Optimisation of Electrical Discharge Machining Processing for AZ91 Magnesium Alloy using Coupled AHP-Taguchi Analyses-GA Method with the Rank Selection Approach

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Abstract

Despite being contemporary, the wire electrical discharge machining (EDM) industry is burdened with complicated and challenging problems. However, the double optimisation method involving the Taguchi analyses and genetic algorithms are a powerful tool to help tackle some of these problems. This article evaluates the wire EDM process through a rank-based genetic algorithm coupled with the AHP-Taguchi analyses using the AZ91 magnesium alloy for the first time in the literature. The rank selection method was used at the selection stage of the operations. Six parameters, namely pulse on time, pulse off time, wire feed, wire tension, pulse current and gap voltage, were the process parameters. For all the methods, the total values were computed and compared for the selection, cross-over and mutation operations. It was found that the total values at the selection stage for each of the methods, namely AHP-Taguchi-GA, AHP-Taguchi-Pareto-GA and AHP-Taguchi-ABC-GA methods, were 2750, 4176 and 6306 (best value as Part A), respectively. For all the methods, there was a 25.35% improvement in total value at the cross-over stage compared with the selection stage. The improvement in the total values of the mutation over cross-over and mutation over selection was 53.84% and 92.84%, respectively. These improvement values were for the AHP-Taguchi-GA method but also turned out to be the same for the AHP-Taguchi-Pareto-GA and AHP-Taguchi-ABC methods. The principal advantage of the rank selection method introduced in the present study is to avoid quick convergence. This article is beneficial to the process engineers aimed at improving the wire electrical discharge machining process.

Keywords: *Genetic algorithm, Optimisation, Prioritisation, Machinery operation*

1. Introduction

In the mechanical processing industry, the concern for profit and sustainability has focused on product manufacturing cost and quality features. The electrical discharge machining process becomes relevant while also considering the demand and product features of the present consumers in the market. Many products nowadays require materials and features that the traditional machining process has failed to incorporate, such as difficult-to-machine materials and multi-featured products with

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complex machining processes. AZ91 magnesium alloy must be studied using an electrical discharge machining process in this context. In the present scenario, optimisation of process parameters using the electrical discharge machining while manufacturing AZ91 magnesium alloy-based components becomes relevant. A literature search found that attempts have been made to study the optimisation of the EDM process. However, very sparse information has been documented on concurrently optimising parameters and prioritising them on the EDM machine using AZ91 magnesium alloy. Furthermore, the issue of robust analysis that provides an opportunity for multiple optimisation points while confronted with sparse data has not been treated. However, the genetic algorithm, which possesses these features, is an excellent candidate to augment the present suggested method of integrating the AHP and Taguchi methods in the literature. The following section presents a literature survey to demonstrate the research gap.

The subject of this article covers two aspects of the literature, namely, prioritisation and optimisation. Therefore, reviewing the literature to identify gaps were tailored to these aspects, commencing with prioritisation methods. Several scholars have attempted to prioritise parameters efficiently using diverse research topics, including the analytic hierarchy process (AHP). The AHP method is an effective decision-making tool used to compare multiple options by utilising the information on criteria provided by each option to choose the best option [1]. This method finds extreme suitability in examining and arranging complicated processes in electrical discharge machinings, such as the work material's melting and partial evaporation processes (i.e. AZ91 magnesium alloy) and the spark production process. The AHP method has been applied in optimisation circumstances [2], and this approach has been enhanced and upgraded with uncertainty and imprecision capturing mechanism to evolve the fuzzy AHP method [3]. The fuzzy AHP method has an orientation rooted in the weightage development based on producing the pairwise comparative matrix, its fuzzification, comparativeness of the fuzzy geometric mean, fuzzy weights, and crisp weights. The method incorporates every criterion, such as weight uncertainty and criterion significance [4]. Furthermore, while mixing the aluminium powder in the discharge machining process, Kazi et al. [3] applied the fuzzified form of the AHP to analyse the EDM experimental results conducted on an Elektra Pulse PS50 ZNC machine. They established the crisp weights of the MRR, TW and SR as 0.238 and 0.628, respectively.

Research on electrical discharge machining regarding the application of the Taguchi method has been increasing in the past few years. Nagaraju et al. [5] proposed the Taguchi method for optimising the electrical discharge machining process while processing the 17-7 PH stainless steel. In turn, Manikandan et al. [6], Kandpal et al. [7] and Chandramouli and Eswaraiah [8] employed the Taguchi technique to analyse the electrical discharge machining process while using the Inconel 625, AA6061/10%$A1_2O_3$ composite and 17-4PH steel. The significant input values to obtain the targeted performance measures were found. On the other hand, the Taguchi method was combined with the grey relational approach by Gohi and Puri [9] to establish the effect of electrical discharge machining parameters on some principal indicators such as the gap voltage, flushing pressure, peak current, spindle speed and pulse on time while considering the performance attributes to reverse polarity. In the earlier reviewed studies on the Taguchi technique, the drawback was associated with the difficulty distinguishing one parameter's importance relative to the other. However, this drawback was overcome by more recent studies that combined the Taguchi technique with the grey relational analysis. Despite this, there are no wide-ranging optimisation options, an important gap to be bridged in the present work.

As regards the genetic algorithm approach, Tajdeen et al. [10] proposed a genetic algorithm to examine the influence of parameters on machining attributes of EN31 steel and evaluate the optimal parameter for the electrical discharge machining parameters, including pulse on time, current and gap voltage. Pandey [11] proposed a computer-oriented genetic algorithm to solve the optimisation problem in electrical discharge machining while processing the titanium alloy (grade 5) sheet. The author reported enhancements in all the quality attributes of the process. Nair et al. [12] proposed an integrated grey relational analysis and genetic algorithm to optimise the wire EDM process for Inconel 617 material. Optimised parameters were experimentally verified and discussed. Rajesh and Anand [13] presented an approach to optimise electrical discharge machining by using the regression method and adjusted genetic algorithm. The studied parameters were oil pressure, working current, pulse on time, spark gap, and working voltage, while the responses analysed were the surface finish and material removal rate. Optimisation results were found and linked to machining conditions. Dutta and Sarma [14] employed the response surface methodology and the genetic algorithm to solve the micro-hole drilling problem using the micro electrical discharge machining process. Optimised values were obtained with reliable results, deviating 5% from the experiments. The major drawback of these genetic algorithm approaches is that the process engineer has to constantly strive to understand the relative importance of the parameters while concurrently optimising them. However, this is impossible with the existing methods and new approaches to overcome this weakness are desired.

Based on the earlier discussions in this article, the researchers applied the rank selection method of the genetic algorithm in an integrated AHP-Taguchi analyses-GA method, broken down into three methods of the AHP-Taguchi-GA, AHP-Taguchi-Pareto-GA and AHP-Taguchi-ABC-GA methods. The analysis was conducted based on the experimental data collected by Muniappan et al. [15]. This is the first time such methods have been developed and tested for the wire electrical discharge machining using the AZ91 magnesium alloy as the work material and the rank selection method. The AHP development framework was first instituted to implement the methods, and the results obtained were introduced to each of the Taguchi, Taguchi-Pareto and Taguchi-ABC platforms for experimental design and prioritisation analysis. The outcome was then used to analyse the rank selection-based genetic algorithm's impact on enhancing the integrated model's optimisation performance. Interestingly, this article offers an outstanding reference value to enhance the parametric selection and optimisation process of the wire electrical discharge machining using the AZ91 magnesium alloy.

The significance of the present study is to offer a framework for process engineers, workshop managers and operators in the machine shop to analyse their machining effectiveness, which may be too difficult to achieve or too easy a frequently achieved standard. Secondly, the paucity of studies on the concurrent optimisation and prioritisation of electrical discharge machining parameters have been conducted to slow down the convergence rate of the genetic algorithm component of the method. Consequently, this approach utilises the rank selection method to slow down the convergence rate of the solution required for bridging the research gap. Thirdly, this study optimised the process parameters of the wire EDM process using the AZ91 magnesium alloy, a material of high significance in the modern manufacturing industry and therefore provides valuable information as a benchmark for comparing performance characteristics of other materials. The fourth significance of this study is that through some insightful literature analysis, the three methods presented are suggested as practical means of assessing the performance of integrated optimisation and prioritisation methods. Holistically, the present research offers a pathway to re-ascertain that optimisation and prioritisation are pressing concerns in the present era of the dwindling economy of organisations within the electrical discharge machining system, and the risk involved extends to sustainability issues, which could wind up with the company except being corrected.

2. Methods

The methods used in the present study are discussed in this section.

AHP– Taguchi analysis-GA (rank selection approach)

The procedures involved in the implementation of the AHP-Taguchi analyses-GA method were as follows:

Step 1: Conduct the AHP method and develop the weights of each parameter.
Step 2: Introduce the AHP weights into the Taguchi response table and compute the product of the weights of parameters and the average signal-to-noise ratios to yield the AHP weight-average signal-to-noise ratio value.
Step 3: Obtain the delta values and rank the parameters according to the adjusted response table output.
Step 4: Refer to the factor-level table provided by the experiment and obtain the average levels for each parameter.
Step 5: Rank the average values of levels in descending order and assign positions accordingly, with the least value achieving the first position, and subsequent grading is made. This is achieved by applying Equation (1):

$$RS_{Area} = \frac{r_i}{\sum_{j=1}^{n} r_j} \tag{1}$$

Then

$$P_i = \frac{F_i}{\sum_{j=1}^{n} F_j} \tag{2}$$

where r_i is the rank of each i^{th} individual in the population, expressed as $F(x)$
RS_{Area} is an area to be occupied by the i^{th} individual
N is the number of individuals in the population
$N \times P_i$ is the number of the expected count
F_i is the fitness for a string i in the population, expressed as $F(x)$

Step 6: Sum up the delta values from the response table of the AHP-Taguchi scheme (i.e. optimal parametric setting table).
Step 7: Formulate a problem statement based on the outcome of step 6
Step 8: Use the fitness function to evaluate the value of each parameter and rank these values according to their importance.
Step 9: Sort the percentage values of the chromosomes (parameters). To achieve this, sum up the ranking, divide each rank by the total and multiply by 100%.
Step 10: Obtain a new value, which is a division of the percentage value by 100% and then multiplied by the average value of levels.
Step 11: Round up the value to the closest unit and the same rounding up for all the parameters. This becomes the new *x* value.
Step 12: Convert all the new *x* values into binary form.
Step 13: Solve the problem statement
Step 14: Obtain the probability count for each parameter by summing up the problem statement for each parameter and dividing each by the sum.
Step 15: Obtain the expected count by multiplying Pi by the number of population and identify the maximum expected count.
Step 16: Continue with the roulette wheel method.
Step 17: Obtain the best values in the selection, cross-over and mutation stages.

Furthermore, to illustrate the working of the proposed method pictorially, a flowchart has been provided in Figure 1.

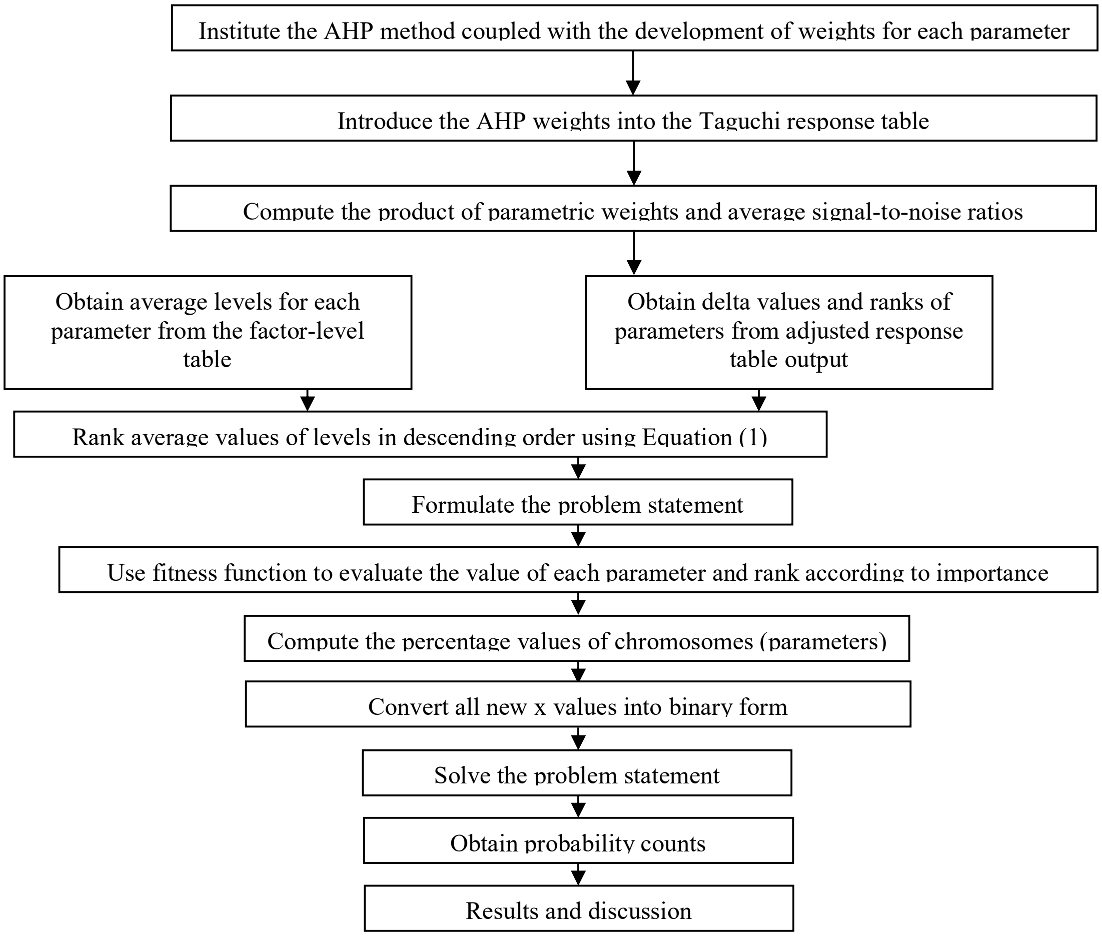

Figure 1. Flowchart illustrating the AHP-Taguchi analyses-GA (rank selection) methodology

3. Results and discussion

In this study, the analysis was conducted based on the experimental data collected by Muniappan et al. [15]. The present study chose the particular experimental data from Muniappan for many reasons. First, it allows the testing of the ideas of the proposed method before embarking on prototype testing and large-scale industrial setup. Moreover, it offers the best dataset to test the proposed method for the researchers of this study to exercise firm control on the parameters (wire tension, pulse current, pulse on time, pulse off time, wire feed, and gap voltage) during the analysis stage. Furthermore, in the absence of capacity to set up new experimental rigs, the researchers of this present study were compelled to search for reliable data on friction stir welding to validate the proposed method. While it is known that a reliable experimental design needs to be conducted in any experimental dataset used for the model testing, the element essential, which ascertains compliance with standard experimental testing was found in Muniappan et al. [15]. These are the use of control group, and sample size, among others. Based on compliance with standard, Muniappan et al. [15]

was chosen as the reference article that provided the experimental data for use in the present study.

Moreover, this study considered the combined AHP-Taguchi analyses and the rank selection method. This work developed and tested three methods: the analytic hierarchy process (AHP)-Taguchi-GA (genetic algorithm), AHP-Taguchi-Pareto-GA and AHP-Taguchi-ABC methods. The genetic algorithm is a search-oriented heuristic that works on the principle of natural evolution, a theory proposed by Charles Darwin [16, 17]. Previously, Ikedue and Oke [18] applied the AHP-Taguchi analyses to solve the concurrent parametric optimisation and prioritisation by combining the analytic hierarchy process with a strong capability for prioritising parameters and the Taguchi method for optimisation. Although two other variants of the methods include the introduction of the Pareto scheme and the ABC classification scheme, the Taguchi method in the three options has limited capabilities as the solution quality may not be as outstandingly high as possible using other methods. Therefore, introducing a method capable of producing high-quality solutions to search and optimisation problems is necessary.

In relation to the quality of the solution in providing optimisation services, the introduced method is expected to be profound. The depth of a solution introduces a robust group of features. Secondly, many problems are complicated and solving such problems smartly is a critical condition for the excellence of performance while addressing the quality of the solution issue. Furthermore, in this work, the researchers decided to use rank selection to further experiment with the chances of particular chromosomes being selected. In a previous study, the roulette wheel selection process was used. However, at variance with previous reports, the present study applied the rank selection method for selecting chromosomes for mating. However, discussing the difference between rank selection and roulette wheel selection is interesting. The roulette wheel selection is more traditional because it gives more advantages to a chromosome. Any chromosome or individual with a higher chance of selection would retain that position. Afterwards, the chances of others will grow, but the chromosome with the higher chances will still maintain its position all through. The roulette wheel is more straightforward, and all the chromosomes in the population are placed in the roulette wheel according to their fitness values. So, each individual is assigned a roulette wheel. That is, their size is proportional to the value of their fitness. Thus, the bigger the value, the larger its segment. However, the rank selection method differs slightly from the roulette wheels'.

In the rank selection method, every chromosome is ranked in descending order, where the lowest value attains the first position, and the second lowest value achieves the second position until the last one. In the present study , the parameters considered were pulse on time, pulse off-time, pulse current, gap voltage, wire feed and wire tension. So, in this situation, the lowest value from the factor level table where averages were computed was wire feed. After taking the average of the levels, the value of the wire feed was 6. This was ranked first. The subsequent ranking was done based on the values obtained. In implementing the rank selection method, two options were available to the researcher. The first option was to find the percentage according to the ranking. Here, the researchers worked with this new ranking, converting them to binary. This was the option adopted in the present study. Nonetheless, the second option was, after converting them to rank, to continue with the original value, which was the state, before ranking them or working with them in that ranking manner. After the numbers were ranked, one could still bring these values into action.

3.1 AHP- Taguchi-GA using the rank selection method

In applying the first method, which was being proposed, the current authors first gave the parameters ranks, put them in order of percentage and then used the percentage values, up all the problem statements for each of the parameters and then divided each of them by the sum (Table 1). For the chromosome of pulse on time, 1000.1802 was divided by 2750 to yield 0.2851. The same procedures were done for all the chromosomes. Then, the expected counts were evaluated by multiplying the P_i, which is the probability that a chromosome will be selected, by the number of the population, which is 6. So, 0.2851 was multiplied by 6 to obtain 1.7105. This procedure was repeated for all other chromosomes. From the analysis, the maximum expected count has a value of 4.0342. However, because the rank selection approach was used in this work, the procedure entailed continuing with the roulette wheel selection approach after applying the rank selection method. Based on this condition, the next selection method was to apply the roulette wheel selection method. Here, the initial population, x value and fitness exist. After this, the maximum value of the fitness function exists as 4.0342.

Table 1. Factor and levels showing the averages for levels (*based on data from Muniappan et al. [15] and selection process - AHP-Taguchi-GA method – Rank selection approach

Symbol	Process parameter	Average Level	Ranking	% Value	% value x Avg value = x value	Approximate value (x value)	Binary form
A	Pulse on time	116	5	23.81	27.6191	28	011100
B	Pulse off time	50	4	19.05	9.5238	10	001010
C	Pulse current	150	6	28.57	42.8571	43	101011
D	Gap Voltage	30	3	14.29	4.2857	4	000100
E	Wire feed	6	1	4.76	0.2857	0	000000
F	Wire tension	8	2	9.52	0.7619	1	000001
		Total	21	100.00			

A cross-over operation was proceeded to where a mating pool was created. First, the chromosomes were grouped in pairs, creating a mating pool at selected positions. The new offspring were created, performing a cross-over and then creating a new offspring after the cross-over. Once this was done, a cut-off for the first pair was done to create a mating after the third bit. For the second pair, a swap was done after the second bit, and for the third pair, swapping was done after the second bit. The new x values were obtained, 26, 12, 36, 11, 33 and 11, respectively, for a pulse on time, pulse off time, pulse current, gap voltage, wire feed and wire tension. After this operation, a new total was obtained. At the selection stage, 2750 was obtained, which was improved to 3447 at the cross-over stage, as shown in Tables 2 and 3.

Table 2. Selection operation - AHP-Taguchi-GA method – Rank selection approach

Symbols	String values	Ranking order	x values	$1.27574x^2$	P_i	Expected count
A	1	5th	28	1000.1802	0.2851	1.7105
B	2	4th	10	127.5740	0.0364	0.2182
C	3	6th	43	2358.8433	0.6724	4.0342
D	4	3rd	4	20.4119	0.0058	0.0350
E	5	1st	0	0	0	0
F	6	2nd	1	1.2757	0.0004	0.0022
			Total	2750	1	6
			Average	458.3333	0.1667	1
			Max	1849	0.6724	4.0342

Table 3. Cross-over process - AHP-Taguchi-GA method – Rank selection approach

Symbols	String number	X Value	Mating pool	Cross-Over Point	Offspring after Cross-over	New X value	Fitness F(x) = $1.27574x^2$
A	1	28	011|100	3	011010	26	862.4002
B	2	10	001|010	3	001100	12	183.7066
C	3	43	10|1011	2	100100	36	1653.3590
D	4	4	00|0100	2	001011	11	154.3645
E	3	0	10|1011	2	100001	33	1389.2809
F	6	1	00|0001	2	001011	11	154.3645
				Total	129	3447	4397.4758
				Average Val.	21.5	574.5	732.9126
				Max. Value	36	1296	1653.3590

It is the turn of mutation operation, where the researchers in this present study decided to conduct mutation at the second, fourth and sixth strings, Table 4.

Table 4. Mutation process - AHP-Taguchi-GA method – Rank selection approach

Symbols	String	Offspring After Cross-Over	Offspring After Mutation	x value	Fitness F(x) $=1.27574x^2$
A	1	011010	011010	26	862.4002
B	2	001100	011100	28	1000.1802
C	3	100100	100100	36	1653.3590
D	4	001011	011011	27	930.0145
E	3	100001	100001	33	1389.2809
F	6	001011	011011	27	930.0145
		Total	177	5303	6765.2492
		Average value.	29.5	883.8333	1127.5415
		Max. value	36	1296	1653.3590

After conducting the mutation, it was noticed that there was an improvement in the results. The pulse on time after cross-over was 12 but rose to 28 after mutation. The gap voltage was 11, but it rose to 27 after mutation. The wire tension was 11 after cross-over, but it rose to 27 after mutation. So, there was a total x value of 177 after mutation as against 129 after cross-over. So, it could be seen that there was an improvement in the parameters and this increased their chances of being selected. It could also be asserted that, in this case, the chances of each parameter being selected were high. This is justified as one looks at the values. The gap between the values was not as much as when the genetic algorithm was done for roulette wheel selection alone. The speed of convenience, in this case, was slow, not as rapid as it was when only the roulette wheel selection method was used on the electrical discharge machining data while processing the AZ91 magnesium alloy.

3.2 AHP- Taguchi-Pareto-GA using the rank selection method

In this method, the same procedure as discussed previously was applied, but what differed was the change in the delta value, which is the summation of the delta values as obtained from the AHP-Taguchi Pareto response table, which contains the optimal parametric settings. The delta value was 1.5188691, used in this case to form the problem statement. It was multiplied by x^2. The new rank was multiplied by the average level value for each parameter. This brought up a new set of x values. As they were in decimal places, they were converted into approximate values to have real integers. In doing this, the selection method was solved, as shown in Tables 5 and 6.

Table 5. Selection process – Approximate value and binary form (AHP-Taguchi-Pareto-GA method) – Rank selection approach

Symbols	Process parameter	Average Level	Ranking (RS)	% Value (% RS)	x value = Avg Val $\times$% RS	Approx. value (x value)	Binary form
A	Pulse on time	116	5	23.81	27.61905	28	011100
B	Pulse off time	50	4	19.05	9.52381	10	001010
C	Pulse current	150	6	28.57	42.85714	43	101011
D	Gap Voltage	30	3	14.29	4.285714	4	000100
E	Wire feed	6	1	4.76	0.285714	0	000000
F	Wire tension	8	2	9.52	0.761905	1	000001
		Total	21	100.00			

Table 6. Selection process – Expected count (AHP-Taguchi-Pareto-GA method) – Rank selection approach

Symbols	String No.	Ranking order	X Values	$1.518691x^2$	P_i	Expected count
A	1	5th	28	1190.6530	0.285091	1.7105
B	2	4th	10	151.8690	0.036364	0.2182
C	3	6th	43	2808.0578	0.672364	4.0342
D	4	3rd	4	24.2990	0.005818	0.0349
E	5	1st	0	0	0	0
F	6	2nd	1	1.5187	0.0004	0.0022
			Total	4176.3975	1	6
			Average	696.0663	0.1667	1
			Max	2808.0578	0.6724	4.0342

After applying the ranking selection method, the roulette wheel selection method was applied in the selection process. After doing this, a maximum value was obtained at the stage as the pulse current with a value of 4.0342. The total after solving the problem statement at the selection stage was 4176.3975. Next, the computation proceeded to the cross-over stage and obtained 5234.9279 after solving the problem statement, shown in Table 7.

Table 7. Cross-over process – (AHP-Taguchi-Pareto-GA method) – Rank selection approach

Symbols	String number	Mating pool	Cross-Over Point	Offspring after Cross-over	New x value	Fitness F(x) =1.5187x^2
A	1	011100	3	011010	26	19736.9135
B	2	001010	3	001100	12	4106.5416
C	3	101011	2	100100	36	34170.5567
D	4	000100	2	001011	11	1366.8223
E	3	000000	2	100001	33	28089.7163
F	6	000001	2	001011	11	735.0466
				Total	129	5234.9279
				Avg. Value	21.5	872.4880
				Max. Value	36	1968.2235

It could be seen that the results have been improved upon after the selection process. Then, the analysis proceeds to the mutation stage, shown in Table 8.

Table 8. Mutation process – (AHP-Taguchi-Pareto-GA method) – Rank selection approach

Symbols	String	Offspring After Cross-Over	Offspring After Mutation	x value	Fitness, F(x) =1.5187x^2
A	1	011010	011010	26	19736.9082
B	2	001100	011100	28	20435.5061
C	3	100100	100100	36	34170.5475
D	4	001011	011011	27	13419.1537
E	3	100001	100001	33	28089.7087
F	6	001011	011011	27	11232.2386
			Total	177	8053.61837
			Avg. Value	29.5	1342.26973
			Max. Value	36	1968.22354

The total after mutation rose to 8053.6184 (Table 8). Thus, by comparing the three totals after each operation method, it could be seen that successively, there was an increase in value at every stage. The aim pursued in this work was achieved: to improve the chances (probability) of each parameter being selected at every level. By applying the rank selection method, the ranges of the x values were not as wide apart as when only the roulette wheel selection method was used. To explain this, consider the roulette wheel selection method that is not reported here. For the same input data and the selection process, the values obtained for strings 1 to 6, for the fitness value $f(x)$ were 17166.3, 3189.4, 28704.2, 1148.2, 45.9, and 81.6, respectively, yielding a range of 28658.3. However, for the rank selection method, considering strings 1 to 6 having the x values of 28, 10, 43, 4, 0 and 1, the range was 43. By comparing these two range values of 43 for rank selection and 28658.3, the earlier method is preferred. Expressed in percentage, the x value range of the roulette wheel selection method was 66547% worse than the rank selection method by the x value range judgement.

3.3 AHP-Taguchi-ABC-GA

In the previous sections, detailed calculations concerning the applications of the methods of AHP-Taguchi-GA and AHP-Taguchi-Pareto-GA were given. However, to achieve the stated objective of presenting and analysing three methods, the analysis concerning the AHP-Taguchi-ABC-GA method is presented here.

3.3.1 Part A of the AHP-Taguchi-ABC-GA method

From Table 1, the information contained is symbols, process parameters, averages of levels, ranking, the percentage value of the rank selection, *x* value, approximate value of *x*, and the value in binary form. The table contains symbols, string no, ranking order, *x* values problem statement, Pi, and expected count. For the *x* values in this study, the following were concerned: 28, 10, 43, 4, 0 and 1. By raising the power to the square of those values, the obtained values ranged from 0 to 1849. Now, multiplying according to the problem statement and obtaining its total at the selection stage was 3270.3579. The average value was 545.0597, and the maximum was for the current parameter, 2198.8697. By working on ranking selection at first, the chromosomes were ranked in order from the smallest, having the first rank. Then, the highest had a rank number according to the number of chromosomes. In this case, a population of six chromosomes was considered where the value of n was 6. Then, the highest value would be in the 6th person according to the *x* values.

Then, the researchers had to rearrange it to obtain a new table for the selection operator of Part A. This table, Part A, is for the selection operator and carries symbols, string numbers, the initial population in binary form, *x* value, x^2 values, problem statement, Pi, which shows the probability for a chromosome to be selected, and the expected value (count). The expected count is the multiplication of P_i and n, where n is the population of 6. In the last table for the selection operation for the initial population, the string number is the arrangement in its symbol order. The initial population is the expression in binary form. Then, there are *x* values and x^2 values. The fitness is the summation of the delta values multiplied by the square of *x*. To obtain the probability value, each fitness value is divided by the total of the whole fitness. The first one would be 932.3493 divided by 3270.3579, which gave 0.2851. For the cross-over operation, it is known that crossing-over can be done in different ways. A one-point cross-over or a two-point cross-over can be chosen. In the present study, the researchers chose a one-point cross-over. Then, the *x* values were brought from the previous table from the selection operation stage and then performed the cross-over on the chromosomes in the mating pool. Notice that there is a column for the cross-over point. Now, the chromosomes that the cross-over operation would be performed on had to be paired. In this case, the first and second chromosomes were paired, the second pair was the third and fourth chromosomes, and the fifth and sixth chromosomes were the third pair. For the first pair, the cross-over point was after the third binary digit. Then, the second pair had its cross-over point after the second binary digit. Then, the third pair was after the second binary digit. After the mating, new values were obtained for the offspring, indicated as the offspring after cross-over in the table. This would yield the *x* values of 26, 12, 36, 11, 33, and 11, respectively, for a pulse on time, pulse off time, pulse current, gap voltage, wire feed, and wire tension. By performing the fitness test, where $f(x) = 1.1892x^2$, the values under the column with a total value of 4099.2450 exists. By comparing this total value with the previous one using the selection operation stage, which was 3270.3579, the researchers in this study had improved the performance of the chromosomes. Notably, improvement of the chromosomes' performance was the principal reason for performing the cross-over operation, and it had been achieved. This improved the chromosomes and enhanced their selection chances at various operation levels. The maximum value became 1541.23049.

In all, the total value had increased. The change in maximum value occurred because a mating operation was performed on them to break some chromosomes' ranks. Some of these chromosomes had very high values compared with others. However, they should be brought to a level of being selected at different operations. Then, the calculations at the mutation operation were done. Here is the problem statement. With this, the *x* value and the total of the fitness test were increased, which rose from 4099.244999 to 6306.4393 at the mutation operation stage, as shown in Table 9.

Table 9. Mutation process – Part A of the AHP-Taguchi-ABC-GA method – Rank selection approach

Symbols	String	Offspring After Cross-Over	Offspring After Mutation	x value	Fitness, F(x) =1.189221x^2
A	1	011010	011010	26	803.9134
B	2	001100	011100	28	932.3493
C	3	100100	100100	36	1541.2305
D	4	001011	011011	27	866.9422
E	3	100001	100001	33	1295.0617
F	6	001011	011011	27	866.9422
			Total	177	6306.4393
			Avg. Value	29.5	1051.0732
			Max. Value	36	1541.2305

3.3.2 Part B of the AHP-Taguchi-ABC-GA method

Here, discussions are made on how the genetic algorithm component of the AHP-Taguchi-ABC-GA part B was implemented in the electrical discharge machining process using the AZ91 magnesium alloy as the processed material. The first table of interest shows the symbols, process parameters, and average levels. Part B of the method followed the same procedure as Part A. The difference was in the delta values, which was 1.04911, as against the value in Part A, which was 1.1892. Every other process was the same except for changes in the delta values. For the selection operation stage, 2885.0612 was obtained for the fitness test. Now, it is the turn of cross-over operation and the total values of the fitness test, which rose from that at the selection operation stage to 3616.2930. At this stage, the maximum value changed as a mating operation was done by breaking the ranks of the chromosome having values on the high side to balance others whose values were very low, bringing them up to a level whereby they could be selected during an operation. It was then the turn of mutation operation in Part B. Here, a new set of x values was obtained, changing the fitness test values. Then, a total of 5563.4471 was obtained, as shown inTable 10.

Table 10. Mutation process – Part B of the AHP-Taguchi-ABC-GA method – Rank selection approach

Symbols	String	Offspring After Cross-Over	Offspring After Mutation	x value	Fitness, F(x) =1.189221x^2
A	1	011010	011010	26	709.2005
B	2	001100	011100	28	822.5047
C	3	100100	100100	36	1359.6506
D	4	001011	011011	27	764.8035
E	3	100001	100001	33	1142.4842
F	6	001011	011011	27	764.8035
			Total	177	5563.4471
			Avg. Value	29.5	927.2412
			Max. Value	36	1359.6507

Thus, it can be declared that the current research has successfully optimised the electrical discharge machine process for the processing of AZ91 magnesium alloy using a genetic algorithm because the previous value at the selection operation stage had been moved to a higher value at the cross-over operation and a higher value was obtained at the mutation operation stage.

3.3.3 Part C of the AHP-Taguchi-ABC-GA method

As discussed in Part B, every other operation remained the same apart from introducing a total delta value of 0.597066 at this stage of Part C. Having introduced the new delta value, the selection operation was started with to have a new set of values. After performing the selection operation, a total of 1641.9308 was obtained for fitness. Then, the analysis progressed to cross-over operation and obtained 2058.0865 as the total value of the fitness test, which was upgraded from a value at the selection stage to a higher value at the cross-over stage. It was then decided to perform a mutation operation on the same x values (Table 11).

Table 11. Mutation process – Part C of the AHP-Taguchi-ABC-GA method – Rank selection approach

Symbols	String	Offspring after cross-over	Offspring after mutation	x value	Fitness, F(x) =0.597066x^2
A	1	011010	011010	26	403.6165
B	2	001100	011100	28	468.0996
C	3	100100	100100	36	773.7972
D	4	001011	011011	27	435.2609
E	3	100001	100001	33	650.2046
F	6	001011	011011	27	435.2609
			Total	177	3166.2397
			Avg. Value	29.5	527.7066
			Max.Value	36	773.7972

After performing the fitness function, muting was done at the second binary digit for B, D, and F and obtained a total of 3166.2397. In summary, the fitness function total at the selection stage was moved from 1641.9308 to 2058.0865 at the cross-over stage. The value at the mutation operation stage was further improved to 3166.2397, as shown in Table 11. Having done this, it could be said that the process had been successfully improved or optimised by improving the fitness and x values, improving their chances of being selected for operations [11, 18]. The summarised results are shown in Table 12 [16, 17].

Table 12. Parts A, B and C of the AHP-Taguchi-ABC-GA method

Operation / Part	Selection	Cross-over	Mutation
Part A	3270.3579	4099.2450	6306.4393*
Part B	2885.0612	3616.2930	5563.4471
Part C	1641.9308	2058.0865	3166.2397**

Key: *Best value, **Worst value

4. Conclusions

This article contributes to the electrical discharge machining literature by offering a robust rank selection-based genetic algorithm to integrate previously proposed coupled AHP and Taguchi analyses, comprising Taguchi, Taguchi-Pareto, and Taguchi-ABC methods. The methods proposed have the unique attribute of a slow convergence whereby a thorough search is provided using multiple solutions before convergence. This is the main difference between this research and previous studies. This research used literature experimental data from Muniappan et al. [15]. It could be concluded for all the methods that after conducting the mutation operation, the total values had improved considerably, thereby confirming the feasibility of the proposed methods. Future research may consider several issues. First, in this study, each bit was assumed to have the same probability of mutating during the mutation process. However, this assumption may change in practice. Thus, a mechanism to establish the probability of mutation may be established. Second, during the cross-over operation, the researchers in this study assumed the one-point cut-off where the strings were divided into two. One half of the first string in the pair combined with the other and vice-versa. However, opportunities abound for a two-point and multiple points cut off. Also, some considerations of multi-objective optimisation and the multi-critical decision may bring out a new path in research [19, 20]. If these new ideas are pursued, a robust evaluation of the wire EDM may be achieved.

Conflict of interest

The authors have no competing interests to declare that are relevant to the content of this article.

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