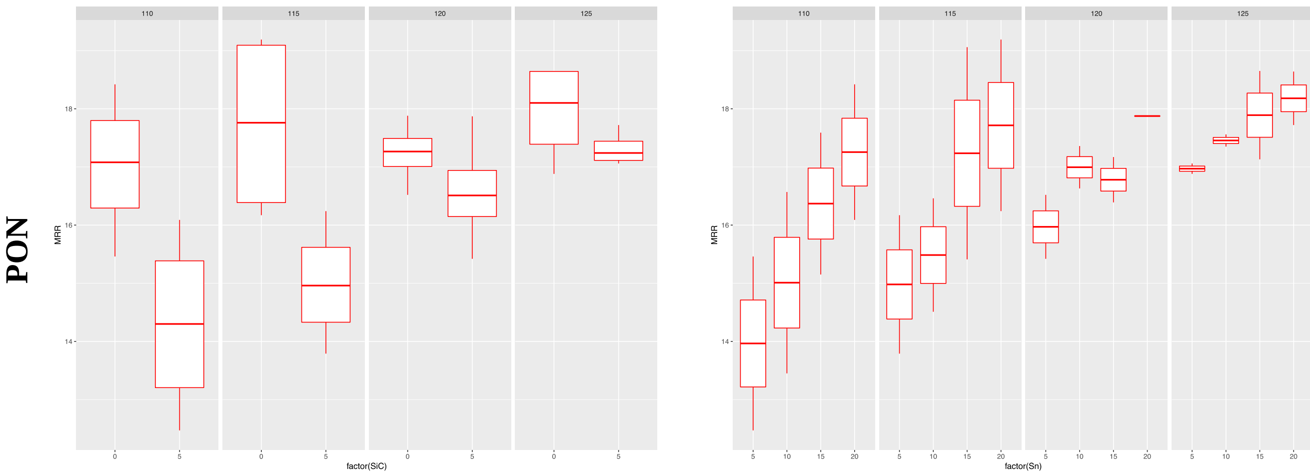


Figure 7 Visualization of analysis of variance between of MRR with SIC and Sn for various WDEM process parameter in box plot.

Considering the operating parameters based on Taguchi analysis, it can be observed that with increase in the PON time, the MRR value tends to increase as shown in figure 5 and 7. WEDM is a discontinuous machining process in which electric sparks will be created during PON time and will be idle over POFF time. The increase in MRR value in this study with respect to PON time can be attributed to the reason that with increase in PON time, the discharged electric sparks tends to increase and this high intensity electric sparks tends to deepen the cut, forming craters on the work piece and thereby increases the MRR values. Apart from the above said reason it can also be stated that the heat generated during the PON time widens the HAZ zone of the work piece which produces deeper craters during next PON cycle. Chances are there that the softened material gets flushed away with high pressure dielectric fluid during the idle time. In the case of composite materials considered in this study, the melting point of SiC particles is far ahead of that of aluminum and with respect to the intensity of PON the HAZ area widens loosening the SiC particles from the matrix material and gets flushed away along with the dielectric fluid increasing the MRR values.

POFF time in this study is considered as one of the major parameter that influence the MRR value and the effect of POFF time increment over the MRR value is as shown in figure 6(a) and 7. It can be observed that with increase in the POFF value, the MRR value decreases and this phenomenon of MRR decrement is due to the reduction in number of electric sparks during the full machining cycle. Again to this, increase in POFF time increasing the flushing time of dielectric fluid which reduces the HAZ zone thereby hardens the soft zone reducing the MRR values. The effects of WFR in influencing the MRR are investigated through Taguchi method and the same is depicted in figure 6(a) and 7. It can be observed that with increase in the WFR values, the MRR values tend to increase slightly. During WEDM, the wire electrode also tends to get eroded during the spark generation and the MRR can be affected by the nature of the wire surface to an extent. With a lower WFR value, the wire electrode exposed to produce sparks gets eroded away leading to production of improper electric sparks which automatically reduces the MRR value on the other hand with increased WFR value unexposed wire electrode gets exposed with the work piece continuously which produces high intensity electric sparks eroding away the work piece material.

Table 4. Analysis of Variance for MRR

Source	**DF**	**Seq SS**	**Adj SS**	**Adj MS**	**F**	**P**	**Contribution%**
SiC wt.%	1	22.6128	22.6128	22.6128	591.36	0.000	28.64
Sn wt%	3	23.6691	23.6691	7.8897	206.33	0.000	29.98
PON	3	16.7987	16.7987	5.5996	146.44	0.000	21.28
POFF	3	10.2956	10.2956	3.4319	89.75	0.000	13.04
WFR	3	4.8805	4.8805	1.6268	42.54	0.000	6.18
Error	18	0.6883	0.6883	0.0382			0.87
Total	31	78.9451					

Significance of the processing parameters over the MRR value based on its ‘P- value’ were investigated based on the evaluated ANOVA table and the contribution percentage of each control factors were calculated and is provided in table 4. R and R Studio was employed for the investigation of ANOVA. From the table it can be observed that the most contributing factors over the MRR values are the material based parameter, which includes Sn wt% (29.98%) and SiC wt% (28.64) respectively. Apart from the material based control factors, PON time influences the MRR value to a significant rate, i.e. 21.28% followed by POFF time (13.04%) and WFR (6.18%). Based on the P value it can be stated that all the processing parameters considered in this study has a significant effect in governing the MRR values of the considered Aluminum based alloys and composites with varying weight fraction of Sn element. The optimal combination of significant control factors to accomplish the maximum output response MRR can be achieved based on the analysis of the SN ratio of the attained MRR values. Based on figure 6(a) and 7, the optimal combination to attain the maximum MRR value are been finalized as

A1B4C4D1E4 in which A, B, C, D and E stands for SiC wt% , Sn wt%, PON, POFF and WFR respectively at levels 1,4,4,1 and 4 accordingly.

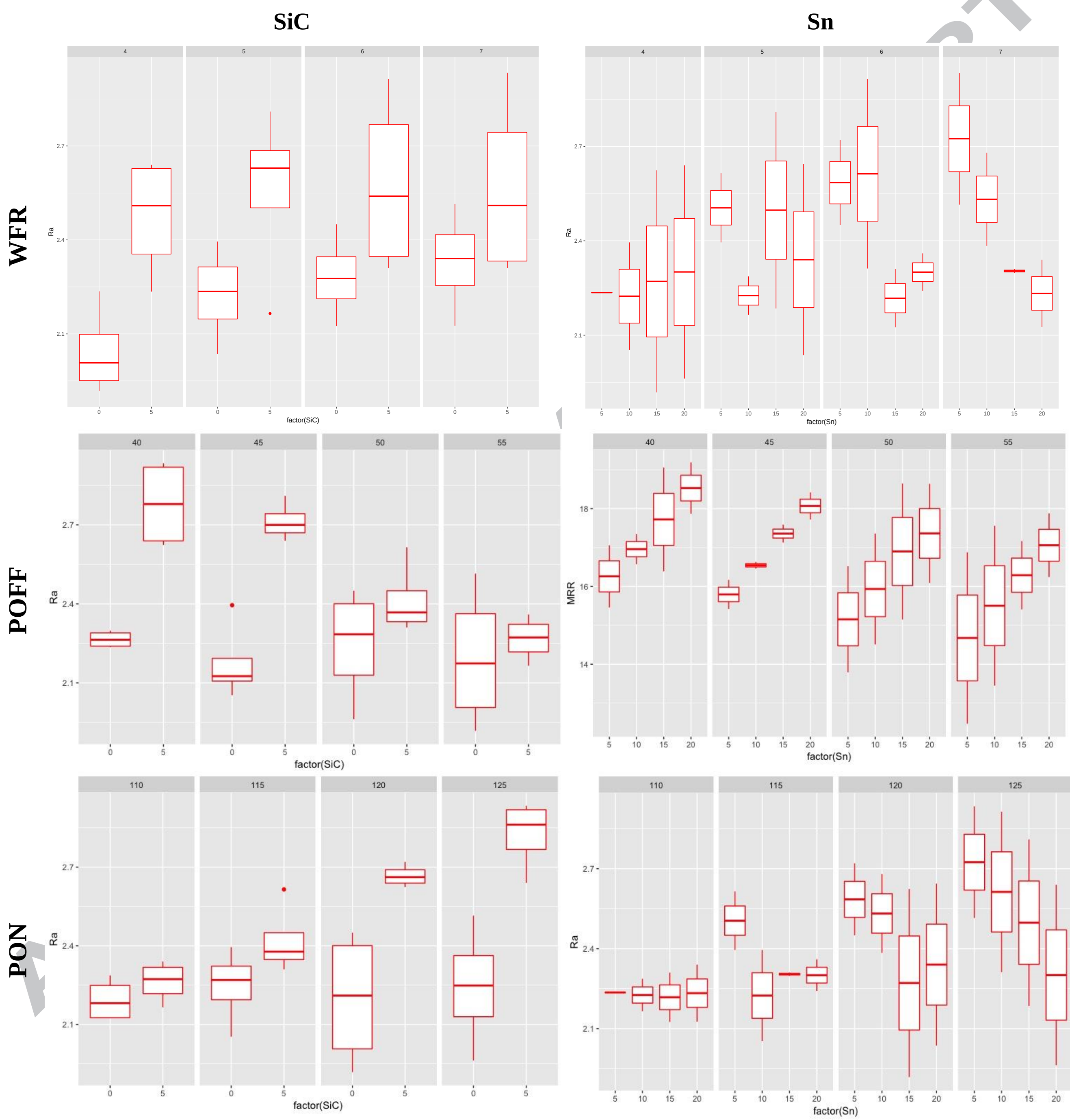


Figure 8. Visualization of analysis of variance between Ra with SIC and Sn for various WDEM process parameter in box plot.

Figure 8 shows the results of analysis of variance between of Ra with SIC and Sn for various WDEM process parameter in box plot. R packages and R Studio are employed for the analysis of variance and its visualization plots. The attained surface roughness value for the designed L32 OA is converted to its SN ratio values based on smaller the better characteristics and is as shown in figure 6(b). Based on the SN ratio value, the influence of each control factors over the Ra value is analyzed using Taguchi method and the same is as shown in figure 6(b). It can be perceived from figure 8 and 6(b) that introduction of SiC particles into Al alloy had an adverse effect over the surface roughness. This reduction in surface roughness value with respect to introduction of SiC particles can be attributed to the presence of hard ceramic particles dispersed into the aluminum alloy matrix. The presence of insulating SiC particles into the aluminum alloy restricts the electric spark generation and at the same time reduces the WFR thereby reducing the Ra values. Improper spark generation leads to uneven melting of work piece material thereby forming craters with irregular depth reducing the surface integrity of the developed material. It can also be stated that with the melting of the aluminum alloy due to electric sparks protrudes the SiC particles over the machined area increasing the Ra values. Influence of Sn wt% as alloying element over the Ra response is described in figure 8 and 6(b) which reveals that with increase in wt% of Sn particles the Ra value tends to increase slightly. This increase in Ra value with respect to increase in tin wt% can be stated as the low melting point and hardness of the Sn element which reduces the overall hardness of the developed set of alloys and composites and at the same time tin gets vaporized due to the high temperature generated during the electric spark generation.

SN ratio based analysis to study the influence of PON over the Ra value is as shown in figure 6(b) and it reveals that with respect to increase in the PON time value, the Ra value is suspect to increase reducing the surface integrity of the machined surface. This reduction in the surface integrity can be an after effect of the localized erosion with increase in the PON time. The increment in PON time increases the HAZ of the work piece specimen melting away the aluminum alloy and tin element in an uneven proportion leading to the formation of irregular craters. This uneven melting of Al alloy and tin will lead to protrusion of the SiC particles in the case of composite thus reducing the surface integrity of the work piece specimen. It can also be seen during the WEDM process that during high PON time value, the electric sparks last long leading to the formation of melt expulsion from the matrix material thereby reducing the surface integrity of the machined surface. Henceforth based on this research it can be stated that to achieve a minimal Ra value, the minimum PON time has to be concentrated.

POFF time and its effects on Ra value based on Taguchi analysis of SN ratio is carried out and the results are demonstrated in figure 6(b). It can be observed that with respect to increase in POFF time, the Ra value of the machined surface tends to decrease. This phenomenon can be due to the reason that as the POFF time increases the flushing time of the dielectric fluid also tends to increase which flushes away the debris and molten expulsions to a large extent so as to attain a clean surface for the subsequent PON time. This flushing of dielectric fluid during the POFF time helps to a great extent in increasing the surface integrity of the work piece specimen. These happenings during the POFF time at higher level attribute to increase the surface finish of the machined specimen during WEDM process. Considering the influence of WFR over the Ra values based analysis of the SN ratio through Taguchi methods was portrayed in figure 6(b) and it consolidates that with increase in WFR value the Ra value tends to decrease. This decrease in Ra value with respect to WFR is due to the high intensity sparks discharged through the newly introduced wire surface during high WFR which creates deeper cracks leading to increased MRR value but reduces the surface integrity of the machined surface.

Table 5. Analysis of Variance (ANOVA) for Ra

Source	**DF**	**Seq SS**	**Adj SS**	**Adj MS**	**F**	**P**	**Contribution%**
SiC wt.%	1	0.83625	0.83625	0.83625	114.52	0.000	38.39
Sn wt%	3	0.22929	0.22929	0.07643	10.47	0.000	10.53
PON	3	0.41347	0.41347	0.13782	18.87	0.000	18.98
POFF	3	0.39077	0.39077	0.13026	17.84	0.000	17.94
WFR	3	0.17699	0.17699	0.059	8.08	0.001	8.13
Error	18	0.13144	0.13144	0.0073			6.03
Total	31	2.17821					

Significance of each processing parameter in governing the Ra value during the WEDM processing of the developed alloys and composites were studied and the attained results are as shown in table 5. Based on table 5 it can be notified that the Ra value of the machined work piece is influenced at the maxima by the presence of SiC particles which means that the composites exhibits the maximum Ra value and hence forth the less surface finish when compared with the alloys. Followed by the SiC particles presence the machining parameter PON time has significant effect over Ra value which is about18.98% trailed by the POFF time with a contribution percentage of 17.94%. Sn wt% contributes to the Ra value at 10.53% followed by the WRF at a percentage of 8.13% contribution percentage.

The optimal combination of the considered set of processing parameters so as to achieve the minimal surface roughness value for the machined set of specimens were figured out from the SN ratio plot graph as shown in figure 6(b). It can be concluded from figure 6(b) that A1B4C1D4E1 set of process parameters can be considered so as to acquire the minimal surface roughness value, were A, B, C, D and E stands for SiC wt% , Sn wt%, PON, POFF and WFR respectively.

2.3.Multi-Objective Optimization Using Grey Relational Analysis

Taguchi based method focuses on single objective optimization of an output response and in the case of industries, the engineers or machinist try to attain the maximum production without sacrificing the surface roughness criteria and in these cases, single objective optimization techniques gets pushed back and multi-objective optimization techniques comes into the focus. Grey Relational Analysis is a technique among many multi criteria optimization techniques which has been proved to be efficient in finding out the optimal set of process combinations so as to achieve maximum efficiency for a particular process. In this research, the machined surface of the developed set of alloys and compounds should have the minimal surface roughness value and at the same time the production time also should be minimal so as to attain the maximum productivity.

Table 6. Normalized values, GRC, GRG and Grade

Exp No	Normalized SN ratio		GRC		GRG	Rank
	MRR	Ra	MRR	Ra		
1	0.4986	0.3608	0.4993	0.44	0.4691	29
2	0.6027	0.5224	0.5573	0.51	0.5344	20
3	0.6524	0.5758	0.5899	0.54	0.5655	17
4	0.7024	0.6374	0.6269	0.58	0.6033	14
5	0.6594	0.4139	0.5949	0.46	0.5276	22
6	0.6440	0.1600	0.5841	0.37	0.4786	26
7	0.7675	0.5116	0.6826	0.51	0.5942	15
8	0.7940	0.4395	0.7083	0.47	0.5899	16

9	0.7980	0.2411	0.7123	0.4	0.5547	19
10	0.9842	0.4252	0.9694	0.47	0.7173	5
11	0.7419	0	0.6596	0.33	0.4965	24
12	0.9337	0.3066	0.8831	0.42	0.651	9
13	0.9049	0.2422	0.8403	0.4	0.6189	10
14	1	0.3661	1	0.44	0.7205	4
15	0.8359	0.1404	0.753	0.37	0.5604	18
16	0.9325	0.0533	0.8811	0.35	0.6134	13
17	0	0.3598	0.3333	0.44	0.3859	30
18	0.2334	0.7292	0.3948	0.65	0.5217	23
19	0.4925	0.8218	0.4963	0.74	0.6168	11
20	0.7270	1	0.6469	1	0.8234	2
21	0.1755	0.2849	0.3775	0.41	0.3945	29
22	0.3514	0.5224	0.4353	0.51	0.4734	28
23	0.6678	0.7869	0.6008	0.7	0.651	8
24	0.7661	0.9839	0.6814	0.97	0.8251	1
25	0.4516	0.4374	0.4769	0.47	0.4738	27
26	0.4910	0.4374	0.4956	0.47	0.4831	25
27	0.6341	0.7373	0.5774	0.66	0.6165	12
28	0.7365	0.8984	0.6549	0.83	0.743	3
29	0.5912	0.4678	0.5502	0.48	0.5173	24
30	0.6127	0.4878	0.5636	0.49	0.5288	21
31	0.8346	0.7551	0.7515	0.67	0.7114	6
32	0.8151	0.7516	0.7301	0.67	0.6991	7

The GRA initiates with considering the SN ratio of the considered output responses and in this study SN ratio values for the MRR and Ra values were evaluated based on larger the better and smaller the better criteria respectively. The SN ratio values were calculated based on equations 2 and 3 and the attained SN ratio values are provided in table 3. Normalizing the output response values is an unavoidable process in GRA technique which gives all the outputs the same influence over the GRG which has to be calculated. In this research maximization and minimization occurs and henceforth the normalization of SN ratios within 0 to 1 is done based on equations 5 and 6 respectively for MRR and Ra values. Based on the normalized values obtained and produced in table 6, the GRC values were established as per equation 7 for both output response values and average of the two were carried out to determine the GRG values and the same is ranked accordingly. The calculated GRC, GRG and rank is produced in table 6. The grading of the GRG is carried out by considering the maximum as rank 1 and the least GRG as the last rank and vice versa. The parameter combination with GRG value ranked 1 is considered as the optimal set of combination that provides the maximum MRR value with considerable Ra value and in this study trial 24 has the maximum GRG value (0.8251) and henceforth is considered as the optimal combination for the machinist to machine for the provided set of alloy and composite specimens. Based on the evaluation the optimum condition can be identified from table 3 and confirmed as the composite material with 5 wt% SiC, 10 wt% Sn element at a PON time of 125, POFF time 40 and WFR value of 6 respectively.

Table 7. Response table for GRG

Parameters	**Level 1**	**Level 2**	**Level 3**	**Level 4**	**Max-Min**
SiC content	0.5810	**0.5916**			0.0106
Sn wt%	0.5650	0.5668	0.5920	**0.6212**	0.0562
PON	0.4927	0.5572	0.6016	**0.6935**	0.2008
POFF	**0.6764**	0.6121	0.5513	0.5053	0.1711
WFR	0.5291	0.5805	0.6094	**0.6261**	0.0970

The response table for the GRG values is as produced in table 7 based on which the optimal levels can be finalized for the multi-machining characteristics in this study. The analysis of the GRG data is mainly carried out with higher the better criteria and in the optimal parameter for the multi-machining characteristics can be obtained by considering the larger value. Based on larger the better criteria, the optimum levels for the parameters was selected from the response table which is found to be SiC = 5wt%, Sn = 20wt%, PON= 125µs, POFF= 40µs, and WFR= 7 m/min respectively.

2.4.Mathematical Modeling

Based on the significance of each control factors from ANOVA table, it was concluded that all the parameters affect in governing the MRR and Ra value and hence a mathematical model was developed to predict the MRR and Ra values which is as provided in the form equation 9 and 10. The predicted values for MRR and Ra values were plotted against the experimentally validated set of readings and are provided in figure 9 and 10 respectively. The regression model developed for the set of MRR values based on the considered set of input control factors yielded an R-Square value of 98.91% while the model for Ra yields an R-square value of 91.89%.It can be concluded from these pictorial representations that the experimental and predicted results correlates to each other to an extent and the same can be used to predict the results for a set of reading for the given set of alloys and composites.

MRR = 3.241 - 0.33625 SiC wt.% + 0.15375 Sn wt% + 0.12945 PON -0.10125 POFF + 0.34725 WFR (9)

Ra = 0.61655 + 0.0646625 SiC wt.% - 0.0146575 Sn wt% + 0.0203325 PON - 0.0197225 POFF + 0.0608375 WFR (10)

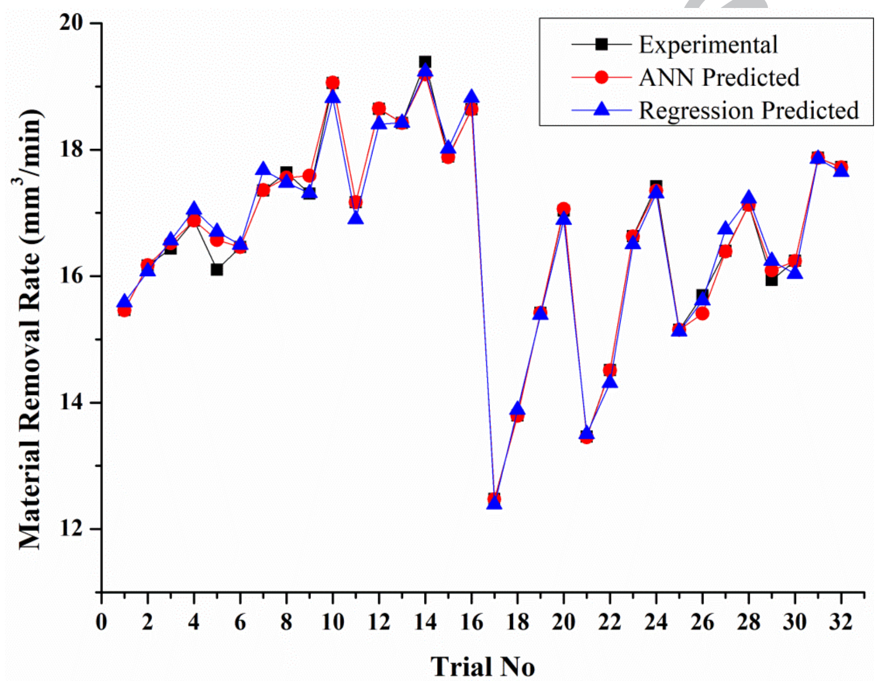


Figure 9. Experimental and Regression Based MRR Results.

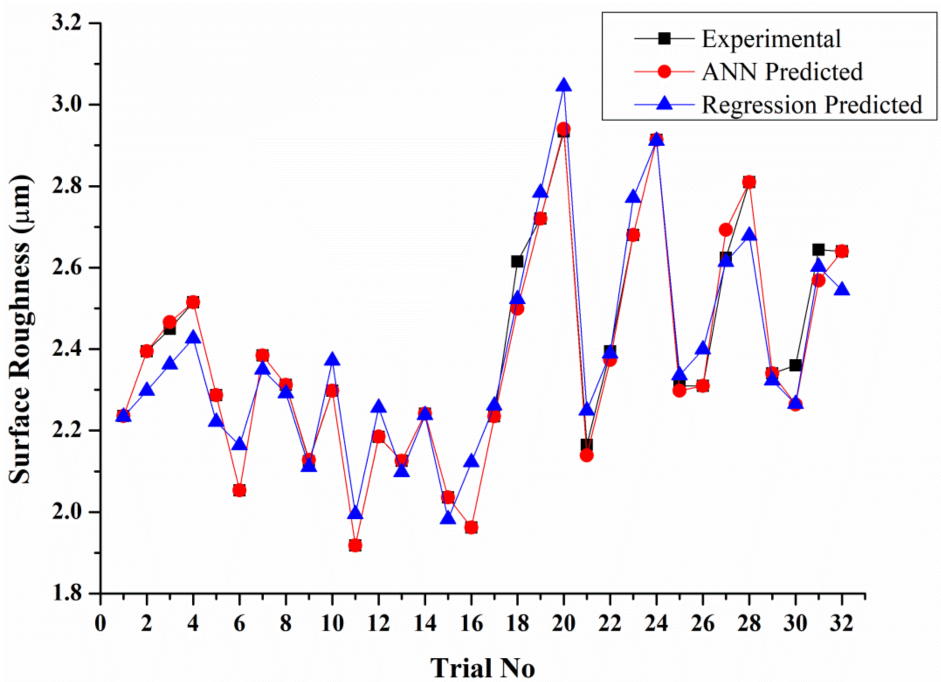


Figure 10. Experimental and Regression Based Ra Results.

2.5.Artificial Neural Network based Modeling

Mathematical modeling has always been in the substantial side when it comes to the correlation of a set of data with its other. In the case of materials, mathematical models has played major role is correlating its parameters with that of its properties, machining characteristics, etc. Even though a large study based on the material property and its control factors has been carried out through mathematical modeling, it can be noticed that the error shown by the developed mathematical model can be considerably high unless all the parameters that affects the output response has been investigated minutely and selected. Such condition of detailed investigation of parameters in the case of material based study is tough, as despite of the out seen parameters various other metallurgical aspects also take place along with every process and that can't be considered during the mathematical modeling of the same. In such scenario the practice of Artificial Neural Network (ANN) based modeling comes into handy where a model will be developed successfully based on the provided set of inputs and outputs.

Artificial Neural Networks developed based on the principle of human brain working has been utilized as an advanced tool in the field of materials to a great extent in developing and correlating the properties of the materials to its relevant properties based on the type of processing carried out. Its computing ability has made it an advanced tool in the field of pattern recognition, optimization, estimation, prediction etc. Similar to neurons in human nervous system, ANN comprises of computing nodes interconnected to each other and organized in layers that enables it to study from a given set of training data and gets trained accordingly to perform the approximation, classification and pattern recognition. ANN model comprises of an input layer, hidden layer and output layer in which nodes from input layer receives all the inputs and sent to the hidden layer where processing of data will be carried out and provided to the user as results through the nodes in output layer.

In this research, ANN models were developed so as to predict the MRR and Ra values based on the input control factors considered in this research including the weight percentage of SiC and tin as the material parameters and machining process parameters which includes PON time, POFF time and WFR. The models were trained based on the designed L32 OA and the attained output response, MRR and Ra values. Feed forward back propagation algorithm which proved to be used for solving non- linear and complex problems was considered in this study based on a detailed survey over literatures and Levenberg-Marquardt was finalized as the training function for updating the weight and bias values during the training procedure [33, 34, 45]. The transfer function considered in this research includes tan-sigmoid transfer function for the hidden layers and purelin transfer function for the output layer respectively. In regards of the above said algorithms and training functions, feed forward back propagation ANN models were trained with a single hidden layer consisting of various hidden nodes. L32 OA parametric combinations with SiC wt%, Sn wt%, PON, POFF and WFR were considered as the input parameters and MRR and Ra values were taken individually as the output response for training the models. Normalization of the inputs and output values were carried out such that all input control factors put forth an identical influence over the output during the training phase and normalization of all values between -1 to 1 were carried out based on equation 11 and is as produced below.

$$X_n = \frac{2(x - x_{min})}{x_{max} - x_{min}} - 1 \tag{11}$$

where X_n symbolize the normalized outcome, x_{max} and x_{min} representsthe maximum and minimum value from the given set of training data. Each model with varying number of hidden nodes were considered in this research and trained with the given set of inputs as optimizing the correct number of hidden nodes in the hidden layer is not practical based on certain relationships. Each model was trained for 1000 epochs and to find out efficient model the same were trained for an iteration of 10,000 in number. Performance of the developed set of models were evaluated based on Mean Square Error(MSE) performance function and the model with the least MSE value were considered as the efficient and best model for prediction purpose. Schematic representation of the model developed to predict the MRR and Ra value is provided in figure 11(a) in which different layers are clearly displayed.

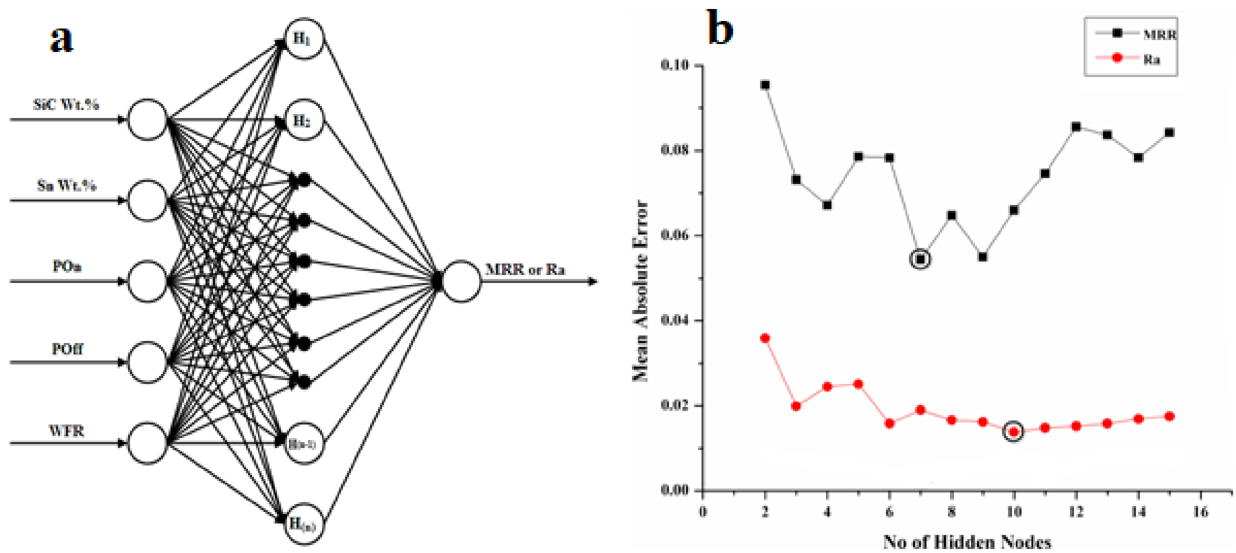


Figure 11. (a) Schematic Representation of ANN model (b) MAE value for the developed models

Based on the Mean Absolute Error (MAE) values, the developed set of ANN models were evaluated and the the model with the minimum MAE value was considered as the best model with better predictability. In this research, MAE values for all the developed set of models for predicting MRR and Ra values were computed and the obtained results were as potrayed in figure 11(b). From figure it can be stated that a feed forward back propagation ANN model with network topology 5-7-1 can be effectively used to model the MRR value and a model with topology 5-10-1 can be successfully utilized for predicting Ra values with better predictability nature. The considered ANN models finalized based on this research was then used to predict the

MRR and Ra values for the given set of inputs that has been used to train the model and the values are as shown in figure 9 and 10.

Results from the developed set of ANN model with topology 5-7-1 to predict the MRR values were attained for the L32 OA combinations and the same were compared with the experimentally validated results as shown in figure 9 which states that the predicted results had a better correlation with the experimental results. The R-Square value for the developed feed forward back propagation ANN model to predict MRR value was estimated to be 99.42% which states that the model seems to be more efficient when compared with that of the mathematical model developed to predict the results. Similarly the other developed ANN model to predict the Ra were used to forecast the results for the considered L32 OA and compared with the experimental results. The predictability of ANN model with network topology 5-10-1 and the R-square value of the developed model tends to be 98.51% which was comparatively higher when compared with the developed regression model.

2.6.Confirmation Results

The optimal parameter combination attained based on the research has to be evaluated to study the improvement of the considered output. The optimal combinations of parameters were considered and the validation experiments were carried out to evaluate the study.

2.6.1. Single-Objective Optimization

The optimal combination for attaining the maximum MRR values during WEDM process was finalized and the combination code for parameters obtained as A1B4C4D1E4 states maximum MRR value can be achieved for aluminum alloyed with 20 wt% of Sn content machined at an operating conditions of PON=125μs, POFF= 40μs and WFR= 7m/min. The parameter combination code to attain the minimal surface roughness value during the WEDEM machining canbe put forward as A1B4C1D4E1 in which the aluminum metal with 20wt% of Sn content can attain the minimum surface roughness value at a minimum PON time(110μs), maximum POFF time (55μs) and minimum WRF value(4 m/min). The experimentaly validated MRR and Ra values along with the regression based model and ANN predicted results are provided in table 8 for the optimal combination of process parameters. This MRR and Ra values obtained for the optimum combination of parameters has proved that these combination can improve the MRR rate and increase the surface integrity of the machined workpiece when considering with the L32 OA parameter combination.

Table 8. Results for Optimal Combination of Control Factors

Output Response	Optimal Combination	Experimental	Predicted	
			Regression	ANN
MRR(mm^3/min)	**A1B4C4D1E4**	20.607	20.878	20.595
R_a (µm)	**A1B4C1D4E1**	1.816	1.716	1.823

2.6.2. Multi-Objective Optimization

To validate the optimal combination of the multi- machining characteristics carried out through GRA, a confirnmation test was carried out and further evaluation of the GRG was carried out. Results obtained from the optimum parameter combination (A2B4C4D1E4) is compared with that of the initial optimum parameter combination (A2B2C4D1E3) obtained during the grey ralational analysis of L32 OA based output response. The results for the MRR and Ra values for the optimum set of parameter combination based on experiments, regression prediction and ANN prediction is produced in table 9. It puts forward that an increase in GRG grade was observed when compared with the intial set of parameters attained from the L32 OA design system. An increase of 0.0205 was distinguished in GRG values between the initial set of parameters and the optimum parameter set which indicates the improvement that takes place in WEDM machining. From table 9 it can also be confirmed that a reduction in Ra value has happened with an increase in MRR and hence made known that at this combination the work piece can be machined for better surface integrity even at higher rate of production.

Table 9. Confirmation Test

	Initial	Predicted		Experimental
		Regression	ANN	
Combination Code	**A2B2C4D1E3**		**A2B4C4D1E4**	
MRR(mm^3/min)	17.350	19.197	19.423	19.323
Ra(µm)	2.914	2.825	2.621	2.668
GRG	0.8251	0.9245	0.8266	0.8456
Improvement in grade		0.0994	0.0015	0.0205

3. Conclusions

In current research aluminum was elected as the matrix material into which 5, 10, 15 and 20 wt% of Sn material is added in order to develop a newer alloy grade namely Al-Sn alloy into which 5 wt% of SiC was further added so as to develop four sets of composite with varying weight percentage of Sn content. The WEDM process parmeters PON, POFF, WFR along with material parameters Sn wt%, SiC wt% were considered in this study based on which L32 OA based experimental design of parameter combinations was formed and trials were taken. The attained results were analysed, optimized and ANN modeled and the results are as provided below.

Taguchi analysis of the MRR results for the defined L32 OA states that with introduction of SiC particles MRR value decreases while it increases with respect to increase in Sn wt%. Outcomes considering the machining parameters states that increase in PON, WFR and decrease in POFF value increases the MRR values.

Taguchi analysis on the Ra values claims that with introduction of hard ceramic SiC particles into the Al-Sn alloy, the Ra values tends to increase reducing the surface quality while with increment in Sn wt% , reduction in Ra value was observed.

Multiple linear regression and ANN models was developed for predicting MRR and Ra values based on the significant input parameters and the results achieved from the models were compared with experimentalvalues and was found efficient.

Multicriteria optimization of the considered WEDM process parameters were performed employing GRA and the optimal combination code of parameters obtained isA2B2C4D1E3which states that the maximum MRR with minimal Ra value can be obtained for an aluminum composite with 5 wt% SiC, 20wt% Sn when operated at an operating condition of 125µs PON, 40µs POFF, and 7 m/min WFR respectively.

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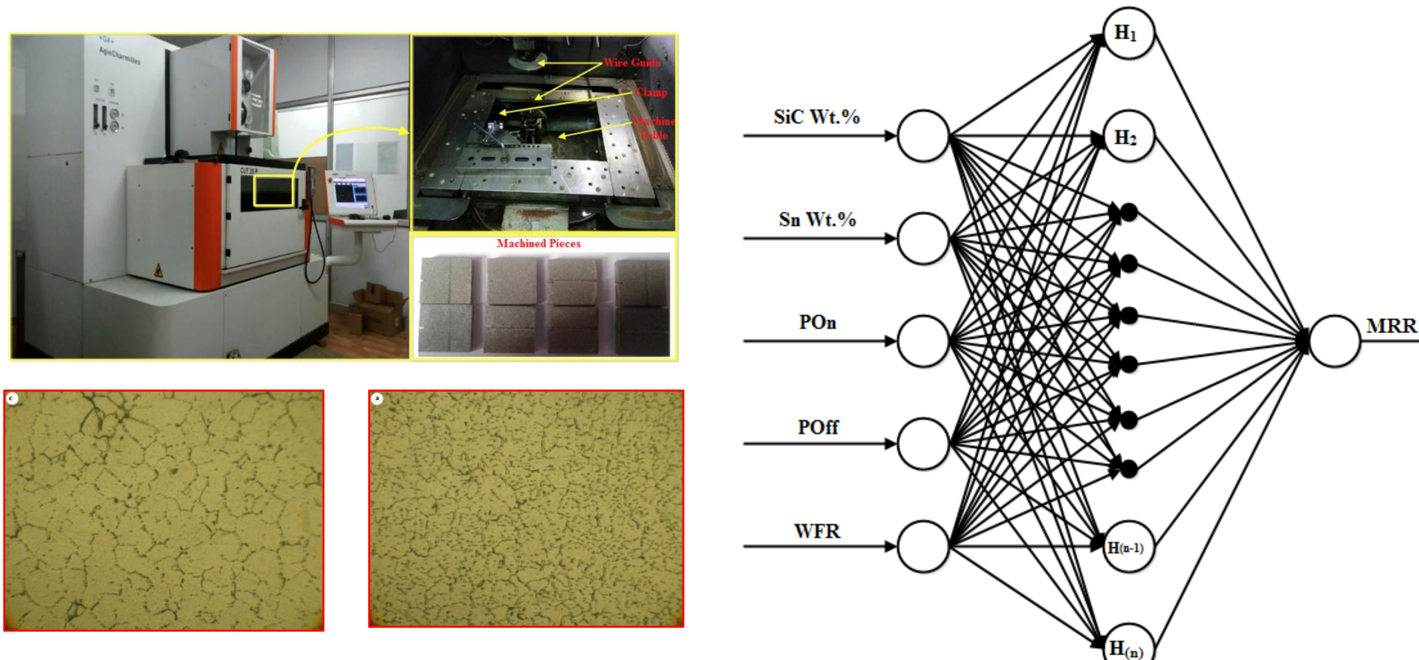
Highlights for review

- Designed and manufactured aluminum alloys and metal matrix composites
- Investigated the effect of surface roughness, microstructures and hardness.
- Investigated the effect of elemental composition and wire electric discharge machining (WEDM) process parameters
- Neural network models was developed using R programming & MATLAB to predict the MRR and Surface roughness.
- Experimental confirmations identified the effectiveness of the developed models to predict the process parameter.

Graphical Abstract



Alloy & Composite Material Composition and Process Parameter

Machine Learning