Research article

Prediction and optimization of tool wear rate during electric discharge machining of Al/Cu/Ni alloy using adaptive neuro-fuzzy inference system

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ARTICLE INFO

Keywords:
Materials science
Mechanical engineering
Al/Cu/Ni alloy
Adaptive neuro-based fuzzy inference system
EDM
Taguchi
TWR

ABSTRACT

Aluminum (Al)-copper (Cu)-nickel (Ni) alloy is a versatile material with lightweight and excellent strength. It also possesses properties such as superior corrosion resistance, fatigue strength. These alloys are essential in sectors viz. automobile, aerospace, defense, aerospace, etc. In this research work, the authors have presented the prediction and analysis of tool wear rate (TWR). The impact of electrical discharge machining (EDM) on process parameters viz. input current (IP), pulse on time (TON), pulse off time (TOFF)/for Al/Cu/Ni alloy with the composition 91/4/5 and 87/8/5 (weight %) is analyzed. Taguchi’s L18 (2^3*3^3) mixed plan is employed to plan the experimentation. A mathematical model develops to correlate these process parameters. A soft computing technique known as an adaptive neuro-fuzzy inference system (ANFIS) utilizes to predict TWR. Taguchi analysis reveals that input current is the most influencing parameter followed by pulse on time. TWR decreases with a decrease in the amount of Aluminium. It increases in the amount of copper in the alloy. TWR firstly decreases with an increase in pulse on time and then starts to grow after the median value of 25 micro-sec. The confirmation experiments have conducted using optimum process parameters to validate the obtained results. The experimental finding shows the superior capability of ANFIS to predict the TWR with acceptable accuracy. The optimized TWR obtained was 0.1238 mm³/min based on the optimal settings of input parameters.

1. Introduction

In today’s competitive market, to cope with new technology for developing new products in metal cutting industries, aluminum-based alloys play a crucial role. Its specific mechanical properties, such as lightweight, take aluminum and its alloys in a superior position. Being tough, ductile, and malleable, copper use in tube drawing, deep drawing, and wire drawing. Copper also resists corrosion due to freshwater and steam. Similarly, nickel is a versatile element and will alloy with most metals. Nickel has a lower hardening rate. Hence, in the past work, aluminum-copper-nickel (Al-Cu-Ni) alloy fabricated and the machining through electrical discharge machining (EDM) examined for its better use in the future. Mohal and Kumar (2017) have experimented with Al/SiCp with multiwalled carbon nanotube (MWCNT). The experiments have conducted with nano-powder mixed electric discharge machining. The author has considered the material removal rate (MRR) and the finished part (Ra) as response functions. Mohanty et al. (2017) have investigated TON, TOFF, and VG’s impact on the performance parameters using response surface methodology (RSM). RSM technique has been implemented for an investigation to know the correlation between process parameters and the response. The second-degree response has developed during the analysis. An analysis of variance (ANOVA) has used to determine significant EDM parameters relating to the process. Zakaria (2014) has fabricated Al/SiC MMC with a 15 % volume fraction of Sili cate. The particle of different diameters has investigated. Hima et al. (2018) have conducted experiments on new composite made-up of graphite, red mud, ash of bagasse and rice husk, fly ash, and aloe-vera powder as a reinforcement material. Abbas et al. (2017) has examined the impact of graphite particles Cu-Al-Ni alloy. They have studied hardness factors for the newly fabricated MMCs. Rui-Song et al. (2016) has reviewed the performance during the processing of TiB2/Al MMCs. The authors have considered the tool’s wear rate, the quality of the finished product, and the chips’ shape obtain during the machining. Phate and Toney (2019) have investigated the effect of W-EDM process parameters on the Al/SiC MMC. The approach of Buckingham’s pi theorem (DA) and ANN has used for useful analysis.

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https://doi.org/10.1016/j.heliyon.2020.e05308
Received 14 May 2020; Received in revised form 9 August 2020; Accepted 15 October 2020
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They have studied the impact of individual process parameters of the MRR. The experimental findings showed that the pulse on time has mostly dominating MRR while a decrease in SiC composition reduced the MRR. Phate et al. (2020a,b) has examined the surface roughness of Al/Cu/Ni alloy in EDM process. The investigation indentified ‘TON’ as the most influencing process parameter. Mohanty et al. (2017) has carried out the experiments with L9 orthogonal array help. Vikor index method (VIM) has been adopted for the multi-parametric response optimization of the process. The ANOVA has been used to know significant parameters with optimum levels, increasing the machining process’s overall performance. Gangil and Pradhan (2018) investigated the optimal process parameters using the RSM technique couple with VIM. Ramanan et al. (2018) have studied Aluminium 7075 MMC with different percentages of reinforcement. In total twenty-seven

Table 1. List of parameters considered for investigation.

| Parameter                  | Unit     | Level of variation |
|----------------------------|----------|--------------------|
| Fraction of Al/Cu/Ni (CP) | %        | 91/4/5             |
| Peak discharge current (IP)| Amp      | 8, 12, 16          |
| Pulse-on-time (TON)       | Micro-sec| 20, 25, 30         |
| Pulse-off-time (TOFF)     | Micro-sec| 3, 6, 9            |

Table 2. Experimental results for Al/Cu/Ni alloy EDM.

| Exp No | Material fraction | EDM process parameters | Actual response |
|--------|-------------------|------------------------|-----------------|
|        | CP (Al/Cu/Ni)     | Input Current (IP)     | Pulse-on-time (TON) | Pulse-off-time (TOFF) | Tool wear rate (TWR) |
| 1      | 91/4/5            | 8                      | 20              | 3               | 0.113                |
| 2      | 91/4/5            | 12                     | 25              | 6               | 0.205                |
| 3      | 91/4/5            | 16                     | 30              | 9               | 0.351                |
| 4      | 91/4/5            | 12                     | 20              | 3               | 0.164                |
| 5      | 91/4/5            | 16                     | 25              | 6               | 0.255                |
| 6      | 91/4/5            | 8                      | 30              | 9               | 0.083                |
| 7      | 91/4/5            | 8                      | 20              | 6               | 0.078                |
| 8      | 91/4/5            | 12                     | 25              | 9               | 0.137                |
| 9      | 91/4/5            | 16                     | 30              | 3               | 0.235                |
| 10     | 87/8/5            | 16                     | 20              | 9               | 0.201                |
| 11     | 87/8/5            | 8                      | 25              | 3               | 0.073                |
| 12     | 87/8/5            | 12                     | 30              | 6               | 0.123                |
| 13     | 87/8/5            | 16                     | 20              | 6               | 0.334                |
| 14     | 87/8/5            | 8                      | 25              | 9               | 0.104                |
| 15     | 87/8/5            | 12                     | 30              | 3               | 0.241                |
| 16     | 87/8/5            | 12                     | 20              | 9               | 0.108                |
| 17     | 87/8/5            | 16                     | 25              | 3               | 0.187                |
| 18     | 87/8/5            | 8                      | 30              | 6               | 0.060                |
experiments have been performed on the matrix composite based RSM technique. The results of the experiments have analyzed with the help of a grey-fuzzy analysis (GRA). The authors analyzed the process and suggested a good set of independent variables, improving overall performance. Jadam et al. (2018) have used EDM process for the machining of Inconel 718 using square cross sectioned Copper tool electrode. The basic objectives were to examine the topography and metallurgical features of the EDM work surface. Das et al. (2016) have examined the influence of process variables on CNC milling performance for Al/Cu/TiC composite with 4.5% Cu. Gaikwad et al. (2018) have optimized material removal rate during EDM of Cryo-Treated NiTi Alloys using Taguchi method. The analysis helps the worldwide researcher to use the efficient way of machining Hameed and Abbas (2019) have effectively used shape memory alloys (SMAs) in two story steel building construction is an effective way. Kumar et al. (2019) and Mardi et al. (2017) have also examined the EDM of Aluminum-based MMC and observed the ease of machining for their useful applications. Pandey et al. (2018) have also studied the fabrication, testing and Characterization of Al/TiC metal matrix composites through different processing technique.

Raju et al. (2018) have studied the tribological behavior of Al-Cu alloys and innovative Al-Cu metal matrix composite fabricated using stir-casting Technique. Singh et al. (2017) has investigated the accuracy of Al alloy fabricated using stir casting and ABS replica based investment casting. The present work will be useful for examining the EDM of Al-based alloys and its effective utilization for various applications. From the literature survey, it has been noted that aluminum-based alloy has a wide range of applications. Also, very few researchers have performed the experimentation on these alloys. Different studies have presented for alloys machining using EDM, but very few have given EDM of Al/Cu/Ni alloy. The present work's uniqueness is to develop the novel composition of the aluminum-based alloy (Al/Cu/Ni alloy) with the composition 91/4/5 and 87/8/5 (weight %). The novelty is not restricted to the development of new alloy but also to find out the ease of effective machining using EDM and its investigation based on ANFIS. The machining has been analyzed for minimum TWR. The adaptive neuro-fuzzy inference system (ANFIS) has used better accuracy in predicting the correlation between actual process responses. The presented work outcomes will help the machining to use and develop composition effectively for different applications.

The detailed discussion of the research work is presented in the following sections. The article is divided into four sections. The first sections deal with the literature related to the report. The second section explains the materials and methods used, the third section presents the results and discussion, and finally, the concluding remarks have given.

Figure 3. The methodology adopted for the TWR analysis during the EDM of Al/Cu/Ni alloy.
2. Material and methods

Aluminum/Copper/Nickel (Al/Cu/Ni) alloy is selected as workpiece material and copper electrode tool. The dimensions of the workpiece used during experimentation were $80 \times 50 \times 10$ mm. Two compositions (Al:Cu: Ni) viz. 91:4:5 and 87:8:5 were developed and considered for the investigation. The pure Cu tool (Electrode) of the square cross-section (10 mm $\times$ 10 mm) with conductivity (thermal) 391 W/m-0K) was used.

Table 3. ANFIS network parameters information.

| Sr. No | Parameters       | Count |
|--------|------------------|-------|
| 1      | Nodes            | 551   |
| 2      | Linear parameters| 256   |
| 3      | Nonlinear parameters | 288 |
| 4      | Fuzzy rules      | 256   |

Table 4. Impact of process parameters on TWR.

| Level | CP    | IP    | TON   | TOFF  |
|-------|-------|-------|-------|-------|
| 1     | 0.1805| 0.1782| 0.1669| 0.1697|
| 2     | 0.1597| 0.1975| 0.1605| 0.1762|
| 3     | ------| 0.1347| 0.1829| 0.1645|
| Delta | 0.0208| 0.0628| 0.0224| 0.0116|
| Rank  | 3     | 1     | 2     | 4     |

Figure 4. ANFIS model (a) Basic structure (b) Actual structure.
during the machining. The dimensions of the workpiece publicize in Figure 1.

The present work aims to examine the effect of EDM process parameters on response TWR during the machining of Al/Cu/Ni alloy with two compositions. ELEKTRA PLUS5 EDM machine use to perform the experiments. The grade 30 oil use during the machining as a dielectric fluid. All experiments performed on the EDM machine setup. The EDM machine components, such as tool holder, machine table, cutting tool, dielectric fluid supply system, are shown in Figure 2. All experiments performed as per the Taguchi’s L18 (21*33) mixed plan of experimentation. The personal computer (Processor: 2.53GHz Intel Core i3, Operating system: Windows7) having MATLAB (Release 2017b) and MINITAB 18 version used for the presented work.

In the present work, different process parameters listed in Tables 1 and 2 selected for the investigation—the ANFIS technique chosen for analysis. The experiments were conducted according to the chosen plan, and the readings tabulated in Table 2. The four critical parameters as alloy composition (CP) with two levels and three EDM process parameters viz. pulse on (TON), pulse off (TOFF), peak current (IP) with three groups selected for the investigation. The tool wear rate considers as a response parameter.

In the present work, EDM response parameter was tool wear rate (TWR) calculated using Eq. (1) (Sultan et al., 2014).

\[
\text{TWR} = \frac{\text{TLb} - \text{TLa}}{\rho g t} \text{mm}^3/\text{min} \tag{1}
\]

Here, TLb and TLa are pre and post-machining tool weights in Newton, \(\rho\) is the mass density of Cu tool material in gm/cc and \(t\) is machining time in min. The methodology adopted for the research work is shown in Figure 3.

- **Adaptive-Neuro Fuzzy Inference System (ANFIS)**

ANFIS combines soft computing techniques viz. neural-network (NN) and fuzzy-logic rule base network. Phate et al. (2019a, b, c, d) analyzed different clustered ANFIS models in predicting the mass of post-harvested sweet-lime fruits. The ANFIS architecture consists of four levels with several nodes on each layer. The nodes use to transmit the input to the successive layer. Figure 4 (a) illustrates the ANFIS Sugeno model. The response of each rule base can be a linear arrangement of input process parameters. The final response is the weighted mean of every single rule's response. Figure 4 (a and b) shows that the ANFIS network includes input signals in the forms of various inputs (IPs) with each information consisting of membership functions. The selection of network structures base on a set of different fuzzy rules. ANFIS model is used to link the inputs (CP, TON, TOFF, and IP) with the output parameter TWR. The input layer consists of four nodes, while the output node consists of a single node. ANFIS is very sensitive to data collection and sampling; hence, the data collection’s accuracy is essential. Therefore, each experiment replicated thrice, and the average value of the response variable note in Table 2.

Steps involved during the modeling using ANFIS are,

Step 1: Fuzzification: This is an input layer with four nodes (equal to the input parameters). In this step, the precise, realistic inputs have converted into fuzzy inputs. It converts crisp information into linguistic inputs with Gaussian mean given by Eq. (2).

\[
\mu_{IP_i(x)} = \frac{1}{1 + \frac{(x - R_i)}{S_i}} \tag{2}
\]

where \(K_i, R_i,\) and \(S_i\) are the parameters associated with function.

Step 2: Product and Normalization: This is also known as a fuzzy rule-based system containing a set of if-then rules. It also includes a database which expresses the membership function used in a fuzzy rule. The purpose of this is to convert given inputs to the targeted output. Here, the multiplier provides the strength by using a rule base.

Let \(\mu_{IP_1(x)}, \mu_{IP_2(x)}, \mu_{IP_3(x)}, \) and \(\mu_{IP_4(x)}\), are the membership function related to the four inputs and \(x\) is the linguistic value associated with the input function. Thus, strength at each node is given by Eq. (3).

\[
\text{w}_i = \mu_{IP_1(x)} * \mu_{IP_2(x)} * \mu_{IP_3(x)} * \mu_{IP_4(x)} \tag{3}
\]

The normalized strength of each rule is given by Eq. (4).

\[
\text{w}_i' = \frac{w_i}{w_1 + w_2 + w_3 + \ldots + w_{n-1}} \tag{4}
\]

Where \(w_i\) is the \(i^{th}\) rule strength which computes the ratio of \(i^{th}\) rule strength to the strength sum of all rules in the rule base.

Step 3: De-Fuzzification: It converts fuzzy outputs into crisp numerical production. It is a process of mapping which creates a non-fuzzy control action. It can convert a fuzzy set into a crisp background. In the present work Gaussian fuzzy membership (gaussmf) function was used for the variables with four levels viz. low, medium, high, and very high. The membership function and designer, as shown in (Annexure-II). The ANFIS network parameters tabulate in Table 3. In this, every node computes a linear process where the coefficient was calculated based on the feed-forward back propagation neural network and given by Eq. (5)
The final output is computed using Eq. (6).

\[
\sum_{i=1}^{m} w_i f_i = \sum_{i=1}^{m} \frac{w_i f_i}{\sum_{i=1}^{m} w_i}
\]

After selecting the membership function for all the variables, the next step is to set the fuzzy rule. The fuzzy rule set for the analysis and the ANFIS execution is as shown in (Annexure- II).

The fuzzy rule set used for the analysis are given below,

a. Rule 1: If CP is very low, IP is very low, TON is very low, TOFF is very low, then TWR is very low.

b. Rule 2: If CP is very low, IP is very low, TON is very low, TOFF is low then TWR is very low.

c. Rule 3: If CP is very low, IP is very low, TON is very low, TOFF is medium then TWR is medium.

d. Rule 256: If CP is high, IP is high, TON is high, TOFF is high, then TWR is high.

3. Result and discussion

In the present work, EDM has been performed on Al/Cu/Ni alloy, and experiments have performed using Taguchi’s L18 mixed plan of experimentations. The experimental design plan for four parameters with two and three levels has designed using MINITAB 18 software. The plan, which consists of eighteen run or experiments with three replicates, has been used. Then each response i.e., TWR for the run set has been determined. A full quadratic model has been developed to analyze the impact of EDM process parameters on TWR in the confidence interval of 95 %.
ANFIS consists of neurons that take numeric inputs and generate a prediction to respond to a very complex problem. Some activation function is applied and passes it to the next layer of neurons. Bias neurons are added in each layer, which simply stores the value of ‘1’. Without a bias neuron, each neuron takes the input and multiplies it by the weight. The high value of bias indicates that the model is not fitted well in the training data set. This shows the large error during training.

ANFIS algorithm is stochastic, and it uses random data of the training the network. Such random data is used to train the networks, which will lead to producing different results. The network's performance is improved, and the effect of randomization is minimize by increasing number hidden layers, changing the activation function, increasing number of neurons, randomization of weight first time etc.

Further, some assumption used during model formation are listed below,

1. The Gaussian membership function and Sugeno system have been used.

2. The architecture consists of four levels with several nodes on each layer.

3. The final response has the weighted mean of every single rule’s response. The input layer consists of four nodes while the output node consists of a single node.

4. ANFIS is very sensitive to data collection and sampling; hence the accuracy in the data collection is essential. For this purpose, each experiment is replicated thrice, and its average value is used.

5. A total of 256 fuzzy rules has employed during the analysis.

### 3.1. Impact of different parameters on TWR

The impact of various input parameters on TWR was analysed; for that, different experiments were performed using Taguchi’s L18 mixed plan of experimentation. In the present work analysis of variance (ANOVA) has been performed at 95% confidence level.

The rank shown in Table 4 indicates the sequence of impact in decreasing order.

From Table 5, It is observed that input current and pulse on-time, followed by the fraction of alloys are the most significant parameters that affect the TWR. At the same time, TOFF is the least sensitive or insignificant parameter. The probability of getting a result at least as intense as that of actually being seen. If the p-value is less than 0.05, it indicates the refutation of the null hypothesis. In the presented work, the null hypothesis is no difference between the means. The significant impact exists if the p-value exceeds 0.05, it reflects no effect of parameters.

The p-value is calculated to know the essential terms. If the p-value is less than 0.05 (95 % confidence interval), all the variables' linear terms significantly impact TWR except TOFF. In contrast, all square and interaction terms are insignificant. Figure 5(a-f) shows the various combinations of process parameters under consideration with response TWR. The three-dimensional surface plots are shown in Figure 5 (a-f). The blue region indicates TWR, and the yellow area means a higher value of tool wear (Phate et al., 2020a,b). The 3D plots explain the relationship between response TWR and the two input process parameters (keeping the other two constants) during the analysis.
The impact of individual parameters on response TWR is tabulated in Table 5. The increase in TWR with an increase in IP is due to the high localized heat, which results in additional material vaporization and melting instantly. TWR increases with an increase in TON; this is due to the effect of the thermal gradient. At a higher current duration, more thermal energy will release at the machining section. These results in highly effective melting and vaporization in that zone and hence increases TWR.

Figure 5(a-f) shows the neuro-fuzzy surface plot of response TWR versus various process parameters. The surface plots indicate the impact of two variables at a time and hold the remaining variables at their mean position. Figure 5(a) shows a significant change in TWR with the increase in TON. TWR increases with an increase in TON from 20 to 25 micro-sec, and then it starts decreasing from 25 to 30 micro-sec. The nature of the TWR curve is curvilinear, while TOFF has an insignificant impact on TWR.

Similarly, Figure 5(b) shows the interdependency of TWR on TOFF and CP. Figure 5(c) shows the effect of Parameter IP and CP on TWR. Figure 5(d) shows the impact of IP and TON. Figure 5(e) shows the effect of TOFF and TON, and Figure 5(f) shows the effect of IP and TOFF.

The type of membership function and the range of various parameters are as shown in Figures 6 and 7. We know that ANFIS works on the set of basic fuzzy rule set. The combination between various rules is as shown Figures 8 and 9.
The ANFIS model has shown a high correlation with the actual TWR, which shows its effectiveness in predicting TWR for the validation of the ANFIS model. Figure 10 shows that the actual and predicted responses are very close to each other, with a correlation of 0.99999 (Table 6). The high value of correlation proves the acceptability of the ANFIS model.

![Figure 10. Comparison between actual and ANFIS predicted TWR.](image)

Table 6. Statistical indices (Error analysis) for ANFIS based predicted TWR.

| Sr. No | Statistical Indices       | ANFIS     |
|--------|---------------------------|-----------|
| 1      | Minimum Percent Error     | -0.28792  |
| 2      | Maximum Percent Error     | 0.42377   |
| 3      | Mean Square Relative Error| 0.000003136|
| 4      | Mean Square Error         | 0.000000798|
| 5      | Root Mean Square Error    | 0.000280001|
| 6      | Mean Absolute Error       | 0.00021741|
| 7      | Coefficient of determination (R²) | 0.99999 |

3.2. Optimization of TWR

The optimum solution is obtained by using Minitab 18 software. The optimum value 0.0388 mm³/min is obtained corresponding the input process parameters, the average value of TWR based on these settings (Eq. (8)).

\[
\mu_{\text{TWR}} = \left[ CP(1), \ IP(8), \ TON(22.92), \ TOFF(9) \right] 
\]

Based on experimental findings, it has been observed that the input current, pulse on time, and composition of alloys are the most significant process parameters which affect TWR. ANFIS model has shown a high correlation with the actual TWR, which shows the effectiveness of it for predicting TWR. Taguchi analysis has been conducted. The optimum process parameters for minimum TWR of 0.0388 mm³/min have been noted as the material composition of 91/4/5, pulse on time of 8 micro-sec, the input current of 22.92 Amp, and the pulse off time of 9 micro-sec. The actual values lie between the 95% confidence interval; hence, the Taguchi method is useful for optimizing a single objective function.

The Al/Cu/Ni alloy is used in an automotive valve to control low-pressure pneumatic bladders in the car seat that adjusts the lumbar support contour of the lumbar support. Hence, the studied alloys can be used for engine radiators, bumpers, cylinder blocks, transmission systems, doors and the frames.

4. Conclusion

This work presents the effective use of ANFIS based prediction coupled with the Taguchi method to analyze the EDM process for machining Al/Cu/Ni alloy. The presented work of Al/Cu/Ni alloy EDM with two variations viz. type 1 (91:4:5) to type 2 (87:8:5) volume fraction of Al:Cu:Ni. The parameter TON, TOFF and IP are utilized as input process parameters. Taguchi’s L₁₈ mixed plan of experimentation used for experimentation. Based on the EDM process's critical analysis, it has been

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commitment with the actual or experimental TWR. Also, it offers a high degree of precision.

The outcome of the present work may apply to the industries for their performance improvement.

**Declarations**

**Author contribution statement**

Mangesh Phate: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Aditya Bendale: Contributed reagents, materials, analysis tools or data.

Shraddha Toney: Analyzed and interpreted the data.

Vikas Phate: Contributed reagents, materials, analysis tools or data.

**Funding statement**

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

**Competing interest statement**

The authors declare no conflict of interest.

**Additional information**

No additional information is available for this paper.

**Acknowledgements**

All authors listed in the manuscript would like to acknowledge all stakeholders of AISSMSCOE, Pune, Maharashtra, India and Kakade Laser Pvt. Limited Pune, Maharashtra, India for Support and motivation.

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