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Review

Current Trends in Monitoring and Analysis of Tool Wear and Delamination in Wood-Based Panels Drilling

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Abstract: Wood-based panels (WBPs) have versatile structural applications and are a suitable alternative to plastic panels and metallic materials. They have appropriate strength parameters that provide the required stiffness and strength for furniture products and construction applications. WBPs are usually processed by cutting, milling and drilling. Especially in the furniture industry, the accuracy of processing is crucial for aesthetic reasons. Ensuring the WBP surface's high quality in the production cycle is associated with the appropriate selection of processing parameters and tools adapted to the specificity of the processed material (properties of wood, glue, type of resin and possible contamination). Therefore, expert assessment of the durability of WBPs is difficult. The interest in the automatic monitoring of cutting tools in sustainable production, according to the concept of Industry 4.0, is constantly growing. The use of flexible automation in the machining of WBPs is related to the provision of tools monitoring the state of tool wear and surface quality. Drilling is the most common machining process that prepares panels for assembly operations and directly affects the surface quality of holes and the aesthetic appearance of products. This paper aimed to synthesize research findings across Medium-Density Fiberboards (MDFs), particleboards and oriented strand boards (OSBs), highlighting the impact of processing parameters and identifying areas for future investigation. This article presents the research trend in the adoption of the new general methodological assumptions that allow one to define both the drill condition and delamination monitoring in the drilling of the most commonly used wood-based boards, i.e., particleboards, MDFs and OSBs.

Keywords: drilling; medium-density fiberboard; oriented strand board; particleboard; tool wear; wear monitoring; wood-based materials

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1. Introduction

Wood-based panels currently constitute a wide range of wood materials in terms of properties, raw materials used and intended use. Depending on the method of their production and the raw materials used, they can be divided into particleboards, plywood, High-Density Fiberboard (HDF) panels, Multi-Functional Panels (MFPs), Medium-Density Fiberboards and oriented strand boards (OSBs) [1,2]. A variety of oriented strand boards are structural insulated boards (SIPs). SIPs for construction applications are most often made based on OSBs, which are the external wall cladding, in which the insulating material

is polyurethane foam or, less often, polystyrene [3]. Medium-Density Fiberboards are materials made of fine wood fibers, compressed under high pressure. They are smooth and uniform, but they may be susceptible to edge damage. OSBs are a type of particleboard made from chips of high slenderness (ribbon chips). The chips are oriented in the board lengthwise in one direction, with the chips of the inner layer most often oriented perpendicularly to the chips of the outer layers [4].

The properties of wood-based panels depend on three basic groups of factors related to the raw materials used, the technological process of fabrication, and the structure of the panels. The strength of the wood-based material results from the resistance to the action of the external forces by its internal intermolecular cohesive forces [5,6]. In the case of OSBs, with increasing thickness, the minimum modulus of rupture (MOR) decreases, while the requirements for the modulus of elasticity (MOE) remain unchanged [5]. To determine the mechanical properties of wood-based panels, similar tests are used as in the case of metals, i.e., the tensile test, compression test, bending test and hardness measurements. The main factors include the density and quality of the raw material, the qualitative and dimensional factors of the particles obtained from it and the density and density profile of the manufactured boards [5]. When assessing the quality of wood-based panels, a general rule is adopted that strength properties increase with the increase in the density of the material. The density of the material is directly influenced primarily by the density of the raw material and the parameters of the pressing process. Knowledge of the density distribution on the cross-section of wood-based materials is extremely important due to the properties of the boards [7]. In addition to the wood raw material, the properties of the manufactured boards are also influenced by chemical substances introduced in the process, such as glues, resins, hydrophobic agents, etc. These properties directly affect how the panels are machined and therefore are relevant to the study of tool wear and delamination during the drilling process. The drilling effects are inherently linked to these material properties.

The use of wood-based panels in industry usually requires machining, for example, by milling or drilling. The machining of wood-based panels is carried out on high-performance CNC machines with the possibility of machining with continuously variable cutting speeds and feed rates. The machining of wood-based panels is as demanding as the machining of polymer-based and metal-based composite materials [8]. The cutting speed and feed rate are machining parameters (Figure 1) that play a key role in the process of blunting drill bits, and they are important to ensure the appropriate quality of hole machining [9]. Cutting process parameters are closely related to machining efficiency [10]. Machining parameters that are too low speed lead to not only increased tool life but directly reduce production efficiency [11]. The variable internal structure of the boards and the content of adhesive resins generally affect the deterioration of their processing quality and faster blunting of tools compared to solid wood. Drill wear is also a result of the contamination of the workpiece material with hard elements [12,13]. Drilling investigations conducted by Borysiuk and Wilkowski [5] showed that, in relation to cutting resistance (Figure 2) and surface quality at entry and exit (Figure 3), there is a significant diversification of the tested parameters among different types of wood-based panels. Delamination factor A was determined according to the methodology presented in Figure 4. When determining relative machinability indices, the MDF was used as a reference material. Obviously, a higher value of the relative index means better machinability for a given criterion [14].

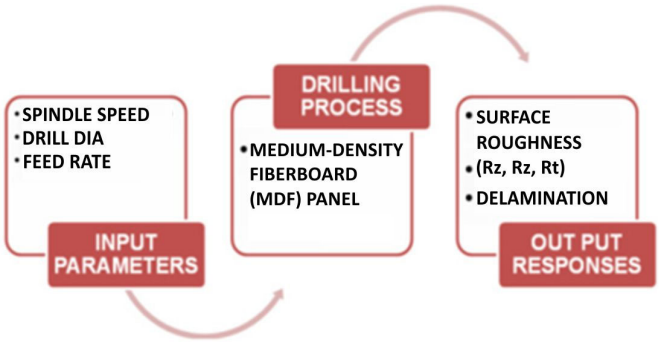


Figure 1. Relations between the input and output parameters in drilling process of MDFs (reproduced with permission from Reference [15]; Copyright © 2015 Elsevier Ltd.).

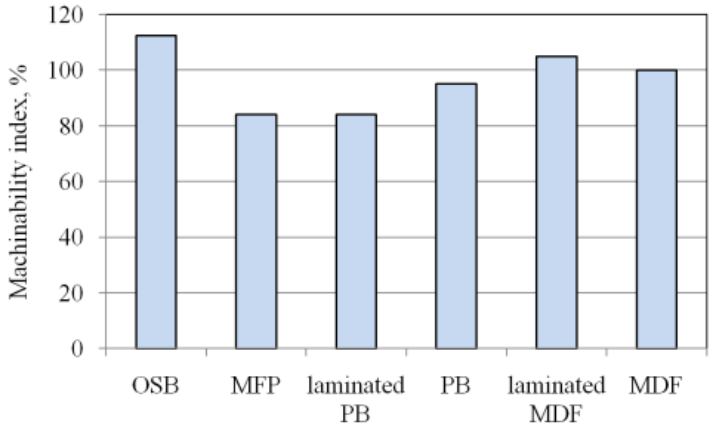


Figure 2. Comparison of the machinability index (cutting resistance when drilling) prepared on the basis of [5].

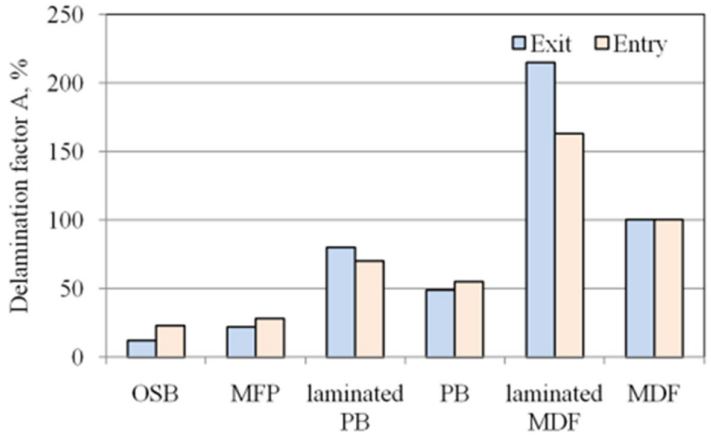


Figure 3. Comparison of the delamination factor at entry and exit of the holes prepared on the basis of [5].

Tool durability T is a value that directly characterizes cutting time or indirectly characterizes the number of operations performed, machined components, or the length of the cutting path until the blade becomes blunt. Manufacturing tools with increasingly better utility properties is the basis of every modern technology [16]. Increasing tool durability fully justifies the increased cost of the material used. In the case of steel tools, the selection of the right steel grade, the correct course of technological operations of manufacturing, heat and thermochemical treatment and the application of wear-resistant coatings are very important [17,18]. Especially in the case of simultaneous multi-tool machining, the requirements for the quality and reliability of tools are growing, and the conditions of their

operation are becoming increasingly difficult to achieve. Increasing the efficiency of tool operation by increasing their durability, efficiency and reliability is still one of the main indicators of increasing production efficiency [10,19]. Low tool durability (indicating a rapid rate of wear of the cutting edges) clearly indicates the low level of machinability of the processed material. The wear of cutting tools and the costs (both direct and indirect) associated with it are usually a significant problem in industrial practice [14].

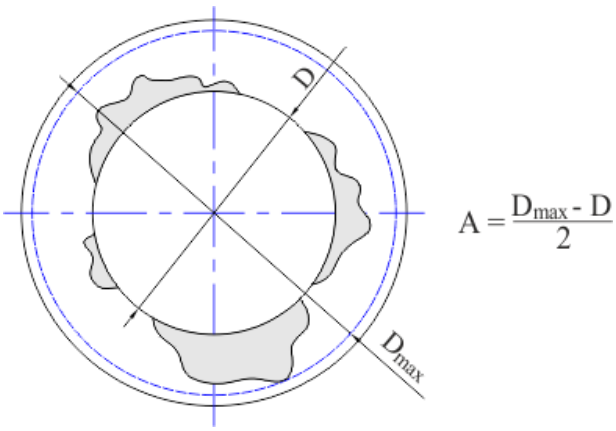


Figure 4. Method of determining delamination factor.

Tool wear, related to the change in tool geometry, is a complex problem resulting from the interaction of many mechanisms. During machining, tools are subjected to high unit pressures and high temperatures. Wilkowski and Wieloch [14] discussed the character of tool wear due to abrasive wear, adhesive wear, diffusion wear, thermal wear and chemical wear. Mechanical abrasive wear occurs when the phenomenon of removal of blade material particles occurs as a result of micro-cutting and the engagement of the peaks of surface asperities [16]. This type of wear may occur between the tool surface and any hard contaminants contained in the boards being machined. Adhesive wear is a phenomenon of very strong adhesion (bonding) of particles of co-rubbing materials under the influence of intermolecular forces [17,20]. Diffusion wear is caused by the penetration of atoms from the blade material into the workpiece and vice versa [9,21]. Chemical wear is caused by the chemical interaction of oxide layers and other chemical compounds on the contact surfaces of the blade with the workpiece. High temperature in the contact zone causes microstructural changes in the tool material that can even lead to plastic deformation of the blade [22]. The quality of the machined surface of wood-based panels is an important factor influencing the final appearance of the product, its mechanical properties and subsequent technological processes [23]. The basic parameter characterizing the quality of the machined surface is its topography characterized by roughness parameters. The surface quality after the machining process depends on the geometry of the cutting tool and its material [24], the properties of the processed material [25], the type of machining process [26], the machining parameters [27] and the grade of the workpiece material [28]. In industrial practice, various types of drills are used, which are adapted to the diameter of the hole, the type of material being drilled and the required surface quality: spade (feather) drills, step drills, spiral drills and crown drills are used for machining large diameter holes. Due to their different construction and cutting conditions, these tools require an individual approach to assessing wear indicators.

Drill condition monitoring systems are based on signals generated during drilling (vibrations, cutting force components, acoustic emission, electrical power) [29]. The hole quality, and thus indirectly the tool condition, can also be monitored offline [30,31]. Statistical parameters (skewness, mean value, kurtosis, etc.) are commonly used as diagnostic

features of the cutting process, derived directly from sensor signals in the time domain. Świderski et al. [32] concluded that the best monitoring results can be obtained by using torque and cutting force transducers. However, due to the high cost of these sensors and the difficulty of mounting, the authors recommend using vibration sensors, which, despite their lower accuracy, are easier to mount. The effectiveness of acoustic emission sensors (microphones) in the analysis of machine processes of wood and wood-based materials is controversial because they are susceptible to background [13,33].

Currently, in highly automated woodworking and wood-based panel processing machines, various approaches are used to monitor the condition of tools. The complexity of the machining process requires solutions based on sensors and signal analysis using analytical methods [34], artificial intelligence methods (Artificial Neural Networks—ANNs), machine learning [35,36], autoregressive models [37] and fuzzy systems [38]. Analytical methods such as analysis of variance (ANOVA) are used to determine the drilling parameters' impact and how they interact [39]. Statistical diagnostic feature models can also be generated using wavelet transformations [38,40]. The division of the main optimization techniques for solving the relationships between process inputs and outputs is presented in Figure 5.

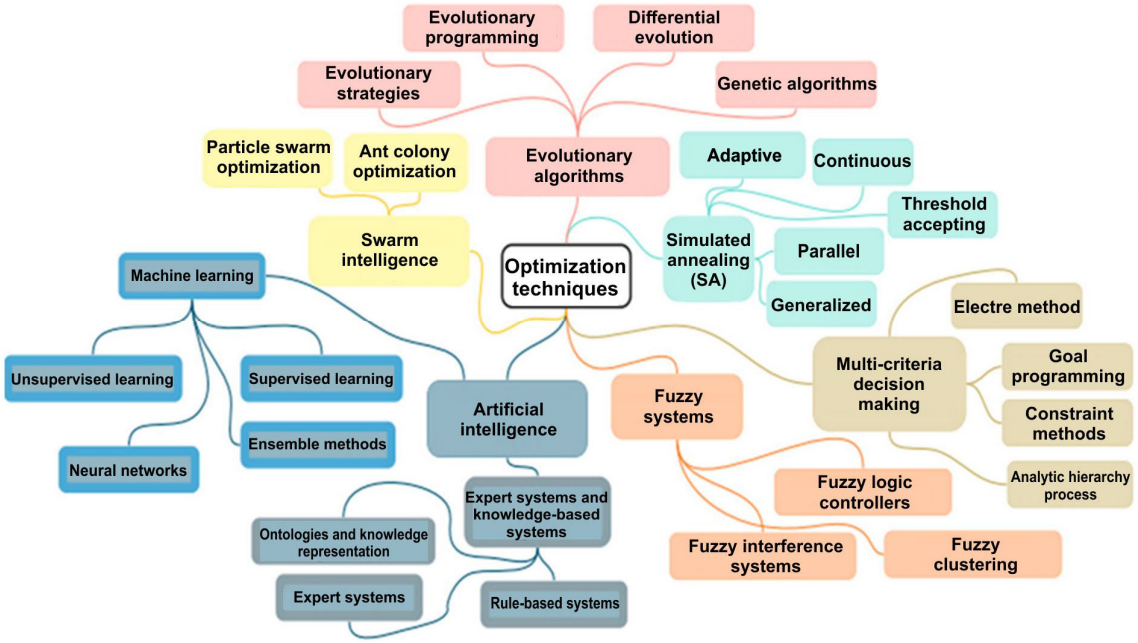


Figure 5. Classification of the optimization method (reproduced from Reference [41]).

In the last decade, the use of machine learning algorithms in the wood industry has been growing rapidly. Despite the growing popularity of artificial intelligence (AI) methods, there are some problems with the use of, for example, deep learning solutions or ANNs. First, these methods require large training sets to work correctly. The greater the amount of data required, the greater the complexity of the analyzed problem. Second, these methods have limited predictive capabilities for the range of output data that were not included in the training set [42].

This paper aimed to synthesize research findings across particleboards, MDFs and OSBs, highlighting the impact of processing parameters and identifying areas for future investigation. Section 2 presents the research methods and the main conclusions concerning the monitoring of the drill bit's condition when drilling holes in particleboards. The influence of the processing parameters on the surface quality of holes drilled in MDFs and their relationship with drill bit wear is presented in Section 3. Section 4 presents the results of the research on OSBs. Section 5 contains the main conclusions from the literature review.

2. Particleboard Drilling

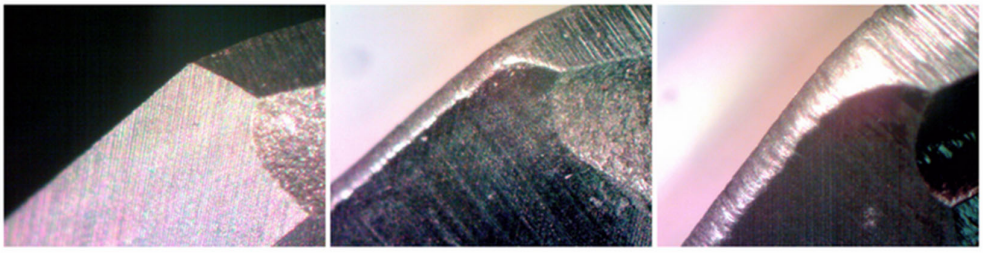
Particleboards are one of the most popular materials used in furniture production. They are made of specially pressed wood chips connected with synthetic glue. They are suitable for sanding, veneering and laminating. Their types are divided into those bound with synthetic and mineral agents, depending on the binder used. However, these boards are only suitable for dry places because they quickly soak up and swell in contact with water. Next to MDF panels, this is the most commonly used material group of wood-based panels.

Kurek et al. [43] classified the wear state of drills with tungsten carbide tips during drilling laminated particleboards as "useless" (worn) and "useful" (sufficiently sharp). Their research focused on the selection of appropriate diagnostic variables to classify the tool state into the above-mentioned two classes. Statistical parameters describing the change in cutting torque, feed force, vibrations, acoustic emission and vibrations were used to classify features using Fourier and wavelet representations. The recognition of drill state (class) was performed using a Decision Tree, Support Vector Machine and Random Forest (RF) of multivariate decision, the results of which were compared with each other. The sequential feature selection algorithm ensured the selection of significant machining features in the time domain. The best results of drill wear recognition were obtained for the RF classifier with an error value below 4%.

Jegorowa et al. [42] used hole images to classify drill wear during the drilling of a melamine-faced particleboard. A regular drill equipped with a tungsten carbide tip was used in the experiments. The wear of the external corner was adopted as a drill condition indicator. Based on the value of this parameter, the wear was classified into three classes: green (good tool condition), yellow (requires operator attention) and red (tool to be replaced) [44]. Convolution neural networks were used to classify images into individual drill condition classes. The best classification accuracy achieved was 80.49% for the largest window used [42].

The application of neural networks for tool wear analysis was combined with the transfer learning methodology [45] based on signals from different sensors, with an accuracy exceeding 93%. The classification index value can be improved by using advanced image recognition algorithms, such as Image Net [46], deep convolutional neural networks [47] and pre-trained networks that include a set of classifiers [48].

Kurek et al. [30] used a Siamese network to classify the wear of double-blade drills equipped with a tungsten carbide tip into three classes (Figure 6) mentioned in the above paragraph. The network was trained based on images of the edges of holes drilled in melamine-faced particleboard. The approach proposed in this article to wear classification is much simpler in the data collection methodology because it does not require specialized sensors to collect signals that are the basis for assessing tool wear. The advantage of the presented methodology is its high universality because, in the case of changes in the drilling process, transfer learning can be used to retrain the previous model. The obtained accuracy of drill wear classification exceeded 82%. The use of Siamese networks is relatively new and requires further research [30].



(**a**) Green (**b**) Yellow (**c**) Red

Figure 6. View of outer drill corner for different classes (reproduced from Reference [30]).

The authors of [45] analyze the application of convolutional neural networks and data augmentation techniques [46,49] to propagate the wear of a regular drill equipped with a tungsten carbide tip during the drilling of laminated particleboards. In contrast to classical deep learning methods, transfer learning requires much smaller training data sets in the form of hole images. The authors used artificial augmentation of the training data of the pre-trained AlexNet network [50]. The pre-trained network required only minimal interference in the last layers and the trained network model had good generalization properties for recognizing wear classes. In another article [51], the size of training data was artificially increased by simple graphic operations (adding noise, scaling and rotation). In this way, the prediction accuracy was increased from about 67% to 95.5%. Unfortunately, this was associated with an increase in the number of images from 600 to 33,300 and an extension of the training time to 20 h.

Świderski et al. [32] presented an automatic approach to monitor the drill condition during the machining of melamine-faced particleboards. An analysis of the measuring signals of cutting torque, feed force, vibration, noise and acoustic emission allowed the selection of 19 features, which were used by classifiers. The TreeBagger machine learning algorithm was extended with a classifier ensemble methodology and compared with the results generated by the Support Vector Machine, K-Nearest Neighbors (k-NNs) algorithm, Naive Bayes classification and Deep Learning (DL) approaches. In the considered problem, the best accuracy results (around 96%) were obtained for the Treebagger, SVM and DL approaches.

Świderski et al. [52] developed an automatic system for online monitoring of drill wear during the machining of laminated chipboards and particleboards. A two-state criterion of drill bit quality was adopted: sharp and worn. The input attributes for the classifier were diagnostic features derived from cutting torque, acoustic emission, feed force and vibration signals. A Support Vector Machine classifier was used for the sequential selection of the feature set. The relative recognition error in the leave-one-out mode of operation varied from 3% to 5%. The same machining signals were used by Yegorova et al. [53] to classify the three-state tool condition (sharp, warning, replacement required) using the k-NN algorithm. The classification accuracy at k = 12 was 76%. The worn tool condition was never considered by the classifier as a sharp tool. Moreover, only about 2% of the real worn drills were recognized as a warning condition. In another article, Jegorova et al. [36] developed an approach to tool condition monitoring in which instead of signals obtained from sensors, an approach of analyzing images of drilled holes in melamine-faced particleboards was used. Five classifiers were used to analyze the edges of holes: Multilayer Perceptron (MLP), Radial Basis Function (RBF) neural network, k-NN, RF and SVM. The analyzed task was used to determine the moment of tool replacement. RF was the best, with a prediction accuracy close to 100%. Three features were enough to properly assess the tool condition: the surface of the holes, circumference and major axis of the ellipse circumscribed on the hole.

The effectiveness of predicting tool change timing using transfer learning, deep learning and classifier ensemble analysis methods has been confirmed in previous works by Kurek et al. [48,51]. Ispas et al. [54] combined the drill wear rate with the quality of the pre-laminated particleboard drilling process to determine the minimum visual resources (drill images) needed to assess the tool condition. The effective delamination area and the delamination coefficient of the hole edges were evaluated. It was found that delamination of pre-laminated particleboard can be avoided by a low feed rate and the use of small point angle drills.

In [55], the durability of drills with cemented carbide blades during the drilling of melamine-faced particleboards was evaluated. Analysis of variance was used to evaluate

the quality of holes, and the output factors were the delamination and maximum radius R_{max} and area of delamination A (Figure 7). Cutting torque and thrust force were acquired using a piezoelectronic dynamometer. The wear parameters of the blade were assumed as the wear of chord length of corners VB_{KE} and wear of the tool flank VB_{max} (Figure 8). It was found that the wear of the flank surface of the drill blade mainly determines the value of thrust force. Moreover, the value of VB_{max} and the cutting speed are correlated with the value of the cutting torque signal.

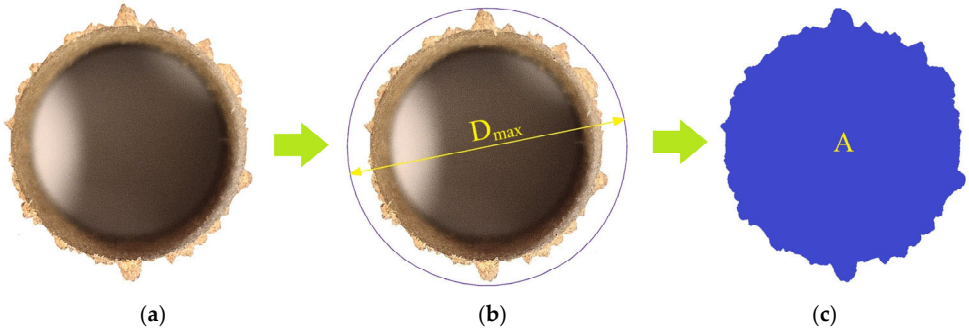


Figure 7. (**a**) Photo of the hole edge and the method of determining the parameters (**b**) R_{max} and (**c**) A.

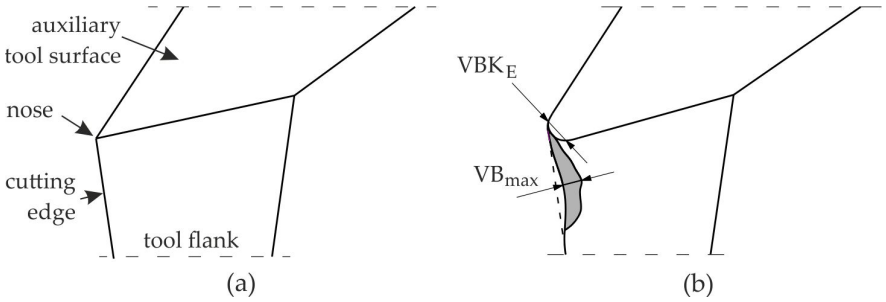


Figure 8. Drill bit wear parameters: (**a**) new tool and (**b**) worn tool.

In machine learning, the selection and extraction method of features is a critical task to ensure the efficiency of tool wear assessment. Antoniuk et al. [56] compared different feature extraction methodologies for the condition of holes made in laminated particleboard. The authors trained 38 sets of different classifiers. The presented approach focuses on the detailed evaluation of different feature extraction approaches. Each selected method produced a set of features, which were then used to train the selected set of classifiers. Five initial feature sets were obtained, and additional ones were derived from them. In the ensemble approaches, different voting methods were used. A total of classifiers (k-NN, Extreme Gradient Boosting, Random Forest, Light Gradient Boosting, Support Vector Machine) were created and evaluated based on features obtained using different extraction approaches: wavelet image scattering, hand-crafted features, deep and shallow embedding features and Histogram of Oriented Gradients (HOG) approaches. The selected feature set was supplemented with a set of features determined using Principal Component Analysis (PCA). The difference between the worst and best solution instances reached about 11%. The best was the XGBoost classifier (64.27%); however, the sensitivity of classification algorithms to selected features was observed. In general, the type of features obtained using different extraction methods has a significant impact on the accuracy of the model. The final result is a compromise between the accuracy of the solution related to the amount of training data and the complexity of the solution.

Czarniak et al. [57] investigated the effectiveness of different types of Physical Vapor Deposition (PVD) coatings: multi-layer TiN/AlTiN and two-layer TiAlN/aC:N during drilling of raw three-layer particleboards. Two-edge drills were tested. The assessment of

the condition of the coated blades was compared with the reference material, which was cemented carbide. The scope of the blade assessment was divided into two phases, before and after drilling 800 holes. Based on the analysis of variance, it was confirmed that in the first phase, both coatings showed an advantage over the cemented carbide drill. After drilling 800 holes, only the TiN/AlTiN coating was statistically more effective than the uncoated tool. The obtained results confirmed the results of previous works [58,59] that in the processing of wood-based materials, the TiN/AlTiN coating shows an advantage over the two-layer TiAlN/aC:N coating. Other coatings used on tools for woodworking and wood-based materials are aluminum compounds (AlTiN, AlCrN and TiAlN) [58,60] and titanium (TiCN and TiN) [61]. The extension of tool life is also achieved by modifying the subsurface layer of the tools using ion implantation [62,63]. The advantage of this method is the lack of the need to heat the tools, which can result in microstructural changes in the material. The implantation temperature usually does not exceed 100 °C [64]. Implantation involves changing the material properties without adding additional layers that may cause delamination or adhesion problems [65].

The analysis of wear of ion-implanted high-speed steel (HSS) drill bits during blind drilling of a three-layer particleboard is presented in [64]. For nitrogen implantation, an implanter without a mass-separated ion beam was used. Based on the measurement of the maximum size of the corner wear, the wear curves of the drill bits were determined (Figure 9). The modification of the surface layer of the drill bit extended the tool life. The average extension of the tool life was 17% compared to non-modified HSS drill bits (Figure 9). The authors also conducted a research campaign aimed at selecting the optimal parameters of accelerating voltages of the nitrogen ion implantation process, and an acceleration voltage of 40 kV provided the highest quality of the implantation.

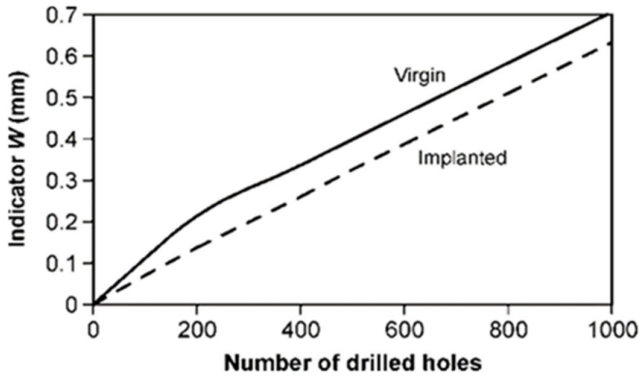


Figure 9. Drill wear curves (reproduced from Reference [64]).

Sieradzki et al. [66] improved the classification of holes in laminated particleboards using Explainable Artificial Intelligence (XAI). Three convolutional neural networks (ResNet101, VGG19 and VGG16) were evaluated. Gradient-Weighted Class Activation Mapping (GWCAM), Local Interpretable Model-agnostic Explanations (LIME) and cross-validation of hole images divided into three categories according to the drill wear state (red, yellow, green) were used to interpret the model results. It was proven that the integration of CNNs with XAI techniques increases the reliability of the drilling condition monitoring systems. The best results were obtained for the VGG19 model with an accuracy of about 67%. A comparison of GWCAM and Local Interpretable Model-agnostic Explanations showed that both methods correctly detected influential regions in the images, although LIME provided more detailed information and was not susceptible to regions that misled the model. By understanding the characteristics that influence the decisions of XAI techniques, it is possible to improve the reliability of automated systems for monitoring the

condition of drill bits [66]. XAI algorithms have been used to identify anomalies in images used for failure analysis in industrial applications [67,68].

An automated concept for monitoring the drill condition during drilling holes in particleboards was developed by Kurek et al. [69]. Ten techniques were evaluated in terms of overall accuracy and the number of misclassification errors: k-NN, Gaussian Naive Bayes, Light Gradient Boosting, Stochastic Gradient Descent, Extreme Gradient Boosting, RF, DT, Support Vector Machine, Gradient Boosting and Multinomial Naive Bayes. The highest accuracy (about 93%) was achieved by the Extreme Gradient Boosting algorithm. At the same time, this algorithm was characterized by the absence of misjudgments in the extreme states of the tool: sharp tool (green) and worn tool (red). Generating signal features using the Short-Time Fourier Transform allowed for the extraction of more detailed variables than the classic Fast Fourier Transform.

Bedelean et al. [70] used Artificial Neural Networks and response surface methodology to determine the optimal parameters of the drilling process of particleboards. Neural network models were created using the cascade correlation algorithm. Experimental data from the literature were used to train the neural networks. The parameters analyzed were the tool (tooth bite and angle of the drill tip), cutting parameters (drilling torque and thrust force) and machining quality (the delamination factor at the outlet and inlet). Furthermore, two types of drills were investigated, flat and helical, with tip angles between 30° and 120°. The delamination factor at the outlet is most dependent on the drill type. The drilling torque is most dependent on the tooth bite. The research presented in [70] is a continuation of the previous works [54,71,72] in which the results of the feed rate and the tip angle of drills on the delamination of laminated particleboard were presented. The increase in the tip angle causes a decrease in the torque and an improvement in the surface quality of the holes. At the same time, the decrease in the tip angle affects the decrease in the thrust force and the decrease in delamination.

Ispas et al. [71] monitored the drill wear state during the machining of pre-laminated particleboards using two dimensionless parameters: the delamination coefficient based on the measurement of the diameters of the circles defining the defect and the delamination index proposed by the authors and determined on the basis of the delamination area. Both parameters were analyzed using image analysis. The four flat drills with tip angles of 30°, 60°, 90° and 120° were considered. The best machining quality was provided by the drill with a tip angle of 60° while ensuring the lowest thrust force. The larger the tip angle, the greater the reduction in torque. The beneficial effect of reducing the tip angle was the reduction in thrust force and delamination. In another article by Ispas et al. [54], the same research methodology was generally used as in [71]. The only difference was testing helical drill bits with the point angle between 30° and 120° and one spur drill bit. The delamination of the hole edges was greatest for the spur drill bit and increased with the increasing feed rate, with less delamination on the exit side of the drill. The best machining quality was provided by the twist drill with a tip angle of 90°.

The aim of the research by Kumar and Jayakumar [73] was to determine the effect of HSS drill geometry (twist and spade) on the surface roughness of holes drilled in particleboards. The tests according to the orthogonal plan (L9) with variable feed, spindle speed and machining conditions showed that the average surface roughness Ra decreased with increasing tool rotational speed. The lower the feed rate, the higher the value of the mean roughness parameter Ra. Due to its construction, the spade drill showed worse performance in terms of machining time and surface quality of holes.

Bukowski et al. [74] focused on adapting the loss function in the XGBoost algorithm used to predict drill wear during the drilling of melamine-faced particleboards. The drill wear after experimental tests was classified into three classes: green (sharp tool), yellow

(warning state; the tool is approaching its replacement period) and red (the tool requires immediate replacement). Several variants of the weighted edge penalty function and the Weighted Softmax Loss Function were investigated to meet the increased importance of accurate class classification. Based on the analysis of over 800 image counts, it was found that the adaptive Weighted Softmax Loss Function significantly reduces critical errors in multiclass classification. While the Adaptive Weighted Softmax Loss Function (AWSLF) shows better performance in reducing critical errors, it comes at the cost of increased computational time. This function is preferred in applications where reducing critical classification errors is of utmost importance. Softmax and Weighted Softmax Loss Functions provide lower computational demand but at the cost of lower critical error reduction efficiency.

The aim of investigations by Valarmathi et al. [75] was to analyze the effect of cutting conditions on the thrust force during the drilling of pre-laminated particleboards using carbide twist drills. This task was carried out based on the response surface methodology, where the variable parameters were feed rate, spindle rotational speed and drill tip angle. The authors presented and discussed a typical course of changes in the thrust force signal (Figure 10). The lowest thrust force was observed at a low feed rate and high spindle speed. An increase in feed rate increases the thrust force, while a decrease in spindle speed increases the thrust force.

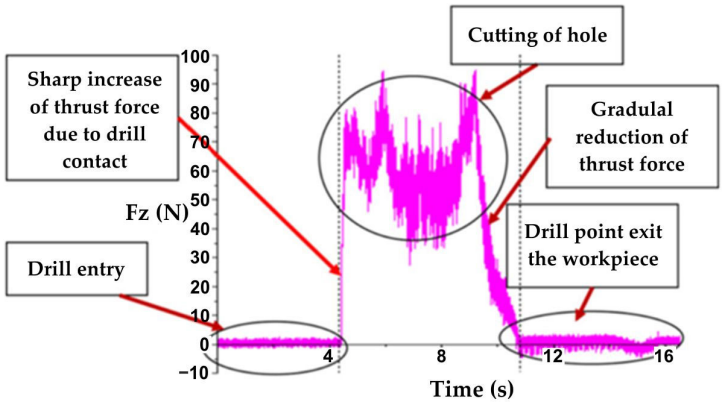


Figure 10. Thrust force signal change during particleboard drilling (reproduced with permission from Reference [75]; Copyright © 2012 Elsevier Ltd.).

Auchet et al. [76] focused on investigating the influence of formaldehyde's rate in particleboards on thrust force during drilling Low Formaldehyde Emission (LFE) particleboard. Contaminants, which are more abundant in LFE particleboards, increase tool wear. The authors investigated equal feed rate configurations during machining with twist drills of different diameters with a round spurt and point spurt. It was found that the formaldehyde emission rate and spindle speed have no effect on the thrust force during the drilling of LPE particleboards. Drill diameter has the largest relative effect on the thrust force of about 43% after the effect of the feed rate (35%). The spur type has the smallest (10%) effect on thrust force.

Kumar and Jayakumar [77] studied the effect of machining parameters during the drilling of particleboards with twist and spade drills on the surface quality of holes. The surface quality decreased with the decrease in the feed rate and the increase in the rotational speed of twist and spade drills. The authors observed that the use of kerosene reduced the machining time and provided better mean roughness Ra of the hole surface compared to other coolants.

3. Medium-Density Fiberboard Drilling

MDFs consist of a mixture of wood fibers (finely ground wood) and organic compounds, which are processed and pressed at very high temperatures. MDF material is hard and uniform, with a density between 500 and 1000 kg/m^3. The appropriate finishing of MDFs with laminate, polyvinyl chloride (PVC) foil or varnish increases its aesthetic value, thanks to which MDFs are commonly used in the furniture industry. This group of wood-like materials includes Low-Density Fiberboards (LDFs), which are used for the production of insulation boards and wall panels. High-Density Fiberboards (HDFs) are a material with increased density in relation to MDFs, characterized by high hardness and resistance to mechanical damage. In furniture, it is used for the production of furniture bodies, and in other applications, it is used for the production of floor panels.

In relation to drilling, MDFs, together with particleboards, are the most studied materials. The effect of drill tip angle on hole quality was studied by Ispas and Răcășan [78]. It was determined that a lower delamination coefficient during low feed rate drilling can be obtained by using drills with a small tip angle. Increasing the cutting speed reduces the delamination effect, while increasing the feed rate adversely affects the surface quality of holes [79,80]. Therefore, Valarmathi et al. [81] found that a low feed rate and high spindle speed should be used when drilling MDF.

Many traditional approaches have been used to determine the optimal process parameters in drilling MDFs: response surface methodology [81], Taguchi optimization methods [82] and Grey Relational Analysis [15]. Palanikumar [83] and Ayyildiz et al. [84] found that surface roughness has the greatest influence on feed rate. The Taguchi optimization method used by Gaitonde et al. [85] allowed for a reduction of the delamination factor during the drilling of MDFs by reducing the feed rate and increasing the cutting speed. The second group of methods for optimizing the MDF drilling process in terms of tool wear and hole surface quality includes artificial intelligence (AI) methods, such as machine learning, Artificial Neural Networks (ANNs), SVM and Neuro-Fuzzy learning. Nasir and Cool [86] used ANNs to predict dust emissions during wood processing based on signals received from an acoustic emission sensor. Rabiei and Yaghoubi [87] used ANNs and the Bees Algorithm (BA) to optimize the processing time and surface roughness during the machining process, taking into account factors such as the spindle speed and feed.

The aim of the study by Davim et al. [88] was to establish the correlation between the parameters of the MDF drilling process (feed rate and spindle speed) on delamination around holes. This study showed a different delamination pattern for two types of MDF panels named SUPERPAN DECOR (melamine coating layer) and LAMIPAN PB (wood coating layer) (Figure 11). In the case of both workpieces, the delamination coefficient decreased with the decrease in the feed rate and increased with the decrease in the cutting speed. SUPERPAN DÉCOR and LAMIPAN PB were also the test materials to determine the relationship between the cutting speed, feed rate and hole delamination coefficient according to the Taguchi orthogonal table (L18) [89]. By using higher cutting speeds, it is possible to reduce the delamination tendency. At low spindle speeds, delamination increases with increasing feed rate. However, at high cutting speeds, hole delamination was minimal and did not depend on the feed rate.

The application of digital image analysis techniques to the analysis of defects in drilled holes showed a relationship between machining parameters and hole damage on the entry and exit sides [90,91]. Studies on drilling MDFs showed that higher cutting speeds support the rapid material removal process and minimize delamination effects. Zhao and Ehmann [92] proposed a new helical grill bit for machining MDFs. Drilling with the proposed tool showed lower torque and thrust force. These parameters have a direct relationship with the tool wear rate [88].

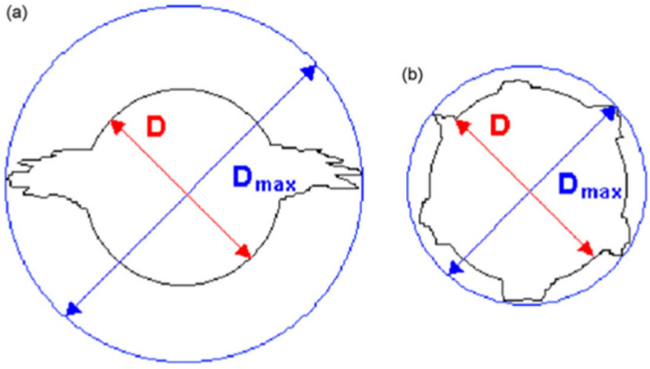


Figure 11. Delamination of (**a**) LAMIPAN PB and (**b**) SUPERPAN DECOR panels (reproduced with permission from Reference [88]; Copyright © 2007 Elsevier B.V.).

Bedelean et al. [85] proposed a combined ANN and response surface methodology approach to optimize the drilling process of MDFs using flat and spherical drills. Quantitative evaluation of the delamination phenomenon was performed for a wide range of drilling parameters. Specifically, the relationship of these parameters with the values of thrust force, drilling torque and delamination coefficient at the inlet and outlet was investigated. Drill type, tooth bite and drill tip angle were also considered as independent variables. Drill type was found to be a key parameter influencing the hole surface quality and thrust force. A twist drill is more efficient in terms of energy consumption when drilling MDFs. Twist drills also provide better surface quality after machining compared to flat drills [85]. By using a lower feed rate and higher cutting speed, it is possible to reduce the delamination tendency when drilling MDFs using carbide drills with two specific spurts [80,88,89]. In another paper, Bedelean et al. [34] used RSM and ANNs to predict hole delamination, thrust force and cutting moment in a wide range of wood-based materials, i.e., particleboards, MDFs and plywood. It was found that thrust force is most dependent on the drill type. The feed rate was identified as the most critical factor influencing the drilling moment and thus drill wear [34]. The change in cutting moment and thrust force is directly related to tool wear [80,93].

Szwajka et al. [23] investigated the effect of the type of tool coating (TiAlN and ZrN) on the cutting torque, thrust force, drill temperature and surface roughness of the hole when drilling MDFs. Based on the experimental drilling tests and their analysis using variance analysis, it was concluded that the value of the maximum tool temperature depends on the feed rate, cutting speed and type of tool coating. Increasing the tool temperature not only affects the deterioration of the hole surface quality but also reduces its durability. The authors identified five areas of thrust force changes (Figure 12) when drilling MDF with variable density over the thickness. The effect of different materials in the process of machining MDFs was also the subject of the study by Djouadi et al. [94]. They found that the main advantage of using a tool made of polycrystalline diamond is its extended durability compared to conventional tool materials such as tool steel and HSS.

Lin et al. [95] analyzed the influence of MDF components on their board machinability. A digital camera was used to record the chip formation. This study proved that board density and untreated particles have a key influence on the machinability of MDFs. Davim et al. [91] established a relationship between machining parameters and damage to holes on the entry and exit sides drilled in MDFs based on the corrected delamination coefficient. Digital analysis of hole surface images showed that a combination of high productivity with the minimization of delamination can be achieved by using a higher cutting speed. Gaitonde et al. [82] proposed a methodology to reduce delamination using ANOVA and Analysis of Means (ANOM) according to the concept of multifunctional

characteristics of Taguchi design (L9). Delamination can be minimized in MDF drilling by using lower feed rates and higher cutting speeds, but an appropriate combination of these interrelated parameters should be used.

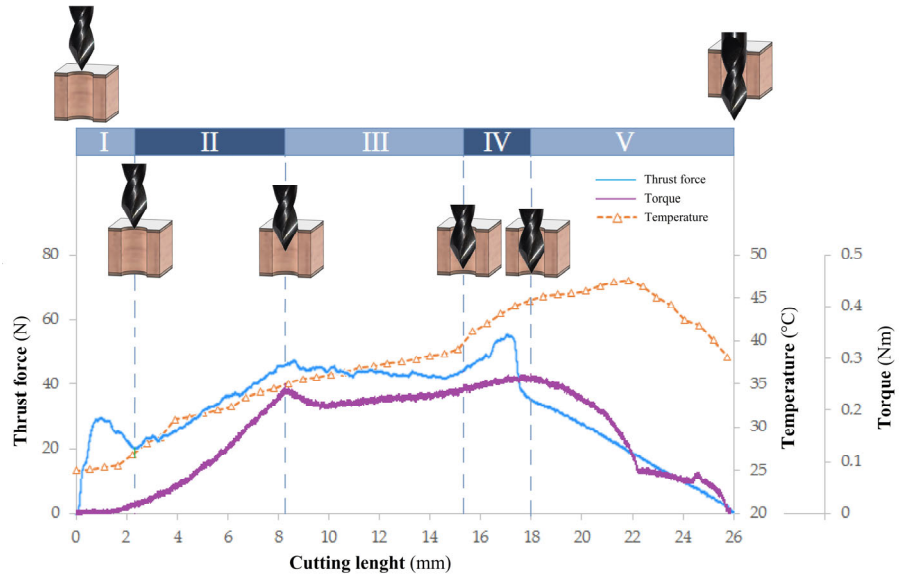


Figure 12. Variation in temperature and process parameters in the MDF drilling process.

Prakash et al. [15] used Gray Relational Analysis (GRA) to determine the effect of drilling parameters on delamination and surface roughness (Ra, Rz, Rt) of holes drilled in MDFs. Based on the gray grade matrix, it was determined that feed rate and drill diameter were most responsible for surface damage of holes during drilling with solid carbide step drills. Palanikumar et al. [79] used an orthogonal design and ANOVA to analyze the drilling process of MDF using carbide twist drills. The drill diameter and feed rate were the main parameters related to the delamination of the board surface. To reduce the damage to the board, the authors recommend a small drill diameter, low feed rate and high spindle speed.

Szwajka et al. [96] conducted comparative drilling experiments of MDF, high-pressure laminate, plywood board and particleboard. The aim of the research was to adjust the feed and cutting speed of various materials to ensure optimal machining efficiency and enable smart drilling based on the "on-line" selection of cutting parameters. The authors proposed a method for identifying the type of material using the Short-Time Fourier Transform (STFT) to automatically adjust cutting parameters during drilling based on process signals. Material identification based on STFT uses the evaluation of dominant frequency amplitudes depending on the material being processed. In the previous paper [97], Szwajka analyzed the axial force and cutting torque signals during the drilling of MDFs. He proposed a methodology to determine the average values of the signals to avoid random changes in the values of these signals. The proposed machinability index did not depend on the cutting parameters, which facilitates the analysis of the machining process.

Shirzaei et al. [98] proposed a randomized factorial design using ANOVA to analyze the delamination of holes in MDFs. The authors focused on the interactive effect of the feed rate, spindle speed and drill diameter on the delamination coefficient of holes. Digital image processing methods were used to digitally image the edges of holes. It was found that the parameters that had the greatest effect on delamination were, in decreasing order of significance, the feed rate and drill diameter. Tool material and tool coating influence the nature of tribological phenomena in the contact zone and the MDF machinability [23,99].

4. Oriented Strand Board Drilling

An OSB is an oriented strand board used mainly in construction. OSBs are produced as single- or multi-layer boards. Their main task is to meet the strength criteria. The surface quality of OSBs and the quality of the edges after processing are usually of secondary importance. For this reason, research studying drilling in oriented strand boards is limited.

Górski et al. [100] compared the workability of several types of wood–plastic particleboards and wood-based panels including raw OSBs. The authors presented the characteristics of the density distribution of wood-based panels and the change in density between different types of panels. Two key indicators of relative workability were determined (cutting force problem index and quality problem index). The workability of wood-polystyrene and wood-polypropylene boards was relatively good and similar to the standard raw particleboard. The worst quality was characterized by holes in OSB panels, which, due to their structure, are difficult to process and ensure low surface roughness of holes.

Chen et al. [101] tested the workability and structure of OSBs and other water-based boards (particleboard, MDF and plywood). X-ray analyses determined that different types of boards have different characteristics of density distribution over thickness and different density variations (±3–6%). This is also confirmed by the results of the study by Chen and Wellwood [102]. This determines the need to ensure optimal machining parameters adapted to the type of board material and their adjustment during the drilling process of OSBs. According to the studies by Brochmann et al. [103] the density of OSBs is highly important in determining thickness swell values, and the structure of OSBs is responsible for the large variability between internal bonds.

Podziewski et al. [104] analyzed the effect of feed rate during the drilling of Multi-Functional Particleboards, laminated particleboards and OSBs on the value of thrust force and drilling torque. The results revealed that at low values of feed per revolution, the thrust force was the smallest for the OSB panel. However, at high feed rates, the thrust force during drilling OSB was greater than during drilling raw particleboard and laminated particleboard.

5. Discussion

Automation and monitoring of production processes, including wood-based panel processing, is necessary to ensure appropriate processing efficiency and economic benefits [32,34]. The trend of sustainable production development is in line with the concept of Industry 4.0, which has recently transformed into Industry 5.0, and there are even known announcements of introducing the next phase of industrialization as Industry 6.0 [105]. Modern manufacturers practically only use automated high-performance machine tools that allow for uninterrupted work. However, humans are still needed to control and manage processing tasks [29].

The key is to control the wear of the tool, which directly interacts with the processed wood-based panels and is subject to natural abrasive and adhesive wear. Drill condition monitoring systems are based on signals generated during drilling. The basic signals used to monitor the condition of the drill include vibrations [32,43,52], cutting force components [32,43,55], acoustic emission [43,86] and electrical power [29]. Tool condition monitoring and testing systems require specialized sensors. The effectiveness of acoustic emission sensors in the analysis of drilling processes of wood and wood-based materials is controversial because they are susceptible to background [13,33]. As noted by Świderski et al. [32], the best monitoring results can be obtained by using cutting force and torque transducers. However, due to the high cost of these sensors and the difficulty of mounting, the authors recommend using vibration sensors are recommended [32]. Unfortunately, fully autonomous drill condition monitoring systems are at the initial development

stage and are awaiting effective solutions [29]. The effectiveness of advanced AI-based systems, such as ANNs [36], Explainable Artificial Intelligence [66], machine learning methods [35,36], Siamese networks [30], autoregressive models [37], Gradient-Weighted Class Activation Mapping [66], wavelet transformations [38,40] and fuzzy systems [38,39] for monitoring tool wear and hole surface quality has been confirmed in the analyzed publications. However, most authors point out the need to develop a useful form of obtaining reliable diagnostic data, which are necessary for training AI algorithms. The greater the amount of data required, the greater the complexity of the analyzed problem [42]. A Decision Tree, Support Vector Machine [52], Stochastic Gradient Descent [69], Random Forest algorithm [36], Light Gradient Boosting [56], data augmentation techniques [46,49], K-Nearest Neighbors (k-NNs) algorithm [36,52], Naive Bayes classification [52,69], DL approach [52] and transfer learning methodology were also successfully applied to recognize the drill state [43,45]. The tool wear classification methodology developed by Kurek et al. [30] does not require specialized sensors to collect signals, which are the basis for assessing tool wear. In the developed approach, the Siamese network was trained based on images of the edges of holes drilled in melamine-faced particleboards.

Delamination is a major technological problem when drilling in wood-based panels. This phenomenon is mainly the result of tool tip wear or incorrect cutting process parameters. Conclusions regarding the influence of these parameters on the delamination phenomenon vary depending on the type of drill used, machining parameters and the type of wood-based panel. Ispas [54] concluded that delamination of pre-laminated particleboard can be avoided by using a low feed rate and small point angle drills. Bedelean et al. [70] found that the delamination factor at the outlet is most dependent on the drill type. They also observed that the decrease in the tip angle affects the decrease in the thrust force and delamination, which is in agreement with the results of Ispas et al. [71]. At the same time, the increase in the tip angle causes a decrease in the torque and an improvement in the surface quality of the holes [70]. The best machining quality when drilling particleboard was achieved by the twist drill with a tip angle of 90° [54]. The surface quality of holes drilled in particleboards decreased with the decrease in feed rate and the increase in rotational speed of twist and spade drills [77]. It has been confirmed in most publications that increasing the cutting speed reduces the delamination effect, while increasing the feed rate adversely affects the surface quality of holes [79,80,82,85,88,89,91]. Davim et al. [89] concluded that at high cutting speeds, hole delamination was minimal and did not depend on the feed rate. To reduce the damage to the MDF, Palanikumar et al. [79] recommend a small drill diameter, low feed rate and high spindle speed. Shirzaei et al. [98] found that the parameters that had the greatest effect on delamination were the drill diameter and feed rate.

6. Conclusions

Wood-based panels are gaining increasing interest in many engineering and construction applications. They are easy-to-manufacture materials, and waste wood can be used for their production. Wood-based panels are connected in a way that requires through or blind holes. Drilling plays an important role in ensuring the strength and durability of the structure. The analysis of the most important achievements in monitoring the drilling process of the most common types of wood-based panels leads the authors to the following conclusions:

- Selecting the right drills, along with the appropriate material and coatings, for wood-like board processing is crucial to achieving high-quality holes and precision drilling. The delamination of the hole edges is greatest for the spur drill bit and increases with

an increasing feed rate. The best machining quality is provided by the twist drill. Twist drills also provide better surface quality after machining compared to flat drills.

- The optimization of drilling parameters is a key factor influencing the quality and efficiency of the machining process. The influence of individual machining parameters, the type of drill and its geometry is not unambiguous. The research results presented in the literature link the influence of individual machining parameters with the type, density and physicochemical properties of wood-based panels, the coolants used, the type of drill material and the stiffness of the machine–holder–tool system. However, the key parameters mentioned by most authors include the spindle speed and feed rate, whereby increasing the rotational speed of the drill and reducing the feed rate lead to an improvement in the quality of holes drilled in wood-based panels.
- Spindle speed is one of the most important drilling parameters. Too high a speed can cause the tool to overheat and damage the material. Too low a speed causes too high a cutting force, which can lead to vibration and damage to the tool. The feed directly affects the value of thrust force, the damage to the surface of the holes and the processing time.
- Monitoring the condition of drills during machining involves many strategies, using the signal from sensors to measure machining force parameters, vibration, noise and acoustic emission. This requires the use of advanced algorithms to filter the signals and determine the features potentially related to the identification of changing tool wear. Currently, feature extraction solutions based on artificial intelligence techniques, including ANNs and machine learning, dominate.
- There are solutions available to assess tool wear status based on the analysis of hole edge images as a direct link between tool damage and drill tip wear. Hole images are used as datasets for machine learning, digital image correlation techniques and drill wear prediction. These approaches are further enhanced by data augmentation and the selection of appropriate classifiers. Literature analysis indicates the need to develop a systematic methodology to select the most convincing feature extraction methods adapted to the type of boards and drills.
- When drilling multi-layered, wood-based panels with non-uniform structures, the quality of the drilled surface influences not only aesthetic features but also affects the potential stress localization in the vicinity of the hole edges. The optimal selection of drilling parameters and the monitoring of the tool condition can minimize or even prevent such defects.

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