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Fuzzy Analytic Hierarchy Process and Markov Chain - WSM/WPM/WASPAS Approaches to solving the Surface Roughness Problem in the Boring of Carbon Steel IS 2062 GR E250 Plates on CNC Machines

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This paper establishes how the process engineer in a machine shop could capture the uncertainty and the transition of process parameters to improve the surfaced finish of bored work material (carbon steel IS 2062 GR E250 plates) and select the best parameters to achieve the aim. The fuzzy analytic hierarchy process method incorporating geometric mean and a novel Markov chain oriented weightage scheme were used as inputs into three multicriteria methods of weighted sum model (WSM), weighted product model (WPM) and weighted product model and weighted aggregated sum-product, assessment (WASPAS) model. Published literature data were used to validate the methods and their integrations. The novel Markov chain model borrows ideas from the orthogonal array, random number generation and the transition states of parameters. Finally, the optimal parametric setting idea is used to interprete the final results based on an initial response table determination, which are the averages of the signal-to-noise ratios summarized. The most important results are obtained from the fuzzy AHP-Markov WASPAS method. These are the feed parameter (preference score of 1.624) as the best parameter and the depth of cut with the preference score of 1.188 as the worst parameter. The findings indicate that process engineers should attach the most important interest to the feed rate as it is the most effective controlling parameter of surface finish during the boring operation of carbon steel IS 2062 GR E250 plates. Machining shops can employ the framework to evaluate and predict system performance before financial resource commitment to operations.

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1. INTRODUCTION

The carbon steel IS 2062 GR E250 plates have recently attracted unprecedented attention of manufacturers in various industries focusing on water pipes, food processing, dairy products and high-pressure components (Patel and Deshpande, 2014; Sharma and Khan, 2014, 2015; Chennaiah et al., 2016a,b; Jagtap et al., 2017; Srivastava and Garg, 2017; Sayed et al., 2019; Bhaskar et al., 2020). Hence, extensive research activities have been reported on the welding and few studies were documented on the boring of the IS 2062 plates. In welding research, examples of previous studies include submerged arc welding (Sharma and Khan, 2014, 2015), gas metal arc welding (Srivastava and Garg, 2017), welding parametric analysis (Jagtap et al., 2017), welding of joints (Chennaiah et al., 2016a,b) and gas tungsten arc welding (Bhaskar et al., 2020). However, in boring, the limited studies include Patel and Deshpande (2014). But whether boring or welding activities are considered, many of the papers are associated with the industries mentioned earlier in this section. Manufacturers are interested in these plates because of their attractive corroding resistance and rustproof finish attributes among others (Chennaiah et al., 2016b; Srivastava and Garg, 2017). However, they have a significant shortcoming during boring activities (Chern and Liang, 2007; Patel and Deshpande, 2014; Vaishnav and Sonawane, 2014; Hintze et al., 2018; Kumar et al., 2018; Izelu et al., 2019; Biju and Shunmugam, 2019; Liu et al., 2019; Klein et al., 2020; Lotfi et al., 2020; Lawrance et al., 2020a,b). Huge boring operations are necessary to convert these plates into different components in the aforementioned industries (Patel and Deshpande, 2014). Coupled with this, materials undergo delamination, excessive thrust force and undesired surface roughness (Patel and Deshpande, 2014).

The thrust force refers to a reactions force (mechanical) that conquers the resistance against movement of the tool as it passes through the material. It is as large as the resistance in an opposite direction to the resistance against the tool. The surface roughness describes the surface texture of the steel plate in quantified deviations from a standard form, directed to the normal force relative to a surface (Beauchamp et al., 1996). The words “rough “and “smooth “often describe achieved surface texture levels, which are large and small deviations from the real surface, respectively. Delamination describes a failure mode of the steel plate, in fractures, occurring later by the actions of cracks and bending, resulting in reduced compressive strength of the plates. Out of these three responses, namely delamination, surface roughness and the thrust force, the surface roughness concept appears to be the most emphasized response by manufacturers since most of their customers are concerned about this response as they receive the delivery of their products (Majumder and Maity, 2018). Therefore, surface roughness is of interest to the present researchers.

The prediction of surface roughness for bored carbon steel IS 2062 GR E250 plates on CNC machines have become increasingly complicated (Patel and Deshpande, 2014). In compliance with the global requirement in steel plate boring, the boring operation parameters such as the speed, feed, depth of cut and nose radius among others need to be evaluated (Patel and Deshpande, 2014). However, despite extensive boring activities on steel plates and pipes in general including AISI 1040 steel (VenkataRao et al., 2013), AISI 316 steel (VenkataRao et al., 2014), AISI 4140 and AISI 304L steel (Schmidt et al., 2020a) and Inconel 718 (Ratnam et al., 2018), bored carbon steel IS 2062 GR E250 plates on CNC machines has been less studied. The social subsystem of the impact of the boring operation is also of an evaluation concern. Besides, the economic aspect which argues for lean manufacturing practices, the ability to repay borrowed loans and the employee performance loan repayment ratio are central issues to consider for the economic aspects of the boring operation. Furthermore, the boring operation environment subsystem that accounts for the ecological aspects of boring is an important consideration.

Taking the technical process parameters of boring as a subsystem and other subsystems such as the social subsystem, economic subsystem, the boring environment subsystem, the problem becomes multiple and difficult to solve with the linear mathematical models. But the solution has a resemblance to multicriteria decision-making techniques that may be best suited to solve this problem (Zavadskas et al., 2012, 2013a,b; Wu et al., 2016; Majumder and Maity, 2018; Priti et al., 2020; Yazdi et al., 2020; Vikram et al., 2020). Furthermore, considering that various aspects of these divisions need to be integrated into the problem formulation and solution, the consequences of the surface roughness problem in the boring operation are often far-reaching and provoking various manufacturing policy option formulations (VenkataRao et al., 2013, 2014; Zhang et al., 2017; Singh et al., 2018; Yuvaraju and Nanda, 2018). This issue further confirms the strong resemblance of the surface roughness problem in boring operations using multicriteria methods of solution.

Besides, the diverse pressure from stakeholders in the boring operations (i.e. process engineer, manufacturing manager, maintenance manager, the general manager and operators) have also emerged, leading to advance complications in the boring operation decision process (Sathianarayanan et al., 2008; Patel and Deshpande, 2014; Ratnam et al., 2018; Melo et al., 2019; Sastry et al., 2019; Prabhu et al., 2020; Schmidt et al., 2020a,b; Saleh et al., 2021). From the roughness problem description, it is acknowledged that consideration of all aspects of the problem, including the boring operations process parameters, social subsystem, economic subsystem and environmental subsystem are important in the problem formulation (Patel and Deshpande, 2014). However, such a formulation may be substantially demanding regarding computations. Hence, as a research strategy to demonstrate the uniqueness of the innovative method proposed in this work, the fuzzy analytic hierarchy process, only the boring process parameters are focused upon. More so, the parameters are streamlined to the four items of speed, feed, depth of cut and nose radius due to the limitation of discussion to these parameters in the published literature on boring.

Surface roughness as a rival to delamination in the boring of steel plates is one of the most promising responses and could impact production cost, operator’s morale, resource utilisation efficiency and customer satisfaction (Patel and Deshpande, 2014; Vaishnav and Sonawane, 2014). During the boring of carbon steel IS 2062 GR E250 plates, the existence of operator changes with varying skill, competence and experience introduce parametric transition monitoring difficulties such as speed, feed, depth of cut and nose radius changes. This is accompanied by inaccuracy and wrong decision making in boring operations. To overcome this challenge, a novel procedure is proposed that borrows from the orthogonal array principle in Taguchi experimentation. Then the ideas of optimal parametric setting and Markov chains are brought in to enhance the procedure and obtain improved surface roughness resulting from the proper coordination of the parameters (Gangil and Pradhan, 2018).

Researchers developing principles and theories on the enhancement of boring operation's performance in machine shops have long been interested in how the surface roughness of steel plates may be enhanced (Patel and Deshpande, 2014). However, as boring operation’s configurations and dimensions of interest in research and practice become more complicated, new approaches to understand how the prominent parameters obtain transitions from one state to another are essential. Besides, as boring operations experience unprecedented changes in manpower structure coupled with the ageing machines, the uncertainty and imprecision introduced by the operators and process engineers appears unavoidable and are continuously enlarging. But our understanding of the mechanism of capturing uncertainty and imprecision is still elementary and limited. The proposed framework signifies an early step to capturing uncertainty using the fuzzy analytical hierarchy process with the geometric mean method (Yadzi et al., 2020).

The proposed framework regarding the transition state capturing is also the first direction toward precise measurement in the planning of boring operations. Nonetheless, there remains substantial research to be conducted to perfect these two approaches. It is hoped that the present approaches will serve as an inspiration for future studies. While new to the boring literature, the proposed model of Markov-based weight determination method that emphasizes the transition of boring operation's parameters extend previous understanding to show that incorrect evaluation of process parameters may not be due to imprecision and uncertainty only but fail to capture the transition states of the boring parameters, including speed, feed, depth of cut and nose radius. It showed that the introduction of Markov-chain principles could intensify the identification of the path followed by the parameters in the transition states, during the boring operation. When the tracking of transition states of parameters is effective, correct judgements that may lead to cost reduction is possible.

In this work, the fuzzy analytical hierarchy process using the extent analysis method has been applied to evaluate the important parameters that reveal the surface roughness of the carbon steel IS 2062 GR E250 plates during the boring operation on the CNC machine. The work is motivated by the following:

- The domain of research on boring operations, although has several industrial studies, omits studies that evaluate the imprecision and uncertainty involved in the surface roughness processing of the carbon steel IS 2062 GR E250 plates regarding the boring operation on the CNC machines.
- Literature has called for more research on machining and the boring operation is a central part of the machining process.

Existing literature on the boring process has recently adopted multicriteria analysis to formulate and solve surface roughness problems but the tools used are limited to VIKOR and decision tree (Patel and Deshpande, 2014; Abiola and Oke, 2020). Although there are several impressions and uncertainty tracking tools, which have been deployed in the literature, including fuzzy TOPSIS, fuzzy DEMATEL, fuzzy BWM, but the effectiveness of the fuzzy analytical hierarchy with its several advantages has made it a preferred option in the study.

2. METHODS

In this study, the following methods were used, namely, the Markov-based weight determination (MWD) method, the fuzzy analytical hierarchy method with the geometric mean component (FHP_g), the weighted sum method (WSM), the weighted product method (WPM) and the weighted aggregated sum product assessment method (WASPAS). To appreciate the usage of the models, theoretical information is provided starting with the MWD method.

Method 1: Markov chain method of weight determination

Markov chains are old in scientific history and have been found successful in water resources applications where the level of water available for distribution has been mapped to the previous state (level) of the water in the reservoir and changes in parameters such as the pumping frequency, the amount of rainfall, among others. In a boring operation, the surface roughness may be viewed as dependent on the corrosive level of the work material (i.e. corroded or not corroded at all), the atmospheric condition of temperature, humidity and pressure before the boring process and while the boring is ongoing. Besides, transition in speed, feed, depth of cut and nose radius may impact the system of boring operation. For example, consider the operator working on the boring of the carbon steel IS 2062 GR E250 plates for 30 minutes. At the commencement of boring, suppose the operator works at a particular speed 5 minutes into the machining process. But at the instruction of the supervisor, the speed was increased or decreased; this is a transition in the speed of boring the plate. At the same time, the feed rate may change over time in the boring process; this is a transition in the feed rate. Furthermore, the depth of the cut may be changed. Besides, the operator may decide to change the tool to a different nose radius over 30 minutes of boring (Patel and Deshpande, 2014).

By considering all these situations, the transition of states of the important boring operation parameters has taken place. However, no literature method accounts for this during the scheme of a selection of the best boring parameters. But the transition of states for parameters in a boring operation resembles the Markov chain process which could easily track the state changes of the parameters. Hence, it was thought to model the weight determination for the parameters of the boring operation by a markovian process. In this method, the factors and levels for the process are first determined and then the orthogonal array is deployed to evaluate the experimental trials and compress them into a manageable scale, say four different rows. Then the stochastic behaviour of the boring operation is introduced by the generation of random numbers. The point of insertion of the Markov chain principle is at the emergence of a new matrix, which undergoes transition depending on the degree of the system's state of disorderliness. However, as an example, two transitions are undertaken. Thus, it is essential to detail out the steps for the implementation of the procedure.

Procedure

Step 1: Produce an orthogonal array and generate values for the factors based on the levels assigned to particular cells in the experimental trials generated.

Step 2: Summaries the data into four rows. This is achieved by merging experimental trails and finding their averages.

Step 3: For each factor along the row, multiply by a random number and progress in the direction of the x-axis. This produces a new matrix for evaluation

Step 4: Obtain the new matrix through the multiple values and the random number

Step 5: Consider the transition of the factors in two states. This implies that the matrix will be multiplied by itself.

Step 6: Determine the optimal parametric setting for the problem

Step 7: Read the weight from the location of the optimal parametric setting.

Step 8: Aggregate these values and compare the values to a range between 0 and 1.

Method 2: Fuzzy analytical hierarchy process

In the present-day practice of steel plate boring, the phenomenon of uncertainty can hardly be ignored. The highly active technical staff turnover rate in machining operations often cause distortions in the prompt services to machining customers. In some cases, orders to machine components are received and the boring operation is scheduled with the key technical personal. However, before the job implementation on the CNC machine, the production schedule may be forced to change due to the unplanned resignation of key staff. For continuity, the machine shop schedule may now be anchored by the less experienced operator. There are differences in the measurement skills of the experienced and less experienced staff. Coupled with this, the old age of the machine may be given the right measurement. Thus, the existence of the phenomenon of uncertainty limits the machining shop process engineer and operator. Uncertainty makes a great challenge to planning and implementation of plans and practically limits the correct decisions during the boring operation. Therefore, to benefit from the sustainability of the boring operation, uncertainty during the boring process needs to be approached proactively and solved quickly. However, the fuzzy analytic hierarchy process could be the problem solver as it has demonstrated effectiveness in the machining operation, which can be extended to boring activities. Thus, in this article, as part of the objective, a novel procedure to capture uncertainty and impression through the mechanism of the fuzzy analytic hierarchy process is proposed to substantially enhance the surface roughness of bored carbon steel IS 2062 GR E250 plates under room temperature and humidity conditions. Previous success efforts in the machining operations generally have offered inspiration to pursue the adoption of the novel FAHP method in this work.

The geometric mean version of the fuzzy analytic hierarchy process ($FAHP_g$) was deployed to compute the weights of the boring operation parameters in this work (Afolayan et al., 2020; Yazdi et al., 2020). In the boring operation, the argument to introduce the fuzzy analytical hierarchy was based on the understanding that in the boring operation of steel plate the operator exhibits imprecision in the evaluation of the comparative importance of the characteristics of the system. For instance, for an old machine, which is prevalent in most boring shops, setting the speed to precision is challenging, as the controlling knob on the machine may be adjusted only by the experience of the operator. What is regarded as a particular speed by an operator may be a little bit different when an experienced operator adjusts the knob of the machine. Thus, the operator is imprecise in the machine setting and this affects the final readings of the data. Other instances that could instigate imprecision are unquantifiable information, unobtainable information, partial information and incomplete information.

Previously, the fuzzy analytical hierarchy has been applied in water absorption studies with success and it is thought that the features of the boring operation of the steel plate resemble a fuzzy situation and the fuzzy analytic hierarchy is a good fit of the model for use (Abiola and Oke, 2021). A good explanation of the fuzzy analytic model may start from the degree of the comparative importance of the analytical hierarchy process, AHP. In this framework, the importance of factors when compared, such as how important is speed compared to feed rate is expressed as crisp numeric values. This expression of scale fails to capture the imprecision in an uncertainty occurring in the boring operation of the machine. However, to accommodate this deficiency, the fuzzy degree of comparative importance evolved in which fuzzy numbers, often expressed in three-component values when the triangular fuzzy tool is used.

For instance, when the operator judges the comparative importance of speed and feeds to be the same in the boring operation, and the triangular fuzzy system is used, then, the representation of this description on the AHP scale, which could have been "1", which is equal importance, is converted to a fuzzy scale as "(1,1,1)" which is a fuzzy number. Furthermore, it is worthwhile to explain why (1,1,1), for example, is used as the domain in the membership function in the triangular fuzzy number. First, in the context of this article, the domain represents an identity string of all possible inputs of the membership function for the triangular fuzzy member. The domain here includes the assigned values of FAHP shown in Table 2 and includes (1, 1, 1), (2, 3, 4) to the last value (1/9, 1/9, 1/9). It contains a triplet such as (1, 1, 1), the triangular fuzzy number, where the first value, "1" is the smallest possible value, the second value "1" is the most probable value, while the last value "1" is the largest probable value for the fuzzy event representing the boring of carbon steel IS 2062 GR E250 plates on the CNC machine. This scale extends to the left and right to capture all the possible omissions that may not be tracked using the AHP system. The procedure for the fuzzy analytic hierarchy process is as follows:

Procedure

The steps taken in the fuzzy analytical hierarchy process approach are listed below (Afolayan et al., 2020; Yazdi et al., 2020):

Step 1: Establish the degree of comparative importance in the analytical hierarchy process approach and change it to a fuzzy degree of comparative importance that employs fuzzy numbers.

Step 2: Develop a pairwise relative matrix by employing the degree of comparative importance

Step 3: The achieved pairwise relative matrix is transformed to fuzzy numbers through the use of a fuzzy degree of comparative importance. The following expression is useful for this step:

$$\overset{\approx}{A}^{-1} = (l, m.u)^{-1} = (\frac{1}{u}, \frac{1}{m}, \frac{1}{l}) \qquad (1)$$

Step 4: Compute the fuzzy geometric mean, $\overset{\approx}{r}_i$ and obtain the product of the individual value in each column. The required expression for the product of the fuzzy numbers is as follows:

$$\overset{\approx}{A}_1 \times \overset{\approx}{A}_2 = (l_1, m_1, u_1) \times (l_2, m_2, u_2)$$
$$= (l_1 \times l_2, m_1 \times m_2, u_1 \times u_2) \qquad (2)$$

Step 5: Compute the fuzzy weights, $\overset{\approx}{w}_i$ as follow:

$$\overset{\approx}{w}_i = \overset{\approx}{r}_i \times (\overset{\approx}{r}_1 + \overset{\approx}{r}_2 + \overset{\approx}{r}_3)^{-1} \quad (3)$$

Step 6: Transform the fuzzy weights to numerical values with the aid of the following expression:

$$w_i = \frac{l+m+u}{3} \quad (4)$$

Method 3: Weighted sum model (Zavadskas et al., 2012)
In this work, the carbon steel IS 2062 GR E250 plates have been used as the work material to choose the best parameters that will enhance the surface roughness of the material during the boring operation. The weighted sum method (WSM) has been selected for evaluation of the parameters of speed, feed, depth of cut and nose radius. This enables the operator or the process engineer to rank the parameters. To identify the parameters that reveal the support to enhance the surface roughness of the steel plate, preference scores were developed. The inputs to the preference score are the weights of the factors and the value given to each criterion. WSM has been a success in implementation within the fields of data processing and robotics. It has been described to perform excellently in cases where single-dimensional concerns are treated. The weights were both derived from the fuzzy analytical hierarchy method with the geometric mean method and also the Markov chain based weight determination approach. These weights are multiple with the value attributed to each criterion and this product is summed up for all criteria. The procedure to implement the WSM is stated henceforth (Zavadskas et al., 2012).

Procedure (Zavadskas et al., 2012)
WSM is associated with the following steps (Zavadskas et al., 2012, 2013a,b):
Step 1: A matrix of the form shown below could be used to represent the decision criteria:

$$T = \begin{bmatrix} t_{11} & t_{12} & . & t_{1k} \\ t_{21} & t_{22} & . & t_{2k} \\ . & . & . & . \\ t_{j1} & t_{j2} & . & t_{jk} \end{bmatrix} \quad (5)$$

where$T$ represents the matrix and t_{ij}constitutes the members of the matrix
Step 2: Attempt to normalize the value in the decision matrix according to their kind of criteria t_{ij} as
(a) To estimate the beneficial criterion, use

$$t_{ij}^{'} = \frac{t_{ij}}{t_{ij}^{\max}} \quad (6)$$

wheret_{ij} constitutes the members of the matrix, $t_{ij}^{\max}$ is the maximum value for the elements and $t_{ij}^{'}$ represents the beneficial criterion value
(b) To estimate the non-beneficial criterion, use

$$t_{ij}^{''} = \frac{t_{ij}^{\min}}{t_{ij}} \quad (7)$$

$$T^{'} = \begin{bmatrix} t_{11}^{'} & t_{12} & . & t_{1n}^{'} \\ t_{21} & t_{21} & . & t_{2n}^{'} \\ . & . & . & . \\ t_{m1}^{'} & t_{m2}^{'} & . & t_{mn}^{'} \end{bmatrix} \quad (8)$$

where$t_{ij}^{\min}$represents the minimum value within the elements and $t_{ij}^{''}$represents the non-beneficial criterion value $t_{ij}^{''}$
Step 3: Compute the weighted normalized decision matrix as

$$S = W_j t_{ij}^{'} \text{ or } W_j t_{ij}^{''} \quad (9)$$

However, S is given as

$$S = \begin{bmatrix} s_{11} & s_{12} & . & s_{1k} \\ s_{21} & s_{22} & . & s_{2k} \\ . & . & . & . \\ s_{j1} & s_{j2} & . & s_{jk} \end{bmatrix} \quad (10)$$

where$S$ represents the weighted normalized value and W_j represents the weight of each criterion. While assigning the weights, care is taken to maintain the weights $W_j$in the power for the performance values, $t_{ij}^{'W_i}$. Notice that weights are mapped to criteria by respecting an order of importance. The sum of the weights should be equal to 1. In this paper, the assignment of weights is achieved through the introduction of the markovian-based weight determination method and fuzzy analytic method with the use of the geometric mean index.

Step 4: Estimation of preference score and ranking

The matrix is summed up across the rows to obtain the preference score for WSM (Zavadskas et al., 2012):

$$A_i^{WSM} = \sum_{i=1}^{m}\sum_{j=1}^{n} W_{ij} p_{ij} \qquad (11)$$

Step 5: Results are obtained as the option having the utmost rank is chosen as the best one. Other ranks follow as second, third to the last option.

Method 4: Weighted product method

The selection procedure for the best boring operation parameter in the processing of the carbon steel IS 2062 GR E250 plates to improve the surface roughness attribute targets to increase customer patronage in the machining of the plates and conversion to the multiple products, which technology permits for nowadays component manufacture. In this section, the preference scores of the weighted product method have been outlined for implementation as part of the procedure to implement the WPM. The WPM shares similarity with the WSM but has the sum dimension in the integration of the results for the individual criterion replaced with product characteristics.

The procedure to implement the WPM is as follows (Zavadskas et al., 2012):

Procedure

Step 1: Repeat step 1 of WSM to determine the decision criteria in matrix format

Step 2: Normalize the value in the decision matrix by judging the criterion as beneficial or non-beneficial

Step 3: Obtain the weight normalized decision matrix according to the degree of importance

Step 4: Obtain the preference score and ranking by multiplying the matrix across rows (Zavadskas et al., 2012).

$$A_i^{WPM} = \prod_{j=1}^{n} p_{ij}^{W_j} \qquad (12)$$

Step 5: Ranking

Rank each preference score in ascending scale while the highest value is assigned a rank of 1 (1^{st}).

Method 5: Weighted aggregated sum product assessment method, WASPAS

The measurement of the surface roughness of the carbon steel IS 2062 GR E250 plates is vital in boring operations because the combined benefits of corrosion resistance may only be delivered if the surface roughness of the steel plate is enhanced. Generally, the enhancement of surface roughness of the steel plate may be achieved if synchronized with the best parameter that controls the boring operation. Then sufficient resources to capture optimal performance of the steel plate may be deployed to the best boring operation parameter. Consequently, the selection and prediction of parameters during boring operations are becoming a priority in boring intensive environments. The selection problem is often classified as a multicriteria problem due to the conflicting nature of the parameters that dictate the progress of the surface roughness of the steel plates, including speed, feed, depth of cut and nose radius.

It is now essential to evaluate the best parameter in the boring operation of carbon steel IS 2062 GR E250 plates with the weights aggregated sum product assessment method, WASPAS (Zavadskas et al., 2012). The literature data regarding Patel and Deshpande (2014) has been analyzed using WASPAS (Zavadskas et al., 2012), which principally depends on performance score and ranking to reveal the strength of the boring operation parameters.

However, while embarking on surface roughness enhancement endeavour, experience in practice often reveals that the development of microcracks and delamination are important challenges faced during the boring operation. To overcome these problems, previous studies have introduced SiCp to restrict the development of micro-cracks and the presence of delamination. Furthermore, cerium and TiO_2 has been deployed to combat micro-crack development and the growth of delamination. While success has been reported on the use of SiCp, cerium and TiO_2 to control deformation and micro-crack development in aluminium metal matrix fabrication and usage, to the best of the author's knowledge, no report was sighted using the steel plates as the working material. This is an open problem to solve in future studies. Besides, in the boring operation, introducing the combined effects of surface roughness, delamination and micro-crack growth on the effectiveness of the drilling situation may be a complicated research route that could be strategically resolved by first tackling the surface roughness problem about the boring operation parameters. This feasible route to research has been adopted in this work by focusing on the surface roughness phenomenon and conflicting parametric problems attempted to be solved using the WASPAS multicriteria (Zavadskas et al., 2012).

Generally, in multicriteria decision making it is thought that by integrating two models the performance of the resultant model exceeds that of the individual models as it synergic ally utilizes the attributes of the individual model in unity. This idea was perhaps adopted from the field of composites which continuously add knowledge on combinations of two or more materials to attain excellent outstanding performance of the unitary material. Consequently, Zavadskas et al. (2012) that initiated the idea of adding the attributes of the weighted sum model and weighted product model to obtain the weighted aggregated sum product model may have been motivated by the success obtained in the field of composite development to produce interesting results in the integration of multicriteria models. So the method described in this section is referred to as the weighted aggregated sum product assessment, WASPAS (Zavadskas et al., 2012). The WASPAS model is the distinctive addition of two multicriteria models, WSM and WPM, fully described as weighted sum model and weighted product model, respectively. In this work, the problem of selecting the best boring operation process parameter is dealt with. Here, the problem is formulated in the multicriteria structure and resembles a problem that could be solved with the three models of WSM, WPM and WASPAS. In solving the problem, the common measures to the three models are the preference scores and rankings of the process parameters.

Procedure (Zavadskas et al., 2012)
WASPAS combines WSM and WPM. The working principle is to smoothen the errors related to WSM and WPM by combining their preference score values, Q_i^1 and Q_i^2, respectively in a joint generalized criterion of WASPAS (Zavadskas et al., 2012):

$$Q_i = \lambda Q_i^1 + (1-\lambda) Q_i^2 \qquad (13)$$

where λ is the WASPAS parameter is 0.5

3. RESULTS AND DISCUSSION

3.1 Fuzzy analytic hierarchy and Markov-based method

The fuzzy analytic hierarchy process has its foundation in the analytic hierarchy process (AHP). So, explanations of its implementation to the surface roughness evaluations for the boring operation are considered here. To evaluate using the FAHP, the analysis of the AHP model is taken as the most important aspect of the computation: Consider the original table extracted from Table 1 of Patel and Deshpande (2014). Now it is desired to create a pairwise comparison matrix based on Saaty's "degree of comparative importance" that is traditionally listed, Table 2.

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	1.00	0.80
Level 2	1000	0.08	1.25	1.20
Level 3	1200	0.10	1.40	0
Level 4	1400	0.12	1.50	0

In this article, the AHP pairwise comparison is used as the foundation of the fuzzy analytic hierarchy process, which relies on expert's judgment. Based on the literature review and discussions with those in practice, it was decided to use one of the authors as the judge for the AHP pairwise comparison. The judgment details are vetted by the senior author with a doctorate in maintenance engineering and substantial workshop experience. The judge has a first degree in mechanical engineering with over five years in mechanical engineering design and project development work. The judge has a good knowledge of the operation of the computer numerically controlled (CNC) machine tool with training in the use of lathe and milling machines in the engineering formative years. The judge knows bore metals in the production of high-quality metal grades for tools, instruments and tools. The judge is capable of operating and maintaining lathe and milling machines and capture precise measurements for shaping or cutting activities on steel plates. Thus, the judge is competent to evaluate the criteria for the AHP comparative matrix. The judge was asked to evaluate the process parameters of speed, feed, depth of cut and nose radius and the relative importance among them. Then the evaluation was cross-checked by the senior author who was meant to agree or disagree and point out corrective actions, if necessary.

Table 2. Degree of comparative importance from the AHP method and fuzzy AHP

Assigned value (AHP)	Assigned value (FAHP)	Description of importance
1	(1,1,1)	Equal
3	(2,3,4)	Moderate
5	(4,5,6)	High
7	(6,7,8)	Very high
9	(9,9,9)	Extremely high
2	(1,2,3)	Intermediate values
4	(3,4,5)	
6	(5,6,7)	
8	(7,8,9)	
1/3	(1/4,1/3,1/2)	Values for inverse comparison
1/5	(1/6,1/5,1/4)	
1/7	(1/8,1/7,1/6)	
1/9	(1/9,1/9,1/9)	

It is interesting to note the values in the degree of comparative importance as crisp numeric values such as 1,3,5,7 and 9. To analyse the problem in fuzzy these crisp numeric values are converted into fuzzy numbers. Figure 1 is general information on fuzzy numbers while Figure 2 may be of assistance in understanding the procedure followed in this work. Figure 2 is guided by several terms, including fuzzification. This refers to the procedure adopted to decompose the set of crisp numeric values into at least a fuzzy set. This area is extensive with different kinds of curves as well as a table that may be deployed. Nonetheless, the triangular or trapezoidal-oriented membership functions are commonly used in the fuzzy analysis literature. The motivation for this is the ease of their usage in controllers, where extensive development of fuzzy principles in electronics has been made.

However, since success has been recorded in this area, we are adopting their principles and concepts to the area of boring operations and particularly the surface roughness evaluation regarding the principal parameters of speed, feed, depth of cut and nose radius. Fuzzification is associated with converting linguistic terms into membership functions. Regarding the boring operation, the parameter speed may be described as high, medium, low or on somehow multiples scales such as very high, somehow high, high, medium, low, somehow low and very low. These are linguistic terms. The same descriptions or slightly different could be used for feed, depth of cut and nose radius regarding their evaluations with the surface roughness. These linguistic terms are represented by membership functions while the group of terms establishes how the speed, for instance, may be shown within the fuzzy representation (Figure 1). Membership functions regarding a fuzzy set are items mapped to it, often bounded from 0 to 1. Figure 2 shows a triangular-shaped often defined as the membership functions. Consequently, the membership functions associated with the triangle are referred to as the triangular membership function: in this work, the analysis is restricted to only the triangular membership function but excludes other interesting functions such as trapezoidal membership functions and the bell-shaped membership function, among others.

Consider the expression in Equation (1), for instance, the right-hand side comprises of a three-number known as the fuzzy number i.e. (4,5,6) taken together.

$$\mu_{\tilde{\tilde{A}}(x)} = \tilde{\tilde{A}} = (4,5,6) \qquad (14)$$

They are associated with the membership functions and associated with the lower, middle and upper ends of the triangle revealed in Fig. 1 and the axis referred to as the x-axis.

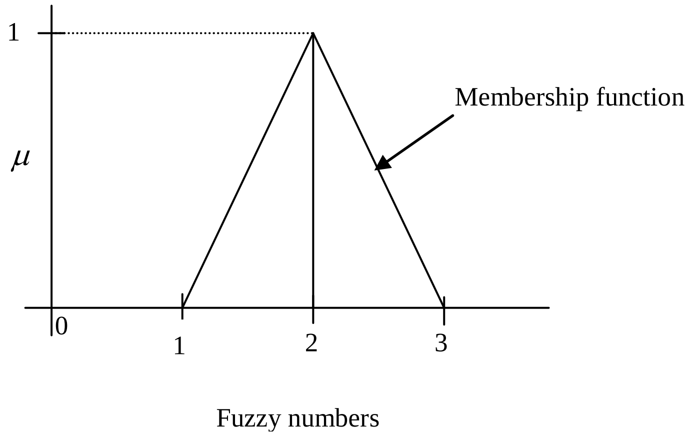

Fig. 1. Membership function for the parameters regarding the boring operation for surface roughness evaluation of carbon steel IS 2062 GR E250 plates

Considering the fuzzy degree of comparative importance, (Fig. 2), it could be noted that the assignment of crisp members such as 1, 3, 5, 7 and 9 have been exchanged with the fuzzy numbers. Besides, we note that assigning a single member to any term may not be justified. For example, high has been given the value 5. However, what could be said about 4.3 or 5.1? Could 4.3 be called moderate or high? It is confusing and challenging to discuss. Therefore, to tackle the problem of the intermediate values, the idea of a fuzzy number was established to resolve the issue. Therefore, combining information from Figure 2 and Table 2, it could be observed that for the description "high", a fuzzy number of (4,5,6) has been assigned to it.

These three components of the fuzzy number correspond to the lower (4), the middle (5) and the upper (6) points of the triangle that could be traced to high. So the triangle that could be traced from point 4 on the x-axis through to “high" still on the x-axis but at the level "1” down to 6 on the x-axis is the membership function of the description "high", represented as a triangular membership function. Table 3 shows the pairwise comparison matrix created through the application of the AHP method. However, details about the evaluation are obtainable in the AHP literature. By referring to Table 2, the first column shows the degree of comparative importance with crisp numeric value while the second column reveals the fuzzy numbers. These two descriptions are equivalent and Table 3 may be transformed into a new Table 4 where these crisp numerical values are replaced with fuzzy numbers. To demonstrate how this could be achieved, please consider the first element in Table 3, which is 1. To construct its equivalent item in the fuzzification pairwise comparison matrix, it is replaced with the fuzzy number (1,1,1).

Likewise, all the other entries in the first row, 9, 5 and 7 are replaced with the fuzzy numbers (9,9,9), (4,5,6) and (6,7,8), respectively. The same idea could be applied for the second row for the second, third and four entries and also for the third row considering the third and fourth entries and also for the last row and the last entry. But the replacement of the crisp numeric values with the fuzzy numbers is incomplete as we are left with numbers 1/9 on the second row as the first entry, numbers 1/5, 1/7 on the third row as first and second entries as well as numbers 1/7, 1/9 and 1/5 on the fourth row as first, second and third entries. In summary, the reciprocal values of 9 (second row), 5 and 7 (third row) and 7,9,5 (fourth row) are not converted into fuzzy numbers. These reciprocal values are then converted into fuzzy numbers. To achieve this conversion, Equation (2) is deployed.

$$\overset{\approx}{A}^{-1} = (l, m.u)^{-1} = (\frac{1}{u}, \frac{1}{m}, \frac{1}{l})$$

To illustrate this conversion process, consider the crisp numeric value along the second row but the first entry, i.e. 1/9. This has the corresponding scale item (Table 2) of extremely high and the fuzzy number of (9,9,9). On the right hand of Equation (2), it may be noted that the reciprocal of the upper point, i.e. 9 (written as 1/9) is described as the first item, followed by the middle item (i.e. the reciprocal of 9 (written as 1/9). The last item within the bracket of the right-hand side of Equation (2) is the reciprocal of the lower point, i.e.8 (written as 1/9). In sum, the fuzzy number is written as (1/9, 1/9, 1/9). This principle was used to transform all the other entries, which is amended in Table 3. Thus, a new Table 4 emerges with complete fuzzified members of all entries. Notice that at the right-hand side of Equation (2), in the entries of the fuzzy number put in brackets, the item at the upper point is written first, followed by the middle number and the lower number is written last. Thus, following the principle the left out crisp numerical values may be converted into their reciprocals, as fuzzy numbers. Table 4 is referred to as the fuzzified pairwise comparison matrix.

Next, the fuzzy geometric mean proposed (Table 5) by Buckley (1985) (see Okponyia and Oke, 2020) is deployed for analysis such that geometric mean is used to calculate the weights of the factors. The symbol r_i often represents the value obtained for the fuzzy geometric mean. Before achieving the values of R_i for each factor, there is a need to understand the logic of multiplying two fuzzy numbers. Equation (3) guides in that respect.

$$\overset{\approx}{A_1} \otimes \overset{\approx}{A_2} = (l_1, m_1, u_1) \otimes (l_2, m_2, u_2)$$
$$= (l_1 \otimes l_2, m_1 \otimes m_2, u_1 \otimes u_2)$$

This reflects the multiplication of two fuzzy numbers A_1 and A_2 with each represented as (l_1, m_1, u_1) and (l_2, m_2, u_2), respectively. The right-hand side of the equation shows that the lower points of each fuzzy number are multiplied (i.e. l_1 and l_2). The middle points are multiplied (i.e. u_1 and u_2). Thus, to calculate the geometric mean values, r_1, r_2, r_3 and r_4, we have the following:

Next, the fuzzy weights, represented by Equation (4) are calculated for every criterion. First, all the fuzzy geometric mean values need to be added and Equation (5) fulfils this need. In this formula to add two fuzzy numbers, the lower values are added, the middle values are added and the upper values are added too. To demonstrate how the fuzzy numbers may be added in the boring operation case considered, Table 6 is referred to. This means that to obtain the lower point in the final fuzzy number obtained, (6.147, 6.692, 7.208), i.e. 6.147 for example, Table 6 is looked at. The lower points for every criterion are summed up. The 6.147 is obtained from the sum of 3.83, which is the lower point for speed, 1.56, which is the lower point for feed, 0.538, which is the lower point for the depth of cut, and 0.219, which is the lower point for nose radius. So, using the same procedure, the other points, the middle point of the final answer being 6.692 as well as the upper point being 7.208

are obtained. Now, back to Equation (4), on the right-hand side, which has two components $\tilde{\tilde{r}}_i$ and $(\tilde{\tilde{r}}_1 \oplus \tilde{\tilde{r}}_2 \oplus \tilde{\tilde{r}}_3 \oplus \tilde{\tilde{r}}_4)^{-1}$, the later part of the two components is of interest to us i.e. $(\tilde{\tilde{r}}_1 \oplus \tilde{\tilde{r}}_2 \oplus \tilde{\tilde{r}}_3 \oplus \tilde{\tilde{r}}_4)^{-1}$. To proceed, the reciprocal of (6.147, 6.692, 7.208) is obtained. But to achieve this, we refer to Equation (2) in which the transformation of this number yields the reciprocal of the upper point written first followed by a comma, item the reciprocal of the middle point followed by a comma and lastly, the reciprocal of the lower point as $\left(\frac{1}{7.208}, \frac{1}{6.692}, \frac{1}{6.147}\right)$.

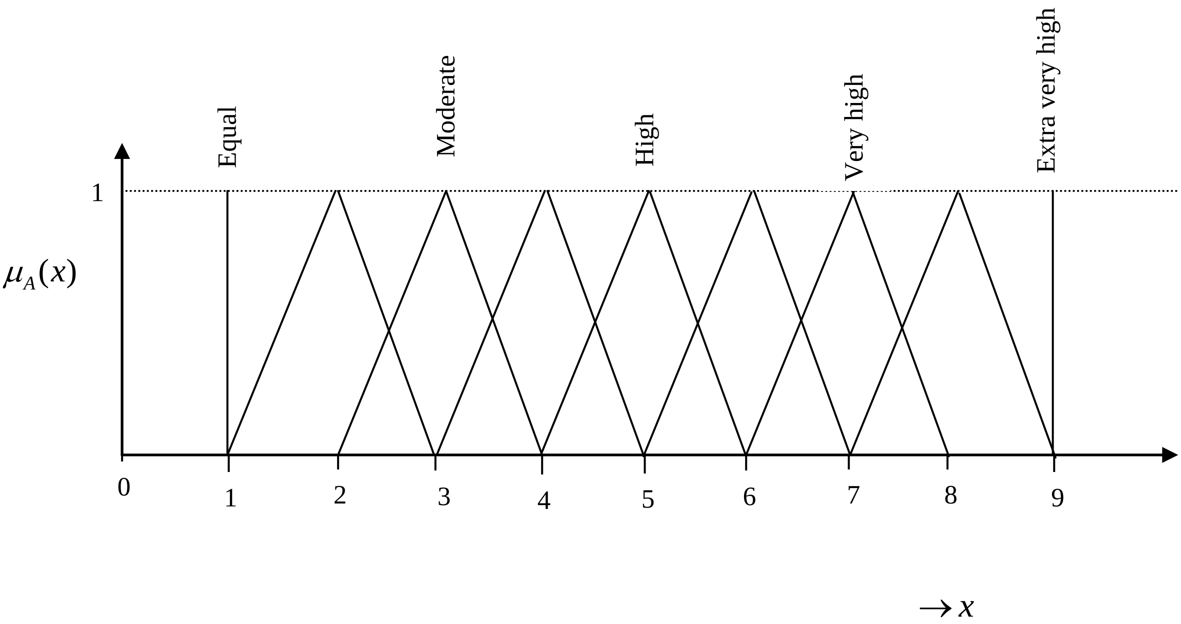

Fig. 2. Fuzzy numbers for the parameters regarding the boring operation for surface roughness evaluation of carbon steel IS 2062 GR E250 plates

Table 3. Pairwise comparison matrix (4x4) from AHP

Description	Speed	Feed	Depth of Cut	Nose Radius
Speed	1	9	5	7
Feed	1/9	1	7	9
Depth of cut	1/5	1/7	1	5
Nose radius	1/7	1/9	1/5	1

Table 4. Complete fuzzication of pairwise comparison matrix for all numbers

Description	Speed	Feed	Depth of cut	Nose radius
Speed	(1, 1, 1)	(9, 9,9)	(4, 5, 6)	(6, 7, 8)
Feed	(1/10,1/9,1/8)	(1, 1, 1)	(6, 7, 8)	(9, 9, 9)
Depth of cut	(1/6,1/5,1/4)	(1/8,1/7,1/6)	(1, 1, 1)	(4, 5, 6)
Nose radius	(1/8,1/7,1/6)	(1/9,1/9,1/9)	(1/6,1/5,1/4)	(1, 1, 1)

Notice that the final value desired is

$(l_1 \otimes l_2, m_1 \otimes m_2, u_1 \otimes u_2)^{\frac{1}{n}}$ where$n$ is the number of criteria

The symbol $\overset{\approx}{r}_i$ is obtained as follows

$\overset{\approx}{r}_1 = ((1 \otimes 9 \otimes 4 \otimes 6)^{\frac{1}{4}}, (1 \otimes 9 \otimes 5 \otimes 7)^{\frac{1}{4}}, (1 \otimes 9 \otimes 6 \otimes 8)^{\frac{1}{4}})$) = (3.84, 4.21, 4.56)

$\overset{\approx}{r}_2 = ((\frac{1}{9} \otimes 1 \otimes 6 \otimes 9)^{\frac{1}{4}}, (\frac{1}{9} \otimes 1 \otimes 7 \otimes 9)^{\frac{1}{4}}, (\frac{1}{9} \otimes 1 \otimes 8 \otimes 9)^{\frac{1}{4}})$) = (1.56, 1.63, 1.68)

$\overset{\approx}{r}_3 = ((\frac{1}{6} \otimes \frac{1}{8} \otimes 1 \otimes 4)^{\frac{1}{4}}, (\frac{1}{5} \otimes \frac{1}{7} \otimes 1 \otimes 5)^{\frac{1}{4}}, (\frac{1}{4} \otimes \frac{1}{6} \otimes 1 \otimes 6)^{\frac{1}{4}})$= (0.538, 0.615, 0.707)

$\overset{\approx}{r}_4 = ((\frac{1}{8} \otimes \frac{1}{9} \otimes \frac{1}{6} \otimes 1)^{\frac{1}{4}}, (\frac{1}{7} \otimes \frac{1}{9} \otimes \frac{1}{5} \otimes 1)^{\frac{1}{4}}, (\frac{1}{6} \otimes \frac{1}{9} \otimes \frac{1}{4} \otimes 1)^{\frac{1}{4}})$= (0.219, 0.237, 0.261)

$$\overset{\approx}{w}_i = \overset{\approx}{r}_i \otimes (\overset{\approx}{r}_1 \oplus \overset{\approx}{r}_2 \oplus \overset{\approx}{r}_3 \oplus \overset{\approx}{r}_4)^{-1} \tag{15}$$

$$\overset{\approx}{A}_1 \oplus \overset{\approx}{A}_2 = (l_1, m_1, u_1) \oplus (l_2, m_2, u_2) = (l_1 \oplus l_2, m_1 \oplus m_2, u_1 \oplus u_2) \tag{16}$$

Table 5. Fuzzy geometric mean value

Factor (criterion)	Fuzzy geometric mean value, $\overset{\approx}{r}_i$
Speed	(3.83, 4.21, 4.56)
Feed	(1.56, 1.63, 1.68)
Depth of cut	(0.538, 0.615, 0.707)
Nose radius	(0.219, 0.237, 0.261)

$(\overset{\approx}{r}_1 \oplus \overset{\approx}{r}_2 \oplus \overset{\approx}{r}_3 \oplus \overset{\approx}{r}_4)$ = (3.83+1.56+0.538+0.219, 4.21+1.63+0.615+0.237, 4.56+1.68+0.707+0.261) = (6.147, 6.692, 7.208)

Table 6. Computation of the fuzzy weight, $\overset{\approx}{w}_i$

Criterion	Fuzzy geometric Mean value, $\overset{\approx}{r}_i$	Fuzzy weight, $\overset{\approx}{w}_i$
Speed	(3.83, 4.21, 4.56)	(3.83, 4.21, 4.56) $\otimes \left(\frac{1}{7.208}, \frac{1}{6.692}, \frac{1}{6.147}\right)$ = (0.529, 1.709, 0.743)
Feed	(1.56, 1.63, 1.68)	(1.56, 1.63, 1.68) $\otimes \left(\frac{1}{7.208}, \frac{1}{6.692}, \frac{1}{6.147}\right)$ = (0.215, 0.243, 0.274)
Depth of cut	(0.538, 0.615, 0.707)	(0.538, 0.615, 0.707) $\otimes \left(\frac{1}{7.208}, \frac{1}{6.692}, \frac{1}{6.147}\right)$ = (0.0742, 0.0916, 0.115)
Nose radius	(0.219, 0.237, 0.261)	(0.219, 0.237, 0.261) $\otimes \left(\frac{1}{7.208}, \frac{1}{6.692}, \frac{1}{6.147}\right)$ = (0.0302, 0.0353, 0.0425)

This is used to obtain the fuzzy weight $\overset{\approx}{w}_1$, the fuzzy geometric mean value, $\overset{\approx}{r}_1$. Each criterion will be multiplied by the reciprocal of the geometric mean summation. Take the criterion, speed, for instance, to obtain the fuzzy weight w_i, the $\overset{\approx}{r}_1$ value is multiplied with $\left(\frac{1}{7.208}, \frac{1}{6.692}, \frac{1}{6.147}\right)$ to obtain (0.5269, 1.709, 0.743). The same procedure is used for the other criteria and Table 7 is completed. But recall that the formula to multiply two fuzzy numbers, Equation (3) is applied. To explain, the computation of the fuzzy weight for the speed criterion, the multiplication

$$(3.83, 4.21, 4.56) \otimes \left(\frac{1}{7.208}, \frac{1}{6.692}, \frac{1}{6.147}\right)$$

is considered. Hence, the authors have multiplied 3.83 by $\frac{1}{7.208}$, 4.21 by $\frac{1}{6.692}$, and 4.56 by $\frac{1}{6.147}$ to obtain (0.529, 1.709, 0.743).

Similar multiplications are made to fill up Table 7. At this stage, the fuzzy weights may be used for other computations or the defuzzification of the weights may be approached. Thus, the obtained four fuzzy numbers may be used to get crisp numerical values and the specific method used to achieve this is the centre of the area in which the weight, w_i is the, l, m, u are respectively lower, middle and upper points of the fuzzy numbers.

Thus, using the centre of area

$$\text{COA, } w_i = \left(\frac{l+m+u}{3}\right) \qquad (17)$$

Take the speed criterion as an instance, the fuzzy weight, $\overset{\approx}{w}_1$, is obtained by adding 0.529, 1.709, and 0.743 together to obtain 0.994. Similarly, the weights $\overset{\approx}{w}_2$, $\overset{\approx}{w}_3$ and $\overset{\approx}{w}_4$ are obtained as 0.244, 0.036 and 0.036, respectively. These last-mentioned values are the defuzzified fuzzy weights that may be used as requirements in other analyses. However, there is a need for the adjustments of the weights where the sum exceeds 1 but the standard is to apportion the values such that each factor is given a value, which when summed up for all factors, become 1. In this case, the sum of all the weights gives 1.3676 and as we normalize the weights to yield values between 0 and 1, the Table 7 is obtained. Thus, it could be concluded that the best criterion is speed with a weight of 0.6900, which is ranked first. The next criterion is feed with a weight of 0.178 and ranked second. The next criterion is a depth of cut with a weight of 0.0684 and ranked third. The last criterion, nose radius, weight of 0.0263 and ranked fourth and the last of the criteria (Table 7).

Table 7. Normalized weights for the criteria

Factor	Weight $\overset{\approx}{w}_i$	Normalized weight
Speed	0.9440	0.6900
Feed	0.2440	0.1780
Depth of cut	0.0936	0.0684
Nose radius	0.0360	0.0263

These weights are used as inputs to the WPM, WSM and WASPAS method of multicriteria analysis in the selection and ranking of the boring operation parameters during the monitoring of the surface roughness during the operation.

3.2 Fuzzy AHP weightage as input for solving WSM, WPM and WASPAS

The starting point is to normalize the values of the parameters, namely speed, feed, depth of cut and nose radius. This was done by applying a normalizing equation and the result in Table 8 is obtained.

Table 8. Normalized decision matrix

	Speed	Feed	Depth of cut	Nose radius
	0.1820	0.1670	0.1940	0.4000
	0.2270	0.2220	0.2430	0.6000
	0.2730	02780	0.2720	0
	0.3180	0.3330	0.2910	0
Weightage	0.6900	0.1780	0.0684	0.0263

The weights obtained from Table 7 are then placed next to the table so that the weighted sum model, WSM, could be applied. The formula for the WSM is given as Equation (18):

Weighted sum model (WSM)

$$= A_i^{WSM} = \sum_{j=1}^{n} W_{ij} P_{ij} \qquad (18)$$

where P_{ij} is the normalized value in the cell while W_{ij} is the normalized weighted

Table 9 shows the result of the application of the WSM method by ranks.

Table 9. Rank computation by WSM

	Parameter/criterion					
	Speed	Feed	Depth of cut	Nose radius	$A_i^{WSM} = \sum_{j=1}^{n} W_{ij} P_{ij}$	Ranking
Speed	0.1260	0.0297	0.0133	0.0105	0.1795	4
Feed	0.1570	0.0395	0.0166	0.0158	0.2289	3
Depth of cut	0.1880	0.0495	0.0186	0	0.2560	2
Nose radius	0.2190	0.0593	0.0199	0	0.2980	1

The WSM ranks are nose radius (1st), depth of cut (2nd), feed (3rd) and speed (4th). A similar procedure is implemented for the weighted product method where Equation (19) was deployed on the normalized data and the results are shown in Table 10.

$$A_i^{WPM} = \prod_{j=1}^{n} P_{ij}^{W_{ij}} \qquad (19)$$

The outcome of the WPM differs from that of the WSM as the first position is assigned to the feed parameter, 2nd position to the speed parameter, 3rd position to the nose radius parameter and the 4th position to the depth of cut parameter. Compared with the WSM, the results of WPM are contradictory with none of the parameters rated by both methods are the same. Now, the research proceeds to evaluation through Taguchi's orthogonal array of L16, Table 11.

Table 10. Rank computation by WPM

	Parameter/criterion					
	Speed	Feed	Depth of cut	Nose radius	$A_i^{WPM} = \prod_{j=1}^{n} P_{ij}^{W_{ij}}$	Ranking
Speed	0.3090	0.7270	0.8940	0.9760	2.9060	2
Feed	0.3590	0.7650	0.9080	0.9870	3.0190	1
Depth of cut	0.4080	0.7960	0.9150	0	2.1190	4
Nose radius	0.4680	0.8220	0.9200	0	2.2100	3

Table 11. Actual values of factors based on orthogonal array elements

S/No.	Speed	Feed	Depth of cut	Nose Radius
1	150	0.015	1.00	0.800
2	150	0.030	1.25	1.200

Table 11 (cont'd). Actual values of factors based on orthogonal array elements

S/No.	Speed	Feed	Depth of cut	Nose Radius
3	150	0.045	1.40	0
4	150	0.060	1.50	0
5	300	0.015	1.25	0
6	300	0.030	1.00	0
7	300	0.045	1.50	0.800
8	300	0.060	1.40	1.200
9	450	0.015	1.40	0
10	450	0.030	1.50	0
11	450	0.045	1.00	1.200
12	450	0.060	1.25	0.800
13	600	0.015	1,50	1.200
14	600	0.030	1.40	0.800
15	600	0.045	1.25	0.800
16	600	0.060	1.00	0

Table 11 was produced from the L16 orthogonal array to reflect the actual values of the orthogonal array elements when picked from the factor-level distribution of the boring operation problem where the enhancement of the surface roughness of the material (carbon steel IS 2062 GR E250 plates) is desired. The original orthogonal array shows an entry of "1" each under speed for the first four experimental trials. However "1" indicates level 1 for speed and the corresponding value in the factor-level table is 150. Thus the value of "1" is replaced with 150 for the first four experimental trials under the factor, "speed". By following the same approach, the new values of Table 11 are produced. Next, the sixteen experimental trials are segmented into four strata, which mean that experimental trials 1 to 4, 5 to 8, 9 to 12 and 13 to 16 are treated each time and the averages of the values are obtained. Consider the value of 150, under the speed category. How did we obtain this? Recall that experimental trials 1 to 4 are to be treated together and averaged. The counts of 4 values under the speed category reads 150 each and the average yields 150, which is recorded under the factor, speed. The same logic was used to fill up Table 12.

Table 12. Averages of experimental trail values for factors

Group	Speed	Feed	Depth of cut	Nose Radius
1	150	0.0375	1.29	0.5
2	300	0.0375	1.29	0.5
3	450	0.0375	1.29	0.5
4	600	0.0375	1.29	0.7

In Table 13, the values of the averages obtained from the summarized experiment trials consisting of four trials each are shown together with the random numbers generated for each of the values. Consider the value under the speed category, "0.5 x 150, 150", the 0.5 is the generated random number obtainable from the calculator or the random number generator in Microsoft Excel. The 150 is the value obtained from the previous Table 12.

Table 13. Averaged experimental trial values with random numbers

Group	Speed	Feed	Depth of cut	Nose radius
1	0.5 x 150	0.8 x 0.0375	0.9 x 1.29	0.2 x 0.5
2	0.7 x 300	0.2 x 0.0375	0.5 x 1.29	0.4 x 0.5
3	0.3 x 450	0.6 x 0.0375	0.4 x 1.29	0.6 x 0.5
4	0.1 x 600	0.7 x 0.0375	0.7 x 1.29	0.8 x 0.7

Table 14. A summarized form of Table 13

Group	Speed	Feed	Depth of cut	Nose radius
1	75	0.0300	1.1610	0.1000
2	210	0.0075	0.6450	0.2000
3	135	0.0225	0.5160	0.3000
4	60	0.0263	0.9030	0.5600

By following the same logic of analysis, all the entries in Table 13 may be obtained. The summary of the contents of Table 13 produces Table 14. Next, the idea of the Markov chain is introduced where the parameters are assumed to undergo a transition from one state to another. In this case study, a two-state transition is assumed, represented by two matrices having identical contents side by side, which will be multiplied, Table 15.

Table 15. Matrix produced from the two-stage transition process

Trial	S	F	D	N		S	Feed	D	N		S	F	D	N
1	75	0.0300	1.161	0.10		75	0.0300	1.161	0.10		5794.04	2.28	87.78	7.91
2	210	0.0075	0.645	0.20	X	210	0.0075	0.645	0.20	=	15850.65	6.32	244.33	21.31
3	135	0.0225	0.516	0.30		135	0.0225	0.516	0.30		10217.39	4.07	157.29	13.83
4	60	0.0263	0.903	0.56		60	0.0263	0.903	0.56		4661.03	1.83	70.65	6.59

Key: S – speed, F – feed, D – depth of cut, N – nose radius

From Table 15, the output of the multiplication of the two 4x4 matrices is shown and could be interpreted as containing four experimental trials. For the speed parameter the highest and lowest values are obtained as 15850.65 and 4661.03 rpm, respectively, and the average of the values for the four experimental trials is 9130.78 rpm. The feed parameter has the highest and lowest values as 6.32 and 1.83 mm/rev, respectively, and the average value of the experimental trials is 3.63 mm/rev. For the depth of cut parameter, the highest and lowest values are 244.33 and 70.65 mm, respectively, while the average of the experimental trials is 140.01 mm. However, for the nose radius, the highest and lowest values are 21.31 and 6.59 mm, respectively, while the average of the experimental trials is 12.41mm. But these values are not realistic as they far exceed the practical values. Again, bearing in mind that the transition is obtained through a squared multiplication of the matrix to the present values, it seems logical therefore to obtain the square root of these computed values as the analysis. Thus, the square root of 9130.78 rpm (speed), 3.63 mm/rev (feed), 140.01 mm (depth of cut) and12.41 mm (nose radius) respectively speeds (95.56rpm), feed (1.91mm/rev), and depth of cut (11.83 mm and nose radius (3.52 mm) are obtained.

3.3 Weightage of markovian chain method WSM, WPM and WASPAS

The determination of correct and relevant weight determination system for multicriteria methods such as the WSM, WPM and WASPAS is fundamental to achieving the surface integrity of bored carbon steel IS 2062 GR E250 plates for component manufacture. The traditional evaluation systems, including the best, worst method, data envelopment analysis, fuzzy analytic hierarchy process (geometric mean method), analytic hierarchy process, among others incorporates several procedures with some having direct and indirect associations with the main multicriteria with which weights are to be used for. But the weakness of these methods is that none of them could track the transition states of the parameter during the boring process. Given this shortcoming, this study considers the gap and introduces the markovian chain method to bridge this gap. This method draws on the orthogonal array, random number generation, Markov theory with the introduction of transition state matrix principles and the fitting of the results with the framework of the optimal parametric setting earlier determined using the average of the signal-to-noise ratio to yield the response table.

To illustrate the proposed method, the evaluation and comparison of the method with the fuzzy analytic hierarchy (geometric mean method) have been modelled as a multicriteria problem while the structure has been applied to real-life manufacturing data from published sources but initially collected from an Indian manufacturing environment. To proceed with the WSM method, the initial matrix containing the factors and levels is normalized to produce a four-by-four matrix, and it is positioned next to the matrix of the results from the markovian-chain method and multiplied to yield Table 16.

Table 16. WSM values with ranks and performance scores

Parameter	WSM preference score	Ranking
Speed	0.182	4**
Feed	0.227	3
Depth of cut	0.272	2
Nose radius	0.317	1*

Key: *Highest ranking, **Lowest ranking

Table 16 reveals the highest performance score of 0.317, indicating nose radius as the best performing parameter. It has a depth of cut with a preference score of 0.272 as the next performing parameter while the feed rate with a performance score of 0.227 is ranked third and speed with a performance score of 0.182 is the least which is ranked the 4th position. In Table 16, the results of the performance score and ranks for the WSM are shown. However, these results are at variance with those obtained with the WPM. In WPM, the highest performance score is attributed to the feed rate (3.211), ranked as first against its second position in WSM (Table 17). The second position in WPM is the speed with a performance score of 3.161 which is positioned as fourth when WSM was applied. The third position by WPM is the nose radius but was positioned first by using the WSM. The fourth position in WPM is the depth of cut. But this parameter has been ranked as second using the WSM (Table 16).

Table 17. WPM results of performance scores and ranking

Parameter	WPM preference score	Ranking
Speed	3.161	2
Feed	3.211	1*
Depth of cut	2.259	4**
Nose radius	2.305	3

Key: *Highest ranking, **Lowest ranking

Table 18. Results of WASPAS method

Description	Q_i^1	Q_i^2	$\lambda Q_i^1 + (1-\lambda)Q_i^2$	Ranking
Speed	0.1795	2.906	1.543	2
Feed	0.2289	3.019	1.624	1*
Depth of cut	0.2560	2.119	1.188	4**
Nose radius	0.2980	2.210	1.254	3

Key: *Highest ranking, **Lowest ranking

Table 18 shows the results of WASPAS. In Table 18, λ =0.5, Q_i^1 and Q_i^2 are preference scores of WSM and WPM, respectively. The first, second, third and fourth positions are allocated to feed, speed, nose radius and depth of cut, respectively.

3.4 Comparison of FAHP$_g$ method with the novel Markov based method and others

In this section, the dissimilarities and similarities in the results offered by our models using the FAHP$_g$ and the markovian chain based method for weight determination and other methods are examined.

Although the same primary data was used, the $FAHP_g$ incorporated uncertainty in the determination of weights, which was routed through the establishment of fuzzy numbers from crisp numeric values. However, the Markov chain based omits these attributes completely in its framework. Instead, the parameters of the boring operations were modelled to exhibit transition states. But how do we quantify the elements of fuzziness or Markov chain embedded in the results? But it is thought that the differences between the actual parametric values and the predicted through the various methods may provide an understanding of the dimension of fuzziness or markovian elements embedded in the results.

To find the actual values for the parameters, the normalized values are referred to consider the initial normalized matrix given such that speed, feed, depth of cut and nose radius at the first row are given values of 0.182, 0.167, 0.194 and 0.4, respectively. The representative values, designated as the averages for speed, feed, depth of cut and nose radius are the sum of the individual parameters across the rows in all four rows, divided by four. If the actual speed value in the normalized form is given as 0.182 and the predicted value using the $FAHP_g$ is 0.690, it means that the difference of 279.12% with which the $FAHP_g$ is higher than the actual value quantities the fuzzy dimension of the speed parameter. The implication is that a wrong decision may be made if this actual value of speed has to be used for planning because the system has a huge amount of variations, which has not been accounted for in normal practice but revealed with the unique $FAHP_g$ model introduced in this study. Since speed was chosen by the methods of $FAHP_g$, and the markovian-based method as the first position comparison of the new models, an outcome with the actual speed value is also made here.

For the markovian-based model, the value of 0.98 was attained against 0.182 which is the actual value. The difference is greatly higher compared with the difference exhibited by the $FAHP_g$ against the actual values. The markovian-based model yielded 438.46%. This is the threshold of the transaction of the boring operation's parameters engaged in. This implies that there is a higher level of the transition of the variables regarding boring operation on the account of transition instead of uncertainty. However, an interesting result may be to search for understanding when fuzziness is combined with the markovian-based model.

3.5 Applying the fuzzy AHP_g weightage as input for solving WSM, WPM and WASPAS

By starting from the normalized matrix, the weightage obtained from the $FAHP_g$ is introduced and multiplied with the matrix. The WSM model is then applied as in Table 2. The results show that the nose radius is the most significant parameter followed by the depth of cut, then feed and lastly, speed. On applying WPM, the feed rate emerged at the topmost position followed by speed, then nose radius and lastly depth of cut. On analysis of the WASPAS method, feed remained as the first choice while speed emerged as the second item, nose radius and depth of cut were positioned as the third and fourth, respectively. By considering the fuzzy AHP_g method as input by weight to WSM, WPM and WASPAS, in two instances (66.7%), feed emerged as the best parameter, speed as the second, nose radius as the third and depth of cut as the fourth rating.

This is representative of the FAHPg input method to WSM, WPM and WASPAS. Notwithstanding, considering the markovian-based method as input by weight to WSM, WPM and WASPAS in 66.7% of cases, feed also emerged as the first candidate, speed as the second best, nose radius as the third position and depth of cut as the fourth position. By comparing the results of WSM, WPM and WASPAS using the two methods of inputs, the results show that feed, speed, nose radius and depth of cut are positioned as the first, second, third and fourth positions, respectively. Thus, the best parameter is feed while the worst parameter is the depth of cut. Accordingly, the operator and process engineer should give the feed rate the utmost priority as it aids the enhancement of surface finish most among other parameters.

In this article, based on the experimental data from the literature, different results were obtained in prioritising the four parameters of speed, feed, depth of cut and nose radius. There are three principal cases considered in this article: fuzzy AHP-Markov WSM method, fuzzy AHP-Markov WPM method and fuzzy AHP-Markov WASPAS method. In the first case (fuzzy AHP-Markov WSM method), nose radius obtained the first position (Table 15). However, feed (Table 16) achieved the first position for the second case (i.e. fuzzy AHP-Markov WPM method) while for the third case (fuzzy AHP-Markov chains WASPAS method), feed obtained the first position. Since WASPAS is superior to WSM and WPM (Zavadskas et al., 2012), the results of the WASPAS hybrid model (i.e. third case) where feed is judged as the best is taken in this article. Furthermore, from Tables 15, 16 and 17, which reveal the results of the three cases, the worst parameter was identified as speed, depth of cut and depth of cut, respectively. Thus, by the same argument for the choice of the best parameter where the results of the WASPAS hybrid method is chosen as the acceptable one, the worst parameter is indicated as the depth of cut.

3.6 Further work

In this article, the surface roughness during the boring operation of the carbon steel IS 2062 GR E250 plates on the CNC machine was considered as the response while the parameters of interest were the speed, feed rate, depth of cut and nose radius. Though the parameters may be restricted to these four, surface roughness is not a sufficient response; delamination is another critical response. Delamination may occur at the peel up of the boring tool to the work material (entrance). It could also occur at the push out of the boring tool from the work material (exit). These could be determined for the steel plate under investigation. The delamination factor may be established at diverse cutting speeds and feed.

Furthermore, both speed and feed rates may decrease or increase jointly. Furthermore, the thrust force and torque were highlighted in the machining literature as important responses but their effect on the feed and the cross-sectional area of the feed and the cross-section area of the displaced chips for the steel plate has not been reported in the literature. Besides, this influence, together with speed, has also not been documented for steel plates and could be insightful.

4. CONCLUSIONS

In the literature, there exists several approaches and usage for the surface roughness enhancement problem in the boring operation of carbon steel IS 2062 GR E250 plates. As the parameters are conflicting, solving the problem using the traditional means of linear models becomes very demanding, complicated and sometimes impossible. To resolve this problem, the resemblance of a multicriteria problem was noticed in the problem and the WSM, WPM and WASPAS methods were adopted in the solution of the problem. However, there are two special concerns in solving this problem. First, uncertainty abounds in the problem and tracking the solution in a meaningful way may not be achieved by the available weight determination methods such as the analytic hierarchy process, data envelopment analysis, and the best-worst method. Therefore a good fit to resolve the problem is the use of the fuzzy analytic hierarchy method, and this was adopted as the solution to the uncertainty problem discussed. The second concern is the transition of the boring process parameters but they are not accounted for in the available literature. To conquer this concern, a novel method, the markovian-based method is developed and applied to the boring problem. Both the FAHPg method and the Markov chain method were adopted as inputs to the WSM, WPM and WASPAS models and found feasible. Based on the results of the study, the following are declared:

1. The fuzzy analytic hierarchy process declared weights of 0.690, 0.178, 0.0684 and 0.0263 for speed, feed, depth of cut and nose radius as first to the last position, respectively.
2. The Markov-chain based method declared weights of 0.98, 0.016, 0.00135 and 0.00026 for speed, depth of cut, nose radius and feed as first to the last position, respectively.

3. The consensus of the FAHPg and Markov-based method is that speed is the best parameter considered as inputs to WSM, WPM and WASPAS methods.
4. For the WSM, WPM and WASPAS, and using the FAHPg as input for weight determination, a majority of the methods approve feed as the best, speed as the second nose, radius as third and depth of cut as fourth.
5. By using the markovian method as input to WSM, WPM and WASPAS methods, these three methods yielded a majority opinion of models to give feed, speed, nose radius and depth of cut as first to the last position, respectively.
6. Since WASPAS is superior to WSM and WPM (Zavadskas et al., 2012), the results of the WASPAS hybrid model (i.e. third case) where nose radius is judged as the best is taken in this article. By the same argument for the choice of the best parameter where the results of the WASPAS hybrid method is chosen as the acceptable one, the worst parameter is indicated as the depth of cut.

The key contributions of this article follow:

1. A new procedure is proposed to enhance the surface roughness of bored carbon steel IS 2062 GR E250 plates based on the Markov chain principle. To a large extent, it solves the problem of lack of tracking of the transition behaviour of the principal parameters of the boring operation such as speed, feed, depth of cut and nose radius. At the same time, it introduces stochastic traits that assist to simulate and model the complicated boring operation.
2. Uncertainty and imprecision in the judgement of the operator and process engineer can be corrected by the proposed fuzzy analytic hierarchy process with geometric mean features. This provides more reliable results for the boring operation process planning and the control of materials.
3. The preference scores and ranks of the boring operation's parameters are given out in methods, including the weighted sum method, weighted product method and the weighted aggregated sum product assessments method incorporating the markov chain and fuzzy analytical hierarchy methods. The accuracy of the proposed methods was verified with published data.

The proposed procedures substantially enhance the surface roughness of the boring steel plates and hence there is a promise of the methods to enhance boring operations planning effectiveness.

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