DOI: https://doi.org/10.26593/jrsi.v10i1.4271.1-14

Jurnal Rekayasa Sistem Industri
Volume 10 No 1 - April 2021
http://journal.unpar.ac.id/index.php/jrsi/index
ISSN 2339-1499 (*online*) – ISSN 0216-1036 (*print*)

Disampaikan : 27 September 2020
Direview : 1 Oktober 2020
Diterima : 4 November 2020

The Application of WSM, WPM and WASPAS Multicriteria Methods for Optimum Operating Conditions Selection in Machining Operations

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Abstract

Optimal condition selection in machining operations is an imperative decision for the process engineer as it influences improved tool life and surface roughness values. As the aluminium market is extremely competitive, process engineers strive to understand what to do to gain preference from prospective customers. From this viewpoint, the criteria responsible for operating decisions should be examined. In this paper the WSM, WPM and WASPAS multicriteria methods are proposed for optimal machining conditions for turned aluminium bars. A stepwise methodology of the WSM, WPM and WASPAS methods is detailed. The proposed technique was tested on published data regarding the turning of an aluminium bar, machined on a lathe machine. The case study consists of three input parameters (spindle speed, feed rate and depth of cut) and four responses (cutting temperature, cutting force, surface roughness and material removal rate). After analysing the experimental data using the models, the entropy method chose material removal rate was chosen as the best. Using the three other models, the best selection was run 17 which correspond to an input parameter of 605 rpm spindle speed, 0.12 mm/rev feed rate and 1.8 mm depth of cut. This article offers a completely new approach to operating condition selection in the turning of the aluminium bar. In the current aluminium market, it is extremely important to understand the operating conditions of the machine for enlarged customer patronage and sustainability. The unique feature of this approach is the elevated level of reliability it exhibits.

Keywords: *Turning process, normalization, preference scores, ranking*

Introduction

Today, modern machining processes focus on achieving enhanced quality of turned bars, dimensional accuracy during production, elevated production rate, acceptable surface roughness and economic impacts for the machining firm (Das et al., 2018; Saravanakumar et al., 2018; Singh et al., 2019; Palaniappan et al., 2020; Ameur, 2020; Kaladhar, 2020; Singh et al., 2020). However, it is surprising that the scarce machining resources quickly get used up. With more than one operator working with resources conflicts sometimes occur on the inadequate distribution of turning resources. This may cause delays in job delivery and increased penalty costs.

Furthermore, the conventional procedure to achieve the best selection of operating parameters during the turning of steel on the CNC lathe machine is well known (Zheng et al., 2008; Mikolajczyk et al., 2018; Zubair and Mansor, 2019; Pathapalli et al., 2019; Singh et al., 2019; Ameur, 2020; Kaladhar, 2020; Singh et al., 2020). At present, it involves the use of experience by the process engineer in combination with trial and error. The weakness of this approach is that trial and error is sometimes frustrating after substantial repeats (Ameur, 2020). Besides, wrong results may be obtained, leading to wrong decisions, which are sometimes irreversible. However, multi-criteria tools offer a reliable approach in the absence of exact mathematical formula; analytical methods may be computationally demanding (Zavadskas et al., 2012, 2013a,b; Pathapalli et al., 2019). While some multicriteria tools have been used to select optimal machining parameters, the unique simplicity and flexibility of the innovative

WASPAS method have not been reported (Nayak, 2014; Chakraborty and Zavadskas, 2014; Pathapalli et al., 2019; Zubair and Mansor, 2019). In this paper, the WASPAS method was used to aid the technological advancement of the subtraction machining literature (Bid and Siddique, 2019).

A brief review of the relevant literature reveals the following. Mali et al. (2019) simulated the cutting forces obtained when aluminium 7075 alloy was turned without lubricant using Deform-3D software using depth of cut, speed and feed. Prakash et al. (2020) turned aluminium/rock dust composites and revealed that the feed has a substantial impact on roughness average and material removal rate but fewer impacts on other parameters. Palaniappan et al. (2020) turned aluminium 6082 alloy during CNC turning to establish the optimal process parameters using L27 in a Taguchi scheme. Saravanakumar et al. (2018) experimentally analyzed the optimal aluminium alloy 6063 turning parameters for surface finish enhancement while the cutting tool used is the carbon nitride inserts. Das et al. (2018) reported that the most impacting parameter on the responses in an experiment is the feed while the depth of cut and spindle speed was rated as insignificant. Rao and Allamraju (2017) established the induced residual stress and micro-hardness of aluminium 7075 alloy during the CNC turning process. Das and Chapgain (2018) studied the impact of machining factors on the responses of the process for silicon carbide powder fortified Al7075 matrix composite using Taguchi scheme.

Jeyaprakash et al. (2020) compared experiments with the turning of aluminium 19000 alloys performed on the CNC machine with an analytical model. The outcome was that electroplated materials showed less value in machining conditions, tool geometry, and surface finish. Kumar et al. (2017) turned aluminium 2219 alloy and concluded that Al2219 and Al2219 composites impact reduced wear effects on the TiN coated carbide inserts as the surface roughness, cutting speed and cutting force heightened. Jayaraman and Maheshkumar (2014) reported on the turning of AA6063 T6 aluminium alloy in an optimisation drive using combined grey relational analysis and Taguchi scheme.

From the review conducted the following important observations are made:

1. The literature has two sets of studies – simulation and experiments.
2. Turning was studied in dry and wet conditions.
3. The work materials include AA 6063, AA 6082, AA 7075 and rock dust reinforced aluminium metal matrix composite.
4. Application areas are automotive components and aircraft fittings, worm gears, meter shafts, missile parts, and valve parts.
5. Turned bars have been tested using micro-hardness and X-ray diffraction
6. There is scope to study the turning of the aluminium bar along with the following directions:
   a. Experimental studies on the aluminium bar on the CNC turning machine.
   b. Selection activities of the responses and parameters of the turning process subjected to entropy WPM, WSM and WASPAS multi-criteria tools.
   c. The HSQ tool of 3-X10% cobalt for a single point application.
   d. Responses to include tool-tip temperature, cutting forces (Fx, Fy and Fz), roughness average (Ra) and material removal rate (MRR). Parameters to include the speed, feed rate and depth of cut.
   e. To compare the TOPSIS results of Nayak (2014) with the outcomes of WSM, WPM and WASPAS methods. This is to enhance our comprehension on the turning of aluminium bar by emphasizing necessary information.

In mechanical engineering, to study the relationship among cutting temperature, cutting speed, feed and depth of cut, it is often noted that for the growth in value for feed (or depth of cut) the chips produced becomes thicker. The consequence is that thickness-to-surface area ratio of the chips produced from the aluminium bar becomes larger. This offers less chance for the heat generated during machining to be dispersed and temperature growth is experienced. However, in the situation studied, the focus is on the responses. As seen in Table 3 of Nayak (2014), the first three experimental trials on tool-tip temperature showed growth in values and declined randomly. The same characteristic is true for all other responses of forces, Ra and MRR. These criteria (responses)

DOI: https://doi.org/10.26593/jrsi.v10i1.4271.1-14

are conflicting, and it is challenging to rank the alternatives without using multicriteria decision-making tools. This makes this problem a ranking and selection class with conflicting criteria which was solved using the WPM, WSM and WASPAS methods. Extremely little research has been conducted on the features of the process and models of selection using multi-criteria analysis for the turning process. The development of a framework to select the responses and parameters during the turning of an aluminium bar of 50 mm diameter x 150 mm length using the WPM, WSM and WASPAS multi-criteria models is the novelty of this article. The multi-criteria models were used to obtain the optimal responses and parameters for the turning process. The following responses were considered in the work: tool-tip temperature, cutting forces, surface roughness and the MRR. Furthermore, the parameters of the turning process are the feed rate, spindle speed and depth of cut. The process parameters and responses were synchronized to achieve the following objectives:

1. To analyze the impacts of parameters on the responses of the turning process.
2. To investigate the influence of the parameters and responses on the outcome of the responses for entropy method, WPM, WSM and WASPAS methods.
3. To compare results of TOPSIS procedure based on Nayak (2014) with the outcomes of WPM, WSM and WASPAS.
4. To propose the optimal configurations based on entropy, WSM, WPM and WASPAS methods.

For the first time, the WSM, WPM and WASPAS multi-criteria methods are proposed to analyse the machining operating conditions in the laboratory using literature experimental data. The unique feature of this approach is the elevated level of reliability it exhibits.

Methods

Before proceeding on the procedures implemented in the present work, it is necessary to briefly mention that the TOPSIS procedure is the benchmark with which our study was compared with in the work of Nayak (2014). The TOPSIS procedure is summarized to contain the following (Nayak, 2014): determination of the choice variables, formation of the normalized and weighted normalized choice variables, institution of the positive and negative ideal solutions, computation of the separation index, computation of the comparative closeness of the solution and establishment of ranks for the preference order.

The idea of weighted sum model (WSM)

This is one of the multi-criteria models that are known for their simplicity in assessing several options regarding the available member of decision criteria. The weighted sum model has competing methods, including WASPAS, VIKOR, WPM, MOORA and GTMA. The idea of beneficial (Equation (1))/(non-beneficial) (Equation (2)) attribute is the characteristics of the parameter being considered in which maximum/minimum values are desired from them.

Beneficial attributes: X = x/xmax Eq. 1

Non-beneficial attributes: X = xmin/x Eq. 2

Where $x_{min}$and x_{max} are the minimum and maximum values of the data set in the group considered and X is the estimated value. Now, the values obtained in Equations (1) are (2) are substituted as weights in Equation (3).

$$A_i^{WSM-score} = \sum_{j=1}^{n} w_i a_{ij} \text{, for } i = 1,2,3, \dots, m \quad \text{Eq. 3}$$

where w_i illustrates the comparative weight of importance of the interior C_j while a_{ij} represents the performance value (normalised scale) of option A_i while it is appraised regarding criterion C_j . It follows that the total (as all criteria are treated concurrently) significance of option A_i, denoted as $A_i^{WSM-score}$

In this work, normalization was applied to determine weights in the entropy method, and to evaluate the preferences scores for the WPM, WSM and WASPAS to avoid using different responses and parameters in diverse units. For instance, the tool-tip temperature is in ^oC , the cutting forces of the tool are in newtons, and the MMR is in mm3/min. Also, for the parameters such as speed, feed and depth of cut, the units are respectively in rpm, mm/rev and mm. Thus, to compare results, there is a need for common ground. The normalized values are restricted between 0 and 1. In this work, the min-max normalization method is adopted with the linear transformation. In this

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instance, the min reflects the minimum while the max shows the maximum values of the response or parameters of interest.

The steps involved in WSM are described as follows (Zavadskas et al., 2012, 2013a,b):

Step 1: The decision criteria can be established in matrix format as

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdot & p_{1n} \\ p_{21} & p_{21} & \cdot & p_{2n} \\ \cdot & \cdot & \cdot & \cdot \\ p_{m1} & p_{m2} & \cdot & p_{mn} \end{bmatrix} \quad \text{Eq. 4}$$

where P is the matrix and p_{ij} are the elements of the matrix.

Step 2: The value in the decision matrix are normalised based on their type of criteria p_{ij} as

(a) For a beneficial criterion

$$p_{ij}^{'} = \frac{p_{ij}}{p_{ij}^{\max}} \quad \text{Eq. 5}$$

where p_{ij} are the elements of the matrix, p_{ij}^{max} is the maximum value among the elements and is the beneficial criterion value

(b) For a non-beneficial criterion

$$p_{ij}^{"} = \frac{p_{ij}^{\min}}{p_{ij}} \quad \text{Eq. 6}$$

$$P^{'} = \begin{bmatrix} p_{11}^{'} & p_{12} & \cdot & p_{1n}^{'} \\ p_{21} & p_{21} & \cdot & p_{2n}^{'} \\ \cdot & \cdot & \cdot & \cdot \\ p_{m1}^{'} & p_{m2}^{'} & \cdot & p_{mn}^{'} \end{bmatrix} \quad \text{Eq. 7}$$

where p_{ij}^{min} is the minimum value among the elements and $p_{ij}^{"}$ is the beneficial criterion value.

Step 3: The weighted normalized decision matrix

$$Y = W_j p_{ij}^{'} \text{ or } W_j p_{ij}^{"} \quad \text{Eq. 8}$$

But Y is given as

$$Y = \begin{bmatrix} y_{11} & y_{12} & \cdot & y_{1n} \\ y_{21} & y_{21} & \cdot & y_{2n} \\ \cdot & \cdot & \cdot & \cdot \\ y_{m1} & y_{m2} & \cdot & y_{mn} \end{bmatrix} \quad \text{Eq. 9}$$

where Y is the weighted normalised value and W_j is the weight of each criterion.

The weights are assigned by keeping the weights W_j in the power of the performance values, $p_{ij}^{'W_i}$. Weights are assigned to criteria according to an order of importance. The sum of the weights must be equal to 1. However, the assignment of weights can be done subjectively (based on the decision maker's consideration) or objectively (through mathematical calculations i.e. entropy and CRITIC methods).

Step 4: Preference score and ranking estimation.

Preference scores show an inclusive summary of the machining-based characteristics of the turning process on a universal grade. It reveals numerous aspects into a single mark fixed at zero as the lower boundary and as the higher boundary. It helps in prioritizing the experimental trial results based on either the parameters through the lens of the global influence of parameters or responses. It evaluates the variations in the turning parameters based on relative value breakdown. To compute the preference scores and ranked values of the parameters of a turning experiment, the preference scores are first produced and related (ranked) such that higher values are positioned above the lower values. To appraise the preference score using the WSM, WPM and WASPAS, the equivalent sub-dimensional scores are initially related while the upper score ascertains the trend of the preference. The preference score was evaluated by producing the values in the cells of the normalized weighted table across rows and then ranked, Equation (8).

The preference score for WSM is derived by summing the matrix across rows.

$$A_i^{WSM} = \sum_{i=1}^{m} \sum_{j=1}^{n} W_{ij} p_{ij} \quad \text{Eq. 10}$$

Step 5: Result - The alternative with the highest rank is selected as the best alternative and the next ranked alternative can be selected in the absence of the highest-ranking alternative.

The concept of WPM

The weighted product model (WPM) is a multi-criteria decision-making method that is used to select the best alternatives from a list. In this method, the preference score is derived by multiplying through the rows in the weighted normalized matrix.

Steps involved in WPM are as follows:

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Step 1: Repeat of Equation (4) to establish the decision criteria in matrix format.
Step 2: The value in the decision matrix are normalized based on the type of criterion pij (Equation (5) for beneficial criterion, Equations (6) and (7) for non-beneficial criterion).
Step 3: The weight normalized decision matrix (Equations (8) and (9))
Weights are assigned to criteria according to an order of importance as shown in Step 3 of the weighted sum method.
Step 4: Estimate the preference score and ranking
The preference score for WPM is derived by multiplying the matrix across rows.

$$A_i^{WPM} = \prod_{j=1}^{n} p_{ij}^{W_j} \quad \text{Eq. 11}$$

Step 5: Ranking
Each preference score will be ranked in ascending order with the highest value assigned a rank of 1.
Step 6: Result: Repeat Step 5 of Section 2.1

The concept of WASPAS

Bid and Siddique's (2019) exposition on the evaluation of WASPAS is noteworthy. The authors traced the initiation of the fundamental principles of WASPAS to Zavadskas et al. (2012). The work integrated the weighted sum model and the weighted product model as a multicriteria tool. To verify the model, Zavadskas collaborated with other researchers to apply WASPAS in several project management initiatives (Zavadskas et al., 2013 a, b; Bagočius et al., 2013; Hashemkhani et al., 2013; Chakraborty and Zavadskas, 2014). Further developments were made on the model by Tosun and Seyrek (2010).

The weighted aggregated sum product assessment is a unique combination of the weighted sum model (WSM) and weighted product model (WPM). It works to smoothen the errors associated with WSM and WPM by making use of their preference score values, Q_i^1 and Q_i^2, respectively to get a joint generalized criterion of WASPAS using Equation (12):

$$Q_i = \lambda Q_i^1 + (1-\lambda) Q_i^2 \quad \text{Eq. 12}$$

where λ is the WASPAS parameter is 0.5.

Qi is ranked according to highest values in the ascending order with the highest value ranked as the 1st position.

Weight determination of criteria

A decision-maker allocates points to each criterion. The more points a criterion receives, the greater its relative importance. The total of all criteria weights must be equal to 1. The weights obtained from point allocation methods are not very precise, and the method becomes more difficult as the number of criteria exceeds five. Therefore an objective approach to finding the weight of criteria is adopted in this case study.

The idea of entropy in the multicriteria analysis was borrowed from how certain physical processes behave based on the principle of diversification. It explains, for example, why the lubricating oil used in the turning process of an aluminium bar spreads. Furthermore, entropy may be explained as a turning evaluation method using the concept of probability. A structure with a higher probability of containing energy than the other, for instance, is declared to have higher entropy. This idea is transferred to machining as a method to define the most important parameters and responses in a turning process involving the use of an aluminium bar. The entropy method is used to calculate the weights of criteria when the decision-maker has conflicting views on the values of weights to be used. The weights calculated by the entropy method can be derived by the following steps:
Step 1: Normalize the decision matrix

$$r_{ij} = \frac{p_{ij}}{\sum_{i=1}^{m}\sum_{j=1}^{n} p_{ij}} \quad \text{Eq. 13}$$

$$r_{ij} = \begin{bmatrix} y_{11} & y_{12} & . & y_{1n} \\ r_{21} & r_{21} & . & r_{2n} \\ . & . & . & . \\ r_{m1} & r_{m2} & . & r_{mn} \end{bmatrix} \quad \text{Eq. 14}$$

where r_{ij} is the normalised value.

Step 2: Compute the entropy

$$e_j = -h \sum_{i=1}^{m}\sum_{j=1}^{n} r_{ij} \ln r_{ij} \quad \text{Eq. 15}$$

where i = 1, 2,…, n; j = 1, 2,…, m and is the entropy

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However, $$h = \frac{1}{\ln(s)} \quad \text{Eq. 16}$$

where s is the number of alternatives

Step 3: Compute the weight vector

$$W_j = \frac{1 - e_j}{\sum_{j=1}^{n}(1 - e_j)} \quad \text{Eq. 17}$$

where j = 1, 2,…, n

Experimental details

The HMT NH 26 lathe machine is the name of the machine tool that produced the experimental data used in the current paper (Nayak, 2014). This data from Nayak (2014) was used to validate the model used in the present work. By comparing Nayak (2014) with the present work, it may interest us to know what needs to be considered so that the experimental conditions can be equalised. In this instance, the normalization of the data needs to be updated to reflect the various methods of entropy, weighted sum model and weighted product model. The turning process uses the aluminium bars (50mm (diameter) x 150mm (length)) with the parameters of interest being the feed, depth of cut and spindle speed. However, the output elements are the cutting forces, the MRR, tool-tip temperature and Ra. In the literature, most efforts at optimizing process characteristics and on prioritisation were directed at parameters such as feed, depth of cut and speed. But at variance with the literature on turning, efforts were directed at prioritising the responses of the turning process by considering the following multi-criteria models: entropy, WPM, WSM and WASPAS. So, the paper establishes an optimal (turning) machining condition on the CNC lathe machine, using an aluminium bar to minimize the MRR, tool-tip temperature, cutting forces and Ra. The controllable parameters of the process, namely feed, depth of cut and spindle speed were chosen from the experimental data generated by Nayak (2014) with twenty-five trials (Table 1 on Design of Experiments from Nayak (2014).

The single point tool used by Nayak (2014) to turn the aluminium bar, eliminating chips through a cutting edge in a single pass was an HSQ tool of 3-X10% cobalt content element. The tool has two principal advantages. First, the design and production of the tool is straightforward as it reduces effort made by the machinist, resulting in less stress to the operator, thereby providing an opportunity for high machine productivity and timely delivery of turned aluminium bar. Second, single tools are relatively cheaper, creating an opportunity to invest the tool budget on other machining areas with enhanced commercial gains. The HSQ (hydrogen silsesquioxane) tool is an inorganic resist item with high resolution and etched confrontation to oxygen. It works well when flooded with lubricants (water), which could cause rusting and reduce tool’s service life. Besides, the 10% cobalt addition on the tool makes it effective on hard materials while machining at elevated speeds. In this circumstance, the single point HSQ tool of 3-X10% cobalt chosen by Nayak (2014) to turn the aluminium bar in the experiment is ideal.

Results and Discussion

To determine the entropy results for parameters or responses in a process, the first step is to determine the normalised values involving different dimensions of the responses. This helped to obtain a magnitude. The outcome of this transformation is the normalised matrix. Recall that the data transformed is the original dataset offered in Nayak (2014). The revised data is shown in Table 1.

Entropy weight determination

The responses, including tool-tip temperature, cutting forces F_x, F_y, F_z in the *x*, *y*, and *z* directions, R_a and *MRR* were subject to an objective weight determination procedure. These responses are treated as criteria and normalized to adjust the values to a general scale from different scales of measurements.

Table 1. Experimental data – revised (Nayak, 2014)*

Sl. No	Tool-tip temperature (°C)	F_x (N)	F_y (N)	F_z (N)	Ra (μ-m)	MRR (mm^3/min)
$\sum_{j=1}^{n} p_j$	912.1	3398.92	2713.67	5512.77	328.5285	602928.4

*The original data that were summed up as the last row on this table is available in the open literature, Nayak (2014), and may be consulted by those interested in the details.

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The normalised data is the format used for pairwise comparison of criteria. The results indicating the matrix obtained for normalisation are displayed in Table 2. In this result, twenty-five trials are considered, with each trial obtained from the turning experiment in the laboratory turning of the aluminium bar.,

The computation of the entropy method was done from the normalised Table 3 using Equations (11) and (12). The objective weight is W_j. The findings from the entropy method reveal that it is possible to prioritise the responses of the turning process. The results obtained are the weights of 0.0074, 0.1589, 0.1587, 0.1754 and 0.3697 for tool-tip temperature, F_x, F_y, F_z, R_a and *MRR*, respectively (Table 3). This translates to the highest weighted criterion as the *MRR* and this was followed by F_x. It means that concerning time and cost invested in machining the aluminium bars, the *MRR* is the major controlling factor. When properly monitored and coordinated it could enhance productivity and output for the machining system. The process engineer could employ the results of the entropy weight in budget decisions concerning the turning process.

Based on the entropy results, the MRR was given a rank of the highest priority. This means that for planning purposes, the utmost attention could be directed to this response in the turning process. Consequently, the correlation coefficient was determined between the MRR and each of the turning process parameters. The correlation coefficient obtained using the Microsoft Excel 2003 produced an output of correlation between the MRR and each of the speed, feed and depth of cut of the machine at a time. This produced a value of 0.1313 to relate the MRR and the spindle speed. The mean square error was obtained when the prediction is compared with the experimental data (Equation 1). The mean square error was applied to the experimental and predicted values with the following Equation (18):

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(f_{pred} - f_{\exp})^2 \quad \text{Eq. 18}$$

where N indicates the experimental trials, fpred is the symbol for the exponential smoothing model outcomes while fexp is the experimental values obtained by Nayak (2014) for the experimental trial i.

The mean square error for the MRR – spindle speed predictive error is 5919.54. Furthermore, the exponential smoothing model was used to predict the feed and the depth of cut while the dumping factors were extracted the correlation coefficients representing the associations between MRR and feed in an instance and MRR and depth of cut in the other instance. The corresponding correlation coefficient is 0.0039 for the MRR-feed association and 0.4326 for the MRR- depth of cut association. The MSE for the MRR– feed association is 0.0006 while for the MRR-depth of cut association, the MSE is 0.2973.

In this paper, entropy weight determination model was used to establish the comparative importance of all the responses used in the turning experiment. The optimum commercial dividend in the turning of an aluminium bar for the given situation, the MRR should be given the utmost attention. The next stage is to choose the MRR as the dependent variable that is influenced by the three process parameters of spindle speed, feed and depth-of-cut. The correlation coefficient was established between MRR and each of the spindle speed, feed and depth of cut parameter. The values so obtained were used as the damping factor introduced into the exponential smoothing model. Predictions were made based on the exponential smoothing model and an error measurement index, the mean square error was determined for each of the associations of MRR and each of the turning process parameters. The results obtained were the mean square error (MSE) of 5919.54, 0.0006 and 0.2973 for the respective associations between MRR and spindle speed, feed and depth of cut. The outcome suggests that the most reliable parameter that the exponential smoothing method predicted properly is the feed. The results concur with the methodology of a recent outcome of Prakash et al. (2000) that declared that feed has a substantial impact on the MRR. This confirms the workability of the model because despite more responses than MRR, the model made a distinction and was sensitive to the data with reliable results.

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Table 2. Normalized experimental data for entropy method, weighted sum model and weighted product model

	Entropy method						Weighted sum model						Weighted product model					
Sl. No.	Tool - tip Temp. (°C)	F_x (N)	F_y (N)	F_z (N)	Ra (µ-m)	MRR (mm^3/ min)	Tool - tip Temp. (°C)	F_x (N)	F_y (N)	F_z (N)	Ra (µ-m)	MRR (mm^3/ min)	Tool - tip Temp. (°C)	F_x (N)	F_y (N)	F_z (N)	Ra (µ-m)	MRR (mm^3/ min)
1	0.0329	0.0132	0.0117	0.0199	0.0106	0.0074	1	1	0.9506	0.5650	1	0.0253	1	1	0.9506	0.5650	1	0.0253
2	0.0370	0.0213	0.0195	0.0204	0.0144	0.0123	0.8902	0.6193	0.5709	0.5511	0.7345	0.0422	0.8902	0.6193	0.5709	0.5511	0.7345	0.0422
3	0.0439	0.0607	0.0483	0.0491	0.0524	0.0381	0.7500	0.2176	0.2306	0.2290	0.2022	0.1308	0.7500	0.2176	0.2306	0.2290	0.2022	0.1308
4	0.0436	0.0994	0.0915	0.0973	0.0970	0.0541	0.7538	0.1329	0.1217	0.1155	0.1093	0.1857	0.7538	0.1329	0.1217	0.1155	0.1093	0.1857
5	0.0543	0.1468	0.1400	0.1466	0.0875	0.0835	0.6061	0.0900	0.0796	0.0767	0.1211	0.2869	0.6061	0.0900	0.0796	0.0767	0.1211	0.2869
6	0.0448	0.0452	0.0359	0.0403	0.0550	0.0369	0.7335	0.2924	0.3101	0.2792	0.1926	0.1266	0.7335	0.2924	0.3101	0.2792	0.1926	0.1266
7	0.0433	0.0269	0.0274	0.0235	0.0164	0.0147	0.7595	0.4918	0.4060	0.4776	0.6459	0.0506	0.7595	0.4918	0.4060	0.4776	0.6459	0.0506
8	0.0335	0.0326	0.0639	0.0737	0.0373	0.0246	0.9804	0.4055	0.1743	0.1525	0.2844	0.0844	0.9804	0.4055	0.1743	0.1525	0.2844	0.0844
9	0.0342	0.0657	0.0571	0.0596	0.0495	0.0295	0.9615	0.2012	0.1950	0.1886	0.2140	0.1013	0.9615	0.2012	0.1950	0.1886	0.2140	0.1013
10	0.0387	0.0282	0.0239	0.0233	0.0388	0.0147	0.8499	0.4691	0.4664	0.4822	0.2733	0.0506	0.8499	0.4691	0.4664	0.4822	0.2733	0.0506
11	0.0361	0.0189	0.0193	0.0151	0.0123	0.0135	0.9119	0.7002	0.5778	0.7449	0.8588	0.0464	0.9119	0.7002	0.5778	0.7449	0.8588	0.0464
12	0.0462	0.0320	0.0520	0.0545	0.0179	0.0258	0.7126	0.4123	0.2143	0.2061	0.5917	0.0886	0.7126	0.4123	0.2143	0.2061	0.5917	0.0886
13	0.0355	0.0468	0.0477	0.0436	0.0251	0.0332	0.9259	0.2825	0.2333	0.2580	0.4230	0.1139	0.9260	0.2825	0.2333	0.2580	0.4230	0.1139
14	0.0330	0.0206	0.0160	0.0156	0.0298	0.0123	0.9967	0.6420	0.7053	0.7224	0.3553	0.0422	0.9967	0.6420	0.7053	0.7224	0.3553	0.0422
15	0.0359	0.0423	0.0300	0.0332	0.0397	0.0197	0.9174	0.3125	0.3711	0.3385	0.2667	0.0675	0.9174	0.3125	0.3711	0.3385	0.2667	0.0675
16	0.0378	0.0209	0.0178	0.0194	0.0276	0.0209	0.8696	0.6316	0.6267	0.5803	0.3835	0.0717	0.8696	0.6316	0.6267	0.5803	0.3835	0.0717
17	0.0421	0.0439	0.0432	0.0380	0.0644	0.2912	0.7813	0.3008	0.2579	0.2960	0.1647	1	0.7813	0.3008	0.2579	0.2960	0.1647	1
18	0.0348	0.0194	0.0174	0.0149	0.0190	0.0172	0.9464	0.6814	0.6398	0.7530	0.5591	0.0591	0.9464	0.6814	0.6398	0.7530	0.5591	0.0591
19	0.0355	0.0304	0.0283	0.0314	0.0262	0.0251	0.9259	0.4344	0.3935	0.3574	0.4044	0.0859	0.9259	0.4344	0.3935	0.3574	0.4044	0.0859
20	0.0408	0.0513	0.0414	0.0485	0.0381	0.0393	0.8065	0.2575	0.2689	0.2317	0.2781	0.1350	0.8065	0.2575	0.2689	0.2317	0.2781	0.1350
21	0.0389	0.0196	0.0111	0.0177	0.0388	0.0295	0.8451	0.6739	1	0.6338	0.2730	0.1013	0.8451	0.6739	1	0.6338	0.2730	0.1013
22	0.0527	0.0154	0.0344	0.0112	0.0136	0.0258	0.6237	0.8552	0.3235	1	0.7768	0.0886	0.6237	0.8553	0.3235	1	0.7768	0.0886
23	0.0408	0.0280	0.0254	0.0222	0.0552	0.0354	0.8065	0.4719	0.4380	0.5067	0.1920	0.1217	0.8065	0.4719	0.4380	0.5067	0.1920	0.1217
24	0.0408	0.0267	0.0321	0.0320	0.0623	0.0476	0.8065	0.4955	0.3470	0.3516	0.1701	0.1635	0.8065	0.4955	0.3470	0.3516	0.1701	0.1635
25	0.0430	0.0440	0.0650	0.0492	0.0707	0.0479	0.7653	0.3005	0.1716	0.2286	0.1498	0.1646	0.7653	0.3005	0.1716	0.2286	0.1498	0.1646

DOI: https://doi.org/10.26593/jrsi.v10i1.4271.1-14

Table 3. Entropy values using $r_{ij}lnr_{ij}$

Expl. No.	Tooltip Temp. (°C)	Fx (N)	Fy (N)	Fz (N)	Ra (μ-m)	MRR (mm^3/min)	$\sum_{j=1}^{n}(1-e_j)$
1	-0.1123	-0.0572	-0.0521	-0.0779	-0.0482	-0.0362	-0.0362
2	-0.1219	-0.0821	-0.0768	-0.0794	-0.0612	-0.0541	-0.0541
3	-0.1371	-0.1701	-0.1464	-0.1479	-0.1546	-0.1245	-0.1245
4	-0.1367	-0.2295	-0.2188	-0.2267	-0.2263	-0.1577	-0.1577
5	-0.1581	-0.2817	-0.2752	-0.2815	-0.2132	-0.2074	-0.2074
6	-0.1392	-0.1399	-0.1195	-0.1293	-0.1596	-0.1217	-0.1217
7	-0.1360	-0.0972	-0.0986	-0.0882	-0.0675	-0.0622	-0.0622
8	-0.1139	-0.1116	-0.1757	-0.1922	-0.1226	-0.0911	-0.0911
9	-0.1155	-0.1788	-0.1635	-0.1680	-0.1489	-0.1039	-0.1039
10	-0.1259	-0.1005	-0.0892	-0.0876	-0.1261	-0.0622	-0.0622
11	-0.1198	-0.0749	-0.0761	-0.0633	-0.0542	-0.0582	-0.0582
12	-0.1420	-0.1103	-0.1537	-0.1586	-0.0721	-0.0944	-0.0944
13	-0.1186	-0.1432	-0.1452	-0.1365	-0.0924	-0.1130	-0.1130
14	-0.1126	-0.0799	-0.0655	-0.0648	-0.1048	-0.0541	-0.0541
15	-0.1193	-0.1337	-0.1052	-0.1131	-0.1282	-0.0772	-0.0772
16	-0.1239	-0.0809	-0.0716	-0.0764	-0.0992	-0.0808	-0.0808
17	-0.1334	-0.1373	-0.1357	-0.1242	-0.1766	-0.3593	-0.3593
18	-0.1168	-0.0764	-0.0705	-0.0628	-0.0752	-0.0700	-0.0700
19	-0.1186	-0.1062	-0.1009	-0.1088	-0.0955	-0.0923	-0.0923
20	-0.1305	-0.1524	-0.1319	-0.1468	-0.1245	-0.1272	-0.1272
21	-0.1264	-0.0771	-0.0501	-0.0715	-0.1261	-0.1039	-0.1039
22	-0.1552	-0.0644	-0.1160	-0.0504	-0.0586	-0.0944	-0.0944
23	-0.1305	-0.1001	-0.0934	-0.0845	-0.1599	-0.1184	-0.1184
24	-0.1305	-0.0966	-0.1104	-0.1101	-0.1730	-0.1450	-0.1450
25	-0.1353	-0.1374	-0.1775	-0.1481	-0.1874	-0.1456	-0.1456
$\sum_{j=1}^{m} r_{ij} \ln r_{ij}$	-3.2095	-3.0192	-3.0193	-2.9984	-3.0556	-2.7542	-2.7542
e_j	0.9971	0.9380	0.9380	0.9315	0.9493	0.8556	0.8556
1- e_j	0.0029	0.0620	0.0620	0.0685	0.0507	0.1444	0.1444
W_j	0.0074	0.1589	0.1587	0.1754	0.1299	0.3697	0.3697

This work proposes a new entropy weight determination model to evaluate the relative importance of the responses within the turning process for an aluminium bar. The start of the method involves obtaining normalisation from the experimental outcomes of Nayak (2014). The normalised values were then subjected to objective weight determination within the framework of entropy method analysis. The data were then analysed by the innovative exponential smoothing model to permit prediction of process parameters.

Weighted sum model

In data analysis, the normalised values are determined to adjust the values measured on different scales to a notionally common scale and a normalised matrix is determined as shown in Equation (1) and Equation (2) for beneficial and non-beneficial criteria. Tool-tip temperature, cutting forces and surface roughness fall into the less is better criterion while MRR is a higher is better criteria since it is desired that the chips formed during machining operations should be removed at a high rate. Applying the objective weights derived from the entropy method on the normalised decision table by multiplying the weights across the corresponding cell. The weights (Wj) are 0.0074, 0.1589, 0.1587, 0.1754, 0.1299 and 0.3697 respectively (Table 2). After summing the values across row to get the preference scores, they are then ranked to select the best alternative among the 25 levels. The first alternative is seen to have the highest preference score and has therefore been assigned a rank of 1 (Table 4). It is, therefore, the best alternative out of the given 25 alternatives as analysed using Weighted Sum Model (WSM). The physical meaning when the values indicated for Experiment 1 is related to the data in Table 3 of Nayak (2014) is as follows: turn the bar at the tool-tip temperature of 30 °C, forces Fx, Fy and Fz, of 44.90N, 31.79N and 109.65 N, respectively. However, Ra should be 3.48 (μ-m) and MRR should be 4444.44 mm3/min.

Weighted product model (WPM)

The experimental data from Nayak (2014) are normalised concerning beneficial and non-beneficial criteria given by Equations (1) and (2) to aid pair-wise comparison by standardizing criteria units; weights are then applied by keeping the objective weights derived from entropy method to the power of the performance values of the table; Values are multiplied across rows to get the preference scores which is ranked to select the best alternative. The Tables 2 and 4 show the normalised decision matrix, performance values, preference score and ranks.

The normalised decision Table 3 is obtained by keeping the entropy weights in the power of the performance value as shown in Equation (7). Note that the entries in the second to the seventh column show the results of the WPN application of entropy weights across criteria. The preference score is obtained by multiplying the cells in the normalised weighted table across rows and ranked according to the magnitude as shown in Equation (8). From Table 4, it is visibly clear that run 17 attains the first rank. This is because it has a preference score of 0.4251 which is the highest in magnitude amongst all other runs. The physical meaning when the values indicated for Experiment 17 is related to the data in Table 3 of Nayak (2014) is as follows: turn the bar at the tool-tip temperature of 38.4 °C, forces Fx, Fy and Fz, of 149.25N, 117.18N and 209.27N, respectively. However, Ra should be 21.15 (μ-m) and MRR should be 175555.56 mm3/min.

WASPAS

In WASPAS, to select the best alternative from the experimental data, a joint generalized criterion was used, Equation (9), where and represent the preference scores from WSM and WPN, respectively (Table 8). From Equation (7), the preference score for WASPAS is . With λ = 0.5, Table 5 is obtained. Run 17 has the highest preference score and is therefore ranked 1st being the best amongst all alternatives. The results of the physical meaning for WPM and WASPAS are the same.

Findings

The following findings are obtained from this investigation:

1. Entropy weight determination approach is efficient to analyse the responses of the turning process, which includes tool-tip temperature, cutting force in the x, y and z directions (Fx, Fy and Fz), surface roughness and MRR.
2. The entropy method reveals the relative weights of 0.007447, 0.158863, 0.158733, 0.175395, 0.129877 and 0.369685 for the respective, Fx, Fy, Fz, Ra and MRR. This indicates MRR as requiring the highest priority possible.
3. When the MRR values were related to processing parameters of speed, feed and depth of cut, correlation coefficients of 0.1313, 0.0039 and 0.4326 were obtained. The values were weak but highest for the MRR-depth-of-cut association. However, it is surprising to observe from further analysis that the analysis of the MRR-feed was the most satisfactory using mean squared error despite its weak correction value.
4. As the MRR-speed, MRR-feed and MRR-depth-of- cut relationship was examined by the mean square error formula, the corresponding values of 5919.54, 0.0006 and 0.2973 were obtained, giving much support for a feed-MRR relationship, which has the least mean squares error.
5. From the results of the preference score and ranking for the weighted sum model, experimental number 1 was ranked as the best (rank of 1). This prompts the researcher to check the original experimental data for decisions. It is concluded that based on the WSM method, the experimental number 1 of the data collected by Nayak (2014), in Table 3 is a tool-tip temperature of 30°C, Fx value of 44.90 N, Fy value of 31.79 N, Fz value of 109.65 N, roughness average of 3.4823 -m and a metal removal rate of 4,444.44 mm3/min.
6. By comparing Nayak (2014) where the TOPSIS result attached the highest priority

DOI: https://doi.org/10.26593/jrsi.v10i1.4271.1-14

to experiment Number 17 of Table 7 (Nayak, 2014) with the weighted sum model (current paper), the following may be mentioned. The WSM's prediction is 28% less than Nayak's TOPSIS prediction. This implies that less energy is used to machine the aluminium bar, which makes it energy efficient. Thus, the WPM result is better. This pattern is maintained throughout the results obtained for other responses using WPM. Thus, Fx, Fy, Fz, Ra and MRR has an improvement of 232.41%, 268.61%, 281.71%, 52.77% and 38.50% when WPM is used. Since cutting forces Fx, Fy and Fz and MRR deal with energy and the use of energy is minimized using the WPM, the method is said to yield energy efficiency results when compared with Nayak's (2014) TOPSIS predicted results. Also, the surface roughness obtained through the use of WPM is better as lower results mean a better surface finish. So WPM is preferable to TOPSIS with the obtained prediction results of both models.

7. Since experiment number 1 is selected in the result given by WSM as the best, to obtain the best values of the input parameters values given by experiment one in the original table is read. It reveals that the optimum spindle speed is 275 rpm, while 0.08 mm/rev and 0/6mm are the optimum feed and depth of art, respectively for the turned aluminium bar.
8. From the results of preference scores and ranking for the weighted product model, the experiment trial 17 was ranked as the best (rank of 1). In checking the experimental data of Table 3 in Nayak (2014), the following values of the responses and parameters were obtained. For the responses, the optimal results were attained at 38.4 °C of tool-tip temperature, 149.25 N for Fx, 117.18N for Fy and 209.27N for Fz. The roughness average was 21.14 -m while the MRR was 175,555.56 mm3/min. These values concur with those suggested by the results of TOPSIS in Nayak (2014). Thus, these results confirm the correctness of Nayak's (2014) outcomes on TOPSIS predictions. For the parameters, the optimum parameters that correspond to experimental trial 17 are 605 rpm for spindle speed, 0.12 mm/rev for feed and 1.8 mm for a depth of cut. This concurs with the suggestion of Nayak (2014) that also picked experiment 17 as the best when the TOPSIS multi-criteria were used for analysis. By interpreting the results obtained in this work compared with Nayak's (2014) outcome, the same energy values are used to process the aluminium bar in machining. Hence the TOPSIS multi-criteria model is not superior to the weighted product model when applied to the turning data by Nayak (2014).
9. The performance scores and ranking of the outcome from the application of WASPAS multi-criteria to Nayak’s (2014) data were determined. It was noticed that experimental number 17 yielded the optimum results. This gives responses of tool-tip temperature as 38.4 °C, Fx as 149.25 N, Fy as 117.18 N and Fz as 209.27N. The value of surface roughness was obtained as 21.14 -m while the MRR yielded 175,555.56 mm3/min. The corresponding values of the parameters were also observed as follows. Using experimental 17, a value of 605rpm was obtained for spindle speed, 0.12 mm/rev was for feed rate while 1.8 mm was obtained for a depth of cut. By considering the optimal values of responses and parameters, they agree with the results that were given by Nayak (2014) using TOPSIS multi-criteria to determine the preference scores and ranks of the responses and parameters. In terms of energy efficiency, the same energy was used by the process using the results from WASPAS and TOPSIS that Nayak (2014) evaluated.

Implications of the work and contributions

Machining criteria are critical parameters to be approximated to operate the lathe machine at a highly efficient level in the subtraction industry. Efficiency will be achieved in energy optimisation because the parameters that control energy usage in the lathe machine are known in advance, prioritised and worked on. Consequently, if these parameters are analysed using multicriteria structures great utility will be observed. Consequently, understanding the challenges facing small scale and free-lance machinists when choosing the best parameters and responses for their machined components and parts offers profound insights into the manning process when considering using WASPAS in such small scale and free-lance machining activates to attain social change.

This work contributes to the turning literature by:

1. Emphasizing responses and parametric selection parameters and their unique attributes that were previously undecided in past turning research. These parameters and responses could assist in widening the understanding of machining researchers on the selection parameters and responses and the procedure to follow in the selection process.
2. Uniquely applying the theories of entropy to understand the underlying principle of diversification that guides its application, which can provide moved analysis and improvement of the current concepts in the selection of turning parameters and responses for optimal condition specifications.
3. Executing the premise of WASPAS innovatively to provide insights into the fundamental notion of the performance of an option regarding a particular criterion when the member of alternatives and criteria is specified. The principles guide its application to normalise and eventually determine the preference scores and ranks of the criteria. This principle may offer new study and enhancement of the present ideas to select responses and parameters in the turning process to attain optimal settings.

Conclusion

In this paper, three multi-criteria models, namely, the WSM, WPM and WASPAS were deployed to select the optimum operating conditions when turning an aluminium bar on a lathe machine. The three models were each used to analyse the model by normalising the data to be in the same units then further analysis was attempted to finally obtain the results. Specifically, an aluminium bar was experimentally investigated and the results recorded based on 25 sets of input parameters of spindle speed, feed rate and depth of cut. Four responses from this investigation (cutting temperature, cutting force, Ra and MRR) were recorded and used as criteria to select the optimum machining input operation. After analysing the experimental data obtained using WSM, WPM and WASPAS by applying entropy weights across the criteria, the most occurring first selection is run 17 which correspond to an input parameter of 605 rpm spindle speed, 0.12 mm/rev feed rate and 1.8mm depth of cut. The combination of these parameters is found to be the optimum in operating the machine to obtain a reasonable low cutting temperature and force with high MRR. Further investigations may be considered for hard metal (difficult-to-machine) materials. Other methods such as artificial removal network may be applied for prediction purpose in the future. Furthermore, in this work, the concerns exclude studies regarding aluminium bar deformation when machined. The dimensional accuracy, characteristics of the chip formed as well as the degree of changes regarding tool nose have all been neglected in the experimental studies by Nayak (2014), which yielded the current analysis. To bridge this gap, future efforts may be directed at these issues. In this context, future analysis using WPM, WSM and WASPAS could treat the changes in tool nose geometry, dimensions (geometry) of the chips produced in turning and the turned bar deformation as an additional response to those used in the work. The result may then analyse if the additional responses yield significant differences in the conclusions regarding the optimal responses and optimal parameters for the turned bar process. Additionally, deterministic values were considered but often in practice, the values dealt with are probabilistic. So, it may enhance the researcher's understanding of the idea of fuzzy could be incorporated into the computation to tackle the uncertainty and impression involved in measurement.

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