Evaluation of Optimal Wire Electrical Discharge Machining Parametric Scenarios of AZ91 Magnesium Alloy Based on AHP-Taguchi Analyses-Genetic Algorithms

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Abstract. *In this article, three robust parametric optimization schemes for the electrical discharge machining of AZ91 magnesium alloy are proposed using a hybrid analytic hierarchy process, Taguchi schemes and a genetic algorithm. The three methods are the AHP-T-GA (analytical hierarchy process-Taguchi method-genetic algorithm approach), AHP-TP-GA and AHP-TAPC-GA, where TP and TABC are Taguchi-Pareto and Taguchi-ABC methods, respectively. The methods were used as the cornerstone approaches to evaluate the parameters and classify them according to their importance. The parameters are namely the pulse on time, pulse off time, pulse current, gap voltage, wire feed and wire tension. The coupled models of AHP-T, AHP-TP and AHP-TABC already exist in the literature. However, the genetic algorithm is coupled with each of these methods to moderate the adverse economic and decision outcomes. Although the coupling of the Taguchi, Taguchi-Pareto and Taguchi-ABC method to AHP reduces errors, the provision of less information in a large-scale decision variable problem may lead to wrong decision making. However, introducing a mechanism capable of producing a large set of solution space, and multiple optimal and global solutions may moderate the tendency to make wrong decisions. The introduction of a genetic algorithm having these preceding features differentiates the three methods proposed in this article from previous research. Results suggest that the proposed robust methods have helped to improve the parametric performance of the wire EDM process and yielded higher values in a maximization scheme pursued in this article. However, the pulse current exhibited the highest value in the analysis. The results adequately represented the parametric scores obtained from ranks of parameters using data from the literature.*

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1. Introduction

In the machining research domain, integrated methods of optimization and prioritization techniques are one of the most promising and recent areas for achieving machining resource distribution effectiveness and improved machining performance [1]. This research area combines one or more optimization approaches with at least one prioritization method to evaluate the parameters and responses of the machining process so that an ordered list of parameters is achieved for resource distribution policy development and implementation [2], [3]. Instances of reports to support this argument include multi-objective optimization integrated with the TOPSIS method [4], a combined non-dominated sorting genetic algorithm with the TOPSIS approach, incorporating the analytic hierarchy process [2], Taguchi's orthogonal array joined to the TOPSIS method [5], combined distance-based Pareto genetic algorithm approach, Taguchi method and analysis of variance [6]. In the (wire) electrical discharge machining, several important combinations have been made [7]. Rajesh and Anand [8] deployed the response surface optimization approach coupled with the genetic algorithms to establish the optimal machining parameters for the electrical discharge machining by focusing on oil pressure, working current, pulse off time, pulse on time, spark gap surface finish and material removal rate was taken as the responses. Ubaid et al. [9] engaged in the optimization of the electro-discharge machining using stainless steel 304 (ASTEMA 240) as the work material and the combined signal-to-noise ratios and fuzzy logic inference system as a tool. Rao et al. [10] used combined artificial neural networks and a genetic algorithm in an electric discharge machining system to optimize the surface roughness outcome while processing the Ti6Al4V, M-250, 15CDV6 and HE15. In Moghaddam and Koalhan [11], the electrical discharge machining of AISI2312 hot worked steel was conducted and the results were analyzed by combining signal-to-noise ratios/regression model/analysis of variance with a genetic algorithm. The concurrent optimization of surface roughness outcome and the parameters of gap voltage, pulse off time discharge current, pulse on time and duty factor were considered.

The idea of merging the Taguchi method as an optimization method with the Pareto method and ABC classification scheme has been interesting and growing since its introduction in 2019. It started with the first level integration where the Taguchi method is integrated with either the Pareto in the following reports. Francis et al. [12] deployed the methods in friction stir welding while choosing the AA6062-T6 alloy as the material to process. Adegoke et al. [13] work on the same methods with application to turning operations while the Inconel X750 alloy was the processed material. Okanminiwei and Oke [14] deployed the three methods of Taguchi, Taguchi-Pareto and Taguchi-ABC to solve the maintenance downtime minimization problem in a container terminal. Soon afterwards, research developed to the second level integration where the Taguchi-Pareto and Taguchi-ABC methods at the first level integration are further enhanced by the addition of another method. Studies that have reported such include Taiwo and Oke [15] that analyzed the drilling process and deplored a second-level combination method of the Taguchi-Pareto-Particle swarm optimization method. Within the domain of wind turbine ducting systems, Abayomi and Oke [16] combined Taguchi, Pareto and DEMATEL methods as a method to determine the process parameters of the system. Abdullahi and Oke [17] presented two methods. In one, the Taguchi, Pareto and Box Behnken design methods were amalgamated while in the second, the fusion of Taguchi, ABC and Box Behnken was done. But the application was made in a boring process. In Nwafor et al. [18], the two-level integration of methods was to fuse the factor analysis, approach, Taguchi approach and Pareto method. The authors applied the method to optimize the parameters of the casting of lightweight wheel rim cover application. Okponyia and Oke [3] combined the EDAS, Taguchi and Pareto methods to select parameters of the wire EDM process while using nitinol as the material.

However, more interesting and relevant to the present research is the integration of the analytical hierarchy process (AHP) method with each of the Taguchi, Taguchi-Pareto and Taguchi-ABC methods. Furthermore, in a study, Ikedue and Oke [19] introduced the idea of integrating the AHP with the Taguchi, Taguchi-Pareto and Taguchi-ABC methods to improve the parametric performance of the wire EDM process while deploying the experimental data obtained from Muniappan et al. [20] in which the AZ91 magnesium alloy is processed. These three methods proposed for the concurrent optimization and prioritization of parameters have their ground set on Saaty’s scale of importance and the prioritization mechanisms are taken into account in the Taguchi-Pareto and Taguchi-ABC components of the methods have the potential for establishing the root causes of the problem and obtaining superior approaches to eliminating wastes. These advantages are frequently used by process engineers in the wire electrical discharge machining industry since they help in improving decisions on the resource distribution scheme while deciding on what resource to allocate to specific parameters for the process effectiveness and the actualization of machining goals.

However, these methods cannot claim robustness in attaining global optimization. In a large-scale parametric system (multiple parameters) with sparse information available, a large set of solution space and multiple optimal points to warrant choice cannot be proved to be achieved. But these features aid the safe computations in achieving reliable and rich decision-making in the wire electrical discharge machining process. Thus, incorrect decisions may be avoided by introducing the mechanisms of global optimization, the creation of large solution space and multiple optimal points as may be found in genetic algorithms. Therefore, the integrated methods of AHP-Pareto, AHP-Taguchi-Pareto and AHP-Taguchi-ABC may be treated to incorporate genetic algorithms as enhanced decisions making models for solving wire electrical discharge machining problems using the AZ91 magnesium alloy as the material for processing.

To the best of the authors' knowledge, previous studies have been deficient in addressing the ideal optimal problem that may exist in diverse wire electrical discharge machining optimization analysis. Also, the creation of a large solution space for choices in the context of the paucity of information from experimental sources has not been addressed in the literature. But the attainment of global optimality is a key concern in establishing unbiased parametric weights and the availability of a large solution space assures that despite the presence of paucity of experimental data, the research could choose the optimal points that best suit the system's goals. For instance, a situation may arise in which shortages of funds exist and enough resources for the wire EDM process could not be purchased at once. However, with the limited resources bought one may not be able to decide on the impacts of the purchased resources on the system performance. The large solution space provides this opportunity for a sensitivity analysis, which cannot be done with previous literature knowledge and past contributions. By tackling this problem using the genetic algorithm a fertile ground for applying the integrated AHP-T-GA, AHP-TP-GA and AHP-TABC-GA methods is created and may be a rich source of information for the process engineers in the wire electrical discharge machining industry.

By examining the various contributions mentioned previously, it seems clear that the Taguchi-Pareto and Taguchi-ABC methods have been successfully utilized in several processes, including friction stir welding, turning operations, boring operations and container terminals. This success may be because of the multiple benefits that the methods deliver in practice. For instance, the Taguchi method component of the hybrid method saves experimental costs with fewer experimental requirements and cost savings is a key pursuit of managers in the industry [1]. Besides, the Taguchi-Pareto method assists in establishing the causal factors for the problem thereby directing effects to yield dramatic changes in performance instead of miniature changes. Moreover, the Taguchi-ABC method permits effective confrontations of the process parameters, giving insights on superior approaches to allocating the process resources and avoiding waste of resources. Furthermore, much quantitative information is often associated with processes and the Taguchi methods provide a rich source of transforming this quantitative information into process-able advantages towards achieving the targeted optimization goal of the process. Nonetheless, if only the Taguchi-Pareto or Taguchi-ABC methods are used the importance of the criteria could be defined in a limited manner and the substantial experience of the experts is ignored and the contributions towards defining robust importance in order with inputs from experts may be lost and several criteria may not be considered.

To overcome this limitation of the Taguchi-Pareto and Taguchi-ABC methods, Ikedue and Oke [19] combined the analytic hierarchy process (AHP) method with each of the Taguchi-Pareto and Taguchi-ABC methods to form AHP-Taguchi-Pareto and AHP-Taguchi-ABC methods. While conducting wire electric discharge machining on the AZ91 magnesium alloy for the optimization of parameters, feasible results were achieved. However, while using the AHP-Taguchi-Pareto and AHP-Taguchi-ABC methods, it is difficult to claim global optimization and large solution spaces may not be created in the presence of paucity of data. The genetic algorithm is well known as an optimization method that enables global optimization and large solution spaces even in the absence of extensive data. The genetic algorithm has already recorded outstanding success in the machining domain among other areas. Nonetheless, until now, no application or method to incorporate the genetic algorithm into the existing AHP-Taguchi-Pareto and AHP-Taguchi-ABC methods exist. But such integration is required to overcome the previously mentioned challenges. In this article, we use the genetic algorithm and not another search heuristic because as distinct from the traditional search method. Firstly, it searches for parallelism within a group of points. This makes it sensitive to the avoidance of locally optimal solutions but the traditional search methods are incapable of this ability.

To establish a research gap in which a fruitful pursuit to bridge the gap may be pursued, the relevant literature on electrical discharge machining (EDM) was analyzed. Interestingly, the whole literature examination reveals that the performance assessment of the EDM process during the fabrication of magnesium AZ91 alloy is a complicated issue: The difficulty arises due to the paucity of published data regarding the magnesium AZ91 alloy. If published data existed in a sufficient quantity, process engineers would form data charts and manuals, which makes the processing low cost as further experiments may not always be needed for decision making. To compound the difficulty, the exact mechanism through which the EDM process operates is not yet fully established. This explains why wide-ranging, extensive time demanding and costly experimental approaches are always required to establish appropriate parameters for the EDM process. Moreover, the EDM process often produces reproduce-able sharp corners on workpieces with a significant effect on electrode wear that is difficult to monitor. Thus, without a robust mechanism to monitor performance coupled with an inadequately planned performance management scheme, poor performance, which affects the quality of the fabricated magnesium AZ91 alloy may result. While confronted with the mentioned issue, the concerns of how the performance measurement for the EDM process could progress with limited information, restricted solution space available and limited number of optimal solutions are also critical for any progress to be achieved in the fabrication of magnesium AZ91 alloy. Consequently, to stimulate and maintain the good quality performance of the fabricated magnesium AZ91 alloy and avoid sub-optimal results, an extensive study should be conducted to evaluate the EDM process performance by combining methods capable of prioritizing parameters according to their importance and at the same tune optimizing these parameters. But to ensure optimal performance, a decision-making hierarchical model, coupled with the Taguchi method might be used.

2. Applying a Genetic Algorithm to the Wire EDM Problem

In previous work, three methods, namely the AHP-Taguchi, AHP-Taguchi-Pareto and AHP-Taguchi-ABC methods were proposed and tested in Ikedue and Oke [19]. In the work, the optimization of wire EDM process parameters was pursued the AZ91 magnesium alloy based on the experimental data proposed by Muniappan et al. [20], a successful prioritization and optimization of the parameters was reported. However, additional work to optimize the process parameters is reported in this article by starting with the output of the previous works on the method and then applying the genetic algorithm. Thus, the application of the genetic algorithm to the results obtained previously is the main advancement of this article. Consequently, the discussions and analysis presented here are based on the traditional approach to the genetic algorithm in any system. Furthermore, in trying to analyses the factors under consideration, the work deploys the use of three operations as applicable in genetic operation. These operators are the selection operator, mutation operation and crossover operator. Brief detail about these operators is given.

2.1 Selection

If starting with the selection operation for the wire EDM process parametric optimization problem, the question of how do we select the candidate solution of chromosomes to the AZ91 magnesium alloy material-oriented wire EDM process from the population and used them to crossover? In this discussion, simply mentioning selection refers to parent selection. This is the procedure undertaken to choose parents that will mate with each other to produce (recombine) offspring representing the next generation of parents that will also mate to yield the next generation and this offspring creation continues until termination. Choosing good parents is a critical issue as it leads to convergence rate behavior it is known that better and fitter solutions are produced with good parents instead of bad parents. In this article, the main challenge is how to select the parents from the parametric data given on the AZ91 magnesium alloy. Recall that a genetic algorithm mimics the natural evolution of genes according to Charles Darwin's theory regarding natural evolution. It is known that due to the conditions impacting on gene's survival, strings may survive and others could be killed. Then to promote a good and healthy future population, the best chromosomes are expected to survive and these chromosomes should demonstrate an ability to create new offspring.

In applying the selection operation to chromosomes, probability describes how likely a chromosome is chosen to be used. This probability is specified according to the fitness of the chromosomes. This is commonly called proportional selection. It is expected that the offspring replace the chromosomes and this idea continues until convergence is reached. In the selection process, the roulette wheel method of choosing the best chromosome is deployed while future research entails the use of the rank selection method and its variants. However, the principle used in the genetic algorithm application is the survival of the fittest.

2.2 Crossover

The crossover, sometimes mentioned as recombination, is the reproduction stage where the genetic information of the chromosomes is combined as two strings are randomly chosen from the mating pool to create better offspring that represent the chromosomes as the next generation. Recall that during the selection stage various results are obtainable due to the varied methods applied such as the roulette wheel selection and the ranks selection method, among others. Similarly, different results could be obtained if different point cut-off methods are chosen such as the single-point cut-off and double-point cut-off methods. For large strings, points of methods beyond two may be considered. However, this is sparsely reported in the literature and could be a subject of future investigation. Also, the two-point cut-off method may be considered and the results obtained compared with the single-point cut-off and multiple-point cut-off methods. Moreover, the principal importance of the crossover stage in the genetic algorithm is to ascertain the interchange of genetic materials between two chromosomes and then produce offspring that promise to live better than the parents. This is a common phenomenon in societies. It is found that natural parents (humans) who through financial limitations are unable to have good former education and hence limited in their income and achievement in life, will likely put all efforts into ensuring that their children are more educated and thrive better as offspring than them. Furthermore, the crossover operation is based on two chromosomes. At the crossover stage, the production of offspring could result in one or two offspring and this depends on the cut-off points during the crossover stage, which could be one or two points.

2.3 Mutation

Similar to biological mutation, a mutation in the genetic algorithm is a miniature random modification in the parent (chromosome) to obtain a new solution, aimed at obtaining different genetics as there is a life transformation of the chromosomes from one generation of the population of AZ91 magnesium alloy material-based wire EDM process parameters to the next one. The purpose of mutation operation is to carefully modify the chromosomes such that local minima during the convergence-seeking efforts avoid a situation where the population of chromosomes is alike. Usually, as the chromosome is to be mutated, the strings carrying a value of 1 are changed to 0 such that as the fitness function is evaluated for a minimization problem, it is reduced considerably. Otherwise, changes are made from 0 to 1 for a maximization problem such that the value of the fitness function is increasing upon reevaluation. The assumption is that each bit has the same probability of mutating.

2.4 Pre-selection Operation's Data Preparation Process

The data of factor-level for the experimental data extracted from Muniappan et al. [20] cannot be used directly as an input to the selection process but needs to be modified as discussed in this section. Thus, the following procedures are essential and representative of the pre-selection operation stage of the genetic algorithm for case consideration.

Step 1: Generate the problem statement, which could be f $(x) = x^2$
This could be derived by combining the values obtained from the table of the work done on AHP-Taguchi/Taguchi-Pareto/Taguchi-ABC methods.

Step 2: Sum up the delta values. Delta values are the differences between the highest and lowest along the column for each parameter across levels.

Step 3: Multiply the outcome of step 2 by x^2.

Step 4: Consider the number of levels for each parameter specified in the factor-level table and average the values as level average with which further computations are to be made. For instance, in the case study considered by Muniappan et al. [20], three levels were defined for each factor/parameter. These three levels are summed up for each parameter and the outcome is averaged. This result is the x value that will be used in the case study discussed here.

Step 5: Specify the intervals for the x. the range considered in this work is 0 to 200.

2.5 Selection Operation's Procedure

The following are the steps that are representative of the selection process.

Step 1: Convert the x values to binary numbers. this first step involves conversion to binary numbers to ease certain computations and obtain the fitness of each chromosome (parameter).

Step 2: Multiply each of the x values generated by the coefficient of x^2. This helps the researcher to come up with a table of average level values in a column and in the other column there are the x^2 values. The next column shows the results of the multiplication of the coefficient of x and x^2

Step 3: Find the probability of strings that a particular parameter will be selected from the pool of the population, Equation (1). This is defined as:

$$P_i = \frac{f_i}{\sum_{i=1}^{n} f_t} \quad (1)$$

P_i is the probability that a string will be selected n is the population or the number of parameters that are being considered.

f_i is the fitness for the strings in the population, expressed as $f(x)$

For the selection operator, the researchers brought out a table with columns showing symbols. Another column shows the string values while another column shows x values. There is another column showing the factor/parameter problem. There is another column showing the probability and the last column showing the expected count. Then the spaces in the table are filled with the required values.

Step 4: From the expected count, the column locates a figure with the maximum expected count. This shows that the particular parameter shows the highest probability i.e. the highest chance of being selected.

2.6 Crossover Operator's Procedure

As the researcher progresses from the selection stage, it reaches the crossover operator's stage. The following steps are applicable at this stage.

Step 1: Identify the parameter with the least chance of being selected and replace it with the parameter with the highest chance of being selected.

Step 2: Performance a crossover operation on the values obtained i.e. on the bits.

Step 3: Observe the improvement in the values of the table generated.

Step 4: Evolve a crossover table, which shows a further improvement on the earlier results.

Step 5: Compare the average results and the total, i.e. maximum value for the table of the selection operator and crossover operator. This is to show if the total value generated from the crossover operation's stage exceeds that generated during the selection operation's stage according to the purpose of optimization. However, if the minimization of the objective function is pursued, the total needs to reduce. By attaining this goal, the researcher could declare attain the aim of improving the process.

2.7 Mutation Operator's Procedure

To improve on the crossover stage's result, the mutation operation on the results obtained from the crossover stage is considered. The mutation is applied individually to the parameters after the crossover operation has been performed. To achieve this, the researchers randomly changed the bits, which are the constituents of the chromosomes that are binary numbers made up of 0 and 1. The changes of bits are either from 0 and 1 or from 1 to 0. However, it needs to improve the process. The following steps are applicable:

Step 1: Select at random the parameters to be improved upon.

Step 2: Alter the bits in the offspring after crossover.

Step 3: Observe the improvement in the parameter after step 2 is used.

Step 4: Express the outcome in the form of the problem statement.

Step 5: Compute the total, average value and maximum value for the mutation operation.

Step 6: Conclude if you can achieve the aim of further improving the fitness values after using the mutation operation on the previous results.

3. Results and discussion

3.1 Pre-selection Operation's Data Analysis

To commence analysis, the problem statement is first developed and the principal issue here is to define an objective function to be optimized. The developed problem statement is

$$f(x) = 1.27574x^2 \quad (2)$$

which was derived by combining the values obtained from the response table of the work done on the AHP-Taguchi method. The delta values were summed up, which yielded 1.27574. However, it is assumed that the function that best describes the machining process for the AZ91 magnesium alloy is $f(x) = x^2$. Thus, the point of connection of the objective function and the data obtained is the multiplication of these summed upped delta values, 1.27574, with x^2 to yield $f(x) = 1.27574x^2$.

Next, from the factor-level table, the parameters considered are pulse on time, pulse off time, pulse current, gap voltage, wire feed and wire tension. There are three levels for each of these parameters. These levels have to be consolidated to one point. To achieve this, the three levels for each parameter are averaged. This level average is then used as the x values in the computational process. This means each of these x values represents the behavior of the parameter in the method used in the present work, which introduces the genetic algorithm as an additional procedure for use. The interval for the x is considered between 0 and 200. Thus, the values considered fall between 0 and 200. As mentioned, the initial random population for this work has the seed of the average of the three levels for each parameter.

3.2 The AHP-Taguchi-GA method

3.2.1 Analysis of The Selection Process

The first step in the selection process is to convert these x values into binary numbers to obtain fitness. Then each of these values (i.e. x values) is multiplied by the coefficient of x^2, which is 1.27574. Afterwards, a table showing the average level values is then developed in a column, Table 1.

String no	Initial population	Symbol	Process parameter	*Average Level (x values)	Fitness, $f(x) = 1.27574x^2$	P_i	Expected count
1	01110100	A	Pulse on time	116	17166.3574	0.3410	2.0462
2	00110010	B	Pulse off time	50	3189.3500	0.0634	0.3802
3	10010110	C	Pulse current	150	28704.1500	0.5703	3.4215
4	00011110	D	Gap Voltage	30	1148.1660	0.0228	0.1369
5	00000110	E	Wire feed	6	45.9266	0.0009	0.0055
6	00001000	F	Wire tension	8	81.6474	0.0016	0.0097
				Total		1	6
				Average		0.1667	1
				Max		0.5703	3.4215

Table 1 Factor and levels showing the averages for levels (*based on data from Muniappan et al. [20] and selection process - AHP-Taguchi-GA method

In Table 1, the column showing x, Pi and the expected count is shown. The P_i, which is the probability that a string selected is the same as f_i divided by the summation of f_j where the counter starts from 1 to n. The term n is the number of parameters to be considered, f_i is the fitness of the string i in the population, which is expressed as $f(x)$, Equation (1). From this formula, P_i in Table 1 was derived. There is a column in the table showing symbols, and another column showing the string values. Another column is showing x values from which the parameter problem is computed. There is another column showing the probability and another column showing the expected count. From the expected count, we were able to determine a parameter which had the maximum expected count. This shows that the particular parameter has the highest probability (chance) of being selected. That parameter happens to be the pulse current from the analysis. The pulse current from the selection stage has the highest probability of being selected.

3.2.2 Analysis of The Crossover Process

Then we proceeded to the crossover operation's stage. Here, the parameter that has the least chance of being selected was replaced with the parameter that has the highest chance of being selected. From Table 1, the wire feed has the least chance of being selected, which was replaced with the value of pulse current and a crossover operation is performed on it. Consequently, we were able to improve on the table being generated and a crossover table emerged. The table allows us to improve further on what we had. Initially, we had a total of 50,335.5974. But after we had the function, we computed a value of 74,094.9792. Having done this, we can confidently say that we have improved on what we have generated and we proceeded. Notice that the crossover aims to improve the outcome we got while performing the selection operation. From the table that we generated at the crossover operation stage (Table 2) and comparing the two results (i.e. Tables 1 and 2), we found out that the average, i.e. the maximum value from the table generated during the crossover operation stage exceeds that of the one obtained from the selection operation's stage, which is one of our aims.

String no	Initial population	Symbol	Mating pool	Cross-over point	Offspring after cross-over	*x* values	Fitness, *f*(*x*) = 1.27574x^2
1	01110100	A	0111|0100	4	01110010	114	16579.5170
2	00110010	B	0011|0010	4	00110100	52	3449.6010
3	10010110	C	10010110	0	10010110	150	28704.1500
4	00011110	D	00011110	0	00011110	30	1148.1660
5	00000110	E	100|10110	3	10001000	136	23596.0870
6	00001000	F	000|01000	3	00010110	22	617.4582
				Total		504	74094.9792
				Average		84	12349.1632
				Max		150	28704.1500

Table 2 The crossover process - AHP-Taguchi-GA method

Now having achieved this, the aim of improving the machining process for the AZ91 magnesium alloy is achieved.

3.2.3 Analysis of The Mutation Process

So, we want to further improve on that process and we move a step further to the mutation operation's stage. The mutation is applied individually to each parameter because a crossover operation has been done. To achieve this, we randomly change the bits. Bits could be understood by noting that binary numbers are made up of bits, which are expressed as 0 and 1. We decided to change random bits of different parameters. We had the option of changing from 0 to 1 or from 1 to 0. But the determinant of what to change from another member is the understanding that the changes must improve the process. In this work, we decided to select at random. We selected from B (Table 3).

String no	Initial population	Symbol	Offspring after Crossover	Offspring after mutation	*x* values	Fitness, *f*(*x*) = 1.27574x^2
1	01110100	A	01110010	01110010	114	16579.5170
2	00110010	B	00110100	01110100	116	17166.3574
3	10010110	C	10010110	10010110	150	28704.1500
4	00011110	D	00011110	01011110	94	11272.4386
3	00000110	E	10001000	10001000	136	23596.0870
6	00001000	F	00010110	01010110	86	9435.3730
				Total	696	106753.9232
				Average	116	17792.3205
				Max	150	28704.1500

Table 3 The mutation process - AHP-Taguchi-GA method

We considered B to be improved upon. We also considered D to be improved upon. B is the pulse off time and D is the gap voltage. We also considered F to be the wire tension. Having considered these three parameters, we changed the bits in these offspring after crossover. We changed them from 0 to 1 for D which is gap voltage, the second number was changed from 0 to 1. Once this is done, the *x* value changed from 52 to 116. For D, we changed the second number from 0 to 1, which brought an improvement to the process. Initially, it was 30 for the offspring at crossover and after mutation, it became 94. For F, being the wire tension, we changed the second number from the left from 0 to 1, which improved the parameter from 22 to 86. Having done this, the authors expressed this in the form of our problem statement which is 1.2758x^2. Then, we came up with another set of total average values and then the maximum value. For this, we could say that our aim is achieved because the result was greater than what was obtained at the crossover stage. By comparing the two results for the total at crossover, we have 74.094.9792 whereas, after mutation, we have 106,753.9232. Then for the maximum value, the maximum value at the two stages did not change but remained constant. However, the average value moved from 12,349.6163 to 17,792.3205. Thus, we can now say that we have achieved our target result at the three stages, which are selection, crossover and mutation levels.

3.3 The AHP-Taguchi-Pareto-GA method

This section deals with the AHP-Taguchi-Pareto-GA method based on the previous work by Ikedue and Oke [19] on the application of the AHP-Taguchi-Pareto method in the optimization of the EDM process parameters while machining the AZ91 magnesium alloy. In this article, the work is modified by using the genetic algorithm procedure. In trying to analyses the parameters under consideration, three operations, which apply to the genetic algorithm are used, namely the selection operator, and crossover operator. First, the problem statement was generated. It was found out operators. First, the problem statement was generated by summing up the delta values obtainable from the AHP-Taguchi-Pareto response table as evaluated in Ikedue and Oke [19]. These summed up delta values, the function used to be x^2 while the problem statement formed f(x), is 1.518591 x^2. Then the factors obtained were converted at the three levels into binary numbers. Furthermore, Equation (1) is used to calculate Pi, a procedure similar to the one followed in the previous computations on the

AHP-Taguchi-GA method. At the selection stage, we have the string numbers 1, 2, 3, 4, 5 and 6, while the x values corresponding to these strings are 116, 50, 150, 30, 6 and 8, respectively, Table 4.

String no	Initial population	x value	x^2 value	Fitness, $f(x)$ = $1.518691x^2$	P_i	Expected value
1	01110100	116	13456	17166.3574	0.3410	2.0462
2	00110010	50	2500	3189.3500	0.0634	0.3802
3	10010110	150	22500	28704.1500	0.5703	3.4215
4	00011110	30	900	1148.1660	0.0228	0.1369
5	00000110	6	36	45.9266	0.0009	0.0055
6	00001000	8	64	81.6474	0.0016	0.0097

Table 4 The selection process - AHP-Taguchi-Pareto-GA method

The x^2 values range from 36 for the symbol E to 22500 for symbol C. However, to illustrate the computational procedure, consider the x^2 value for symbol A, which yields 13456. The problem statement formed for parameter A is $1.518691x^2$. The P_i has been computed from Equation (1) as 0.341038. Since the expected count is the product of the problem statement and P_i, the problem statement is evaluated from the product of the average level value (i.e. x value), which is 116 for parameter A and 1345, which is x^2, to yield 17166.3574. This later value when multiplied by 0.34104 yields 2.0462 as the expected count. Now, the total values for the computed problem statements for all the parameters considered for each row are 1 and 6, respectively. The averages of the problem statements, P_is and expects counts are 9986.9147, 0.1667 and 1, respectively and the maximum values for the problem statements, P_is and expected counts are 34170.5567, 0.5703, and 3.4222 respectively. These averages, totals and maximum values are benchmarks to evaluate the performance of the AHP-Taguchi-Pareto-GA method and determine if there is an improvement as the evaluations progress from the selection to the crossover and the mutations stages. From the evaluation, it was noted that the expected count has a maximum value of 3.4215, which has the highest chance of being selected. Then the table is rearranged to obtain a new table where the initial population is shown in binary numbers.

Now, we proceed to the crossover stage where a particular string with the lowest chance of being selected (Table 5).

Symbols	String number	Mating pool	Cross-over point	Offspring after cross-over	x value	Fitness $F(x)$ $=1.518691\ x^2$
A	1	0111|0100	4	01110010	114	19736.9135
B	2	0011|0010	4	00110100	52	4106.5416
C	3	10010110	0	10010110	150	34170.5567
D	4	00011110	0	00011110	30	1366.8223
E	3	100|10110	3	10001000	136	28089.7163
F	6	000|01000	3	00010110	22	735.0466
				Total	504	88205.5970
				Average Value	84	14700.9328
				Max. Value	150	34170.5567

Table 5 The crossover process - AHP-Taguchi-Pareto-GA method

This number will be upgraded to come up with a reasonable value so that if it is further optimized using a genetic algorithm for the second time it can also stand the chance of being selected. Thus the wire feed has the lowest chance with 6. This number was replaced with the number that has the highest chance of being selected. This was done and translated into binary numbers and conducted mating on them. Then the researcher decided to choose a crossover point where these factors are paired. These are the first two factors, then the next two factors also. For the first two parameters, the researcher chose the crossover point after the 4th binary digit. For the next one, which is the second factor it was left without conducting any mating on them because if it is done, what will happen is that it either decreases the smaller value (i.e. 30) or increases the higher value (i.e. 150). However, our primary aim is to increase the lower number. However, any change that is done on the 30 and 150 will not achieve our objective. So it is left without being changed. For the third factor, the researcher specified the crossover point after the third binary digit. Then the result is an offspring after the crossover as 114, 52, 150, 30, 136 and 22, respectively. Then we decided to check the fitness such that the problem statement is expressed for each of these strings. It means squaring the values and multiplying them by the coefficient of x^2. We obtained 19, 736.9135 for A, 4,106.5460 for B, 34,170.5567 for C, 1366.8223 for D, 28,089.7166 for E and 735.01641 for F. Then we summed up these values as 88205.597 as against 59921.4882 at the selection stage. It can be said that the operations at the crossover stage have enhanced over the results obtained at the selection stage. However, the maximum value remained the same, while the average values also increased. We proceeded to the mutation operations stage, Table 6.

Symbols	String number	Offspring after crossover	Offspring after mutation	x value	Fitness $F(x)$ =1.27574 x^2
A	1	01110010	01110010	114	19736.9082
B	2	00110100	01110100	116	20435.5061
C	3	10010110	10010110	150	34170.5475
D	4	00011110	01011110	94	13419.1537
E	3	10001000	10001000	136	28089.7087
F	6	00010110	01010110	86	11232.2386
			Total	696	127084.0629
			Avg value	116	21180.6772
			Max. Value	150	34170.5475

Table 6 The mutation process - AHP-Taguchi-Pareto-GA method

The mutation operation is applied individually to each parameter after the crossover operation to achieve further optimization of the parametric values obtained at the crossover stage. At the mutation stage, we randomly selected values that the researcher felt had very minimal chances of being selected. We will now look at how to upgrade them to a level that they will have a chance of being selected at a point in time. We considered the second, fourth and sixth for this operation. To achieve this, we randomly selected string values and changed binary bits from 0 and 1 or vice-versa increasing the overall values.

This was done for pulse off time, gap voltage and wire tension. Then pulse off time moved from 52 to 116, gap voltage moved from 30 to 94 and wire tension moved from 22 to 86. The total was obtained after conducting the fitness operation as 127, 084.0629 and the average value rose to 21,180.67715. But the maximum value remained the same, which is the pulse current. It could then be stated that we have achieved the aim for this activity, which is to upgrade the values of individual strings to a position where they could be chosen, it can be said that the aim of this article for the section has been achieved. We have the string with the maximum chance of being selected is pulse current followed by wire feed, then pulse off time, then pulse on time, followed by gap voltage and finally by wire tension. Also for the total value at the end of each operation, the total value at the selection stage rose from 59,921.4882 with an average value of 9,9886.9147 to 88,205.5970 for the total at the crossover stage with an average value of 14,700.9328. This value rose to 127084.0629 as the total at the mutation stage and 21,180.6772 for the average value at the mutation stage. An observation that was noted is that the Pi done for AHP-Taguchi-GA and AHP-Taguchi-Pareto-GA methods remains constant.

3.4 The AHP-Taguchi-ABC-GA method

The work to be presented in the section is on the results of applying to AHP-Taguchi-ABC-GA method to the electro-discharge machining of AZ91 magnesium alloy. The AHP-Taguchi-ABC aspect has been reported in Ikedue and Oke [19] but the genetic algorithm has been appended to the method used previously for further optimization efforts. Having the work of Ikedue and Oke [19] as a foundation; the present authors used the genetic algorithm to further optimize the results previously reported. In the previous work, the parameters of the wire EDM were optimized while processing the AZ91 magnesium alloy. The authors at first generated the problem statement by adding all the delta values for the Part A of the ABC is 1.18922. This is now multiplied by x^2 such that it is made the coefficient of x^2. We also generated the x values by finding the average of the three levels 1, 2 and 3 as submitted by Muniappan et al. [20]. This average was computed for the rest of the parameters. For the first parameter, we had 116, i.e. A, which is the pulse on time. For pulse off time, pulse current, gap voltage, wire feed and wire tension, the averages of the levels were 50, 150, 30, 6 and 8, respectively. We first converted the x values into a binary form and evaluated the fitness as previously done. By solving the $f(x) = x^2$, problem statement, we had 116 and squaring it, we have 13456. This process of squaring was conducted for the rest parameters and the values obtained are 2500, 22500, 900, 36 and 64, for B, C, D, E and F parameters, respectively. Furthermore, to compute $f(x)$, 1.18922 was multiplied with the square of 116, which is for parameter A to yield 16002.1586. Subsequently, the $f(x)$ values for the other parameters were computed.

We now tried to evaluate the formula in Equation (1) using the roulette wheel selection method given in terms of P_i, which is the probability of a string is selected. To obtain the expected count, we multiply the number in the population by the probability of a strung being selected, P_i. This leads us to a table have columns for symbols, strung numbers, x, x^2 values, problem statements and the probability of a string being selected. Lastly is the column for the expected count. On the computing, we obtained the expected count value of 2.0462 for parameter A, 0.3802, while 3.4215, 0.1369, 0.0055 and 0.0097 for B, C, D, E and F, respectively. By summing the problem statement up, there is a total of 46921.90609 obtained. The average value on that point is 7820.317682 and the maximum value is 26757.4738. After this, the authors came up with a table showing the positioning at the selection of how the expected counts rank. In this case, pulse current ranks first, pulse on time as second, pulse off time as third, gap voltage as fourth, wire tension as fifth and wire feed as sixth then we move over to crossover operation. Here, we have brought over the symbols and string numbers. However, during the selection operation, it was found that according to the ranking, a particular parameter has the highest chance of being selected, which is pulse current. Then the parameter with the least probability of being selected, which ranks sixth, is wire feed. So we alternated them by copying the one with the first position is replaced the strings of the one with the sixth position. We copied them in their binary forms and did a crossover operation on them. For the first two strings, we kept the strings in pairs, the first two being the first pair and the third and fourth strings being the second pair. For the first two, we conducted a crossover operation at the first point. For the second one, we did not do any crossover operation but were left there because performing the crossover operation in the item will either increase the higher one or reduce the lower one. However, we wanted to increase or leave it as it is. For the third one, we did a crossover operation at the third figure. Then the new x value became 114, 52, 150, 30 135 and 22, respectively. So, solving for the fitness at the crossover point, we had 15,455.1169, 3.215.6537, 26757.4738, 1070.2990, 21995.8327 and 575.5830 for parameters A to F, respectively. So the total at this point was 69069.9590. Then the average value became 11.511.6599 and the maximum value at the stage remained pulse current with 2675.4738. We were able to achieve our aim for crossover operation, which is to further optimize the value. Here, the total value changed from the value at the section stage which is 46921.9061 to 69069.5509. This is evidence of further optimization at the crossover point. Then we moved over to the mutation operation to further optimize the parameters that could not be optimized at the crossover stage. Then we selected the strings that needed to be increased and these are the gap voltage, pulse off time and wire tension. To achieve this aim, we need to alternate the bit values at selected locations we will change the values from D to 1. For the pulse-off time, we change the bit value of the second from the left from 0 to 1. For that gap voltage, we changed the second value from the left from 0 to 1. For wire tension, we change the second value from the left from 0 to 1. We were able to improve the values of the parameters (offspring after mutation) to 114, 116, 150, 94, 136, and 86, respectively. By conducting the fitness test on them, we arrived at 15,455.1169, 16002.1586, 26757.4738, 10507.9573, 21995.8327 and 8795.47905 for parameters A to F, respectively. The total value increased from what was achieved at the crossover average value become 15,585.6697. This led us to declare that we have achieved our aim, which is to further improve the values that require improvement from the crossover stage. The above activities relate to the Part A of the AHP-Taguchi-ABC-GA method. The details of the final stage, the mutation process, for the AHP-Taguchi-ABC-GA method (Part A) are given in Table 7.

Symbols	String number	Offspring after crossover	Offspring after mutation	x value	Fitness $F(x)$ =1.18922 x^2
A	1	01110010	01110010	114	15455.1169
B	2	00110100	01110100	116	16002.1586
C	3	10010110	10010110	150	26757.4738
D	4	00011110	01011110	94	10507.9573
E	3	10001000	10001000	136	21995.8327
F	6	00010110	01010110	86	8795.4790
			Total	696	99514.0182
			Avg Value	116	16585.6697
			Max. Value	150	26757.4738

Table 7 The mutation process - AHP-Taguchi-ABC-GA method (Part A)

Moving on to Part B, every step as explained in Part A applies to Part B. but the changes here are delta values. The reason is that in Part A, the total delta value is 1.1892 but here in Part B, the total of the delta values is 1.0491. The final results from the selection stage using the expected count as the criterion are 2.0462, 0.3802, 3.4215, 0.1369, 0.0055 and 0.0097 for parameters A to F respectively. The total, average value and maximum values are 41393.8086, 6898.9681 and 23605.0460, respectively. These values relate to the section stage. However, we were able to expand the figures at the crossover stage with a total, average value and maximum value of 60932.4920, 10155.4153 and 23605.0460, respectively. The total value of 60932.49196 is higher than what was obtained at the selection stage 4139.8086, implying an improvement in value the mutation operation aims to further optimize the obtained value as the crossover stage. This is to enhance their chances of being selected in subsequent evaluations (operation). Here, the total after solving for the fitness became 87789.5200. The average value became 14631.5875 while the maximum value was 23604.9750. This is the summary of the results of Part B. The details of the final stage, the mutation process, for the AHP-Taguchi-ABC-GA method (Part A) are given in Table 8.

Symbols	String number	Offspring after crossover	Offspring after mutation	x value	Fitness $F(x)$ =1.04911 x^2
A	1	01110010	01110010	114	13634.2336
B	2	00110100	01110100	116	14116.8242
C	3	10010110	10010110	150	23604.9750
D	4	00011110	01011110	94	9269.9360
E	3	10001000	10001000	136	19404.3386
F	6	00010110	01010110	86	7759.2176
			Total	696	87789.5248
			Avg Value	116	14631.5875
			Max. Value	150	23604.9750

Table 8 The mutation process - AHP-Taguchi-ABC-GA method (Part B)

Now moving to Part C. similar computations of Part B applies to Part C. the only changes are the delta value to 0.5971. Solving for the selection stage yields a total of 23557.8261 while the average and maximum marks ate 3926.3044 and 13433.9793, respectively. The ranking happens to be the same for the first one too. Moving over to the crossover operation stage, we were able to improve the values at the selection stage to 34677.578. the average value and maximum value are 5779.5943 and 13433.9793, respectively. We move over to the mutation stage. Here, we have further improved our x value. After solving for the fitness, we were able to obtain 49962.4617, 8327.0770 and 13433.9793 as the total, average values and maximum values, respectively. This result for Part C ends the computation of the results. These results show how a genetic algorithm could be combined with AHP-Taguchi, AHP-Taguchi-Pareto and AHP-Taguchi-ABC methods to optimize the wire EDM parameters using the AZ91 magnesium alloy as the material being machined. The details of the final stage, the mutation process, for the AHP-Taguchi-ABC-GA method (Part A) are given in Table 9.

Symbols	String number	Offspring after crossover	Offspring after mutation	x value	Fitness $F(x)$ =0.597066 x^2
A	1	01110010	01110010	114	7759.4665
B	2	00110100	01110100	116	8034.1167
C	3	10010110	10010110	150	13433.9793
D	4	00011110	01011110	94	5275.6729
E	3	10001000	10001000	136	11043.3281
F	6	00010110	01010110	86	4415.8983
			Total	696	49962.4617
			Avg Value	116	8327.0770
			Max. Value	150	13433.9793

Table 9 The mutation process - AHP-Taguchi-ABC-GA method (Part C)

4. Conclusions

The present study aimed at improving the individual members of the population for the wire EDM process while processing the AZ91 magnesium alloy material. By using the roulette wheel selection method of the genetic algorithm method, the data obtained from Muniappan et al. [20] was analyzed and tested with the newly proposed models of the AHP-Taguchi-Genetic algorithm, AHP-Taguchi-Pareto-Genetic algorithm and AHP-Taguchi-ABC-genetic algorithm methods. The parameters optimized by the genetic algorithm are the pulse on time, pulse off time, pulse current, gap voltage, wire feed and wire tension. In conclusion, the integration of the genetic algorithm with the AHP-Taguchi, AHP-Taguchi-Pareto and AHP-Taguchi-ABC has helped to improve the mentioned parameters and come up with high values for each parameter. The following conclusions concern the analysis using the experimental data of Muniappan et al. [20] using the AHP-Taguchi-GA approach during the wire EDM process for the AZ91 magnesium alloy. Having achieved results, it could be stated that the factor values have been improved upon at both the crossover and mutation stages of the AHP-Taguchi-GA method. The only value, which remained constant in all, is the pulse current being the highest value maintained its position as the parameter with the highest outcome throughout the operations. Using the AHP-Taguchi-Pareto-GA method the key results are the continuous improvement in the maximized parametric values of the process of electro discharge machining of AZ91 magnesium alloy from 59921.4882 at the selection stage to 88205.5970 at the crossover stage and finally to 127084.0629 at the mutation stage of the combined AHP-Taguchi-Pareto-GA method. The results in Parts A, B and C of the article show that the genetic algorithm could be successfully combined with AHP-Taguchi, AHP-Taguchi-Pareto and AHP-Taguchi-ABC methods to optimize the wire EDM parameters using the AZ91 magnesium alloy as the material being machined.

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