



Exploiting Tournament Selection-Based Genetic Algorithm in Integrated AHP-Taguchi Analyses-GA Method for Wire Electrical Discharge Machining of AZ91 Magnesium Alloy

Meshach Chukwuebuka Ikedue^{1*}, Wasiu Oyediran Adedeji², Sunday Ayoola Oke³, John Rajan⁴

^{1,3}Department of Mechanical Engineering, University of Lagos, Lagos, Nigeria

²Department of Mechanical Engineering, Osun State University, Osogbo, Nigeria

⁴Department of Manufacturing Engineering, School of Mechanical Engineering, Vellore Institute of Technology, Vellore, India

ARTICLE INFORMATION

Article history:

Received: 4 October 2022

Revised: 30 November 2022

Accepted: 2 December 2022

Category: Research paper

Keywords:

Optimization

Prioritization

AZ91 magnesium alloy

Tournament

DOI: 10.22441/ijiem.v4i1.17387

ABSTRACT

Concurrent optimization and prioritization of wire EDM parameters can improve resource allocations in material processing and should be effective. This study advances the integrated analytic (AHP)-Taguchi(T)-tournament-based-genetic algorithm (tGA) method to moderate the influence of erroneous resource allocation in parametric analysis decisions in wire electrical discharge machining. The structure builds on the AHP-T method's platform obtained from the literature and develops it by including the tGA while processing the AZ91 magnesium alloy. The article evaluates the delta values for the average signal-to-noise ratios in the response table and deploys them to arrive at the winners in a league and consequently mutate the chromosomes for performance improvement. The scale of relative importance, consistency index, optimal parametric setting, delta values, and ranks are all established and coupled with the total value and maximum value evaluation at the selection crossover and mutation stages of the genetic algorithm. The results at the mutation, crossover, and selection stages of the tournament selection process showed total values of 124410, 96650, and 70564, respectively. At the selection stage, the maximum value to be the winner of the tournament is 28704. The crossover operation was accomplished after the 5th, 5th, and 6th bit for the first three pairs, respectively. For the selection and crossover operations, the maximum value is 28604 and 27944, respectively. The research clarifies which parameters are the best and worst during optimization using the AHP-T-tGA method.

*Corresponding Author

Sunday Ayoola Oke

E-mail: sa_oke@yahoo.com

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1. INTRODUCTION

1.1 General

The Taguchi method is considered by many researchers and practitioners within the wire electrical discharge machining domain as the principal driver of optimization performance problems and the source of performance advancement within the machining industry. Optimization, as applied to the wire electrical discharge machining process for the AZ91 material processing, is a method to minimize the machining costs, reduce material wastage and drive up the wire EDM equipment utilization for a function in consideration of a set of constraints (see Rahaman et al., 2020; Biswas et al., 2022). From this viewpoint, regulatory bodies in government build up and implement operational policies in machining organizations aimed at benefiting the employees and the society where the machining organization operates. Consequently, machining organizations are challenged and strive to meet the regulations of the governments and reduce the negative impacts of their operations on the employees and society. However, while the new point depends, on the Taguchi method for the optimization of wire EDM process resources and programs, it underestimates the role of prioritization of resources and programs within the wire EDM process. Prioritization is the arrangement of wire electrical discharge machining parameters according to their degrees of importance and process goals.

For decades and with increasing visibility due to economic hardship in companies, managements of machining organizations have been promoting prioritization and selection of the best parameters are made for wire EDM process decisions. With their perceptions, process engineers and managers are shaping machining decision-making substantially to improve the profit margin of the organization. However, the majority of their prioritization efforts have been based on tuition and no justifiable support by quantitative measures exists for such decisions.

1.2 Motivation and novelties

Precisely and impartially establishing the concurrent optimization and prioritization of wire electrical discharge machining process

parameters is a striking goal while fabricating the AZ91 magnesium alloy in the engineering establishment. However, to successfully execute parametric performance values, it compels the use of a practical, realistic, and systematically-sound evaluation method. Recently, the integrated AHP-Taguchi method has been applied to the experimental data involving the wire EDM processing of AZ91 magnesium alloy (Ikedue and Oke, 2023). The article contains rich data on the optimized parameters in form of average signal-to-noise ratios, which were summarized into a response table and eventually developed into an AHP-Taguchi method minifying matrix from where the optimal parametric settings, delta values, and ranks of the parameters could be found. How to further improve this result to assist in precisely and impartially establishing the concurrent optimization and prioritization of parameters then becomes a hot research topic (Fang and Li, 2010).

The tGA method (Fang and Li, 2010), one of the search algorithms within the sub-group of metaheuristics and the larger class of evolutionary algorithms, is based on the running of leagues among chosen chromosomes which brings out winners and losers in a random activity and winners are passed from this selection stage to the crossover phase. The strategy adopted at the selection phase in a tGA method focuses on the fitness of candidates such that a better offspring is developed during the mating process. In a K-manner tournament selection, L chromosomes are chosen and a tournament is run among them. Its distinctive feature of straightforwardness where the user randomly picks solutions from a population where replacement may or may not be sought places the tournament method as being extremely attractive. Consequently, the present authors aim to use the tGA on the results of a unified AHP-Taguchi method which produces the response table with delta values for the wire EDM process of the AZ91 magnesium alloy. To be able to introduce the tGA to the response table of the AHP-Taguchi method's result for the processed AZ91 magnesium alloy, it is essential to fall back to the factor-level table that produces the final result (responses) for the AHP-Taguchi method and find the average of the levels for the parameters, which will be

represented in the computations of the expected counts for the genetic algorithm process. The data of averages for levels are combined with those of the fitness values to obtain the final solution.

However, Fang and Li (2010) declared that selection is a principal issue that strongly influences the performance of the system being assessed, which is the wire EDM process for this instance, within the evolutionary algorithm domain. Furthermore, Fang and Li (2010) declared that the commonly used mating schemes in the genetic algorithm are rank selection, fitness proportionate selection, and tournament selection methods. This declaration was reinforced by Holland (1975) that elaborated on the fitness proportionate selection, Grefenstette and Baker (1989) whose focus was on a discussion on the rank selection method and Brindle (1981) that extensively discussed the tournament selection process. However, in Fang and Li's (2010) view, the tGA method appears as a better choice. Consequently, this article chooses the tGA method to be integrated with the AHP-Taguchi method as the AHP-Taguchi-tGA method. This mission is pursued to offer a deep understanding of the tGA method's behavior and how it impacts the overall method in the formulated hybrid method.

Furthermore, for triple methods, the AHP-Taguchi method had been integrated with TOPSIS (as Taguchi/AHP/TOPSIS method). Moreover, the triple methods had been formed with the combination of AHP-Taguchi and other methods such as the fuzzy-AHP-Taguchi method by Majumder (2016). The combinations of AHP-Taguchi had been made with TOPSIS by Mojaver et al. (2020) and Taguchi/AHP/TOPSIS). It has also been accomplished with TOPSIS in a different order by Kumar et al. (2019) as Taguchi loss function/TOPSIS/AHP. Others are the combination of Taguchi-AHP with goal programming by Liao and Kao (2010) as Taguchi loss/AHP/multi-choice goal

programming. However, when these triple methods were compared with the triple method of AHP-Taguchi-tGA, studies are almost non-existent. Besides, the triple method proposed in the present article had not previously benefited the wire electrical discharge machining domain. The articles mentioned above were applied in the domains of power generation and supply chain, which is completely outside the knowledge frontier of machining that is the concern of the present article. The implication is that there is a wide gap in the application of the triple method of AHP/Taguchi/tGA in the wire EDM area. Finally, there is the absence of any study on the triple method of AHP-Taguchi-tGA that established results concerning the use of AZ91 magnesium alloy in the wire EDM process. In addition, Table 1 is presented from the literature to indicate some previous research in the area of the present article. It is observed from the papers that many of the authors used the same inputs examined in the present article under the "input parameter" column of Table 1. However, all the papers differed in methods as no single paper was identified to have used the combined AHP-Taguchi-GA method where the GA has a bias for the tournament method.

Consequently, the present study aims to bridge the established gap in the wire EDM literature. The principal characteristics of this article are as follows:

- Simplifying the wire EDM process, which is complicated to analyze and manage by conceptualizing it as a triple method of combining the AHP, Taguchi method, and tournament-based genetic algorithm with the principal parameters of the process in focus.
- Introducing the tGA method into an already established dual method of AHP and Taguchi and processing it with defined characteristics such as population size.

Table 1. Summarised literature review

Sr. No.	Authors (Year)	Work material	Input parameters	Output(s)	Tool(s)/method(s)	Conclusion
1	Dayal et al. (2022)	Magnesium alloy AZ31 and AZ31B	Wire feed, wire tension, peak current, servo voltage, pulse off time, and pulse on time.	Cutting rate	One factor approach at a time	Pulse on time, pulse off time, servo voltage, and servo feed significantly influence the cutting rate but peak current, wire tension, and wire feed exhibited insignificant influence on the cutting rate.
2	Panwar et al. (2022)	AZ61 Mg alloy	Pulse on time, pulse off time, servo gap voltage, peak current, wire feed, rate, water pressure, wire tension, servo feed on response	Cutting speed	Artificial neural networks and EDM machining	There are no noticeable differences between the predicted and experimental values of the process
3	Batra et al. (2022)	Aluminum-tungsten metal matrix (Al6063-W)	Pulse on time, pulse off time, servo voltage	Cutting speed, surface roughness	Stir casting process, ANOVA, response surface method, EDM machine genetic algorithm	Pulse on time > servo voltage > pulse off time significantly in affecting the cutting speed
4	Kumawat et al. (2020)	EN-31 steel materials	Peak current, pulse on time, pulse off time, wire feed rate	Material removal rate	One factor at a time approach, design of experiment methodology, regression model, wEDM machine Taguchi technique	The peak current and pulse on time are the most important machining parameters for the WEDM process of EN-31 steel material
5	Gupta and Dubey (2021)	Nickel-based titanium	Pulse on time, pulse off time, peak current	Material removal rate, surface roughness	Taguchi technique	Pulse on time is the most important parameter to the materials removal rate and surface roughness
6	Mohamed and Lenin (2020)	AA6082-T6	Pulse on time, pulse off time, current	Surface roughness	Taguchi method, Minitab 18 software	The method is effective on the work material
7	Tata et al. (2021)	Inconel 625 alloy	Peak current, pulse on time, pulse off time, supply voltage	Surface finish, the material removal rate	Analysis of variance, Minitab17, grey relational analysis	The approach is feasible
8	Juliyana and Prakash (2022)	Aluminium matrix composite (LM5/3,6,9%ZrO ₂)	Pulse on time, pulse off time, gap voltage, wire feed	Surface roughness, material removal rate, less cutting width (kerfs)	Taguchi method, grey relational analysis	The method is effective

1.3 Tournament-based genetic algorithm

The tournament method is a kind of selection method in the genetic algorithm that offers the investigator the opportunity to select parents (parameters) for mating based on competition among all the contestants where winners emerge as the best participants in the tournaments. However, the choice of the parameters (chromosomes) is random. The primary objective of this work is to use the tournament selection genetic algorithm as a coupling method to the existing AHP-Taguchi method to analyze the wire EDM process and compute the parametric values in an order of

importance within the process to choose the best and worst performing parameters while machining the AZ91 magnesium alloy. The first and main approach of this study was to evaluate the AHP-Taguchi method whose output may be the response table from which the interpretation of the genetic algorithm is made.

Kumar et al. (2022) examined the effect of the process parameters of the wire EDM system on three responses, namely the corrosion rate, material removal rate, and surface attributes of the 7E41A magnesium alloy. The similarity between the study and the present work is the

common usage of Taguchi in the two works. But the dissimilates are the different choices of responses, where kerf width and cutting speed were considered in the Muniappan et al.'s (2018) article adopted in the work why at variance, corrosion rate, material removal rate, and surface attributes were considered in the work. In addition, there is variance in the specific material adopted for use in the current study and that of the work being reviewed. While rarely considered in the reviewed article, it is absent in the present study. Nonetheless, Zinc 4% and aluminium as additives in small quantities were added to the present study while in Muniappan et al. (2018) whose data is used in our work Zinc and aluminium were also considered but to the tune of 1% and 9%, respectively. Besides, the domain of the sectoral application of the work for the reviewed article is the health sector while the automobile sector is the target of Muniappan et al.'s (2018) study. In another study, Dayal et al. (2022) analyzed the effects of diverse parameters on the cutting rate.

There are similarities in outputs considered in the reviewed article and the present study: The cutting rate, equivalent to cutting speed, in the present article and the reviewed article are the same. Besides, the AZ31 magnesium alloy considered has a resemblance with the AZ91 magnesium alloy considered in the present work. The similarity is that both contain aluminium and zinc. This is in the proportion of 3% aluminium to 1% Zinc in the reviewed article to 9% aluminium to 1% Zinc. Besides, it is interesting to note that all the parameters in both articles are the same: Gap (servo) voltage, wire feed, wire tension, pulse (peak) current, pulse off time, and pulse on time. Yet in another work, Kishore et al. (2022) analyzed the AZ31B magnesium alloy in the wire EDM process. There are differences in the responses considered in both articles. While the focus of the reviewed work is on surface roughness, material removal rate, and tool wear, different responses of cutting speed and kerf width were considered in the present study. Nonetheless, the materials used in both studies are similar as in the reviewed study, AZ31B magnesium alloy was considered against AZ91 magnesium alloy. This means 3% of aluminium and 1% zinc together with other additives were used in the

reviewed article while the percentage of aluminium was 9% in the present study and the same 1% of zinc was used in both articles.

1.4 Objectives of the present work

This study highlights the focus on the concurrent optimization and prioritization of wire EDM process parameters based on the AZ91 magnesium alloy. Although the wire EDM process has a wide adoption because of its techno-economic advantage, it is generally susceptible to resource wastage allocated to parametric functional centers and this increases the overall cost of fabrication. Hence, the wire EDM process resources distribution during fabrication requires considerable importance. The poor knowledge of the optimization of the wire process parameters coupled with the dearth of knowledge about the placement scale has been responsible for this problem with the wire EDM domain. The success of wire EDM processing is a function of the processing parameters, which in the case studied, where data was extracted from Muniappan et al. (2018), include the pulse on time, pulse off time, pulse current, wire feed, wire tension, and gap voltage. Hence, the specific objectives implemented in this study are as follows:

- (1) To develop a quantitative method by connecting the tournament selection method of the genetic algorithm with the couple analytic hierarchy process and the Taguchi method.
- (2) Evaluate the maximum and total values at the different stages of the genetic algorithm process of selection, crossover, and mutation

2. PROBLEM DESCRIPTION

Wire electrical discharge machining is a major electrothermal production process in use in several industrial sectors of the economy. For instance, in the health sector, several studies have been conducted to improve the sectoral output using the WEDM process, including Kumar et al. (2022), Dayal et al. (2022) and Kishore et al. (2022). In the manufacturing sector, the contributions of the following are important: Dulta et al. (2020) and Golabczak et al. (2019). Besides, in recent years, the technological advancement of wire EDM has aided the machining of difficult-to-machine

parts. The wire EDM refers to a group of procedures utilizing an electrically charged hair-thin wire for removing metals through electrical sparks. Hence, optimizing the parameters in wire EDM must be established to obtain optimal values such that an increase in the production rate without a corresponding increase in the cost of operations and with a consequential increase in cycle time is achieved. However, in these days of dwindling purchasing fortunes of customers and patronizing of fabricated machining, focusing on reducing the cost of fabrication is compelling as higher fabrication overheads result in higher prices of processed components and parts.

Consequently, if the machining industry generates high amounts of overheads, it may trigger inflationary conditions in the country. Besides, it is important to reduce cycle time since producing more components in the fabrication process within less time implies a potential improvement in the profit margin for the machining industry. Reduced cycle time also uses fewer processing materials and reduced working hours for machinists, implying lower labour costs. Furthermore, computer simulations have been used to predict the machining behavior of the AZ91 magnesium alloy and this provided an avenue to reduce machining time substantially. Nonetheless, there is a scope to validate the machining models with experimental testing data.

Currently, the wire EDM process is characterized by several aspects to be experimented upon. These include the filer, fixture, pulse generator, dielectric fluid, spark, workpiece, tool holder, tool, and pump. Producing a full-scale experiment to tackle all these aspects at once and obtaining actual parameters of the wire EDM in real-time experimental studies is excessively costly and time-consuming. To overcome these cost and time challenges, new methods are required to predict optimal wire EDM process parametric solutions. Consequently, the tournament selection-based genetic algorithm, a metaheuristic inspired by the natural selection process is appended to a coupled analytic hierarchy process and Taguchi method and used in the present investigation to establish the optimal parameters as well as the best and worst

parameters in the wire EDM process while processing the AZ91 magnesium alloy having 9% aluminium and 1% zinc as its constituent elements in addition to magnesium.

2.1 Notations

This article engages the following notations:

N_p	Number of population size
N_u	Number of participants per tournament
N_p	Number of individuals to be selected in a particular operation
$F(x)$	Fitness function of the chromosome considered
O_c	Offspring after crossover operation
O_m	Offspring after mutation operation
A_v	Average value
M_v	Maximum value
X	Fitness value of the chromosome
A_{vl}	Average values of levels

2.2 Assumptions

To develop the tournament selection method for the wire EDM process while processing the AZ91 magnesium alloy, the following assumptions prevail:

1. In tournament selection, chromosomes are chosen at random in performing a league
2. In the population, during the league, chromosomes with the highest value are known to have the best candidate capacity.
3. The pairing of chromosomes is assumed during the tournament process.
4. We are analyzing a machining system with easily identifiable inputs and outputs.
5. The reciprocal assumption, states that when two parameters are paired and compared the preference values should comply with the reciprocal condition (Song and Kong, 2016)
6. Homogeneity, which reveals the significance of a bounded scale within a restricted range (Song and Kang, 2016)
7. Dependency, which states that the elements at a level depend on those at the upper echelon (Song and Kang, 2016)
8. Expectations assume that decision-making has aims that are embedded at the corresponding level (Song and Kang, 2016).
9. The population size in the case of the tournament selection process is fixed.
10. Tournament size is often limited to 2, which means pairs of individuals are assessed,

while one individual is a winner, the other is termed the loser,

11. The population is wholly diverse which implies that each chromosome exhibits a distinguished fitness value (Fang and Li, 2010).

3. METHODS

3.1 Research Scheme

This study is based on the integrated AHP–Taguchi–tGA approach. Consequently, the following steps were pursued in implementing the evaluation scheme. Process and data insight: this stage of the study emphasized gaining insight into the objective and the need of the research. The principal goal of this study is to further optimize a previously optimized process, which had passed through a concurrent process of optimizing through the use of the Taguchi method and prioritization by the application of the analytic hierarchy process method. The production process of AZ91 magnesium alloy using the wire EDM process is complicated and costly to maintain. But the process owners and process engineers welcome ideas that will further improve the operational efficiency of the process through the introduction of robust and reliable scientific methods. This is thought to promote profitable maintenance of the fabrication process and guarantee sustained operations. Therefore, according to previous studies in the engineering domain, the AHP–Taguchi method integration is not sufficient to meet the concurrent optimization and optimization needs of the wire EDM process that fabricates the AZ91 magnesium alloy. In this research, in addition to the AHP–Taguchi method, which had been presented in the literature by Ikedue and Oke (2023), the method of the tournament-based genetic algorithm has also been considered, and the previous method of the AHP–Taguchi method has the tournament–based genetic algorithm fused to it.

- *Data Preparation*: Because of the different variety of data types needed (i.e. factors and levels as well as binary coded data) by this study, the essential cleaning process, primarily the compensation of average of levels for each factor obtained from the factor level table has been done.

- *Modeling*: At this stage of the work, the primary concern is to define the problem. The idea is to utilize the simple linear function, which is easy to apply to bear in mind that binary digits are involved in the genetic algorithm processes and complicated functions may lead to several aspects of cleaning the data before they can be used for the model.
- *Assessment and Development*: three principal parameters have been used for assessment at each stage of selection, crossover, and mutation. These evaluation parameters are the total value, the average value, and the maximum value for the X^2 and fitness function at the selection stage, the new X value, X^2 and fitness function at the crossover stage, and X value, X^2 and fitness function at the mutation stage.

3.2 The Selection, crossover, and mutation stages

This article discusses the application of the integrated AHP–Taguchi analyses–genetic algorithms of the tournament selection version. Previously, the AHP–Taguchi analyses consisting of the AHP–Taguchi, AHP–Taguchi–Pareto, and AHP–Taguchi–ABC methods had been reported in the literature by Ikedue and Oke (2023). However, integration of the tournament-based selection method of the genetic algorithm is essential for further performance improvement of the wire EDM process for the production of components made up of AZ91 magnesium alloy. Consequently, the principal focus of this article is to emphasize the tournament selection process on the AHP–Taguchi analyses.

From a series of a survey on tournament selection, it was noted that different samples could be used as examples of the tournament selection process. Tournament selection was conceived as a league where different competitors are involved. These competitors are screened until the final candidate is chosen as the winner. These contestants are paired at random. When compared with the mating pool where we choose from the two succeeding chromosomes on the list, they are paired according to the arrangement. However, in the tournament selection process, the authors

choose at random and perform a league among these chromosomes by selecting the chromosome that has the highest value. So this process continues until the process reaches a satisfactory level. If for instance, there is a population of eight chromosomes, they are paired at random and a selection is done among them. Whichever is being selected takes a new position. Then the tournament will be performed according to the number of chromosomes. These are the number of individuals on the list. For example, if n is 12, the twelve chromosomes will be paired at random until the researcher comes up with an author list of twelve chromosomes. This is the stage where some researchers stop before proceeding to the crossover and mutation stages.

Additionally, another perspective entails performing an elimination series where the researcher keeps on eliminating until a final winner is known which will be the selected candidate, which has the highest possibility of being selected at the selection stage. This is similar to the roulette wheel selection process where the candidate with the highest fitness is chosen for the crossover and mutation processes. After performing the tournament and emerging with a new set of values, the researcher proceeds to the crossover operation stage. It is important to state that for this tournament selection method, no problem statement was used at the selection stage. Finally, the mutation stage is decided upon.

4. RESULTS AND DISCUSSION

According to the present authors' research plan and design, data was collected from the literature; particularly the experimental data displayed in Muniappan et al. (2018) was used. In the article, the source of the data reflected experiments conducted on the AZ91 magnesium alloy, and the MOORA algorithm was used to implement the analysis. The principal data extracted from Muniappan et al. (2018) is the factor and level data, where six factors, namely pulse on time, pulse off time, gap voltage, wire feed, wire tension, and pulse current were measured at three levels. However, it was judged to be sensible to find the average of the level values for each factor as a summary of the data that applied to the present study. The

analysis according to the binary transformation of data was made to decide on which of the factors should be selected for the next stage of operation, which is the crossover before being worked on by the mutation process and the conclusion reached.

Furthermore, the aspect of the selection approach tackled in this article is the tournament selection method. The tournament selection method competes with other selection methods such as the roulette wheel selection and rank selection methods among others. It presents an interesting series of procedures that could be easily applied but understanding the rudiments are important at this stage. The tournament selection method is a process of selecting two or more parents from a population of parameters. In particular, using a tournament, the researchers have to play a game (tournament). In tournament selection, we have N_p , which is the population size. In this case, the population that we are considering is 6 since 6 parameters are involved. The notation N_u refers to the number of participants per tournament. In that population of 6 parameters, the researcher chooses the participants that we desire to play tournament. Here, we paired parameters, until we obtain N_p , which is the number of individuals to be selected in a particular operation. Once this is accomplished, the researchers keep pairing until the results of the three pairs are achieved. This will give the researchers an equivalent of what is considered.

4.1 AHP-Taguchi-tournament-based GA

4.1.1 Tournament selection process

In Table 2, there are numerous columns. One contains symbols, which reflect the process parameters. Next is the average from the three levels shown. Then the next column has trials, which are equivalent to string numbers from the applications of rank selection and roulette wheel selection methods. Then the parameters which are paired are worked on, which is the selection of parameters for the tournament from the paired individual. Then the researchers come up with an X value, referred to as the fitness value. The last column is a conversion of the X values. For the tournament played, the researchers played with 1 and 6, in which 1 was selected. The researchers played with 2 and 5 which 2 were selected. Furthermore, the

researchers played with 3 and 4 while 3 was selected. The researchers played with 4 and 2 which 2 were selected. Besides, the researchers played 5 and 1 which 1 was selected. The researchers played with 4 and 6 of them 4 were selected.

Thus, the tournament playing for the electrical discharge machining process of AZ91 magnesium alloy was conducted with the parameters while they were paired randomly. After the pairs had been selected, the next table, Table 2 was generated. What is presented as the X values are 116, 50, 150, 50, 116, and 30. So converting them to binary forms, the

researchers consider the next column containing X^2 values. Then solving for the fitness, we have $1.27574 X^2$, with the X^2 , we solved with the coefficient of X and we obtained other values as in Table 2. The total for the problem statement is 7,563.72875. Then we obtained the average value of 11,760.62146. Then the maximum value is 28,704.14914. From there, we selected our maximum value to be the winner of the tournament at the first stage, which is 28,704.14914. The parameter has the maximum chance of being selected. The representation of the implementation of the tournament-based selection is shown in Fig. 1.

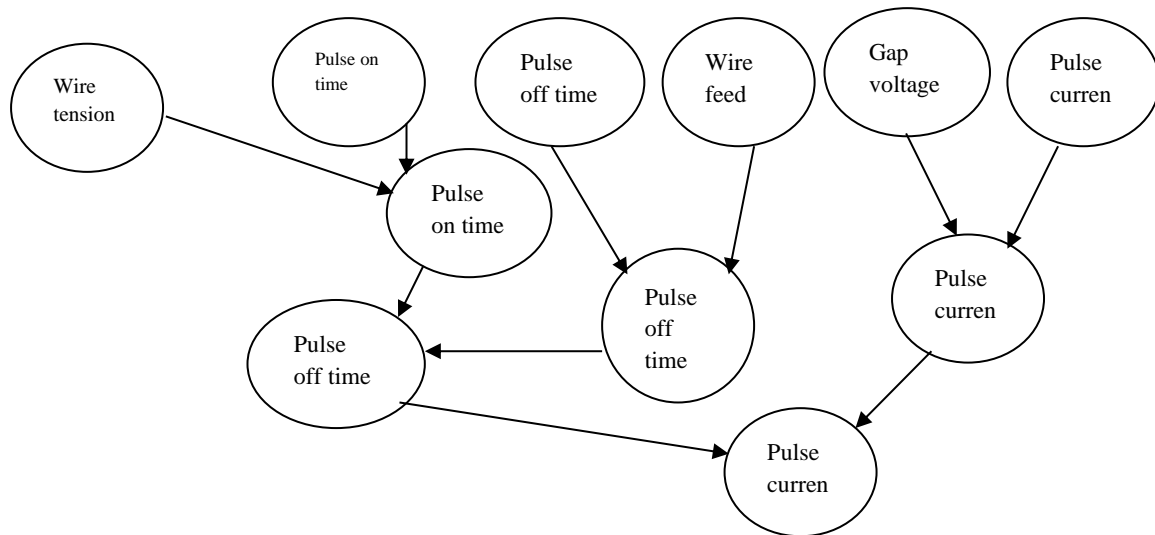


Fig. 1. Diagrammatic representation of the tournament selection process in this work

In conducting the genetic algorithm tests of experimental data on the electrical discharge machining of AZ91 magnesium alloy using the tournament-based selection method, the total value obtained after the selection, cross over and mutation processes, the total fitness value is of interest to the researcher at each of the stages. Now, it is important to obtain the sensitivity analysis, which is a model that establishes how the total fitness is influenced based on changes in each of the parameters, namely, A, B, C, D, E, and F (i.e. the process parameters also known

as u input variables). To proceed, each of the parameters A, B, C, D, E, and F was increased by 10%(randomly chosen), and the corresponding changes in the total fitness values were considered, furthermore, from the table containing the tournament selection process detail (Table 2), the authors after playing the tournament on the average level values, the fitness values were obtained (i.e. the X values). From here, the authors worked on the fitness value column in Table 3 and started the sensitivity analysis.

Table 2. Tournament selection process parametric details

Symbol	A_{vi}	Trials	Individuals N_u	Selected	Fitness value (X)	Binary form	X^2	Fitness, $F(x)$ $=1.27574X^2$
A (Pulse on time)	116	1	1,6	1	116	01110100	13456	17166.36
B (Pulse off time)	50	2	2,5	2	50	00110010	2500	3189.35
C (Pulse current)	150	3	3,4	3	150	10010110	22500	28704.15
D (Gap voltage)	30	4	4,2	2	50	00110010	2500	3189.35
E (Wire feed)	6	5	5,1	1	116	01110100	13456	17166.36
F (Wire tension)	8	6	4,6	4	30	00011110	900	1148.17
Total					512		55312	70563.73
A_v					85.33		9218.67	11760.62
M_v					150		22500	28704.15

Table 3. Sensitivity analysis (10% increase) on Parameter A and the corresponding fitness values

Symbol	Average level Values	Trials	Individuals N_u	Selected	Fitness value (X)	Binary form	X^2	Fitness, $F(x)$ $=1.27574X^2$
A	116	1	1,6	1	128	10000000	16384	20901.724
B	50	2	2,5	2	50	00110010	2500	3189.35
C	150	3	3,4	3	150	10010110	22500	28704.15
D	30	4	4,2	2	50	00110010	2500	3189.35
E	6	5	5,1	1	116	01110100	13456	17166.357
F	8	6	4,6	4	30	00011110	900	1148.166
Total					524		58240	74299.0976
Average Value					87.333333		9706.667	12383.1829
Max. Val					150		22500	28704.15

For the first parameter, A, the authors added 10% to 116 to become 127.68, which is approximated to 128. This brings about a new set of values noting that as A is changed by 10%, all other parameters of B, C, D, E, and F are kept constant. Definitely, on parameter A, a new set of binary numbers is obtained. The X^2 value will change and the fitness function from the problem statement will also change. The problem is $F(X) = 1.27574 X^2$. Next, a new value is obtained for parameter A. Then every other function is performed accordingly by summing up the values to obtain a new total, a new average value, and the maximum values. For this case, the maximum value is constant in comparison in Table 2. To summarize the whole

work at the selection stage, the same procedure was followed for all the other parameters by keeping the initial parameters constant. It interests us to know the differences in total fitness value, average fitness value and maximum value when Table 3 is compared with Table 2.

As parameter A increased by 10%, the total fitness value became 74299.0976 as opposed to 70,563.73 for parameter A, which is a 5.29% increase. Now summarizing these results, Table 4 may be helpful. Table 4 shows a range of changes in the total fitness values when adjustments are made to each parameter.

Table 4. Percentage changes in total value at selection, crossover, and mutation phases

Sr. No.	Parameter	% change in total value (selection)	% change in total value (crossover)	% change in total value (mutation)	Average value	Positioning
1	A	5.29	4.20	3.00	4.16	1st
2	B	0.95	1.03	1.19	1.06	6th
3	C	8.54	-0.14	-0.24	2.72	4th
4	D	0.95	1.71	1.46	1.37	5th
5	E	5.29	3.78	2.94	4.00	2 nd
6	F	0.34	6.28	4.88	3.83	3 rd

To further explain Table 4, for parameter B, when it is increased by 10% at the selection stage while keeping the values of parameters A, C, D, E, and F constant, a 0.5% change in the total fitness value was obtained. By conducting the same activity at the crossover stage, a 1.03% increase was recorded and a 1.19% increase was reported at the mutation phase since a comprehensive sensitivity across the phases of selection, crossover, and mutation phases are desired, obtaining an average fitness value across phases may be a good representative of the sensitivity of each of the parameter in the implementation of the tournament – selection-based process for the electrical discharge machining problem considered using the AZ91 magnesium alloy. Thus, for parameter B, the average fitness functions across the phases of the GA scheme is 1.06, Now, the idea of average computation is deployed to all parameters, and the results are shown in Table 4, it is interesting to note that parameter A has the highest value of parametric influence on total such that a 10% change in parameter A across all the phases yields 4.16% change in the total fitness function and termed as the most sensitive parameter in the wire EDM process considered in this work. By the same procedure of evaluation, parameter B is the least-sensitive parameter. It means that for any significant system changes focus should be on parameter A to have an effective result.

4.1.2 Crossover operation

To make some terms understandable, explanations are given in this part of the article starting with the next statement. The crossover point is a reproduction state at which the fitness value for a particular chromosome becomes lower at the crossover stage than the fitness value at the selection stage during the transition

from the selection stage to the crossover stage for a minimization problem. An example is the cost minimization during the EDM process of the AZ91 magnesium alloy. However, in the present case, where the maximization of the parameters is desired for the AZ91 magnesium alloy material during the EDM process, the crossover point is a reproduction stage at which the fitness value for a specific chromosome achieves a higher status at the crossover stage than the fitness value at the selection stage during the transition from selection stage to crossover stage for a maximization problem. It may also be conceived as a point within a group of pairwise chromosomes for mating at the selection stage pathway, where an element of a chromosome is particularly made the boundary of an individual chromosome in the old framework and the rent element after the boundary is transferred to and the rent element after the boundary is transferred to another chromosome that has been bounded similarly to increase or reduce the fitness value of the newly formed chromosome after crossover operation according to the nature of the problem i.e. minimization or maximization.

Furthermore, at the crossover operation, the researchers transferred what was obtained at the selection stage, particularly the X values, to a new table. Hence, a mating operation is performed on them. The purpose is to upgrade the parameters from a state where they have minimum chances of being selected to acceptable states. From this point, the researchers have prepared the first two, the second two and the third two. After being paired, the researchers then performed a crossover operation on them. As this was accomplished, for the first two individuals, the researchers performed a crossover operation on

them after the 5th bit. Then, for the second pair, also, after the 5th bit was when the crossover operation was performed on them. For the last pair, the crossover operation was performed on them after the 6th bit. Once the mating operation

was conducted, we developed a new set of values, which are 114, 52, 146, 54, 118, and 148, respectively. So, we performed the same operation on them with X^2 and we have 12996, 2704, 21316, 2916, 13924, and 21904 (Table 5).

Table 5. Crossover operation process parametric details

Symbol	Trials	X value	Mating pool	Crossover point	Offspring after crossover	New X value	X^2	Fitness, $F(x) = 1.27574X^2$
A	1	116	01110 100	5	01110010	114	12996	16579.52
B	2	50	00110 010	5	00110100	52	2704	3449.60
C	3	150	10010 110	5	10010010	146	21316	27193.67
D	4	50	00110 010	5	00110110	54	2916	3720.06
E	5	116	011101 00	6	01110110	118	13924	17763.40
F	3	150	100101 10	6	10010100	148	21904	27943.81
Total						632	75760	96650.06
A_v						105.33	12626.67	16108.34
M_v						148	21904	27943.81

So, when we multiplied by the coefficients, we have 16579.52, 3449.60, 27193.67, 3720.06, 17763.40, and 27943.81, respectively. We obtained a total value of 96650.06. The obtained average value was 16108.3425 and the maximum value of 27943.81. So it could be seen that our total value had been augmented from 70563.73 at the selection stage to 96650.06 at the crossover stage. It could be seen that an improvement has been experienced. Next is the mutation operation.

4.1.3 Mutation operation

It was observed from the crossover stage that some X values needed to be improved to boost their chances of being selected. With this, it was found that parameter B, which is the pulse of time, and parameter D, which is the gap voltage needed to be upgraded. Upgrading was done by changing them from 52 for B (pulse off time) to 116 and parameter D (gap voltage) from 54 to 118. In upgrading the mechanism followed was to mutate some of the bits to upgrade their values. So, for the second one, we changed the second bit from 0 to 1 and for the fourth one, we did the same thing by changing the second bit from 0 to 1 (Table 6).

This upgraded it from 52 to 116 for pulse off time and from 54 to 118 for gap voltage. Having established this, we were able to raise our total value from 96650.05949 to 124410.1611. So we can see that our values have been successfully upgraded with all the participants having a very high chance of being selected. This achieves our primary aim, which is to upgrade the participating parameters so that their chances of being selected can be also upgraded.

The results obtained in the present study are consistent with the concept of integrated AHP-Taguchi-Genetic algorithm in a previous study by Ikedue and Oke (2023), demonstrating the influence of a genetic algorithm in further optimization of an electrical discharge machining problem while machining AZ91 magnesium alloy. However, it reinforces the triple method on the combination of three methods with two of the method and the genetic algorithm method having positive effects on the parametric optimization and the third method, the analytic hierarchy process introducing the prioritization idea to the triple method.

Table 6. Mutation operation process parametric details

Symbol	Trials	Offspring after crossover (O _c)	Offspring after mutation (O _m)	X value	X ²	Fitness, F(x) = 1.27574X ²
A	1	01110010	01110010	114	12996	16579.52
B	2	00110100	01110100	116	13456	17166.36
C	3	10010010	10010010	146	21316	27193.67
D	4	00110110	01110110	118	13924	17763.40
E	5	01110110	01110110	118	13924	17763.40
F	3	10010100	10010100	148	21904	27943.81
Total				760	97520	124410.16
A_v				126.67	16253.33	20735.03
M_v				148	21904	27943.81

4.2 Comparison of tournament, rank and roulette wheel selection processes

Furthermore, it is interesting to note the differences between the present approach of tournament selection and rank selection on one side and roulette wheel selection on the other side. This means the differences between tournament and rank selection and tournament and roulette wheel. The starting point of the explanation is the differences between a tournament and a roulette wheel. In this comparison, the difference is that in the roulette wheel, one has to work with the original numbers given or found out by the researchers and the researchers see how one can be able to raise their values to be able to obtain satisfactory results. In the roulette wheel selection, from the theory, the researchers place the parameters in a wheel (pie chart) and one that possesses the higher value or the highest area from the wheel happens to be with the highest chance of being selected. In that can, one can already tell the results as there is no fair play for others.

At the selection stage, fair play is absent for others participating until one reaches the crossover stage and the mutation stage. In other words, from the selection, and the appearance of the parameters, the researcher will be able to disclose which parameter has the highest chance of being selected because it has the highest value. However, in tournament selection, the researchers paired them and then played a tournament. From the tournament selection, one can upgrade the values of the selection parameters that are being used. Then

the competition becomes very high. The numbers of parameters that have a high chance of being selected are also high in tournament selection because you have eliminated those that we have very minimum chances of being selected and you are now working with those that have a high chance of being selected at the selection stage. So, for tournament rank selection, the difference is explained as follows.

The rank selection works hand-in-hand with the roulette wheel selection method. But before the roulette wheel selection method, the researcher needs to arrange one's parameters in ascending order with the least value having the first position and then the highest values ranking in the nth position. Once this is done, one can divide the one at the first position as the total of all the parameters completed. This is done by virtual ranking which is divided and ranked in terms of percentage. Once this is achieved the researcher is also upgrading the parameters so that they can also be able to stand the chance of being selected at the section stage. So, one could say that rank selection also gives a fair ground for competing with other parameters but the tournament selection method is faster and gives other parameters higher chances of being selected right from the beginning. So, comparing the tournament selection process with others, it may be safe to state that the tournament section has a very high level of convergence at the selection point. From the research experience in this article and working with the tournament selection, roulette wheel, and rank selection process, rating the three processes results in the following assertions.

The first position will be given for tournament selection, then the second position to rank selection, and the third position for the roulette wheel selection process. Although the roulette wheel appears to have a larger application than the tournament and rank section processes, the experience of the present authors shows more favor for selecting the tournament process than the other two processes.

4.3 Managerial insights

Managerial insights can be drawn from the results of the application of the tournament-based selection genetic algorithm method and also from the sensitivity analysis performed on the parameters of the process. These insights are discussed as follows:

- At the selection stage, winners and losers of the tournaments are mentioned. Eventually, the pulse current is the winner of the tournament at the selection stage after a vigorous league. Pulse current contains charge particles that flow either in one or two directions. These particles are short paused with extended off periods where no current flows at all. As a machining engineer or manager differentiating the best from the most parameters helps in keeping a close watch on the performance of the wire electrical discharge machining system. Technologies allow organizations to enhance the performance of the system. Therefore, the use of technologies which will enhance pulse generation that is interpreted in the waveform, amplitude and duration should be encouraged. Also, pulse current information can provide valuable, real-time insights capable of revealing the wire EDM's current performance and the degree to which the machining operator utilizes this parameter. This insight is helpful but the utilization of the information is equally important. Also, more concentration of resources is suggested on the pulse current than any of the other parameters of pulse on time, pulse off time, gap voltage, wire feed and wire tension in a practical sense, machining engineers may utilize more sensitive technologies to detect the pulse current.
- From the crossover state, pulse off time and gap voltage were upgraded to improve their

chances of being selected. It is recommended that the machining engineers ought to take measures to boost the performance of both the pulse off time and the gap voltage. This is possible by also deploying the best technology to reveal they are true states during measurements.

5. CONCLUSIONS

The principal aim of this research was to propose concurrent optimization and prioritization to the machining process of AZ91 magnesium alloy through the wire electrical discharge machining scheme. The wire EDM can engage materials with narrower angles, roughly between 10° and 45°, and more complex configurations than the EDM by adopting a contemporary computerized numerical control technology. From the viewpoint of playing a league with different competitors, candidates undergo screening until a final candidate emerges as a winner. This selection phase precedes the crossover and mutation phases' after which the total value (contribution) to each chromosome and the system is evaluated. Decisions on the AZ91 magnesium alloy processing in the wire EDM process are made. Through the conversion of crisp numeric values into binary numbers, crossover, which involves mutual switching of sizeable fragments of genetic material is conducted. Then the mutation process that involves deletion and insertions of binary bits is made on the fitness value obtained. To solve the problem of the wire EDM process, procedures are laid down and followed using the experimental data from Muniappan et al. (2018). Thus, the objective of the research set out for achievement was fulfilled. This provided a framework for the process engineer in the wire EDM process to decide on issues regarding the machining process. Furthermore, it contributed to the literature on wire electrical discharge machining involving the processing of AZ91 magnesium alloy.

Regarding alternatives for future research, the authors suggest the development of other selection methods such as steady state selection, elitism selection, and Boltzmann selection based on the same dataset of the AZ91 magnesium alloy, and comparing results among these selection approaches is important. This

may be considered with the AHP and different kinds of fuzzy tools such as the hesitant fuzzy method (Ghorui et al., 2021a) and hexagonal fuzzy (Ghosh et al., 2021b), TOPSIS (Ghosh et al., 2021c and Ghorui et al., 2020). Furthermore, it was observed that the tournament selection, process has its basic elements and philosophy, which are different from others such as the roulette wheel selection process and the rank selection process. But it should be understood from further studies if synergic benefits of the tournament selection and one or more selection approaches could be made. Thus, a study focused on the integration of the tournament selection process and the rank selection process would offer more detailed insight into the deficiency in the synergic benefits of the selection process on the AZ92 magnesium alloy material during the wire electrical discharge machining process.

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