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Improving Thermal Friction Drilling Performance of AISI 304 Stainless Steel Using the Harris Hawk Optimization Method

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ABSTRACT

Presently, in friction drilling optimization schemes, quick convergence of solutions and simplicity of methods are still challenging. These issues are drawbacks in obtaining the maximum potential benefits from the optimization process. Therefore, this paper applies a new optimization method, Harris Hawk optimization to the thermal drilling process of AISI 304 stainless steel. The algorithm minimizes the axial force, determination error, radial force, and radial error and maximizes the bushing length as the major output of the process. The proposed approach was tested with experimental data obtained from the literature. The obtained results indicate that the optimal production is feasible. An example is given here of the results of the input parameters for the minimum axial force, which is as follows: After 500 iterations, the optimal axial force yields a tool cylindrical region diameter of 5.78593 mm, a friction angle of 60 degrees, a friction contact area ratio of 57.7082, workpiece thickness of 3 mm, feed rate of 140 mm/min and rotational speed of 3002.85 rpm, which can be applied. The results assist engineers in implementing optimal conditions for the drilling process. The outcome of this study strengthens decisions to establish thresholds of values that are less or more than expected thereby providing a basis for comparison, reward, and reprimand for workers. Thus the drilling process can be optimized.

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1. INTRODUCTION

In these challenging manufacturing days, friction drilling has been used as a process improvement strategy to sustain manufacturing systems. The advantages of friction drilling include efficient processes, reduced set-up times, minimized production errors, and reduced material waste generation. In drilling, most of the activities are focused on either improving the inputs, outputs, or both. This shows that inputs and outputs play important roles in drilling operations. It is known that drilling costs and the overall profit of the drilling organization are important concerns in the present economic challenges. Thus, leading global drilling organizations and work centers know the urgency of optimizing drilling inputs and outputs and have made conscious efforts to draw up optimization schedules for drilling activities.

The above discussion has led to the issue of friction drilling performance optimization, which has attracted the attention of industry and academia. Studies on friction drilling performance evaluation are intensive and some available literature is as follows: El-Bahloul et al. (2018) worked on how to optimize the process parameters in the transformation of AISI 304 stainless steel. Dehghan et al. (2021) examined the process parameters using three main difficult-to-machine materials Inconel 718, AISI304 and Ti6Al-4V. Kumar and Hynes (2020) worked on optimizing process parameters. The galvanized steel was used as the working material and the parameters focused on are the spindle speed, angle of tool and workpiece thickness. Kumar et al. (2019) obtained optimal process parameters to include roundness errors as one of the parameters to be minimized apart from surface roughness, which is common in many papers. Bilgin (2021) checked the effect of the drilling environment on the formation of the thrust force during the thermal drilling process.

From the present authors' understanding of the literature, many studies on the friction drilling of AISI 314 stainless steel are centred on the experimental side where the choice of tool and materials for the friction drilling process have been the major concern. Unfortunately, there have been few academic papers discussing the optimization problem. In many instances, the optimization used is the traditional type, such as the Taguchi method, response surface methodology and desirability function analysis with less concern for the quick solution convergence for the problem. Simplicity in the implementation of optimization procedures has also been ignored.

In contrast, the aim of this study is to provide a novel evolutionary framework, called the Harris Hawk algorithm, and apply it to evaluate the optimization capability of friction drilling while drilling the AISI 304 stainless steel. The proposed method entails an objective function based on an empirical model in a non-linear structure to maximize or minimize the output of the process according to the desired outcomes, Experimental data was extracted from El Bahloul et al. (2018) based on the AISI 304 stainless steel material as the first stage of the analysis. Then, the objective functions are formulated and introduced into the Harris Hawk algorithm and the solutions are compared with literature results. The difference between the present work and previous studies lies in that the traditional optimization measures such as the Taguchi method and the response surface methodology attempt to find optimum solutions at a slow convergence rate. However, the Harris Hawk algorithm proposed here attempts to achieve this in a quick convergence of the optimal solution to the problem.

The outputs of the drilling process are the axial force, determination error, radial force, and bushing length. The inputs to the process are the tool cylindrical region diameter, friction angle, friction contact area ratio, workpiece thickness, feed rate and rotational speed. To the best of our knowledge non-conventional optimization techniques in the thermal drilling literature, particularly, optimizing the outputs of the thermal drilling process using the Harris Hawk algorithm have no previous representation in the drilling literature. Thus, the novelty of this article stands as filling this important gap in the perspective expressed here. In summary, an optimization method of the Harris Hawk optimization is developed, formulated as a linear programming model and solved by running a computer programme in C++. Compared to the traditional optimization model such as goal programming, the Harris hawk optimization combines the unique attributes of requiring fewer parameters, a straightforward platform for implementation, quick convergence and a strong capability in attaining local search.

The contribution of the present study is the application of the Harris Hawk algorithm to the friction drilling process of AISI 314 stainless steel. It reveals diverse chasing patterns that mimic the dynamic form of scenarios and escape trends of the prey in an optimization procedure. Moreover, this study applies the Harris Hawk algorithm to analyze the optimization thresholds of outputs thereby eliminating reliance on the operator's judgment or the decision maker's opinion. Using experimental data exhibits more confidence in the Harris-Hawk algorithm's predictive ability. Furthermore, the study developed a relatively new method, the Harris Hawk algorithm, which has numerous advantages such as robustness, promising convergence speed, fewer parameters, exploration and exploitation and simplicity.

Furthermore, robustness describes the ability of HHO to handle the diverse non-linear and linear optimization problems in the industry. Besides, on convergence speed, the HHO has demonstrated quick convergence in obtaining optional solutions when run on benchmark problems. Also, HHO has shown an effective balancing of exploitation and exploration when subjected to problem-solving. This attribute is demonstrated as the HHO searches the solution space efficiently for solutions. Next, weighted against other metaheuristics, the HHO requires only fewer parameters thus making it straightforward to tune and use for optimization purposes. Furthermore, from the simplicity standpoint, the algorithm from the Harris Hawk optimizer has a comparatively straightforward implementation procedure. It is also easy to understand, possesses a simple structure and needs only fewer hyperparameters for tuning.

2. LITERATURE REVIEW

The literature review for this research was aimed at revealing the newness of the Harris Hawk friction drilling optimization problem, the methodology deployed to solve this problem and the results obtained from applying the Harris Hawk model to a case study involving the friction drilling of AISI304 stainless steel. Consequently, the review is categorized into (1) optimization of the process parameters in the transformational AISI 304 stainless steel, and (2) the Harris Hawk algorithm. These reviews are important to state the contribution of this research.

2.1. Optimization of process parameters for AISI 304 stainless steel

The optimization procedure establishes the best possible set of process parameters while processing the AISI304 stainless steel through different processes, including laser cutting (Jadhav and Kumar, 2019), electropulsing – oriented turning (Wang et al., 2015), formability studies (Vaz and Tomiyama, 2020), among others. Jadhav and Kumar (2019) analysed the laser cutting parameters, namely, gas pressure, cutting speed and laser power while using the surface roughness as the response in processing AISI304 material. The results showed that the principal influential parameters for the laser-cutting process are the gas pressure and laser power. It was added that as the laser power and gas pressure increased, a corresponding reduction of surface roughness was experienced, which is a desirable result. The differences, between the article being reviewed and the current article are as follows: A substantial number of outputs, precisely five, namely the axial force radial force, bushing length, roundness error, and hole diameter dimensional error are explored in the present study, which is more comprehensive than only the surface roughness analysed in the reviewed article.

Moreover, the number of input parameters considered in the present work is more than three, which is below the number for the current study. More importantly, the Harris Hawk algorithm shows great flexibility in being modified and adapted to solve several complicated problems whereas the desirability approach adopted to solve the problem in the reviewed article is short of that capability. Vaz and Tomiyama (2020) analysed the formability process parameters of AISI 304 stainless steel while conducting tensile tests with multi-geometric samples. It was shown that at least, an improvement value of 30.43% of the global error index was attained for the process. Compared with the present study, the limited scope of the parameters in the review article to hardening parameters, including failure response is lower in comprehensiveness compared to the five responses considered in the present study. Wang et al. (2015) conducted a turning experiment to highlight the significance of the process parameters of electropulsing while machining the AISI 304 stainless steel. It was concluded that the machined surface was less affected by the axial roughness, principal cutting force and microhardness. Weighted against the present study which focuses on five outputs, the focus of the reviewed article is less, which is limited to axial roughness, principal cutting force and microhardness. Moreover, the optimization focuses on the possibility of obtaining multiple solutions in the current study, which is a characteristic of evolutionary methods like the Harris Hawk model against a single solution provided by the reviewed article.

Furthermore, Nehri et al. (2024) conducted a machining experiment to optimize the process parameters of AISI 304L stainless steel deploying three optimization methods of artificial neural networks, Taguchi method and response surface methodology. The parameters analysed were the cutting depths, cutting speeds and feed as opposed to tool diameter, friction angle, friction contact area ratio, feed rate, and rotational speed, among other outputs. It was reported that the optimal results are the Al_2O_3 +TiCN coating with a depth of cut at 1.1mm, a cutting speed of 170m/min and a feed of 0.13mm/rev. Kalidass and Palanisamy (2014) studied the joint influence of cutting parameters (i.e. depth of cut, spindle speed, and feed rate) and helix angle for the cutting tool on surface roughness while machining AISI304 stainless steel. It was concluded that the utmost surface roughness value was 1.2 micrometre. Although multiple parameters are used in this reviewed article, they are not as wide-ranging as in the present study. Also, only the surface roughness was used in the reviewed article against five outputs utilized in the present study. In addition, the unique advantage of providing multiple but reliable solutions distinguishes the present study and places it at an edge over the reviewed article.

2.2. Harris Hawk algorithm

The application of the Harris Hawk algorithm could be found in several areas such as energy distribution system (Dey and Marungsri, 2024) intrusion detection (Zhou et al., 2023), power flow (Akpamukcu et al., 2023), reactive power (Jiao et al., 2024). Dey and Marungsri (2024) contributed an optimal sizing and photovoltaic locational study using the adjusted Harris hauk optimization procedure. It was declared that the optimal location of the PV system and sizing yielded superior voltage stability. Zhou et al. (2023) utilized the enhanced Harris Hawk algorithm to optimize detection accuracy by the conventional intrusion detection approaches. It was shown that feature choice and data balance structure significantly enhanced the accuracy of detection.

Moreover, the detection accomplishment outperforms the available intrusion detection approaches. Akpamukcu et al. (2023) combined the Harris Hawk procedure with an electromagnetic field to achieve optimal power flow. It was declared that optimization performance grew with the optimization to optimization method which the philosophy of the electromagnetic field optimization remains constant. Jiao et al. (2024) hybridized the Harris Hawk algorithm with the sine cosine optimization procedure in power system planning. It was reported that the hybrid method reduce the power loss by 33.19% compared with analysis involving no optimization. Babu and Swarnasri (2020) use the Harris Hawk algorithm and the teaching learning-oriented optimization to efficiently distribute renewable distributed generation. It was concluded that a significant power loss reduction, voltage profile enrichment and exactness of the proposed approaches occurred.

Song et al. (2020) contributed a novel approach to the choice of optimal parameters for the Proton Exchange Membrane Fuel cell using the improved Harris Hawk algorithm to reduce the sum of the square deviations between the projected data and output voltage. It was reported that the total of the squared deviations is 2.0164, 0.0594 and 0.014 for the NedSstack PS6 of 6.KW, Horizon H-12 and Ballard Mark V., respectively, which are the lowest values (0.0189, 0.0016 and 0.014) for the cases weighed against other approaches in the literature. Mary et al. (2020) optimized the parameters of the feedback control in a controller for the automatic voltage regulator system. The performance of the suggested controller competes favourably with other proportional integral derivative controllers using various algorithms. Upputuri et al. (2024) formulated the power flow problem as an optimization problem and solved it using the improved Harris Hawk algorithm combined with the pattern search method. It was reported that the proposed integrated method performed better than others. Swetha et al. (2021) applied the Harris Hawk algorithm combination with the particle swarm optimization to the voltage control problem. The result of the method was superior to those compared with. Swetha et al. (2021) applied the Harris Hawk algorithm combination with the particle swarm optimization to the voltage control problem. The result of the method was superior to those compared with.

2.3. Summary of the literature review

From the literature review of the two separate topics examined under the survey, it was found that the AISI 304 stainless steel is a widely used engineering material that has experienced significant applications in processes such as laser cutting and turning among others. However, none of these studies has applied the Harris Hawk algorithm. It is also known that several optimization methods have been used in previous research while processing the AISI 304 stainless steel in diverse processes such as laser cutting and turning, among others. These optimization methods include the Taguchi method, response surface methodology and desirability function analysis. In general, these methods have their merits in that they are effective and offer useful values with which the performance of workers may be compared. Yet, they have the general weakness of slow convergence. However, in the present complex manufacturing era, time is of the essence and fast convergence of solutions is desired for operational competition. Therefore, the Harris Hawk algorithm, which converges fast in obtaining a solution is preferable to the mentioned methods in terms of performance.

3. METHODOLOGY OF THE HHO ALGORITHM

The Harris Hawk Optimization (HHO) algorithm is an optimization technique that was inspired by the behaviour of Harris's Hawks during hunting. It is a method that was introduced by Heidari et al. in 2019 and it draws its inspiration from the hunting strategy of the Harris Hawks which is cooperative. The Harris Hawks are considered to be among the most intelligent birds and this is shown in the way they hunt. Their diet typically consists of large insects, birds, lizards and small-sized mammals like rabbits and rats. The HHO algorithm utilizes a set of hawks to represent possible solutions in the search region. By adapting behaviours like exploration, exploitation and sharing of information, the HHO algorithm strives to maintain a balance between the several strategies. This then brings about the convergence towards an optimal or near-optimal solution. The HHO algorithm has multiple applications in diverse domains some of which are engineering design, feature selection and numerical optimization. It is utilized in solving different engineering problems and it has also demonstrated promising results in terms of the quality of the solutions and the speed with which convergence is attained. The Harris Hawk Optimization algorithm has two main phases according to the hunting behaviour of the Hawks and they are as follows:

1. The exploratory phase
2. The Exploitative phase

3.1. The exploratory phase

In the exploratory phase, the Hawks monitor the area to see prey. There are two main strategies employed by the Hawk to achieve this, and to choose between the two strategies, a random number "q" between 0 and 1 is chosen. N.B. For the sake of illustration, a rabbit is used to represent the prey.

3.1.1. Equal chance (when $q < 0.5$)

This implies that the perch of the Hawk is based on the positions of the other family members of the Hawk and of the rabbit. The rabbit in this case is the intended prey, this at every stage of the hunting or at every iteration in this case, the best candidate solution is considered as the intended prey or near optimum. In this strategy, the equation used to obtain the next potential location is given in Equation (1) for the next potential location for equal chance situations in the exploratory phase.

$$X(t+1) = (X_{rabbit}(t) - X_m(t)) - r_3(LB + r_4(UB - LB)) \quad (1)$$

3.1.2. Random Perch (when $q < 0.5$)

In this case, the Hawks perch on random tall trees. As applied in the algorithm, they perch on random locations inside the hunting group's range. The Equation (2) is the equation for obtaining the next potential location for random perch in the exploratory phase.

$$X(t+1) = (X_{rand}(t) - r_1 \,|\, X_{rand}(t) - 2r_2 X(t) \,| \quad (2)$$

where,
$X(t+1)$ – Position vector of Hawks in the next iteration t
$X_{rabbit}(t)$ – Position of rabbit
$X(t)$ – Current position vector of Hawks
r_1, r_2, r_3, r_4, q – Random numbers inside (0,1) which are updated with each Hawk
LB and UB – Lower and upper bounds of variables
X_{rand} (t) – Randomly selected Hawk from the current population
X_m – Average position of the current population of Hawks

The method of obtaining the average position of Hawks:
Equation (3) is used to obtain the mean position of the population.

$$X_m(t) = \frac{1}{N}\sum_{i=1}^{N} X_i(t) \quad (3)$$

$X_i(t)$ – location of each Hawk in iteration (t)
N – total number of Hawks
It is possible to have multiple arrivals of Hawks at the average position of the Hawks but the HHO adopts a simple way.

3.1.3. Transition from exploration to exploitation

The HHO algorithm can migrate from exploration which is simply surveying the area to exploitation and also change from exhibiting exploitative to explorative behaviors. The adoption and migration of one hunting behaviour to the other all hinges upon the escaping energy of the prey "E". Typically, the energy of the prey diminishes as it tries to escape since it exerts energy in running and hopping to safety. The energy of the prey is modelled as follows:

Equation (4) is the equation used to obtain the energy of the prey.

$$E = 2E_0\left(1 - \frac{t}{T}\right) \quad (4)$$

where,

E – Escaping energy of the prey (with a range of -1 to 1)

T – Maximum number of iterations

E_0—Initial state of the energy of the prey

Equation 5 is used to obtain the initial state of the energy of the prey.

$$E_0 = 2 \text{ rand ( )} - 1 \quad (5)$$

rand ( ) – Random number inside (0,1)

a. When E_0 decreases from 0 to -1, this means that the rabbit is very weak and is physically flagging.
b. When E_0 increases from 0 to 1, the rabbit is growing in strength.
c. If $|E| \geq 1$, then the Hawk searches different regions to explore a rabbit location.
d. If $|E| < 1$, the algorithm tries to exploit the neighbourhood of the solutions during the exploitation steps.

In summary;

Where $|E| \geq 1$, exploration takes place, and where $|E| < 1$, exploitation takes place.

3.2. Exploitation phase

The Harris Hawks carry out the surprise pounce in this phase by executing an attack on the prey which has been detected in the exploratory phase. The prey also attempts to escape and flee these situations and thus the prey utilizes different techniques to do so. There are four techniques for chasing and hunting down the prey in the HHO modelled here and it all depends on the escaping behaviour of the prey. As we see, the Harris Hawks manifest their intelligence by adapting their hunting at every stage so that it is optimal enough to suit the escaping behavior of the prey. To select the technique of hunting in this phase, we choose a random number between 0 and 1 called "r" which represents the chances of prey escaping.

r - chances of escape for a prey.

if ($r < 0.5$) – there are chances that the prey will escape before the surprise pounce.

if ($r \geq 0.5$) – there are chances that the prey will not successfully escape.

Therefore the reaction and response of the prey determines whether the Hawks will perform a hard or soft besiege to catch the prey.

3.2.1. Soft besiege

In this exploitation phase, the rabbit still has sufficient energy, since $\{|E| \geq 0.5,\ r < 0.5\}$. The Hawks therefore encircle the prey softly and gently as it flees and hops away and this is done in ++ order to exhaust the rabbit. The model of this haunting phase is shown below.

Equation (6) is used to obtain the prospective location in the soft besiege.

$$X(t+1) = \Delta X(t) - E\,|\,JX_{rabbit}(t) - X(t)\,| \quad (6)$$

where,

$\Delta X(t)$ - The difference between the position vector of the rabbit and the current location in iteration "t".

Equation 7 is used to obtain $\Delta X(t)$, a variable in the equation for the next prospective solution.

$$\Delta X(t) = X_{rabbit}(t) - X(t) \quad (7)$$

Equation (8) is used to obtain J which represents the random jump strength of the rabbit (changes for each Hawk in each iteration).

$$J = 2\,(1 - r_s) \quad (8)$$

r_s – random number inside (0, 1)

3.2.2. Hard besiege

In this phase, the prey is exhausted and thus it has a low escaping energy making it more vulnerable to being captured. In this case, in this exploitation phase, the rabbit still has sufficient energy, since $\{|E| < 0.5,\ r \geq 0.5\}$. The modelling of this phase is depicted in the mathematical model below. Equation (9) is used to obtain the prospective location for Hard Besiege.

$$X(t+1) = X_{rabbit}(t) - E\,|\,\Delta X(t)\,| \quad (9)$$

3.2.3. Soft besiege with progressive rapid dives

When $|E| \geq 0.5$ but $r < 0.5$, the rabbit has enough energy to successfully escape, however, a soft besiege is still executed before the surprise pounce. This procedure depicts a superior intelligence than the previous case. This situation is competitive; thus the Hawks evaluate their next move using the rule depicted below. Equation 10 is utilized in obtaining Y, a possible prospective location.

$$Y = X_{rabbit}(t) - E\,|\,JX_{rabbit}(t) - X_m(t)\,| \quad (10)$$

If the prey then notices that the prey is performing more deceptive motions to facilitate its escape, it also performs irregular abrupt and rapid dives as it approaches the prey. The Levy Flight (LF) is used to mimic the real zigzag deceptive motion of the prey as shown below. Equation (11) is utilized in obtaining Z, a possible prospective location.

$$Z = Y + S \times LF(D) \quad (11)$$

where,

D – Dimension of the problem (i.e. population size)

S – Random vector by size 1 x D

LF – Levy flight function

The levy flight function that introduces the aspect of the zigzag motion of the birds and the elements that constitute the obtaining of the Levy function is shown below. Equation (12) is used to obtain the Levy distribution

$$\text{Levy }(D) = s \times \frac{u \times \sigma}{|\,v\,|^{\frac{1}{\beta}}} \quad (12)$$

s — constant values fixed at 0.01

U and v — random numbers between 0 and 1

Equation (13) is utilized in obtaining the value of sigma (σ) which is utilized in the Levy function.

$$\sigma = \left(\frac{\Gamma(1+\beta)\times\sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right)\times\beta\times 2^{\left(\frac{\beta-1}{2}\right)}} \right)^{\frac{1}{\beta}} \quad (13)$$

where β = a constant fixed at 1.5

To decide on Y or Z as the next location, the following criteria is followed:

$$X(t+1) = \begin{cases} Y \text{ if } F(Y) < F(X(t)) \\ Z \text{ if } F(Z) < F(X(t)) \end{cases}$$

Hard besiege with progressive rapid dives

The rabbit does not have enough energy in this phase to escape the Hawks and a hard besiege is carried out before the surprise pounce to catch and kill the prey. A simple mathematical illustration of this phase is shown below.

$$X(t+1) = \begin{cases} Y \text{ if } F(Y) < F(X(t)) \\ Z \text{ if } F(Z) < F(X(t)) \end{cases}$$

Equation (14) is used to obtain the value of Y, a prospective location in the Hard besiege phase with progressive rapid dives.

$$Y = X_{rabbit}(t) - E\,|\,JX_{rabbit}(t) - X_m(t)\,| \quad (14)$$

Z is obtained as in Equation (11).

4. APPLICATION OF THE HARRIS HAWK ALGORITHM TO THE THERMAL DRILLING PROBLEM

The input variables used in the present study are explained as follows: The inputs are namely rotational speed (RS), tool cylindrical region diameter (d), feed rate (FR), frictional angle (B), workpiece thickness (T) and friction contact area/circumference area (FCAR). These inputs are explained as follows:

1. The rotational speed indicates the frequency of rotation of the tool applied under pressure and friction on the AISI 304 stainless steel material around an axis.
2. Tool cylindrical region diameter is the measurable size of the tool that engages the workpiece while drilling a circular hole. It should match the material's strength to avoid breakage. The total diameter is measured with a calliper.
3. Feed rate is the distance cutting tools cover in a revolution of the tool. To determine the feed rate of the tool, the drill type and the material to be drilled as the two major factors to consider.
4. Friction angle is the angle that the resultant of a normal reaction and the limiting factors make with the normal reaction. It is important because the strength of many materials is impacted by friction.
5. Workpiece thickness is the width or height of the metallic piece being worked on or machined.
6. Friction contact area/ circumference area is the surface area of the contact force that does not influence friction since friction merely relies on the object's mass, frictional coefficient and gravity.

The objectives to be achieved with the HHO algorithm in the thermal drilling problem are shown in Table 1.

4.1. Description of the outputs and their importance in the thermal drilling process

Axial Force (AF): The axial force simply is the force which is applied along the axis of the drill bit during the process of the drilling. Having a minimal axial force in the

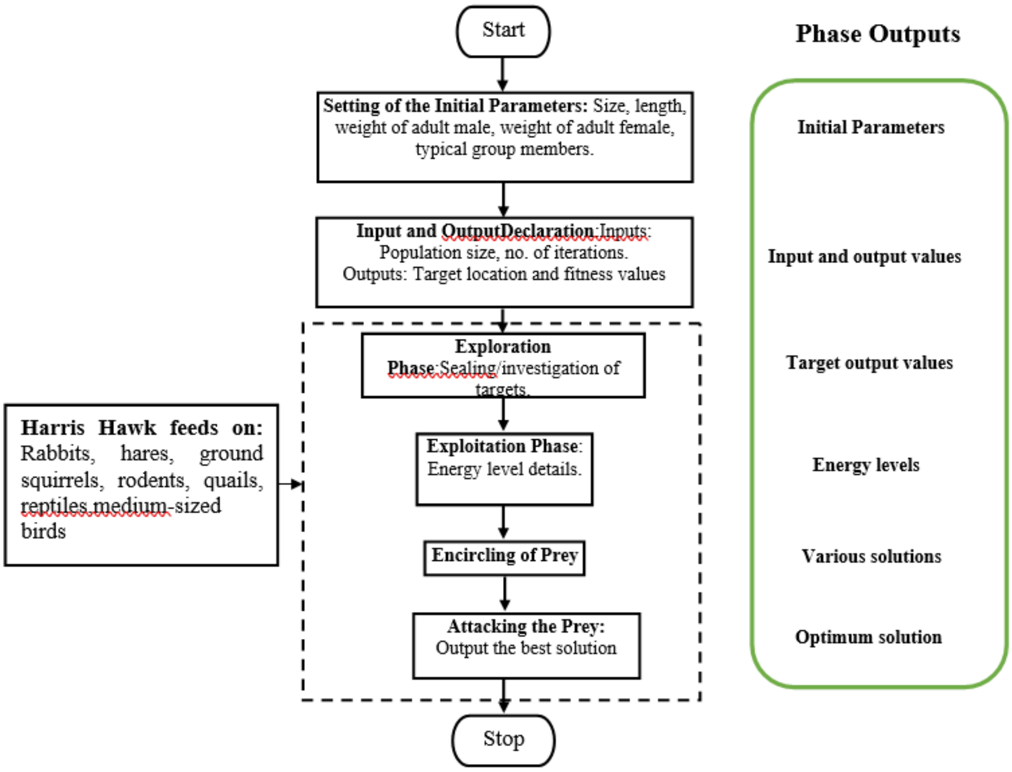

Figure 1. Simplified step-by-step implementation of Harris Hawk algorithm

Table 1. The Output values of the thermal drilling problem and the optimization objectives

S/N	Output	Operation
1	Axial Force (AF)	Minimize
2	Radial Force (RF)	Minimize
3	Hole Diameter dimensional error (DE)	Minimize
4	Roundness Error (RE)	Minimize
5	Bushing Length (BL)	Maximize

thermal drilling process therefore significantly improves the thermal drilling process in the following concrete ways. Reduction of Axial force reduces the tool wear and thus prevents excessive deformation of the material. Reduction of the axial force also has economic implications as there is a cut in power requirements due to reduced required force.

Radial Force (RF): Radial Force is the force applied perpendicular to the axis of the drill bit in the drilling process. When the Radial force is minimized, there is a reduction in the lateral pressure that is exerted on the material being drilled. The reduction of the radial force also brings about better hole quality as well as more dimensional accuracy.

Hole Diameter Dimensional Error (DE): The hole diameter dimensional error is simply the amount of deviation between the hole diameter that was desired and the actual diameter obtained. The minimizing of the Hole diameter dimensional error therefore is very important in the optimization of the thermal drilling process, and this is because when the error is reduced, the process obtains greater accuracy and consistency in terms of the size of the hole thus ensuring that the important standards are fulfilled. Another benefit that comes from minimizing DE is that the functionality and integrity of drilled products are maintained, thus allowing for better alignment and better product quality.

Roundness Error (RE): Roundness error is simply the deviation of the thermal drilled hole from a perfect circular shape. Therefore, minimizing the roundness error is very important for an optimal thermal drilling process. A minimal roundness error yields an improved circularity and concentricity of the drilled hole. The minimizing of the roundness error also ensures proper fit, alignment and optimal functioning of thermal drilled components especially in cases where precision and tight tolerances are compulsory.

Bushing Length (BL): The bushing length is the portion of material which is thermally deformed as well as displaced to bring about a cylindrical bushing around the drilled hole. A longer bushing length means a larger contact area between the bushing and the surrounding material bringing about a better stability and load-bearing capacity. Extended bushing length also increases the ability of the material to have a secure and durable connection between the drilled component and other parts in a thermal drilled joint.

4.2. Objective function formulation

For each of these output parameters, objective functions have been obtained and they are the starting point for optimizing of any output in Single Objective optimization scenarios. The several objective functions for each of the output parameters are shown below.

Objective 1: Minimize AF

$$AF = 0.5701D - 0.01711\beta + 0.004136FCAR - 0.8286T - 0.006045FR + 0.000148RS - 0.04019D^2 + 0.000244\beta^2 \quad (15)$$

Objective 2: Minimize DE

$$DE = 0.6657D - 0.05554\beta + 0.002693FCAR - 0.004186T - 0.008202FR + 0.000200RS - 0.05726D^2 - 0.000671\beta^2 \quad (16)$$

Objective 3: Maximize BL

$$BL = 0.05361D - 0.001201\beta - 0.001920FCAR + 0.2180T - 0.001325FR - 0.000003RS - 0.002078D^2 - 0.00000\beta^2 \quad (17)$$

Objective 4: Minimize RF

$$RF = 0.4580D + 0.008589\beta + 0.001332FCAR - 0.3035T + 0.005417FR - 0.000007RS - 0.03882D^2 - 0.000023\beta^2 \quad (18)$$

Objective 5: Minimize RE

$$RE = -0.01057D + 0.03423\beta + 0.005979FCAR - 0.34798T + 0.000947FR - 0.000027RS - 0.008459D^2 - 0.000259\beta^2 \quad (19)$$

4.3. Optimizing the axial force

For the sake of illustration, the HHO optimization is illustrated in detail for the first member of the population (the first Hawk) in the first iteration. A population of 10 Hawks and a maximum iteration of 500 is adopted for the Harris Hawk optimization.

Step 1: Random Initialization of the matrix

Formula for Randomly initialized value: $L + R\,(U - L)$

The procedure followed in obtaining the first variable in the first Hawk of the population is shown below.

Lower Boundary: 5.4, Upper Boundary: 9.2, Random Number: 0.104678

5.4 + 0.104678(9.2) – 5.4 = 5.79778

The same procedure was used to obtain the values for the randomly initialized matrix. The fitness values for the Axial Force (AF) were thus obtained by inserting the randomly initialized values into the objective function for Axial force. The randomly initialized matrix is shown below (together with their fitness values in the last column). Table 2 simply shows the randomly initialized matrix i.e. the Hawks that have been randomly initialized at the 10 different locations. The last column is the fitness value of the locations after they were inserted in the objective function for the Axial Force.

4.4. Purpose of randomizing in the Harris Hawk Optimization Algorithm

The cooperative hunting style of Harris Hawks served as the basis for the Harris Hawk Optimization (HHO)

Table 2. The randomly initialized matrix alongside the fitness values at all the 10 prospective locations

D	β	FCAR	T	FR	RS	AF
5.79778	43.9705	53.148	2.66698	102.062	3229.24	-0.455305
8.51299	56.6207	92.5794	1.11945	124.948	3276.3	0.939019
8.34275	57.951	51.3245	1.99332	136.699	1592.41	-0.243247
7.6373	41.0416	92.201	1.74111	79.1778	3199.21	0.652095
6.0688	54.135	68.4317	1.01715	103.851	2863.57	1.00468
5.90482	41.904	86.6665	2.79754	115.793	2414.52	-0.625697
5.73701	54.7823	56.2304	2.95965	125.07	2819.68	-0.815711
8.9938	45.363	67.0553	1.73733	135.596	1763.07	-0.118549
7.86704	56.7718	59.4012	1.97	121.147	2998.15	0.137418
8.53955	45.0691	62.3524	2.4135	116.513	2879.74	-0.35798

D – Tool diameter, mm; β - Friction angle – degree; FCAR – Friction contact area ratio – unitless; FR – Feed rate – mm/min; RS – Rotational speed – rpm; AF – axial force

Table 3. The most optimal location obtained from the randomly initialized matrix

D	β	FCAR	T	FR	RS	AF
5.73701	54.7823	56.2304	2.95965	125.07	2819.68	-0.815711

Table 4. The mean location obtained from the randomly initialized matrix

D	β	FCAR	T	FR	RS	AF
5.73701	54.7823	56.2304	2.95965	125.07	2819.68	-0.815711

algorithm. The HHO method incorporates randomness in several places to add variety and exploration to the search space. Here are some examples of when randomization is used:

a. Initialization: The initial population of potential solutions is given random values at the start of the procedure. This randomness contributes to the creation of a varied collection of initial solutions, enabling the exploration of various search space locations. The HHO algorithm selects leaders (or global best solutions) from the population based on the fitness values of those solutions. To add an element of chance, randomness might be included throughout the leader-choosing process. For instance, to promote exploration and avoid hasty convergence, a random leader could periodically be chosen rather than always choosing the optimal answer.
b. Movement of Solutions: Randomness can be included to introduce stochasticity during the movement phase, in which solutions modify their positions. This can be accomplished by adding arbitrary disturbances or arbitrary steps in the movement's direction. Randomness aids in better search space exploration and prevents solutions from becoming snared in local optima.
c. Crossover and Mutation: Randomness is essential for the execution of operators like crossover and mutation used in the HHO algorithm. Solutions are combined or altered at random to produce new offspring with diverse traits. This randomization encourages population variety and helps to explore new parts of the search space.

The HHO method can achieve a balance between exploration and exploitation by introducing randomization at these various points, making it possible to quickly find the best solutions to challenging optimization problems.

4.5. Information about the first iteration

Step 2: Obtain X_{rabbit}

Since we are minimizing, the X_{rabbit} is the best candidate solution with the smallest fitness and it is given as in Table 3. Table 3 simply shows the location in the population which has the lowest fitness value (i.e. the smallest value of the Axial Force).

Step 3: Obtain X_{mean}

X_{mean} is the average position of the current population of the Hawks. It is obtained using the following equation:

$$X_{mean}(t) = \frac{1}{N}\sum_{i=1}^{N} X_i(t) \tag{20}$$

The values of X_{mean} obtained are shown below. Table 4 depicts the mean location obtained in the first iteration. The mean has been arrived at for each of the variables by taking their sum and dividing them by the number of Hawks in the population.

4.6. Information about the first Hawk in the first iteration (Iteration 0)

Step 4: Initialize the values of E_0 and J

E_0 = 2 rand ( ) – 1

Random number chosen between (0 & 1): 0.936155

Table 5. The population after carrying out the optimization operation on the first Hawk in the population in the first iteration

D	β	FCAR	T	FR	RS	AF
5.79778	43.9705	53.148	2.66698	102.062	3229.24	-0.455305
8.51299	56.6207	92.5794	1.11945	124.948	3276.3	0.939019
8.34275	57.951	51.3245	1.99332	136.699	1592.41	-0.243247
7.6373	41.0416	92.201	1.74111	79.1778	3199.21	0.652095
6.0688	54.135	68.4317	1.01715	103.851	2863.57	1.00468
5.90482	41.904	86.6665	2.79754	115.793	2414.52	-0.625697
5.73701	54.7823	56.2304	2.95965	125.07	2819.68	-0.815711
8.9938	45.363	67.0553	1.73733	135.596	1763.07	-0.118549
7.86704	56.7718	59.4012	1.97	121.147	2998.15	0.137418
8.53955	45.0691	62.3524	2.4135	116.513	2879.74	-0.35798

E_0 = 2 (0.936155) – 1 = 0.872311
J = 2 (1- rand ())
Random number chosen between (0 and 1): 0.675375
J = 2 (1- 0.675375) = 0.649251
Step 5: Obtain the energy E of the prey
The energy E of the prey is modelled and can be obtained as follows:

$$E = 2E_0\left(1-\frac{t}{T}\right)$$

Substituting the respective values, we have:

$$E = 2*0.872311\left(1-\frac{0}{500}\right)=1.74462$$

Since $|E| \geq 1$, the exploration phase is adopted.

4.7. Source of the energy of the prey

From inspection, it is possible to discover from the energy equation that it is directly proportional to the number of iterations already carried out. Therefore, an analogy can be struck between the number of iterations and the escape energy of the rabbit such that in the early iterations, the rabbit has ample energy, which decreases gradually as the number of iterations increase and eventually becomes 0 when the number of iterations carried out is equals to the maximum number of iterations.

4.8. Exploration phase

Step 6: Obtain the potential new location $X(t + 1)$

To decide the strategy to adopt, we first of all obtain random numbers r_3, r_4 and q all within (0, 1). The perch is based on the positions of other family members and the location of the rabbit are chosen as the random numbers.
r_3: 0.11948; r_4: 0.0559404; q: 0.410474
Since q < 0.5, then the following formula will be used to evaluate $X(t + 1)$.

$$X(t+1) = (X_{rabbit}(t) - X_m(t)) - r_3(LB + r_4(UB - LB))$$

Other values required to obtained $X(t + 1)$ are shown.

X_{rabbit}	$X_m(t)$	$X(t)$
5.73701	7.34018	5.79778
54.7823	49.7609	43.9705
56.2304	68.939	53.148
2.95965	2.0416	2.66698
125.07	116.086	102.062
2819.68	2703.59	3229.24

The above formula for X_{New} is illustrated via the first variable in the first Hawk of the first iteration as shown below.
X_{New} = (5.73701 54.7823 56.2304 2.95965 125.07 2819.68) – (7.34018 49.7609 68.939 2.0416 116.086 2703.59) – 0.11948 *(5.4 + 0.0559404 (9.2 - 5.4))

Checking if the values fall within the upper and lower bounds given for each of the input parameters. X_{New} obtained (before checking if each value fall within the bounds): -2.27376 1.23645 -19.0169 0.785204 1.28115 -76.495. X_{New} obtained (After checking if each falls within bounds): 5.4 30 50 1 60 1500. X_{New} obtained (after checking if each falls within bounds) together with the fitness values: 5.4 30 50 1 60 1500 0.8504.

4.9. Greedy selection

Since we are minimizing the Axial Force (AF), we desire that this prospective location would have a fitness value that is better than the already existing fitness value. I.e. the fitness value should be smaller before replacement of the entire location can occur.
$F(X(t))$: -0.455305; $F(X_{New})$: 0.8504
Since we are maximizing AF, and $F(X_{New}) < F(X(t))$ replacement does not take place as the prospective location is not desirable.

4.10. Effect of the greedy selection

The greedy selection is at the heart of all optimization algorithms. The fundamental implication of greedy selection is that the optimization algorithm will adopt a potential solution if and only if it offers superior benefits in the pursuit of the particular goal in question which can be the maximization or the minimization of the objective. For this particular optimization problem, the effect of the greedy selection is shown in the sense that since the prospective location yields an axial force of 0.8504, the current location has a value of -0.455305 for axial force. Since we intend to minimize axial force, the greedy selection will reject the prospective location since it does not provide benefits superior to the already existing location given the final goal.

After Carrying out the Harris Hawk Operations on the first Hawk in the first Iteration, the randomly initialized matrix remains unchanged as shown below, since replacement did not take place. Table 5 shows the state of

Table 6. The optimal parametric setting for AF after 500 iterations

D	β	FCAR	T	FR	RS	AF
5.78593	60	57.7082	3	140	3002.85	-0.844078

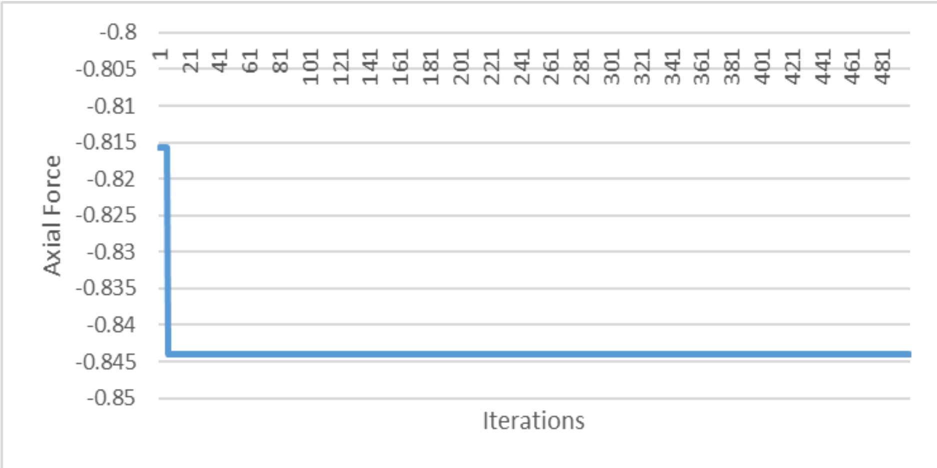

Figure 2. Axial force against the number of iterations

the population after carrying out the Harris Hawk optimization on the first Hawk of the iteration. From the table we can observe that the replacement did not take place, therefore the values for the matrix after optimizing the first Hawk with HHO remain the same with the initial randomly initialized matrix.

At the end of the 500th iteration, the optimal parametric setting for obtaining minimal Axial Force (AF) presented by Harris Hawk Algorithm is shown in Table 6. Table 6 implies that at the end of 500 iterations, to obtain an optimal value of Axial force, a tool cylindrical region diameter of 5.78593, a friction angle of 60, a friction contact area ratio of 57.7082, Workpiece thickness of 3, feed rate of 140 and rotational speed of 3002.85 can be applied (see Figure 2). The results are not discreet and possess decimal values, however, they are all within the range of what is obtainable in the industry. Thus in cases where strict adherence to the results obtained as optimal parametric setting is not possible, insight is still to be gained from the values obtained. The Optimal parametric settings and the plot summary at the end of the iterations are shown for the other outputs that are to be optimized.

4.11. Effect of minimization on the axial force

As can be seen from Figure 2, there is an early convergence of the values of axial force during the Harris Hawk computation. This is because the Harris Hawk optimization algorithm is very efficient and it arrives at its goal with speed. The minimization of the Axial Force using the HHO has yielded negative values of AF which is -0.844078 in this case, which in practice is not possible but which shows that carrying out the thermal drilling process at this optimal parametric setting will yield lower values of axial force. The value yielded as the optimal value for AF, is smaller than all the values for the AF in the reference paper, El-Bahloul et al. (2018), where the experiment was carried out.

The minimum value of AF from the reference paper: 0 (El-Bahloul et al., 2018). The minimum value of AF from the HHO algorithm: is -0.844078. % reduction in the value of AF: 84.4%.

It is important to note that the value of AF from the reference paper is 0 because they are normalized values, simply representatives of the magnitudes of their original values with respect to the other values.

4.12. Minimize Delamination Error (DE)

At the end of the 500th Iteration, the optimal parametric setting for obtaining minimal Delamination Error (DE) presented by Harris Hawk Algorithm is shown in Table 7. Table 7 implies that at the end of 500 iterations, in order to obtain an optimal value of Delamination Error, a tool cylindrical region diameter of 9.2, a friction angle of 54.7235, a friction contact area ratio of 61.3808, Work piece thickness of 1.96018, Feed rate of 89.1133 and rotational speed of 2224.02 can be applied (Figure 3).

4.13. Effect of minimizing Delamination Error (DE)

The minimizing of delamination error after 500 iterations has yielded 0.119017 to be the minimum value obtainable given the optimal parametric setting. The minimum value of AF from the reference paper: is 0 (El-Bahloul et al., 2018) while the minimum value of DE yielded by HHO is 0.119017. % reduction of DE: -12%.

Therefore, the value from the reference paper is smaller, hence more desirable with respect to the objective of optimal Delamination Error.

4.14. Maximize Bushing Length (BL)

At the end of the 500th Iteration, the optimal parametric setting for obtaining maximum Bushing Length (BL) presented by the Harris Hawk Algorithm is

Table 7. The optimal parametric setting for DE after 500 iterations

D	β	FCAR	T	FR	RS	DE
9.2	54.7235	61.3808	1.96018	89.1133	2224.02	0.119017

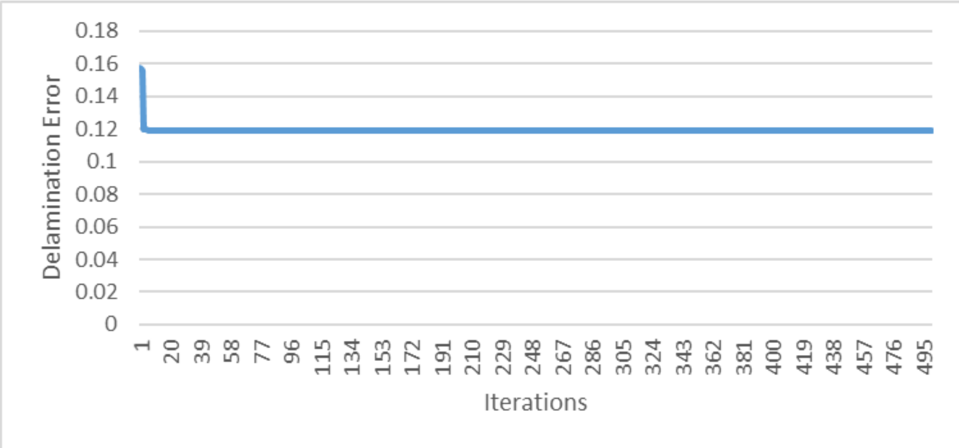

Figure 3. Delamination Error against the iterations

Table 8. The optimal parametric setting for BL after 500 iterations

D	β	FCAR	T	FR	RS	BL
9.2	40.3913	66.0103	3	138.662	3436.16	0.953808

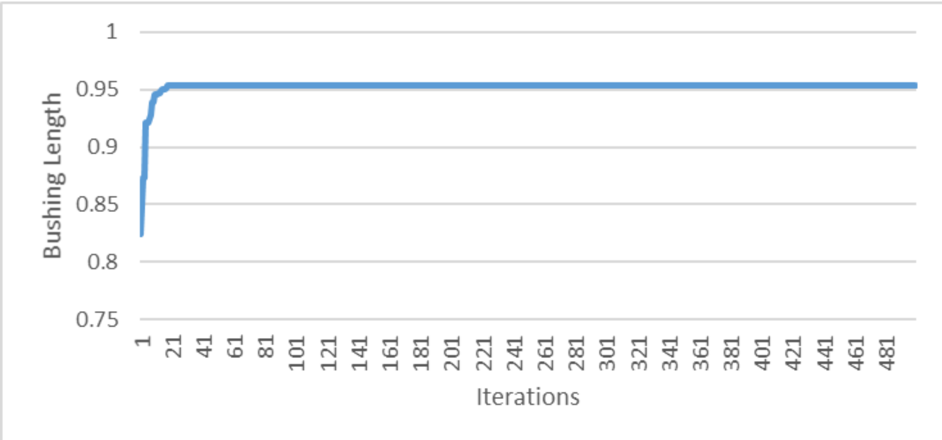

Figure 4. Bushing length against the iterations

shown in Table 8. Table 8 implies that at the end of 500 iterations, in order to obtain an optimal value of Bushing Length, a tool cylindrical region diameter of 9.2, a friction angle of 40.3913, a friction contact area ratio of 66.0103, Work piece thickness of 3, Feed rate of 138.662 and rotational speed of 3436.16 can be applied (Figure 4).

4.15. Effect of maximizing the Bushing Length

From the normalized values of the reference paper (El-Bahloul et al., 2018), as expected, the maximum value is 1. The maximum value yielded by the Harris Hawk algorithm however is 0.953808. % increase in value of BL: -5%. This value again is smaller than the value in the reference paper hence less desirable to the parametric setting in the reference paper. This does not however discredit to effect of maximization brought about by the HHO in the Bushing Length value.

4.16. Minimize Radial Force (RF)

At the end of the 500th Iteration, the optimal parametric setting for obtaining minimal Radial Force (RF) presented by Harris Hawk Algorithm is shown in Table 9. Table 9 implies that at the end of 500 iterations, in order to obtain an optimal value of Radial Force, a tool cylindrical region diameter of 9.2, a friction angle of 48.5444, a friction contact area ratio of 100, Work piece thickness of 3, Feed rate of 140 and rotational speed of 3500 can be applied (Figure 5).

4.17. Effect of minimizing Radial Force

The radial force obtained from the optimal parametric setting yielded by the HHO is - 0.269558. The value which was obtained as minimum from the reference paper for the radial force is 0. % decrease in the value of Radial

Table 9. The optimal parametric setting for RF after 500 iterations

D	β	FCAR	T	FR	RS	RF
9.2	48.5444	100	3	140	3500	-0.269558

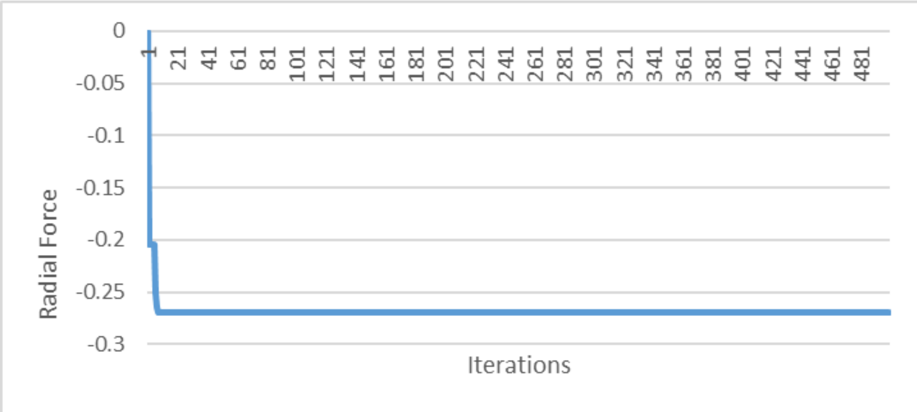

Figure 5. Radial force against the iterations

Table 10. The optimal parametric setting for RE after 500 iterations

D	β	FCAR	T	FR	RS	RE
8.83195	42.6124	93.696	2.96595	60	1500	-0.220422

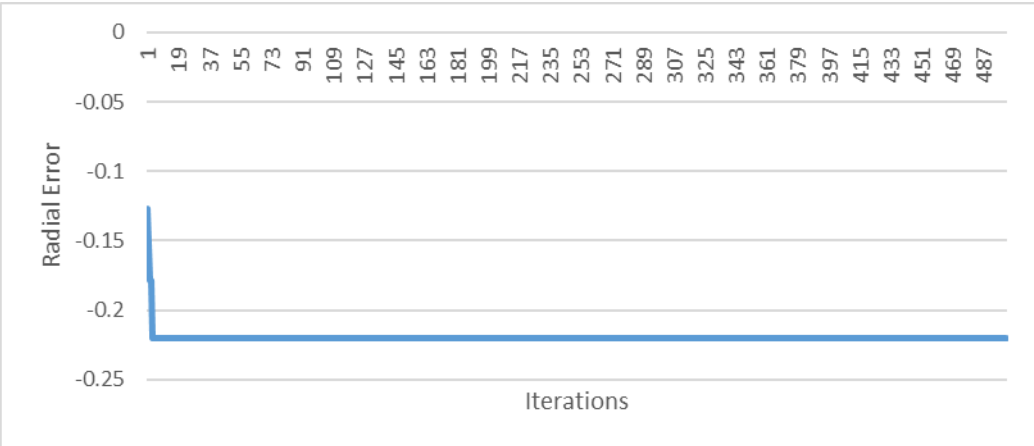

Figure 6. Radial error against the iterations

Force: 26.96%. This implies that the value yielded here by the Harris Hawk optimization algorithm is more desirable than the parametric setting yielded in the reference paper, El-Bahloul et al. (2018).

4.18. Minimize Radial Error (RE)

At the end of the 500th Iteration, the optimal parametric setting for obtaining minimal Radial Error (RE) presented by Harris Hawk Algorithm is shown in Table 10. In Table 10, at the end of 500 iterations, in order to obtain an optimal value of Radial Error, a tool cylindrical region diameter of 8.83195, a friction angle of 42.6124, a friction contact area ratio of 93.696, Work piece thickness of 2.96595, Feed rate of 60 and rotational speed of 1500 can be applied (Figure 6).

4.19. Effect of minimizing the Radial Error

The radial error obtained from the optimal parametric setting yielded by the HHO is -0.220422. The value which was obtained as minimum from the reference paper for the radial error is 0. % decrease in the value of Radial Error: 22.04%. This implies that the value yielded here by the Harris Hawk optimization algorithm is more desirable than the parametric setting yielded in the reference paper, El-Bahloul et al. (2018).

4.20. Validation of the proposed method

To demonstrate the effectiveness of the method and showcase its validity, the present study was compared with the literature data that was developed from the integrated taguchi-Pareto–grey wolf-desirability function analysis optimization technique. The values obtained from both methods were subjected to the Wilcoxon signed rank test, a non-parametric statistical test. Thus, this paper discusses the implementation of the Wilcoxon signed rank

Table 11. Comparison of the literature data with the current study (Output is axial force, AF)

S/N	Parameters	Literature data (Nwankiti and Oke, 2022)	Current study data	Difference	Modulus of difference	Rank
1	d (mm)	5.43	5.7859	-0.3559	0.3559	3
2	β (degree)	60.0	60	0	0	1
3	FCAR (%)	100.0	57.7082	42.2918	42.2918	4
4	T (mm)	3.0	3	0	0	1
5	FR (mm/min)	71.66	140	-68.34	68.34	5
6	RS (rpm)	1614.04	3002.85	-1388.81	1388.81	6

Note: Literature data was developed from the Integrated taguchi-pareto–grey wolf-desirability function analysis optimization technique while the current study data was developed from the Harris Hawk optimization method. Both studies worked on the drilling performance of AIS1 304 stainless steel

Table 12. Summary for all outputs

S/N	Outputs	T-	T+	W_{stat}	$W_{critical}$	Decision
1	AF	14	6	6	0	Accept
2	RF	6	5	5	0	Accept
3	DE	8	13	8	0	Accept
4	RE	0	21	0	0	Reject
5	BL	11	9	9	0	Accept

test based on the literature data from Nwankiti and Oke (2022) and the present study. Table 11 reveals the results of the literature sources in the third column with the current study results shown in the fourth column.

The figures in these two columns represent data on the various parameters. Since the same data source is used in both cases, an easy comparison of results is made. The aim is to determine if significant differences exist between the literature data and the present study results. It implies that the two are paired data. The authors did not use the t-test since the data pairs are minimal and it is suspected that the data are not normally distributed. In that case, it was decided to use the Wilcoxon signed rank test which works well on small samples and data suspected not to have normal distribution. To stand the test, there is a need to formulate the null hypothesis (H_0) which states that the mean value, H_{value}, of the literature data is greater than the H_{value} of the present data. The alternative hypothesis (H_1) is formulated, which states that the mean value, H_{value}, of the literature data is less than the H_{value} of the present data. Also, the significant level is fixed at $\alpha = 0.05$ (i.e. 95% acceptability) and the value of the data, set, n, is 5. The first set of computations tests the paired parametric values when the output of AF (i.e. axial force).

The results are shown in Table 11. Computations are made by subtracting a set of values from the other set. Considering the first row, 5.7859 is subtracted from 5.43 to give -0.3559. Likewise, 60 subtracted from 60 along the second row yields 0. Similar computations have been made for serial numbers 3 to 7 to obtain 0, 42.2918, 0, -68.34 and -1388.81, respectively. Next is to obtain the absolute numbers from the differences, which involves removing the negative signs from numbers having these. In this instance, serial numbers 1, 5 and 6 were affected to give 0.3559, 68.34 and 1388.81, respectively.

By reviewing the absolute difference column, the smallest value, which is 0 is given a rank of 1. The next value to the smallest is 0.3559, which is given a rank of 3 since a rank of 1 has been given to two serial numbers (i.e. serial numbers 2 and 4). The next rank is 4 given to serial number 3, which has a value of 42.2918. Other ranks such as 5 and 6 are attached to serial numbers 5 and 6 with 68.34 and 1388.81, respectively. In this particular test, it is important to know all the negative and positive signs of the values before obtaining the absolute values of the negatives. Correspondingly, the researcher needs to know the ranks of all the positives and those of the negatives. Then, they can be summed for further analysis. These are mentioned as the ranks for the T – and T+. To achieve this goal, consider the difference column where all the negative values are -0.3559, -68.34, and -1388.81 and the corresponding ranks are 3, 5 and 6, which sums up to 14. Also, in the difference column, all the positive values are 0, 0 and 42.2918 which have the corresponding ranks of 1, 4 and 1 sum up to 6. Thus, T- is 14 and T+ is 6. The test, W_{stat} is the smaller of 6 and 14, which is 6. There is a need to determine a critical value $W_{critical}$ to compare with the W_{stat} to answer the questions posed by the hypothesis. To achieve this, Wilcoxon critical value table is used. The summarized results for all the outputs are given in Table 12.

From the last column of Table 12, the decision on the calculations in Table 11 is shown as accepting the null hypothesis (H_0) which states that the mean value, H_{value}, of the literature data is greater than the H_{value} of the present data. The two means are not the same. Thus the results given by the output, AF, are not the same for the literature method and the present method. Results for other outputs are shown. In all, only 20% of all cases show similarity in results while in 80% of the cases, the results change.

In addition to the statistical test, it was found that the optimization capabilities of the Harris Hawk algorithm while processing the inputs for outputs using the AISI 304 L stainless steel are superior to the optimal parametric settings produced in El-Bahloul et al. (2018) in 60% of the case. The Harris Hawk algorithm exhibited higher optimal values of axial force, radial force and radical error compared with the optimal setting approach in El-Bahloul et al. (2018). From this research, it could be inferred that the Harris Hawk algorithm suitably replaces the optimal setting approach of El-Bahloul et al. (2018). Moreover, little research has been conducted to optimize friction drilling parameters considering quick convergence and simplicity. Furthermore, this work analyzed the frictional drilling parameters uniquely using the Harris Hawk algorithm on the AISI 304 stainless steel material.

4.21. Modifications to the original HHO method

The original HHO method proposed by Hiedari *et al.*, (2019) was shown to have results from computations. However, very little information is available on how the computations were made. In recent times, Heidari and colleagues presented Matlab codes, which ease computations. However, given the utility and adaptability of the C_{++} programme, the present authors abandoned the Matlab programme developed by Heidari and colleagues to present the C_{++} programme of our own, contributing to the automation of the procedure and permitting a wide circulation of the ideas as different group of users may be interested in using the C_{++} computer codes as opposed to the Matlab programme proposal by Heidai and colleagues. Furthermore, the present study showed that the objectives function utilized to run the Harris Hawk optimizer could be developed as an empirical non-linear model. The Minitab of Software was used to generate this. This objective function type could be adopted in many engineering situations. In Heidari et al., (2019), the choice of the objective function to introduce into the Harris Hawk optimizer is not explicitly stated.

4.22. Implementation of the HHO method in industry and implications for workers' reward

In the industry, the Harris Hawk optimizer can be used to solve various engineering problems such that benchmarks that show how the Harris Hawk optimizer scales better to obtain good solutions to large problems in a short period weighted against exact analytical solutions. The HHO method, being new in the industry has not been fully tested. However, the following problems, which are envisaged in the future should be managed and corrected for a huge diffusion of the knowledge of the HHO method in the industry and its application. The first issue that should be tackled is the lack of reproducibility. As some evolutionary algorithms are known for, in an instance the user may obtain a fine solution. In another instance of the sample problem, a power solution may be obtained. This is a practical problem that should be guided against in the future. The second issue deals with the lack of interpretability.

Moreover, given the optimal values obtained in this study, they may be used in setting up standards with which the performance of parameters is compared. Periodic performance are monitored and recorded. There could be instances where the performance is equal to the standard set. In other instances the attained performance could be below or above the set standards. For above – the standard performance, the workers are commended and rewards with money or other things such certificates. However, when the performance is below the standard, the worker undergoes reprimand. Discussion is held with the worker on why and how the standard is missed for corrections. The next performance is then compared to ascertain that corrections are made. The loop of activities continues until the best performance is maintained by the workers.

5. CONCLUSIONS

In this work, the Harris Hawk algorithm was proposed and applied to drill AISI 304 stainless steel for optimization purposes. Thus, the thermal drilling process was optimized in a real process. However, the findings from the implementation of the Harris Hawk algorithm on the AISI 304 stainless steel data led to the following conclusions:

1. The findings reveal that the application of the Harris Hawk algorithm to optimize the input parameters with the utmost output results is feasible.
2. The optimal values revealed in the application of Harris Hawk algorithm are more desirable in 60% of the cases than the parametric setting provided by El-Bahloul et al. (2018). The desirable cases involve the predicted values for the axial force, radical force and radical error in favour of the Harris Hawk algorithm. However, the results are in favour of the optimal setting generated El-Bahloul et al. (2018) for delamination error and bushing length. Nonetheless, the Harris Hawk algorithm is superior to the optimal settings in the reference paper according to the present findings.

The future studies concerning the subjected treated here are discussed as follows:

1. In friction drilling operations, machines and humans are the major elements driving the process. While machines and equipment may introduce imprecision in measurements, humans (operators) could also allow imprecision while interpreting the data. Thus, the process may be subjected to imprecision and uncertainty that needs to be evaluated in future studies.
2. In the future, this research could be extended to consider hybrids of the Harris Hawk algorithm with other methods such as multi-criteria approaches to include, Decision making, Trial and Eliminating Laboratory (DEMATEL). The DEMATEL method is to assist the managers of the workshop to understand the association between the parameters of the friction drilling process both before and after the drilling process.
3. The authors have evaluated the optimal outputs as single objective functions, in empirical form, substituted into Harris Hawk algorithm for solutions. This limitation of not combining the various empirical models can be overcome in a future study if desirability function analysis could be used to integrate the separate empirical models to obtain a single solution instead of the several solutions.

NOMENCLATURE

D	Tool diameter
β	Friction angle

FCAR	Friction contact area ratio
FR	Feed rate
RS	Rotational speed
AF	Axial force
DE	Delamination error
BL	Bushing length
RF	Radial force
RE	Roundness error
$X(t+1)$	Position vector of Hawks in the next iteration t
$X_{rabbit}(t)$	Position of rabbit
$X(t)$	Current position vector of Hawks
r_1, r_2, r_3, r_4, q	Random numbers inside (0,1) which are updated with each Hawk
LB and UB	Lower and upper bounds of variables
$X_{rand}(t)$	Randomly selected Hawk from the current population
X_m	Average position of the current population of Hawks
$X_i(t)$	Location of each Hawk in iteration (t)
N	Total number of Hawks
E	Escaping energy of the prey (with a range of -1 to 1)
T	Maximum number of iterations
E_0	Initial state of the energy of the prey
r	Chances of escape for a prey
$\Delta X(t)$	The difference between the position vector of the rabbit and the current location in iteration “t”
r_s	Random number inside (0, 1)
Z	A possible prospective location
D_p	Dimension of the problem (i.e. population size)
S	Random vector by size 1 x D_p
LF	Levy flight function
s	Constant values fixed at 0.01
U and v	Random numbers between 0 and 1
β	A constant fixed at 1.5

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