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Optimization of MQL-Turning Process Parameters to Produce Environmentally-Benign AISI 4340 Alloy with Nano-Lubricants using Cuckoo Search Algorithm

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A B S T R A C T

The current research consists of a machining process involving AISI steel where the input parameters are the cutting depth, feed rate and cutting speed while the responses include the cutting force, surface roughness and tool wear. Usually, heat is generated during the turning process and various machining processes, and to reduce it, coolants are considered. In this work, CuO and Al_2O_3 were used as nano lubricants (MQL). Data obtained from the machining process were inserted into Minitab 18 software where quadratic objective functions were formulated as related to each output concerning the input parameters. Objective functions were optimized with the aid of C++ programming code. The cuckoo search algorithm was used for the optimization process of the work. This work clearly shows a reduction of the output parameters that is, cutting force from 243N to 127.20N, surface roughness from 0.66μm to 0.368μm and tool wear from 0.069mm to 0.0046mm using CuO as the nano lubricant. While using Al_2O_3, cutting force was lowered from 363N to 197.63N, surface roughness from 1.98μm to 0.148μm and tool wear from 0.219mm to 0.063mm. This clearly shows that using CuO helps to obtain a better cutting force coupled with elongation of the tool life but Al_2O_3 best gives a better surface finish.

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1. INTRODUCTION

Environmentally benign manufacturing (EBM) may be reliably linked with analyzing alloy production and its influences on the environment (Gupta et al., 2020). Research at different levels has been reported on several aspects including lifecycle evaluations, thermodynamic and economic aspects of steel alloys using nano-lubricants (Gupta et al., 2020). EBM projects the idea of producing turned steel alloys using economically fit turning approaches that will yield extremely low negative influences on the environment **(**Venkatesan et al., 2020**)**. The EBM scheme is achieved by modifying the turning process to adopt the minimum quantity lubrication, a clean method, also referred to as wear-dry machining (Dubey et al., 2021; Tuan et al., 2022; Arun and Devendiran, 2023). The introduction of a monitored flow rate of cutting fluid discharge, the use of a sophisticated spraying method for the cutting zone and the reduction of the quantity of cutting fluid discharged to the steel alloy are the principal aspects of using the EBM scheme (Tuan et al., 2022).

Also, during the implementation of the EBM schemes, claims of optimality are often made, but very little empirical evidence exists in this regard (Patole and Kulkarni, 2018). With the advent of computer technology, information explosion and the unimaginable capability of computer equipment to program, the MQL-related aspects are unprecedented. The timely delivery of results on the computation of the MQL metrics is also amazing. The effect of these opportunities is that the burden of computations of optimization aspects of the MQL process in turn is being lowered. This is important as the strict government regulations on the operations of companies globally continue to be intense. Unfortunately, several researchers and practitioners pay less attention to the aspects of efficient random walk and balance mixing. Also, the speed of computations has been relegated to the background. While this gap is prevalent in the turning of steel alloys, for instance, the gaps have been closed in the area of data mining, image processing and the Internet of Things, for example.

Notwithstanding, the result of the persistent gaps in knowledge concerning adherence to sub-optimal decisions in turning steel alloys is a whole lot of wrong decision-making and wasteful resources accompanying sub-optimal decisions using other approaches, including the traditional lubrication system in steel alloy turning operation. Specifically, in the turning of AISI 4340 alloy, evidence suggests that optimally generated results are important aspects of obtaining resource conservation and high machining performance (Dhar et al., 2006; Sahoo and Sahoo, 2012; Patole and Kulkarni, 2018). Nevertheless, it is not fully clear whether the deployment of metaheuristics bridges this gap. A recent method by Ozule et al. (2022) deployed the grey wolf optimizer under the condition of turning the AISI 4340 alloy with the MOL lubrication scheme. Moreover, extensive deployment of metaheuristics with various characteristics such as the random walk category and comparatively speedy animals has not been made. Therefore, the purpose of this research was to optimize the turning parameters of AISI 4340 alloy using the cuckoo search technique. Given that optimal values are the best thresholds of results with which we may compare any attained performance in the turning process for reprimand or commendation, it is important to understand how the cuckoo search technique performs in its application to turning the AISI 4340 alloy under lubricated conditions.

Moreover, in approaching the optimal parametric determination problem for the MQL scheme for the AISI 4340 alloy in the turning process, the cuckoo search algorithm was deployed for several significant reasons, including the following (Yang and Suash, 2009): It is superior to simulated annealing and the genetic algorithm methods in that it produces efficient random walks and often and balanced mixing. These random walks are of the levy flight category preferred to other types of walks. Besides, the cuckoo search algorithm has credit for maintaining accuracy in computation and convergence rate. It contributes to computational efficiency by considering each next to contain one egg of cuckoo in a set of multiple eggs that could be fertilized and hatched by the bird, which is a set of solutions upon which one or more eggs may be hatched. In using the cuckoo search algorithm, the user produces novel and possible superior solutions that replace seemingly weak solutions in the bird's next. This is based on the scheme of actions of the cuckoo bird in replacing its egg (single egg in most cases) with the egg of the other bird, which is similar. But the cuckoo's egg is superior to the other bird's eggs and hatches faster. This action and the possibility of producing superior hatched eggs make the cuckoo search technique widely applied in areas such as data mining and image processing. Thus, the superior demonstration of the strength of the parameters, including the number of iterations, population size and switching parameters places the cuckoo search method as a top-rated metaheuristic.

This study introduces a novel method tackling the problem of turning the AISI 4340 alloy by focusing on the environment alloy-benign aspects of the turning process. The proposed method involves optimizing the turning parameter while testing the Al_2O_3 and CuO nanoparticles in lubricants to ensure green machining. This method will mitigate the environmental concerns associated with turning and assist in reducing conventional thirds. The study entails employing nano-lubricants to turn AISI 4340 alloy, making the process efficient, sustainable and cost-effective. Then, the following summarizes the chief contributions of the present study:

1. This article makes a valuable contribution to the machining of AISI 4340 alloy, which is widely used in industrial applications by signalling the optimized parameters at which turning is most profitable for the organization.
2. The concern about the optimization of turning parameters has been effectively tackled through the application of the cuckoo search algorithm method.
3. The nanoparticles, namely, the Al_2O_3 and CuO have been compared to select the better choice of the nanoparticle alternatives.

2. LITERATURE REVIEW

In recent times, industries carrying out machining processes require standard quality and dimensional precision. In the past, machinists had challenges in dealing with the extreme heat generated during the machining process as stated by Sharma et al. (2009). As a result of this, Sahoo and Sahoo (2012) found out that dimensional precisions are hardly met also causing a reduction to tool life. Coupled with this, Dhar et al, (2006) stated that the surface integrity of the job is being tampered with because of accumulated stresses, and micro-crack formations with corrosion and oxidation reactions. In addition, Mithu et al. (2008) propounded that heat generated during the machining processes cannot be adequately cooled using the convectional cooling procedures. Therefore, Prabhu and Vinayagam (2011) suggested a better method which is referred to as minimum quality lubrication which was found to be very effective in the reduction of the heat generated, enhancing the surface finish of the workpiece and prolonging the tool life. A renowned alloy found to be of a very high pedigree and has easy machinability characteristics is the AISI 4340 steel.

In light of the limitations associated with conventional optimization methods, there is a growing interest in employing evolutionary optimization techniques to enhance the optimization of multi-pass machining problems (Vijayakumar et al., 2003; Samanta and Chakraborty, 2011). In this context, the weighted mayfly algorithm (Arun and Devendiran, 2023), ant colony system (Vijayakumar et al; 2003), artificial bee colony algorithm (Samanta and Chakraborty, 2011), combined particle swarm optimization and neural networks (Karpat and Ozet, 2006) have been applied in machining operations to overcome these limitations.

Moreover, researchers have explored the application of logical fuzzy reasoning to achieve multiple output optimizations in machining processes (Tzeng and Chen, 2007). Previous investigations have demonstrated the effectiveness of utilizing artificial neural networks (ANNs) as a potent tool to address the intricate aspects of the cutting process (Karpat and Özel, 2006). Additionally, several research endeavours have been undertaken by Senthil and Joseph (2020) to investigate the experimental aspects of machining duplex stainless steels (DSSs).

Furthermore, a lot of researchers have given their reports of turning parameters on tool wear, surface integrity and other cooling systems concerning the Minimum Quality Lubrication method (MQL). Arun and Devendiran (2023) found out that surface finish, cutting force and induced stresses were lowered by 30%, 3% and 10% respectively while using graphene oxide dispersed rice bran oil as their MQL and the Mayfly algorithm coupled with a grey relational coefficient (GRC) in the machining of Nimonic 75. However, the issue with this method is that there is a reduced speed of convergence or premature convergence, which requires tweaking of data etc. to achieve the desired result. Also in the machining of Nimonic 90 by Venkatesan, et al. (2020), nano hexagonal boron nitride (hBN) was thoroughly integrated into groundnut oil which served as the nanofluid. Taguchi method was used in the computation of their experimental results which should improve in ratios of the chip thickness and shear angle.

In addition, Patole and Kulkarni (2018) experimented with the optimization of process parameters using MQL coupled with the use of Taguchi L16 orthogonal arrays for the data obtained and then analyzed the data obtained with ANOVA. They observed that the surface finish of the workpiece had a ±10% percentage error between the predicted and the experimental. Tuan et al., (2022) also used ANOVA in the experimental analysis of 90CrSi steel using MQL and Minimum Quantity Cooling Lubrication (MQCL). Their input variables considered for the research were cutting speed, feed rate etc. They observed that the machinability of the carbide tool was significantly improved coupled with the fact that the feed rate had the greatest influence on the surface finish.

Another method used was the multi-objective optimization techniques which included methods such as MOORA, VIKOR and TOPSIS by Dubey et al. (2021) in the validation of muticriterion decision-making technique (MCDM) of the turning of AISI 304 steel using Alumina-Graphene as nano lubricants. The optimum responses obtained were 0.6mm for the cutting depth, 90 m/min for the cutting speed, 0.08 mm/min for the feed rate and 1.5% for the concentration of nanoparticles with the aid of ANOVA. Philip et al, (2014) conducted an optimization study on dry turning parameters for two distinct grades of nitrogen-alloyed duplex stainless steel. They employed the Taguchi method and found that the feed rate had a greater impact on both surface roughness and cutting force. On the other hand, the cutting speed was identified as the more significant parameter affecting tool wear in their research. In recent times, Yang and Suash (2009) introduced a novel metaheuristic search algorithm known as cuckoo search (CS). Initial investigations indicate its great potential and suggest that it might surpass the performance of current algorithms. In this aspect of research, the cuckoo search algorithm has not been used and that is what we intend to do in this work.

3. METHODOLOGY

The cuckoo search algorithm (CSA), an appealing scheme for the MQL turning of the AISI 4340 alloy, was first proposed in 2009 by famous researchers. Yang and Deb. The development of the CSA follows the inspiration obtained by the brood parasitism habitual of cuckoo birds, consisting of their egg laying, breeding and lifestyle of the cuckoo bird. In laying eggs, the most striking feature of the cuckoo birds is that they target and achieve laying of eggs in other birds' nests. In doing so, they pretend and deceive the host bird that their eggs, which are similar to the host's eggs belong to the host. In so doing, the host breeds the eggs and what comes out is the cuckoo chicks. However, the cuckoo bird does not always have its way. There are situations in which the host bird discovers that one of the eggs is not its own. In this case, it throws out the alien eggs and sits only on its eggs. Otherwise, on suspecting that it could not be sure about which egg belongs to it, it may abandon its nest and create a new nest somewhere else. These features in breeding, laying of eggs and lifestyle are combined to develop the algorithm of the cuckoo search. However, first, the assumptions guiding the development of the cuckoo search algorithm are stated as follows:

3.1 Assumption of the cuckoo search algorithm

To apply the algorithm of the cuckoo search successfully to the turning data of AISI 4340 alloy, three principal assumptions are made:

1. Only one egg is laid by every cuckoo at a time and the cuckoo sets the eggs carefully in a nest. Here the nest is randomly selected.
2. A nest containing superior-quality eggs progresses to the next phase of computation.
3. An increase in the number of nests is not permitted once the computational process commences while the quality of the nest remains the same throughout the study period.

Next, the main purpose is to study the optimal process parameters for on cutting process on hardened AISI 4340 steel. Table 1 below shows the output parameters, and the optimization operations on them to yield optimal machining performance with the use of lubricants such as CuO and Al_2O_3.

Table 1. Input parameters and outputs with objectives

S/N	Inputs	Outputs	Operations on outputs
1	Cutting speed (m/mm)	Cutting force (N)	Minimize
2	Feed (mm/rev)	Surface roughness Ra (μm)	Minimize
3	Cutting depth (mm)	Tool wear (mm)	Minimize

This information in Table 1 provides some hints on the direction of the present research. Thus, in this research, the minimization goal for each of the cutting force surface roughness and tool wear is pursued for both nanolubricants CuO and Al_2O_3. This makes it possible to construct six objective functions with three for the CuO nanoparticles and the other three objective functions for the Al_2O_3 nanoparticles. However, to proceed in the development of these objective functions, boundaries for the component parameters of the objective function, including the cutting speed (CS), feed (F) and cutting depth (CD) are needed, which are fed into the Minitab 18 software. This led to the development of non-linear equations with which substitutions will be eventually made to obtain the optimal threshold values for the parameters. Notice that in the objective function formulations, each of the responses CF, SR, and TW will be taken as the dependent values while the independent variables will be the Cs, F, and CD. Now, in an attempt to formulate the objective functions, the boundaries of the process parameters for the on-cutting problem are 80 and 140 as lower and upper boundaries of the cutting speed (CS), respectively, and it is represented as X_1. Furthermore, in X_2, the lower and upper boundaries are 0.05 and 0.20, respectively. Next, the cutting depth (CD) parameter, represented as X_3, has the lower and upper boundaries as 0.1 and 0.4, respectively, while solving this problem using the cuckoo search algorithm, three measures of the turning system need to be defined. These are the population size (number of nests), which is 5, the number of iterations to be conducted, which is 200 and the probability (Pa) measure of interest, given as 0.25. Next is the development of the objective function as given in the results section.

3.2 Objective function formulation

From all the input and output considered in the section on methods, these details are entered into the spreadsheet provided by Minitab 18 and the relevant functions are valued to obtain the following objective functions:

Objective function 1: Minimize CF while using the CuO lubricant. Here, the formulated objective function is shown in Equation (1):

$$CF = 52.7 - 0.531\,CS + 531\,F + 280\,CD + 0.00922\,CS*CS - 900\,F*F - 212\,CD*CD + 0.47\,CS*F - 0.61\,CS*CD - 925\,F*CD \quad (1)$$

where Cs, CD and F ≥ O

This is the objective function formulated to minimize the cutting force on processing the AISI 4340 alloy using the CuO lubricant. However, to facilitate comparison with the Al_2O_3 nanoparticle lubricant, the next objective function is formulated while still considering the cutting force as the response of the MOL turning system. This is shown in Equation (2)

Objective function 2: Minimize CF while using the Al_2O_3 lubricant. Here, the formulated objective function is shown in Equation (2):

$$CF = -18 + 0.29\,CS + 1352\,F + 607\,CD + 0.00781\,CS*CS - 1850\,F*F - 437\,CD*CD - 0.47\,CS*F - 0.77\,CS*CD - 2350\,F*CD \quad (2)$$

where CS, CD and F≥ O

This objective function was developed to minimize the cutting force while processing the AISI 4340 alloy using the Al_2O_3 lubricant. Next, the description of the objective function for the surface roughness follows. Here, the consideration for the CuO nanoparticle lubricant is made in Equation (3).

Objective function 3: Minimize SR while using the CuO lubricant. The intention of developing this function is to promote the surface integrity of the output while machining the AISI steel alloy. The formulated objective function in Equation (3):

SR = 0.266 - 0.00341 CS + 1.39 F + 0.918 CD + 0.000028 CS*CS - 2.30 F*F - 0.612 CD*CD + 0.00465 CS*F - 0.00145 CS*CD - 4.00 F*CD (3)

where CS, CD and F ≥ O. Moreover, the Al_2O_3 nanoparticle is considered in the next formulation.

Objective function 4: Minimize SR while using the Al_2O_3 lubricant. Here, the formulated objective function is shown in Equation (4)

SR = 2.18 - 0.0882 CS + 15.7 F + 11.57 CD + 0.000442 CS*CS - 43.9 F*F - 10.36 CD*CD + 0.0729 CS*F - 0.0106 CS*CD - 42.8 F*CD (4)

where CS, CD and F ≥ O.

Next, a description of the objective function for the tool wear is given as Equation (5).

Objective function 5: Minimize TW using the CuO lubricant. Here, the formulated objective function is shown in Equation (5):

TW = 2.18 - 0.0882 CS + 15.7 F + 11.57 CD + 0.000442 CS*CS - 43.9 F*F - 10.36 CD*CD + 0.0729 CS*F - 0.0106 CS*CD - 42.8 F*CD (5)

where CS, CD and F ≥ O.

This objective function was developed to minimize the tool wear while processing the AISI 4340 alloy using the CuO lubricant. However, the next consideration is for the Al_2O_3 nanoparticle lubricant scheme, shown in Equation (6).

Objective function 6: Minimize TW while using the Al_2O_3 lubricant. The aim is to develop a function as in Equation (6):

TW = -0.007 - 0.00014 CS - 0.15 F + 0.223 CD + 0.000009 CS*CS + 1.10 F*F + 0.112 CD*CD + 0.00263 CS*F - 0.00169 CS*CD - 1.03 F*CD (6)

where CS, CD and F ≥ O.

In addition to the objective function formulations, there is a need to identify an equation, which will be useful in monitoring the values of all input parameters concerning egg generation. The Equation (7) is useful for the attainment of this goal:

$$x = L + r\,(U - L) \qquad (7)$$

where x is the obtained value, U represents the upper boundary for the respective parameters of cutting speed, feed and cutting depth. L is the lower boundary of the stated parameters. Also, r is the random number generated between 0 and 1.

Furthermore, in generating new solutions, the equation for u is given in Equation (8)

$$\sigma_u = \frac{\Gamma(1+\beta)\sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\frac{(1+\beta)}{2} * \beta * 2^{\frac{\beta-1}{2}}} \qquad (8)$$

where β is the parameter, which is set as 1.5, Also, in the generation of the new solution X_{new}, Equations (9), (10) and (11) are used:

$$u = randn * \sigma_u \qquad (9)$$

$$v = randn * u \qquad (10)$$

where u and v are normal distributions while and represents random numbers that are normally distributed.

$$s = \frac{u}{|v|^{\frac{1}{\beta}}} \qquad (11)$$

$X_{new} = x_1 + randn * 0.01 * s\,(x_1 - Best)$ (12)

where s is defined by another Equation (12).

4. RESULTS AND DISCUSSION

Now that the empirical models have been developed in the previous section, they will be optimized using the Cuckoo Search Algorithm. This will be achieved with the aid of C++ programming language. Recall that earlier, in the section on methods, after defining the boundaries of the parameters, representations of X_1, X_2 and X_3 are made for each of the parameters, namely cutting speed, feed and cutting depth, respectively, Now, five eggs are to be arbitrarily considered, namely egg 1, egg 2, egg 3, egg 4 and egg 5. For each of these eggs, the computation of CS, F and CD has to be done and these parameters may be represented as X_1, X_2 and X_3 as previously defined. The implication is that a 5-row by 3-column matrix is to be generated for the results of processing the egg in the brooding process by the cuckoo search algorithm. To start with, egg 1 is considered where X_1, X_2 and X_3 are to be evaluated. Notice that having known these values of X_1, X_2 and X_3, they are substituted into the objective functions earlier developed in the section on the method to obtain the f(x). It is this $f(x)$ value that provides additional information for the researcher to progress in evaluating the performance of the nano lubricants and facilitate comparison between CuO and Al_2O_3nano lubricants to generate results for egg 1, f(x) is to be computed. But at first, X_1, X_2 and X_3 are analyzed. To analyze X_1, notice that Equation (7) is used where L = 80, u = 140, r = 0.448592. By substituting these values of L, U and r into Equation (7), a value of x as 106.915 is obtained. This is the value of X_1 intended for use. To obtain X_2, we note that L = 0.05, u = 0.20 and r = 0.222205. It is also noted that to obtain X_3, L = 0.1, u = 0.4 and r = 0.961516. Therefore, by substituting these values in Equation (7), X_2 is 0.0833308 while X_3 is 0.388455. it is important at this stage to substitute these unique values into the objective function in Equation (1) under the methods section. This substitution gives f(x) as 0.388455 for egg 1 being considered. Then, by following this routine, the f 9x) for other eggs, i.e. egg 2, egg 3, egg 4, and egg 5 yield 167.350, 180.668, 159.039 and 199.412, respectively. Notice that all these values are obtained for the Minimization of CF while the lubricant is CuO. To proceed, recall that solutions for five eggs were generated.

However, since minimization is pursued, all the f(x) values for egg 1 to egg 5 are compared and the minimum is chosen as egg 4. However, the corresponding values of X_1, X_2 and X_3 should be identified as the best parameters. Thus, the best parameters at this stage are the CS of. 98.2031, F of 0.122585 is carried forward and compared with new solutions obtained afterwards. If these values are better, the researcher sticks to it, otherwise, the analyst adopts the latter, which is better. Thus, the next stage is to generate new solutions. At this stage, the analyst generates solutions for egg 1 only and compares values of the various parameters of CS, F and CD with the previously generated ones. For clarity, the CS, F and CD are represented by egg 1 parameter CS, egg 1 parameter F and egg 1 parameter CS, Equations (9), (10), and (11) utilized. In this case, by using Equation (9), the parameter 11 is calculated as – 0.0849614 and a value of – 1.08682 is obtained when Equation (10) is used in the computation. However, to evaluate the X new, the parameter s needs to be evaluated first. This is obtained as – 0.0803742. a further step is taken to substitute the parameter s into Equation (12) to obtain 106.911. here X_{new} is within range and it is retained. However, notice that this value is for egg 1 parameter CS while egg 1 parameters F and CD are to be calculated next. Now, by following the procedure, X_{new} is obtained as 0.08544799 and 0.3884660 for egg 1 parameter F and egg 1 parameter CD, respectively. These two values are retained for comparison until the next stage.

At this point where the generated values of egg 1 parameter CS, egg 1 parameter F and egg 1 parameter CD are obtained, they are substituted into the objective function Equation (1) to obtain 165.0666. Recall that the earlier value obtained was 164.925, compared with this new value of 165.0666, which is higher, an update will not take place. As the analyst proceeds, these computations are done for each of the remaining egg 2, egg 3, egg 4 and egg 5 and the values of 167.3498, 180.6684, 159.0394 and 198.5910, respectively, are obtained. At this stage, the researcher moves to the second phase of the analysis where the replacement of an egg with a new solution is done. At this stage, one needs to consider egg 1 in the context of three parameters: egg 1 and egg 1 parameter CD. So, egg 1 parameter CS is considered. At this point, a random number is chosen, between 0 and 1, which is 0.1315378. the analyst then proceeds to check that Pa. However, it is known that the generated random number is less than Pa, and this provides an opportunity for CS to be selected and modified. If not, there is no need for an update. The next sub-stage is to modify the new equation by using Equation (12) and noting that random integers are generated from 1 to 5. Here d_1 = 3 while d_2 = 2. The peculiar issues here are that X_1 is the first value in the egg 1 parameter CS, Xd_1 = 3 is the first value in the egg 3 parameter CS while $Xd_2 = 2$ is the first value in the egg 2 parameter CS. Then X new is obtained as 127.6101. Moving on to egg 1, parameter F, the random number generated is 0.678864717. However, since r is greater than Pa, there will be no need to update the process.

Next is the consideration of egg 1 parameter CD. Here, the random number chosen is 0.934692896 where *r* is greater than Pa and there will be no need for an update. The next phase of the work is to conduct a greedy solution. Here, the values of the process parameters are inserted into the objective function to obtain an output of CF, if the value obtained is smaller than the value of CF, previously obtained at the nest (egg), x new replaces that nest. Moreover, if the reverse is the case, then the nest remains as it is. This process is called the greedy solution. Now, F (X new) yields 194.5749. Through comparison of the values of F (X_{new}) and F(X), it is known that if F (X new) ≥ F(X), then, a replacement will not take place. The previous steps are repeated for the remaining nests and Table 2 shows the values obtained. Now, after the 200th iteration, while using CuO as a lubricant, the best values obtained are cutting speed, 80.0000 000, feed, 0.0697630370, cutting depth, 0.175442214, and cutting force, 127.202457.

Table 2. The best values after each iteration

Number of Iterations	Cutting Speed(m/min)	Feed (mm/rev)	Cutting depth (mm)	Cutting Force(N)
2	98.2030708	0.122585225	0.321060818	159.039409
3	98.2030708	0.122585225	0.321060818	159.039409
4	98.2030708	0.122585225	0.321060818	159.039409
…	…	…	…	…
…	…	…	…	…
…	…	…	…	…
197	80.0000000	0.0697630370	0.175442214	127.202457
198	80.0000000	0.0697630370	0.175442214	127.202457
199	80.0000000	0.0697630370	0.175442214	127.202457
200	80.0000000	0.0697630370	0.175442214	127.202457

Now, the results of other computations are shown in Table 3. Furthermore, by obtaining the objective function from the application of the Minitab software while activating the non-linear models of the software, the values for CF, which represents the cutting force are obtained. The values of X_1, X_2, and X_3 were input into the objective function equation to obtain specific values. Notice that the aim is to minimize the cutting force. Thus, drawing from Equation (2), the best set of values is Best = [98.2031, 0.122585, 0.321061] where the cutting force is obtained as f(*x*), which gives 197.6318N when the objective function for CF while using the Al_2O_3 lubricant (Equation 2) was introduced into the C++ computer program. This obtained minimum value for CF has some optimal process parameters associated with it, which are as follows: The cutting speed which had the value of X_1 substituted for it yielded 94.4268m/min. the feed parameter represented by X_2 was obtained as 0.07003693mm/rev while the parameter named cutting depth, represented by the symbol X_3 in Equation (2) when substitutions are made yielded 0.1116916mm. Notice that these obtained values were after the 200th iteration with previously unchanged conditions of boundaries, population size and number of iterations.

Table 3. Optimal process parameters required to obtain the various objectives

Objective	Parameter 1	Parameter 2	Parameter 3	Output
Objective 1	Cutting Speed (x_1) 80.0000000	Feed (x_2) 0.0697630370	Cutting Depth (x_3) 0.175442214	Cutting Force [f(x)] 127.202457
Objective 2	Cutting Speed (x_1) 80.0000000	Feed (x_2) 0.0697630370	Cutting Depth (x_3) 0.175442214	Cutting Force [f(x)] 127.202457
Objective 3	Cutting speed (x_1)	Feed (x_2)	Cutting depth (x_3)	Surface roughness [f(x)]
	89.29289	0.05000000	0.2192969	0.3689020

Objective 4	Cutting Speed (x_1) 116.7211	Feed (x_2) 0.07509995	Cutting Depth (x_3) 0.1127079	Surface Roughness [f(x)] 0.1481263
Objective 5	Cutting Speed (x_1) 85.88343	Feed (x_2) 0.05008859	Cutting Depth (x_3) 0.1702522	Tool Wear[f(x)] 0.004656710
Objective 6	Cutting Speed (x_1) 80.71834	Feed (x_2) 0.1713245	Cutting Depth (x_3) 0.3647047	Tool Wear[f(x)] 0.06339916

This work is on the optimization of the research carried out by Elsheikh et al., (2021) using the Cuckoo Search Algorithm. A cutting force of 127.20N was obtained when CuO was used as the nano lubricant at a cutting speed of 80m/min, feed rate of 0.06976mm/rev and cutting depth of 0.1754mm. The cutting force obtained was greatly reduced compared to 129N and 243N which happened to be the minimum and maximum values respectively. In another case, Al_2O_3 was used as the nano lubricant on the cutting force during the turning process. After the optimization process, the cutting force of 197.63N at 94.542m/min, 0.070mm/rev, and 0.111mm which were the cutting feed, feed rate and cutting depth respectively. The value obtained was drastically lower than the maximum cutting force obtained in the research work validated.

On the other hand, the surface roughness was put to test in the optimization of the machining process. A value of 0.368µm was obtained at a cutting speed 0f 89.292m/min, feed rate of 0.050mm/rev and cutting depth of 0.219mm. This result was obtained while using CuO as the nano lubricant in the machining process. As compared to the minimum and maximum values obtained in the original research which were 0.375µm and 0.66µm respectively, the optimized output was lower. Moreover, $Al_2O_3$was also used as a nano lubricant for the surface roughness during the optimization process in the turning process where a value of 0.148µm at a cutting speed of 116.721m/min, feed rate of 0.075mm/rev and cutting depth of 0.112mm. The result obtained in this work was greatly decreased from 1.98µm obtained from the original research.

Tool wear happened to be the last output considered in this work. As stated above, CuO and Al_2O_3 were also used as the nano lubricants during the machining process. When CuO was used, a value of 0.0046mm for the tool wear was obtained at a cutting speed of 85.883m/min, feed rate of 0.050mm/rev and cutting depth of 0.170mm. The tool wear output obtained during the optimization process was lower than the value obtained from the original work which happened to be 0.0089mm. When Al_2O_3 was used, a value of 0.063mm for the tool wear was obtained at a cutting speed of 80.719m/min, 0.171mm/rev and a cutting depth of 0.364mm. The value of the tool wear obtained during the optimization process was largely reduced. Moreover, the ranks of Al_2O_3 and CuO nanoparticle performance in the turning of AISI 4340 alloy are in good agreement with the relevant literature as revealed by Ozule et al. (2022).

Validation

The present study on the application of the cuckoo search algorithm was validated using published data on the same subject but using the grey wolf analysis by Ozule et al. (2022) (Table 4).

Table 4. Validation data for the input parameters

	Cutting speed (CS)			Feed (F)			Cutting depth (CD)		
Objective	Ozule (2022)	Present Paper	Error%	Ozule (2022)	Present paper	Error%	Ozule (2022)	Present paper	Error%
Objective 1 (Min CF (CuO lubricant)	80.00	80.00	0.00	0.05	0.07	-40.00	0.10	0.18	-80.00
Objective 2 (Min CF (Al_2O_3 lubricant)	80.00	80.00	0.00	0.05	0.07	-40.00	0.10	0.18	-80.00
Objective 3 (Min SR (CuO lubricant)	80.00	89.29	-11.61	0.07	0.05	28.57	0.10	0.22	-120.00

Objective 4 (Min SR (Al_2O_3 lubricant)	80.16	116.72	-45.61	0.06	0.08	-33.33	0.29	0.11	62.07
Objective 5 (Min TW (CuO lubricant)	80.00	85.88	-7.35	0.05	0.05	0.00	0.25	0.17	32.00
Objective 6 (Min TW (Al_2O_3 lubricant)	80.00	80.72	-0.90	0.05	0.17	-240.00	0.12	0.36	-200.00
		Sum	-65.47			-324.76			-385.93
		Average	-10.91			-54.13			-64.32

The input data considered are the cutting speed (CS), feed(F) and Cutting Depth (CD) while the outputs considered are the cutting force (CF) Surface Roughness (SR) and tool wear (TW) for each of the CuO and Al_2O_3 nanolubricants. From Ozule et al. (2022), the minimum CFSR and TW for CuO nanolubricants were achieved at 80m/mm (cutting speed), 0.05mm/rev (feed) and 0.10mm (cutting depth). However, for the present method, they were achieved at 80m/mm (cutting speed) 0.05mm/rev(feed) and 0.17mm (cutting depth). The errors in the minimum cutting speed, feed and cutting depth were an average of -10.91%-54.13% and -64.32%. This implies that the published work of grey wolf optimization performs better than the cuckoo search algorithm but the latter could be used as an effective alternative to optimise the turning process. Furthermore from the report by Ozule et al. (2022), the minimum CF, SR and TW for Al_2O_3 nanolubricant were attained at 80m/mm (cutting speed), 0.05mm/rev (feed) and 0.10mm (cutting depth). Nonetheless, considering the current approach, the results shown are as follows: 80m/mm (cutting speed), 0.07mm/rev (feed) and 0.11mm (cutting depth). The error results previously reported apply here and the conclusions. There of since they represent an overall evaluation of the performance of the current method of cuckoo search algorithm compared with the grey wolf algorithm reported earlier in the literature.

5. CONCLUSIONS

The work showed that the output variables such as cutting force, surface roughness and tool wear are not wanted in the machining process but in fact cannot be done without. The best option is to reduce their effects because, with an increase in the cutting force, there is also an increase in the surface roughness and tool wear. Hence, the outcome of this research indicates that deploying the cuckoo search algorithm to determine the optimal turning variables is feasible. Future research should be conducted on using new and upcoming optimization methods like Aquilla to obtain better results and other nanolubricants such as the hybrid ones should be considered too.

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