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A MULTIPLE CRITERIA ANALYSIS OF FACTORS INFLUENCING SURFACE ROUGHNESS OF WOOD AND WOOD-BASED MATERIALS IN THE PLANING PROCESS

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HIGHLIGHTS

Some factors influencing the surface roughness of wood and wood-based materials in the planing process are analyzed.

The FAHP method is proposed to determine the weights of the factors.

The most significant factors are feed speed, tool geometry, and material defect.

The findings of this study can be used in the wood industry to enhance product quality.

Keywords:
Fuzzy analytical hierarchy process
Multicriteria decision-making
Planing
Wood

ABSTRACT

This paper presents a study of the fuzzy analytical hierarchy process (FAHP) for the prioritization of factors having important effects on the surface roughness of wood and wood-based materials in the planing process. Firstly, a three-level hierarchical model was devised. Secondly, the FAHP method was employed to determine the weights of the factors. Finally, the prioritization of the factors was carried out taking into account the weights. The results showed that the most significant factors are feed speed (0.300), tool geometry (0.222), and material defect (0.107). Consequently, this study provides a valuable guide to the wood industry to improve the surface quality of wood and wood-based products.

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INTRODUCTION

Surface roughness can be defined as fine irregularities on a machined surface (Magoss, 2008). The surface roughness of wood influences further manufacturing processes such as joining application, bonding quality, and its strength characteristics, and the appearance of a final product (Kilic et al., 2006; Buyuksari et al., 2011; Li et al., 2017). However, the determination of surface roughness is a complex process owing to cutting processes, machining conditions, and the anatomical structure of wood (Malkoçoğlu, 2007). Although many roughness measurement methods (laser, light sectioning, pneumatic, stylus, etc.) are available, there is no accepted standard method to determine the surface roughness of wood and wood products. The stylus method has been successfully used in many studies (Tan et al., 2012; Hiziroglu et al., 2013; Ulker, 2018).

Wood materials are processed through various steps, including planing, sawing, and sanding. The surface quality of wood subjected to machining is influenced by many factors related to wood characteristics and machining conditions (Pinkowski et al., 2018). The most significant factors related to the wood characteristics are wood species, anatomical properties, density, and moisture content (Aguilera, 2011; Ugulino and Hernández, 2017). In addition to these factors, process parameters such as cutting speed, cutting depth, feed speed, and tool geometry significantly affect the surface quality of wood (Lu, 2008; İşleyen and Karamanoğlu, 2019). To improve the surface quality of the final product, it is essential to have a basic knowledge of the factors related to both wood characteristics and machining conditions (Gurleyen, 2010).

Many researchers have evaluated the effects of various factors on the surface roughness of wood (Sütçü, 2013; Lopes et al., 2014; Tiryaki et al., 2015; Tiryaki et al., 2017). The studies in the related literature have revealed that the importance of each factor is different. Therefore, the determination of the importance of factors influencing the surface roughness of wood is necessary. Multicriteria decision-making (MCDM) methods can be used to obtain the priority values of main factors and subfactors. However, tangible and intangible factors cause vagueness and ambiguity in the decision-making process. The fuzzy set theory can convert human judgments into meaningful results. Therefore, in this study, the use of the fuzzy MCDM is preferred. The fuzzy analytical hierarchy process (FAHP) is the most popular fuzzy MCDM method. Prioritizing the factors by utilizing FAHP yields supportive and logical results (Bozbura et al., 2007; Heo et al., 2010; Beşikçi et al., 2016).

The MCDM methods have been successfully employed in the field of wood science. Smith et al. (1995) employed the analytical hierarchy process (AHP) to analyze factors affecting the adoption of timber as a bridge material. Azizi (2008) selected the best wood supply alternative by employing the analytic network process (ANP) and the BOCR approach. Lipušček et al. (2010) employed the AHP method to classify wood products in terms of their impact on the environment. Azizi and Modarres (2011) selected the best construction panel by using the AHP and ANP methods. Azizi et al. (2012) used the AHP method to select the best medium density fiberboard (MDF) product. Kuzman and Grošelj (2012) compared different construction types by utilizing the AHP method. Sarfi et al. (2013) used the AHP method to analyze factors influencing the markets of particleboard and MDF. Karakuş et al. (2017) employed the technique for order preference by similarity to ideal solutions (TOPSIS), the multiple attribute utility theory (MAUT), and the compromise programming (CP) to predict the optimum properties of some nanocomposites.

There are many attempts on solving various decision-making problems in the field of wood science. However, a MCDM method has not yet been used to prioritize factors influencing the surface roughness of wood and wood-based materials in the planing process. Therefore, the objectives of this study are to determine the importance of each factor by employing the FAHP method and to provide a useful guide to the wood industry.

MATERIAL AND METHODS

Fuzzy Sets and Fuzzy Numbers

The fuzzy set theory was developed by Zadeh (1965) in order to represent the uncertainty, vagueness, and ambiguity of judgments (Lee et al., 2011). In a classical set, an element belongs to, or does not belong to, a set whereas an element of a fuzzy set naturally belongs to the set with a membership value from the interval [0,1] (Kahraman and Kaya, 2010).

The most commonly used fuzzy numbers are triangular and trapezoidal fuzzy numbers (Ebadi et al., 2013). In this study, triangular fuzzy numbers will be used to represent the linguistic terms due to their ease of calculation (Tsai and Chou, 2011). A triangular fuzzy number $\tilde{M}$ can be represented as (l, m, u), and its membership function $\mu_M(x)$ can be given as follows (Büyüközkan and Çifçi, 2012):

$$\mu_{\tilde{M}}(x) = \begin{cases} 0, & x < l \text{ or } x > u \\ (x-l)/(m-l), & l \le x \le m \\ (u-x)/(u-m), & m \le x \le u \end{cases} \quad \text{where } l \le m \le u. \qquad [1]$$

Let $\tilde{M}_1 = (l_1, m_1, u_1)$and $\tilde{M}_2 = (l_2, m_2, u_2)$ be triangular fuzzy numbers. The operations on these triangular *fuzzy* numbers are defined as follows (Lee et al., 2011):

$$\tilde{M}_1 \oplus \tilde{M}_2 = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \qquad [2]$$

$$\tilde{M}_1 \otimes \tilde{M}_2 = (l_1 l_2, m_1 m_2, u_1 u_2) \qquad [3]$$

$$\tilde{M}_1^{-1} = (1/u_1, 1/m_1, 1/l_1) \qquad [4]$$

The triangular *fuzzy* conversion scale used in this study is given in Table 1.

TABLE 1 The triangular *fuzzy* conversion scale.

Linguistic scale	Triangular *fuzzy* scale	Triangular *fuzzy* reciprocal scale
Absolutely important	(9,9,9)	(1/9,1/9,1/9)
Intermediate	(7,8,9)	(1/9,1/8,1/7)
Very strong	(6,7,8)	(1/8,1/7,1/6)
Intermediate	(5,6,7)	(1/7,1/6,1/5)
Strong	(4,5,6)	(1/6,1/5,1/4)
Intermediate	(3,4,5)	(1/5,1/4,1/3)
Weak	(2,3,4)	(1/4,1/3,1/2)
Intermediate	(1,2,3)	(1/3,1/2,1)
Equally important	(1,1,1)	(1,1,1)

Fuzzy Analytical Hierarchy Process Method

AHP is a useful method to solve complex MCDM problems involving multiple qualitative and quantitative criteria (Saaty, 1980). The AHP method breaks down a complex MCDM problem into a hierarchy of decision elements (see Figure 1). To construct evaluation matrices, pairwise comparisons must be made by experts. Once pairwise comparison matrices are normalized, the rows of these matrices are averaged to determine the importance of each decision element. Moreover, the consistency ratio (CR) can be computed to check the consistency of judgments. If the CR value exceeds 0.10, the decision-maker must revise comparisons (Saaty, 1980; Işıklar and Büyüközkan, 2007; Rajak et al., 2016).

The traditional AHP method is based on crisp judgments. However, it is very difficult to acquire

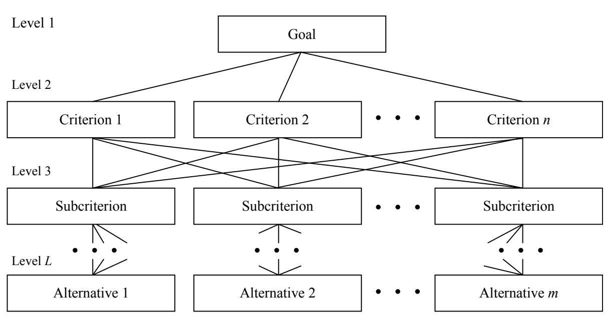

FIGURE 1 The general structure of AHP.

precise data owing to the uncertainty on the judgments of decision-makers. Each decision-maker prefers natural language expressions rather than crisp numbers. In order to capture uncertainties, the FAHP method has been employed by several researchers (Heo et al., 2010). There are various FAHP methods. Brief information about some FAHP methods can be found in Bozbura et al. (2007). In this study, Chang's extent analysis method (Chang, 1996) is used owing to its computational simplicity and effectiveness. The procedure of the FAHP approach is as follows (Bozbura et al., 2007; Beşikçi et al., 2016):

Step 1: The value of fuzzy synthetic extent with respect to the *i*th object is calculated using the following equation, where $M_{g_i}^j$ shows a triangular *fuzzy* number related to the *j*th target.

$$S_i = \sum_{j=1}^{m} M_{g_i}^j \otimes \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^j \right]^{-1} \qquad [5]$$

To obtain $\sum_{j=1}^{m} M_{g_i}^j$, the fuzzy addition operation of *m* extent analysis values is performed using Equation (6).

$$\sum_{j=1}^{m} M_{g_i}^j = \left(\sum_{j=1}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j \right) \qquad [6]$$

The fuzzy addition operation of $M_{g_i}^j$ ($j = 1,2,\ldots,m$) values is performed to obtain .

$$\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^j \right]^{-1} \qquad [7]$$

$$\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^j = \left(\sum_{i=1}^{n} l_i, \sum_{i=1}^{n} m_i, \sum_{i=1}^{n} u_i \right) \qquad [8]$$

The inverse of the vector in Equation (8) is calculated using the following equation:

$$\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^j \right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} l_i} \right) \qquad [9]$$

Step 2: The degree of possibility of 10 is defined as follows, where *d* is the ordinate of the highest intersection point between μ_{M_1} and μ_{M_2} (see Figure 2).

$$M_2 = (l_2, m_2, u_2) \ge M_1 = (l_1, m_1, u_1) \qquad [10]$$

$$V(M_2 \ge M_1) = \sup_{y \ge x} [\min(\mu_{M_1}(x), \mu_{M_2}(y))] = \text{hgt}(M_1 \cap M_2) = \mu_{M_2}(d)$$

$$= \begin{cases} 1, & m_2 \ge m_1 \\ 0, & l_1 \ge u_2 \\ \dfrac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)}, & \text{otherwise} \end{cases} \qquad [11]$$

In order to compare M_1 and M_2 the values of $V(M_1 \ge M_2)$ and $V(M_2 \ge M_1)$ are required.

Step 3: The degree of possibility for a convex fuzzy number to be greater than *k* convex fuzzy numbers $M_i (i = 1,2,\ldots,k)$ can be defined as follows:

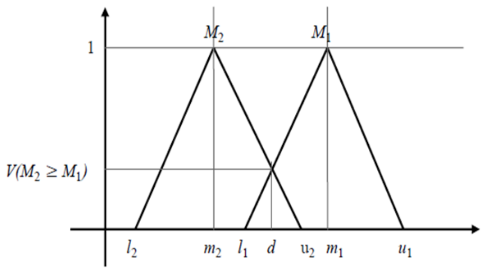

FIGURE 2 The intersection between M_2 and M_1

$$V(M \geq M_1, M_2, \ldots, M_k) = V[(M \geq M_1) \text{ and } (M \geq M_2) \text{ and} \ldots \text{and } (M \geq M_k)] = \min V(M \geq M_i),\ i = 1,2,3,\ldots,k. \quad [12]$$

Assume that 13 for 14 . Then the weight vector is given by 15 where A_i $(i = 1,2,\ldots,n)$ are n elements.

$$d'(A_i) = \min V(S_i \geq S_k) \quad [13]$$

$$k = 1,2,\ldots,n;\ k \neq i. \quad [14]$$

$$W' = (d'(A_1), d'(A_2), \ldots, d'(A_n))^T \quad [15]$$

Step 4: The normalized weight vector is obtained as below, where W is a non-fuzzy number.

$$W = (d(A_1), d(A_2), \ldots, d(A_n))^T \quad [16]$$

Fuzzy Analytical Hierarchy Process Analysis

In this study, the FAHP method is used to determine the importance of some factors affecting the surface roughness of wood and wood-based materials in the planing process. The solution methodology adopted for this study is given in Figure 3.

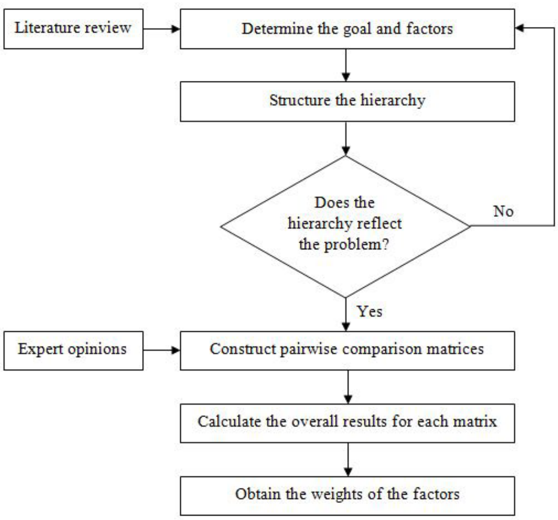

FIGURE 3 The flow chart of the research.

A three-level hierarchical model is devised to prioritize the factors. The research model is presented in Figure 4. As seen in this figure, the goal of the decision-making problem is placed at the highest level of the hierarchy. Moreover, there are four main factors at the second level and eighteen subfactors at the third level.

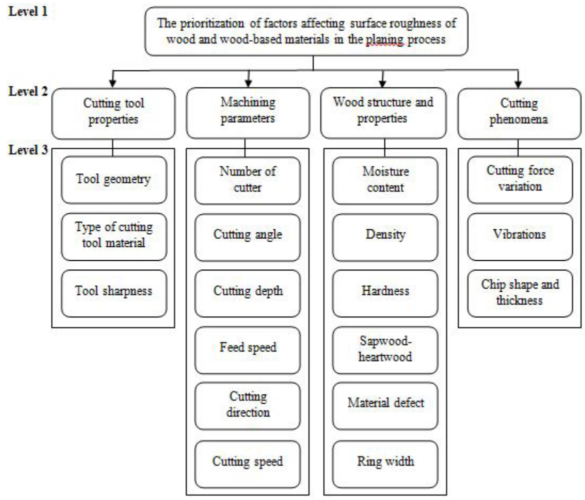

FIGURE 4 The hierarchical structure of the decision-making problem.

The main factors of this study are cutting tool properties (F_1), machining parameters (F_2), wood structure and properties (F_3), and cutting phenomena (F_4). The cutting tool properties factor includes three subfactors: tool geometry (F_{11}), type of cutting tool material (F_{12}), and tool sharpness (F_{13}). The machining parameters factor consists of six subfactors: number of cutter (F_{21}), cutting angle (F_{22}), cutting depth (F_{23}), feed speed (F_{24}), cutting direction (F_{25}), and cutting speed (F_{26}). The wood structure and properties factor is composed of six subfactors: moisture content (F_{31}), density (F_{32}), hardness (F_{33}), sapwood-heartwood (F_{34}), material defect (F_{35}), *and* ring width (F_{36}). Finally, the cutting phenomena factor includes three subfactors: cutting force variation (F_{41}), vibrations (F_{42}), and chip shape and thickness (F_{43}).

After creating the hierarchical structure, the factors used in this study are assigned weights by using the FAHP method. This method employs pairwise comparisons to determine the importance of each decision element (Işıklar and Büyüközkan, 2007). Therefore, a decision-making team consisting of wood science experts is constructed. The experts of this study are academicians who have at least 10 years' experience on surface roughness.

A questionnaire is used to collect the data. The experts use the linguistic terms to make the pairwise comparisons of the factors. It is not possible to carry out arithmetical operations with the linguistic terms. Therefore, each linguistic term is associated with a triangular fuzzy number. The overall results are computed by taking the geometric mean of the individual evaluations. The final evaluation matrix of the main factors is given in Table 2. The calculation of the weights of the main factors will be explained below.

The values of fuzzy synthetic extents are calculated using Equation (5).

TABLE 2 The comparison matrix of the main factors.

Main factor	F1	F2	F3	F4	Weight
F1	(1.000, 1.000, 1.000)	(0.485, 0.669, 0.931)	(0.855, 1.170, 1.682)	(1.414, 1.495, 1.565)	0.258
F2	(1.075, 1.495, 2.060)	(1.000, 1.000, 1.000)	(1.189, 1.495, 1.861)	(1.682, 2.340, 2.913)	0.491
F3	(0.595, 0.855, 1.170)	(0.537, 0.669, 0.841)	(1.000, 1.000, 1.000)	(1.189, 1.682, 2.178)	0.251
F4	(0.639, 0.669, 0.707)	(0.343, 0.427, 0.595)	(0.459, 0.595, 0.841)	(1.000, 1.000, 1.000)	0.000

$$S_{F_1} = (3.754, 4.334, 5.178) \otimes (14.462, 17.561, 21.344)^{-1} = (0.176, 0.247, 0.358) \quad [17]$$

$$S_{F_2} = (4.946, 6.330, 7.834) \otimes (14.462, 17.561, 21.344)^{-1} = (0.232, 0.361, 0.542) \quad [18]$$

$$S_{F_4} = (2.441, 2.691, 3.143) \otimes (14.462, 17.561, 21.344)^{-1} = (0.114, 0.153, 0.217) \quad [19]$$

$$S_{F_3} = (3.321, 4.206, 5.189) \otimes (14.462, 17.561, 21.344)^{-1} = (0.156, 0.240, 0.359) \quad [20]$$

The values of S_i are compared, and the degrees of possibility are calculated using Equation (11). Table 3 shows the values of $V(S_i \geq S_j)$.

TABLE 3 The values of $V(S_i \geq S_j)$.

$V(S_{F1} \geq S_j)$	Value	$V(S_{F2} \geq S_j)$	Value	$V(S_{F3} \geq S_j)$	Value	$V(S_{F4} \geq S_j)$	Value
$V(S_{F1} \geq S_{F2})$	0.526	$V(S_{F2} \geq S_{F1})$	1.000	$V(S_{F3} \geq S_{F1})$	0.961	$V(S_{F4} \geq S_{F1})$	0.307
$V(S_{F1} \geq S_{F3})$	1.000	$V(S_{F2} \geq S_{F3})$	1.000	$V(S_{F3} \geq S_{F2})$	0.512	$V(S_{F4} \geq S_{F2})$	0.000
$V(S_{F1} \geq S_{F4})$	1.000	$V(S_{F2} \geq S_{F4})$	1.000	$V(S_{F3} \geq S_{F4})$	1.000	$V(S_{F4} \geq S_{F3})$	0.417

The minimum of the degrees of possibility are found as follows:

$$d'(F_1) = \min(0.526, 1.000, 1.000) = 0.526 \quad [21]$$

$$d'(F_2) = \min(1.000, 1.000, 1.000) = 1.000 \quad [22]$$

$$d'(F_3) = \min(0.961, 0.512, 1.000) = 0.512 \quad [23]$$

$$d'(F_4) = \min(0.307, 0.000, 0.417) = 0.000 \quad [24]$$

The weight vector is obtained as W=(0.526, 1.000, 0.512, 0.000). After the normalization process, the weights of the cutting tool properties, machining parameters, wood structure and properties, and cutting phenomena factors are obtained as 0.258, 0.491, 0.251, and 0.000, respectively. The results obtained for the main factors are compatible with the results of Laina et al. (2017).

The same calculations are applied to the other matrices. The pairwise comparison matrices of the subfactors can be seen from Tables 4-7.

The weights of the factors are summarized in Table 8. The global weight of the subfactor can be computed by multiplying its local weight with its corresponding weight. The global weights calculated for the subfactors are presented in the last column of Table 8.

RESULTS AND DISCUSSION

In this study, the importance of each factor is determined by employing the FAHP method. The pairwise comparison matrices are obtained through experts' opinions. Then the weights of the factors are calculated. The weights calculated for each factor are summarized in Table 8.

When the weights given in Table 8 are analyzed, it is observed that the highest weighted main factor is machining parameters (0.491). Therefore, machining parameters should be considered as the most significant main factor. The subfactor with the highest weight of this main factor is tool geometry (0.860). It is followed by tool sharpness with the weight of 0.140.

The second highest weighted main factor is cutting tool properties (0.258), and the highest weighted subfactors of this main factor are feed speed (0.611) and cutting speed (0.149). From Table 8, it is clear that feed speed (0.300) is the main factor that significantly influences the surface roughness of wood and wood-based materials in the planing process.

The third highest weighted main factor is wood structure and properties (0.251), and the highest weighted subfactors of this main factor are material defect (0.425), density (0.267), and moisture content (0.246). The lowest important degree is allocated to sapwood-heartwood (weight is 0.000).

TABLE 4 The comparison matrix of the subfactors within cutting tool properties.

Subfactor	F11	F12	F13	Weight
F11	(1.000, 1.000, 1.000)	(4.120, 5.207, 6.260)	(1.189, 1.627, 2.213)	0.860
F12	(0.160, 0.192, 0.243)	(1.000, 1.000, 1.000)	(0.330, 0.435, 0.604)	0.000
F13	(0.452, 0.615, 0.841)	(1.655, 2.300, 3.027)	(1.000, 1.000, 1.000)	0.140

TABLE 5 The comparison matrix of the subfactors within machining parameters.

Subfactor	F21	F22	F23	F24	F25	F26	Weight
F21	(1.000, 1.000, 1.000)	(1.861, 2.913, 3.936)	(0.537, 0.760, 1.107)	(0.343, 0.427, 0.595)	(0.562, 0.841, 1.189)	(0.760, 1.047, 1.316)	0.120
F22	(0.254, 0.343, 0.537)	(1.000, 1.000, 1.000)	(0.485, 0.669, 1.057)	(0.193, 0.240, 0.319)	(0.473, 0.639, 0.841)	(0.325, 0.398, 0.537)	0.000
F23	(0.904, 1.316, 1.861)	(0.946, 1.495, 2.060)	(1.000, 1.000, 1.000)	(0.316, 0.380, 0.485)	(1.125, 1.612, 2.149)	(0.795, 1.107, 1.607)	0.120
F24	(1.682, 2.340, 2.913)	(3.130, 4.162, 5.180)	(2.060, 2.632, 3.162)	(1.000, 1.000, 1.000)	(2.378, 2.943, 3.464)	(2.060, 2.632, 3.162)	0.611
F25	(0.841, 1.189, 1.778)	(1.189, 1.565, 2.115)	(0.465, 0.620, 0.889)	(0.289, 0.340, 0.420)	(1.000, 1.000, 1.000)	(0.420, 0.546, 0.748)	0.000
F26	(0.760, 0.955, 1.316)	(1.861, 2.515, 3.080)	(0.622, 0.904, 1.257)	(0.316, 0.380, 0.485)	(1.337, 1.831, 2.378)	(1.000, 1.000, 1.000)	0.149

TABLE 6 The comparison matrix of the subfactors within wood structure and properties.

Subfactor	F31	F32	F33	F34	F35	F36	Weight
F31	(1.000, 1.000, 1.000)	(0.760, 0.955, 1.316)	(1.075, 1.257, 1.565)	(2.000, 2.590, 3.130)	(0.452, 0.604, 0.783)	(1.732, 2.000, 2.236)	0.246
F32	(0.760, 1.047, 1.316)	(1.000, 1.000, 1.000)	(1.189, 1.565, 1.861)	(2.632, 3.162, 3.663)	(0.427, 0.562, 0.707)	(1.278, 1.495, 1.732)	0.267
F33	(0.639, 0.795, 0.931)	(0.537, 0.639, 0.841)	(1.000, 1.000, 1.000)	(1.316, 1.682, 1.968)	(0.302, 0.435, 0.639)	(0.809, 1.075, 1.316)	0.034
F34	(0.319, 0.386, 0.500)	(0.273, 0.316, 0.380)	(0.508, 0.595, 0.760)	(1.000, 1.000, 1.000)	(0.237, 0.319, 0.411)	(0.427, 0.473, 0.537)	0.000
F35	(1.278, 1.655, 2.213)	(1.414, 1.778, 2.340)	(1.565, 2.300, 3.310)	(2.432, 3.130, 4.213)	(1.000, 1.000, 1.000)	(1.495, 1.861, 2.432)	0.425
F36	(0.447, 0.500, 0.577)	(0.577, 0.669, 0.783)	(0.760, 0.931, 1.236)	(1.861, 2.115, 2.340)	(0.411, 0.537, 0.669)	(1.000, 1.000, 1.000)	0.028

TABLE 7 The comparison matrix of the subfactors within cutting phenomena

Subfactor	F41	F42	F43	Weight
F41	(1.000, 1.000, 1.000)	(0.748, 0.904, 1.150)	(0.429, 0.537, 0.727)	0.000
F42	(0.869, 1.107, 1.337)	(1.000, 1.000, 1.000)	(0.310, 0.376, 0.500)	0.000
F43	(1.375, 1.861, 2.329)	(2.000, 2.659, 3.224)	(1.000, 1.000, 1.000)	1.000

TABLE 8 Summary of the weights

Main factor	Local weight	Subfactor	Local weight	Global weight
Cutting tool properties (F1)	0.258	Tool geometry (F11)	0.860	0.222
		Type of cutting tool material (F12)	0.000	0.000
		Tool sharpness (F13)	0.140	0.036
Machining parameters (F2)	0.491	Number of cutter (F21)	0.120	0.059
		Cutting angle (F22)	0.000	0.000
		Cutting depth (F23)	0.120	0.059
		Feed speed (F24)	0.611	0.300
		Cutting direction (F25)	0.000	0.000
		Cutting speed (F26)	0.149	0.073
Wood structure and properties (F3)	0.251	Moisture content (F31)	0.246	0.062
		Density (F32)	0.267	0.067
		Hardness (F33)	0.034	0.008
		Sapwood-heartwood (F34)	0.000	0.000
		Material defect (F35)	0.425	0.107
		Ring width (F36)	0.028	0.007
Cutting phenomena (F4)	0.000	Cutting force variation (F41)	0.000	0.000
		Vibrations (F42)	0.000	0.000
		Chip shape and thickness (F43)	1.000	0.000

The results presented in Table 8 show that the lowest weighted main factor is cutting phenomena (0.000). The ranking of the subfactors of this main factor in descending order with respective weights is chip shape and thickness (1.000) > cutting force variation (0.000) = vibrations (0.000). This ranking result shows that chip shape and thickness is the most important subfactor.

From the last column of Table 8, it can be concluded that feed speed, tool geometry, and material defect play an important role in enhancing the product quality. The wood industry should focus on the above-mentioned factors to improve surface quality. Many researchers have investigated the influence of feed speed on surface roughness. The experimental results have showed that feed speed is the most dominating factor for surface roughness (De Deus et al., 2015; Stanojevic et al., 2017; Hazir et al., 2018). Several researchers have stated that tool geometry has a large impact on the quality of the machined surface (Sinn et al., 2009; Öhman et al., 2016). On the other hand, previous studies have noted that material defect is the subfactor that significantly influences surface roughness (Sütçü, 2013; Cetiner et al., 2016). Consequently, it can be said that the results of this study are compatible with the literature.

The type of cutting tool material, cutting angle, cutting direction, sapwood-heartwood, cutting force variation, and vibrations are undoubtedly important factors. However, the obtained results indicate that the contribution of these subfactors to surface roughness is less than the other subfactors.

Wood is the basic raw material for the furniture industry. Machining is applied to wood materials to create different geometries and shapes. Surface defects due to a machining process reduce the quality of wood and wood-based products. Therefore, the analysis of factors affecting the surface roughness of wood and wood-based materials is very important. There are many studies about surface roughness. However, the use of the FAHP method to prioritize factors affecting the surface roughness of wood and wood-based materials in planing is a new concept.

The main contributions of the current study are twofold. First, the evaluation of factors influencing the surface roughness of wood and wood-based materials in planing is considered as a complex MCDM problem. Second, this study prioritizes the weights of these factors. The findings of this study are highly important from an industrial viewpoint. Consequently, it can be said that this study presents a route map for further studies on surface roughness.

CONCLUSION

The objective of this study is to prioritize some factors affecting the surface roughness of wood and wood-based materials in the planing process. Four main factors and eighteen subfactors are analyzed using the FAHP method. The data obtained from the experts are used in the prioritization model to determine the importance of the factors.

According to the prioritization model, the most significant subfactors are feed speed, tool geometry, and material defect. The wood industry should focus on these subfactors to achieve a high quality surface. Consequently, the results obtained in this study can provide a useful guide to the wood industry to improve the surface quality of wood and wood-based products. In further research, the findings of this study can be compared with the results of experimental studies.

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