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Optimizing the Process Parameters for Eco-Friendly Minimum Quantity Lubrication-Turning of AISI 4340 Alloy with Nano-Lubricants Using a Grey Wolf Optimization Approach

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Optimization of turning process parameters in minimum quantity lubrication (MQL)-assisted mode is obligatory for enhanced efficiency and product integrity. However, little attention has been paid to analyzing situations where high search precision is needed when evaluating the optimal turning process parameters. This article applies the grey wolf optimization (GWO) approach to optimize the turning of parameters AISI 4340 alloy to enhance cutting force, surface roughness and tool wear. Based on the literature data, turning was conducted with MQL-assisted CuO and Al_2O_3 nanofluids. The problem was formulated by mimicking six wolves in six different objective functions. The objective functions have the responses as the dependent variables and the parameters including cutting speed, feed and cutting depth as independent variables. The hunting behavior of the wolves as they encircle the prey is interpreted to the machining task optimization. It involves three hierarchically-evaluated guides- the alpha, beta and delta wolves- positioned optimally and other wolves are updated accordingly. The cutting speed, feed and cutting depth are bound in the lower and upper limits as 80 and 140m/min, 0.05 and 0.20m/m/rev and 0.1 and 0.4mm, respectively. The grey wolf optimization algorithm optimizes the parameters to yield the cutting force, surface roughness and tool wear using Al_2O_3 as 199.50N, -23.54mm and 0.06mm, respectively. For the CuO, the corresponding cutting force, surface roughness and tool wear, the CuO, Al_2O_3 and CuO nano lubricants produced the best results. However, for mass production, selective use of CuO and Al_2O_3 should be made. The usefulness of this research endeavor is to help process engineers to make decisions in producing low-cost components in manufacturing.

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1. INTRODUCTION

Optimization of turning processes is probably the most reliable route to achieving the best results based on the desire to maximize operation's productivity, efficiency, plant longevity and resource utilization (Kelly, 2010; Al-Shayea et al., 2020; Yıldırım, 2020; El-Sheikh et al., 2021). Turning optimization has its prevailing components comprising of decision variables such as the cutting tool characteristics (tool rigidity, geometry, coating, material; (Sahoo and Sahoo, 2012; Fan et al., 2016; Yadav and Kumar, 2020), work material properties (ductility, tensile strength, thermal conductivity, workpiece rigidity; Yadav and Kumar, 2020). Other decision variables are the nano-cutting fluids such as Al_2O_3 and CuO to include their characteristics and properties (Srikant et al., 2008; Padmini et al., 2016; Kumar et al., 2019; Yadav and Kumar, 2020). Still, the machine tool is another decision variable in turning whose accuracy, rigidity and capacity are important attributes of study (Yadav and Kumar, 2020). Besides decision variables, the objectives and constants are important elements of the turning optimization process.

Probably the most popular optimization method within the turning scenario is the Taguchi method (Roy, 1990; Reddy and Hari, 2018). The method is competent in minimizing the emerging disparity within the turning process. This method has wide acceptability among process engineers and turning operators as it is easy to apply with useful quantitative and qualitative outcomes for turning decision-making (Reddy and Hari, 2018). Nonetheless, in applying the Taguchi method to turning operations data, process engineers and operators are often confronted with the difficulty of interpreting the more influential decision variables on resource conservation and control. Critics argue that it is rare to obtain limits on how to determine the superiority of one variable over another except if the Taguchi method is integrated with other methods or replaced with competing optimization methods. Therefore, the Taguchi method in this turning scenario may be replaced with an evolutionary algorithm, probably the grey wolf optimization procedure. To the utmost knowledge of the present authors, previous studies could not tackle the high search precision problem when confronted with multiple conflicting variables each struggling for recognition. While implementing the turning process in a multiproduct and multi-variable scenario, an important concern is the search precision attribute of the process. But engaging an optimization method such as the grey wolf optimization procedure assures high search precision and timely delivery of decision outcomes.

Besides, methods such as Taguchi (Onuoha et al., 2016), ANOVA (Onuoha et al., 2016), artificial neural network model (Shankar et al., 2019), correlation analysis (Bouacha et al., 2010), signal-to-noise ratios of Taguchi (Venkatesan et al., 2019), orthogonal array (Manivel & Gandhinathan., 2016), heuristics (Kharwar and Verma., 2021), integrated Taguchi and grey wolf optimization (Khalilpourazari and Khalilpourazary, 2016) have been applied in machining. Being attracted by the ability to reduce experimental costs, and enhance product quality, the Taguchi method was deployed by Onuoha et al. (2016) to examine the effects of cutting fluids on surface repulsiveness in turning AISI 1330 compound steel using the machining process (El-Baradie, 1996). Furthermore, Venkatesan et al. (2019) might have stimulated the fractionated ability of Taguchi designs and the special attribute of a selective partial fraction of a full factorial design where experimental cost and time are greatly reduced. The author articulated the result of machinability while using the least amount of oil (MQL) on CNC turning of 617 compounds using the Taguchi method. It was reported that wear and surface roughness expanded due to cutting speed increment while the decline in force was experienced. Moreover, the wear factor increased with the addition of weighted nano-particles in vegetable oils while decreasing the surface roughness. Nonetheless, the ANOVA method was promoted as a useful tool to access the fluctuations in cutting rate, feed rate as well as the significance of cut on surface roughness under different cutting fluids. Shankar et al. (2019) also applied ANOVA to understand the fluctuations in cutting power, flank wear and surface hardness of the workpiece. The connection of feed and depth of cut had a significant commitment of 50.39%

followed by the depth of cut and feed of 27.72% and 14.52%, respectively. Moreover, Labidi et al. (2018), using the ANOVA table, expressed that the cutting power had an F-worth of 177.65, which affirmed that the model was huge. At the point when the depth of cut expanded, the tool became dull which built the device's workpiece contact region and the cutting power increased in value. Besides, Manivel & Gandhinathan (2016) used the ANOVA method. It was found that the contributory parameters influencing the surface roughness and tool wear were the cutting rate with 49.1% and 50.2%, respectively.

The artificial neural network is another method that has been used by authors in the turning process literature (Zerti et al., 2019). Shankar et al. (2019) utilized the ANN model to reveal the tool wear using the feed-forward type of ANN. Related work was conducted by Ahmadi et al. (2019) with the deployment of ANN in the turning perspective. In the turning process, the coefficient of determination has been used to establish the degree of variability of a factor stimulated by its association with another factor. Sometimes, some scholars use the square root of this coefficient value known as the correlation coefficient. Bouacha et al. (2010) explored this idea to establish the relationship between cutting power, depth of cut and tool wear. In these cases, the minimum coefficient of determination reported by the authors was 0.9882. Furthermore, Bhuiyan and Choudhury. (2015) also explored the idea of coefficient of determination and discussed the possible outcomes of two sets of values, notably 0.9211 and 0.9585.

Research on machining, particularly focusing on minimum quantity lubrication has been extensive in the previous years (Gajrani et al., 2019). For instance, Sen et al. (2017) proposed adaptive neuro-fuzzy inference systems (ANFIS) to associate the control variables and objective function while mulling the Inconel 90 alloys during CNC machining. It was concluded that the ANFIS results supersede the outcome of the competing artificial neural network method. Sen et al. (2021) declared the necessity of adopting the sustainability viewpoint machining. The principal focus is the minimum quantity of lubrication which is recommended for modern usage in machining. Sen et al. (2020) analysed the accomplishment of a green lubricant to mill the Inconel 690 material. It was concluded that for all machining responses, the 1% silica accumulated on palm-oil medium provided outstanding performance. Furthermore, Sen et al. (2019a) established the utmost arrangement of milling parameters in an MQL mode while considering Inconel 690 and castor oil lubricant. The response surface methodology, non-dominated sorting genetic algorithm-II and technique for order preference by similarity to the ideal solution were applied. The conclusion is that a less than 0.01 error value was obtained when the experimental responses were compared with the prediction. In another study, Sen et al. (2019b) established the advantages of MQL-assisted milling using a blend of palm oil and $A1_2O_3$ and processing the Inconel 690 material. In conclusion, the indices representing the multi-performance characteristics established a 2.5% as the optimum concentration of the Al_2O_3 within the MQL situation. This result was declared superior to other lubricating sources analysed. Besides, Sen et al. (2019c) proposed a Pareto-oriented optimization scheme using an integrated gene expression programming, TOPSIS and NSGA-II) to process Inconel 690 in milling operation. Based on a comparison between predictions and experimental data, a 3.13% error was reported. The drawback of this group of studies is that no defined optimization procedure is capable of guaranteeing high search precision in a complicated scenario such as turning. This drawback has an exception, which is Sen et al. (2017) that proposed a metaheuristic that is capable of high search precision. However, even the application is in the milling process which may be treated differently from the turning process which is the focus of this research.

Furthermore, interestingly, in the past few years, some studies (Venkatesan et al., 2019; El-Sheikh et al., 2021) have established that optimization procedures in lubricated machining environments enhance efficiency. Consequently, several studies have been skewed towards the use of the Taguchi method in the past (Manivel and Goandhinathan, 2016; Onuoha et al., 2016; Reddy and Harry, 2018). However, extremely little attention has been paid to study optimization procedures in machining where high search precision is compelling. Laouissi et al. (2019) are among the few studies that have responded to the call for high search precision using the genetic algorithm method. Notwithstanding, high search precision is the basis for efficiency in complicated multiproduct optimization systems where heavy and multi-feature parts needed to be turned. Therefore, the novelty of this article is the focus on the use of the grey wolf optimization method in turning the AISI 4340 alloy through lubrication-assisted turning using Al_2O_3 and CuO nano lubricants. Besides, this article analyses the parameters of cutting speed, feed and cutting depth in producing the best surface roughness, cutting force and tool wear. Moreover, this article enhances the machining process of turning AISI 4340 alloy.

Accordingly, this article applies the grey wolf optimization (GWO) to efficiently deliver results that will propel prosperity while turning AISI 4340 alloy under a lubricated environment (Medjahed et al., 2016; Pradhan et al., 2016; Kharwar and Verma, 2021). The theory of the grey wolf is deployed as an illustration of the effectiveness of the grey wolf optimization method (Kharwar et al., 2021). This method mimics the grey wolves which are territorial animals with habitation in packs championed by alpha pairs. The social prey-seeking and prey-attacking behaviours of the grey wolves are the fundamental components of the optimization scheme used in the present work. This study is substantial since it provides a framework to address the essential deficiencies of optimization methods presently adopted in the turning operation. Some of these optimization schemes are difficult to implement as a result of their complicated structures such as the Cuckoo search (Labidi et al., 2018; Laouissi et al., 2019). The optimization schemes also have the problem of requiring more storage and computational needs (Pradhan et al., 2016). Thus, by introducing the grey wolf optimizers, these problems are subdued.

This study contributes to the literature on turning operations by highlighting the grey wolf optimization as a strong tool that exceeds the capacity of the Taguchi method through the introduction of the high search precision attribute in making turning optimization decisions. Also, the study contributes by:

- Highlighting the essential parameters in optimization procedures that are unclear to date
- Determining research weaknesses on turning process optimization while opening up a new research direction

Although previous articles have highlighted the importance of optimization in turning, little attempt was made to establish to tool to attain high search precision in turning. Furthermore, no systematic deployment of any optimization tool with the high search precision attribute has been made so far in the literature.

2. METHOD

2.1 Research gap

Turning the AISI 4340 using eco-friendly nano lubricants under the minimum quantity lubrication scheme seems to be a viable method for the economic production of machined parts and would aid the sustainability of the machining process (Roy et al., 2018). However, earlier studies seem to have downplayed optimization procedures. In cases where optimization has been considered, the Taguchi method is at best the preferred method. But the Taguchi method has the deficiency that it is difficult to know to what degree a factor in the process exceeds the other in the deployment of the optimal parametric setting to solve the optimization problem. Unfortunately, the potential of the grey wolf optimization procedure has not been sufficiently studied in the engineering manufacturing instance. More specifically, it has not been analyzed in the domain of turning, under the minimum quantity lubrication system and an eco-friendly environment. Furthermore, though several nano lubricants exist, copper oxide and aluminium oxide are two widely successful applications in enhancing the surface roughness of machine parts and the reduction of tool wear used to process the material subtraction. It is believed that the novel procedure of grey wolf optimization may be useful in attaining reduced surface roughness and tool wear in the eco-friendly manufacturing process. Thus, this paper revolves around the establishment of the novel optimization procedure of grey wolf optimization for improving the surface integrity of the machined materials while reducing the tool wear.

2.2 Objective function formulation

From the literature review, a gap in research was established. Consequently, it is resolved that to obtain effective computational outcomes, an optimization (linear) program should be formulated with the objective and constraints with the three outputs terms in focus. It then implies that for each output term, for instance, cutting force, a linear program should be formulated such that the experimental data generated for each of CuO and Al_2O_3 will be used in the formulation. In essence, this result section shows six linear programs. But a linear program comprises the objective function and constraints. Thus from the experimental data obtained in the referenced article, a regression equation is formulated for each of the objective functions and then substituted in the linear program to be formulated afterwards. To demonstrate how these regression equations are formed, the data from Table 5 of the referenced material is used. The data are inputted into the Minitab 18 software, where the inputs and each output at a time are computed to obtain the regression equations.
Having obtained the regression equations, the linear programs formed are as follows:

Objective function 1
Minimize
CF_{CuO} =11.17+1.3970CS+121.1F-5.2CD
Subject to:

$$80 \le CS \le 140 \qquad (1)$$
$$0.05 \le F \le 0.20 \qquad (2)$$
$$0.1 \le CD \le 0.4 \qquad (3)$$

where CD, F, CS ≥ 0

Objective function 2
Minimize
$CF_{Al_2O_3}$ = 39.8+1.8150CS+261.1F+14.4CD
Subject to:
Constraint Equations (1), (2) and (3) above

Objective function 3
Minimize
SF_{CuO} = 0,318+0.00091CS-0.176F+0.196CD
Subject to:
Constraint Equations (1), (2) and (3) above

Objective function 4
Minimize
$SR_{Al_2O_3}$ = -70+0.752CS+165F-82CD
Subject to:
Constraint Equations (1), (2) and (3) above

Objective function 5
Minimize
TW_{CuO} =-0.0089+0.000542CS+0.0579F-0.0109CD
Subject to:
Constraint Equations (1), (2) and (3) above

Objective function 6
Minimize
$TW_{Al_2O_3}$ =-0.0824+0.001679CS+0.164F-0.0343CD
Subject to:
Constraints Equations (1), (2) and (3) above

Furthermore, the objective functions and constraints (1), (2) and (3) were developed as codes using the C++ programming environment. At first, a preliminary program testing was made to observe the convergence or program termination point will be. For the program, the Population Size (number of wolves) is taken as 5 and the Number of iterations is taken as 100. After executing the codes, it was found that 100 iterations are sufficient to run to terminate the program after this. Thus for each linear program, the expressions that mimic the grey wolf optimizer were coded and run with the following results obtained.

Besides, the following Equation (4) is used to generate the value of *x* (Mairjalili et al., 2014):

$$x = L + r(U - L) \qquad (4)$$

where
L is the lower boundary
U is the upper boundary
r is the random numbers between 0 and 1

Some parameters are obtained from the following (Mairjalili et al., 2014; Jayakumar et al., 2016):

$$a = 2\left(\frac{iteration}{\max imum\ iteration}\right) \quad (5)$$

In Equation (5), the "a" reduces in a linear manner starting from 2 and gradually reducing to zero when the iteration number starts from 1 to the point of convergence of the program. Furthermore, for the first wolf, the formulae for obtaining X_1, X_2 and X_3 are shown in Equations (6) to (17) (Mairjalili et al., 2014; Jayakumar et al., 2016). These equations were adapted for the other wolves 2 to 5. While the mentioned equations relate to the situation when wolves encircle the prey, the behaviour of the wolves during this process is illustrated in Fig. 1.

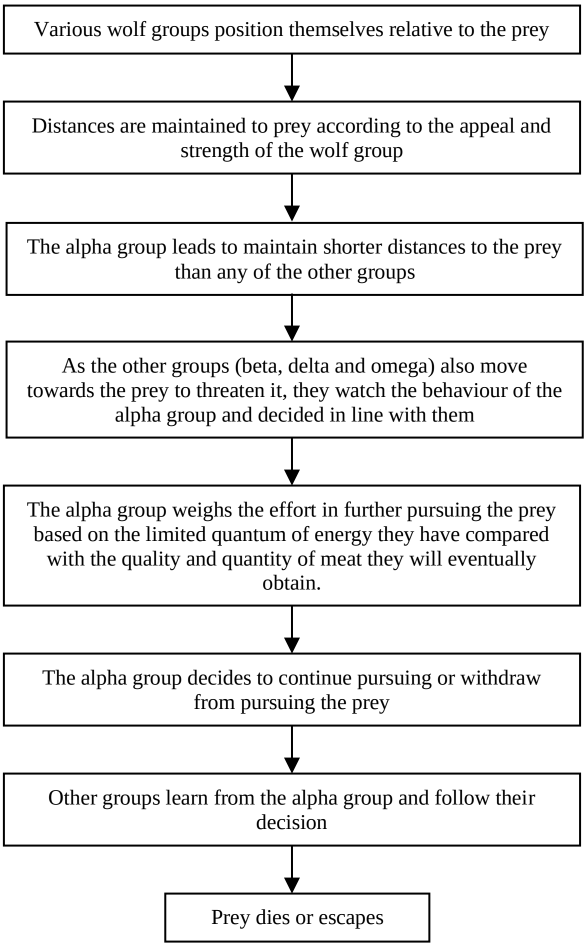

Fig. 1. Wolves' behaviour while encircling the prey

For X_1,

$$A_1 = 2a.r - a \quad (6)$$

$$C_1 = 2.r \quad (7)$$

$$D_\alpha = |C_1 X_\alpha - X(t)| \quad (8)$$

$$X_1 = X_\alpha - A_1 D_\alpha \quad (9)$$

For X_2,

$$A_2 = 2a.r - a \quad (10)$$

$$C_2 = 2.r \quad (11)$$

$$D_\beta = |C_2 X_\alpha - X(t)| \quad (12)$$

$$X_2 = X_\beta - A_2 D_\beta \quad (13)$$

For X_3,

$$A_3 = 2a.r - a \quad (14)$$

$$C_3 = 2.r \quad (15)$$

$$D_\gamma = |C_3 X_\alpha - X(t)| \quad (16)$$

$$X_3 = X_\gamma - A_3 D_\gamma \quad (17)$$

Equations (6) to (17) capture all the attempts of the various groups of wolves in capturing the prey that they have encircled after a hunting attempt. Naturally, wolves separate themselves into four groups, namely the alpha, beta, delta and omega guides. The alpha is the most authoritative and probably the strongest in the wolf park that leads the battle in conquering the prey. Except for the omega grey wolf category who are considered inexperienced, all other wolf categories (i.e. alpha, beta and delta guides) position themselves strategically in encircling the prey. The omega group is the very young wolves that watch the older ones on how they change tactics to combat the prey as the prey also change tactics to escape. The relative distance that each group maintains to the prey depends on how powerful and experienced the group is. For example, if a group of wolves know that it is less powerful in conquering the prey (i.e. omega wolf), it maintains further distance from the prey to avoid its attack. Consequently, the most powerful group, alpha guides are the first to face the prey with the understanding that they possess the skill and stamina to scare the prey and eventually conquer it. When the wolves encircle the prey, each group of wolves forms imaginary circular fences about themselves. This concept is brought to the computation and it affects the positioning and final results of the wolves catching the prey in that engagement. These circular fences are measured in radii; often there are two radii in concentric circles. But there is also a measurable distance in some instances, of the centre position of another, often measured as D.

Equations (6) to (17) could be classified into three: Equations (6) to (9), Equations (10) to (13) and Equations (14) to (17). Each of these sets of equations evaluated X_1, X_2, and X_3, respectively. This idea, obtained from Mairjalili et al. (2014), is that once the different groups of wolves encircle their prey, they do the capturing fast in a timeframe in which their positions to the prey change. They draw closer until they bite the prey and eventually kill it or it escapes the group of wolves. The measures of the closeness of the groups to each other and the prey are the As, Cs and Ds. It is believed that the alpha wolf guides may be unsuccessful in an encircling event for prey if the group counts it profitable to remain hungry instead of using their energy in pursuing small prey with relatively very small meat to eat.

In the encircling endeavour, what is done is to find a newly consolidated position of all groups of wolves (alpha, beta, delta and omega guides) by finding the average of the X outcomes only for the alpha, beta and delta guides, i.e. X_1, X_2, and X_3 represented by Equations (6) to (9), Equations (10) to (13) and Equations (14) to (17), respectively (Mairjalili et al., 2014; Jayakumar et al., 2016). The reason is that the contribution of the omega guides is marginal as the group consists of very young wolves that watch what happens in the food-searching endeavour. The distances maintained by the alpha guides, beta guides and delta guides to the other group of wolves are termed as D_α, D_β and D_γ, respectively. However, Equations (6) to (9), which are meant for the alpha guides is computed by extracting the parameter "a" from Equation (5), generate random numbers, which are fed into Equations (6) to (7) to obtain Equations (8) to (9). The A, and C, are the imaginary circles formed by the alpha guides at distances from the centre positioning of the alpha guides. Next, X_2 represents the position of the beta guides which depends on the two imaginary radii to form A_2 and C_2. Also, theX_3 represents the position of the delta guides with two imaginary radii of A_3 and C_3.

3. RESULTS AND DISCUSSION

In a search of the literature on turning, the attention of the present authors was drawn to the research problem in El-Sheikh et al. (2021) where the turning of the AISI 4340 alloy was made. To the authors' surprise, it was found that high manufacturing costs are expended in the implementation of the research. There are unexpected high cutting forces that need to be minimized, poor surface finish that need to be improved and a high rate of tool wear, which needs to be drastically reduced. To solve this problem, the authors examined the parameters used in the work, which are the cutting speed, feed and cutting depth. The outputs were identified as cutting force, tool wear and surface roughness. With this information, it was thought that the energy costs could be reduced by reducing all the response values. The tool was having greater wear but it was thought that this gap could be bridged using the grey wolf optimization algorithm. Thus, in this article, the optimization process parameters regarding the turning of AISI 4340 alloy in an eco-friendly minimum quantity lubrication environment was achieved using the grey wolf optimization approach. Thus, the application of the GWO algorithm minimized the cutting speed, feed and cutting depth to obtain reduced values compared to those reported in El-Sheikh et al. (2021). The choice of the grey wolf optimization procedure was made to simplify the work and obtain accuracy from the computation of each value of responses and inputs that were given in El-Sheikh et al. (2021).

Furthermore, the grey wolf optimizer was of choice because of its efficiency in convergence while running the iterative program using the C++ programming environment. More importantly, the work was chosen as the work material AISI 4340 alloy has a four-digit crystalline structure and could be heat treated for improved performance during the turning process. Though there have been some studies on lubrication-aided turning experiments on AISI 4340 alloy, the literature knowledge indicates that few studies have been dedicated to its optimization during the turning process. Furthermore, it is extremely rare to find the turning of the material under controlled lubrication with nanofluids such as copper oxide and aluminium oxide. More difficult to observe in the literature are studies that have deployed the grey wolf optimizer in improving the efficiency of the turning process while processing the AISI 4340 alloy material.

However, it is believed that the application of the grey wolf optimizer is better than the non-optimized situation reported by the referenced material. Thus, the grey wolf optimizer is regarded as a suitable optimization tool that may fulfil the requirements of the optimization of AISI 4340 alloy during the turning process. In the analysis, a fundamental first step is to identify the inputs, outputs and optimization activities to be implemented. Accordingly, from the referenced material adopted in this article, the inputs are the cutting speed (m/mm), feed (mm/rev) and the cutting depth (mm). However, the outputs are the cutting force (N), surface roughness, Ra (μm) and tool wear. In the turning operation, the overall goal is to be efficient such that minimum processing time is used to process the AISI 4340 alloy while the operational cost is minimized. But regarding the attainment of the turning goal about the outputs, the cutting force should be minimized, so that excessive force will not damage the workpiece material. Also, the surface roughness should be minimized to boast the surface integrity of the material.

In addition, the tool wear should be minimized to reduce tool regrinding and changing costs. From these viewpoints, the grey wolf optimization (GWO) procedure fits as the solution procedure for the turning problem. But it is confusing which of the two nano-lubricants of the CuO and Al_2O_3 should be chosen to achieve each of the three main goals of cutting force minimization, surface roughness minimization and tool wear minimization. Consequently, it is resolved that to obtain effective computational outcomes, an optimization (linear) programme should be formulated with the objective and constraints with the three outputs terms in focus. It then implies that for each output term, for instance, cutting force, a linear programme should be formulated such that the experimental data generated for each of CuO and Al_2O_3 will be used in the formulation. In essence, this result section shows six linear programmes. But a linear programme comprises the objective function and constraints. Thus from the experimental data obtained in the referenced article, a regression equation is formulated for each of the objective functions and then substituted in the linear programme to be formulated afterwards. To demonstrate how these regression equations are formed, the data from Table 5 of the referenced material is used. The data are inputted into the Minitab 18 software, where the inputs and each output at a time are computed to obtain the regression equations.

Notice that in each set of results, at convergence, the optimal values given were those associated with the response and the parameters. In the first linear program, where copper oxide was the nano-lubricant employed, the optimal cutting force suggested by the GWO procedure is 128.21N. The corresponding inputs of the cutting speed, feed and cutting depth that produced the cutting force are 80m/mm, 0.05mm/rev and 0.1mm respectively. This is the linear program tagged objective 1. However, for the second linear programme tagged objective 2, the nano-fluid used is Al_2O_3. This alternative is compared with the results from objective 1 to choose the better option for manufacturing decisions. For this option, when the GWO procedure was run on the C++ computer codes, the suggested optimal cutting force is 199.50N. The corresponding inputs of the cutting speed, feed and cutting depth that yielded the cutting force are 80m/mm, 0.05mm/rev and 0.1mm respectively. However, on comparison of the results from the objective 1 and objective 2 to choose the better option for manufacturing decisions, it was noted that objective 2 yielded a better minimum cutting force of 199.50N having reduced the cutting force relative to objective 1 by 37.73%, which is equivalent to the savings in energy costs. With the nano-lubricants being considered, the tool wear was reduced and a low cost of production was guaranteed. However, comparing the results obtained using either objectives 1 or 2 exceeds the performance of using the method stated in El-Sheikh et al. (2021), which is higher than that of objective 1 by 0.609% and objective 2 by 0.247%.

3.1 Grey wolf optimization method

Now that the empirical models have been developed, they will be optimized using the grey wolf optimization algorithm. This will be achieved with the aid of the C++ programming language. Optimal process parameters will be determined for each of the output variables. In analyzing the optimum process parameters of cutting force (CF), the steps will be explained for the first iteration, after which the optimal values would be shown for the remainder of the iterations. For subsequent output parameters, the optimal values obtained would be displayed. In this article, the grey wolf is mimicked in its natural behaviour along with the parameters of the extent to which the wolf chases its prey understood as cutting speed from the turning perspective (Mairjalili et al., 2014). The grey wolf is known to eat its prey with its claws and teeth which may be referred to as the feed rate in the turning process. Besides, the wolf is also known to have a great impact on the eating process by exerting force on the prey with a measurable distance into the prey's body. This is equivalent to the cutting depth in the turning process. Thus, this work recognizes these important parameters of cutting speeds, feed and cutting depth as representatives of the grey behaviour which could be symbolized as X1, X2 and X3 respectively. But since the capacity, ability and strength of wolves differ, the parameters of the cutting speed also have lower and upper boundaries which represent the minimum and maximum effort the grey wolf exerts while chasing its prey.

In this instant, the cutting speeds are set at 80 and 140 m/min respectively. Furthermore, there is a varying range of the ability of the grey wolf to eat its prey with its claws and teeth taken as 0.05 and 0.20 mm/rev as the lower and upper boundaries respectively for the feed rate. Besides, the lower and upper boundary of 0.1 and 0.4mm respectively for the cutting depth defines the exerted force on the prey's body. Given the above, boundaries are values in a range at which parameters of the turning process may be set. Furthermore, for the first objective, the population size which is interpreted as the number of wolves considered for this problem is 5. The number of iterations is 100. In addition, the population of the grey wolves is modelled randomly with initialization steps following.

Step 1 – Random initialization of Grey Wolf population

Random numbers are stochastically generated values that are programmed based on an initial value called the seed (Mairjalili et al., 2014). This enables the reproduction of numbers in random sequences often produced by random number generators. The idea of random number generation to provide an opportunity to capture the stochastic behaviour of the grey wolves is of interest. Each row containing values of process parameters with the upper and lower boundaries is referred to as a wolf. A matrix of 5 wolves comprising several values between the boundaries of all input parameters is generated randomly using Equation (4). However, random numbers are required for these transformations. Then, a detailed analysis of how to obtain the predicted input parameters which are randomly generated follows for the first wolf. This means that the random numbers for the wolf are 0.806787, 0.7026585 and 0.279458 while the corresponding values obtained using each of these sequential arranged random numbers in Equation 4 to obtain CS, F and CD are 128.407m/min, 0.159mm/rev and 0.184mm. Then by substituting these values into the objective functions obtained earlier, the CF value obtained is 208.852N for the first wolf. By following the same arrangement, CF is determined for all the other wolves where they are 204.581N, 187.372N, 196.753N and 204.674N for wolves 2, 3, 4 and 5 respectively.

Furthermore, in optimizing the process parameters while turning AISI 4340 alloy, the development of an optimized schedule imitates the behaviour of grey wolves. While numerous iterations are made on several program runs of interest, computations are obtained from the formula of cutting force being the independent variable. The cutting force has been related to independent variables such as cutting speed, feed and cutting depth. To obtain the best X_α, second-best X_β and third-best X_γ, iterations of the objective equations are run. In the context of a steel alloy turning environment, iteration represents a period substitute for completing the task in a short time. Iteration offers a uniform period for the computational program to offer a value change and compare previously obtained values with the current values.

Step 2 – Find the best X_α, second-best X_β and third-best X_γ positions.

The preceding computations are referred to as iteration 1. Then, since the researchers are minimizing the outcomes the least values are picked and taken in sequence of α, β and γ (Mairjalili et al., 2014). Here, the value α is the least, β is the next to it and γ is the greatest. This is the mechanism for implementing step 2.

Since our objective is to minimize CF, the best position will be the wolf with the smallest AF S/N ratio; the second best will be the wolf with the second smallest S/N value and the third best will be the wolf with the third smallest CF S/N ratio

X_α	114.967	0.135678	0.160976	187.372
X_β	128.814	0.0602268	0.319825	196.753
X_γ	133.069	0.0764595	0.335792	204.581

Step 3 – Find X_1, X_2 and X_3

Some parameters are obtained in the iteration process by making use of Equation (5), which shows an iteration of 1, maximum iteration as 100 and *a* as 1.98 (Mairjalili et al., 2014).

The steps that were followed in obtaining X_1 are shown as follows:

Calculating $A_1 = 2a.r\text{-}a$, where a = 1.98, r = 0.807489, A_1 = 2 x 1.98 x 0.807489 -1.98 = 1.2177

while C_1 = 2.r = 2 x 0.0249336 = 0.00499.

Then, $D_\alpha = | C_1.X_\alpha – X (t) |$

where C_1= 0.00499

X_α	114.967	0.135678	0.160976
X(t)	128.407	0.158988	0.183837

D_α= | 0.00499 (114.967 0.135678 0.160976) – (128.407 0.158988 0.183837)

D_α = | 127.833 0.158 0.183 |

$X_1 = X_\alpha – A_1 D_\alpha$

X_1 = (114.967 0.135678 0.160976) - 1.2177(127.833 0.158 0.183)

X_1 = -35.917 -0.0515486 -0.0552627

The values for X_2 and X_3 are obtained following similar procedures using the C++ programming language.

X_1:	-35.917	-0.0515486	-0.0552627
X_2:	187.146	0.276427	0.432708
X_3:	194.333	0.179074	0.717135

Step 4 – Find X_{new}

Then X_{new} is obtained by finding the average of X_1, X_2 and X_3 (Mairjalili et al., 2014)

X_{new}: 115.187 0.134651 0.36486

Since it is observed that the values of X_{new} lie in the boundaries given, they are retained.

Step 5 – Carry out the greedy selection

The values of X process parameters are inserted into the objective function to obtain an output of CF (Mairjalili et al., 2014). Since our objective is to minimize CF, if the value obtained is smaller than the value of CF previously at that wolf, X_{new} replaces that wolf. However, if the reverse is the case, then the wolf remains as it is. This process is called greedy selection.

Carrying out Greedy Selection:

Previous Value: 208.852

F (X_{new}): 186.496

The result obtained for CF is smaller than the old. Therefore, since the operation is about minimization, we replaced the old with the new.

Therefore the current population of the wolf would be

CF	F	CD	CF
115.187	0.134651	0.36486	186.496
133.069	0.0764595	0.335792	204.581
114.967	0.135678	0.160976	187.372
128.814	0.0602268	0.319825	196.753
133.904	0.0633625	0.237223	204.674

The same operations from step 2 to step 5 are carried out for the other wolves in the population. After each iteration, the best values obtained will be the current X_α i.e. the best wolf with the smallest S/N value. These values are obtained for each of the iterations. At the 100th iteration, the process parameters that makeup X_α are adopted as the optimal process parameters for CF, Table 1.

Table 1. Optimal process parameters

Sr./No.	Criterion	CS (m/min)	F (mm/rev)	CD (mm)	CF (N)	SR (μm)	TW (mm)
1	Minimize CF (CuO)	80.00	0.05	0.10	128.21	-	-
2	Minimize CF (Al_2O_3)	80.00	0.05	0.10	199.50	-	-
3	Minimize SR (CuO)	80.00	0.07	0.10	-	0.40	-
4	Minimize SR (Al_2O_3)	80.16	0.06	0.29	-	-23.59	-
5	Minimize TW (CuO)	80.00	0.05	0.25	-	-	0.03
6	Minimize TW (Al_2O_3)	80.00	0.05	0.12	-	-	0.06

Furthermore, the results of iterations for the first wolf are as follows:

Iteration 1 : 179.871 Iteration 2 : 128.214
Iteration 3 : 128.214 …
Iteration 98 : 128.214 Iteration 99 : 128.214
Iteration 100 : 128.21

3.2 Benefits of adopting grey wolf optimization in turning operations

For several years, new methods have been suggested in the turning process, believed to have improved turning efficiency. Overtime and recently, newly proposed methods are expected to be based on theoretical and practical aspects of the turning operation. What exactly do process engineers and operators in the workshop expect from adopting the grey wolf optimization? Is it just a concern for high search precision or several other benefits are beyond the search precision process? This section of the article answers with a yes response. Adopting the grey wolf optimization procedure benefits the search precision of the process engineer and the turning operator. High search precision implies more appropriate source identification quickly. Mimicking the grey wolf optimization in turn works on the characteristics of the animal in prey searching and killing. Such attributes such as recognition of the alpha, beta and delta guides' actions and the understanding that they are in a better position than other members of the group to attain the target of catching the prey are critical to the present article and of immense practical significance to the process engineer and the turning operator.

Next, a critical benefit of adopting the grey wolf optimization procedure in this article is to enhance the turning efficiency. Before the introduction of the present study, several workshops rely on the intuition and experience of the process engineer and operator but measures could be determined using the grey wolf optimization procedure. Thus, wasted resources and time due to intuition and experience usage are saved. This promotes the workshop's ability to enhance its operating profit margin and relieve workers of unnecessary stress using the old method of intuition and experience. Furthermore, by implementing the grey wolf optimization based on turning, accurate yet current turning operation data are attained to promote the success level of the turning activities in the workshop. Besides, a high-quality AISI 4340 alloy with surface integrity is expected to be produced. Consequently, the goodwill of the turning workshop will be enhanced. This is indirect to enhancing the profit of the workshop.

Besides, this article has several industrial and managerial insinuations. First, the article assists process engineers and operators of workshops to tackle optimization procedures and use this as a tool to enhance the profit of the turning operation. Next, it assists the workshop to establish the worth of jobs and resources deployed to execute them through optimization procedure using the grey wolf optimization method. Furthermore, it will empower the process engineer to target the prudent utilization of resources as optimal values are compared with the achieved thresholds.

4. CONCLUSIONS

This study has established how to optimize the process parameters during the turning of AISI 4340 alloy on the alternative minimum quantity lubrication of $A1_2O_3$and CuO using the grey wolf optimization approach. The use of the grey wolf optimization approach with the right quantity of input parameters and MQL for the alternative nanofluids is found to favour $A1_2O_3$ for optimum cutting force and surface roughness. However, it favours CuO for optimum tool wear attainment. Compared with response optimization predicted from Taguchi and response surface methodology, the use of grey wolf optimization is very effective for high search precision. This provides quicker information for decision-making in a pool of conflicting data. This implies that the grey wolf optimization approach is a good option to optimize the responses of the AISI 4340 alloy during the turning operation.

REFERENCES

Ahmadi, M.H., Mohseni-Gharyehsafa, B., Farzaneh-Gord, M., Jilte, R.D., Kumar, R. & Chau, K.-W. (2019) Applicability of Connectionist Methods to Predict Dynamic Viscosity of Silver/Water Nanofluid by Using ANN-MLP, MARS and MPR Algorithms. Engineering *Applications of Computational Fluid Mechanics*, 13, 220–228. https://doi.org/10.1080/19942060.2019.1571442

Al-Shayea, A., Abdullah, F. M., Noman, M. A., Kaid, H., &Abouel Nasr, E. (2020). Studying and Optimizing the Effect of Process Parameters on Machining Vibration in Turning Process of AISI 1040 Steel. *Advances in Materials Science and Engineering*. 2020, 1-15. https://doi.org/10.1155/2020/5480614

Bhuiyan, M.S.H. and Choudhury, I.A. (2015).Investigation of Tool Wear and Surface Finish by Analyzing Vibration Signals in Turning Assab-705 Steel. *Machining Science and Technology*. 19, 236–261.

Bouacha, K., Yallese, M.A., Mabrouki, T., Rigal, J.-F. (2010) Statistical Analysis of Surface Roughness and Cutting Forces using Response Surface Methodology in Hard Turning of AISI 52100 Bearing Steel with CBN Tool. *International Journal of Refractory Metals and Hard Materials*, 28, 349–361. https://doi.org/10.1016/j.ijrmhm.2009.11.011

Das, S.R., Panda, A., Davim, J.P., Dhupal, D. (2018). Hard Turning of HSLA Steel with Coated Ceramic Tool Based on Evaluation of Surface Roughness, Tool Wear, Chip Morphology and Economic Analysis. *Journal of Manufacturing Technology Management*, 10, 113–141.

El-Sheikh, A.H., AbdElaziz, M., Das, S.R., Muthuramalingam, T., Lu, S., 2021. A New Optimized Predictive Model Based on Political Optimizer for Eco-Friendly MQL-Turning of AISI 4340 Alloy with Nano-Lubricants. *Journal of Manufacturing Processes*, 67, 567-578. https://doi.org/10.1016/j.jmapro.2021.05.014

El-Baradie, M. A. (1996). Cutting Fluids, Part 1: Characterization. *Journal of Material Processing Technology*, 56, 786–787. https://doi.org/10.12691/ajmse-3-2-3

Fan, Y.,Hao, Z., Zheng, M. & Yang, S. (2016). Wear Characteristics of Cemented Carbide Tool in Dry-Machining Ti-6Al-4V. *Machining Science and Technology: An International Journal*, 20(2), 249-261. https://doi.org/10.1080/10910344.2016.1165837

Gajrani, K.K., Suvin, P.S., Kailas, S.V., Mamilla, R.S. (2019). Thermal, Rheological, Wettability and Hard Machining Performance of MoS2 and CaF2 Based Minimum Quantity Hybrid Nano-Green Cutting Fluids, *Journal of Materials Processing Technology*, 266, 125-139. https://doi.org/10.1016/j.jmatprotec.2018.10.036

Jayakumar, N., Subramanian, S., Ganesan, S., Elanchezhian, E.B. (2016). Grey Wolf Optimization for Combined Heat and Power Dispatch with Cogeneration Systems. *International Journal of Electrical Power & Energy Systems*. 74, 252–264. https://doi.org/10.1016/j.ijepes.2015.07.031

Kelly, T.P., 2010, Optimization, an Important Stage of Engineering Design. *The Technology Teacher*, 69(5), 18-23.

Khalilpourazari, S., & Khalilpourazary, S. (2016).Optimization of Production Time in the Multi-Pass Milling Process via a Robust Grey Wolf Optimizer. *Neural Computing and Applications*, 29(12), 1321-1336. https://doi.org/10.1007/s00521-016-2644-6

Kharwar, P. K., & Verma, R. K. (2021). Nature Instigated Grey Wolf Algorithm for Parametric Optimization During

Machining (Milling) of Polymer Nano Composites. *Journal of Thermoplastic Composite Materials*, 089270572199320. https://doi.org/10.1177/0892705721993202

Kumar, R., Sahoo, A.K., Mishra, P.C., Das, R.K. (2019). Influence of Al_2O_3 and TiO_2 Nanofluid on Hard Turning Performance. *International Journal of Advanced Manufacturing Technology*, 1– 16. https://doi.org/10.1007/s00170-019-04754-3

Labidi, A., Tebassi, H., Belhadi, S., Khettabi, R. & Yallese, M.A. (2018). Cutting Conditions Modeling and Optimization in Hard Turning using RSM, ANN And Desirability Function. *Journal of Failure Analysis and Prevention*, 18, 1017–1033. https://doi.org/10.1007/s11668-018-0501-x

Laouissi, A., Yallese, M.A., Belbah, A., Belhadi, S. & Haddad, A. (2019). Investigation, Modeling, and Optimization of Cutting Parameters in Turning of Gray Cast Iron using Coated and Uncoated Silicon Nitride Ceramic Tools Based on ANN, RSM and GA Optimization. *International Journal of Advanced Manufacturing Technology*, 101, 523–548. https://doi.org/10.1007/s00170-018-2931-8

Manivel, D., & Gandhinathan, R. (2016). Optimization of Surface Roughness and Tool Wear in Hard Turning of Austempered Ductile Iron (Grade 3) using Taguchi Method. *Measurement*. 93, 108-116. https://doi.org/10.1016/j.measurement.2016.06.055

Mirjalili S., Marjalili S.M. and Lewis A., 2014, Grey Wolf Optimiser, *Advances in Engineering software*, 69, 46-61. http://doi.org /10.1016/j adveng soft.2013.12.007

Medjahed, S.A., Saadi, T.A., Benyettou, A., Ouali, M. (2016). Gray Wolf Optimizer for Hyperspectral Band Selection. *Applied Soft Computing*, 40, 178–186. https://doi.org/10.1016/j.asoc.2015.09.045 11

Onuoha, O. J., Abu, J. O., Lawal, S. A., Mudiare, E., & Adeyemi, M. B. (2016). Determining the Effect of Cutting Fluids on Surface Roughness in Turning AISI 1330 Alloy Steel using Taguchi Method. *Modern Mechanical Engineering*. 6(2), 51-59. https://doi.org/10.4236/mme.2016.62006

Padmini, R., Krishna, P.V., Rao, G.K.M., (2016). Effectiveness of Vegetable Oil Based Nanofluids as Potential Cutting Fluids in Turning AISI 1040 Steel. *Tribology International*, 490–501. https://doi.org/10.1016/j.triboint.2015.10.006

Pradhan, M., Roy, P.K., Pal, T. (2016). Grey Wolf Optimization Applied to Economic Load Dispatch Problems. *International Journal of Electrical Power & Energy Systems*, 83, 325–334. https://doi.org/10.1016/j.ijepes.2016.04.034.

Reddy, S. A., &Hari, M. J. (2018). Optimization of Cutting Parameters in Turning Operation by using Taguchi Method. *International Journal of Trend in Scientific Research and Development*, 3(1), 935-940. https://z/doi.org/10.31142/ijtsrd19108

Roy, R. (1990). *A Primer on the Taguchi Method*. Society of Manufacturing Engineers, New York

Roy, S., Kumar, R., Das, R. K., & Sahoo, A. K. (2018). A Comprehensive Review on Machinability Aspects in Hard Turning of AISI 4340 Steel. *IOP Conference Series: Materials Science and Engineering*, 390, 012009. https://doi.org/10.1088/1757-899x/390/1/012009

Sahoo, A. K. and Sahoo, B. (2012). Experimental Investigations on Machinability Aspects in Finish Hard Turning of AISI 4340 Steel using Uncoated and Multilayer Coated Carbide Inserts, *Measurement*. 45, 2153-2165. https://doi.org/10.1016/j.measurement.2012.05.015

Sen, B., Mandal, U. K., & Mondal, S. P. (2017). Advancement of an Intelligent System Based on ANFIS for Predicting Machining Performance Parameters of Inconel 690–A Perspective of Metaheuristic Approach. *Measurement*, 109, 9-17.

https://doi.org/10.1016/j.measurement.2017.05.050

Sen, B., Mia, M., Krolczyk, G. M., Mandal, U. K., & Mondal, S. P. (2021). Eco-Friendly Cutting Fluids in Minimum Quantity Lubrication Assisted Machining: A Review on the Perception of Sustainable Manufacturing. *International Journal of Precision Engineering and Manufacturing-Green Technology*, 8(1), 249-280. https://doi.org/10.1007/s40684-019-00158-6

Sen, B., Mia, M., Mandal, U. K., & Mondal, S. P. (2020). Synergistic Effect of Silica and Pure Palm Oil on the Machining Performances of Inconel 690: A Study for Promoting Minimum Quantity Nano Doped-Green Lubricants. *Journal of Cleaner Production*, 258, 120755. https://doi.org/10.1016/j.jclepro.2020.120755

Sen, B., Hussain, S. A. I., Mia, M., Mandal, U. K., & Mondal, S. P. (2019a). Selection of an Ideal MQL-Assisted Milling Condition: An NSGA-II-Coupled TOPSIS Approach for Improving Machinability of Inconel 690. *The International Journal of Advanced Manufacturing Technology*, 103(5), 1811-1829. https://doi.org/10.1007/s00170-019-03620-6

Sen, B., Mia, M., Gupta, M. K., Rahman, M. A., Mandal, U. K., & Mondal, S. P. (2019b). Influence Of Al_2O_3 and Palm Oil–Mixed Nano-Fluid on Machining Performances of Inconel-690: IF-THEN Rules–Based FIS Model in Eco-Benign Milling. *The International Journal of Advanced Manufacturing Technology*. 103(9), 3389-3403. https://doi.org/10.1007/s00170-019-03814-y

Sen, B., Mia, M., Mandal, U. K., Dutta, B., & Mondal, S. P. (2019c). Multi-Objective Optimization for MQL-Assisted End Milling Operation: An Intelligent Hybrid Strategy Combining GEP and NTOPSIS. *Neural Computing and Applications*. 31(12), 8693-8717. https://doi.org/10.1007/s00521-019-04450-z

Shankar S., Mohanraj T., Rajasekar R., 2019, Prediction of Cutting Tool Wear during Milling Process using Artificial Intelligence Techniques. *International Journal of Computer Integrated Manufacturing* 32(2), 174-182. https://doi.org/10.1080/0951192X.2018.1550681

Srikant, R. R., Rao, D. N., Subrahmanyam, M. S., & Krishna, V. P. (2008). Applicability of Cutting Fluids with Nanoparticle Inclusion as Coolants In Machining. *Proceedings of the Institution of Mechanical Engineers, Part J: Journal of Engineering Tribology*, 223(2), 221-225. https://doi.org/10.1243/13506501jet463

Venkatesan, K., Mathew, A. T., Devendiran, S., Ghazaly, N. M., Sanjith, S., & Raghul, R. (2019). Machinability Study and Multi-Response Optimization of Cutting Force, Surface Roughness and Tool Wear on CNC Turned Inconel 617 Superalloy using Al_2O_3 Nanofluids in Coconut Oil. *Procedia Manufacturing*. 30, 396-403. https://doi.org/10.1016/j.promfg.2019.02.055

Yadav, P., Kumar, N. 2020, A Review on Selection of Input Decision Variables and Response Variables of Machining Process by using Optimization Techniques. *Suresh Gyan, Vihar University Journal of Engineering and Technology*, 6(1), 26-29.

Yıldırım, Ç. V. (2020). Investigation of Hard Turning Performance of Eco-Friendly Cooling Strategies: Cryogenic Cooling and Nanofluid Based MQL. *Tribology International*, 144, 106127. https://doi.org/10.1016/j.triboint.2019.106127

Zerti, A., Yallese, M.A., Zerti, O., Nouioua, M., Khettabi, R. (2019) Prediction of Machining Performance using RSM and ANN Models in Hard Turning of Martensitic Stainless Steel AISI 420. *Proceedings of IMechE, Part C: Journal of Mechanical Engineering Science*, 13, 233. https://doi.org/10.1177/0954406218820557