Coupled Taguchi-Pareto-Box Behnken Design-Grey Wolf Optimization Methods for Optimization Decisions when Boring IS 2062 E250 Steel Plates on CNC Machine

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Abstract. *Optimizing process parameters in boring operation is extremely important as aids to maintain high resource conservation and efficiency and the free flow of boring data while optimally using boring resources. With optimal parameters, real-time information is offered to process engineers for the practical control the boring operation thus reducing the cost of boring operations. This article presents an investigation on the use of optimization and prioritization in the boring process of IS 2062 E250 steel plates using coupled Taguchi-Pareto-Box Behnken Design-grey wolf optimization approach. The experimental data, drawn from the literature, was initially provided by Patel and Deshpande on CNC TC machine. The objective function, constraints, population size, number of iterations, and fitness function were determined. Then the solution for the grey wolf optimization is generated using the python programming language. Three representative parameters of speed, feed and depth of cut were foundations of the Taguchi's experimental design used for solving the problem. The optimal parameters were determined from the experiments. For the first time, the coupled Taguchi-Pareto-Box Behnken Design-grey wolf optimization method to make optimization decisions for the boring process. Using 50 iterations and 200 wolfs, the best fitness value of wolves at the end of the 50th iteration is 872728.53 when the objective function is generated from optimized Box Behnken Design parameters. It also has an optimal solution of speed, feed, depth of cut and nose radius as 800rpm, 0.06,1 and 0, respectively. However, on the application of the regression equation from the Box Behnken Design to form an objective function, using the same 50 iteration and 200 wolves the best fitness value of wolves at the end of 50th iteration is -51.49 while the optimal parameters are 1189.58, 0.089, 1.22, 0.55 for the speed, feed, depth of cut and nose radius, respectively. Hence, the outcome of this study may be a route to reducing time and money associated with unnecessary usage of non-optimal boring data during operations planning decisions.*

Keywords: Grey wolf optimization, CNC machine, Taguchi-Pareto, fitness values, parameters

1. Introduction

The attainment of substantially low surface roughness has been the principal pursuit of process engineers in most machining activities [1], [2], [3], [4]. This challenge is even more compelling and requires an urgent attention because boring operation is widely recognized as a secondary procedure used to finish up a pre-existing hole or enlarge it [1], [5], [6]. Thus, many machine parts cannot be delivered to customers until boring actions are completed, holding on the profits in investments that should have been made by the company. Alongside, Trung [1] argued on the constraint of low productivity imposed on the machining process since the depth of cut is marginally chosen in such processes as grinding. By extension, boring process has the same limitations [7]. Furthermore, Trung [1] declared that while machining productivity greatly influence the principal cutting parameters such as the speed, feed rate, depth of cut and nose radius used in the present study, the surface roughness outcome is also affected by these parameters. Besides, the surface roughness, which is the dominant response in the present study also associate with cooling parameters, experimental equipment situations, the dressing process and machining materials according to Trung [1]. The feasible approach is then to consider merely a few parameters from this pool of parameters and establish the thresholds of these parameters that produce the least possible surface roughness considered as the output of the IS 2062 E250 steel grade boring process.

For some time, researchers have recognized this approach and produced several experimental studies to actualize this goal [1], [8], [9], [10], [11], [12]. Also, by evaluating some of these reports, it is evident Taguchi technique has played a dominant role to the successful enhancement of machining performance. An explanation for this success story is the nature of the Taguchi method being an experimental design framework. This philosophy allows several researchers and practicing process engineers to obtain solutions to machining problems using lesser experiments and the opportunity of working with several inputs that could be scaled to various levels [1]. Trung [1] added that Taguchi methods success is based on the ability of the process engineer with fewer data to utilize qualitative data such as the kind of boring tool as in the present article's case. Despite these merits, there is difficulty in applying Taguchi alone for the boring process problem formulated in this article. If Taguchi method alone is applied to the experimental matrix in Taguchi design, and the signal to noise quotients determined, the obtained parametric values for the boring process, for instance, can be evaluated for only a criterion at a time. It implies that if there exists more responses than the surface roughness discussed in the present article, the Taguchi method cannot obtain results at the same time. But the present article is laying a foundation to work with several responses and multiple input despite merely focusing on only one response, surface roughness used an example in the present study. Thus, the argument here is that Taguchi method is not capable for multiple response treatment at the same time. If a widely acceptable method is to be developed in this article as anticipated, this weakness of the Taguchi method should be overcome [1]. Fortunately, previous researchers have identified and proffered some solutions to the mentioned problem.

Nonetheless, unfortunately, it seems no research has applied the combination of Taguchi-Pareto method, Box Behnken Design method and grey wolf optimization method to analyses the optimization status in boring process. But it is known that the IS 2062 E250 steel plates is extensively used in tanks and application entailing non-pressure parts in industries such as marine, seawater, gas process and chemical processes [13]. Thus, the IS 2062 E250 steel plates is a first choice in these industries. In these industries, as machining process are performed for elevated level of precision, the boring process, it is a surprise to be unable to identify at least one study that has applied the Taguchi-Pareto-Box Behnken Design grey wolf method to the boring operation of the IS 2062 E250 steel plates. Given the scenario described in the preceding paragraphs, it is revealed that the several advantages of Taguchi method are important but coupling the Taguchi technique and three approaches in evaluation (Pareto, Box Behnken design and grey wolf optimization) is also absent in all studies so far reported on boring process. The closure of the gap is pursued in the present article. In particular, based on the experiments reported by Patel and Deshpande [14], which followed experimental design principle and focusing on IS 2062 E250 steel plates, the combined Taguchi-Pareto Box Behnken design–grey wolf optimization method will be applied in this article.

In this article, the authors employed the grey wolf optimization as an added optimization method to the Taguchi-Pareto-Box Behnken methodical combination and not another optimization method since, distinct from other optimization approaches, the process engineer (decision maker) can adjust the procedure as often as needed. Moreover, the grey wolf optimization approach demonstrate ability to search through self-adaptation to optimize solutions based on the wolves behavior in hunting, where the wolves divides themselves into groups and encircle their preys. Furthermore, the other benefits of the grey wolf optimization procedure are their fast-seeking speed, simplicity in principle, easily realizable method and high search precision.

2. Literature review

Sustainable development challenges have made energy and environmental issues relevant to all industries around the world. However, the ever-increasing demand for quality from customers has resulted in a superior surface polish and, as a result, higher energy usage. Machine tools have usually low energy efficiency, especially during discrete item manufacture [15]. Table 1 is a summary of the literature. Several studies have applied the ANOVA method in their CNC turning machine operations [15], [16], [17], [18], [19], [20]. Others have used the following methods in their studies - Taguchi [17], grasshopper optimization algorithm [21], response surface methodology [20], [21], ANN and regression analysis [18], grey wolf optimization algorithm [16],

[19], [20], genetic algorithms [16], [20], Jaya optimization, whale optimization, particle swarm optimization, and simulated annealing algorithm [20] and principal component analysis [15].

Table 1 Summary of the literature

Author(s)	Material	Machining operation/ machine tool	Output parameters	Input parameters	Methodology	Conclusions
Mary et al. [22]	EN24	Drilling/LV-45, three-axis milling centre	Tool wear	Spindle speed, feed rate, acceleration, force signals	Grey wolf and neural controller	Tool life increased by varying the machining condition. Greywolf optimization achieved optimized speed and feed parameter.
Chakraborty and Mitra [23]		Abrasive water-jet machining (AWJM)	Surface roughness Material removal rate, overcut,and taper	Water pressure, nozzle diameter, jet velocity, abrasive concentration, nozzle tip distance e	Grey wolf optimizer	Algorithm avoids local optima. GWO improved in response values
Kharwar and Verma [19]	Polymer nanocomposites	Milling	Surface roughness (Ra), Cutting force (Fc), and Material removal rate (MRR)	MWCNT weight percent, spindle speed, depth of cut, and feed rate	Grey wolf optimization algorithm, ANOVA	A 1.5wt% MWCNT, 1500 rpm spindle speed, 50 mm/min feed rate, and 3 mm depth of cut are the best combinations to reduce surface roughness.
Imani et al. [24]	Inconel 738	Milling	Milling forces and surface roughness	Cutting speed, feed rate, the axial depth of cutting, and coolant	Artificial neural network, and Genetic algorithm	The optimized artificial network can predict machining force and surface roughness of milling Also, when the cutting speed is increased, the machining forces are reduced.
Sekulic et al. [16]	Hardened steel	Ball end milling/CNC milling center	Surface roughness	Spindle speed, feed per tooth, axial depth and radial depth of cut	ANOVA, GA and GWO	The GWO model was the best solution in all the three models. -
Kant and Sangwan [15]	AISI 1045 steel	machining	Power consumption and surface roughness	Cutting speed,feed rate,and depth of cut	Grey relational analysis, principle component analysis, and response surface methodology	Based on ANOVA results, the feed rate is the most important input parameter, followed by depth of cut, and finally cutting speed for reduced surface roughness and power usage.
Kulkarni and Kulkarni [25]	High carbon high chromium steel	Wire Electrical Discharge Machining (WEDM)	Material removal rate	Pulse off time (TOFF), upper flush (UF), lower flush (LF) and wire tension (WT).	Taguchi and Gray wolf optimization	It was found that the most influential component for MRR is determined to be TON.
Burande et al. [17]	EN8 steel	CNC turning/ Turning	Surface roughness	cutting speed, depth of cut and feed rate	ANOVA and Taguchi	Feed rate is the most important parameter for obtaining an optimal surface roughness
Kulkarni et al. [21]	AISI 316 austenitic stainless steel	CNC lathe/Turning	Surface roughness	Feed rate (fd), speed (vc), and depth of cut (DoC)	Grasshopper optimization algorithm, response surface methodology	The grasshopper optimization algorithm was effective in finding the best surface roughness (Ra) values in dry, wet, and cryogenic environments.
Ramalingam et al. [26]	304L stainless steel	Plasma arc cutting (PAC)	Surface roughness and kerf width	Arc current, torch stand-off, cutting speed and gas pressure play	Grey Taguchi-based response surface methodology (GT-RSM), Taguchi, response surface methodology	The GT-RSM method was shown to significantly improve the quality characteristics of components

Khalilpourazari and Khalilpourazary [27]		multi-pass milling	Total production time	Convergence constant, population size of gray wolf, and number of iteration	Robust Grey Wolf Optimizer (RGWO) and Taguchi method	The best possible trade-off between the algorithm's exploration and exploitation abilities is guaranteed by the optimal settings of the GWO's main parameters and that the RGWO was able to get the best viable solution for various cutting strategies.
Khalilpourazari and Khalilpourazary [28]		milling and machining processes	Surface quality, grinding cost and total process time	maximum number of iteration and numbers of dragon fly	multi-objective dragonfly algorithm and Taguchi method	Multi-objective dragonfly algorithm with an efficient constraint handling technique is able to find non-dominated Pareto optimum solutions.
Seçgin [29]	Ms58 Brass	Multi-axis CNC Lathe	Surface roughness (Ra), cutting time (t) and dimensional deviation (dev)	Tool diameter, feedrate and rotation speed	surface response method and Grey relationship analysis ·	The most significant parameter on surface roughness and dimensional deviation is the tool diameter. Feed is the most beneficial parameter in reducing cutting time.
Mangaraj et al. [20]	stainless steel (AISI 304)	Portable plasma arc cutting system	Material removal rate, chamfer, heat-affected zone, surface roughness, kerf width, and dross	Stand-off gap, gas pressure, cutting speed, and cutting current.	hybrid RSM-nature inspired optimization technique, RSM(BBD), Genetic algorithm, Grey wolf optimization, Jaya optimization, Whale optimization, Particle Swarm optimization, and simulated annealing algorithm	The most influential cutting parameters are cutting speed, square value of the current, and the interaction between speed and cutting current.
Pradhan et al. [30]	Dissimilar material (aluminum alloy and commercially used copper alloy)	Friction stir spot welding (FSSW) process	Maximum force required to break workpiece, maximum stress developed and heat affected zone at the welding joint	Rotational speed, pin length and tool tilt angle	Hybrid RSM-WASPAS (weighted aggregated sum product assessment)-grey wolf	Compared to other process factors, pin length has the biggest impact to controlling Max. Force, Max. Stress, and HAZ.
Fountas et al. [31]	CuZn39Pb3 brass alloy.	Turning	Surface roughness , cutting force and maximum height of the profile Rt (μm)	Rotational speed n (rpm); feed rate f (mm/rev) and depth of cut a (mm).	Multi-parameter analysis;Optimization, Grey Wolf algorithm.	Low speeds and moderate feeds are used to reduce main cutting force, while high speeds and moderate feeds are used to reduce roughness parameters Ra and Rt
Hanief et al. [18]	Red brass (C23000)	Turning	Cutting forces	speed, depth of cut and feed rate	ANN , regression analysis and ANOVA	Feed rate had the greatest influence on the resultant cutting force of the three cutting parameters, while the depth of cut had the least

3. Method

In the objective statement, it was declared that the grey wolf algorithm will be deployed in solving the boring operation process optimization. This means that the parametric optimization when boring will be modelled and solved by using the social hierarchy (leadership structure) of the grey wolves and their hunting characteristics. While implementing the grey wolf algorithm, the social hierarchy of the grey wolves which identifies members of the park as having varied authorities and influences on the decision of the parle as a whole is adapted to solve the boring operation parametric optimization. This social hierarchy identifies the alpha wolves as the parle leaders with powers given to them to decide on major issues on the parle, including when the parle members should wake up and sleep and whether the prey that enters their territories should be encircled and killed or not. Beyond this mathematics, the algorithm that shows the implementation also reveals the behaviors during hunting. Often the alpha wolves, which consist of the male and female decide on whether to pursue prey or not through the facial signals sent to the members of the pack.

In the following steps, the procedure for implementing the grey wolf algorithm is explained here using illustrative data besides the experimental data obtained from the literature. It is thought that such an effort will permit an easy replication of the method since it is difficult to obtain intermediate data from the implemental experimental data used in the literature. It should be noted that as a result of implementing the procedure using the python programming code only the values at certain iterations are declared by the programmer. Now, the following are the steps to implement the grey wolf algorithm for the boring process in this work.

Step 1: Determine the objective function of the problem, its constraints and the projected population size. However, the objective function is a mathematical model used to either maximize a benefit to the boring operation or minimize a disadvantage to the boring operation. Thus in the results section that comes afterwards, the data from the literature by Abdullahi and Oke [32] is used as the objective function of the present work but in this section on methods, an objective function for the first scenario that is similar to the actual one used in the results section suggests as

$$F(x) = 5S + 0.005F + 0.08DC + 0.013NR \quad (1)$$

This data comes with constraints that declare the limits to which the variables are feasible. These constraints for the first and second scenarios are as follows:

$1 \leq S \leq 4$, $0.001 \leq f \leq 0.01$, $0.07 \leq dc \leq 0.17$, and $0.2 \leq nr \leq 0.005$

Next, the grey wolf expects the user to define the population size. Interestingly, population size is defined as the number of individuals contained in a population. The meaning is that several series of experiments may be run for the boring process. Here, the number of experiments defines the population size. In each experimental trial, several parameters may be captured in the experiment, which include speed, nose radius, depth of cut and feed. Now, in this illustration, the population of the grey wolves is limited to 4 for illustration ease but extended to 200 for the implementation of the experimental data from the boring operation. Next is the number of iterations, which could be defined as the repeated computation of the fitness function (objective function) whose output at each step gives information as to whether the desired output value has been produced or not. Thus, in the present study, as the fitness function is run, if convergence is reached then the iteration could be terminated. It means that values obtained at the next iteration are not substantially different from those at the earlier stages. From the above illustration, the objective function, which is the fitness function has been declared, it is also accompanied by constraint. The population of the grey wolves at this illustrative stage is 4 while the number of iterations is fixed at 3. Now, the objective function under the guiding principles of the social hierarchy and hunting behaviors of the grey wolves is run for the parameters of speed, feed, depth of cut and nose radius that characterize each boring operation task. Hence, a grey wolf in the population, a grey wolf may be computed to have [1, 0.004, 0.05, 0.01]. Here, each component of the matrix is a data item of speed, feed, nose radius and depth of cut, respectively. It implies that there should be four of these matrices because the population of wolves considered is four. By introducing each of these parameters into the objective function earlier stated, the fitness value of the population may be computed as 5.0042, 2.5052, 6.0029 and 5.5015.

Step 2: The sorting of the computed fitness value is made in ascending order to determine the three best fitness values with the lowest value being the best and the highest value being the worst. The objective criterion is minimization. By following up on step 1 and with four values given in the last statement of the step, 2.5052 is the lowest fitness value while its corresponding wolf has the characteristic matrix component of speed, feed, nose radius and depth of cut as [0.5 0.004, 0.06 0.03]. Since the pursued objective criterion is minimization, the lowest value is the best and it is chosen as the alpha wolf, designated as X_α. The second to the lowest fitness value is 5.0042 and its corresponding wolf's matrix is [10.004, 0.05, 0.01], which is referred to as the beta wolf and represented as X_β. Lastly, the third to the lowest fitness value and its corresponding wolf matrix are 5.5015 and [1.1 0.006 0.01 0.05] respectively while the variable representation for this wolf is X_δ.

Step3a: New solutions are generated using the grey wolf mathematical model. Here, the contributions of the wolves to the hunting task are considered in the evaluation of the X_{new}. It is known that the alpha wolf, X_α, represented by X_1 leads the hunting and communicates the next task to the pack through facial expressions. In response, the beta wolves, X_β, represented by X_2, which are next in the social hierarchy, follow the alpha wolves closely. Next, the delta wolves, X_δ also matches the alpha wolves, and follows the beta involves since the beta involves is higher in the hierarchy than the alpha wolves. This delta involves are represented as X_3 in the evaluation of the X_{new} (i.e. the new position of the pack members when pursuing the prey). However, the omega wolves are neglected from the updating mathematics on the assumption that they do not contribute to the hunting success of the pack directly. Their indirect contributions could be as caregivers to the wounded wolves during hunting. They also protect the elders, which are the old wolves that had served as the alpha wolves but due to old age cannot cope with the responsibility of the alpha group and are hence relegated to the omega group where extremely less demands are made from them. So it could be noted that such efforts made by the omega wolves do not interpret into position changes of the wolf's pack and they are ignored in the computation of the position updating. Thus, the updated position of the pack is known as X_{new} and represented as Equation (1):

$$X_{new} = \frac{X_1 + X_2 + X_3}{3} \tag{1}$$

Equation (1) contains three variables, X_1, X_2 and X_3, which are the positions of the wolves obtained from different equations that follow.

The next step is to check the terminating criterion, which states that if t is less than 3 the researchers continue and otherwise stop. This condition is mathematically stated as follows:

$$\text{Check } (t < \max t) \tag{2}$$

This means check t if it is less than the maximum value of the iteration set for the programme. In this particular instance, in the beginning, $t = 0$. Therefore the condition $0 < 3$ is true and the researchers move to the next step. This next step is referred to as updating the position of the present search agent. Thus, the researchers are using the coefficient factors A_1 and C_1. But A_1 is a function of "a", where the value of "a" linearly decreases from 2 to 0 as in Equation (3):

$$a = 2 - (t/\text{Max } t)) \tag{3}$$

Then A, is expressed in Equation (4) as follows:

$$A_1 = 2ar_1 - a \tag{4}$$

Also, the second coefficient factor C_1 is expressed in Equation (5) as follows:

$$C_1 = 2r_2 \tag{5}$$

For both Equations (4) and (5), r_1 and r_2 are random numbers which are differently generated in each case and range between 0 and 1. So by using Equations (4) and (5), the values for A_1 and C_1 could be obtained for further processing. Now, we progress the grey wolf hunting model, which consists of six set of Equations (6) to (11).

$$D_\alpha = C_1 X_\alpha - X_t \tag{6}$$

$$D_\beta = C_2 X_\beta - X_t \tag{7}$$

$$D_\delta = C_3 X_\delta - X_t \tag{8}$$

$$X_1 = X_\alpha - A_1 D_\alpha \tag{9}$$

$$X_2 = X_\beta - A_2 D_\beta \tag{10}$$

$$X_3 = X_\delta - A_3 D_\delta \tag{11}$$

In Equations (6) to (11), the values of the coefficient factors A_1 and C_1 earlier obtained are substituted in them. It should be noted that different random numbers are used to compute the variables D_α, D_β, D_δ. The researchers should note that the values of the coefficient factor "a" obtained in Equations (4) and (5) change with that of Equation (4) changing in a linearly decreasing manner. Now, to illustrate the working of the coefficient factor "a", if the maximum number of iterations is given as 5, then a is computed as 2(1-1/5), which gives 1.6

Step 3b: Next is the computation of X_1, X_2, X_3

To achieve this computation, reference is made to Equation (4) where the previously computed value of "a" as 1.6 is substituted and Equation (4) yields a value of -1.088 from the computation, which is the value for A_1. Now to compute the coefficient factor C_1, consider a new random number 0.3. Thus random number, when substituted into Equation (5) with a value of "a" as 1.6, which was previously obtained yields the coefficient factor C_1as 0.6. Recall that we are illustrating the working of the mathematical model for the grey wolf and are at the point of evaluating Equation (6). For this equation to be computed C_1 has already been evaluated as 0.6,X_α is also already known, which was declared as [0.5, 0.004, 0.06, 0.03]in step 2. The only variable left to be specified is X_t, which is given as [0.4, 0.05, 0.02, 0.04] for the current wolf under consideration, as stated earlier. Then a matrix multiplication is conducted between the co-efficient factor C_1 0.6 and the matrix X_α and the matrix X_t is subtracted from the results to yield a matrix

$$D_\delta = \begin{vmatrix} 0.1 \\ 0.0026 \\ 0.016 \\ 0.022 \end{vmatrix}$$

But Equation (9) relates D_α, A_1, X_α and X_1, which already has all the values of the component variables to be substituted to obtain

$$X_1 = \begin{vmatrix} 0.3912 \\ 0.0012 \\ 0.0426 \\ 0.0061 \end{vmatrix}$$

From this evaluation of X_1, the interpretation of the results for the boring problem is a speed of 0.3912, feed as 0.0012, depth of cut 0.0426 and nose radius being 0.0061. Therefore, X_2 and X_3 could be computed using the same process to obtain

$$X_2 = \begin{vmatrix} 0.5132 \\ 0.0023 \\ 0.0325 \\ 0.0052 \end{vmatrix} \text{ and } X_3 = \begin{vmatrix} 0.3132 \\ 0.0013 \\ 0.0265 \\ 0.0032 \end{vmatrix}$$

Step 3c. Step 3b is followed by the computation of the new wolf's position, X_{new} has declared in Equation (1). Thus, the values of X_1, X_2 and X_3 obtained from step 3b are substituted in the equation to obtain X_{new} for each parameter of speed, feed, depth of cut and nose radius as 0.4059, 0.0016, 0.0339 and 0.0048, respectively. Therefore, the new wolf position $X_{new}$is given by [0.4049, 0.0016. 0.0339, 0.0048].

Step 4: Next, check if the new computed wolf position is within the search space of each parameters, if it is less than the lower bound of a particular parameter, then the lower bound value of that parameter replaces the computed value in X_{new} of that parameter, and if the computed value in X_{new} of a particular parameter is greater than the upper bounds of that parameter, then the upper bound value of the parameter replaces the computed value in X_{new} of that parameter. Therefore, applying the boundary check to X_{new} we have

X_{new}=[1, 0.0016, 0.07, 0.0048]

Step 5a: Compute the fitness value of X_{new} using the objective function described in step 1, we have $F(x) = 5 \times 1 + 0.005 \times 0.0016 + 0.08 \times 0.07 + 0.013 \times 0.0048 = 5.0561$

Step 5b: Perform the greedy selection to check if the new wolf fitness value is better than the fitness value of the current wolf under consideration, which was earlier computed in step 3b as X_t fitness = 2.0021, being better means if X_{new} fitness is smaller than X_t fitness, in this case, the fitness value of the current wolf under consideration is better than the fitness value of the newly computed wolf position. Therefore, the newly computed wolf position and it fitness value is discarded, while the wolf under consider and it fitness value is retained as before, Note: that the objective being illustrated here is minimization.

Step 6: Complete the first iteration by repeating step 3a to step 5b above for all the wolf in the population, at the end of which the wolf in the population is then sort again as in step 2 in this procedure, while taking note of the alpha wolf and it fitness value as the best in the population and store it.

Step 7: Repeat the procedure from step 2 to step 6 for the chosen maximum number of iteration, therefore in this case we chose 5 as the maximum iteration to be perform, so the procedure should be repeated 5 times, and at the end of each iteration the best wolf and it fitness value is capture and stored.

Step 8: Code the above procedures using python programming language, for accuracy and ease of computation using high population size and high maximum number iteration, and lastly ease of visualization of the output using plots.

4. Results and discussion

This section presents the details of the results at the implementation of the mathematical models and equations presented and illustrated with numerical examples in the section on method. Thus, the equations and the grey wolf optimizer are applied to the boring operation data previously presented in Patel and Deshpande [14] and worked on to an integrated model of Taguchi-Box Behnken design firefly, Fasina et al. [33]. The objective function developed in the later study serves as the input to the present study while the experimental details of Patel and Deshpande [14] were also utilized in the analysis presented here. In the previous section, the present authors discussed about the main motivations to develop the grey wolf optimizer as the social hierarchy and hunting mechanism of the grey wolves. In the hierarchy, which is strictly followed in the wolf pack are have, the alpha, beta, delta and omega wolves representing the top down to the lowest in the hierarchy. For the hunting mechanism, the wolves' chases a prey that enters its territory until its energy exhaust and can hardly run and move again. As it pants, resting to gather more energy the wolves attack it. As it bleeds and become weak they overcome and kill to prey.

In the application of the mathematical model and equation for the grey, the starting point here is to apply the social hierarchy aspect of the grey as solutions to work with. In this case, the objective function formulated in Abdullahi and Oke [32] for grey wolf data when the objective function is generated from the optimized Box Behnken design parameters is introduced into the python programme used for computational efficiency of the solution. The objective function is stated as follows:

Minimize S/N ratio, SNR = -70.00 + 0.0233 speed -3 feed +3.8 depth of cut +10.92 nose radius -0.000010 speed × speed + 35 feed × feed -1.6 depth of cut × depth of cut -7.72 nose radius × nose radius 0.0000 speed × feed -0.00092 speed × nose radius -9.2 feed × nose radius (12)

Next, the population of wolves considered in the work is 200 wolves while 50 iterations are considered. First, the population of the grey wolves is initialized with X_i stated to have varying from 1 to n. Also the coefficient factors a, A and C are initialized. Then, the fitness function of each search agent is computed to establish the best, second best and third best search agent. The search agents A_1, A_2, A_3, C_1, C_2 and C_3 are evaluated using various random numbers as 0.61424, 0.90222, and 0.50349, 0.85676, 0.024209 and 0.90519, respectively. First, consider Equation (3) where t = 0, the value of "a" becomes 2. In this case, all the values of A_1, A_2, A_3, C_1, C_2 and C_3will be computed based on a= 2 at the first iteration. This gives A_1= 0.45696 since 0.61424 is substituted into Equation (4). By using the structure of Equation (4) and 0.90222 and 0.50349 as the random numbers for the equations to compute A_2 and A_3, then these values of A_2 and A_3 are computed as 1.60888 and 0.01396, respectively. To compute C_1, C_2 and C_3, Equation (5) is adopted and the corresponding random numbers used are 0.85676, 0.02429 and 0.90519, respectively. Thus, C_1, C_2 and C_3 are 1.71352, 0.04858 and 1.81038, respectively. Next, the fitness of each search agent X_α, X_β and X_δ is calculated. To achieve this purpose, the researchers substituted the values of speed, feed, depth of cut and nose radius it each of levels 1,2,3 and 4 as in Table 4 of Patel and Deshpande [14] to the Equation (12) for the optimized values of the Box Behnken Design fitness value to obtain four sets of SN ratios, from which X_α, X_β and X_δ will be brought out. To start this evaluation, Equation (12) is recalled and the values of the experiment for the boring operation substituted into it at level 1, which is [800, 0.06, 1, and 0.08] for speed, feed, depth of cut and nose radius, respectively. A Microsoft Excel spreadsheet was set up to calculate the solution. On substituting the values of these parameters into Equation (12), the SNR obtained is 3.9016. Next, considering levels 2, 3 and 4 and the corresponding data on parameters from Table 1 of Patel and Deshpande [14], the values of SNR obtained are 81.984, 80.474 and 79.564, respectively. Now, it is from these calculate values of SNR, which are four items that the best, second best and third best search agents will be chosen. By considering these SNR values, X_α, X_β and X_δ are 79.564, 80.474 and 81.984, respectively. Recall that these values are being awaited for further substitution into Equations (6) to (11). Then the values of D_α, D_β, D_δ, X_1, X_2 and X_3 could be obtained when the previous results are substituted into Equations (6) to (11). It should be noted that X_α is taken as X_t at this stage since we do not know the prey's location and this assumption is that X is the best solution for determining the prey's position since it is known to be the leading wolf to attack the prey. Then, D_α = 56.77051 based on the values of C_1= 1.71352, X_α = 79.564, and X_t = 79.564. Also, D_β= -75.6546 where the component variables that yielded D_β are C_2= 0.04858, X_β= 80.474 and X_t= 79.564. Furthermore, D_δ = 68.85819 where the component variables are C_3=1.81038, X_δ =81.984 and X_t=79.564. Besides, X_1, X_2, X_3 are computed based on Equations (9) to (11) as 53.62215, 202.1931 and 81.02274 and X_{new}, which is the average of these X_1, X_2 and X_3 yields 112.2793.

Next, the coefficient factor "a" is updated by increasing t from 0 to 1. This gives a = 1.98. It should be noted that t = 1, maximum iteration=50. Then the whole process of computing A_1, A_2, A_3, C_1, C_2, C_3, X_1, X_2, X_3, D_α, D_β and D_δ is repeated. However, before increasing t to 1, the value of X noted which is at the first iteration. Having obtained X_α, the speed, feed, depth of cut and nose radius are then read from the python programme results as [800, 0.06, 1, 0] where speed =800rpm, feed=0.06mm/rev, depth of cut=1mm while nose radius is 0. Furthermore, the programme is repeated to t=1 and till t = 10, X_α = 872829.534 obtained after t = 10. More results are generated as shown in section 4.1. Besides, the same procedure is run but using the regression equation from the BBD as the objective function. The results are shown in section 4.2.

4.1 Grey wolf data when objective function is generated from optimized the BBD parameters

Maximum iteration = 50 iterations

Population = 200wolfs

1 [800, 0.06, 1, 0]
2 [800, 0.06, 1, 0]
3 [800, 0.06, 1, 0]
4 [800, 0.06, 1, 0]
5 [800, 0.06, 1, 0]
6 [800, 0.06, 1, 0]
7 [800, 0.06, 1, 0]
8 [800, 0.06, 1, 0]
9 [800, 0.06, 1, 0]
10 [800, 0.06, 1, 0]

The best fitness value of wolfs at the end of 10th iteration is 872728.534

11 [800, 0.06, 1, 0]
12 [800, 0.06, 1, 0]
13 [800, 0.06, 1, 0]
14 [800, 0.06, 1, 0]
15 [800, 0.06, 1, 0]
16 [800, 0.06, 1, 0]
17 [800, 0.06, 1, 0]
18 [800, 0.06, 1, 0]
19 [800, 0.06, 1, 0]
20 [800, 0.06, 1, 0]

The best fitness value of wolfs at the end of 20th iteration is 872728.534

21 [800, 0.06, 1, 0]
22 [800, 0.06, 1, 0]
23 [800, 0.06, 1, 0]
24 [800, 0.06, 1, 0]
25 [800, 0.06, 1, 0]
26 [800, 0.06, 1, 0]

27	[800, 0.06, 1, 0]
28	[800, 0.06, 1, 0]
29	[800, 0.06, 1, 0]
30	[800, 0.06, 1, 0]
	The best fitness value of wolfs at the end of 30th iteration is 872728.534
31	[800, 0.06, 1, 0]
32	[800, 0.06, 1, 0]
33	[800, 0.06, 1, 0]
34	[800, 0.06, 1, 0]
35	[800, 0.06, 1, 0]
36	[800, 0.06, 1, 0]
37	[800, 0.06, 1, 0]
38	[800, 0.06, 1, 0]
39	[800, 0.06, 1, 0]
40	[800, 0.06, 1, 0]
	The best fitness value of wolfs at the end of 50th iteration is 872728.534
41	[800, 0.06, 1, 0]
42	[800, 0.06, 1, 0]
43	[800, 0.06, 1, 0]
44	[800, 0.06, 1, 0]
45	[800, 0.06, 1, 0]
46	[800, 0.06, 1, 0]
47	[800, 0.06, 1, 0]
48	[800, 0.06, 1, 0]
49	[800, 0.06, 1, 0]
50	[800, 0.06, 1, 0]
	The best fitness value of wolfs at the end of 50th iteration is 872728.5336000001
Optimal solution	**[800, 0.06, 1, 0]**

Figure 1 shows the performance of the objective function value during iterations but when grey wolf data when objective function is generated from optimized the BBD parameters.

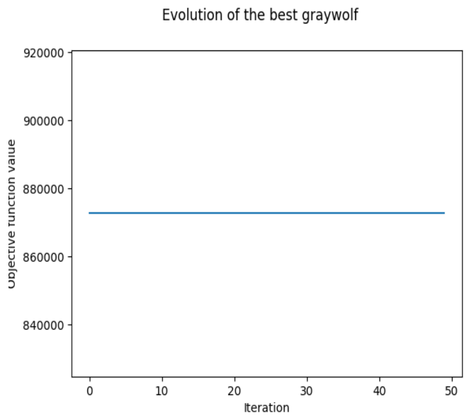

Fig. 1 Performance of the objective function value during iterations (optimized the BBD parameters)

4.2 Grey wolf optimization data when regression equation from the BBD is used as objective function

Maximum iteration = 50 iterations

Population = 200wolfs

Iterations	Optimal Solution
1	[1400, 0.12, 1.5, 0.7998494077077948]
2	[1400, 0.12, 1.5, 0.9266947131496583]
3	[1400, 0.12, 1.5, 0.9266947131496583]
4	[1400, 0.12, 1.5, 0.9266947131496583]
5	[1400, 0.12, 1.5, 0.9142809822476746]
6	[1400, 0.12, 1.5, 0.9521322355263552]
7	[1400, 0.12, 1.5, 0.9521322355263552]
8	[1400, 0.12, 1.5, 0.8183576525571928]
9	[1400, 0.12, 1.5, 0.8183576525571928]
10	[1400, 0.12, 1.5, 0.7561705480213964]
	The best fitness value of wolfs at the end of 50th iteration is -51.503
11	[1400, 0.12, 1.5, 0.7561705480213964]
12	[1400, 0.12, 1.5, 0.716205386390976]
13	[1400, 0.12, 1.5, 0.716205386390976]
14	[1296.808766906948, 0.07848402333756388, 1.2611786713610218, 0.5549105218827534]
15	[1400, 0.09702983228255345, 1.4174285579294976, 0.6354410778039873]
16	[1400, 0.09702983228255345, 1.4174285579294976, 0.6354410778039873]
17	[1373.3029436160589, 0.11103574045667443, 1.45937413100888, 0.6506974336568464]
18	[1373.3029436160589, 0.11103574045667443,

1.45937413100888, 0.6506974336568464]

19 [1373.3029436160589, 0.11103574045667443, 1.45937413100888, 0.6506974336568464]

20 [1373.3029436160589, 0.11103574045667443, 1.45937413100888, 0.6506974336568464]

The best fitness value of wolfs at the end of 20th iteration is -51.491

21 [1261.962817283115, 0.10310164068682792, 1.3289511875202542, 0.5589682380329987]

22 [1261.7130515163246, 0.10282916683807825, 1.311130279921355, 0.5792279196248411]

23 [1261.7130515163246, 0.10282916683807825, 1.311130279921355, 0.5792279196248411]

24 [1261.7130515163246, 0.10282916683807825, 1.311130279921355, 0.5792279196248411]

25 [1261.7130515163246, 0.10282916683807825, 1.311130279921355, 0.5792279196248411]

26 [1261.7130515163246, 0.10282916683807825, 1.311130279921355, 0.5792279196248411]

27 [1261.7130515163246, 0.10282916683807825, 1.311130279921355, 0.5792279196248411]

28 [1219.5872615697167, 0.10073983475277971, 1.2930126720521737, 0.5548516693871298]

29 [1219.2308636187952, 0.09963767363948217, 1.2719779555196427, 0.5587624065696885]

30 [1219.2308636187952, 0.09963767363948217, 1.2719779555196427, 0.5587624065696885]

The best fitness value of wolfs at the end of 300th iteration is -51.491

31 [1219.2308636187952, 0.09963767363948217, 1.2719779555196427, 0.5587624065696885]

32 [1219.2308636187952, 0.09963767363948217, 1.2719779555196427, 0.5587624065696885]

33 [1219.2308636187952, 0.09963767363948217, 1.2719779555196427, 0.5587624065696885]

34 [1203.7105458112567, 0.09094659333978998, 1.229814154259614, 0.5497731543278458]

35 [1203.7105458112567, 0.09094659333978998, 1.229814154259614, 0.5497731543278458]

36 [1203.7105458112567, 0.09094659333978998, 1.229814154259614, 0.5497731543278458]

37 [1203.7105458112567, 0.09094659333978998, 1.229814154259614, 0.5497731543278458]

38 [1201.8667639024052, 0.0887649120312805, 1.2203543256198701, 0.5439837121669641]

39 [1201.8667639024052, 0.0887649120312805, 1.2203543256198701, 0.5439837121669641]

40 [1210.3384470690364, 0.08762136214580944, 1.2274828370791884, 0.5252834771242613]

The best fitness value of wolfs at the end of 40th iteration is -51.491

41 [1210.3384470690364, 0.08762136214580944, 1.2274828370791884, 0.5252834771242613]

42 [1201.8667639024052, 0.0887649120312805, 1.2203543256198701, 0.5439837121669641]

43 [1195.9500476927262, 0.08840038928613259, 1.2151842043706027, 0.5414881583854834]

44 [1192.2572986211783, 0.08876374377039566, 1.2379604158569308, 0.5677748329471014]

45	[1200.2592201959799, 0.08921811572217586, 1.2320789942692294, 0.5580975612783549]
46	[1191.9781951023076, 0.08865634140918455, 1.2249697415298957, 0.5556227389395847]
47	[1197.1766315752343, 0.08894149220735675, 1.2264405222570909, 0.554543131504797]
48	[1192.2151387835816, 0.08861160035971917, 1.2209222486320466, 0.5518671776660374]
49	[1191.9781951023076, 0.08865634140918455, 1.2249697415298957, 0.5556227389395847]
50	[1189.5771506857511, 0.08848085594306532, 1.2202638619101076, 0.5523376994219448]
	The best fitness value of wolfs at the end of 50th iteration is -51.490994127543615
Optimal solution	**[1189.5771506857511, 0.08848085594306532, 1.2202638619101076, 0.5523376994219448]**

Figure 2 also shows the performance of the objective function value during iterations but when the grey wolf optimization data when regression equation from the BBD is used as objective function

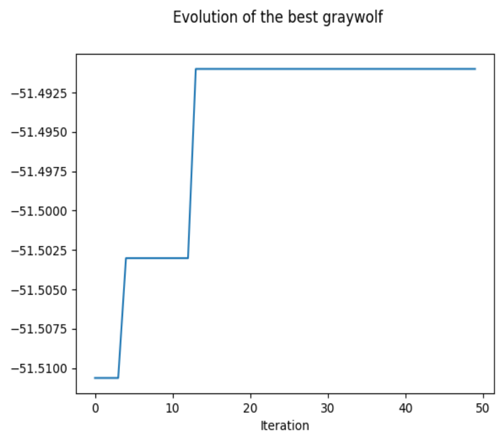

Fig. 2 Performance of the objective function value during iterations (linear equation)

4.3 Sensitivity analysis

The aim of embarking on the sensitivity of the data is to estimate the degree of responsiveness of each input relative to the output. To this end a brief sensitivity analysis was conducted where for each input, namely speed, feed, depth of cut and nose radius, 10% increases and reductions were made consecutively on the parameters (optimized) and the new values of the surface roughness which is the output were noticed for six simulations (Table 2). Microsoft Excel was used to aid the computations. While increasing and decreasing these values of a particular variable (say speed), other variables were not adjusted (i.e. feed, depth of cut and nose radius). In all, four scenarios of analysis were created, representing scenarios, 2, 3 and 4 for the respective adjustments made on 10% and decrease for speed, feed, depth of cut and nose radius. For scenario 1, for feed, this optimized parameter initially has a value of 1189.58. It was increased by 10% at each count in six counts to a maximum of 1824.37. This yielded a decrease of surface roughness value from -51.55056424 at the first count -56.21341419. However, when the speed parameter was reduced by 10% in six counts the response was decreases in the surface roughness from the first count of -51.5734018 to -54.80794278 in the fifth count but a sudden increase in the surface roughness value to -51.55056424. The implication of the results is that for the increase of speed variable by 10%, a negative correlation between the speed and the optimal surface roughness exist. Furthermore, the value of the optimized output does not show large variable suggesting that the speed parameter might not have a strong impact on the surface roughness. However, considering the situation of 10% decrease in speed, it is suggested that the optimal surface roughness shows sensitivity to changes in the speed parameter with a non-linear response. Also, it shows that the speed parameter has a strong impact on the output (surface roughness). Moreover, scenarios 2 to 4 were explored using the same procedure followed in scenario 1. The results are shown in Figures 2 to 5.

The conclusion from scenario 2 where feed is increased by 10% in each count of six is that as the feed parameter increases, the optimal surface roughness starts to decrease and then at a point begins to increase linearly, revealing that the optimal surface roughness is sensitive to changes in the feed parameter. Also, it shows that the feed parameter is critical to the surface roughness. Still on the feed parameter, as it is decreased by 10% in each of the six counts, the optimal surface roughness shows a non-linear response. It shows an initial decrease in the optimal surface roughness followed by an increase in the surface roughness. It implies that surface roughness is sensitive to changes in the feed parameter and it is important in this aspect. For the nose radius, as a 10% increase in this parameter was initiated, the surface roughness gradually decreases. It shows a negative correlation between depth of cut and the optimized outputs. Besides, the optimized surface roughness shows sensitivity to changes in the depth of cut and the sensitivity is shown in the consistent decrease in the surface roughness as depth of cut increases. As the nose radius is reduced by 10% in each of the six counts, the optimized surface roughness shows a non-linear response. There was an initial increase in the output followed by a decrease, suggesting that the optimized surface roughness shows sensitivity it changes in the depth of cut variable with a non-linear response.

Now, the last parameter tested (scenario 4) is the nose radius. As a 10% increase was initiated, for the nose radius, the optimized surface roughness shows a non-linear response. There was an initial decrease in the surface roughness followed by an increase in the surface roughness. The optimized output shows sensitivity to changes in the nose radius variable and this sensitivity is reflected in the non-linear response observed in the output. When a 10% decrease in the nose radius was initiated, the optimized surface roughness showed a non-linear response. It exhibited an initial increase in the surface roughness followed by a decrease in the surface roughness optimal value. The optimized output shows sensitivity to changes in the nose radius variable with a non-linear response.

Table 2 10% increase and decrease in Speed, feed, depth of cut and nose radius with the corresponding changes in surface roughness

	10% increase		10% decrease	
	Speed	SR	Speed	SR
1	1189.58	-51.550564	1070.622	-51.5734
2	1308.538	-51.810747	944.664	-51.9061
3	1437.496	-52.412509	818.706	-52.5561
4	1566.454	-53.346874	692.748	-53.5233
5	1695.412	-54.613842	566.79	-54.8079
6	1824.37	-56.213414	1189.58	-51.5506
	10% increase		10% decrease	
	Feed	SR	Feed	SR
1	0.089	-51.550564	0.0801	-51.5315
2	0.0979	-51.564079	0.07209	-51.5096
3	0.10769	-51.572541	0.064881	-51.4861
4	0.118459	-51.5741	0.058393	-51.4618
5	0.130305	-51.566439	0.052554	-51.4374
6	0.143335	-51.546666	0.089	-51.5506
	10% increase		10% decrease	
	DC	SR	DC	SR
1	1.22	-51.550564	1.098	-51.5617
2	1.342	-51.587067	0.9882	-51.6124
3	1.4762	-51.682231	0.88938	-51.6911
4	1.62382	-51.853474	0.800442	-51.7886
5	1.786202	-52.122385	0.720398	-51.898
6	1.964822	-52.515641	1.22	-51.5506
	10% increase		10% decrease	
	NR	SR	NR	SR
1	0.55	-51.550564	0.495	-51.6022
2	0.605	-51.545604	0.4455	-51.6887
3	0.6655	-51.594093	0.40195	-51.796
4	0.73205	-51.712705	0.361755	-51.921
5	0.805255	-51.92216	0.32558	-52.0549
6	0.885781	-52.248128	0.55	-51.5506

5. Conclusions

In this article, the boring process involves the machining of IS 2062 E250 steel plates was analyzed from the literature data of Patel and Deshpande [14]. The method of Taguchi-Pareto-Box Behnken Design-grey wolf optimization was applied with the design of experiments as the foundation of the analysis. The speed, feed rate, depth of cut and nose radius were the variables of the process used in the experiment. The principal response for the boring process is the surface roughness, which was to be optimized. For the objective function, two methods were adopted. The first method is when the objective function is generated from optimized Box Behnken design parameters. The second is the case where the grey wolf optimization data contains an objective from the perspective of regression equation generated from the Box Behnken Design method. The principal conclusions from this work are as follows:

- The use of Taguchi-Pareto-Box Behnken Design-Grey Wolf Optimization methods for the boring process is feasible.
- To ascertain utmost surface roughness of the process values of the IS 2062 E250 steel plates, process value of speed, feed rate, depth of cut and nose radius are 800, 0.06, 1 and 0 when the objective function was obtained from optimized Box Behnken Design parameters. However, it was 1189.58, 0.089, 1.22 and 0.55 for the respective parameters when the regression model was introduced from the Box Behnken Design as an objective function.
- For the first time, the coupling of Taguchi-Pareto, Box Behnken Design, grey wolf optimization methods was done to implement optimization decisions for the boring process to obtain the best solution for the surface roughness of the IS 2062 E250 steel plates.

The combined method helps to reduce time and money during operational planning decision. To understand this claim, it is acknowledged that engineers spend time and money to obtain reliable results for decision making. However, much of this information is obtainable from trial and error cases and the past experiences of the engineer. This involves searching past records of performance during the previous planning operations, interviewing operators responsible for the success of previous boring operations to obtain the critical elements of success. Moreover, as the engineer deploys optimal results obtained from the hybrid method proposed in planning, there is no need for extensive past record searching, which is man-hours saved.

In the future, other optimization procedures could be substituted for the grey wolf optimization procedure. Such methods as particle swarm optimization and ant colony optimization methods are promising to obtain new objectives of the articles. Furthermore, the industrial usage of the IS 2062 E250 steel plates analyzed in the present study are diverse. They include storage tanks, pipeline construction and for equipment in oil and gas industries. To manufacture components under the mentioned categories, milling, drilling and cutting processes could be applied to the IS 2062 E250 steel for processing. For instance, consider the storage tank where several cutting activities are to be made. The researchers need to collect information on the cutting speed, depth of cut and the cutting angle, at different levels. Then the orthogonal arrays and objective functions could be formulated. Afterwards, this work could be applied to obtain result from which conclusions may be drawn. Thus, it is suggested that future studies should focus on applying the suggested method to the IS 2062 E250 steel for processing in milling, drilling and cutting processes.

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