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Thermal Friction Drilling Process Parametric Optimization for AISI 304 Stainless Steel Using an Integrated Taguchi-Pareto–Grey Wolf-Desirability Function Analysis Optimization Technique

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Thermal friction estimations are presently essential on steel for manufacturing applications as they predict the aggregated energy required for the required process. However, the current thermal friction estimates are inaccurate as they exclude the optimized thresholds of both the input and output quantities. In this article, the optimization of the drilling operation process is accounted for by introducing a new method of combined Taguchi-Pareto–grey wolf-desirability function analysis applied on the AISI 304 stainless steel. An objective function was formulated using the delta values developed from the average signal-to-noise into the response table of the Taguchi method. Besides, the ranks of the parameters through the response table are taken in the reciprocal mode to evaluate the values of the linear program formulated according to the objective function and some constraints taken from the system. Six input parameters were considered tool cylindrical region diameter, friction angle, friction contact area ratio, mouthpiece thickness, feed rate and reciprocal speed. The outputs are the axial force, radial force, hole diameter dimensional error, roundness error and bushing length. These inputs and outputs were analyzed for the optimization process. Based on the results, which were solved using the C++ software, the best value converges in iteration 8 with the starting value of 1699.2. Iteration 1 drops to 11016.3 in six iterations (iterations 2 to 7) and finally converges at 11015.9 in iterations 8 through 20. The usefulness of the effort is to help process engineers to execute cost-effective energy conservation decisions in optimization that could be obtained using optimized thermal friction values.

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1. INTRODUCTION

In 2015, it was declared that about 100 terajoules were spent on overcoming friction every year and this accounts for 20% of the world's aggregate energy (Holmberg and Erdemir, 2015). Yet, the friction generated from manufacturing activities and friction drilling, in particular, is a large quantity of this energy threshold. Unfortunately, the control and optimization of friction in friction drilling regarding the AISI 304 stainless steel are reportedly understudied in the friction drilling literature. This limits the process engineer in achieving the full advantage of thermal friction drilling over the conventional drilling method. Consequently, insight into the optimization of thermal friction is essential to deriving the utmost benefits from the process. However, because of the increasingly difficult business operations benchmarking new efficiencies in manufacturing performance as a sense of urgency has placed the friction drilling innovation as a dominant trend in the manufacturing of steel nowadays (Wheatherl, 2021).

To the best of the authors' knowledge, previous studies fail to address the problem of concurrent optimization and prioritisation that exists among the friction drilling parameters of AISI 304 stainless steel. However, while tracking the prioritisation of parameters and also their optimization, the mechanism to ascertain that the valuable time resource is conserved and the energy is diverted to the most important parameters during the process of implementation is absent in studies. This makes it a fertile ground to apply the Taguchi-Pareto in a coupled manner to the grey wolf optimization.

This study focuses on the thermal drilling optimization of AISI 304 stainless steel. It is an attempt to reexamine the assumptions in the reported study of EI-Bahloul et al. (2018) that collected experimental data and analyzed the thermal parameters of AISI 304 stainless steel. The previous study is credited for the Taguchi application but the present authors argue that alternative solutions are feasible by introducing a combination of the Taguchi method and evolutionary algorithms. In the present study, a combined technique of Taguchi-Pareto, grey wolf optimiser and desirability function analysis. Since few studies have been performed to concurrently prioritise the state of the thermal function drilling parameters were fast determined. This was done by introducing the Pareto analysis into the Taguchi framework. Also, as an alternative method, the present author used the grey wolf optimization. Finally, the desirability function analysis was applied to obtain all the outputs of the process at once. This is at variance with the grey wolf optimization which attempts only one output analysis at a time.

Thermal friction drilling is a process of cutting that utilizes friction to achieve the removal of materials (Monroe, 2019). In the process of friction drilling, friction is created by the tool bit as it notables into the workpiece (Monroe, 2019). The friction then creates heat which in turn gives rise to the removal of material from inside the workpiece. Thermal friction drilling is a unique cutting process that makes use of friction to achieve the removal of material. However, this drilling process is achieved through the rotation of a heat-tolerant conical tool bit into the workpiece, thereby creating friction. The friction creates heat which gives rise to the removal of the material from inside the workpiece (Monroe, 2019). But within the application domain of thermal friction drilling, steel plates and pipes have been a central focus of research while the AISI 304 stainless steel is the application product in the current research.

Regarding the AISI 304 stainless steel, the study of the enhancement and optimization of thermal friction drilling is still insufficient. This implies that whenever thermal drilling is done on the given material, there is no assurance of achieving the full benefits of the drilling process asides from being prone to excess cost as well as underproduction and lack of variety in the process result. The excess cost that may arise simply stems from the fact that more material will be used than is needed during the thermal drilling operation. To the best of the authors' knowledge, an extremely few papers have analyzed the thermal friction of the AISI 304 stainless steel regarding the optimization of parameters and outputs. This is because of the heavy commercial investment required for the monitoring equipment of the thermal friction drilling and the seemingly challenging tasks of clearly defining the key inputs and outputs that will yield the true threshold of frictional values required from the drilling system. The drilling resource plan of several machine shops, particularly the large-scale component producers, including the AISI 304 stainless steel is still being initiatively made and based on the judgment of the process engineer.

Unfortunately, this intuition and resource planning for the drilling function by the experience of the process engineer can no longer satisfy the requirement for a sustainable drilling process, which is the current state-of-the-art in drilling that advocates for detailed attention to environment, economic and social perspectives of the drilling process. Besides, several limitations exist that should be overcome. First, in heavy industries, where multi-feature components are processed, the whole components need to be planned for drilling but this is a huge workload for process engineers where intention and experience may fail as the frequency of activities is beyond what the human intention could suitably cope with. Second, the wide complex components and tasks possess a significant challenge to the process engineers to utilize the restricted human and non-human resources within the budgeted framework. Third, the intention and personnel experience of process engineers as judgments get trapped into local optional decisions as opposed to the global optimal decisions needed for maximum business prosperity. Consequently, an urgent requirement to develop optimal procedures for thermal friction drilling exists.

Interestingly, El-Bahloul et al. (2013) emphasized the necessity to carry out further studies in this area of friction drilling optimization where important parameters of the machining process are considered with the aid of competent emerging algorithms. Worthy of note is the fact that the bushing length is a very important output parameter when it pertains to thermal drilling, therefore its numerous applications in engineering demand that the consequences of varying the thermal drilling input parameters are well known and understood (Hynes and Kumar, 2017). Besides, the Taguchi design approach is a method that discovers input factors that will significantly affect the response variable and corrective action is taken when a factor of an undesired variation is discovered. It is a particularly useful method especially in enhancing the quality of products and operations (Jaharah et al, 2013). However, the Grey Wolf Optimizer (GWO) is an optimization method that efficiently searches for near-optimal solutions in its iterative process, mimicking the hunting behavior of grey wolves (Mehdi et al, 2021).

The solution proposed thus is the use of Taguchi–grey wolf optimization method to arrive at optimal process parameters for five outputs in consideration (including bushing length) that will yield optimal machining. The utilization of the Taguchi–grey wolf method is a fast and accurate way of arriving at optimal solutions hence the choice. There will be parameters that yield the satisfaction to the most optimal possible values of all the outputs in question. In conclusion, the paper simply aims to address the paucity of study of optimization of the thermal drilling process on AISI 304 stainless steel by optimizing choice process parameters like the workpiece thickness (t), friction angle (β), feed rate (FR), friction contact area ratio (FCAR), tool cylindrical region diameter (d) and rotational speed (RS) to give optimized values of axial force (AF), radial force (RF), hole diameter dimensional error (DE), roundness error (RE) and bushing length (BL).

2. LITERATURE REVIEW

2.1 Thermal friction drilling

Thermal friction drilling is a non-conventional method of drilling that is achieved by applying a conical tool to the surface that is to be drilled. In the rotation of this conical tool against the surface, friction is generated that melts the surface and the aim of this whole process is to form a cylindrical indentation. The surface that melts paves in the shape of the cylinder and forms a bushing. So the bushing now serves as an extended surface area where threading can be done to have screws and bolts, depending on what is to be produced.

But how this differs from the conventional drilling process is that there is no material removed and there is no other machining operation that gives one more surface area than thread-like thermal drilling does. Thus, these are the two key advantages of thermal drilling over the conventional method. Also, it is applicable in the aerospace industry whereby much dependence is given to the integrity of joints. Thus, joints are not expected to fail, which may happen through other methods and including fracture. But in thermal drilling, there is more integrity since the bushing length is longer. In the aerospace industry, intensive usage of aluminum sheets is made. But these sheets are relatively thin compared to metals used in other industries because they are required to be as light as possible to be functional.

2.2 The review process and literature classification

To conduct the literature review, papers within the domain of thermal drilling were surveyed. In this context, they were downloaded from the database of ScienceDirect and grouped based on what the papers tried to achieve. Then a synthesis table was made where the several aspects of each paper were analyzed such as the authors, the focus of study, the materials studied, the parameters, the methods adopted, observations and the results. Consequently, the relevant information extracted from the papers was filled into the table to be treated group wisely. In summary, there are about five group classifications of articles in the literature. The first group focuses on optimizing the process parameters. This group contains papers associated with determining the adequate inputs that will lead to the expected outputs. However, it depends on what the outputs will be. In some cases, there is a single output while in others there are multiple outputs. The second is the group of papers that attempt to study the effects that some factors have on the machining results. Some of the factors are external such as the environment, temperature, and lubricant addition while some of the factors are internal, including how the variations of feed rate or the spindle speed lead to the increase in thrust force and any other output that author finds necessary. Then the third group simply refers to the papers that deal with modeling and simulation of the thermal drilling process using the software. In some cases, the authors try to use these models to also predict the effects of inputs on outputs by variation of input, for instance. In all cases, the models were validated. The fourth group deals with papers that consider enhancing machining procedures. In this case, ultrasonic vibration was attempted in the thermal drilling process. However, many of these papers are relatively recent. The oldest paper deals with suggesting tungsten carbide as a reliable tool for carrying out a thermal drilling process. Interestingly, many papers have adopted the paper. The last group relates to those dealing with assessing the quality of thermal drilled products. In some cases, they compared other products achieved by other conventional drilling methods. Thus, in the following discussions, each of the sub-groups of papers under the thermal friction drilling is expanded in explanations. These explanations commence with the first sub-group as follows:

2.3 Papers attempting to achieve optimal process parameters

These papers strive to evaluate the outputs to obtain their optimal thresholds of the input set of parameters. For example, the authors pursued optimal spindle speed and feed rate that will yield the choice outputs i.e. to minimize the surface roughness. In certain instances, two outputs may be considered for optimization. In this group of papers, authors made use of principal methods such as Taguchi and genetic algorithms. However, the Taguchi method has more overwhelming applications than other methods. In the group of optimizing process parameters, the first paper is by El-Bahhoul et al. (2018), which attempted to optimize the process parameters in the transformation of AISI 304 stainless steel into a product, namely the tool diameter, friction angle, rotational speed, friction contact area ratio and feed rate to obtain the utmost responses represented by the axial force and bushing length. The adopted methods by the authors are ANOVA, design of experiments and fuzzy logic. The relevance of their method to the present article is that they were able to obtain the process parameters by making use of the relevant analysis. They also successfully compared the experimental results with the regression analysis introduced to the problem.

The second paper in the group is by Dehghan et al. (2021) which analyzed the process parameters using three main difficult-to-machine materials of Inconel 718, AISI304 and Ti6Al-4V. The authors tried to obtain the optimal drilling speed and feed rates while the responses defined in the study are the thread length and the screw coupling. They arrived at the conclusion regarding the spindle speed as a larger more significant parameter compared with the feed rate. The analysis of variance was used to establish the results and this was coupled with the full factorial. In the third paper, Kumar and Hynes (2020) worked in the domain of optimizing process parameters but the galvanized steel was used as the working material and the parameters focused on are the spindle speed, angle of tool and workpiece thickness. To minimize the surface roughness, the authors utilized a genetic algorithm and Taguchi. It was found that the spindle speed and the angle of the tool affect the surface roughness. They also arrived at the optimum process parameters for the minimum surface roughness.

The next paper in this group is by Kumar et al. (2019) who obtained optimal process parameters by the inclusion of roundness errors as one of the parameters to be minimized apart from surface roughness, which is common in many papers. The work material used is galvanized steel. A grey-based fuzzy logic system was used to analyze the problem while multi-objective optimization was also embarked upon. The paper was able to establish the contributions of the geometric angles and rotational speed using a multi-objective framework and the optimum process parameters specified. Also, they attained minimum roundness error and surface roughness, which is similar to what is being obtained in the present article. It can be concluded the papers treated under this group, within the domain of influence of process parameters on the output are related to the present article on the optimization of process parameters as optimization brings the process parameters out from the local optimal to global optimal and improves the values of the process parameters.

2.4 Papers that consider the effects of factors on machining results

In this group of papers, the authors attempt to find out if some factors affect the results. As an example, the authors studied the results of the tools that were coated. They also sought to understand the tool's behavior and that of the work material if the tools were used in an uncoated condition. They also showed interest in understanding the effects on the output if drilling was conducted in a hot (dry) condition as opposed to a lubricated situation. Thus, the authors aimed to find out, first, if these changing conditions have any effects on the machining results. Second, if the effects are pronounced.

The author, Bilgin (2021) in this group, for instance, checked the effect of the drilling environment on the formation of the thrust force during the thermal drilling process. They also discovered that the main damage mechanisms like delamination, and eccentricity, among others occur in the conventional drilling system but are absent in the thermal drilling process. The way this article relates to the article being developed is that it is mainly because we are dealing with thermal drilling. In a second paper by the same author co-authored with another person (Karabulut and Bilgin (2021). Still studied the effect of process factors on machining results using a set of alloys (i.e. AA7075-T6 and AZ31B alloys) as the work material and the parameters include the thrust force, temperature, hole surface quality, bushing profile and thread stripping strength. The feasibility of the approach was confirmed. The similarity between this paper and the current one being developed are as follows. First, both are on thermal drilling. Second, the two papers consider the thrust force and bushing profile. These are considered factors that may impact the process.

The next paper is by Bonnet et al (2020) which studied the effects of sliding velocity and contact pressure on the work material, which is titanium TiAlL4V alloy. The authors also compared the friction at the flank faces drills rake as well as on its margin. In relationship to the paper being developed, the two papers are on thermal drilling. In another work, Lee et al. (2009) studied the effects of process factors on machining results by considering the work materials known as austenitic stainless steel while comparing the coated and uncoated tools' performance on the work material. Furthermore, Miller et al (2006) also studied the effects of process factors on machining results using cast aluminum-magnesium alloys as the work material and the parameters are the spindle speed, workpiece temperature and feed rate. The outputs are the thrust force, torque and bushing shape. It can be said that the effects of process factors on machining results are related to optimization. Nonetheless, the paper relates to the proposed paper in this work in that both papers are fundamentally on drilling. However, it is observed that the authors did not consider a large number of process parameters but a few. The paper by Miller is a foundational paper that studies how the effect of spindle speed, workpiece temperature and feed rate influence the thrust force, torque and bushing shape. The paper tries to answer the question that for the several outputs which inputs do these outputs depend upon? This is similar to what is being achieved in the present article.

2.5 Papers dealing with the modeling and simulation of machining processes

In the third grouping, the modeling of machining processes, the authors utilize software to simulate the thermal drilling process to achieve the goal. The authors iterate to turn the input variable and obtain outputs. These outputs are compared to the actual drilling experiments to check if the results are close to each other. The first paper considered here is by Dehghan et al. (2020) that worked on three difficult-to-machine materials, namely Inconel 718, AISI 304 and Ti-6Al-4V while the output is surface quality and thrust force. Often the experimental results are compared with modeling results. The second paper by Zhang et al. (2022) simulated the prediction of the penetration force of torque during the thermal friction drilling. What was used as the input is the temperature at the contact interface between the rivet and the workpiece. The other paper under this group is by Hynes et al. (2018) which predicted the torque, thrust force and temperature distribution. Also, there was a modeling of temperature and material flow with emphasis on the temperature distribution during the friction drilling. Both the Zhang et al. (2022) paper and Hynes et al. (2018) paper has the similarity of being in the area of thermal drilling with the present article being developed. The last paper in this group is Shalamov et al. (2016) which simulated the thermal drilling process using ANSYS. The authors worked on the mechanism of flange formation by the rotating punch, using ANSYS.

2.6 Papers dealing with the enhancement of machining procedures

The outcome of this group is to provide a possible suggestion that will yield more optimal thermal drilled products. In the review, the authors notice that this group may sometimes include work on optimizing process parameters. The first paper considered in this group is by Baraheni et al. (2021) which applied ultrasonic vibration during the thermal friction drilling process. Thus, the ultrasonic vibration-assisted the friction drilling, it was noticed that there were lower axial forces that occurred in this process. The way the paper relates to the current paper being developed is that the consideration that their output and inputs are similar to those worked on in the present article. Their output is the axial force and surface roughness. Interestingly, the present authors noticed that surface roughness is the most common output being considered in this process. In the paper, the rotational speed and feed rates were considered as their inputs. These mentioned inputs are also common parameters in the literature.

The second paper in this group is by Alphonse et al. (2021) that attempted to arrive at an optimal coating for the tool and they eventually arrived at one, namely the PVD titanium nitride H13-D2 tool. They arrived at the tool as the best for the AZ31B alloy the authors worked on. The authors made use of response surface methodology and ANOVA and the output was the surface roughness while the parameters utilized the chose the best coating was the time each of the tools consumed during the friction drilling process. This is because, in principle, thermal friction is a process that saves time, i.e. equivalent to machining time. Concerning the present article, the output is considered common in both papers. In their paper, they considered the surface roughness as the choice parameter for determining a better thermal drilling product. In this same group of papers that enhance machine procedures, the next paper is Chow et al. (2008) and Alphonse et al. (2021) also deviated from the common enhancement tasks of machining procedures to optimize process parameters. Besides, Chow et al. (2008) utilized the Taguchi method and reported from the viewpoint of arriving at an optimal tool for the thermal drilling process. Initially, the twist dull tool was considered, which was used to conduct thermal drilling. They also utilized tungsten carbide in the thermal drilling process. It was reported that twist drilling failed after three or four times but the resilience of the tungsten carbide was shown in it failing only after 60 times of drilling. This shows a process of setting the foundation that tungsten carbide is better for thermal drilling, especially for stainless steel. Besides, what was noticed is that subsequent publications made use of tungsten carbide in their experiments by keeping in mind the recommendation of these researchers. Concerning the present article developed, some of the inputs considered in the article are the same as those in the present paper being developed. Furthermore, the authors utilized the Taguchi method and the sole output is the surface roughness. Note that the friction angle, friction contact area ratio and feed rate and drilling are in speed. This reviewed paper and the present paper worked on. Though drilling speed is referred to as rotational speed in the present work, all these inputs are common to the present article.

2.7 Papers assessing the quality of thermally-drilled products

This group of papers set procedures to assess the quality of thermal drilled products and in some cases compared them to other drilled products i.e. products from other machining processes. The first paper reviewed by Wu et al. (2021) compared thermal drilled holes to holes from the conventional process. However, this conventional process involves holes that are drilled and tapped. It was reported that when these products were subjected to loads, the thermal drilled products gave peak loads that were 35% higher than those of the conventional types because of the extended bushing length. To explain bushing length, in other drilling processes, the holes are the same as the sheet but in the thermal drilling process, the materials are not removed but pushed to form a bushing that extends the area to be threaded. Therefore, as opposed to conventional drilling where the materials are removed, thermal drilling makes use of the material being removed for the benefit of the drilled product. It does so by extending it so that it forms more surface area to be threaded. Thus, this additional surface area in thermal drilling implies that it can withstand more loads than drilling arrived by conventional methods. How the present paper relates to the one being developed is that it shows one of the important aspects of thermal drilling. Thus, thermal drilling is better than conventional drilling considering the holes bear more loads. Then another paper in this category of assessing the quality of thermal drilled products is by Pereira et al. (200x). The surface quality obtained by thermal drilling seems to be more appropriate ecologically regarding wastage; less wastage was experienced during the thermal drilling process according to the parameters provided by them. Also, they provided a solution that improved the current drilling process of metal sheets. The next paper is by Shalamov et al. (2021) by considering thermal drilling as a technological advanced solution to increasing the length of unscrewing compared to rival methods. The idea is that normally when processors are working on sheets, bolts and nuts are being made use of because the thickness is too small and this may not be counted upon, the processors tend to extend the surface area of threading by some processes like sheet bending while the bushes are welded to the sheets and seven the use of nuts and stamping. However, these processes are not as technologically advanced as thermal drilling. The paper highlights the strengths of thermal drilling in terms of technological advancement. The next paper is by Elisseey et al. (2017) which pointed out that in the thermal drilling process, there is a deformation that takes place, which leads to recrystallization of the material since the crystals change configurations and a new shape is taken. But the summary is that even that new shape leads to an increase in microhardness. Therefore, the thermal drilled product is even stronger in terms of that hole that had been drilled concerning the other aspects of the sheet that is in question. So the author summarized that there is an increase in microhardness in the recrystallized material. The last paper is by Boopathi et al (2013) which arrived at the fact that the thrust force in the thermal drilling process increases when the feed rate increases. (Transfer to the effect of process factors). How this paper relates to the current paper is that spindle speed was made use of as input as well as feed rates. As outputs, they considered thrust force, which are elements considered in the present study.

In the literature review, efforts were made to understand how many investments of efforts of authors were made and which of the groups identified experienced intensive patronage. So, the authors were interested in knowing where authors have worked more than others. To respond to this issue, the authors' experience through the survey is that the major work has been done on comparing thermal drilling products with those of other conventional methods. The reason that could be advanced for this is that thermal drilling is relatively recent. In the authors' literature search, the earliest paper on thermal drilling was by Miller et al. (2006). The paper explained the advantages of thermal friction drilling to stimulate intensive research in the relatively new technology that they considered of high potential for development and use. The paper also created awareness of the area for more intensive explorations by researchers. Furthermore, the present authors were interested in understanding which of the areas have not been highly studied and the reasons for this. From all these studies, fewer efforts have been devoted to optimizing process parameters. The reason for the low intensity of research in this area is that the area appears to be a very rigorous one. Here several input parameters need to be monitored and the inputs yield the utmost output. So, the monitoring of several inputs and output is very rigorous and researchers showed less interest in this. In addition to working in this area, the machines and equipment needed to evaluate the parameters need to be available. But they are very expensive and very few research centres could afford this, leading to a low level of work in this area. For instance, researchers need surface roughness equipment and other high-precision equipment, which might not be cheap for the procedure. Even in this area, when authors are optimizing process parameters, they do not optimize many process parameters at a time because of the challenge in the area. Many authors while optimizing only utilize at most three inputs and two outputs. It is only in a study that the authors discovered a work that optimized six outputs and five inputs. These variations in the number of outputs and input parameters tackled also reveal the differences in the degrees of intensity and tacking of the parameters and outcomes. Furthermore, a summary of studies is presented in Table 1.

2.8 Observations and gaps in the literature

With the conduct of the literature review, some observations and research gaps that are revealed are as follows:

1. The principal perspectives of literature discussion have been five, notably the articles that address optimal process parameters, those that examine the effect of factors on machining results and articles that introduces modeling and simulation in machining processes. Others are articles that tackle the enhancement of machining procedures and articles that assess the quality of thermally-drilled products.
2. Within the group of articles that address the influence of process parameters on outputs, which the present paper fits in, most papers are limited to the treatment of two or three input parameters and at most two output parameters. None, except El-Bahloul et al. (2018) has considered up to five inputs and six outputs for the process being studied.
3. For outputs, surface roughness appears to be the commonest output chosen by researchers while other outputs such as axial force, thread length, screw coupling indicator, and drill surface temperature are less common.
4. The recent trend in machining is to tackle difficult-to-machine materials such as

Inconel 718, Ti-6Al-4V and AISI 204 stainless steel. This is meant to create a real technological breakthrough because of the bias of contemporary manufacturers that prefer difficult to machine materials to others given their outstanding properties of elevated strength and corrosive confrontation.

5. A broad array of materials have been studied by authors, including aluminum alloys (2024, 6082, 7075), stainless steel (AISI 304), brass, dual-phase steel, and magnesium alloys (AZ31B) and galvanized steel.
6. Many studies have taken the experimental approach while several others have adopted the modeling and simulation perspectives. In the latter group, software such as ANSYS has been useful as a tool. In modeling, prediction of outputs has been pursued with model validation often pursued.
7. Optimization of process parameters has often been approached using the Taguchi method. However, no study was located to have combined prioritization with the Taguchi method i.e. Pareto analysis has been completely omitted in studies on thermal friction drilling. Considering the research gap earlier indicated, it is clear that incomplete efforts were invested in the optimization of process parameters while machining the AISI 304 stainless steel. Further, extremely little effort, if any, was found in the concurrent usage of prioritization and optimization while processing the AISI 304 steel in thermal drilling. Moreover, no effort was found to further improve the performance of the results by further reintroducing grey wolf analysis and desirability function analysis into the integrated optimization and prioritization structure of the Taguchi method and Pareto analysis.

Table 1. Summarised studies on the thermal friction drilling problem

S/No	Author & year	Focus of study	Materials studied	Parameters (input)	Responses (output)	Adopted methods	Observations/Results
1	El-Bahloul *et al.* (2018)	Optimizing process parameters	AISI 304 Stainless steel	-Tool Diameter -Friction angle -Friction contact area ratio -Feed rate -Rotational Speed	-Axial force -Bushing length	-Design of experiment method -Fuzzy logic -Anova	-Optimal process parameters obtained -Regression analysis used to predict BL and AF -Experimental results of AF are compared to model
2	Dehghan*et al*. (2021)	Optimizing process parameters	Difficult to machine materials -AISI304 -Ti-6Al-4V -Inconel718	Spindle Speed Feed rate	Thread length Screw coupling	Full factorial method ANOVA	Spindle speed is a more significant parameter than feed rate in affecting machining and drilling tool performance Optimum parameters combination for AISI304 is obtained
3	Kumar and Hynes (2020)	Optimizing process parameters Modeling/Simulation and software investigations of the machining process	Galvanized steel	Spindle Speed Angle of tool Workpiece thickness	Surface Roughness	Genetic Algorithm Taguchi Integrated ANFIS and GA	The effect of spindle speed and angle of the tool on surface roughness is significant. ANFIS model is developed for the prediction of surface roughness The predicted results give rise to an objective function that is minimized and optimal values are obtained Model is validated

Table 1. (cont'd) Summarised studies on the thermal friction drilling problem

S/No	Author & year	Focus of study	Materials studied	Parameters (input)	Responses (output)	Adopted methods	Observations/Results
4	Kumar et al. (2019)	Optimizing process parameters	Galvanized Steel Thermal drilling tool: (M2 steel)	Geometry angles Rotational Speed	Roundness Error Surface Roughness	Grey Fuzzy logic	Contribution of each parameter discovered Multi-Objective optimization carried out
5	Bilgin (2021)	Effects of process factors on machining results	AA7075-T6 aluminum alloy	Feed rate	Thrust Force Temperature Hole bushing profile		-The drilling environment directly affects the formation of heat and thrust forces during the process -The main damage mechanism occurred in the transition zone from the heat-affected zone to the base material
6	Karabulut and Bilgin (2021)	Effects of process factors on machining results	AA7075-T6 and AZ31B alloys	Dry and cutting oil mixtures	Thrust Force Temperature Hole Surface quality Bushing Profile Thread stripping strength	`	This study investigates the friction drilling behaviors of AA7075-T6 aluminum and AZ31B magnesium alloys containing ceramic powders of B4C, SiC, and Al_2O_3 under dry and minimum quantity lubrication **(**MQL)
7	Bonnet et al. (2020)	Effects of process factors on machining results	Titanium TiAl6V4 alloy				Effect of sliding velocity and contact pressure on titanium discovered Friction at the drill's rake /flank faces and on its margins are compared
8	Lee et al. (2009)	Effects of process factors on machining results	austenitic stainless steel Tool: Uncoated PVD AlCrN TiAlN coated tungsten carbide tools		Drill Surface temp Tool wear Axial thrust force		Effects of the coating and uncoating of the tools are examined under different spindle speeds and discovered.
9	Miller et al (2006)	Effects of process factors on machining results	cast-aluminum magnesium alloys	Spindle Speed Workpiece Temperature Feed rate	Thrust Force Torque Bushing shape		The dependence of the outputs on the given inputs was discovered
10	Dehghan et al. (2020)	Modeling/Simulation and software investigations of the machining process	Difficult to Machine materials: AISI304 Ti-6Al-4 V Inconel718 Tool: WC		Surface Quality Thrust Force		Thermo mechanical modeling of friction drilling on the given materials Values are compared to experimentally obtained values
11	Zhang et al (2022)	Modeling/Simulation and software investigations of the machining process	AA7075-T6	The temperature at the contact interface between the rivet and workpiece.			The relationship between the coefficient of friction at the contact interface between the rivet and workpiece and temperature was developed from the analytical model Prediction of penetration force and torque during flow drilling was achieved Model was validated

Table 1. (cont'd) Summarised studies on the thermal friction drilling problem

S/No	Author & year	Focus of study	Materials studied	Parameters (input)	Responses (output)	Adopted methods	Observations/Results
12	Hynes et al. (2018)	Modeling/Simulation and software investigations of the machining process	Cu_2C		Torque Thrust Force Temperature distribution		Modeling and simulation of the material flow and temperature distribution during friction drilling Numerical analysis of the quality of bush formation in Cu_2C Prediction of Torque, thrust force, temperature distribution
13	Shalamov et al (2016)	Modeling/Simulation and software investigations of the machining process					The mechanism of flanging formation by the rotating punch is considered The process is simulated using the ANSYS software
14	Baraheni et al (2021)	Enhancement of machining procedure	aerospace aluminum alloy (AA7075)	Rotational Speed Feed rate	Axial Force Surface Roughness	Finite Element method	Application of ultrasonic vibration on the tool to assist friction drilling Lower Axial Forces occurred in ultrasonic-assisted friction drilling
15	Alphonse et al. (2021)	Enhancement of machining procedure Effects of process factors on machining results	AZ31B magnesium alloy Tool: Nitrided, liquid Nitrided& PVD TiN coated H13-D2		Surface Roughness Time consumed during friction drilling	Response Surface Methodology ANOVA	An optimized coated tool was obtained PVD Titanium Nitrided H13-D2 tool was observed to be the best for machining the AZ31B alloy
16	Chow et al. (2008)	Enhancement of machining procedure Optimizing process parameters	AISI 304 stainless steel	Drill shape Friction angle Friction contact area ratio Feed rate Drilling Speed	Surface Roughness	Taguchi	A new type of thermal friction drill with a sintered carbide was developed Optimal Process parameters were arrived at The performance of the friction drill was compared to the tungsten carbide twist drill and the friction drill had a better performance
17	Wu et al. (2021)	Accessing quality of thermal drilled products	aluminum alloy				Friction drilling followed by thread-forming gave peak loads 35% higher than conventionally drilled and tapped holes. Hardness also increased in the parent material.
18	Kamble et al (2021)	Effects of process factors on machining results	Al 6082 workpiece Tool: high-speed steel M2	Spindle Speed Work Piece Temperature Feed rate	Torque	Dimensional Analysis Buckingham pi theorem	Attempts to find parameters influencing friction drilling process using dimensionless parameters Parameters of friction drilling are optimized by dimensional analysis

Table 1. (cont'd) Summarised studies on the thermal friction drilling problem

S/No	Author & year	Focus of study	Materials studied	Parameters (input)	Responses (output)	Adopted methods	Observations/Results
19	Pereira et al.	Accessing the quality of thermal drilled products	dual-phase steel	-	-	-	The surface quality obtained in friction drilling is more appropriate. It also presents an ecologic improvement. It is presented as a solution that improves the current drilling processes of metal sheets
20	Shalamov et al (2021)	Accessing the quality of thermal drilled products	-	-	-	-	Proposes thermal drilling as a technologically advanced solution to increasing the length of unscrewing as opposed to sheet bending, welding of bushings and nuts and stamping in closed and open dies.
21	Eliseey et al (2017)	Accessing the quality of thermal drilled products	2024 aluminum alloy	-	-	-	The thermal drilling carried out on the aluminum led to the increase in the microhardness of the recrystallized material.
22	Boopathi et al (2013)	Accessing the quality of thermal drilled products	Brass, Aluminum and Stainless Steel Tool: Conical Tungsten Carbide	Spindle Speed Feed rate	Thrust Force	-	Thrust forces showed gradual increment for the increase in feed rates.

3. METHODS

This study aims at performing an in-depth analysis of the thermal friction drilling of AISI 304 stainless steel. The current trend and the quantity of energy utilized in the drilling industry have been unprecedentedly high but the industry cannot maintain high energy costs but opt for cheaper alternative sources through effective thermal management techniques. Consequently, there is an urgent need for the drilling industry to adopt optimization techniques as a survival strategy and Taguchi-Pareto, grey wolf analysis has become the major player in the optimization routes within the drilling industry while the desirability function analysis has remained an integral function for the optimization success. The Taguchi-Pareto-grey wolf analyzer desirability function analysis method brings several computational benefits to the drilling industry and this article will examine the benefits comprehensively by deploying the method on experimental data. Thus, it is essential to analyze the performance of each composite method of the system in a stepwise manner. Consequently, this section presents some details on the approach adopted in this article in a stage-wise manner.

3.1 Signal-to-noise ratio criterion selection and normalization

Furthermore, in this paper, the criteria for the signal-to-noise ratio have been stated in terms of lower the better criterion, and the higher the better criterion, respectively, in Equations (1) and (2) while the normalization equation is stated in Equation (3).

$$\text{S/N} = -10 \log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \qquad (1)$$

$$\text{S/N} = -10 \log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} \frac{1}{y_i^2}\right) \qquad (2)$$

$$\text{S/N} = -10 \log_{10} y_i^2 / s^2 \qquad (3)$$

where y_i associates with the performance attribute of the i^{th} observed value; n is the experimental trial number; s^2 is the variance of the observations

Next is the consideration for normalization. Normalization here simply means converting all the values of signal to noise ratios to be between 0 and 1 since they have different ranges above 0 and 1. This is shown in Equation (4)

$$N\eta_p = \frac{\left(\frac{S}{N}\right)_p - \left(\frac{S}{N}\right)_{\min}}{\left(\frac{S}{N}\right)_{\max} - \left(\frac{S}{N}\right)_{\min}} \quad (4)$$

where
$(S/N)_p$ is the value of S/N for each experimental number denoted by p
$(S/N)_{max}$ is the maximum value of S/N for all experiments
$(S/N)_{min}$ is the minimum value of S/N for all experiments

3.2 Procedure involved in obtaining the Taguchi-Pareto method

In the earlier parts of this article, it was argued that the introduction of the Taguchi-Pareto method to solving the thermal friction drilling problem will be beneficial to the process and that the process engineer will concentrate on a fewer number of experimental trials generated from the orthogonal array based on the 80-20 rule of Pareto analysis. Since this is the first platform developed in this article, using the Taguchi-Pareto method, it is essential to detail the steps for its adoption in the thermal friction drilling process. Although the term Taguchi-Pareto method was coined in the composite development article by Ajibade et al. (2019), however, before this event, researchers utilized the Taguchi method complemented by the analysis of variance (ANOVA) method. In researchers' opinion, the combination of the Taguchi method and ANOVA yielded the capturing of factors that are significant or not to the process being examined. While this approach is feasible in application to the thermal friction drilling process, however, no emphasis has been placed on reducing the attention of the process engineer to the vital process parameters, either from the input perspective or the output consideration. Thus, for the Taguchi method-ANOVA analysis, no connection has been made to the 80-20 rule of the Pareto scheme. Thus, the Taguchi-Pareto method pronounced in Ajibade et al. (2019), which is often extended to the experimental trials generated from the combination of thermal friction drilling factors and the number of levels associated with the factors. These are often generated from the orthogonal array (matrix) of the thermal friction drilling process. Thus, the procedure in the article by Ajibade et al. (2019) is adopted for the statistical analysis of the thermal drilling process by the Taguchi-Pareto method as follows.

Step 1. Obtain the factor and level table based on the experience of the decision-maker in extracting significant factors from the process and the understanding of how to segment different parametric values into ranges.

Step 2. Develop the orthogonal array based on the combination of the highest numbers of factors and levels in the problem formulated. The Minitab 18 (2020) may be a useful tool to generate the orthogonal array.

Step 3. Compute the signal-to-noise ratio. Usually, the first step is to determine what criterion or combination of criteria to utilize based on the decision maker's knowledge of what is desired about the parameters. For some parameters, minimization is desired. However, for others, maximization is desired. If a sole criterion is chosen, then the signal-to-noise ratio becomes the sole input into the renting stage of the computation. However, if conflicting criteria are used such as nominal-the-best in one instance, smaller-the-best in another and larger-the-better in another instance, each signal-to-noise ratio set is determined and an aggregate is obtained as input to the next stage of computation.

Step 4. Sort out the data from the largest to the smallest according to an input or output at a time. Usually, after computing the signal-to-noise ratio, the distribution of the values is varied and not sequential. However, an effort is made to rearrange with a decreasing value of the signal-to-noise ratio in perspective. It thus implies that the order of the experimental trial may be disorganized as it is guided by the values of the highest signal-to-noise ratio to the lowest.

Step 5. Obtain the sum of the normalized S/N ratios for the first input or output being considered.

Step 6. Obtain the cumulative of the first input or output then to the last in another column.

Step 7. Obtain the percentage cumulative for each of the input or output as desired in another column.

Step 8. Choose the values that fall between 0% and 80% of the data

Step 9. Apply the same procedure to other inputs, or outputs as desired.

3.3 Development of empirical models

The following steps are essential for the development of empirical models

Step 1. Insert the input table into the workspace of the spreadsheet (i.e. Minitab).

Step 2. Activate the regression module of the Minitab software

Step 3. Activate the responses that are to be used for the empirical model

Step 4. Generate the normal plot of residuals for the first output.

3.4 Procedure for grey wolf optimization (Ghalambaz et al., 2021)

The following are the standard steps used to solve problems formulated as a grey wolf optimization problem (Ghalambaz et al., 2021).

Step 1. Formulate the linear program for the problem. In the present circumstance, six mathematical programs were formed as follows:

Now consider the outputs, by addressing AF, the objective function formulated is a minimization problem, stated as

Objective 1:

Minimize AF = 1.3693+0.01313d – 0.00372â-0.00210FCAR-0.3009+0.000329FR + 0.000024RS

Subject to:

$5.4 \leq d \leq 9.2$ (5)

$30° \leq â \leq 60°$ (6)

$50\% \leq FCAR \leq 100\%$ (7)

$1 \leq t \leq 3$ (8)

$60 \leq FR \leq 140$ (9)

$1500 \leq RS \leq 3500$ (10)

Objective 2:

Minimize RF = 1.806-0.0860d +0.0023â + 0.00074FCAR -0.1707t – 0.00309FR – 0.000040RS

Subject to:

$5.4 \leq d \leq 9.2$

$30° \leq â \leq 60°$

$50\% \leq FCAR \leq 100\%$

$1 \leq t \leq 3$

$60 \leq FR \leq 140$

$1500 \leq RS \leq 3500$

Objective 3:

Minimize DE = 1.505-0.0730d-0.0051â + 0.00025FCAR – 0.090t – 0.00402FR + 0.000116RS

Subject to:

$5.4 \leq d \leq 9.2$

$30° \leq â \leq 60°$

$50\% \leq FCAR \leq 100\%$

$1 \leq t \leq 3$

$60 \leq FR \leq 140$

$1500 \leq RS \leq 3500$

Objective 4:

Minimize RE = 0.978-0.1405D + 0.01184â + 0.00616FCAR – 0.3735t + 0.00116FR – 0.000053RS

Subject to:

$5.4 \leq d \leq 9.2$

$30° \leq â \leq 60°$

$50\% \leq FCAR \leq 100\%$

$1 \leq t \leq 3$

$60 \leq FR \leq 140$

$1500 \leq RS \leq 3500$

Objective 5:

Maximize BL = -0.2265 + 0.08978d - 0.000458â – 0.001613FCAR + 0.21064t – 0.001149FR

Subject to:

$5.4 \leq d \leq 9.2$

$30° \leq â \leq 60°$

$50\% \leq$ FCAR $\leq 100\%$
$1 \leq t \leq 3$
$60 \leq$ FR ≤ 140
$1500 \leq$ RS ≤ 3500

Step 2. Random initialization of grey wolf population: Here the inputs are generated randomly using the following Equation (11)

$x = L + r\,(U - L)$ (11a)

where *L* is the lower boundary, *U* is the upper boundary and *r* is the random number between 0 and 1.

Here, the C++ used in the coding exercise to solve this problem has a way of generating random numbers very efficiently such that if the same procedure is repeated, different random numbers will be obtained at every stage. Consequently, Equation (11a) is the formula for randomly initializing the matrices for the optimization problem. Interestingly, this same Equation (11a), which is used in the grey wolf optimization method has been adopted in other optimization methods such as the artificial bee colony method and the Cuckoo search method, which announces its reliability as a random initializing matrix generator. Consequently, Equation (11a) was used to generate the 1st wolf which consists of seven elements, six of which are the input elements of d, â, FCAR, t, FR and RS while the last element is for the output, which is AF as the first case considered.

Step 3. Find the best $X_á$, second-best $X_â$ and third-best X_γ positions.

Step 3 is summarily about finding the third-best positions and specifying items for the next operation. The choice of the positions depends on the objective function formulated as either a minimization or maximization problem. However, since the objective function developed for the first wolf being considered is to minimize the axial force, the best position obtained by the wolf will be that with the smallest axial force signal-to-noise ratio. Then the second best will be the second smallest signal-to-noise value and the third-best will be the wolf with the third smallest axial force signal-to-noise ratio.

Step 4. Step 4: Find X_1, X_2 and X_3

Some parameters are obtained in the iteration process make use of Equation (11b):

$$a = 2\left(\frac{iteration}{\max imum\ iteration}\right) \quad (11b)$$

Iteration = 1, Maximum iteration = 200 while a gives 1.99

Furthermore, the computations of X_1, X_2, and X_3 depend on several GWO-defined parameters, including a, A_i, C_i, $D_á$, $D_â$ and D_r, $X_á$, $X_â$ and X_r, X (*t*) and r. While these parameters are commonly used by GWO researchers, their nomenclatures are yet to be identified by the present authors as they are defined by their letter representations in the present study. In this article, a parameter has been defined in the section on methods, likewise other parameters.

For X_1,

$$A_1 = 2a.r - a \quad (12)$$

$$C_1 = 2.r \quad (13)$$

$$D_\alpha = | C_1 X_\alpha - X(t) | \quad (14)$$

$$X_1 = X_\alpha - A_1 D_\alpha \quad (15)$$

For X_2,

$$A_2 = 2a.r - a \quad (16)$$

$$C_2 = 2.r \quad (17)$$

$$D_\beta = | C_2 X_\alpha - X(t) | \quad (18)$$

$$X_2 = X_\beta - A_2 D_\beta \quad (19)$$

For X_3,

$$A_3 = 2a.r - a \quad (20)$$

$$C_3 = 2.r \quad (21)$$

$$D_\gamma = | C_3 X_\alpha - X(t) | \quad (22)$$

$$X_3 = X_\gamma - A_3 D_\gamma \quad (23)$$

Step 5. Step 5: Find X_{new}

The GWO procedure at this stage states the X_{new} should be obtained by finding average of X_1, X_2 and X_3.

4. RESULTS AND DISCUSSION

This section reports on the analysis and interpretations of the thermal function drilling problem considered in the present article. The first step in this section is a list of the output parameters regarding the formulated objectives for the mathematical equations. Primarily, five output parameters, adopted from the experimental data of El-Bahloul et al. (2018) are used. All the outputs except bushing length were minimized, including the hole diameters dimensional error (DE), axial force, roundness error (RE) and radial force (RF). It is through that minimizing most of these outputs will yield the optimal machining performance. However, the bushing length should be maximized. Furthermore, the process parameters considered are six, namely the feed rate (FR), friction contact area ratio (FCAR), workpiece thickness (T), rotational speed (RS), and tool cylindrical region diameters (D) and Frictional angle (B). Besides, to implement the mathematics that supports the Taguchi method, an orthogonal array, which presents a table with entries from a present finite symbol set (i.e.1,2,3…q) organized to reveal the strength of the orthogonal matrix. The term levels "defies this strength of the orthogonal matrix. In the article by El-Bahloul et al. (2018) whose experimental data is used in the present work, levels are fixed at three (Table 2) and this form the foundation of the analysis presented in this section.

Table 2. Process parameters for the thermal friction drilling problem in three levels (El-Bhaloul et al., 2018)

Process parameter	Unit	Level 1	Level 2	Level 3
d	Mm	5.4	7.3	9.2
β	degree	30°	45°	60°
FCAR	-	50 %	75 %	100 %
T	Mm	1	2	3
RS	Rpm	1500	2500	3500
FR	mm/min	60	100	140

The orthogonal array has been conducted and an L18 has been used, which was adopted from El-Bhaloul et al. (2019). Since they have experimented with L18, it is logical to adopt the data from El-Bhaloul et al. (2019). But this is done only for the inputs in the paper while it was not done for the outputs. Table 3 shows the process parameters for the experiments carried out in eighteen trials.

Table 3. Process parameters developed by Taguchi and experimental S/N ratios obtained at each stage of the experiment (see El-Bhaloul et al., 2018)

S/No.	d (mm)	β°	FCAR (%)	t (mm)	FR (mm/min)	RS (rpm)	AF	RF	DE	RE	BL
1	5.4	30	50	1	60	2500	1.00	1.00	1.00	0.43	0.22
2	5.4	30	75	3	140	1500	*	*	*	*	*
3	5.4	45	50	2	100	1500	0.37	0.47	0.39	0.37	0.47
4	5.4	45	100	1	140	3500	0.89	0.73	0.60	1.00	0.00
5	5.4	60	75	2	60	3500	0.57	0.46	0.28	0.24	0.48
6	5.4	60	100	3	100	2500	0.05	0.03	0.19	0.4	0.6
7	7.3	30	100	1	100	1500	0.93	0.79	0.49	0.57	0.22
8	7.3	30	100	2	60	3500	0.64	0.69	0.19	0.05	0.62
9	7.3	45	50	3	140	3500	0.24	0.38	0.34	0.24	0.81
10	7.3	45	75	2	100	2500	0.48	0.55	0.54	0.21	0.60
11	7.3	60	50	3	60	1500	*	*	*	*	*
12	7.3	60	75	1	140	2500	0.88	0.73	0.44	0.76	0.16
13	9.2	30	50	2	140	2500	0.51	0.33	0.34	0.07	0.78
14	9.2	30	75	3	100	3500	0.39	0.00	0.00	0.00	1.00
15	9.2	45	75	1	60	1500	0.91	0.73	0.24	0.32	0.33
16	9.2	45	100	3	60	2500	0.00	0.23	0.03	0.09	0.99
17	9.2	60	50	1	100	3500	0.99	0.56	0.37	0.26	0.45
18	9.2	60	100	2	140	1500	*	*	*	*	*

With inputs on the first half of the table to the left while the outputs are expressed on the second half of the table to the right. However, on observing the table, experimental trials 2, 11 and 18 are having no figures for the outputs. This is because, at this point, the experiment, failed because they performed under the lowest rotational and high workpiece thickness, which are not described in the study for instance, at experimental trial 2, the thickness is 3mm and the rotational speed is 1,500 rpm, which is undesirable. The scene weakness is attributed to experimental trials 11 and 18. At those points, the tungsten carbide broke the workpiece as they performed under the lowest rotational speed and high workpiece thickness. However, the Taguchi Pareto method was implemented for all the outputs. The procedure adopted is to take an output i.e. (AF) combine it with the parameters of the price (inputs) then obtain the cumulative AF and the percentage commutative AF. However, before any other step, the values of the AF are arranged from the highest to the lowest and the percentage cumulative AF is obtained. Then the cut-off of 80% is set according to the Taguchi Pareto principle of 80–20 rule. The same procedure was adopted for all the outputs. The next step is to form empirical models based on the experimental trials 1 to 18 that provide the data for this development. The empirical models were formed one by one by placing the corresponding output side by side of the inputs. Then the regression function in Minitab 18 (2020) is used from the empirical models for each of outputs RF, DE RE, and BK. Next is the validation of the empirical model to assess the degree of errors present while predicting them. If the empirical models are not accurate, it will not be useful to rely on them for predictive purposes.

4.1 Implementing the Taguchi Pareto method

In this section, the principle of Taguchi-Pareto of obtaining 80% of the experimental data (from experimental trials) is applied in the study and this is complemented by eliminating 20% of the data, which is least relevant to the study. This implies that for the output parameters that are minimized, the largest values of the normalized S/N ratio will be discarded to attain the more accurate results (Table 4). However, to explain the procedure developed in Table 4, the following are considered important. The data used is extracted from the literature being the Experimental trial of L18 generated by El-Bahloul et al. (2018) and adopted in the present study. Here, the first column indicates the experimental trial number while the 2nd to the 7th column represents the process parameters considered. Different from the source table, the first output, AF, is brought in as the 8th column to be associated with each of the six process parameters earlier defined. But for each of the experimental trials, the value of AF staggers from 0 to 1. Thus, another column is created (9th column) to sum up the cumulative frequency, which is later transferred into the percentage cumulative frequency (10th column). Notwithstanding, consider experimental trial 1, under the AF (cumulative), a value of 1 is assigned. For experimental trial 2, the value under the AF (cumulative) changes to 1.99 and consequently similar computations are done until the value of 8.85 is obtained for the 15th experimental trial. Then, the next column depends of the 9th column and the cumulative (percentage) is obtained, which starts from 11% to 100% at the 15th experimental trial. Furthermore, similar computations are made for the outputs RF, DE, RE and BL. These results are summarized in Table 4. From Tables 4, it is understood that (1) the cut-off mark is 77% where experimental trials 1 to 8 are within the captured area. Furthermore, the cut off mark for RF is 75% where experimental trials 1 to 8 are captured. For the output DE, the cut-off is 77%, capturing experimental trials 1 to 8 only. For RE, the cut-off is 77% where the experimental trials 1 to 7 are captured. Finally, for the BL, 76% is the cut-off where experimental trials 1 to 8 are captured.

Table 4. Pareto implementation for a table with process parameters and AF, RF, DE, RE and BL

Exp. No.	D	β	FCAR	t	FR	RS	AF	Cum AF	% Cum (AF)	% Cum (RF)	% Cum (DE)	% Cum (RE)	% Cum (BL)
1	5.4	30	50	1	60	2500	1.00	1.00	11%	13%	18%	20%	13%
2	9.2	60	50	1	100	3500	0.99	1.99	22%	23%	29%	35%	26%
3	7.3	30	100	1	100	1500	0.93	2.92	33%	33%	39%	47%	36%
4	9.2	45	75	1	60	1500	0.91	3.83	43%	42%	48%	55%	46%
5	5.4	45	100	1	140	3500	0.89	4.72	53%	52%	56%	63%	54%
6	7.3	60	75	1	140	2500	0.88	5.60	63%	61%	64%	70%	62%
7	7.3	30	100	2	60	3500	0.64	6.24	71%	68%	70%	77%	70%
8	5.4	60	75	2	60	3500	0.57	6.81	77%	75%	77%	82%	76%
9	9.2	30	50	2	140	2500	0.51	7.32	83%	81%	83%	87%	82%
10	7.3	45	75	2	100	2500	0.48	7.80	88%	87%	88%	92%	88%
11	9.2	30	75	3	100	3500	0.39	8.19	93%	92%	92%	96%	92%
12	5.4	45	50	2	100	1500	0.37	8.56	97%	97%	96%	98%	95%
13	7.3	45	50	3	140	3500	0.24	8.80	99%	100%	99%	99%	98%
14	5.4	60	100	3	100	2500	0.05	8.85	100%	100%	100%	100%	100%
15	9.2	45	100	3	60	2500	0.00	8.85	100%	100%	100%	100%	100%
							8.85						

Key: Units of factor are as follows: d (mm), β (degree), FCAR (%), t (mm), FR (mm/min), RS (rpm)

4.2 Implementing the grey wolf optimization algorithm

Step 1: Formulate the linear program for the problem

To proceed with the problem formulation, the constraint Equations (5) to (10) are recalled where the upper and lower boundaries of the process parameters for the thermal friction drilling problem are specified and represented by mathematical symbols. , since each parameter will have a mathematical representation, there will be six representations in all, represented as X_1, X_2, X_4, X_5, and X_6 for d, β, FCAR, t, FR and RS, respectively. To proceed, consider the first parameter, d, which means the tool's cylindrical region diameter. The second column of Table 4 is noted where variations of the d values are given. Based on this, the lowest and highest values are 5.4mm and 9.2mm, respectively, which are set as the lower and upper boundary of d, represented as X_1. Similarly, for each of β, the lowest and highest values are 300 and 600, respectively, represented by X_2. For FCAR, 50%, and 100% are the respective lower and upper bounds of the problem symbolized as X_3. The X_4 is the symbol for β whose lower and upper boundaries are 1 and 3, respectively. The X_5 is the symbol for FR whose lower and upper boundaries are 60 and 140, respectively. Finally, the X_5 is the symbol for RS whose lower and upper boundaries are 1500 and 3500, respectively. In this case, since six inputs are considered, this number is equal to the population size of wolves, which is six. However, based on experience, the number of iterations to run is set at 200.

Step 2: Random initialization of grey wolf population

Furthermore, having defined the problem, the first step is the randomization of the initialization of the grey wolf population. In this work, each set of data containing values of process parameters with the upper and lower boundaries is referred to as a wolf. This, a matrix of 6 wolves (Table 5) comprising several values between the boundaries of all input parameters is randomly generated.

Table 5. Optimal process parameters required to obtain minimum AF

Wolf identity	d (mm)	β (degree)	FCAR (%)	t (mm)	FR (mm/min)	RS (rpm)	AF
Wolf 1	7.63	57.7	74.34	2.26	104.88	2745.52	0.4506
Wolf 2	7.53	53.9	59.80	1.82	124.42	1825.02	0.5967
Wolf 3	9.19	50.7	88.21	1.73	119.88	2515.23	0.6151
Wolf 4	7.69	44.2	54.74	2.84	113.02	2323.51	0.3543
Wolf 5	8.58	37.5	65.58	2.20	115.59	3334.28	0.5843
Wolf 6	5.67	49.4	91.53	2.96	107.83	2560.95	0.2029

For the first wolf, which is considered to be the first row in Table 5, each of the new values for the parameters is calculated as follows. Consider the first parameter β . Suppose from the random number table, which is obtainable from internet searches, a value of 0.0528 is obtained. This value will be introduced into Equation (11) as r. However, notice that all other terms on the right-hand side of Equation (11) are known, where L is 5.4, and U is 9.2. Thus, by substituting these values into Equation (11), the value of 7.6315 should be obtained. Nonetheless, the above random number is used as an example and may not be the one used in the initial computation. Furthermore, only a parameter of the first wolf has been predicted. But other parameters such as β, FCAR, t, FR, RS and AF need to be predicted. Thus, by following the procedure adopted for the prediction of d for the first wolf, other parameters are predicted as 57.7075, 74.3355, 2.25828, 104.884 and 2745.52 for the respective parameters of β, FCAR, t, FR, and RS. However, it should be noted that the values obtained are within the lower and upper boundaries of each parameter, as observed previously. By following the procedure used for the first wolf, predictions for the subsequent wolves such as the second, third, fourth fifth and sixth are made (Table 6).

Table 6. Predicted outputs using the empirical models

	Input						Outputs				
S/N	d (mm)	β°	FCAR (%)	t (mm)	FR (mm/min)	RS (rpm)	AF	RF	DE	RE	BL
1	5.4	30	50	1	60	2500	1.0024	0.9915	0.9291	0.4461	0.3156
2	5.4	30	75	3	140	1500	0.3505	0.4614	0.3178	-0.0011	0.6007
3	5.4	45	50	2	100	1500	0.6349	0.7717	0.4858	0.3496	0.4694
4	5.4	45	100	1	140	3500	0.8920	0.7758	0.6595	0.9715	0.1402
5	5.4	60	75	2	60	3500	0.5614	0.8683	0.8084	0.5288	0.4762
6	5.4	60	100	3	100	2500	0.1972	0.6325	0.4478	0.4087	0.5966
7	7.3	30	100	1	100	1500	0.9116	0.7815	0.5261	0.5866	0.3556
8	7.3	30	100	2	60	3500	0.6455	0.6544	0.8289	0.0607	0.6202
9	7.3	45	50	3	140	3500	0.4201	0.2340	0.3283	-0.3505	0.8127
10	7.3	45	75	2	100	2500	0.6313	0.5868	0.4694	0.1837	0.6037
11	7.3	60	50	3	60	1500	0.2900	0.5957	0.3414	-0.1597	0.8897
12	7.3	60	75	1	140	2500	0.8896	0.6684	0.3221	0.7812	0.3402
13	9.2	30	50	2	140	2500	0.7778	0.2468	0.2401	-0.3685	0.7755
14	9.2	30	75	3	100	3500	0.4352	0.1782	0.4332	-0.6874	0.9958
15	9.2	45	75	1	60	1500	0.9200	0.7577	0.4655	0.2968	0.6056
16	9.2	45	100	3	60	2500	0.2897	0.3948	0.4077	-0.3492	0.9905
17	9.2	60	50	1	100	3500	0.9779	0.5701	0.4539	0.2608	0.6011
18	9.2	60	100	2	140	1500	0.5372	0.3928	-0.0164	0.3477	0.6771

Step 3: Find the best X_α, second-best X_β and third-best X_γ positions.

Recall that the first output is considered and the objective is to minimize AF, the best position will be the wolf with the smallest AF S/N ratio, the second best will be the wolf with the second smallest S/N value and the third-best will be the wolf with the third smallest AF S/N ratio.

Step 4: Find X_1, X_2 and X_3 are implemented
Step 5: Find X_{new} is also implemented

4.3 Forming empirical models with Minitab 18

The grey wolf optimization is commonly used to solve single-objective optimization problems. This implies that it can be used to optimize only one output at a time. But despite this limitation, the grey wolf optimization technique is easy and accurate in predictions, which are attributes that make the present author retain the method to solve the thermal friction welding problem. Thus, to overcome the weakness of the grey wolf optimizer, the desirability function analysis (DFA) is implemented. Notwithstanding, before the implementation of the grey wolf optimization procedure empirical models are to be formed for each output. This will eventually serve as the objective function and could be utilized to optimize the process parameters to yield the choice output (minimum, maximum or nominal). However, by following the steps discussed in the section on methods, empirical models in Equations (1) to (5) are formed, corresponding to each of the outputs AF, RF, DE, RE and BL.

$$AF = 1.3693 + 0.01313\, d - 0.00372\, \beta - 0.00210\, FCAR - 0.3009\, t + 0.000329\, FR + 0.000024\, RS \quad (24)$$

$$RF = 1.806 - 0.0860\, d + 0.0023\, \beta + 0.00074\, FCAR - 0.1707\, t - 0.00309\, FR - 0.000040\, RS \quad (25)$$

$$DE = 1.505 - 0.0730\ d - 0.0051\ \beta + 0.00025\ FCAR - 0.090\ t - 0.00402\ FR + 0.000116\ RS \quad (26)$$

$$RE = 0.978 - 0.1405\ d + 0.01184\ \beta + 0.00616\ FCAR - 0.3735\ t + 0.00116\ FR - 0.000053\ RS \quad (27)$$

$$BL = -0.2265 + 0.08978\ d - 0.000458\ \beta - 0.001613\ FCAR + 0.21064\ t - 0.001149\ FR + 0.000004\ RS \quad (28)$$

Equations (24) to (27) are those with which the various input parameters may be substituted to obtain predicted outputs. To illustrate how these equations work, consider Equation (24) where the output is AF and the various inputs related to this output are d, β, FCAR, t, FR and RS. Recall that to implement the Taguchi-Pareto method, the most important data terminates at 77% (Table 6) where the cut-off is the experimental trial 8. This implies that to obtain the predicted AF for the experimental data of 1, each of the inputs need to be substituted into the empirical model in Equation (24). To do this, experimental trial 1 is of interest to the decision-maker. Here, drawing from Equation (24), the known values of the parameters are introduced and multiplied by the parameters, which yield the values to be summed up. In this instance, d is 5.4, which should be multiplied by its coefficient of 0.01313. Likewise, the value of β as 30 is multiplied by 0.0023, the value of t = 1 is multiplied by 0.3009, and the value of FCAR as 50 is multiplied by 0.00210. Furthermore, the value of FR = 60 is multiplied by 0.000329 and lastly, the value of RS = 2500 is multiplied by 0.00024. These products are summed up together with the intercept of 1.3693 in Equation (24) to yield 1.00244. This is the predicted AF while the value of 1 for the AF is the preciously quoted experimental value from the literature. Thus, for the eight experimental trials of 1 to 8 in the treated region (77%) of Taguchi-Pareto, the displayed predicted values are shown in Table 8. Similarly, for all other outputs, the summary is displayed. But having obtained these predicted output values, to what extent are the errors introduced? By answering this question, the decision-making has the information on the degree to which the predictions can be relied upon. But to answer this question, it is persuasive to utilize the MSE and MAD values, which have experienced success in the scientific field of engineering enquiry. To compute the MAD and MSE, which are mean absolute deviation and mean square error, respectively, the error is first computed, which is the difference between the experimental values and predicted values for each experimental trial. Then the absolute error and error square is computed. The MSE is the average of the squares of the error values, which yields 0.00099, 0.00119, 0.00564, 0.00035 and 0.00001, respectively, for AF, RF, DE, RE and BL. Also, the computed MAD are 0.00858, 0.02933, 0.06831, 0.01693 and 0.00289 for the respective outputs of AF, RF, DE, RE and BL (Table 7).

Table 7. MSE and MAD values were obtained for the empirical model for AF, RF, DE, RE and BL

	AF	RF	DE	RE	BL
MAD	0.00858	0.02933	0.06831	0.01693	0.00289
MSE	0.00010	0.00119	0.00564	0.00035	0.00001

Key. EV – Experimental values, PV – predicted values

However, observing the MSE data for all the predictions matched against the experimental data, the BL is the best prediction that is closest to the experimental results by displaying an MSE value of 0.00001 while the DE is the worst predicted value. For the MAD values, the best empirical model is the representation of BL, obtained at 0.002886 while the worst prediction is for DE with a MAD error of 0.06831. Now, considering the two error evaluation methods of MSE and MAD, it is conclusive that BL maintains the best predictive model while the DE is the worst predictor. It means that the predictions from BL can be rest relied upon while prediction from DE is the worst to be relied upon.

4.4 Obtaining predicted output values

It is worthy of note that in forming the empirical models, not all the combinations of process parameters were considered because some were already truncated by the Pareto operation. What is done now however is that the empirical model is used to find the predicted output S/N ratios at all the combinations of the inputs. That will mean thus that for some of the predicted values, there will be slightly more deviation from the actual values, while for those sets of process parameters that contributed to the forming of the empirical models, there will be much less deviation from the actual values obtained in the experiment. This does not imply however that the table thus obtained is inaccurate as it portrays an approximate behavior of how the output parameters respond to the combination of the input parameters at the several levels (Table 8).

Table 8. Validation of an empirical model for AF, RF, DE, RE and BL

	AF		RF		DE		RE		BL	
S/N	EV	PV	EV	PV	EV	PV	EV	PV	EV	PV
1	1	1.002442	1	0.9915	1	0.9291	1	0.9715	1	0.995781
2	0.99	0.977896	0.79	0.7815	0.6	0.6595	0.76	0.78115	0.99	0.990546
3	0.93	0.911549	0.73	0.7758	0.54	0.46935	0.57	0.58655	0.81	0.812694
4	0.91	0.920036	0.73	0.6684	0.49	0.5261	0.43	0.4461	0.78	0.775506
5	0.89	0.891962	0.73	0.7577	0.44	0.32205	0.4	0.4087	0.62	0.620194
6	0.88	0.889609	0.69	0.6544	0.39	0.4858	0.37	0.3496	0.6	0.596552
7	0.64	0.645489	0.56	0.5701	0.37	0.4539	0.32	0.2968	0.6	0.603689
8	0.57	0.561442	0.55	0.5868	0.34	0.3283	0.26	0.2608	0.48	0.476197

Key. EV – Experimental values, PV – predicted values

Step 5: Conduct the greedy selection

Greedy selection pertains to a particular optimization method that we are trying to achieve. In a situation where we are trying to achieve a minimization of a particular output, greedy selection means when one puts in the factors for the X_{new} into the objective function, if it gives an output that is lower than the current set of factors that is expected, due to greedy selection, X_{new} factors are adopted as the new ones. Thus the $_{New}$ factors replace the values of the factors that you are using. However, if the decision-maker attempts to minimize the objective function, the values of the X_{new} are inserted into the objective function. If it gives one what is higher than what one has, it means that the X_{new} is not desired. Therefore, it is not adopted. Thus, the basic idea of the greedy concept is that it only takes the X_{new} that helps it to achieve its goal. That is, it takes only the X_{new} values that will benefit it. In this situation, the previous value of the first wolf is 0.332257. However, when the X_{new} value was substituted into the objective function, a value of 0.982346 was obtained, which is greater than what we had earlier. Therefore, the value is not replaced according to greedy selection since we are trying to minimize the objective function. Thus, there is no replacement for the first wolf. However, the current population of wolves is as follows:

Wolf 1 7.6315 57.7065 74.3355 2.25828 104.884 2745.52 0.450599
Wolf 2 7.52829 53.8923 59.7995 1.82211 124.421 1825.02 0.596682
Wolf 3 9.19223 50.6778 88.2122 1.73495 119.877 2515.23 0.615107
Wolf 4 7.6852 44.2094 54.7426 2.84167 113.022 2323.51 0.35431
Wolf 5 8.58199 37.5396 65.5828 2.20109 115.593 3334.28 0.584296
Wolf 6 5.6658 49.397 91.5265 2.96039 107.831 2560.95 0.202935

Now, the same operations from step 3 to step 5 are conducted for the other wolves in the population. Consequently, after each iteration, the best values obtained will be the current X_{α} i.e. the best wolf with the smallest S/N value. These values are obtained for each of the iterations. However, at the 200th iteration, the process parameters that makeup X_{α} are adopted as the optimal process parameters of the axial force. In summary, the best values at each iteration up to 200 iterations are as follows:

Iteration 1: 0.202935, Iteration 2: 0.202935, Iteration 3: 0.202935, Iteration 4: 0.158234, Iteration 5: 0.158234, Iteration 6: 0.158234, Iteration 7: 0.158234, Iteration 8: 0.158234, Iteration 9: 0.158234, Iteration 10: 0.158234, Iteration 11: 0.141105, …, …, Iteration 190: 0.119916, Iteration 191: 0.119916, Iteration 192: 0.119916, Iteration 193: 0.119916, Iteration 194: 0.119916, Iteration 195: 0.119916, Iteration 196: 0.119916, Iteration 197: 0.119916, Iteration 198: 0.119916, Iteration 199: 0.119916, Iteration 200: 0.119916

It is observed that after the 200th iteration, the X_{α} is obtained to be: d as 8.5804, β as 59.4835, FCAR as 100, t as 3, FR as 76.3273, RS as 32.86.21 while AF gives 0.251963. Now, having computed the first output, which is AF, the same procedure is given for other outputs such as stated in objectives 2 to 5. Hence, from the above computations, as the values of the inputs are substituted into the empirical models, RF gives 0.09171116, DE is obtained as 0.0621711, RE is -0.297739 and BL gives 0.940006 (Table 9).

Table 9. Optimal process parameters required to obtain minimum AF, RF, DE, RE and BL

S/N	d (mm)	β (degree)	FCAR (%)	t (mm)	FR (mm/min)	RS (rpm)	Output
1	5.43	60.0	100.00	3.0	71.66	1614.04	AF, 0.11990
2	9.20	38.1	100.00	3.0	140.00	3500.00	RF, 0.09171
3	9.20	60.0	100.00	1.7	140.00	1953.57	DE, 0.06217
4	9.20	47.7	100.00	3.0	122.14	3500.00	RE, -0.29774
5	9.20	60.0	95.22	3.0	102.85	1962.42	BL, 0.94001

4.5 Introducing the desirability function

The next phase of the work is to apply the desirability function analysis (DFA). The DFA has the advantage of obtaining the optimal process parameters for all the outputs at once. Consequently, the DFA yield the optimal parametric setting. From this discussion, one can infer that the weakness of the grey wolf optimization (GWO) algorithm was improved upon by the DFA method. Thus, the major weakness of the GWO method overcome by introducing the DFA method is that it can optimize only one output at a time. But by introducing the DFA, method, it is possible to overcome this method as all outputs are optimized concurrently. For instance, consider the axial force and the bushing length as outputs. The GWO method can only optimize the axial force at once and then be applied to the bushing length on which it optimizes afterwards. However, in a typical situation, the decision-maker may be interested in optimizing both outputs at the same time. In other words, the main aim of the DFA method is to obtain multi-objective optimization and is one of the most widely used in the area of manufacturing. To solve the thermal friction drilling problem, three fundamental steps of the DFA method are applied. The details of the desirability function are embedded in the C++ codes and not shown here since it is an intermediate step in the whole process.

5. CONCLUSIONS

The Taguchi-Pareto method, which appears probably for the first time in 2019 (Ajibade et al., 2019) was first applied in composite development and the recent past, its application has been extended to maintenance engineering for downtime predictions. As the literature on the Taguchi-Pareto method continues to expand, a less well-established aspect concerns the capacity of the Taguchi-Pareto method to improve its performance in optimization while additional optimization methods are added. In the present study, based on the excellent success performance of the grey wolf optimization, it is introduced into the thermal friction drilling of AISI 304 stainless steel where its weakness has been complimented into the desirability functional analysis and an integrated method known as the Taguchi-Pareto-grey wolf optimization-desirability functional analysis has been formed.

In this article, the Taguchi-Pareto method was used to streamline the values generated in the system to obtain more relevant parametric measures. To achieve this result, the orthogonal array was adopted from the literature and then enhanced by using Taguchi-Pareto to obtain more relevant contributors to the experimental results using the 80-20 Pareto rule. After this, empirical models were formed, which were utilized in actualizing the grey wolf analysis that works for single-objective optimization. Consequently, for each of the outputs, optimal process parameters were arrived at using the grey wolf analysis. Then the desirability function analysis (PFA) was implemented with the advantage of obtaining the optimum process parameters for all the outputs at once. Afterwards, the optimal parametric setting was arrived at.

From the discussions in this article, it can be concluded that the thermal drilling process has been optimized from the results of the desirability function analysis displayed. Thus, the final results arrived at are as follows: diameter of 9.2 mm, the angle of 45°, the friction area ratio of 100, workpiece thickness of 3mm, feed rate of 60, and rotational speed of 2500 rpm were discovered to satisfy all the outputs and objectives optimization methods.

In this work, the major weakness of the grey wolf analysis is that it can only analyze an output parameter at a time, which is complemented with the strength of desirability function analysis with the ability to treat multiple outputs at the same time. For instance, this work tackles several outputs, including the axial force and the bushing length. So, the grey wolf optimizer could only optimize the optimal process parameter for the axial force and then the bushing length, for instance. However, in a typical scenario, the decision-maker is interested in optimizing both at the same time. It is hardly the case that the decision-maker wants to use less of the axial force at the expense of obtaining more bushing length. Thus, there is a need to consider both parameters in this case and many output parameters in general than just an output parameter. This challenge is what the desirability function analysis has overcome. Despite the weakness of the grey wolf optimizer regarding the inability to treat multiple outputs at the same time, it demonstrates strengths in accuracy and arrives at the chosen value faster as it mimics the behavior of the grey wolf. Besides, it is easy to use, making it a potentially useful tool to process engineers in practice. Also, it is an evolutionary algorithm is one of the top methods being used for drilling and engineering problems.

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