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Performance Evaluation of Surface Roughness in the Boring Operation of IS 2062 E250 Plate on CNC Machine Using Combined Entropy-Decision Tree-VIKOR Approach

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In boring E250 B0 steel material, the selection of process parameters is one of the most challenging tasks to achieve. The boring literature lacks understanding and fails to reveal how to select the important boring parameters for utmost resource distribution to the most important parameters. This article proposes a novel method to analyse the importance of parameters in boring to produce utmost surface roughness using the entropy-decision tree-VIKOR approach as a multi-criteria decision-making solution to the choice of process materials for superior surface roughness. The choice parameters include speed, depth of cut, feed and nose radius. The entropy approach was instituted to attain the weight of the diverse parameters. The decision tree approach is deployed through the classification of the parameters as beneficial and non-beneficial and the expected values at each node evaluated. The desirable weightage is then established and serves as the input to the VIKOR approach. This converts the desirable weightage into unit measures through the best/worst value and weightage evaluation. The individual regrets are then analyzed and the final ranking is obtained. Results revealed that the depth of cut is the most important parameter, then nose radius (0.98), feed (0.307) and speed (0), respectively. Therefore, a plan to assign more measures to the depth of cut may be developed and the least resources may be assigned to speed. This detail may be helpful to prepare the annual budgets for the boring operation on the factory floor.

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1. INTRODUCTION

An important way that modern manufacturing industries can enhance surface quality through the reduction of roughness in boring operations is to ascertain that the process parameters are first evaluated to properly position each element in its important position (Zhang et al., 2017; Yuvaraju and Nanda, 2018; Melo et al., 2019; Klein et al., 2020; Lotfi et al., 2020). Then, elements with utmost importance should be adequately provided with the necessary resources to achieve an optimal level of performance (Ratnam et al., 2018; Izelu et al., 2019). Since the efficiency of the system is only guaranteed if the key components of the process are efficient, it is thought that optimally deploying resources to these key process parameters in the ratios of their importance in the system may bring about the best performance from the system (Izelu et al., 2019).

The boring literature has established that several factors impact on the surface roughness of work materials to be machined (Melo et al., 2019). It was also established in Patel and Deshpande (2014) that these factors depend on the cutting actions, the tool used and the work materials. They are consequently called work material variables including the mechanical characteristics and hardness of the material. The other group include the cutting condition, including speed, feed and depth of cut (Yuvaraju and Nanda, 2018). The last group include the tool variables such as the nose radius, cutting edge geometry, tool overhang, tool material, tool vibration and rake angle (Venkata rao et al., 2014). In several studies, speed, feed and depth of cut have been validated as the most important cutting conditions (Yuvaraju and Nanda, 2018). Besides, the nose radius has been pointed out as the principal tool variable in many experiments (Venkata rao et al., 2014). Upon consensus of research opinions on the tool variables, cutting conditions and work materials, the speed, depth of cut, feed and nose radius were selected as the dominant variables in the boring operations by Patel and Deshpande (2014). The experimental data was used in the present study.

Although the several boring process parameters were streamlined to four important parameters of speed, feed depth of cut and nose radius, it is not clear which of these parameters has the greatest importance and should be given the utmost resource allocation attention (Venkata rao et al., 2014; Yuvaraju and Nanda, 2018). There are many resources to consider and it is challenging to achieve this through intuition and experience of the factory manager or machine operator. Take the boring energy requirement, for instance. To machine monel with the Brinell hardness number of 225 and specific cutting energy of roughly 2.72 W/mm^3 per second, higher speed will consume significant energy resource. But even at higher speeds, if the process counts speed as not significant the extra energy spent will be a waste. A similar situation abounds for other parameters. It is thought therefore that the optimal distribution and use of resources such as energy, considering specific parameters may be guaranteed only by identifying the relative importance of one parameter to the other. This work will assist the factory floor manager to choose the most important cutting parameters by ranking, using the combined entropy-decision tree (EDT)-VIKOR method.

2. LITERATURE REVIEW

2.1. General

In the boring literature, since the mechanical vibrations of the boring bar are strongly associated with surface integrity of the work material, many published literature spotlight on studying the influence of vibration on surface roughness. For example, Singh et al. (2018), Venkata rao et al. (2013, 2014), Liang (2007), Yavaraja and Nanda (2018) examined the mechanical vibrations induced owing to tool overhang and how they affect the surface roughness of the work material. These authors reported strong associations between chatter suppression and surface integrity of the work material. While tool vibration was the focus of some studies, including Singh et al. (2018), Lawrance et al. (2020a), Prabhu et al. (2020), Biju and Shunmugam (2019), Saleh et al. (2021) and Yavaraju and Nanda (2018), several other studies analyzed vibration of the work material (Venkata rao et al., 2013, 2014). However, in both cases, their results failed to reveal a ranking according to a common scale to guide resource distribution during the boring process. Yet, their discussion reveals the potential for further analysis aspiring to provide a deeper understanding of the relationships among the boring parameters.

Nonetheless, the following brief literature account is given. Singh et al. (2018) deployed a pioneering chatter suppression approach founded on the particle damping procedure to moderate chatter in the boring tool and consequently enhance surface furnish. Damping was confirmed to influence significantly. Venkata rao et al. (2014) deployed a barometer for an online acquisition of data on workpiece vibration. The authors used the fast Fourier transform probe to convert signals into the frequency domain. The prediction of surface roughness was aided by the artificial neural network. In Venkata rao et al. (2013), an examination of the interface concerning cutting parametric influences, work material vibration and surface roughness of the AISI 1040 during boring was considered. A multiple regression model was deployed to associate tool life with a surface roughness of work material, the amount of metal removed as well as the vibration of work materials.

Lotfi et al. (2020) analyzed a three-dimensional vibration approach to assess its impact on surface integrity during the boring process. Lawrance et al. (2020a) built up an impact damper attached to the boring tool to lessen the tool vibration and enhance the tribological characteristics of the work material. The attempt yielded positive results of tool vibration suppression and the improvement of the work material's tribological characteristics. With the interesting tools of the multiple regression model, artificial rural network, the use of particle dampers and vibration and surface roughness of materials, the research domain of boring has been extended. However, the researcher striving to obtain differences among the boring parameters may be helpless to attach importance to parameters. This situation often exists when faced with scare operation resources that demand prudent sharing among deserving parameters.

Melo et al. (2019) considered a selected group of parameters, including cutting effort, surface roughness and form errors when bore reaming materials made of hardened steel and discussed their interactions. It was concluded that the cutting speed is the most crucial parameter to produce superior surface quality during the bore reaming process. Beauchamp et al. (1996) studied the effects of cutting pointers on the surface integrity the work material during boring by deploying factorial design to assess the parameters, notably the kind of boring bar, feed rate, tool nose radius, cutting speed, tool length and depth of cut with their echelon interfaces. It was reported that short tool length often lead to high structural integrity. However, negligible enhancement of the surface integrity was attained by monitoring the kind of boring bar employed and/or cutting parameters. Lawrance et al. (2020b) analyzed the effect of coating on the cutting accomplishment when boring hardened steel. By using the Taguchi method and observations from the results revealed that two strata T_1T_2r02 deposits placed in series is preferred to the option of A103r02 as well as r02.

Prabhu et al. (2020) suppressed the boring bar vibration when engaging on the improvement of size for a pre-drilled hole. This goal was achieved by using a semi-active, radially-positioned fluid damper with magneto rheological properties. Schmidt et al. (2020a) examined the association of the cutting parameters as well as the process forces while engaging on the deep hole-drilling endeavor. They also studied the functional characteristic during the boring of AISI 304L and AISI 4140. Biju and Shunmugam (2019) designed a new boring bar having an inverse cantilever rod that vibrates within the magneto-rheological fluid. The authors varied the stiffness and damping of the viscosity of the fluid. Schmidt et al. (2020b) examined the deep hole drilling procedure to establish associations between the procedure-structure and the residual stress for enhanced work material enhancement during the boring process. Liu et al. (2019) considered the boring of a complicated component having an uneven shape. The authors examined the spread of the magnetic field within the polishing domain of the whole finishing path.

Fine surface quality was established, indicating the effectiveness of the method.

Ratnam et al. (2018) experimented on boring using the Inconel 718. The response surface methodology was deployed to optimize the parameters. Saleh et al. (2021) constructed a novel damper based on magneto-rheological properties to analyse the chatter stability in boring tools. An enhancement in the damping, as well as the damping stiffness for the system was established. Hintze et al. (2018) provided experimental details to remove support structure in the production of Ti6Al4V parts for the aviation sector. The experiments focused on boring holes using the helical milling process. It was shown that the process attained superior hole quality during machining in one stage. Klein et al. (2020) evaluated the surface quality of honed bores by applying machine learning schemes.

Chern and Liang (2007) analyzed the boring process with vibration cutting by applying a vibration apparatus. Furthermore, the authors examined the influence of vibration by deploying the Taguchi approach and the analysis of variance method. The vibration cutting method was found to enhance surface roughness notably. Zhang et al. (2017) elaborated on surface integrity in the boring trepanning relationship hole drilling and studied the microstructure. Yuvaraju and Nanda (2018) evaluated the amplitude of vibration and surface integrity in the course of the boring operation. The response surface methodology was deployed for the optimization of the surface integrity for the parts.

Kumar et al. (2018) conducted boring on the electrical discharge machining while focusing on the Inconel 718 material. The paper used the Taguchi method. The instituted procedure guarantees a route to direct choice of adequate combination of parameters in the boring of Inconel 718 by the EDM process. Sathianarayanan et al. (2008) analyzed chatter censorship in boring activities by using the magnetorheological fluid damper. The outcome of the study revealed that the damper's usage lowers the potential chatter in the boring process and enhanced stability of the boring operation was attained. Sastry et al. (2019) analysed the boring of AA 7075 alloy under cryogenic, wet and dry conditions for applications in a water environment, aeronautics and automobiles. It was reported that the cryogenic boring of AA7075 alloy produced a substantial decline of the cutting force, surface roughness and cutting temperature weighed against dry and wet boring situations. Izelu et al. (2019) studied the influence of machine conditions on performance factors in the course of hard and dry boring of ASTM A304 steel. It was declared that the optimal situations obtained in the experiment are useful in practice.

Briefly, a few papers on VIKOR are reviewed as follows. Gangil and Pradhan (2018) found the utmost values for the electrical discharge machining parameters by using an amalgamated model of response surface methodology and VIKOR method. The outcome confirmed superior MRR and precision EDM products. Vikram et al. (2020) dealt with the multi-response optimization of process parameters with an illustration of the surface roughness, work material temperature and tools phenomenon using the VIKOR approach. Wu et al. (2016) deployed fuzzy VIKOR approach to select a CNC machine tool with linguistic variable representation at the centre of the model's description. Majumder and Maity (2018) used a multivariate VIKOR-fuzzy technique to optimize the various associated outcomes of Ni-Ti shape memory alloy machining.

2.2 Summary and observations from the literature review

In this study, a literature review was conducted and the following issues are the outcomes of the review:

1. Multicriteria analysis in boring operation is an established promising research gap since it is currently absent in the boring literature. The literature review conducted above was complemented with searches of the databases of well-known publishers from the earliest literature on boring till 2020 publications. The outcome was amazing, indicating the absence of studies on multicriteria analysis and

boring. The concepts of entropy, decision tree and VIKOR has not been analyzed either independently or jointly in the boring operation domain. For example, using the search terms "multi-criteria analysis, boring operation," to find articles in sciencedirect database, only 1 article out of 139 returns featured on multicriteria analysis. The article was concerned with the selection of tunnel boring machine by using the analytic hierarchy process and fuzzy technique for order performance by similarity to ideal solution. The technical details of the article are outside boring parametric selection and therefore offer very little assistance to the ranking of parameters of boring operation in the processing of ISO 2062 E250 plate.

Besides, using the mentioned search terms on the database from the Taylor and Francis publishers, only 56 articles emerged. Surprisingly the only article was on boring operations and none of these articles considered multicriteria analysis. Furthermore, the mentioned search terms were used on the database from Springer. While 134 results emanated, there was no article on multicriteria analysis in the domain of boring operations. In sum, the checks from the three databases among others confirm the absence of multicriteria analysis on VIKOR, entropy and decision tree in sole or joint forms. In all, only one multicriteria study was noted and dates back to 2012.

2. There are several surface integrity enhancement models deployed in the past on boring operations. They include multiple regression model, artificial neural network, response surface methodology machine learning, Taguchi method, analysis of variance, full factorial design and Box Behnken design.
3. Many published sources are related to vibration from tools and work materials with surface integrity of boring work materials at the center of discussion.
4. For the vibration through the boring bars, overhanging of the bar has been known as a major problem. The use of a shorter bar had offered enhanced surface integrity of work materials.
5. While treating surface roughness as the dependent variable, the boring literature has treated the following as independent variable: tool overhang values, feed rates, thrust force, roughness, spindle speeds, torque cylindricity errors, the volume of material removed, tool's nose radius and spindle rotation speed. These include activities on the drilling machine, CNC lathes, among others.
6. It was established that surface roughness plays a dominant role in attaining outstanding results desired by the customer.
7. No study was located to have investigated the IS 2062 E250 plate in the selection domain using the novel hydrid method of entropy-decision tree (EDT)-VIKOR insightfully, to reveal the relative importance of the dominant parameters of the boring operation.
8. An urgent necessity for a new selection method is revealed.

3. EXPERIMENTAL DETAILS

The experimental details concerning the study, particularly as demonstrated by Patel and Deshpande (2014), are shown herein. First, a description of the machine tool is given. Next, work material is stated. The cutting material, as well as the tool holder is afterwards presented. Besides, insight on the measurement of surface roughness is offered to create a broader understanding of the experiment details.

Machine tool

The Batliboi CNC sprint 20TC is the name given to the machine tool that generated the experimental data used in the present work (Patel and Deshpande, 2014). This data, originally produced by Patel and Deshpande (2014), was established as a validation data to the model presented in the current paper. The CNC machine was manufactured by Batliboi Engineering Limited using the finest level of raw materials and sophisticated know how to ensure superior quality outputs regarding the manufacturing parameters offered by the Batliboi machine. With detailed specification of the machine offered in Patel and Deshpande

(2014), additional information on the features of the machine were obtained from the manufacturer's site. Thus, the selection criteria for the Batliboi CNC sprint 20 TC used in this work are motivated as follows.

In the boring process, the location of slides is a leading obstruction to productivity. While determining the choice of a CNC machine, the location of the slides is largely responsible for determining how many units of products per hour to make. However, given the LM guide-ways that allow for the rapid and precise location of slides, the Batliboi CNC sprint 20 TC is chosen. Second, during the boring operation, if chips are not cleaned up soon enough, more streams of the chips from the tool material is hindered, triggering lately developed chips to be entrapped in the environment of the tool. This may reduce the final quality of the work material and poses great risk and safety hazards to the machine operator and potential damage to the machine. Thus, the slant angle of the machine during a boring operation is a key parameter to decide. The Batliboi CNC sprint 20 offer 45° slant angle for convenient chip clean up and therefore chosen for the experiment. Thirdly, cutting performance is dictated by several important variables such as cutting temperature, friction between the work material and tool, among others. To have control over the cutting performance during boring the hydraulic torrent is important. For the Batliboi CNC sprint 20, the hydraulic torrent is provided with 8 stations and two directions. This feature attracted the researchers to choose this machine.

Third, in the boring operation, a key problem is how the shaking and vibration of the CNC machine can reduce. The side effect of this problem is the reduced surface quality of bored E250 steel, for instance. For existing machines at the factory floor, instituting the plug and play concept into them is expensive and complicated. Thus, on noticing the presence of plug and play concept in the Batliboi CNC Sprint 20, it becomes an attractive criterion to choose the machine, among others. Fourth, the space for keeping the CNC machine for the boring operation costs money. Compared with other competing machines for the boring operation, if an alternative is found to save space, it means more space for other activities. This includes work-in-process inventory for queued jobs. On noticing that the Batliboi CNC sprint 20 is compact and requires less floor space for its hydraulic power pack, and the electrical cabinet, among others, it was an attractive selection criterion for the boring operation.

Fifth, the ease of cleaning of the chip tray and the possibility to have independent cooling tank are important criteria in the choice of a turning centre. However, on noticing the fulfilment of this requirement in the Batliboi CNC sprint 20, its choice was made for the boring operation and experiment used in this work. Sixth, the possibility of coupling the servo motors directly to the ball screws by the servo couplings is an attractive criterion that the Batliboi CNC sprint 20 possesses. Besides, the servo motors are trouble-free. On noticing this in the Batliboi machine, it becomes a choice in the experiment whose data is used in the present work.

Work Material

The work material understudied in the current research is labelled as the structural steel IS 2062 E250 B0. The IS 2062 E250 plate is a hot rolled medium with high tensile strength, formability, oxidation resistance, long service life, corrosion resistance, workability and durability. The IS 206 2E 250 B0 plates are with varying dimension sizes and shapes upon request by the customer. The plates are also of high tensile strength, which is ideal for structural uses. The steel sheets or slab are the main inputs transformed into the IS 2062 E250 B0 plates. Often, to guarantee quality output during use, customers who buy the plates subject them to several tests, including third-party inspection, positive materials establishment test, flaring test, radiography test, flattering test and ultrasonic test.

To have selected this plate for experimentation by Patel and Deshpande (2014), the following bases have been made. First, for the broad application base, including sugar, paper, fertilizer and chemical industries, a prime obstruction is oxidation, which involves loss of electrons from the influence of atmospheric moisture and oxygen. While choosing plates for structural application in the aforementioned industries, establishing plates that may resist chemical reactions at the surfaces of the plate together with oxygen, leading to the corrosion of metals and the formation of oxides is an important action. The IS 2060 E250 plate is substantially capable to resist oxidation. Hence, it became an attractive choice for researchers.

Second, in the task of choosing plates for structural applications in the target industry, there is the capacity to integrate high tensile strength. Tensile strength is a crucial property in structural members since structural masses are highly susceptible to tensile cracking propelled by the applied load and diverse types of influences. On detecting that the IS 2062 E250 plate possesses high tensile strength, it became a choice for the researcher on experimentation. Third, formability is a vital factor, which ought to be considered in choosing a plate for structural applications in the target industry. The researcher is enthusiastic to know whether the plate could be formed into an expected shape devoid of necking or cracking. As it undergoes plastic deformation successfully, the IS 2062 E250 plate became a choice in the experimentation. Fourth, consumers are attracted to plates that remain serviceable in a given environment in their service lives, devoid of damage and unanticipated maintenance cost. It means that the plates can overcome elements of moisture content, exposure time, humidity and temperature. These elements weaken the properties of the material such as the mechanical and corrosive properties. As the IS 2062 E250 plate was noted to exhibit this desirable feature, it was chosen for the experimentation.

Fifth, industries, in general, are interested in working with plates of attractive workability. This attribute is the ease with which the plate can be worked. The factors that assist to determine the workability of the plates include the grade of the plate, material content and mix proportions, among others. On noting that the IS 2062 E250 plate has the workability attribute, it was chosen as the work material for the experiment.

Cutting tool material and tool holder

The experiment referred to in this work used the chemical vapour deposition (CVD). Here are the benefits for the choice of the CVD coating with $Ti(C,N)+Al_2O_3$ coated cemented carbide insert with nose radii having 0.8 as well as 1.2 mm (Patel and Deshpande, 2014). The CVD coating refers to a surface material applied using the approach called chemical vapour deposition. The CVD coating system uses titanium nitride, carbon and Al_2O_3 in process phases comprising of surface preparation, followed by process control and finally material quality checks. The coating material can endure contact with high and low-temperature with severe temperature distinctions. Besides, the coating has a broad range of usage, including metal alloys, glass, ceramics and metals. In the experimental work (Patel and Deshpande, 2014), the cutting inserts of the Sandvik make was used, specified as the CNMG 12 04 08 PF and CNMG 120412 PF.

The principal advantages of using these inserts include an assurance of high metal removal rates. Second, the tool inserts eradicate regrinding time for tools. Besides, it assures of reduced machine downtime. The tool holder used by Patel and Deshpande (2014) is the MCL NL 25 25 M 12. Tool holders offer optimum machine efficiency and reduce the total production cost.

Surface roughness evaluation

In the experiment by Patel and Deshpande (2014), the evaluation of surface roughness was done using the Mitutoyo surf test SJ-301 as the roughness evaluation tool. The attraction to this tool follows many reasons, including being portable, having an in-built printer and a liquid crystal display that has a tough panel. On noticing that the ST-301 model is capable to store five measuring situations and can be recalled when desired, this brand of surface roughness tool was chosen. Furthermore, on observing that the keypads offer outstanding durability such that oil stains from the users hardly affect it, the ST-301 brand became the choice tool.

4. RESULTS AND DISCUSSION

The selection approach introduced in this paper highlights the importance of ranking in a three-stage process. In the first stage, the multi-criteria, entropy is initiated with the normalisation of the decision matrix (Priti et al., 2020). The elements of the decision matrix are the factors and levels in the boring process. As such, if any machining process may be expressed in terms of factors and levels then it is feasible to apply the approach developed in this paper. Following the normalisation is the computation of the entropy value. Next is the computation of the weight vector. The results of the process factor assessments place the nose radius as the most important parameter (1^{st}, 0.913), feed as the next substantial parameter (2^{nd}, 0.043), while speed follows (3^{rd}, 0.0283) and depth of cut as the least important parameter (4^{th}, 0.016).

As advocated by Patel and Deshpande (2014), this work considered the performance analysis of the surface roughness parameters for the boring operation. The principal parameters of interest are the speed, feed, depth of cut and the nose radius. By adopting the framework of Patel and Deshpande (2014), a comparison was made between the results indicated by the analysis of variance for the roughness average for the boring operation and each of the constituent methods of entropy (Priti et al., 2020), decision tree analysis and VIKOR. Compared with the results of ANOVA obtained by Patel and Deshpande (2014), there is the concurrence of results. However, there is disagreement in the results. Consider Table 7 of Patel and Deshpande (2014), the authors concluded that the depth of cut is not significant with a p-value of 0.054 when the Taguchi method for the roughness average for boring was applied at 95% confidence level. This concurs with our results that place depth of cut as the last item in priority using the entropy method (Priti et al., 2020).

Though the idea that speed (74.92% contribution), feed (11.12% contribution) and nose radius (11.09% contribution) are significant also concur with our findings using entropy to obtain the first, second and third positions for these parameters, using entropy, there are differences in the results. While the entropy method places substantial value on the nose radius as the most important parameter that impacts on surface roughness, the report by Patel and Deshpande (2014) positions nose radius as the third grade and uplifts speed as the most important. A striking issue is that the differences between the first position holders in the two methods and each of the second and third position holders are at least 63.80% in Patel and Deshpande (2014) and 87% with the entropy results. The differences in the results may be due to the variations in the units. The entropy method takes care of this while the ANOVA method ignores it (Priti et al., 2020).

In this section, Tables 1 to 9 show the results of the study

Table 1. Boring process parameters with levels (Patel and Deshpande, 2014)

Parameters	Speed (rpm)	Feed (min/rev)	Depth of cut (mm)	Nose radius (mm)
Level 1	800	0.06	1	0.8
Level 2	1000	0.08	1.25	1.2
Level 3	1200	0.10	1.4	0
Level 4	1400	0.12	1.5	0

Step 1: Determine the entropy weightage (Priti et al., 2020)
Step 1.1 Normalise the decision matrix

$$r_{ij} = \frac{X_{ij}}{\sum_{i=1}^{m} X_{ij}} \qquad (1)$$

Table 2. Normalised matrix

Description	Speed	Feed	Depth of cut	Nose radius
	Parameters			
$\sum_{i=1}^{m} X_{ij}$	4400	0.36	5.15	2.0
	0.182	0.169	0.194	0.400
	0.227	0.222	0.243	0.600
	0.273	0.278	0.272	0
	0.318	0.333	0.291	0

Step 1.2 Compute entropy (Priti et al., 2020)

$$e_j = -h \sum_{j=1}^{n} r_{ij} \ln(r_{ij}) \tag{2}$$

But $h = \dfrac{1}{\ln(m)}$ (2.1)

where j = 1, 2, 3, …, n and m is the number of alternatives

By using Equation (2.1), $h = \dfrac{1}{\ln(4)}$ = 0.721. Then the antilog of this value is 1.386 where –h = -1.386

Table 3. Computation of $r_{ij} \ln(r_{ij})$

Description	Speed	Feed	Depth of cut	Nose radius
	Parameters			
	-0.310	-0.298	-0.318	-0.367
	-0.337	-0.334	-0.344	-0.306
	-0.354	-0.356	-0.354	0
	-0.364	-0.366	0.359	0
$\sum r_{ij} \ln(r_{ij})$	-1.365	-1.354	-1.375	-0.673
e_j	0.984	0.976	0.991	0.485

Calculate the weight vector

$$w_j = \frac{1-e_j}{\sum_{i=1}^{n}(1-e_j)} \tag{3}$$

Table 4. Computation of weight vector

Description	Speed	Feed	Depth of cut	Nose radius	$\sum_{i=1}^{n}(1-e_j)$
	Parameters				
$1-e_j$	0.016	0.024	0.009	0.515	
w_j	$\frac{0.016}{0.564}$	$\frac{0.024}{0.564}$	$\frac{0.009}{0.564}$	$\frac{0.515}{0.564}$	
w_j	0.0283	0.043	0.016	0.913	

Step 2 Determine the decision tree using entropy weightage as input (Fig. 1) (Priti et al., 2020)

Step 2.1: Develop a model structure indicating the objective of the problem. For example, the objective is to enhance the surface roughness during the boring operation of IS2062

E250 B0.
Step 2.2: Consider the initial nodes as beneficial and non-beneficial. The beneficial route ends with a node tagged "A" while the non-beneficial route ends with a node tagged "B". A beneficial instance is one whose increase will support the objective of the work. Otherwise, the instance is non-beneficial.
Step 2.3: Indicate all the criteria that fall under the beneficial option and state their weightage, minimum and maximum values of their levels.
Step 2.4: Actualize step 4 but focusing on non-beneficial criteria instead of beneficial criteria.
Step 2.5: Calculate the expected value at node A (i.e. beneficial route). This is the product of the probability, the value attached to each criterion (i.e. speed) and the difference between the maximum and minimum thresholds of levels. For instance, the expected value along the route of the speed beneficial criterion is 0.5 (i.e. for beneficial) x 0.5 (for speed) x 0.984 (for speed) x 600 (the difference between the highest and the lowest level. This gives 147.6.

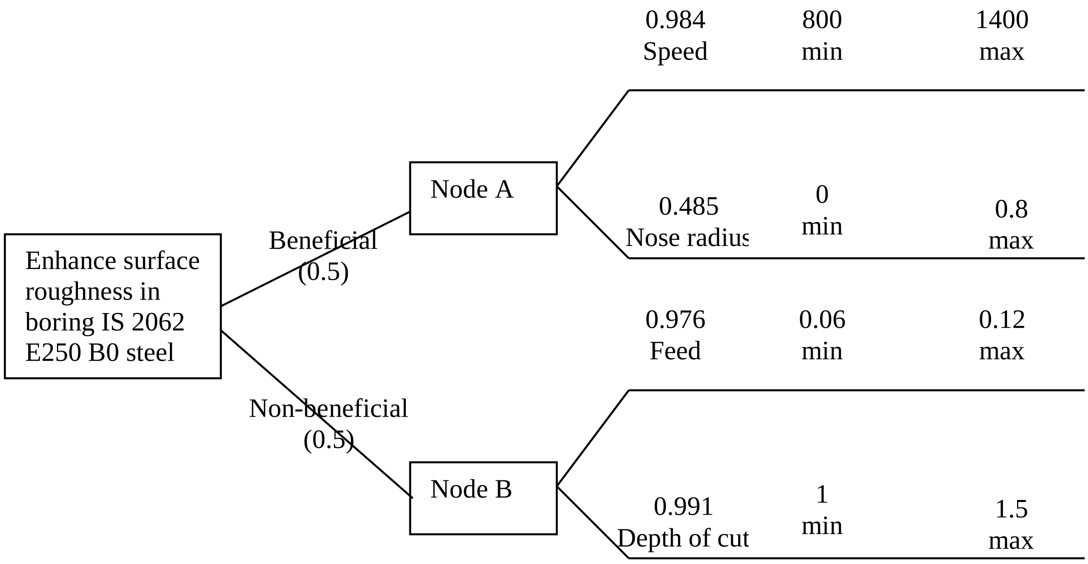

Fig. 1. The EDT-VIKOR model

The representation for analysing the work (Fig. 1) consists of the objective specification point, which is the head and the two nodes. Each of the nodes has branches depending on the nature of the problem. Generally, the hydrid EDT-VIKOR method requires the weights of entropy (Priti et al., 2020) to be evaluated and inserted into the decision tree, which calculates its weights to be substituted into the VIKOR framework. The most fascinating aspect of the method is the incorporation of the decision tree concept into the work. A decision tree is perceived to require a root that defines the objective of the work. There are two important terms when considering decision tree application in the model: beneficial and non-beneficial parameters.

In the multi-criteria analysis, the beneficial concept is defined regarding the parameters of the boring operation of speed, feed, depth of cut and the nose radius. Here, each parameter is analysed as to whether its increase favors the system and this is considered beneficial, otherwise, non-beneficial. Emerging from the objective specification root of the decision tree are two branches with each labelled as either beneficial or non-beneficial branch. Consider the beneficial route being taken. This terminates at a node, probably defined as "A". At this point, all the parameters that are considered as beneficial are analysed each at a time based on the following issues. In the boring instance, the speed and the nose radius are considered as beneficial. Take the speed for analysis as an instance. There are three points on the branch evolving from node A that are necessary. The first point is labelled as "0.984 (speed)". This means that from the previous computation using entropy, speed was finally established to have an e_j value of 0.984. The second point, "800 (min)", has a term, which is "min" and a value of "800". The term means minimum value of all levels, which was obtained as 800. The 800 obtain is then placed beside "min".

The third point is "1400 (max)". Similarly, 1400 is the maximum value of levels under speed and a "max" term is shown. The value 1400 is then indicated next to it. Subsequently, all the other beneficial and non-beneficial parameters are analysed in the same manner. The next stage is to obtain the expected value at each node. The idea of expectation is to consider all the beneficial parameters into an analysis such that each component of the node can be multiplied by the minimum and maximum values. These are afterwards summed up as the expected value from each node. The expected value for node A is then obtained as the product of 0.984, 800 and 1400 regarding speed. Concerning the nose radius parameter, the product of 0.485, 0 and 0.8 is obtained. Consequently, the values from the speed product computation are added to the value from the nose radius product computation. The final answer yields 1,102,080. Similarly, for node B, the final value is obtained as 1.4935

Expected value of node A
$= (0.984 \times 800 \times 1400) + (0.485 \times 0 \times 0.8)$
$= 1,102,080$
Expected value of node B
$= (0.976 \times 0.06 \times 0.12) + (0.991 \times 1 \times 1.5)$
$= 1.4935$

Desirable weightage
= 1,102,080 [0.0283 0.043 0.016 0.913]
= [31188.86 47389.44 17633.28 1006119]
Percentage desirable weightage
= [0.0283 0.043 0.016 0.913]
= [Speed Feed Depth of cut Nose radius]

Step 3. Application of decision tree weightage on VIKOR process

Table 5. The decision tree-VIKOR process

Weightage	0.0283 Speed	0.043 Feed	0.016 Depth of cut	0.913 Nose radius
	800	0.06	1	0.8
	1000	0.08	1.25	1.2
	1200	0.10	1.4	0
	1400	0.12	1.5	0

Calculate the unit measure S_i (Wu et al., 2016; Gangil and Pradhan, 2018; Majumder and Maity, 2018; Priti et al., 2020; Vikram et al., 2020):

$$S_i = \sum_{j=1}^{M} W_i \left[\frac{X_i^+ - X_{ij}}{X_i^+ - X_2^-} \right] \qquad (4)$$

where
W_j Weightage of the decision tree method
X_i^+ best value
X_{ij} value in the cell
X_i^- worst value

Table 6. Best and worst values

Description	Speed	Feed	Depth of cut	Nose radius
Best X_2^+	1400	0.06	1.5	1.2
Worst X_2^-	800	0.12	1	0

Table 7. Summary of S_i values

Description	Value	Description	Value	Description	Value	Description	Value
S_{11}	0.0283	S_{21}	0.0189	S_{31}	0.0094	S_{41}	0
S_{12}	0	S_{22}	0.0143	S_{32}	0.0287	S_{42}	0.043
S_{13}	0.016	S_{23}	0.5	S_{33}	0.032	S_{43}	0
S_{14}	0.304	S_{24}	0	S_{34}	0.913	S_{44}	0.913

Table 8. Computation based on unit measure, S_i and individual regret, R_i

i	Speed	Feed	Depth of cut	Nose radius	S_i	R_i
1	0.2830	0	0.016	0.304	0.348	0.304
2	0.0189	0.0143	0.500	0	0.533	0.5
3	0.0094	0.0287	0.032	0.913	0.983	0.913
4	0	0.043	0	0.913	0.956	0.913

To calculate Q_i, the following formula is used Equation (5) (Wu et al., 2016; Gangil and Pradhan, 2018; Majumder and Maity, 2018; Priti et al., 2020; Vikram et al., 2020):

$$Q_i = \upsilon \times \left[\frac{S_i - S_i^*}{S_i^- - S_i^+} \right] + (1-\upsilon) \times \left[\frac{R_i - R_i^*}{R_i^- - R_i^+} \right] \tag{5}$$

where υ = 0.5 (Risk for strategy for maximum utility)

Notice that υ is a particular value that may fall between 0 and 1. However, it shows the comparative weight for he normalised utility indicator beside the normalised regret indicator.

S^+ means minimum S_i, S^- indicates maximum S_i, R^+ means minimum R_i, R^- indicates maximum R_i

In the VIKOR technique, Equation (5) is regarded as a VIKOR index representing the ith option (Q_i) in the analysis. For instance, to calculate $Q_{1,}$ the following is true:

$$Q_1 = 0.5 \times \left[\frac{0.348 - 0.348}{0.983 - 0.348} \right] + (1-0.5) \times \left[\frac{0.304 - 0.304}{0.913 - 0.304} \right] = 0$$

It follows that Q_2 = 0.307, Q_3 = 1, Q_4 = 0.98

Table 9. Ranking based on Q_i

S/No.	Q_i	Ranking	Comment
1	0	1	Lowest ranking
2	0.307	2	
3	1	4	Highest ranking
4	0.98	3	

Comparison results regarding the Q_i revealed that Q_3 [1], Q_4 [0.98], and Q_2 [0.307] aspects of the work have the utmost importance, correspondingly. The results as well revealed that depth of cut, nose radius and feed have the greatest preference for the boring operation while speed has the least preference among all the factors. However, for certain instances, the compromise solution schemes are deployed to arrive at the utmost solution.

5. CONCLUSIONS

Breakthroughs in resource utilization and control in boring operations will be paced by a proper classification of boring process parameters according to their importance and the distribution of resources in the proportions of their weights. To meet the forthcoming demand for resource conservation and management on the boring process, the process parameters may have to be actively controlled and resources directed at them on merits. Unfortunately, today no diagnostic method exists to establish the order of importance of boring operations parameters. Moreover, the methods to group parameters according to beneficial and non-beneficial contexts and therefore maximise the benefits to the system are missing in the literature. In this article, a novel method was introduced to evaluate the boring operations parameters using the hybrid EDT-VIKOR approach. Literature data was used to validate the models. Accordingly, the following conclusions are given:

(1) The EDT-VIKOR approach offers a verified and feasible method to distinguish parameters of the boring operation and rank them in order of importance.
(2) The depth cut is the most important parameter in the boring operation while speed was found to be the least important parameter.

Abbreviations
CNC machine - Computer Numerical Control machine
VIKOR - VIse Kriterijumska Optimizacija I Kompromisno Resenje (Multicriteria Optimization and Compromise Solution)
EDT – Entropy Decision Tree
MRR – Material removal rate
EDM – Electrical discharge machining
AISI – American Iron and Steel Institute
AA 7075 alloy – Aluminium Alloy 7075 alloy

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