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EVOLUTIONARY OPTIMIZATION OF WIRE EDM PROCESS FOR THE SURFACE FINISH ON A MAGNESIUM AZ91D ALLOY USING AN ANN AND A GENETIC ALGORITHM

RAZVOJ OPTIMIZACIJE PROCESA ŽIČNE EROZIJE ZA KONČNO POVRŠINSKO OBDELAVO MAGNEZIJEVE ZLITINE AZ91D Z UPORABO UMETNE NEVRONSKE MREŽE IN GENETSKEGA ALGORITMA

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In this research the optimizations of the wire EDM process parameters to achieve a minimal surface roughness on a magnesium AZ91D alloy have been carried out. The experiments were conducted with three machining factors, i.e., the pulse-on time, the pulse-off time, and the wire feed, using a Box-Behnken design of experiment. The effects of the Artificial Neural Network (ANN) and the Response Surface Methodology (RSM) models were compared and studied, and it has been found that the ANN approach predicts the perfect output response. The genetic algorithm (GA) was then utilized to determine the best machining parameters to provide a better surface finish using the projected ANN outcomes, which were then used to build a quadratic equation. Furthermore, the optimum machining parameters were identified for a better surface finish through the integration of the ANN and GA approach. Based on the aforementioned findings, this study showed that the suggested methods are capable of predicting the optimum machining parameters, which would be beneficial in the low-cost manufacturing sector.

Keywords: ANN, genetic algorithm, magnesium alloy, wire EDM, optimization

V članku avtorji opisujejo raziskavo optimizacije procesnih parametrov žične erozije (EDM; angl.: Electrical Discharge Machining), da bi dosegli najmanjšo možno hrapavost površine na Mg zlitini tipa AZ91D. Avtorji so, na osnovi Box-Behnkenovega eksperimentalnega dizajna, izvajali preizkuse pri treh izbranih faktorjih mehanske obdelave in sicer: času vžiga električnega impulza, času izklopa električnega impulza in hitrosti dodajanja žice. Med seboj so primerjali in študirali učinke modelov umetne nevronske mreže (ANN; angl.: Artificial Neural Network) in metodologije površinskega odgovora (RSM; angl.: Response Surface Methodology). Ugotovili so, da z ANN modeliranjem lahko napovejo mnogo boljše izhodne odgovore kot z RSM modelom. Genetski algoritm (GA) so uporabili za določitev najboljših procesnih parametrov erozije z uporabo dobljenih ANN podatkov, ki so jih nato uporabili za izdelavo kvadratne enečbe. Nadalje pa so avtorji ugotovili, da so optimalne procesne parametre mehanske obdelave z žično erozijo za najboljšo kakovost površine dobili z integracijo ANN in GA pristopa. Na osnovi v članku navedenih ugotovitev so avtorji sposobni napovedati optimalne procesne parametre EDM, ki bi lahko bili cenovno zelo ugodni tudi za druge uporabnike mehanske obdelave materialov z postopkom žične erozije.

Ključne besede: umetne nevronske mreže, genetski algoritm, zlitina na osnovi magnezija, žična erozija, optimizacija

1 INTRODUCTION

Magnesium alloys have exceptional strength-to-weight ratios and are extensively utilized in industries; a number of aircraft and automobile industries are focusing on products made with magnesium alloys.[1] Wire EDM is an un-conventional thermo-electrical machining process where the work materials are machined by a continuous discrete spark among the work and the tool electrode while they are immersed in a liquefied dielectric medium. The continuous discrete spark erodes the work piece in complex shapes in accordance with a computerized, numerically controlled program.[2] The evaluation of the quality of a component, the surface finish, is a necessary element for production industries. Surface roughness is an important performance characteristic for the EDM process, and it became a factor in the quality and economy characteristics. The operator's expertise and the manufacturer's guidelines play a big role in choosing the right machining parameters for the wire EDM. As a result, for newer materials, the machining parameters in wire EDM must be optimized using experimental techniques. The main objective of the wire EDM manufacturers and users is to succeed in establishing better stability and higher productivity of the wire EDM process.[3]

Dewangan et al.[4] studied the influence of pulse current, pulse-on time, tool work time, and tool lift time in relation to the surface integrity on the EDM of AISI P20 tool steel using the RSM and the TOPSIS methods. The study reports that the optimal solution was obtained

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based on five decision makers' preferences for different process parameters. Vinoth and Pradeep[5] have studied the conventional EDM and the cryogenic EDM processes on the machining of an aluminum metal matrix composite and they reported that the discharge current, pulse-on time, and gap voltage have a significant effect on the electrode wear and surface roughness. Kavimani et al.[6] have studied the impact of the machining parameters on wire electrical discharge machining performance in magnesium composites, finding that the MRR and surface roughness are factors to consider. Gangadharudu et al.[7] studied a multi-response optimization with the use of the principal component analysis based on the grey technique to find the optimum process parameters for a metal-matrix composite on the EDM process; they discovered a setting of the process parameters through evolutionary optimization techniques. Murahari et al.[8] have evaluated the effects of the EDM process parameters in terms of the output response material removal rate, surface roughness, tool wear rate, and recast layer thickness on the machining of Ti-6Al-4V using an analysis of the variance and the F-test. Tripathy et al.[9] studied the machining parameter optimization for multiple responses on the numeral process variables on the EDM of the H-11 die steel using the TOPSIS and the grey relational analysis and they investigated the effect of process variables like powder concentration, peak current, pulse-on time, duty cycle, and gap voltage based on the response of the material removal rate, tool wear rate, electrode wear ratio, and surface roughness. Rai et al.[10] investigated the cutting forces and the shear plane temperature in end milling with the use of an ANN. They used 15 neurons in the feedforward neural network with a backpropagation algorithm. In terms of the cutting tool, the geometrical parameters, the cutting parameters, and the work piece material properties, as well as the three components of the cutting forces and the shear plane temperature were used as the output layers. The study demonstrated that the ANN model shows a close agreement between the experimental and the numerical results. Vishal et al.[11] studied the optimization of the process parameters in terms of kerf width in the EDM process on a stainless-steel 304L. They used the Taguchi L32 orthogonal design of experiment to conduct experiments and analysis of the variance, and the study discovered that the mathematical model has a 4 % error in comparison to the experimental results. Yıldızel et al.[12] have investigated the modulus of rapture values for glass fiber reinforced in a concrete block with the use of an ANN integrated with an artificial bee colony and they concluded that the model provides most appropriate performance compared with multiple linear regression.

The literature survey of this research has helped in furthering a number of researchers on the process parameters optimization by the use of the RSM, and ANN tools for different materials; however the researches on the EDM process of advanced materials like magnesium AZ91D alloy were rarely conducted. In addition, the conventional optimization techniques were preferred in the research over the evolutionary techniques. In this research work we focus on a prediction of best machining parameters to attain minimal surface roughness on wire EDM of a Mg AZ91D alloy through the integration of two evolutionary optimization techniques of the RSM technique, the ANN methodology, and the GA methodology.

2 EXPERIMENTAL PART

In this paper the study was conducted on a wire EDM on a modern material, i.e., a magnesium AZ91D alloy, and the effective RSM Box-Behnken experimental

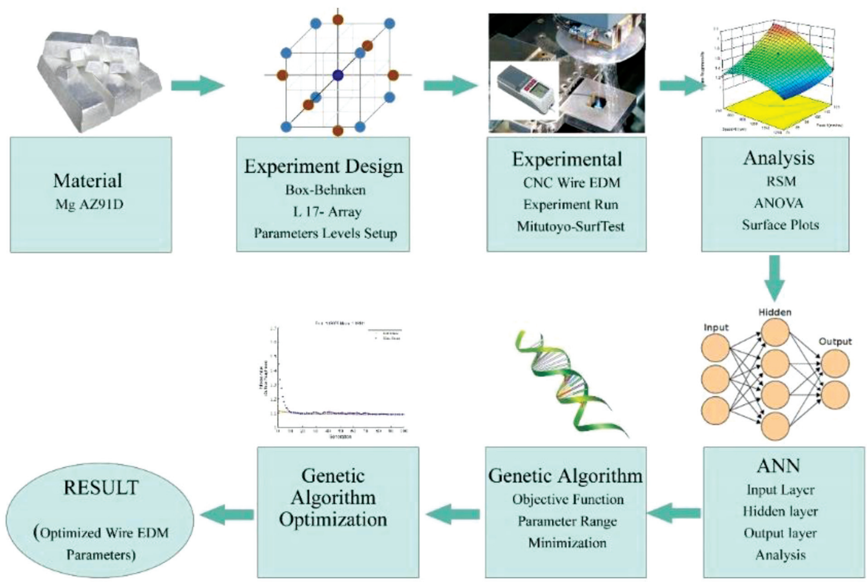

Figure 1: Proposed investigational methodology

design[13] was chosen to conduct the experiments.[14] Box-Behnken designs are a robust and efficient design for a quadratic model for optimization by avoiding unnecessary combinations of experiments like corner points and star points of the design. The purpose of the identical experiments in Box-Bhenken design is to identify the proper experimentation and minimize bias from uncontrolled variables. The results were analyzed as well as compared with the ANN methodology,[15] and the ANN resulting model was employed to produce a quadratic equation, which was then used as the fitness function for a GA to forecast the optimum machining parameters for an excellent surface quality. The proposed investigational methodology is shown in **Figure 1**.

2.1 Experimental Process

The wire cut EDM process was conducted on a magnesium alloy with use of a CNC Wire EDM machine ELECTRONICA-ELCOT EL-10 VGA. The machining parameters of pulse-on time (T_{on}), pulse-off time off (T_{off}), and wire feed (W_f) were set at the three levels as shown in **Table 1**. The cutting process was performed with the use of a copper wire of 0.25 mm diameter. A total of 17 trials were conducted using the interaction of the three machining parameters at the lower, medium, and higher levels in accordance with the recommendations of the Box-Behnken design of experiment. The results of the output response surface-roughness measurement using the Mitutoyo Surftest 211 equipment are shown in **Table 2**.

Table 1: Machining parameters and their levels

Wire-EDM-Machining Parameters	Unit	Levels		
		Lower (–1)	Medium (0)	Higher (1)
T_{on}	μs	4	7	10
T_{off}	μs	4	7	10
W_f	mm/min	1	2	3

Table 2: Box-Behnken Design of Experiments

Run	T_{on} (μs)	T_{off} (μs)	W_f (mm/min)	Experiment R_a (μm)
1	–1	–1	0	1.25
2	1	–1	0	1.04
3	–1	1	0	1.4
4	1	1	0	0.74
5	–1	0	–1	1.19
6	1	0	–1	0.81
7	–1	0	1	1.13
8	1	0	1	0.71
9	0	–1	–1	0.89
10	0	1	–1	1.15
11	0	–1	1	1.12
12	0	1	1	0.69
13	0	0	0	0.84
14	0	0	0	0.89
15	0	0	0	0.91
16	0	0	0	0.87
17	0	0	0	0.90

2.2 Response surface methodology (RSM)

An experimental modeling method known as the RSM is used to establish the relationship among the responses and the control variables[16]. To determine the effects of wire feed (W_f), pulse-on time (T_{on}), and pulse-off time (T_{off}) on the surface finish (R_a), the present research employs RSM.

The response

$$Y = \psi\ N, f, ap \qquad Y = \psi\ (T_{on}, T_{off}, W_f) \tag{1}$$

$$R_a = \psi\ (T_{on}, T_{off}, W_f) \tag{2}$$

The present study's second-order RSM model is provided by:

$$Y = \alpha_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=j}^{k} \beta_{ij} X_i X_j + \sum_{i=1}^{k} \beta_{ii} X_i^2 \tag{3}$$

n are the interacting coefficient terms.[17]

2.3 Artificial Neural Network (ANN)

ANNs are based on biological nervous systems. They consist of an enormous number of interconnected factors called neurons. The interactions between the neurons and the process information are stored in the brain by regulation among the neurons; as a result, the neurons form a network which mimics a biological nervous machine.[18] The input layer, hidden layer, and output layer are the three levels that make up the ANN computational method. Each layer contains a distinct type of neuron, and all the layers are connected in succeeding layers.[19]

In this wire EDM operation, the ANN tool was utilized to identify the optimum machining parameters for obtaining a minimal surface roughness. A 3-8-1 neural network structure was developed by using the three machining parameters T_{on}, T_{off}, and W_f as the input neurons (input layer) and one hidden layer of eight neurons to generate one output neuron as surface roughness (output layer). The experimental data was used as the training data for the ANN model. The experiment was conducted with the training and testing sample datasets of 15 each. A random training data set was utilized to train the neural network, and a backpropagation technique was employed to train the feedforward network. The backpropagation algorithm is based on the gradient-descent method, and it uses iterations of the weights to update the goal and training mean square error values. The hidden-layer and output-layer activation functions were set to logsig and tansig, respectively to achievie the surface roughness output.[20] In MATLAB, learning functions were assigned to traingdx and learngd, respectively, for the ANN training function.

2.4 Genetic Algorithm (GA)

The use of evolutionary biology principles is utilized to address problems using the evolutionary optimization technique known as Genetic Algorithm (GA), and it includes genetic inheritance, natural selection, mutation, and crossover.[21] Starting from a set of chromosomes or capability solutions that are randomly selected from the character of bit strings, a GA optimal solution is generated. As a result, a population is formed by a whole set of these chromosomes, and the chromosomes change across many iterations or generations; as a result, new generations are created using the crossover and mutation approach. The chromosomes are further evaluated using certain fitness condition standards and the most appropriate chromosomes are stored, while the others are discarded. This system repeats till one chromosome ascends to high-quality fitness, whereupon it is assumed to be the most appropriate solution to the problem.[22] The GA has been successfully used in an extensive variety of problems due to its simplicity, ease of procedure, and global perception. The ANN resultant quadratic model **Equation (4)** was utilized for the objective function, the population size was set at 200, and the crossover probability was at 0.8, the mutation rate was distributed uniformly at 0.1, the stall generation was set at 100, and the stopping criteria were best fit. The GA was conducted to minimize the objective function, and the ranges of the input parameters are as shown in **Table 3**.

Table 3: Parameter range for GA optimization

Parameter	Range for GA optimization
T_{on}	1 µs ≤ T_{on} ≥ 10 µs
T_{off}	1 µs ≤ T_{on} ≥ 10 µs
W_f	1 mm/min ≤ W_f ≥ 5 mm/min
Objective function as Minimize: R_a (T_{on}, T_{off}, W_f)	

3 RESULTS AND DISCUSSION

3.1 Parameter Effects on Surface Roughness

The analysis of the values of the machining parameters in the wire EDM process, developed by the use of the RSM method, is presented in **Figure 2**. It demonstrates that as the value of T_{on} increases the surface roughness decreases linearly, predicting that a small change in T_{on} would severely affect the surface roughness. In terms of T_{off}, a lower rate of T_{off} produces a higher surface roughness; moreover, when the T_{off} increases the roughness value decreases until the middle level. Thereafter, it slightly increases until the higher level. In terms of W_f, the figure depicts that increasing W_f provides a greater surface roughness till level 2 (2 mm/min); thereafter, the roughness value decreases until the higher level of W_f.

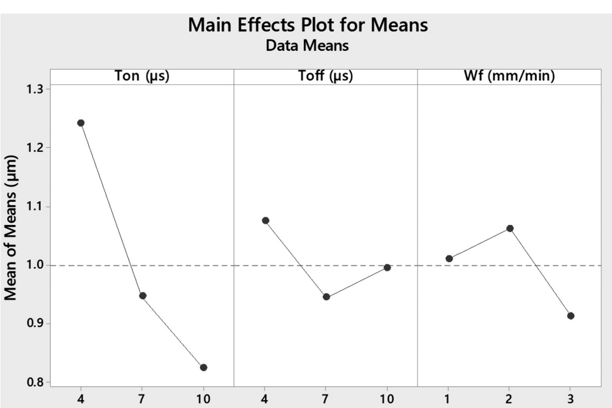

Figure 2: Main effect plots for surface roughness

The analysis of the variance (ANOVA) was derived on the basis of the RSM Box-Behnken experimental design and is presented in **Table 4.** The primary objective of the ANOVA is to pinpoint cutting parameters that influence thc characteristics of quality. According to ANOVA **Table 4**, the model contributed 99.50 percent of the total variance, whereas the errors percentage contribution was only 0.65 percent. This indicated that the experiment was carried out with the proper machining parameters. Therefore, it can be observed that in the first-order interactions T_{on} has a larger percentage (52.05%) contribution to the surface roughness while the remaining parameters T_{off} and W_f have a significantly smaller contribution of 1.911% and 2.83%, respectively.

Table 4: Analysis of variance

Source	DF	SS	MS	F-Value	Contribution
T_{on}	1	0.348613	0.026042	41.86	52.05%
T_{off}	1	0.012800	0.000165	0.26	1.911%
W_f	1	0.019012	0.039296	63.16	2.83%
T_{on}*T_{on}	1	0.056963	0.052346	84.14	8.50%
T_{off}*T_{off}	1	0.053188	0.054720	87.95	7.94%
W_f*W_f	1	0.053188	0.004725	7.60	0.70%
T_{on}*T_{off}	1	0.050625	0.050625	81.37	7.55%
T_{on}*W_f	1	0.000400	0.000400	0.64	0.05%
T_{off}*W_f	1	0.119025	0.119025	191.31	17.77%
Error	7	0.004355	0.000622		0.65%
Total	16	0.669706			

Furthermore, the analysis suggests that a small variation in the T_{on} factor would affect the surface-finish characteristics on the magnesium material. In view of the second order, T_{on} has a higher influence of 8.50 % compared to the other factors; moreover, **Table 4** presents that the T_{on} and T_{off} has an effect on the surface roughness. The regression value for this operation was 99.35 %, which says that the Box-Behnken design of the experiment was the best technique to design for evaluating the parameters in this wire EDM process. The ANOVA suggests that T_{on} has a larger contribution in the wire cut EDM operation in comparison to the other parameters.

For better visibility and understanding of the effects of machining parameters on the output response surface roughness, the 3D surface plots in **Figure 3** were created. **Figure 3a** indicates that a lower rate of T_{on} and a higher rate of T_{off} produce a higher surface roughness of 1.3 µm on this wire EDM process; furthermore, higher rates of both T_{on} and T_{off} would yield a better surface finish. **Figure 3b** displays the contribution of T_{on} and W_f in the wire EDM process. It shows that both the factors at lower levels give a higher surface roughness; consequently, higher levels of both the parameters yield a better surface finish. In terms of the interaction of T_{off} and W_f, the 3D surface plot was drawn, see **Figure 3c**. The figure shows that when the EDM process is conducted with a lower level of T_{off} in correspondence to a higher level of W_f, a higher surface roughness on the material is produced. Similarly, a lower level of W_f with a higher level of T_{off} also produces a higher roughness on the surface of the magnesium alloy. However, higher levels of both the parameters gave a better surface finish of 0.69 µm in this EDM process on the magnesium alloy.

The RSM evaluation reveals the relationship between input parameters and the output response in terms of a quadratic model and the 3D surface plots indicate that T_{on} and W_f have the most impact on the output response when considering the surface roughness. The RSM predicted values are closer to the experimental values at a higher level of T_{on} at 10 µs, a middle level of T_{off} at 7 µs, and a higher level of W_f at 3 mm/min provide a better surface finish of approximately 0.69 µm and displayed in **Table 5**.

$$R_a = 1.18947 - (0.1488*T_{on}) + (0.0118*T_{off}) + (0.5110*W_f) + (0.0123*T_{on}*T_{on}) + (0.01267*T_{off}*T_{off}) - (0.0335*W_f*W_f) - (0.0125*T_{on}*T_{off}) - (0.00333*T_{on}*W_f) - (0.0575*T_{off}*W_f) \quad (4)$$

3.2 Optimization

Once the proposed neural network model has undergone 1000 training iterations, the predicted surface roughness results were generated. An analysis of the network reveals a 0.99 correlation coefficient, meaning that there is a strong relationship between the experimental and projected values for this ANN model. **Figure 4** displays the results of the ANN model's evaluation of the network's performance, which is based on the correlation coefficient between the output and target values for the test data. A well-trained network can accurately predict surface roughness values, as shown by the ANN model's average relative error between the experimental and predicted values of 1.31 percent.

An error % line chart of the predicted surface roughness values using RSM and ANN approaches is shown in **Figure 5**. A comparison between the chart and actual values shows that the ANN model generates a smaller error than the RSM model. The ANN model's predicted values are closer to the experimental values; consequently, it provides a better surface finish value of 0.71 µm with the optimal combination of the machining parameters in the higher level of T_{on} at 10 µs, the middle level of T_{off} at 7 µs, and the higher level of W_f at 3 mm/min. In this optimization study, the ANN model

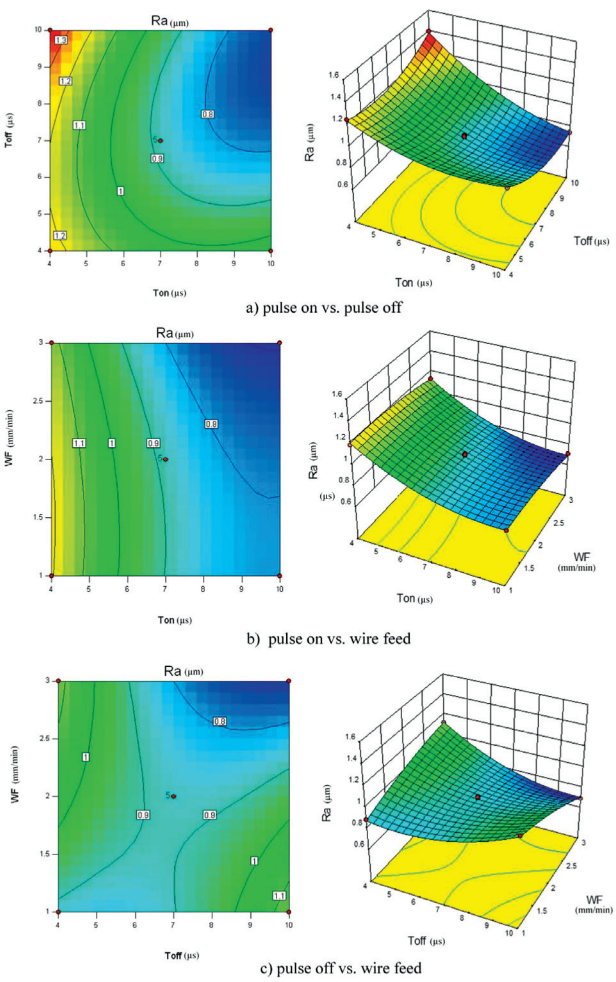

Figure 3: 3D Surface plot for surface roughness

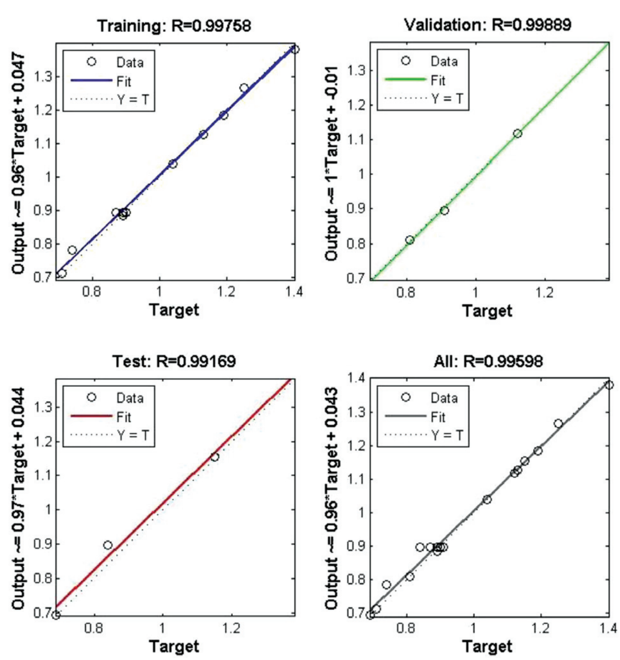

Figure 4: Artificial neural network - regression model

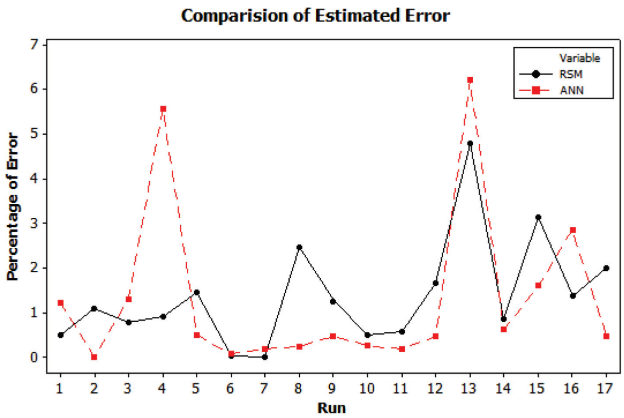

Figure 5: Error percentage chart of experimental vs. predicted values

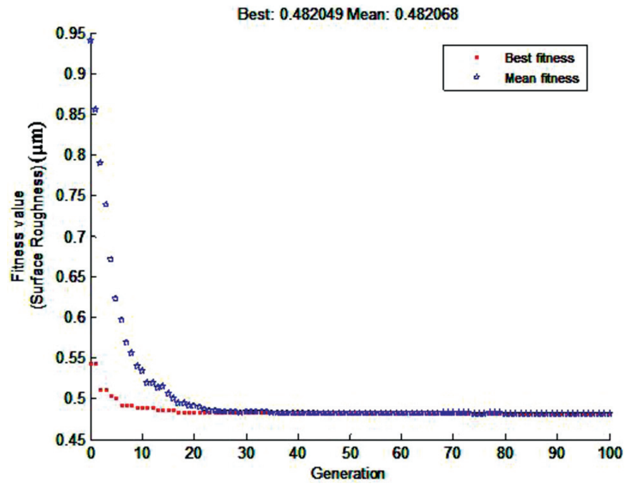

Figure 6: Best fitness of surface roughness on GA

provides accurate values of the output response in comparison to the experimental values; thereby proving its ability to train the model more efficiently.

The GA optimization was conducted based on the genetic parameters stated above with integration of results obtained from ANN; moreover, the best fit was attained for the given machining parameters ranges. **Figure 6** depicts that the better the surface roughness has achieved a value of 0.4820 µm with the optimized values of the cutting parameters are at the higher levels with T_{on} at 10 µs, T_{off} at 10 µs, and W_f at 3 mm/min. The outcomes of the confirmation test, which was carried out in accordance with the suggestions of the ANN and GA procedures, are shown in **Table 5**. It is noted that both the ANN and GA model provide a lower error percentage; moreover, both approaches work better as optimization tools for machining parameter optimization for modern materials.

Table 5: Evaluation of predicted model

Machining Parameters			Surface Roughness R_a (µm)				Error %
T_{on}	T_{off}	W_f	RSM Predicted	ANN Predicted	GA Predicted	Confirmation Test	
10	7	3	0.691			0.73	5.47
10	7	3		0.711		0.74	3.91
10	10	3			0.4820	0.50	3.60

4 CONCLUSIONS

The application of evolutionary techniques to predict optimized cutting parameters in the wire EDM process on a modern material, i.e., the magnesium alloy AZ91D, is the focus of this research. Through the Box-Behnken experimental methodology, the RSM quadratic model has been developed to predict and examine analytical models for attaining better cutting parameters on achieving a minimal surface roughness. Using the evolutionary method of the ANN and GA approaches, the following conclusions were drawn:

- The RSM main effect plot suggests a minimum surface roughness of 0.69 µm with the desired parameter levels; also, the Box-Behnken experimental design yields a predicted regression (R^2) value of 96.36, indicating the Box-Behnken design to be the most efficient way of designing an experiment. The ANOVA shows that the T_{on} has a bigger contribution of 52.32 percent in this experiment; additionally, it shows that even the smallest adjustment in this parameter affects the component's surface finish.
- When compared to t heexperimental values, the ANN model projected values are more accurate, resulting in a better surface finish value of 0.71 µm with the optimal combination of machining parameters of T_{on} at 10 µs, T_{off} at 7 µs and W_f at 3 mm/min. The RSM and ANN methodologies had an average error of 1.38 % and 1.31 %, respectively, when compared to the experimental results. The experiment shows that the ANN model predicts the optimal output response better than the RSM model.
- The evolutionary GA suggests that the minimal surface roughness of 0.48 µm can be achieved with the optimized cutting parameters of T_{on} at 10 µs T_{off} at 10 µs, and W_f at 3 mm/min. In this study, the integrated GA model provides a better output response in terms of optimization of the machining parameters with minimal surface roughness in comparison to the RSM and the ANN models.

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