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Optimizing The Machining Process of IS 2062 E250 Steel Plates with The Boring Operation Using a Hybrid Taguchi-Pareto Box Behnken-teaching Learning-based Algorithm

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ABSTRACT

In this article, a new method termed the Taguchi-Pareto-Box Behnken design teaching learning-based optimization (TPBBD–TLBO) was developed to optimize the boring process, which promotes surface roughness as the output. At the same time, the speed, feed, and depth of cut are taken as the inputs. The case examines experimental data from the literature on the boring of IS 2062 E250 steel plates. The proposed method draws from a recent idea on the Taguchi-Pareto-Box Behnken design method that argues for a possible relationship between the Taguchi-Pareto method and the Box Behnken design method. This idea was used as a basis for the further argument that teaching learning-based optimization has a role in the further optimization of the established TPBBD method. The optimal solutions were investigated when the objective function was generated using the Box Behnken design in a case. It was replaced with the regression method in the other case, and the python programming codes were used to execute the computations. Then the optimal solutions concerning the parameters of speed, feed rate, depth of cut, and nose radius were evaluated. With the Box Behnken as the objective function for the TLBO method, convergence was reached at 50 iterations with a class population of 5. The optimal parametric solutions are 800 rpm of speed, 0.06 min/min of feed rate, 1 min for depth of cut, and 0 min for nose radius. On the use of the regression method for the objective function, while the TLBO method was deployed, convergence was experienced after 50 iterations with a class population of 200 students. The optimal parametric solution is 1135rpm of speed, 0.06 min/min of feed rate, 1024 min of the depth of cut, and 0.61 min of nose radius. The speed, depth of cut, and nose radius showed higher values, indicating the use of more energy resources to accomplish the optimal goals using the regression method-based objective function. Therefore, the proposed method constitutes a promising route to optimize further the results of the Taguchi-Pareto-Box Behnken design for boring operation improvement.

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1. INTRODUCTION

Today, boring operation is a principal element in the world's machining economy, and its significance is growing day by day because of increased manufacturing activities (Khan et al., 2022). However, despite intensive research activities on boring operations, the overwhelming economic challenge has downsized the power of local currencies, and trading above the break-even point has become difficult (Luthra et al., 2019; Sharma et al., 2021; Reslan et al., 2022). This economic challenge is aided by market forces, poorer skill sets, and frequent job turnover for experienced operators resigning from the machining industry to the oil and gas sector and the dwindling foreign exchange power to purchase inputs for manufacturing (Luthra et al., 2019). The market forces, for instance, include socioeconomic, geopolitical, and technological factors, which modify everything known about manufacturing.

From the above discussion, there is necessary to establish and improve process optimization procedures to control the economic challenge to the extent possible within the boring industry. Consequently, boring optimization research has commenced for some years now. It has attracted several scholars worldwide in the search for optimization procedures to reduce the external influence of certain forces on the prosperity of the boring industry (Patel & Deshpande, 2014; Rao & Murthy, 2018; Kumar et al., 2019a,b; Abiola & Oke, 2021; Abiola & Oke, 2022; Hassan et al., 2022). However, with the continuing quest for the enhanced economic performance of the boring industry, the advent of the Taguchi performance optimization method has been noticed (Patel & Deshpande, 2014). Before this advent, diverse conditions such as downsizing the workforce, retraining of retained workforce, stricter work schedules, and performance monitoring were specified (Mori et al., 2015; Qu et al., 2016). But it was soon realized that the economics of experimentation and simplicity in applying performance measures were essential (Patel & Deshpande, 2014).

Therefore, process engineers have no option but to install Taguchi methodical principles in their systems (Patel & Deshpande, 2014). Thus, in the boring industry, optimization has been attempted principally using the Taguchi method because of its simplicity. Still, its shortcoming remains the inability to distinguish among the factors which exceed in performance more than the others (Patel & Deshpande, 2014). This shortcoming must be addressed for a huge benefit to research progress on the Taguchi method in the dull area. Also, despite being critical in performance enhancement drive, much less about the synergic benefits of the Taguchi method with other methods are known. Specifically, the literature has failed to clearly understand how the Taguchi method's weaknesses could be complemented with methods such as the Box Behnken design and the teaching-learning-based optimization method. Besides, the engineering literature has established the usefulness and preference of integrating methods for enhanced results instead of deploying only one method at a time. Therefore, the present article is motivated by this idea by integrating the Taguchi-Pareto method, Box Behnken design, and the teaching-learning-based optimization (TLBO) method. In this article, a novel method named Taguchi-Pareto Box Behnken design–Teaching Learning Based Optimisation method was tested with the experimental literature data by Patel and Deshpande (2014) and used the IS 2062 E250 steel plates on the CNC machine during the boring operation is presented. Using the same data set as a previous study, where the Taguchi-Box Behnken design method had been validated, the addition in the present study is the augmentation of the TLBO procedure to the established results in the previous documentation to develop the objective function for the new integrated method.

In this article, two performance measures are deployed to evaluate the performance of the two variants of the proposed method, the TPBDD-TLBO process, which is discussed in this work. Estimating the signal-to-noise ratios from the python programming codes executed when the objective functions are developed from Box Behnken design and regression equation is one method adopted in the present work. The second method is to observe the values of the parameters and choose the lower one since it leads to lower energy consumption. Thus, the potential to consume energy from the results of the two variants is used to evaluate them for a choice of the better alternative. The second performance measurement approach, energy consumption, is further elaborated in the following discussion. Furthermore, the purpose of this article is to propose a new method referred to as the TPBBD-TLBO method and test it with the IS 2062 E250 steel plate work material in the boring operation, using literature data from Patel & Deshpande (2014). The used energy as a performance measurement criterion of the proposed method to judge which routes to optimization are preferred has been exercised. The first route is formulating the objective function as a Taguchi-Pareto box Behnken design, while the second is formulating the objective function as a regression method. Each of these methods is substituted into the TLBO method for performance comparison. It is argued that machine utilization is closely tied to time, which is proportional to the energy consumption by the machine. Suppose the optimal parameters have values in a methodical route higher than the other. In that case, it implies that it requires a greater amount of energy consumption to attain the system's goal using the method than one with a lower optimal value since less time and interaction with the machine is involved. Consequently, both routes show results of which the one with the lower optimal parametric values is preferable.

2. LITERATURE REVIEW

It is a common fact that optimization of process parameters in machining operations is very important in the manufacturing industries for various reasons, including the demand for high-quality products at affordable cost. The ways and manners involved in obtaining these process parameters are also very crucial to achieving high accuracy optimized parameters for high-quality outputs. While there has been much research on various meta-heuristic evolutionary approaches and their combination with various other methods for optimization of process parameters, very few researchers have employed the approach used in the current paper; this approach is a combination of Taguchi, Pareto, Box Behnken design and TLBO which is a meta-heuristic evolutionary approach.

2.1. Aspects studied

The overall material used in the literature under review ranges from steel (alloys and grades), titanium (alloys and grades), Inconel of different grades, aluminum (alloys and composites), and different polymer materials. Patel et al. (2018) used AISI D2 steel to determine the optimal input parameters, including torch height, gas pressure, and cutting speed, using TLBO with a genetic algorithm to obtain an optimal surface roughness in a plasma cutting machining operation and found out that the predicted and experimental surface roughness shows a percentage error of 3.7781% which is low enough to conclude that both results are in agreement.

Several other authors have also focused on different materials as work material for optimization of machining input parameters to acquire optimal out parameters; those that used steel (alloys and grades) are Dave (2019), Patel et al. (2018), Upadhyay (2022), Aouici et al. (2012), Patil et al. (2021), Suresh et al. (2002). Some of the authors that employed titanium (alloys and grades) are Sharma et al. (2020), Singh et al. (2019), Upadhyay et al. (2013), Sahu & Andhare (2015), and Zain et al. (2010). Inconel was also used by the following authors: Dave (2019), Kumar et al. (2020), Gupta et al. (2019), Rao & Kalyankar (2011), George et al. (2019), and Bhopale et al. (2015). Pure magnesium was used by only one author: Kumari et al. (2020). Some others that used aluminum (alloy and composites) are Dikshit et al. (2017), Abdallah et al. (2014), Rudrapati et al. (2016), Prakash & Gopalakannan (2021), Patel et al. (2020), Pare et al. (2015). Lastly, those that made use of Polymer materials are Abhishek, Datta, & Mahapatra (2017), Natarajan et al. (2018), and Abhishek, Kumar, Datta, & Mahapatra (2017). According to this review, no research has been done using the E250 B0 grade of steel as a workpiece material to establish the best ideal parameters for the lowest surface roughness by any of the authors listed above. Hence it was chosen as the material for the current study.

The machining operations performed by authors in the literature under review on various materials are drilling, grinding, turning, and milling; these operations were performed either by conventional or unconventional machining processes. Conventional machining is a human-controlled process where direct interaction of the operator and the tool exists. However, as an improvement in technology, the non-conventional machining process was developed to eliminate the direct interaction of the operator/machine tool with the workpiece. To achieve the aim of non-conventional machining processes, sophisticated tools such as the laser beam, electric arc, infra-red beam, electric beam, and plasma cutting have replaced machine tools. Nonetheless, machine tools are relevant where cost and technological skill availability have restricted the use of non-conventional machining. Unconventional machining processes like helical path orbital EDM process, electrochemical machining (ECM) process, electrochemical discharge machining (ECDM) process, electric discharge machining (EDM), ultrasonic machining (USM), wire electrical discharge machining (WEDM) process, abrasive jet machining (AJM), micro electrochemical machining (μECM), electrical wire discharge turning (WEDT), electric discharge drilling (EDD) were widely used for various machining operations in the literature under review. Dave (2019) used a helical path orbital EDM process for a machining operation with material removal rate as its output parameter. Rao & Kalyankar (2011) engaged the ECM and ECMD for a machining operation with output parameters such as material removal rate, radii cutout (ROC), and heat-affected zone (HAZ). Kumar et al. (2020) and Rao & Kalyankar (2013) used wire electrical discharge turning (WEDT) as a machining process in their studies. Prakash & Gopalakannan (2021) made use of microelectrochemical machining (μECM) for a machining operation with material removal rate (MRR), radial overcut, tool electrode wear, and surface roughness as output parameters. Another author, Sharma et al. (2020), used electric discharge drilling (EDD) for drilling operation with drilling rate (DR) and electrode wear ratio (EWR) as output parameters.

Meanwhile, conventional machining processes were mostly performed on CNC machines. For instance, Abdallah et al. (2014), Rudrapati et al. (2016), Natarajan et al. (2018), and Pare et al. (2015) all performed turning operations on a CNC turning machine. Furthermore, Patil et al. (2021) used a VMC five-axis CNC milling machine as a machine tool. Due to availability, convenience, and the second machine tool trend in the literature under review, the E Batilbio CNC Sprint 20TC was chosen as the machine tool for the current work. Because no author in the literature under examination chose to bore as a machining operation for the various experiments in finding the optimal parameters that result in an outmost output parameter, the boring operation is chosen as the machining operation for the current studies.

Material removal rate (MRR), Radii cutout (ROC), heat affected zone (HAZ), surface roughness, minimum carbon emission, operation time, production cost (cp), tool life (T), cutting force, tool wear, length of tool-chip contact, wear on tool electrode, roundness, cylindricity, drilling rate (DR), electrode wear ratio (EWR), deflection, the microhardness of plate, tool-tip temperature, cylindricity error and circularity error, are the output parameters considered by authors throughout the literature under review.

In their numerous studies, authors in the literature took into account singly or multiple output parameters. Surface roughness as a single output parameter was not only prevalent throughout the literature under examination. Still, it was also present as a parameter in multiple output parameters across the literature under review. The authors who used surface roughness as their sole output parameter are Pare et al. (2015), Suresh et al. (2002), Rudrapati et al. (2016), Upadhyay et al. (2013), Kumari et al. (2020), Patel et al. (2018), Sahu & Andhare (2015), Dikshit et al. (2017), Zain et al. (2010). However, only one author in the literature considered a single output parameter other than surface roughness; Dave (2019) considered the material removal rate a single output parameter.

A few authors that considered multiple output parameters (multi-objective problems) are Rao & Kalyankar (2011), Kumar et al. (2020), and Lin et al. (2015). From the above, surface roughness, an output parameter that requires an outmost finish in a boring operation, is chosen as the only input parameter in the current study. Secondly, a single output parameter was chosen due to the scope of the methodology used in the current study. The input parameters depend on the type of machining process being used for various studies in the literature; unconventional machining process input parameters common in the literature are applied voltage, electrolyte flow rate, the volumetric concentration of abrasive particles in slurry, orbital radius, inter-electrode gap, pulse on time, static feed force, peak current, mass flow rate of abrasive particles, the amplitude of vibration, current, a mass flow rate of abrasive particles, electrolyte concentration, pulse off time, orbital speed, the mean radius of abrasive particles, gap voltage, duty factor, frequency of vibration, mean diameter of abrasive grains, the velocity of abrasive particles, electrolyte concentration, servo feed and the mean radius of abrasive particles. Sharma et al. (2020) and Rao & Kalyankar (2012) are authors that use pulse on time, pulse off time, and current as common output parameters in their studies. As for the conventional machining process, nose radius, feed rate, depth of cut, and spindle speed are the most commonly used input parameters for CNC machining, and it is like throughout the literature. Singh et al. (2019), Abdallah et al. (2014), and Natarajan et al. (2018) are a few authors that used spindle speed, depth of cut, and feed rate as input parameters. Input parameters considered in the current studies are also spindle speed, depth of cut, and feed rate, with the inclusion of the cutting tool nose radius. Patel et al. (2020) is the only author who used the exact input parameters in the current study.

In the literature under evaluation, the authors used various methodologies, including the Taguchi method, response surface methodology, analysis of variance, grey relational analysis, fuzzy inference system (FIS), and multi-performance characteristic index (MPCI). These methodologies were mostly used in conjunction with various meta-heuristic evolutionary approaches like TLBO, genetic algorithm (GA), gravitational search algorithm, JAYA algorithm, harmony search algorithm, particle swarm optimization (PSO), and bacterial foraging optimization. TLBO being part of the methodology of the current study was widely used throughout the literature to find the ideal machining parameter that yields the best values for various output parameters; it was used either alone or integrated with other methods. Rao & Kalyankar (2013), Patel et al. (2018), and Rao & Kalyankar (2013) are a few authors who used TLBO alone without integration with other methods. A few authors that integrated other methods into TLBO are Dikshit et al. (2017), Sahu & Andhare (2015), and Gupta et al. (2019).

Lastly, there are authors in the literature under review that did not use TLBO or integrate it with other methods but instead used a different method singly or in combination with another method. These are as follows: Suresh et al. (2002) used response surface methodology (RSM) and GA. Patel et al. (2020) used principal component analysis and the JAYA algorithm. The methodology used in the current study is the integration of four approaches, namely the Taguchi method, Pareto principle, Box Behnken design, and TLBO, in short, code-named TP-BBD-TLBO methodology.

Some findings in the literature compared the results from TLBO and other evolutionary approaches. The comparison was based on the optimized input parameters' precision and the methods' convergence rate. Dave (2019) found that TLBO converges faster than PSO. Rao & Kalyankar (2011) found that when the results of TLBO and ABC were compared, it was found that the results in both methods were similar, i.e., in agreement but that the TLBO algorithm converges to the optimal result using a tiny population size and fewer numbers of iteration to converge.

Finally, the current study has attempted to introduce a novel approach to the boring operation literature, which offers a promising result that is of high accuracy than those obtainable in the boring operation literature.

2.2. General

Dave (2019) claimed that upon a comparison of results from TLBO and PSO based on precision and rate of convergence, it was found that TLBO gave a higher value of material removal rate than PSO and that TLBO also converges faster than PSO when the machining process performed on Helical path orbital EDM process and work material are AISI 304 and Inconel 718. In support of this result, it was mentioned that TLBO does not need an algorithm-specific parameter for optimization, hence its superiority over PSO; the proposed method could be applied to other output parameters, such as surface roughness.

Rao & Kalyankar (2011) claimed that the machining process used in the experiment is the electrochemical machining (ECM) process and electrochemical discharge machining (ECDM) process and the results obtained from TLBO and ABC were compared. It was found that the results in both methods were similar but that the TLBO algorithm converges to the optimal result using a tiny population size and fewer numbers of iterations to converge. To support this, the claimed result was concluded that TLBO is superior over the ABC and other new approaches based on population size, number of generations, and computational time. Zain et al. (2010) claimed that with conditions of the highest speed, lowest feed rate, and highest rake angle, the genetic algorithm outputted the most desirable optimal surface roughness as 0.138 micrometers when end milling machining operation is performed on titanium alloy work material. It was concluded that the GA approach in the present study is capable of reducing the minimum surface roughness value of experimental sample data by 25%.

Lin et al. (2015) claimed that when the analytic hierarchy process is used to determine the optimal solution, the solutions found were more environmentally friendly than those found by the experiment method's design. By evaluation, it shows that the proposed method can be used to optimize another machining parameter. Rao & Kalyankar (2013) claimed that the TLBO is free from algorithm parameters like other evolutionary approaches and also found that TLBO offers a better result in terms of performance and computational time when compared to other evolutionary methods; by evaluation, It was concluded that the extension of TLBO to other conventional and advanced machining process used in manufacturing industries could easily be achieved. Dikshit et al. (2017) claimed that from the ANOVA result, the cutting speed is the most significant parameter, followed by the axial depth of the cut. And that the optimal parameters from TLBO were found to be 0.06mm, 0.74 mm, 145.8 m/min, and 0.38 mm for feed per tooth, axial depth of cut, cutting speed, radial depth of cut, respectively, with a resulting surface roughness of 1.11micrometer, when Al2014-T6 alloy is milled on a high-speed ball-end milling machine, this results is supported by a validation experiment, upon evaluation, it was concluded that it could be further applied to the optimization of cutting forces and RMS in HSM process.

Sahu & Andhare (2015) claimed that from the RSM analysis, increases in cutting speed decrease the surface roughness and that surface roughness increases with an increase in feed rate. Furthermore, the depth of cut is found not to affect the surface roughness in the turning operation of Ti-6Al-4V material, and the low maximum error is computed when comparing the predicted. The measured surface roughness shows that the model effectively predicts surface roughness. In conclusion, the obtained optimal input parameters gave an optimized surface roughness of 0.3120 µm.

Gupta et al. (2019) claimed that both PSO and TLBO were very effective in determining the optimal input parameters and that PSO provided a better result than TLBO in a turning of Inconel-800 under minimum quantity lubrication; furthermore, it was found that the minimum quantity of lubrication was a better lubrication process than flooded and dry lubrication processes in the studies. Patel et al. (2018) claimed that the predicted and experimental surface roughness shows a percentage error of 3.7781% in the plasma cutting operation of AISI D2 steel. In conclusion, the result from the TLBO approach was compared to that obtained by the GA approach, and it was observed that the TLBO was better after evaluation.

Kumari et al. (2020) claimed that the optimal surface roughness found with the Taguchi method is 2.4 micrometer with an optimized set of peak current = 1 amp, Ton = 40 µs, Toff = 9 µs, and that pulse on time and pulse off time had a significant effect on surface roughness in the electric discharge machining process of pure magnesium (Mg), and that the optimized parameters from both TLBO and Taguchi are very close but that from Taguchi was better, this claim was supported by comparison of both results. Upon further evaluation, it shows that when multimodal is required, TLBO is more effective. Rao & Kalyankar (2013) claimed that with USM, TLBO has shown an improvement of 12% over GA, and also better results than another optimization algorithm, using the same model, in the same fashion, with AJM 8% and 20% were recorded over GA and simulated annealing algorithm for brittle and ductile material respectively, furthermore, with WEDM, TLBO showed better result than ABC, all in a process where Inconel 601 and alumina ceramics is used as work materials. It was concluded that TLBO, in the present work, shows superiority over other optimization algorithms and that it would be used for the optimization of other process parameters like welding process parameters. Last it is further evaluated and concluded that the TLBO process could be further worked upon in the aspect of having different teachers for different subjects and further learning by tutorials.

Upadhyay et al. (2013) claimed that when the acceleration amplitude of tool vibrations in axial, radial, and tangential directions was used to develop multiple regression models for surface roughness prediction in the turning operation of Ti–6Al–4V alloy, both models developed were of low prediction accuracy of 24% maximum percentage error, but when the regression model is built with feed rate, depth of cut and acceleration amplitude of vibration in the radial and tangential direction. The accuracy of surface roughness prediction was high, with a 7.45% maximum percentage error. Singh et al. (2019) claimed that RHVT was very effective in improving the MQL process by 15% for all responses in the turning process of Titanium (Grade 2); upon evaluation, it is concluded that TLBO was the best optimization method in this regard with a success rate of 90% and average time of 1.09s. Abdallah et al. (2014) claimed that precise knowledge of the optimal cutting parameters would lead to a reduction in machining cost and improved quality of products. The result from the ANOVA shows that the feed rate, depth of cut, and speed have a significant influence on the MRR and surface roughness in the CNC turning operation of Aluminum alloy 6061. It is concluded that the result from Taguchi shows a surface roughness of 1.98 micrometers and that the final surface roughness obtained using the optimized parameter is 0.256 using RSM.

Rudrapati et al. (2016) claimed that from the ANOVA result, the feed rate and depth of cut, excluding the spindle speed, including the squares of all parameters, were significant to the surface roughness. It is concluded that optimal parameters from the TLBO process are spindle speed = 700 rpm, feed rate = 25 mm/min, depth of cut = 0.2 mm, and the resulting surface roughness is 0.42081 µm. Abhishek, Kumar, Datta, & Mahapatra (2017) claimed that the TLBO was a better method than GA when their results were compared to the current study. It was further argued that the TLBO approach utilizes less computational effort for solving constraints and unconstraint problems. Upon evaluation, It is concluded that the TLBO approach needs quite a small size of population and low maximum iteration to reach optimal process parameters. Prakash & Gopalakannan (2021) claimed that when the input parameters are increased, the MRR, surface roughness, and tool wears. Radial overcut increases also when Aluminum alloy (AA) 7075 reinforced with nano silicon carbide particles (1.5 wt%) goes through Micro Electro Chemical Machining (µECM) process. It is concluded that when a target surface roughness of 0.4micrometer was set, the TLBO approach performed better than RSM. However, the result from both methods was in close agreement.

George et al. (2019) claimed the output parameters machined using the WEDT process with Inconel 825 as work material obtained from the validation experiment and TLBO were in close agreement. Natarajan et al. (2018) claimed that EMOTLBO produced a uniformly distributed Pareto front, making it better than the optimization algorithms in the CNC turning of ACETAL homopolymer material (Delrin). It was concluded that validation of the simulation result was done experimentally with a difference of less than 5%, which shows that the simulated and experimental results are in agreement. Sharma et al. (2020) declared that the proposed model provided an optimal parameter setting of Ip: 3A; Ton: 40 ms; Toff: 42 ms for both drilling rate and electrode wear rate in the electric discharge drilling of Titanium and that the predicted and experimental results percentage errors are 8.1 and 7.5% for drilling rate and electrode wear rate respectively, In conclusion, the author suggested that instead of using conventional statistical or artificial intelligence methods, the proposed methods can be used to optimize process parameter of the different machining process. Gadekula et al. (2018) maintained that the optimal parameters for MRR are 2000, 60, and 0.8 for spindle speed, feed rate, and depth of cut, respectively, while those obtained for surface roughness are 1500, 40, 0.8, respectively, for the turning operation of high carbon high chromium steel (HCHCR) on a CNC Turning machine (dry turning). It is concluded that the Taguchi method successfully optimizes the input and output parameters by minimizing the surface roughness and maximizing the MRR.

From the discussion above, the literature has shown that (1) several material grades have been used by authors with the concern of how they impact performance during machining (2) modern-day manufacturing is gradually displacing the conventional machining of CNC technology like boring with novel and attractive systems such as electrochemical discharge machining, abrasive jet machining, and electrical discharge machining, which are non-conventional, systems nonetheless, not all countries and economics have accepted the non-conventional machining probably partly because of the investment and maintenance cost of such equipment. (3) A broad range of parameters and responses have been deployed and tested in machining systems, particularly in conventional machining, such as boring, turning, and mulling (4) diverse optimization methods have been tested in the boring area and machining in general. The earlier set of optimization methods includes the Taguchi method, grey relational analysis, and response surface methodology. However, of late non-conventional optimization methods have been deployed to improve machine performance. These methods include evolutionary algorithms such as genetic algorithms and particle optimization, among others.

Furthermore, viewing the literature closely, several studies have established that machining performance could be improved through the choice of adequate boring parameters. It was also known that responses such as surface roughness could be reduced through an efficient boring process that ignores intuition and experience but depends largely on scientific tools of optimization that are appropriately chosen. Consequently, the research gap in boring optimization and the wide range of economic activities in boring operations for components stimulate the need to gain insight into and optimize the critical parameters impacting the boring process. This article presents a new method referred to as the TPBBD-TLBO method, which has been tested to optimize the boring parameters of IS 2062 E250 steel plates. The work studies diverse boring parameters that influence the operational performance of a CNC machine during the boring operation. Four parameters were concerned with this article, depth of cut, speed, feed rate, and nose radius. This article offers a novel method that optimizes and predicts the largely impacting boring parameters on the accomplishment of the boring system. The regression model was developed as an objective function of the TLBO method and run on a C++ code using a computer system. An alternative to the Taguchi-box Behnken method was also deployed as an objective function to optimize the TLBO method. Validation of the method was conducted using the data from the literature extracted from experimental means. The TLBO method was used to ascertain the contribution of each parameter to the operations performance. The TLBO revealed itself as a reliable and straightforward approach suitable for boring operations. The outcome of the TLBO method was used to establish the superior groups of parameters for performance optimization for the boring process.

3. METHODS

3.1. Teaching-learning process

Among the several optimization methods, such as particle swarm optimization and genetic algorithms, which are non-conventional techniques, the TLBO method is a newly developed tool with the credit of development to Rao & Kalyankar (2011). In this article, the TLBO method is adopted for use in the perspective of boring the IS 2062 E250 steel plates on the CNC, gaining insight into its implementation steps. Next, it avoids complexity in its turning process since only two turning parameters are involved. However, in other methods, the turning parameters are many, bringing complications in their implementations and requiring a high level of intellectual development in programming to solve and utilize the algorithm. Because the TLBO avoids this challenge with a low number of turning parameters, it is gradually gaining acceptance in various fields of engineering, energy, and material science, among other areas.

Furthermore, as demonstrated in the present article, the TLBO may be conveniently implemented through computer-assisted coding in a python programming language. It possesses the attribute of a single optimization characteristic such that in a process, if there are multiple parameters and multiple outcomes, the objective functions are formulated based on individual outcomes and introduced into the TLBO method. In a boring operation, for instance, where the critical parameters are the feed rate, depth of cut, spindle speed, and nose radius while machining time and surface roughness are the outcomes, the TLBO method will consider an objective function formed on machining time as the dependent variable (outcome) while the spindle speed, feed rate, depth of cut and nose radius will be taken as the independent (input) parameters and predictions conducted based on this relationship. Next, the surface roughness is adopted as the outcome while the mentioned four parameters are considered as inputs. Since this method adopts only one output at a time about the inputs, it follows a single objective function development scenario.

In this article, to solve the surface roughness optimization problem while solving the boring operation optimization problem, the TLBO method was introduced. This work is one of the integration methods to process the IS 2062 E250 steel plates. The real-life teaching and learning process is imitated to solve the boring process optimization problem. The philosophy on which the TLBO method is built is such that the teacher evaluates the understanding requirements of the students, determines the specific learning objectives in the course being taught, and develops strategies to teach the students, including memorizing strategies for the students. Furthermore, the teacher imposes a work plan and evaluates the effectiveness of the instructional program. This idea of the teaching-learning model is thought to be suitable for analyzing the boring operation while processing the IS 2062 E250 steel plates on the CNC machine.

3.2 Procedure for Taguchi-Pareto-Box Behnken Design-TLBO approach

Step 1a. Implement step 1a of the work of Abdullahi and Oke (2022) for scenarios 1 and 2.

For scenario 1, where for instance, assuming the optimized parameter from the Box Behnken design approach were 30 rpm of spindle speed, 0.001 mm/min for feed rate, 0.02 mm for depth of cut, and 0.005 mm for nose radius.

Two scenarios describe the work done in this article, scenarios 1 and 2. In scenario 1, the regression equation was established based on linear programming. This was based on the already optimized parameters from the Box Behnken equation. This optimized method is the Taguchi-Pareto-Box Behnken design method. Then the optimized parameters are used to create the objective function. However, still working with the Taguchi-Pareto Box Behnken design, there is a part of the method in the computer code developed that the authors created to include regression equation. Scenario 2 uses this regression equation to run the TLBO as an objective function. At some points in the computations, the authors compared the two results, i.e., when the regression equation is used and when the optimized parameter from Box Behnken is used to generate the objective function.

Using the linear programming concept, we have the objective function generated as

$$F(X) = 30S + 0.001F + 0.02DC + 0.005\ NR \quad (1)$$

Step 1b. Implement step 1b of the work of Abdullahi and Oke (2022). Take, for instance, the experimental value in three levels for the four parameters under consideration, which says the speed parameter for the three levels of the experiment are 10rpm for level 1, 25rpm for level 2, and 70rpm for level 3. Therefore, the constraint for the speed parameter would be generated as $10 \leq S \leq 70$. The same process is followed to generate constraints for the feed rate, depth of cut, and nose radius parameters. Assuming the constraint for the feed rate parameter is $0.001 \leq F \leq 0.003$ and that of the depth of cut is $0.002 \leq DC \leq 0.04$, while that of nose radius is also assumed to be $0.0 \leq NR \leq 0.005$.

Step 2a. Set the population size of the class to be considered. The maximum number of iterations to be performed on the population, take, for instance, the population of the class to be four, i.e., there would be four students in the class. The maximum iteration to be performed is five iterations, i.e., the TLBO procedure would be performed five times to obtain an optimal solution.

Step 2b. Populate the class based on the population size chosen using Equation (2):

$$x = L + \text{rand x } (U - L) \quad (2)$$

Where L is the lower bound of a parameter, U is the upper bound of a parameter, and a rand is a random number between 0 and 1. For instance, the feed rate parameter having a lower bound of 0.001 and upper bound of 0.003 is populated based on the chosen population size by substituting into the above expression for the population size chosen (i.e., the substitution and computation would be done four times), while changing the random number each time, resulting to:

$x_1 = 0.001 + 0.02 \text{ x } (0.003 - 0.001) = 0.00104$
$x_2 = 0.001 + 0.05 \text{ x } (0.003 - 0.001) = 0.0011$
$x_3 = 0.001 + 0.04 \text{ x } (0.003 - 0.001) = 0.00108$
$x_4 = 0.001 + 0.06 \text{ x } (0.003 - 0.001) = 0.00112$

This represents the population of the feed rate parameter for the chosen population or class size. The same computations are done for the speed, depth of cut, and nose radius parameters. To fully populate the class, a fully populated class is composed of all computed values of each factor in consideration. Therefore a student in the class is represented by each computed parameter. For instance, [45 0.0011 0.0023 0.045] represents a student, where 45, 0.0011, 0.0023, 0.045, are the computed value of the speed, feed rate, depth of cut, and nose radius parameters, respectively, so a fully populated class in our regard would have four of such student.

Step 3a. Next is the computation of the fitness values of each student in the class; this is done by substituting each factor in or representing a student appropriately into the objective function, for example, using the above instance of a student, i.e. [45 0.0011 0.0023 0.045] and substituting accordingly into the objective function gives:

$F(X) = 30 \text{ x } 45 + 0.001 \text{ x } 0.0011 + 0.02 \text{ x } 0.0023 + 0.005 \text{ x } 0.045 = 1350.0014$

The value 1350.0014 is the fitness value of the student [45 0.0011 0.0023 0.045] in the class. In the same manner, the fitness values of all students in the class are computed. Assuming fitness values of student in the class was computed as 1350.0014, 1405.0022, 1503.0450, 1405.7902.

Step 3b. Select a teacher among the students in the class by choosing the fitness value of the student that is the largest or smallest in the class, based on your objective of maximization or minimization.

Since our objective is minimization, the student with the smallest fitness value is taken as the teacher in the class, that is 1350,0014, which corresponds to this [45, 0.0011, 0.0023, 0.045] student in the class and is designated as $X_{best.}$

Step 3c. Compute the mean of each factor in each student in the class. For instance, take the speed parameter in each student as 45.56, 50.55, 30.34, and 25.67, i.e., each value represents the speed parameter in students 1, 2, 3, and 4, respectively. Therefore computing the mean, we have:

(45.56 + 50.55 + 30.34 + 25.67)/4 = 30.03 as the mean of the speed parameter in each student.

The mean of all other factors in the class is computed in the same manner. For instance, take the mean of all factors in the class as [30.03, 0.0034, 0.022, 0.045], where 30.03, 0.0034, 0.022, and 0.045 represents the mean of the speed, feed rate, depth of cut, and nose radius parameters respectively, and designated as X_{mean} = [30.03, 0.0034, 0.022, 0.045].

Step 4. The first iteration in the TLBO starts with taking the first student in the class through the teaching phase to improve its performance using the expression:

$X_{new} = X + r(X_{best} - T_f \ \text{x}\ X_{mean})$,

where X = current student assumed to be [39.45 0.0021 0.0013 0.035]

r is a random number between 0 and 1

Therefore, substituting each factor represented in X_{best}, $X_{mean,}$ and X into X_{new} accordingly gives:

x_1 = 39.45 + 0.3(45-1(30.3)) = 43.86 for the speed parameter.

x_2 = 0.0021 + 0.32(0.0011-1(0.0021)) = 0.00178 for the feed rate parameter.

x_3 = 0.0013 + 0.81(0.0023-1(0.022)) = -0.014657 for the depth of cut parameter.

x_4 = 0.035 + 0.9(0.045-1(0.045)) = 0.035 for the nose radius parameter.

Therefore, the resulting X_{new} = [43.86, 0.00178, -0.014657, 0.035]

Step 5. The next step is to check if the factors in X_{new} are within the constraints bound for each parameter, that is to say, that if the value of a factor in X_{new} is less than the value of the lower bounds of that particular parameter, then that value in X_{new} is discarded and replaced with the value of the lower bound of that particular parameter in X_{new}.

Furthermore, if the value of a factor in X_{new} is greater than the value of the upper bound of a particular parameter, then that value is discarded from X_{new} and replaced by the value of the upper bound of that particular parameter. For instance, comparing the value of the factors in X_{new} with the values of bounds of each parameter we have, X_{new} = [43.86, 0.00178, 0.002, 0.005], representing X_{new} after checking.

Step 6. Next is the computation of the fitness value of X_{new} using the objective function, so we have: F(X) = 30 x 43.86 + 0.001 x 0.00178 + 0.02 x 0.002 + 0.005 x 0.005 = 1315.8001 as the fitness value of $X_{new.}$

Step 7. Perform the greedy selection by checking if the fitness value of X_{new} is better than the fitness value of the current solution. In our case of minimization, we would check if the fitness value of $X_{new,}$ computed as 1315.8001, is less than the fitness value of the current solution, which was 1350.0014. By comparing the two values, the fitness value of X_{new} is smaller and so better for our objective. Therefore, the current solution would be updated with the new solution that is $X_{new,}$ including its fitness value, i.e., the current solution is now X_{new} = [43.86, 0.00178, 0.002, 0.005], and its fitness value is 1315.8001. This process ends the teacher phase of the TLBO algorithm.

Step 8a. The same current solution, i.e., the student would then go through the learner phase of the TLBO algorithm, where the current student would randomly select a reading partner in the class to help him improve using Equation (3):

$$X_{new} = X + r(X - X_p) \ \text{if} \ f < f_p$$

$$\text{or} \ X_{new} = X - r(X - X_p) \ \text{if} \ f > f_p \tag{3}$$

as our objective is minimization,

where X is the current solution/student,

r is a random number between 0 and 1,

X_p is the student reading partner,

f is the fitness value of the current solution,

f_p is the fitness value of the reading partner.

Step 8b. Assuming that the third student in the class was randomly chosen as the reading partner of the current solution/student and represented by X_p = [39.86, 0.00154, 0.001, 0.003] and a fitness value of 1195.8000, using $X_{new} = X - r(X - X_p)$ if $f > f_p$ since the fitness value of the current solution/student is greater than the fitness value of the reading partner.

Step 9. Repeat step 5 to check if the factors in X_{new} are within the constraints bound of each parameter.

After the check we have X_{new} = [43.06, 0.00185, 0.0028, 0.005].

Step 10. Compute the fitness value of X_{new}

F(X) = 30 x 43.06 + 0.001 x 0.00185 + 0.02 x 0.0028 + 0.005 x 0.005 = 1291.8000

Step 11. Repeat step 7 above. By doing so, it was observed that the fitness value of $X_{new,}$ i.e., 1291.8000 is better than that of the current

Table 1. Original reference data for model and data analysis (Patel and Deshpande (2014)

	Levels			
Parameters	**Level 1**	**Level 2**	**Level 3**	**Level 4**
Speed (rpm)	800	1000	1200	1400
Feed (mm/rev)	0.06	0.08	0.10	0.12
Depth of cut (mm)	1.00	1.25	1.40	1.50
Nose radius (mm)	0.8	1.2	-	-

solution/student, i.e., 1315.8001, since it is less than it. Therefore, the current solution would be updated with X_{new} as the current solution, including its fitness value updated accordingly.

This process signifies the end of the learner phase and the end of the TLBO process for the first student in the class.

Step 12. The next step is to perform the whole TLBO algorithm of teacher and learner phases on the rest of the students in the class to complete the first iteration, resulting in new solutions and fitness values.

Step 13. The procedure from step 3b to step 12 is repeatedly performed on the new solutions each time for the chosen maximum number of iterations. Assuming the maximum number of iterations is 5, the procedure from step 3b to step 12 would be repeated five times, each time on the new solution to complete the whole TLBO algorithm procedure, of which at the end of each iteration, the best solution and its fitness value is a capture.

Step 14. Relate the output from the first scenario back to the signal-to-noise ratio by inputting its optimal parameters into the regression equation used for scenario two, as its output is not related to the signal-to-noise ratio—still, some function of the input parameters to establish a comparison platform for the two scenarios.

For instance, if the optimized output from the first scenario are 10, 0.03, .0.01 and 1.2 for the speed, feed, depth of cut, and nose ratio respectively, substituting this figures into the regression equation which for instance is signal to noise ratio = 12.3+10S + 0.0021F + 0.12DC + 0.003 NR.

We have, signal to noise ratio = -12.3 + 10*10 + 0.0021 * 0.03 + 0.01 * 1.2 + 0.003 * 1.2 = -12.4157db, with this, the two results of the two scenarios can be compared.

Step 15. The TLBO approach explained above is then coded using the python programming language.

Step 16. Report results from the two scenarios outputted from the python-coded genetic algorithm optimization approach.

The reference data used in the present work, obtained from Patel and Deshpande (2014), is shown in Table 1.

4. RESULTS AND DISCUSSION

In the present reporting, the objective function was generated using the Box Behnken design optimized parameters and the TLBO method run for optimal solutions. Results were recorded after running ten iterations each in steps of ten to observe if there is any convergence behavior at those iteration points. Consequently, the best solution fitness value in the class at the end of the 10^{th} iteration was 872728.534. This value has been maintained at the ends of the 20^{th}, $30^{th,}$ and 40^{th}. It also remained at the same value of 872728.5336000001 at the end of the 50^{th} iteration. These results are shown in Table 2.

The full results at optimal points are [800,0.06,1, 0] interpreted as 800 rpm for the spindle speed, 0.06 mm/min for the feed rate, 1 for the depth of cut mm, and 0 for the nose radius. These optimized values are then substituted into the regression equation, as explained in step 14 of the procedure for the TP-BBD-TLBO approach. We have the optimized input parameter SNR value as -55.6239dB. The convergence behavior using the TLBO method, where the number of iterations is studied against the objective function, is shown in Figure 1.

Furthermore, also in the present article, the objective function was developed using the regression equations optimized parameters and the TLBO approach to obtain the best solutions. Following the previous alternative, iterations were stopped for observations after ten iterations with an increment of 10, subject to a maximum of 50 iterations and using the python programming codes (Table 3).

Consequently, the fitness function was observed at the end of the 10^{th}, 20^{th}, 30^{th}, 40^{th} and 50^{th} iterations and observed to be the parametric values are 1135.46 rpm (speed), 0.06 mm/min feed rate, 1.24mm (depth of cut) and 0.16 mm (nose radius) (Table 3). At the 50th iteration, the final results containing the optimal feed rate, nose radius, speed, and depth of cut are shown to be at convergence (Figure 2).

Table 2 is for the simulation of the objective function when linear programming, while Table 3 is for the simulation obtained for the objective function when the regression equation is used as the objective function. Tables 2 and 3 are related in that both are developed from the values obtained from different objective functions. But for, Table 3's output is the signal-to-noise ratio (SNR), but Table 2's output merely mimics the surface roughness. However, it has to be related to the SNRs to compare them. So, all the works are linked backed to SNRs to compare the two results. Thus, for the method that uses linear programming at the end of the computations, the optimized parameters are what the present authors are interested in and not the output because the outputs are just figures. Then the optimized parameters are then reintroduced into the regression equation to obtain the SNRs of the particular optimized parameters. Then the outputs of the SNRs are compared from the linear programming and that of the regression equation to observe which one is bigger.

Moreover, Tables 2 and 3 are associated with tolerance and accuracy values, which may be determined for iterations. However, in this article, the tolerance of the whole analysis was based on the maximum number of iterations. This is one of the approaches to conducting simulation tests using the TLBO method. Besides, the authors did not specify any tolerance for the work. However, in some literature, a divergent view is specified. If the iteration reaches the tolerance value or if a specific value reaches the tolerance value, often represented by epsilon, ε, then the iteration will cut. Thus, the final results were obtained in this work based on the maximum number of iterations. If the chosen iteration through preliminary tests was reached without convergence, then the number of iterations is increased until convergence happens.

Table 2. TLBO data when the objective function is generated using the Box Behnken design optimized parameters [max_iter = 50, class_size = 5]

Iterations	Optimal Solutions
1	[800, 0.06, 1, 0.3146362103590515]
2	[800, 0.06, 1, 0.10012624948486523]
3	[800, 0.06, 1, 0.0543481853418365]
4	[800, 0.07450965866303144, 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 solution fitness value in the class at the end 10th iteration is 872728.5340
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 solution fitness value in the class at the end 20th iteration is 872728.5340
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 solution fitness value in the class at the end 30th iteration is 872728.5340
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 solution fitness value in the class at the end 40th iteration is 872728.5340

Table 2. (Cont.')

Iterations	Optimal Solutions
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 solution fitness value in the class at the end 50th iteration is 872728.5336
Optimal solution	[800, 0.06, 1, 0]

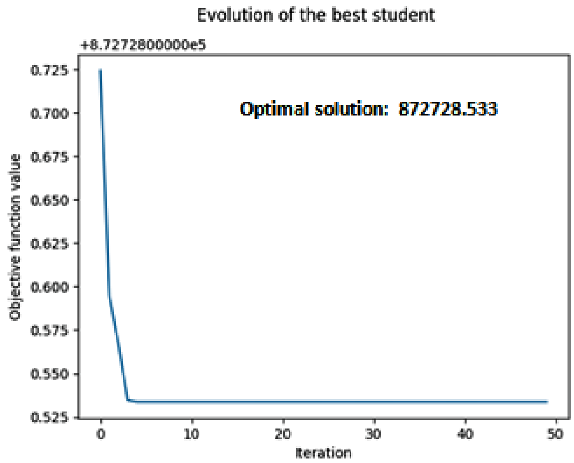

Figure 1. The plot when the objective function is generated using optimized BBD parameters

Table 3. TLBO data regression equation is used as the objective function
[max_iter = 50, class_size = 200]

Iterations	Optimal Solutions
1	[1155.7142318863941, 0.06060514517313923, 1.1749776076676919, 0.5391166182509953]
2	[1155.7142318863941, 0.06060514517313923, 1.1749776076676919, 0.5391166182509953]
3	[1155.7142318863941, 0.06060514517313923, 1.1749776076676919, 0.5391166182509953]
4	[1155.7142318863941, 0.06060514517313923, 1.1749776076676919, 0.5391166182509953]
5	[1177.2328749172084, 0.06, 1.1742777777746425, 0.5555631932916197]
6	[1178.3005360654347, 0.06, 1.144180892343662, 0.6015570430334648]
7	[1178.3005360654347, 0.06, 1.144180892343662, 0.6015570430334648]
8	[1110.3944863509373, 0.06, 1.1112340701431114, 0.608295301782312]
9	[1110.3944863509373, 0.06, 1.1112340701431114, 0.608295301782312]
10	[1110.3944863509373, 0.06, 1.1112340701431114, 0.608295301782312]
	The best solutions fitness value in the class at the end 10th iteration is -51.4520
11	[1110.3944863509373, 0.06, 1.1112340701431114, 0.608295301782312]
12	[1110.3944863509373, 0.06, 1.1112340701431114, 0.608295301782312]
13	[1110.3944863509373, 0.06, 1.1112340701431114, 0.608295301782312]
14	[1110.3944863509373, 0.06, 1.1112340701431114, 0.608295301782312]
15	[1146.8652944192565, 0.06, 1.2163985170102332, 0.5735783327630838]
16	[1146.8652944192565, 0.06, 1.2163985170102332, 0.5735783327630838]
17	[1146.8652944192565, 0.06, 1.2163985170102332, 0.5735783327630838]
18	[1127.3018452792455, 0.06, 1.227564208049099, 0.6063413226827501]
19	[1127.3018452792455, 0.06, 1.227564208049099, 0.6063413226827501]
20	[1127.3018452792455, 0.06, 1.227564208049099, 0.6063413226827501]
	The best solutions fitness value in the class at the end 20th iteration is -51.4300

Table 3. (Cont.')

Iterations	Optimal Solutions
21	[1127.3018452792455, 0.06, 1.227564208049099, 0.6063413226827501]
22	[1127.3018452792455, 0.06, 1.227564208049099, 0.6063413226827501]
23	[1135.4600939755744, 0.06, 1.2407655631447283, 0.6123977479575711]
24	[1135.4600939755744, 0.06, 1.2407655631447283, 0.6123977479575711]
25	[1135.4600939755744, 0.06, 1.2407655631447283, 0.6123977479575711]
26	[1135.4600939755744, 0.06, 1.2407655631447283, 0.6123977479575711]
27	[1135.4600939755744, 0.06, 1.2407655631447283, 0.6123977479575711]
28	[1135.4600939755744, 0.06, 1.2407655631447283, 0.6123977479575711]
29	[1135.4600939755744, 0.06, 1.2407655631447283, 0.6123977479575711]
30	[1135.4600939755744, 0.06, 1.2407655631447283, 0.6123977479575711]
	The best solutions fitness value in the class at the end 30th iteration is -51.4290
31	[1135.4600939755744, 0.06, 1.2407655631447283, 0.6123977479575711]
32	[1135.4600939755744, 0.06, 1.2407655631447283, 0.6123977479575711]
33	[1135.4600939755744, 0.06, 1.2407655631447283, 0.6123977479575711]
34	[1135.4600939755744, 0.06, 1.2407655631447283, 0.6123977479575711]
35	[1135.4600939755744, 0.06, 1.2407655631447283, 0.6123977479575711]
36	[1135.4600939755744, 0.06, 1.2407655631447283, 0.6123977479575711]
37	[1135.4600939755744, 0.06, 1.2407655631447283, 0.6123977479575711]
38	[1135.4600939755744, 0.06, 1.2407655631447283, 0.6123977479575711]
39	[1135.4600939755744, 0.06, 1.2407655631447283, 0.6123977479575711]
40	[1135.4600939755744, 0.06, 1.2407655631447283, 0.6123977479575711]
	The best solutions fitness value in the class at the end 40th iteration is -51.4290
41	[1135.4600939755744, 0.06, 1.2407655631447283, 0.6123977479575711]
42	[1135.4600939755744, 0.06, 1.2407655631447283, 0.6123977479575711]
43	[1135.4600939755744, 0.06, 1.2407655631447283, 0.6123977479575711]
44	[1135.4600939755744, 0.06, 1.2407655631447283, 0.6123977479575711]
45	[1135.4600939755744, 0.06, 1.2407655631447283, 0.6123977479575711]
46	[1135.4600939755744, 0.06, 1.2407655631447283, 0.6123977479575711]
47	[1135.4600939755744, 0.06, 1.2407655631447283, 0.6123977479575711]
48	[1135.4600939755744, 0.06, 1.2407655631447283, 0.6123977479575711]
49	[1135.4600939755744, 0.06, 1.2407655631447283, 0.6123977479575711]
50	[1135.4600939755744, 0.06, 1.2407655631447283, 0.6123977479575711]
	The best solutions fitness value in the class at the end 50th iteration is -51.4291
Optimal solutions	[1135.4601, 0.06, 1.2408, 0.6124]

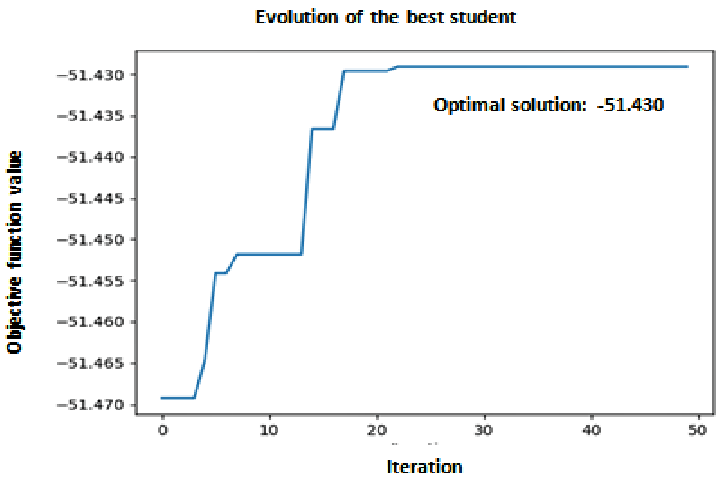

Figure 2. The plot when regression equation is used as the objective function

In some simulations, convergence happens very fast, and in others, convergence takes time to happen. It is common that in most cases, if the number of iterations is too small, convergence will not occur. In this situation, the number of iterations increases, and the simulation experiment will be rerun. Based on the authors' experience, accuracy is the calculation of mean square error values. However, the authors did not follow the approach in this work.

Now, from the above results, it is interesting to know the possible advantages of the proposed method as follows. Moreover, this article develops a three-phase optimization method, TPBDD-TLBO, to take full advantage of the computational potentials of the python programming language where the quantitative and qualitative attribute of the Taguchi-Pareto method is combined with the highly interactive quality of the Box Behnken design together with the straightforward and less complicated tuning capabilities of the TLBO method is exploited for further optimization. The optimization is done first by the Taguchi-Pareto method and then by the Box-Behnken design, and then finalized by the TLBO method. The superb advantage of the TLBO method is that the number of tuning required is limited to two, which is extremely less compared with other evolutionary techniques. Furthermore, as the boring activities have a defined operational period bounded by the maximum working hours per day, the boring process has a limited number of operators to manage the large requests for the boring operations. Thus, responding to these time-bound activities and the limited number of operators, this article makes improvements in introducing precision search to obtain feature information about the component being a bored and timely reference to them and for task completion. Thus, the use of the TPBBD-TLBO method is better than the TPBBD method.

5. CONCLUSION

Upon review of previous studies on the boring operation and the degree of perpetration in the machining literature, there is an impression that further optimizing the results provided by the Taguchi-Box Behnken design method for the IS 2062 E250 steel plates with the TLBO is not in dispute. Consequently, a new method referred to as the TPBBD-TLBO method has been proposed and tested with the IS 2062 E250 steel plate work material in a boring process, using literature data from Patel and Deshpande (2014). From the results of the study, the following conclusions are made:

1. By applying the TPBBD-TLBO method in a case situation, the goal of the present study has been achieved.
2. The use of the TPBBD-TLBO method is a feasible approach to optimize the results from the TPBBD method while engaging in the boring operation using the IS 2062 E250 steel plates.
3. Using the Box Behnken as the objective function for the teaching learning-based model, convergence was reached at 50 iterations with a class population of 5. The optimal parametric solutions are 800 rpm of speed, 0.06 min/min of feed rate, 1 min for depth of cut, and 0 min for nose radius.
4. On using the regression method for the objective function, while the TLBO is deployed, convergence was experienced after 50 iterations with a class population of 200 students. The optimal parametric solution is 1135rpm of speed, 0.06 min/min of feed rate, 1024 min of the depth of cut, and 0.61 min of nose radius.
5. In comparing the two output types, the regression method requires higher optimal values in three parameters: speed, depth of cut, and nose radius. This implies that if the option is adopted, the process engineer will require higher energy usage, and hence the method is less efficient. On the other hand, the method optimized by the TLBO method while the objective function is then optimized Box Behnken design result is more energy-efficient and should be adopted. This is an additional perspective toward the analysis of the problem.
6. By comparing the results from the two scenarios based on the SNR values, the second scenario having a higher SNR of -51.4291dB is more efficient in this regard as compared to the SNR of the first scenario, which was computed to be -55.6239dB.

In the future, the optimization action methods, such as the whale optimization approach, may be tested to expand the method's performance.

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