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Prediction of Machining Characteristics using Artificial Neural Network in Wire EDM of Al7075 based In-situ Composite

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Abstract

This paper focuses on prediction and comparison of machining performances during Wire Electrical Discharge Machining (WEDM) of Al7075-TiB_2 in-situ composite to achieve maximum Material Removal Rate (MRR), minimum Dimensional Error (DE) and better surface roughness. The control factors considered for the studies are pulse-on time, pulse-off time, current and bed speed. Process parameters have been selected based on Taguchi's L_{27} orthogonal array. An Artificial Neural Network (ANN) model has been developed in order to predict the response parameters. Predicted machining characteristics are in good agreement with experimental values.

Keywords: Wire EDM; In-situ composite; ANN.

1. Introduction

Aluminium based metal matrix composites are potential candidate materials for aeronautical and aerospace industries because of their most favourable properties like excellent strength, high stiffness, elevated temperature performances and low density in many high tech engineering applications. Heavy steel composites are being

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replaced by aluminium based composite materials. However, these composites are categorized as difficult to cut materials by conventional machining techniques, which limit their applications.

Non-uniform distribution of reinforced particles, anistropes, high hardness, higher brittleness are the other properties leads to reduced machinability of composites by conventional techniques. In order to achieve complex shapes in the composite materials, researches are focusing on non-conventional machining techniques in particular EDM process which can be successfully employed to machine composite materials. Material removal rate, dimensional accuracy and surface roughness are the three factors which defines the machinability of the process along with cost effect. A composite is a material that consists of two or more combined constituents that are combined at a macroscopic level and are not soluble in each other. Advanced composites are composite materials that are traditionally used in the aerospace industries. These composites have high performance reinforcements of a thin diameter in a matrix such as epoxy and aluminum.

Wire Electrical Discharge machining (WEDM) is a specialized thermal machining process capable of accurately machining parts of hard materials with complex shapes. WEDM has evolved as a simple means of making tools and dies to the best alternative of producing micro-scale parts with the highest degree of dimensional accuracy and surface finish. Molybdenum wire is used in limited applications which require very high tensile strength to provide a reasonable load carrying capacity in small diameter wire.

The cutting of Al_2O_3/6061 Al composite using rotary electro-discharging machining (EDM) with a disk like electrode by using Taguchi methodology was studied. The Taguchi method is used to formulate the experimental layout, to analyse the effect of each EDM parameter on the machining characteristics, and to predict the optimal choice for each EDM parameter. Four observed values, MRR, EWR, Relative EWR (REWR), and SR, are used to verify this optimization of the machining technique. In addition, six independent parameters are chosen as variables in evaluating the Taguchi method and are categorised into two groups such as Electrical parameters, e.g. polarity, peak current, pulse duration, and powder supply voltage, and Non-electrical parameters, e.g. circumferential speed of electrode, reciprocating speed. The analysis of the Taguchi method reveals that, in general, the electrical group more significantly affects the machining characteristics than the non-electrical group. From the results have observed the polarity of EDM largely affects the MRR. The peak current of EDM mainly affects the EWR and REWR. The polarity, the peak current, the pulse duration, and the circumferential speed of EDM mainly affect the SR. Semi-empirical expressions are successfully proposed to simplify the evaluation of MRR, EWR, REWR and SR using several parameters under various machining conditions [1]. A second order multi-variable regression model and a feed-forward Back-Propagation Neural Network (BPNN) model were developed to correlate the input process parameters, such as pulse on-time, pulse off time, peak current, and capacitance with the performance measures namely, cutting speed and surface roughness while wire electro- discharge machining (WEDM) of tungsten carbide-cobalt (WC-Co) composite material. From a large number of neural network architectures, 4-11-2 has been found to be the optimal one, which can predict cutting speed and surface roughness with 3.29% overall mean prediction error. The multivariable regression model yields an overall mean prediction error of 6.02%. Both the models have been used to study the effect of input parameters on the cutting speed and surface roughness, and finally to corroborate them with those of the experimental results [2]. The relationship of process parameters in electro-discharge of CK45 steel with novel tool electrode material such as Al–Cu–Si–TiC composite produced using powder metallurgy (P/M) technique. The central composite second-order rotatable design had been utilized to plan the experiments, and response surface methodology (RSM) was employed for developing experimental models. Analysis on machining characteristics of EDM die sinking was made based on the developed models. Titanium carbide percent (TiC%), peak current, dielectric flushing pressure, and pulse on-time are considered as input process parameters. The process performances such as material removal rate (MRR) and tool wear rate (TWR) were evaluated. Analysis of variance test had also been carried out to check the adequacy of the developed regression models. Al–Cu–Si–TiC P/M electrodes are found to be more sensitive to peak current and pulse on time than conventional electrodes. A good agreement is observed between the results based on the RSM model and the actual experimental observations. The error between experimental and predicted values at the optimal combination of parameter settings for MRR and TWR lie within 7.2% and 4.74%, respectively [3]. Mathematical models for the modeling and analysis of the effects of machining parameters on the performance characteristics in the EDM process of Al2O3+TiC mixed ceramic which are developed using the response surface methodology (RSM) to explain the influences of four machining parameters (the discharge current, pulse on time, duty factor and open discharge voltage) on the performance characteristics of the MRR, EWR, and SR. The experiment plan adopts the centered Central Composite Design (CCD). The development of mathematical models for investigating the influences of machining parameters on performance characteristics and the proposed mathematical models in this study have proven to fit and predict values of performance characteristics close to those readings recorded experimentally with a 95% confidence interval. Results show that the main two significant factors on the value of the MRR are the discharge current and the duty factor. The discharge current and the pulse on time also have statistical significance on both the value of the EWR and the SR [4]. The effects of EDM parameters on drilled-hole quality such as taper and surface finish are evaluated. Microwave-sintered magnesium nano composites (reinforced with 0.8 and 1.2 wt. % of nano alumina) were used as work materials. Experiments were conducted using Taguchi methodology to ascertain the effects of EDM process parameter. The process parameters such as pulse-on time, pulse-off time, voltage gap, and servo speed were optimized to get better surface finish and reduced taper. Pulse-on time and the servo speed are identified as major response variables. By optimizing the process parameters, the damages on the mechanical surfaces such as recast layer and hairline cracks are minimized [5].

The effect of EDM parameters namely polarity, current, electrode material, pulse duration and rotation of electrode on MRR, TWR and SR value in EDM of Al-SiC MMCs with 20 and 25 vol.% SiC. Irrespective of the electrode material, polarity of the electrode and volume percentage of SiC, the MRR increased with increase in discharge current and for a specific current it decreased with increase in pulse duration. Increase in the volume percentage of SiC had an inverse effect on MRR, and positive effect on TWR and SR. Increasing the speed of rotating electrode resulted in a positive effect with MRR, TWR and better SR than at stationary [6]. The lack of correlation between the cutting rate, the surface roughness and the physical material parameters confirms that the removal mechanisms for machining conductive ceramics differ from those involved in metal machining. Results of wire cutting and electro-discharge sinking tests reveal a wide variation in removal rates and surface finishes, indicating differing removal mechanisms. Partly with a view to providing a further effective method of processing ceramics, an electrically conductive form of sialon has been developed. It is marketed as Syalon's-501, a registered trademark product especially sintered for EDM [7]. The material removal mechanisms of some commercially available electrical conductive ceramic materials through analysis of the debris and the surface/sub-surface quality were investigated. ZrO_2-based, Si_3N_4-based and Al_2O_3-based ceramic materials, with additions of electrical conductive phases like TiN and TiCN, have been studied. The latter especially occurs in wire EDM of Si_3N_4–TiN when using de-ionized water. Further, the spalling effect is proven to be strongly related to the formation of cracks. The formation of cracks on itself depends, among other factors like thermal conductivity of the material, melting point and strength, on the fracture toughness of the material. In this respect, spalling was not recognized in the machining of ZrO_2–TiN which has a higher fracture toughness value, compared to the other investigated materials [8]. The machining of Al_2O_3p/6061 Al composites using WEDM was examined. The machining parameters of pulse-on time were changed to explore their effects on machining performance, including the cutting speed, the width of slit and surface roughness. Moreover, the wire electrode is easily broken during the machining Al_2O_3p/6061 Al composite, so this work comprehensively investigates into the locations of the broken wire and the reason of wire breaking. The experimental results indicate that the cutting speed (material removal rate), the surface roughness and the width of the slit of cutting test material significantly depend on volume fraction of reinforcement (Al_2O_3 particles). Furthermore, bands on the machined surface for cutting 20 vol.% Al_2O_3p/6061Al composite are easily formed, basically due to some embedded reinforcing Al_2O_3 particles on the surface of 6061 aluminum matrix, interrupt the machining process. Test results reveal that in machining Al_2O_3p/6061 Al composites a very low wire tension, a high flushing rate and a high wire speed are required to prevent wire breakage; an appropriate servo voltage, a short pulse-on time, and a short pulse-off time, which are normally associated with a high cutting speed, have little effect on the surface roughness [9].

An experimental investigation of the influence of parametric setting on machining performance during EDM of Al_2O_3/SiCw/TiC ceramic composite was carried out. The investigation indicates that parameters discharge current, pulse-on time, and duty cycle are the primary factors influencing the SR of AlSiTi ceramic composite during EDM. Second order regression model has been developed for predicting SR in terms of machining parameters using the response surface methodology. The significance of machining parameters selected has been established using analysis of variance. The surface roughness prediction model has been optimized using a trust region method. Pulse-on time is found to be the dominant parameter influencing SR. They have also observed that an increase in discharge current increases the SR. This methodology helps to determine the best possible parametric setting for electrical discharge machining of ceramic composite [10]. The variation of cutting velocity and workpiece surface finish depending on WEDM process parameters during manufacture of pure tungsten profiles was studied. A method integrating BPNN and Simulated Annealing Algorithm (SAA) is proposed to determine an optimal parameter setting of the WEDM process. The specimens are prepared under different WEDM process conditions based on a Taguchi orthogonal array table. The results of 18 experimental runs were utilized to train the BPNN predicting the cutting velocity, roughness average (Ra), and roughness maximum (Rt) properties at various WEDM process conditions and then the SAA approaches was applied to search for an optimal setting. At the same time, the BPNN prediction models yield smaller MSE after training, namely, the BPNN was gave reasonable prediction in the experimental runs based on the BPNN approach. In addition, the ANOVA was implemented to identify significant factors for the WEDM process and the proposed algorithm was also compared with respect to the confirmation experiments. Through ANOVA, the percentage of contribution to the WEDM process, the pulse on time is the most significant controlled factor for the WEDM operation when the cutting speed, roughness average, and roughness maximum are simultaneously considered. The results of proposed algorithm and confirmation experiments are show that the BPNN/SAA method is effective tool for the optimization of WEDM process parameters [11]. ANN is used for analyzing the material removal of µ-EDM to establish the parameter optimization model. A feed forward neural network with back propagation algorithm is trained to optimize the number of neurons and number of hidden layers to predict a better material removal rate. These studies are to investigate the effects of gap voltage, capacitance, feed rate, and speed on the MRR of aluminium plate 1mm thick. Tool material is tungsten carbide of 500µm diameter with EDM-3 synthetic oil as dielectric medium. By the design of experiments, a total of 81 experimental runs-three-level four factorial (34) are considered. When experimental and network model results are compared for the performance considered, it is observed that the developed model is within the limits of the agreeable error. Then, genetic algorithms (GAs) have been employed to determine optimum process parameters for any desired output value of machining characteristics. Optimum neural network with 4-6-6-1 was found to give reasonably good prediction accuracy for MMR. The developed neural network appropriately trained gave an average prediction error of 0.8312% for training and 3.94% while testing. The developed models are in close agreement when experimental results and the predicted values are compared. The back-propagation network data along with the GA that can successfully synthesize optimum input conditions to maximize the MRR are 124.3V, 0.2µF, 9µm/s, and 900rpm. This well-trained neural network model is shown to be effective in estimating the MRR and is improved using optimized machining parameters [12].

The effectiveness of the EDM process with tungsten carbide and cobalt composites in terms of the material removal rate and the surface finish quality of the workpiece produced. The influence of operating parameters of EDM such as pulse current, pulse on time, electrode rotation and flushing pressure on material removal rate and surface roughness. The experimental results are used to develop the statistical models based on second order polynomial equations for the different process characteristics. The non-dominated sorting genetic algorithm (NSGA-II) has been used to optimize the processing conditions. A non-dominated solution set has been obtained and reported [13]. The effect of machining parameters (discharge current, pulse-on time, pulse-off time, voltage) on the machining feed rate and surface roughness during wire electrical discharge machining (WEDM) of metal matrix composite $AlSi_7Mg/SiC$ and $AlSi_7Mg/Al_2O_3$. Generally, the machining characteristics of WEDM metal matrix composites are similar to those which occur in the base material ($AlSi_7Mg$ aluminium alloy). The machining feed rate of WEDM cutting composites significantly depends on the kind of reinforcement. The maximum cutting speed of $AlSi_7Mg/SiC$ and $AlSi_7Mg/Al_2O_3$ composites are approximately 3 times and 6.5 times lower than the cutting speed of aluminium alloy, respectively [14]. Prediction and comparison of the tribological behavior of Al-2024 TiB_2 in-situ metal matrix composites using Group method data handling (GMDH) and ANN were carried out. The prediction of responses was carried out using GMDH and Artificial Neural Network Fitting Tool. Training sets of 50%, 62.5% and 75% of data is used in GMDH and 50%, 60% and 70% of data is used ANN. After training, the network performances were verified for any changes need to be made to the training process, network architecture or the data sets [15]. The effects of addition of copper as alloying element and silicon carbide as reinforcement particles to Al–4 wt.%Mg metal matrix. Different Al–Cu alloys and composites were subjected to dry sliding wear test using pin-on-disk apparatus under 40N normal load with rotational speed of counter face disk of 150rpm at room conditions, The experimental results show that copper and/or silicon carbide will improve wear resistance of Al–4 wt.%Mg alloys. The experimental values of mass loss of the worn specimens were firstly coded prior to use them in the training and testing of ANN. Satisfactory agreement between the experimental and ANN results was obtained from using this type of neural network [16]. An experimental investigation and optimization of the various machining parameters for the electrical discharge machining (EDM) processes on Inconel 718 super alloy using a Multi Objective Particle Swarm Optimization (MOPSO) algorithm were proposed. A Box-Behnkin design of response surface methodology has been used to collect data for the study. The machining performances of the process are evaluated in terms of MRR and surface quality which are functions of process variables such as open circuit voltage, discharge current, pulse-on-time, duty factor, flushing pressure and tool material. Mathematical model is developed relating responses with process variables [17].

A new method to determine multi-objective optimal condition using Principal Component Analysis (PCA) based on Grey Relational Analysis (GRA) Method for Characteristics as MRR, Tool Wear Rate (TWR) and Ra on EDM. They have made an attempt to machining the AISI P20 tool steel by using cylindrical copper electrode performs on EDM. A well-designed L_{27} orthogonal array based on the Taguchi method were conducted on input parameters as current, pulse on time, up-time, working time and inter electrode gap [18]. A unified approach is presented to model and optimize the electro-discharge machining (EDM) parameters on WC/6%Co using Response Surface Methodology (RSM) and Desirability Function (DF) concept. In the first part, four controllable parameters, viz., discharge current (A), pulse on-time (B), duty cycle (C), and average gap voltage (D) have been selected as the input variables to evaluate the process performance in terms of MRR, TWR, and arithmetic mean Ra as the performance characteristics. The modeling phase begins applying Face-Centered Central (FCC) composite design to plan and analyze the experiments in accordance with the RSM. For every response, the significant forms of influential parameters were properly identified conducting a comprehensive analysis of variance (ANOVA) at 1, 5 and 7% level of significance. They have been revealed that all the direct effects of input parameters are extremely momentous affecting both the MRR and TWR. On the other hand, for the Ra, the only significant parameters are the main effects of the first two inputs (A and B) plus the interactions of current with pulse on-time (A×B) and with gap voltage (A×D). The results indicate that the suitably proposed step-by-step implemented approach can substantially elucidate the highly multifaceted behavior of the chosen grade WC-Co under different EDM conditions providing a reliable platform to both navigating the operational region and seeking for optimal working circumstances confidently [19]. Following the first part, in the second part, a complete parametric analysis including main effects along with the joint effects of significant two-way interactive factors are performed over each previously developed response (MRR, TWR and Ra). They have mainly been revealed that all the responses are affected by the rate and extent of discharge energy but in a controversial manner. The MRR increases by either enhancing electrical discharge density or rising sparking frequency. Low TWRs can essentially be established by a combination of low current levels with prolonged pulse on-times or longer pulse on times with smaller duty cycles. Less rough surfaces are achievable via a blend of either low current intensity with shorter pulse on-time or low current level with higher gap voltage [20].

2. Experimental details

2.1. Material Selection

Aluminum 7075 is an aluminum alloy was selected as the matrix material because of excellent mechanical properties. With zinc as the primary alloying element, it is strong, with strength comparable to many steels, and has good fatigue strength and average machinability, but has less resistance to corrosion than many other Al alloys. The chemical composition of Al7075 is given in the Table 1 below.

Table 1. Chemical composition of Al7075

Elements	Zn	Mg	Cu	Cr	Fe	Si	Mn	Ti	Al
Percentage	6	3	2	0.3	0.6	0.5	0.4	0.3	Balance

2.2. Reinforcement: Titanium di-boride (TiB_2)

Titanium di-boride (TiB_2) was chosen as reinforcement owing to its attractive properties such as high Young's modulus, low density, superior hardness good thermal conductivity and high electrical conductivity. Commercially available Al-10%Ti and Al-3%Br master alloys were used to synthesis TiB2 particles. The chemical composition of Al-10%Ti and Al-3%Br master alloys used in the present study is reported in the Table 2 and Table 3 respectively. Equation (1) shows in-situ TiB_2 formation by alloy reaction technique.

$$2Ti + 2B + 3Al \rightarrow TiB_2 + Al_3Ti \quad (1)$$

Table 2. Chemical composition of Al-3%Br

Element	Boron	Ferrous	Others	Aluminium
Percentage	3.08	0.19	0.10	Balance

Table 3. Chemical composition of Al-10%Ti

Element	Titanium	Ferrous	Silicon	Aluminium
Percentage	10.23	0.23	0.10	Balance

The experiments were carried out on CONCORD DK7720C four axes CNC WED machine. The basic parts of the WED machine consist of a wire electrode, a work table, a servo control system, a power supply and dielectric supply system. The gap between wire and work piece is 0.02 mm and is constantly maintained by a computer controlled positioning system. Molybdenum wire having diameter of 0.18 mm was used as an electrode.

The experimental design employed an L_{27} orthogonal array Taguchi method in order to reduce the number of experiments and to achieve the best possible combination of process parameters to achieve maximum material removal rate, minimum surface roughness and optimal dimensional accuracy as shown in Table 4. Orthogonal array accommodate many design factors simultaneously and design of experiments with orthogonal array assures a balanced comparison and interaction of design factors. The columns of an orthogonal array represent the experimental process parameters to be optimized and the rows represent the levels of each parameter. The mean and the variance of the response at each parameter setting in orthogonal array are then combined into a single performance measure known as S/N ratio.

After conducting the experiment, response values were noted down and analysis has been carried out. Taguchi's analysis was conducted to determine the optimal parameters and ANOVA was also performed to estimate magnitude of factors effect on the responses. The experiment was conducted in the same environmental condition for all the runs so that environmental noise factors can be minimized.

Table 4. Machining settings used in experiments

Factors		Control Level		
		I	II	III
A	Pulse –on	7	14	21
B	Pulse-off	9	10	11
C	Current	3	4	5
D	Bed speed	100	150	200

Table 5 shows experimental results as per L_{27} orthogonal array for WEDM of Al7075-TiB_2 composite and corresponding surface roughness (µm), volumetric material removal rate (mm^3/min) and dimensional accuracy (µm).

Table 5. Experimental results for WEDM of Al7075-TiB_2 composite as per L_{27} orthogonal array

Run	Pulse-on (μs)	Pulse-off (μs)	Current (Amps)	Bed speed (μm/s)	Ra (μm)	VMRR mm^3/min	Dimensional accuracy (μm)
1	7	9	3	100	3.666	6.65	4
2	7	9	4	150	3.8	6.77	5
3	7	9	5	200	3.833	6.92	6
4	7	10	3	150	3.856	7.41	7
5	7	10	4	200	3.933	7.87	8
6	7	10	5	100	3.966	7.98	8
7	7	11	3	200	4.066	8.21	9
8	7	11	4	100	4.133	8.28	9
9	7	11	5	150	4.212	8.65	10
10	14	9	3	150	4.233	8.99	11
11	14	9	4	200	4.333	9.0	11
12	14	9	5	100	4.456	9.08	12
13	14	10	3	200	4.554	9.09	12
14	14	10	4	100	4.633	9.18	13
15	14	10	5	150	4.692	9.29	13
16	14	11	3	100	4.719	9.48	14
17	14	11	4	150	4.728	9.5	14
18	14	11	5	200	4.752	9.61	15
19	21	9	3	200	4.756	9.75	16
20	21	9	4	100	4.781	9.76	16
21	21	9	5	150	4.847	10.07	18
22	21	10	3	100	4.855	10.13	18
23	21	10	4	150	4.871	10.31	19
24	21	10	5	200	4.875	11.0	22
25	21	11	3	150	4.881	11.4	23
26	21	11	4	200	4.902	11.5	24
27	21	11	5	100	4.921	11.6	26

3. Results and discussions

3.1. Prediction of machining characteristics using Artificial Neural Network

Fig. 1 shows the performance plot for training, validation and testing. It is observed that the error is minimized by increasing the number of epochs. Figure shows the regression line of data used for training. The highly trained data is closer to regression line. This indicates reasonably good performance of the network. The best validation performance is 0.0032605 (Mean squared error).

It is observed from the Fig. 1 that developed ANN model shows good performance for prediction of surface roughness, material removal rate and dimensional accuracy. Regression analysis shows R=0.9999 the best fit with minimum error. Fig. 1 also shows the gradient during ANN training indicating validation checks.

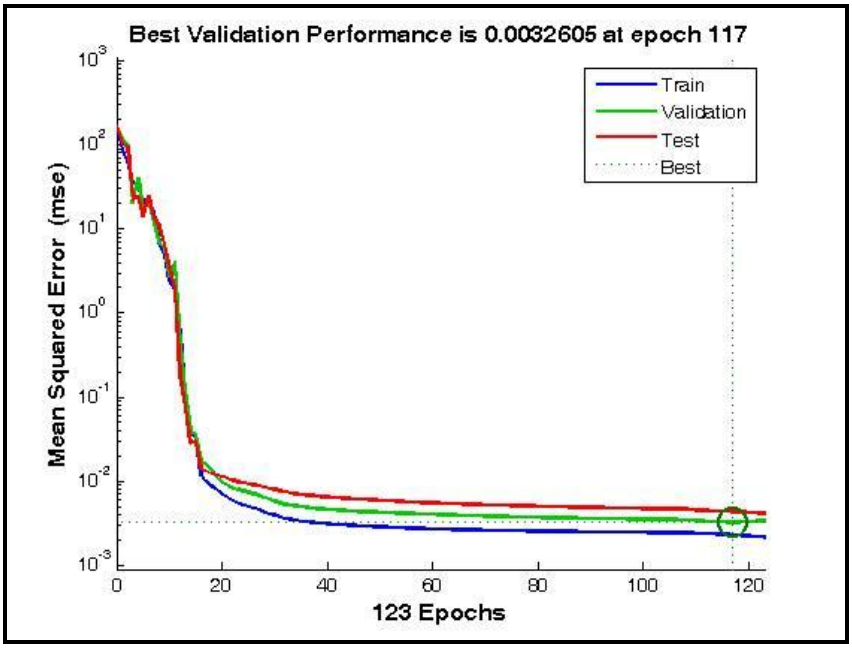

Fig. 1. Performance plot using MATLAB

3.2. Prediction of Surface roughness

Fig. 2 shows the comparison of experimentally measured surface roughness values and predicted values using ANN. It is clearly observed that measured surface roughness is correlating well with the predicted surface roughness values. The minimum and the maximum deviation are found to be 1.3% and 12.51% respectively. Thus, the percentage error value establishes the validity of the artificial neural network computation.

3.3. Prediction of volumetric material removal rate

Fig. 3 shows the comparison of measured VMRR and VMRR predicted using ANN. It is clearly observed from the Fig. 3 that measured VMRR is correlating well with the predicted VMRR. Further, it is also observed that ANN prediction shows a similar trend in all the runs studied. The ANN predicted values of volumetric material removal rate very closely matches with the experimental value. The minimum and the maximum errors were observed to be in the range of 0.003% to 6.78%.

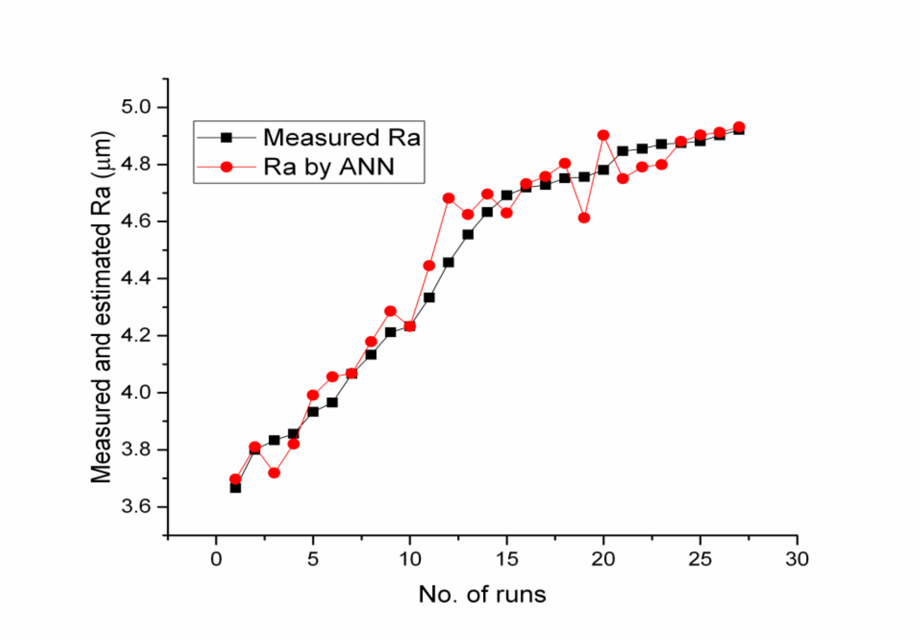

Fig. 2. Variation of experimental and ANN predicted surface roughness

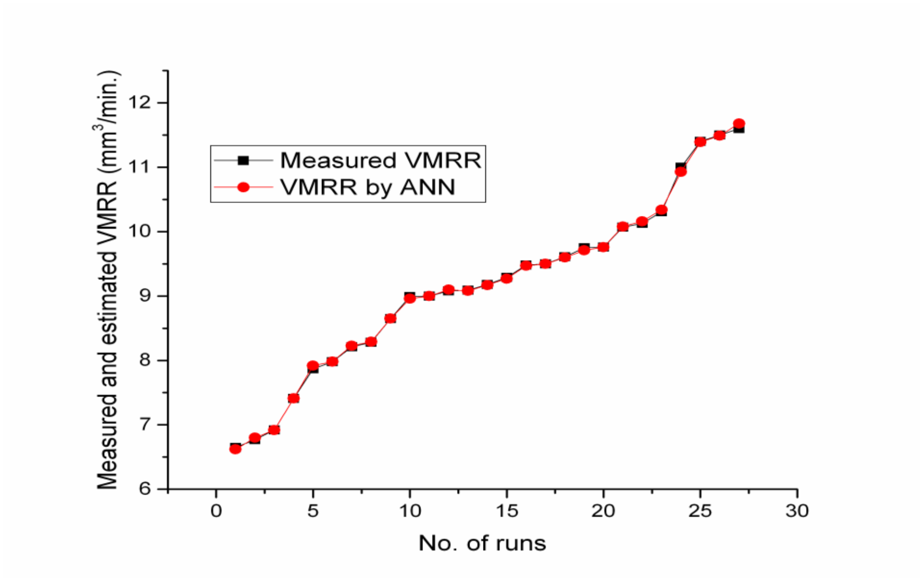

Fig. 3. Variation of experimental and ANN predicted VMRR

3.4. Prediction of dimensional accuracy

Fig. 4 shows the comparison of measured dimensional accuracy and dimensional accuracy predicted using ANN. It is clearly observed from the Fig. 4 that, in all the cases studied the predicted and experimental values are very close to each other. The minimum and the maximum errors are 0.03% and 1.31% respectively.

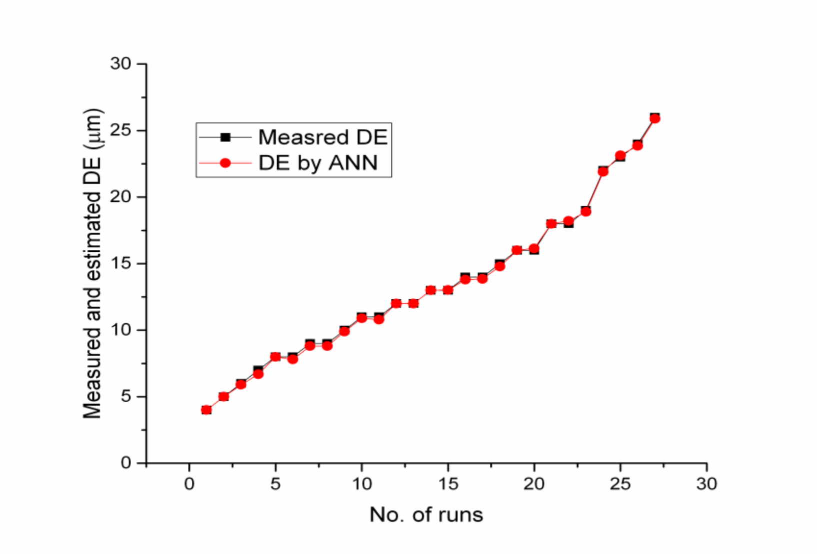

Fig. 4. Variation of experimental and ANN predicted dimensional accuracy

4. Conclusion

Machining characteristics of Al7075-TiB_2 composite was successfully predicted using Artificial Neural Network (ANN). Predicted values of 70% training set correlates well with the measured values.

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