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CRITICAL SYNTHESIS OF CNC WOOD MACHINING RESEARCH IN THE INDUSTRY 5.0 ERA

BY

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Abstract. This paper reviews computer numerical control wood machining research published between 2020 and 2025, exploring how to choose cutting parameters so that surface quality, energy use, tool wear, and environmental impact are balanced. Wood’s anisotropy, hygroscopicity, and biological variability make it so different, even for the same species or board. Two clear shifts have emerged. Optimization work is moving from one-factor-at-a-time experiments toward multi-objective methods built on neural networks, genetic algorithms, and hybrid artificial intelligence schemes. In parallel, edge computing and predictive maintenance are bringing real-time decision-making down to the machine itself. Two gaps also stand out: few studies test sensors and artificial intelligence models under dusty, high-vibration conditions, and existing digital twins remain static and ignore the internal stresses, knots, and grain irregularities revealed during cutting. The paper closes by arguing for a total-process view of sustainability, optimizing surface quality, dust emissions, auxiliary energy use, and tool life simultaneously.

Keywords: Cutting parameters, surface roughness, process optimization, sustainable manufacturing, Smart Automation.

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1. Introduction

Wood has become a manufacturing material that moves toward greener production with lower environmental impact and a stronger emphasis on natural aesthetics (Garcia *et al.*, 2024; Hermawan *et al.*, 2023). CNC machines have become the workhorse of this transition, since they deliver geometric accuracy and repeatability that complex furniture parts and high production volumes both demand. Another capability of CNC machines is delivering good surface quality (low roughness) at the lowest possible specific energy consumption (kWh/m³) while keeping tool wear under control (Çakıroğlu *et al.*, 2022; Pinkowski *et al.*, 2024; Rabiei and Yaghoubi, 2023). Manufacturing sectors try continuously improving the processes, beginning with classical parameter optimization and moving toward the integration of artificial intelligence (AI), with the goal of turning CNC machines into predictive systems that can adapt to material variation in real time (Kariz *et al.*, 2024).

Most of the studies considered here come from the 2020–2025 period. The dominant topic remains the search for cutting parameters that produce the best possible surface, which entails considering the material, the cutting variables, and the machine itself together. Surface finish matters not only for the look and feel of the finished part, but also because it determines how much sanding, finishing, and reworking the next process step will need.

The tendencies didn't change during the time, manufacturers demand a clean surface, fast cycle times, low scrap, infrequent tool changes, controlled tool wear, and minimal energy use, all in the same shift. With the advent of AI-based technologies, it is slightly integrated into more processes and operations.

Several of these objectives pull in opposite directions. Pushing for a finer surface usually wears the tool faster, and a worn tool that is left in service eventually produces rejects. The same fine-surface settings tend to slow the process down, lengthen cycle times, and raise the energy bill, at least under classical single-objective optimization.

AI offers a way to automate some tasks of decision-making, but it is not totally free. This usually requires an initial capital investment, operator training, and a non-trivial integration effort with existing equipment and software. A realistic adoption time is at least a year, during which other parts of the operation often suffer while resources are redirected. Even though the development of the usable AI system itself is difficult, it has to be done, as it offers a big contribution for the future, where AI could be a competitive advantage for the conquerors.

Environmental performance is the other major objective. Controlling dust, fumes, and noise is mandatory by law in most jurisdictions, but the authorities consider this tendency and new laws appear. Also, compliance costs money that decreases the profit, main objective of a business. Managers look for combinations of parameters and equipment that hold environmental impact below the legal threshold.

The present paper analyzes the CNC wood machining research from 2020 to 2025. The aim is to state where current optimization methods do and do not deliver, and the trends most likely to shape the next generation of production lines. The central question is how to balance surface quality, processing time, energy consumption, and tool wear under realistic industrial conditions, rather than under any single criterion in laboratory isolation.

The contributions of this paper are threefold. First, it brings the recent methodological literature together in one place and assesses what each method delivers in practice rather than in principle. Second, it compares solutions across four linked criteria, namely energy, surface quality and tool wear, processing time, and sustainability, instead of treating them as separate problems. Third, it identifies the gaps that have so far blocked broader uptake of AI for adaptive control on composite wood substrates and indicates which of those gaps are realistic targets for near-term work.

2. Material Foundations: Anisotropy, Variability, and Machining Challenges

Wood-based materials range from solid timber to processed composites, and that spectrum largely determines how they behave during cutting. Solid wood is the hardest case, since every board has the biological variability of the tree it came from (Kariz *et al.*, 2024). Engineered products such as medium-density fiberboard (MDF) and particleboard are more uniform, because the manufacturing process redistributes fibers and binders, so the local defects are absorbed in the volume of material (Garcia *et al.*, 2024). What does not change across these categories is that the cellular structure of wood and the orientation of its fibers have an influence on both output parameters: surface quality and the energy required to remove material (Hermawan *et al.*, 2023).

Wood is orthotropic: its mechanical and physical properties differ along the longitudinal, radial, and tangential axes of the fibers (Rabiei and Yaghoubi, 2023). The angle between the tool path and the grain has a big influence on the cutting resistance. Cutting along the grain shears the cells in a different mode than cutting across them, and this directly changes how does each fiber separate. The visible consequences are torn-out fibers, crushed cells, and other surface defects that depend on how the material responds to the cutting force and stress (Çakıroğlu *et al.*, 2022). Because the wood's response shifts with grain orientation, any process design has to account for the property variations.

Three intrinsic properties have an effect on the tool–workpiece interaction: density, moisture content, and fiber direction. Higher-density species require higher cutting forces and more specific energy to remove material (Pinkowski *et al.*, 2024). Moisture content acts on plasticity, so wetter fibers deform rather than fracture, which leaves a fuzzy surface; very dry stock embrittles, splits unpredictably, and produces more airborne dust (Hermawan *et*

al., 2023). Local variations in fiber orientation are harder to control. Earlywood–latewood transitions and embedded knots impose non-uniform loads on the spindle, so even a well-tuned program produces variable surface textures and roughness values across a single board (Rabiei and Yaghoubi, 2023). These properties together explain why wood machining is harder to stabilize than metal cutting: the substrate, not the program, sets most of the limits.

Figure 1 collects these factors in a single Ishikawa diagram. The diagram is useful less as a quantitative tool than as a way of keeping the full set of cause elements in view when discussing parameter choices.

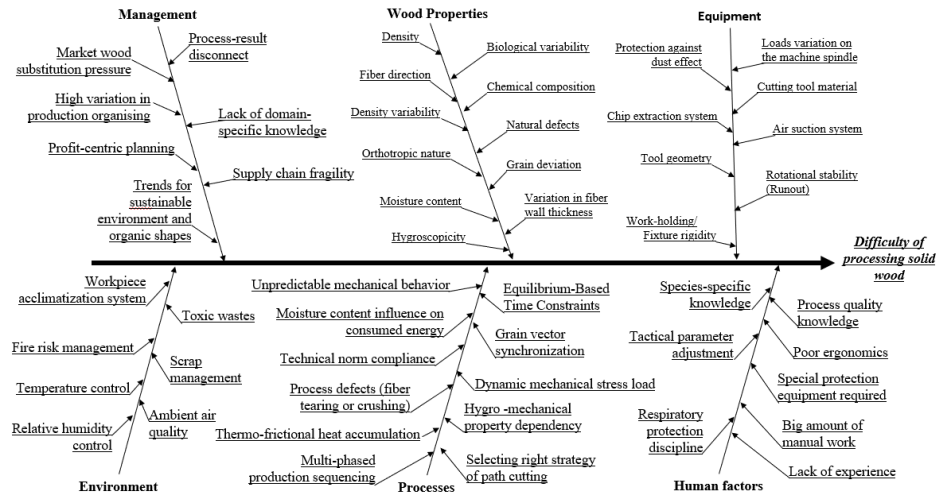


Fig. 1 – Ishikawa diagram for visualizing the factors that make processing solid wood difficult.

3. Cutting Parameters and their Impact on Energy Efficiency and Surface Integrity

3.1. Energy Dynamics and Methodological Optimization

Energy efficiency is no longer treated only as a cost lever; it is a sustainability metric, and the literature uses specific energy consumption (*SEC*), expressed in [kWh/m³] or [kJ/mm³] of material removed, as the headline indicator. Reducing *SEC* requires breaking the cycle into stages and assigning energy figures to each. Since energy *E* is power *P* multiplied by time *t* (Eq. (1)), Fig. 2 shows the contribution of each stage of a typical CNC machining cycle.

$$E = P \cdot t \quad (1)$$

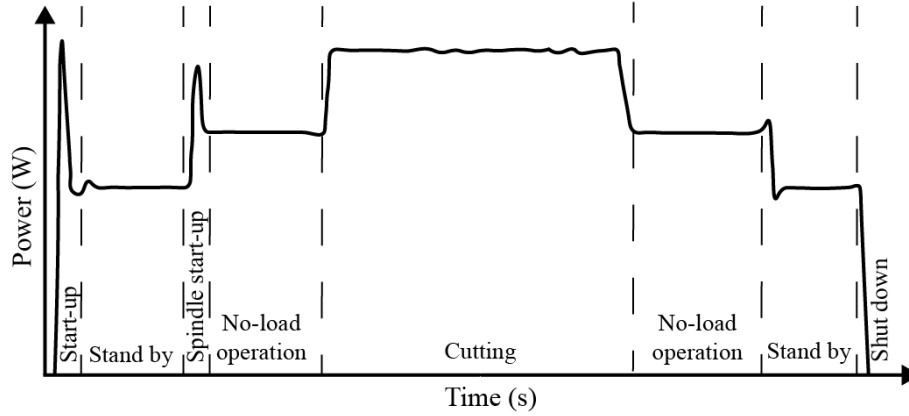


Fig. 2 – Representation of energy consumption in the processing stages of a CNC machine (adapted from Zhao *et al.*, 2020).

Cutting itself accounts for only part of the energy bill, as Fig. 2 makes clear. Zhao *et al.* (2020) decompose the total consumption as in Eq. (2):

$$E_{total} = E_{cutting} + E_{standby} + E_{spindle0} \quad (2)$$

where: E_{total} represents the total power consumption, $E_{standby}$ is the power consumed by the machine in standby mode (idle state while powered on) and $E_{spindle0}$ is the power consumed during the air-cutting (no-load) rotation of the spindle.

Figure 2 and Eq. (2) make the same point from different angles: cutting itself accounts for only part of the energy used during a job. Auxiliary energy, consumed while the spindle idles, retracts, or repositions, is the part that most plants still leave on the table when looking for savings.

The methodologies used to minimize energy consumption span a wide range, from classical experimental designs to neural networks and other AI-based approaches. The classical end of the spectrum relies on direct experimentation and on tools such as regression, graphical analysis, analytical models, and Taguchi designs. These approaches are well suited to testing specific hypotheses or isolating the contribution of a single mechanism.

A common next step is to combine Design of Experiments (DOE) with statistical tools such as ANOVA (Korkmaz *et al.*, 2024; Pinkowski *et al.*, 2024). DOE/ANOVA reliably identifies parameter combinations that satisfy a target, but it rarely returns the actual trade-off optimum when several objectives conflict. The trade-off matters because cutting parameters are coupled. A higher-quality surface usually calls for higher spindle speeds, lower feed rates, smaller tool diameters, and shallower passes. The same settings increase processing time and,

because the spindle runs longer at high speed, total energy consumption. The practical task is therefore to fix an acceptable threshold for the dependent variable (typically R_a) and then find the parameter set that meets it in the shortest time with the lowest energy use.

The more recent direction in the literature is multi-objective optimization (MOO), where the algorithm explores the parameter space rather than picking the best row from a fixed experimental table. Common tools include artificial neural networks (ANNs), backpropagation neural networks (BPNNs), genetic programming (GP), the group method of data handling (GMDH), the bee algorithm (BA), and genetic algorithms (GAs). For problems with several conflicting objectives, these methods generally produce better solutions than classical approaches and do so faster once the model has been trained.

Hybrid methods that chain two or three of these techniques tend to be the most accurate. The typical recipe is to collect a focused experimental dataset, to fit a learned model to it, and then to run a metaheuristic search over that model.

Rabiei and Yaghoubi (2023) used GMDH to build a neural-network-style surrogate model and then applied the bees algorithm to search it; the resulting parameter set improved the process by 23% compared with the best experimental result. Gürgeç *et al.* (2022) followed a similar pattern with an ANN and a genetic algorithm. Both groups argue that the combined approach finds usable industrial settings without the time and capital cost of a much larger physical experiment.

3.2. Surface integrity, tool wear and material interactions

The quality of the machined surface, primarily characterized by surface roughness (R_a), depends on both the material and the way the cut is set up. Demir *et al.* (2022) list the substrate-side variables as wood species, density, mechanical strength, moisture content, and fiber direction. The process-side variables that interact with them include spindle speed, feed rate, depth of cut, tool sharpness, cutting-edge radius, rake angle, cutting direction, and process-induced vibration.

The literature points consistently to the same recipe for a finer surface: higher-density wood, lower feed rates, higher spindle speeds, and sharp tools (Demir *et al.*, 2022; Ibrisevic *et al.*, 2023a). However, better surface quality means faster tool wear, higher energy consumption, and longer cycle times (Pinkowski *et al.*, 2024). Worn tools increase both cutting forces and spindle power as the edge degrades, and the *SEC* follows suit (Zhao *et al.*, 2020; Pinkowski *et al.*, 2024). Pushing too hard on either productivity or surface quality therefore accelerates the wear that undermines both.

Table 1 represents the parameters that were used in several experimental tests found in the literature. The output parameter was set as surface roughness, which differs from case to case, being influenced by the input parameters considered in the table: density, spindle speed, feed rate, depth of cut and cutter diameter and material.

Table 1
Parameters that have influence on the roughness

Wood Species	Density ρ , kg/m ³	Spindle speed, n , RPM	Feed rate, f , m/min	Depth of cut, d , mm	Cutter diameter, D , mm	Surface roughness, R_a , μm	Source
Beech	710	17930	2.37	2.8	6	4.36	Rabiei and Yaghoubi, 2023
Scotch Pine	510	17900	3.0	9.7	11	3.8314	Gürgeç <i>et al.</i> , 2022
Walnut	640	18000	3.8	3.0	3	4.22	Cakiroglu <i>et al.</i> , 2022
Ash	670	14800	3.4	3.0	6	2.37	Cakiroglu <i>et al.</i> , 2022
Scots Pine	510	6000	3.0	-	10	6.651	Korkmaz <i>et al.</i> , 2024
Beech	710	12000	6.0	-	10	8.255	Korkmaz <i>et al.</i> , 2024
Poplar	450	18000	-	-	10	9.732	Korkmaz <i>et al.</i> , 2024

Several strategies have been tested as compromises between these demands. Adding cutting edges or moving to a finer abrasive grit improves surface quality and decreases the tool wear rate. Thermal pre-treatment of the wood changes its properties, but raising the treatment temperature beyond a low threshold does little to improve the final finish. Toolpath strategy also matters, among conventional milling, climb milling, and raster strategies, raster milling tends to produce the lowest R_a values. Other levers identified by Yaghoubi and Rabiei (2024) include raising spindle speed (to reduce feed per tooth), using smaller tool diameters (to reduce contact friction), and using lower rake angles (to limit deformation forces).

The effect of feed rate is less settled. The majority view is that higher feed rates degrade surface quality, but several studies report either the opposite or no measurable effect. Demir *et al.* (2022) attribute these discrepancies to differences in the feed-rate ranges tested and to interactions with other variables that are not always controlled for. Substrate type plays a role too. In solid wood, high feed rates produce larger chips and larger grain-fracture forces, both of which raise R_a . In composite panels, the response is different because the binder

and abrasive particles can favor controlled fracture at higher feeds, while lower feeds increase friction and can cause local burning (Çakıroğlu *et al.*, 2019).

A persistent difficulty in this work is that wood is organic, hygroscopic, and anisotropic. Properties vary not only between species but within a species: trees of the same species from different regions can machine quite differently (İlşekerçi and Sofuoğlu, 2025). The reported results themselves are sensitive to moisture content, the choice of measurement protocol, and the accuracy of the machine used in the experiment (Demir *et al.*, 2022).

Cutting direction relative to the grain remains one of the most decisive factors. Machining parallel to the grain gives the best surface; tangential cutting raises R_a by 25 to 65%, and radial cutting raises it by 45 to 60% (Ibrisevic *et al.*, 2023b).

These multitude of dependencies presented above are easier to read off a diagram than a paragraph. Figure 3 plots the input and output parameters and their interactions as a causal loop diagram.

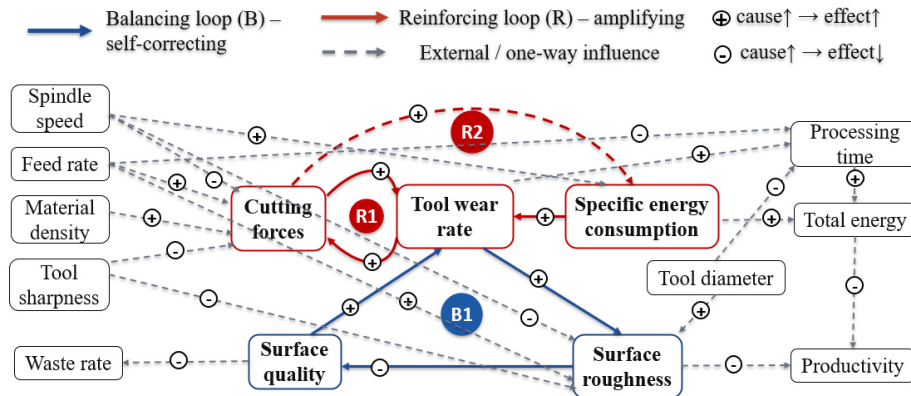


Fig. 3 – Casual loop diagram – interdependence of processing parameters.

A causal loop diagram (CLD) uses two types of loops. A balancing loop indicates that the variables involved settle into an equilibrium. A reinforcing loop indicates the opposite, that they amplify each other into runaway growth or runaway collapse.

The B1 balancing loops in Fig. 3 is surface roughness → surface quality → tool wear rate → surface roughness. A lower R_a value (better quality) accelerates tool wear, meanwhile faster wear increases R_a value. Several parameters feed into this loop: feed rate, spindle speed, and tool sharpness.

The reinforcing loop R1 represented in Figure 3 shows the continuous relation of degradation, where tool wear means bigger cutting force needed, which means more tool wear in return and so on. R2 loop is the case of R1 loop if considered consumed energy, because the growth of tool wear and cutting force increases a lot of energy consumption.

The diagram also shows that productivity can be eroded from two sides: by poor quality and high scrap, or by good quality bought at the cost of long cycle times and high *SEC*. High scrap rates and high *SEC* both feed total energy consumption, although through different mechanisms.

3.3. Sustainability, Industry 5.0 and Artificial Intelligence Integration

Wood machining produces shavings, wood chips and fine dust, last ones have particle diameters in the range of 1 to 500 μm . The fine particles have to be controlled and filtered out of the workspace air, both because they damage equipment and degrade surface quality and because they represent respiratory risks for the workforce.

Particles produced on a CNC machine are among the finest, and therefore among the hardest to detect and capture. The dust dimension range in the air is characterized using the *PM* parameter (defined as particulate matter), usually followed by a number representing the upper limit of the particle diameter, measured in [μm]. Respectively, dust concentration is measured as the mass concentration of the dust in the air, expressed in [$\mu\text{g}/\text{m}^3$]. The recent literature reports two practical mitigations. Sharp cutting edges with a 75° rake angle measurably reduce fine dust, because the chips leave the cutting zone with less kinetic energy. For helical tools, an inclination angle in the $5\text{--}10^\circ$ band gives the lowest emissions. The total dust volume is also a function of the substrate: species with higher Brinell hardness and density emit the most (Çakıroğlu *et al.*, 2025). Figure 4 (Çakıroğlu *et al.*, 2025) shows why the suction system is essential in any dust strategy. The largest emissions come from softwood species such as pine and chestnut. For the last two materials in Fig. 4, beech and sapelli, the number of particles is much less, and the difference between the closed and open extraction systems is much smaller than for the other softwoods.

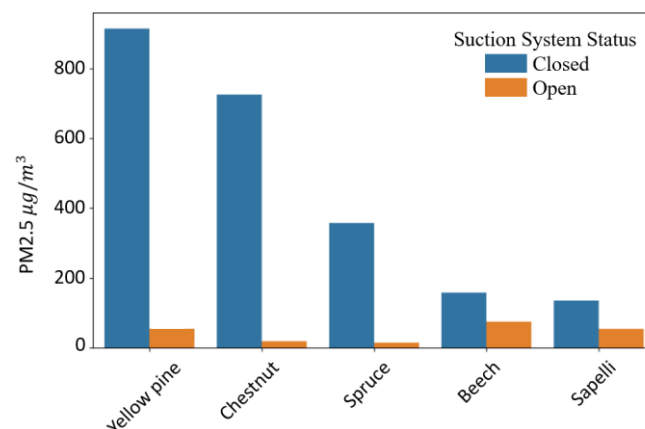


Fig. 4 – PM2.5 dust concentration by wood species and suction-system Status (data from Çakıroğlu *et al.*, 2025).

The reason is density: beech and sapelli are denser, so the residues left after cutting are heavier and the $PM_{2.5}$ fraction is correspondingly smaller. The heavier particles fall to the surface rather than remaining suspended in air.

The standards for wooden dust emissions are 3 mg/m^3 for hardwood and 5 mg/m^3 for softwood (Puntaric *et al.*, 2005). Sustained exposure above these limits is associated with increased morbidity and premature mortality, and with elevated risk of nasal cancer, mucous-membrane irritation, reduced lung function, asthma, and allergic reactions. The dust also acts as a vector for biological agents including fungi, bacteria, and endotoxins (Kasangana *et al.*, 2017).

A good solution to control dust exposure is local exhaust ventilation (LEV) that is well designed, has good maintenance and regularly checks for properly working. It is necessary to avoid using compressed airlines to blow off furniture when it's not required, because it creates clouds of dust. An important note is that nuisance dust mask should not be used as a wood dust filter, as cannot provide protection. Instead, good practice is disposable respirator (filtering facepiece), but because it can make breathing difficult it is not recommended for a long use (more than 1 hour). A solution of mask for a long duration is considered reusable half-mask respirator (HSE, 2022).

Sustainability in modern wood processing includes dust control and robotic integration into the cutting cell. This innovation improves geometric accuracy, reduces offcut waste, and supports circular-economy goals through automated sorting of residues (Brunello *et al.*, 2025).

Combining the multi-objective character of the optimization problem (Section 3.1), the material variability discussed in Sections 2 and 3.2, and the environmental constraint of this section is what has pushed the field toward machine learning (ML). ML, a sub-field of AI, is concerned with systems that learn patterns from data and make predictions with minimum human input (Kariz *et al.*, 2024).

Digitalization is changing the way wood-processing manufacturing systems are designed. AI is now applied across 3D product modelling, raw-material optimization, scheduling, planning, HR management and early defect detection. Detecting flaws that an operator cannot see by eye reduces both scrap rates and reprocessing. Yazici *et al.* (2023) argue that 5G/6G networks will be the enabler that finally allows real-time monitoring of the full production flow. Within Industry 5.0, this monitoring is integrated with robotics: CNC machines communicate directly with robotic arms that handle and finish complex components (Brunello *et al.*, 2025).

Edge computing and predictive maintenance transfer processing to the machine itself, therefore cutting parameters can be adjusted in real time as the tool wears gradually. Digital twins, virtual replicas built from scanned material, bring wood processing to a new level: an AI agent can simulate the cut on the twin first, taking knot positions and local fiber density into account, and adjust the toolpath before the tool engages the physical workpiece (Yazici *et al.*, 2023).

These technologies are nevertheless unevenly distributed. Eurostat (2025) data show a clear digital divide within Europe: only about 5% of Romanian companies use AI, against an EU average of 20% and a high of 42% in Denmark. Closing that gap will require AI implementation frameworks that are cheap and accessible enough for the smaller manufacturers that make up most of the regional industry.

Taken together, an evolution of a manufacturing system is observed, moving from isolated parameter optimization toward integrated models that handle economic factors (cycle time), technological factors (R_a and tool wear) and environmental factors (dust emissions) at the same time. The bottleneck lies in the complexity of wood processing, which requires high precision from the AI: models have to be robust enough to absorb the variability of wood, including anisotropy and moisture-related effects, before fully automated and sustainable CNC production becomes routine.

Table 2 summarizes the studies discussed above, listing each one against its substrate, the input parameters varied, the outputs measured, and the methodology used. Reading down the methodology column makes the trajectory of the field clear, from classical ANOVA-based studies to hybrid AI-based optimization.

Table 2

Comparative analysis of research methodologies, material substrates, and optimization parameters in wood CNC machining (2020–2025)

Nr.	Author	Material type	Input parameters	Output parameters	Research Methodology
1	Cakiroglu <i>et al.</i> , 2022	walnut ash wood	D n f	R_a θ E T	ED ANN (MATLAB)
2	Cakiroglu <i>et al.</i> , 2025	Yellow Pine spruce chestnut sapelli beech	n v_c f D ASS (c/o)	PM	ED Kruskal-Wallis test Dunn test
3	Demir <i>et al.</i> , 2022	particleboard MDF birch plywood	D n f v_c	R_a	ED ANOVA Student-Newmann-Keuls test
4	Gürgeç <i>et al.</i> , 2022	scotch pine	n f d a_p	R_a	ED ANN GA

5	Ibrisevic <i>et al.</i> , 2023a	beech oak fir	n f	R_a	ED ANOVA Tukey Pairwise Comparison test
6	Ibrisevic <i>et al.</i> , 2023b	beech oak fir	CD GD f	R_a	ED JASP software ANOVA Pairwise comparison Tukey's test
7	İlşekerci <i>et al.</i> , 2025	larch south eastern beech	aspect (northern/ southern) f n	R_a	ED ANOVA
8	Korkmaz <i>et al.</i> , 2024	Scots pine beech poplar	T_w n f	R_a	ED statistical analysis software ANOVA Ducan's Multiple Range Test
9	Pinkowski <i>et al.</i> , 2024	Balsa Obeche Alder Beech	f w a_{av}	P_c R_a	ED ANOVA Ducan's test Statistica version 13.3
10	Rabiei and Yaghoubi, 2023	beech wood	d f n SO	R_a T	ED MATLAB BA
11	Sharma <i>et al.</i> , 2023	Teak Deodar Mindi Sheesham Sal	v_c CD P_c	F_c	FEA Analysis
12	Yaghoubi and Rabiei, 2024	beech wood	D f n SO MS	R_a	ED
13	Zhao <i>et al.</i> , 2020	beech wood	d a_e f n	w SEC	ED

Note: a_{av} – chip thickness, a_e – side cutting depth, a_p – axial depth of cut, ASS (c/o) – Air Suction System (closed/open), CD – cutting direction, d – cutting depth, D – tool diameter, E – energy consumption, ED – experimental design, f – feed rate, F_c – cutting force, GD – grain direction, MS – milling strategies, n – spindle speed, P_c – cutting power, PM – concentration of dust, R_a – surface roughness, SEC – specific energy consumption, SO – step over, T – processing time, T_w – wood temperature, v_c – cutting speed, w – tool wear, θ – wettability

4. Critical Analysis and Synthesis of CNC Wood Machining Research

Table 2 highlights the move toward multi-objective frameworks. Earlier studies focused primarily on the correlation of feed rate, spindle speed, cutting depth with surface roughness (R_a), whereas more recent work (e.g., Rabiei and Yaghoubi, 2023; Çakıroğlu *et al.*, 2025) incorporates energy use, tool wear, and dust emissions into a single experimental model. The growing role of ANN and GA reflects a transition from static experimental observation to dynamic, predictive systems. The rest of this section discusses the practical implications and the remaining gaps, as presented in Figure 5.

The literature on digitalization (e.g., Yazici *et al.*, 2023; Islam *et al.*, 2025) is enthusiastic but the research tends to overlook real-life practices, as most published ML models are trained in laboratory conditions, that do not match the sensory realities.

Fine wood dust is not only a respiratory issue. It is abrasive and thermally insulating, which means it degrades optical sensors and impairs heat dissipation in the edge-computing hardware mounted on the machine. The robustness of AI systems and IoT sensors under sustained micro-dust loading and high-frequency vibration, both characteristics of high-speed CNC machining, has not been studied in any depth. This is the largest practical gap between the current research literature and routine industrial deployment.

A second gap, visible when Fewella (2025) is read alongside Cervený *et al.* (2022), concerns the fidelity of virtual models. Metal cutting can usually assume a homogeneous workpiece, but woodworking cannot: fiber orientation, knots, and moisture content all vary within and between boards. Most published digital twins are essentially advanced CAD models that remain static during the cut. However, in practice wood deforms under the tool as internal stresses are released. What is needed is a dynamic digital twin that ingests real-time sensor data and revises the cutting strategy when a hidden defect appears, at the moment the tool reaches it.

Optimization studies such as Çakıroğlu *et al.* (2025) and Kariz *et al.* (2024) show that the conflict between productivity and environmental indicators remains unresolved. The current optimization literature is fragmented: lowering spindle speed reduces dust emissions, but it also lengthens cycle time and therefore raises the total energy consumption of the surrounding facility (lighting, centralized extraction). A more useful target is total process sustainability, in which auxiliary energy use is accounted for alongside the achieved surface quality.

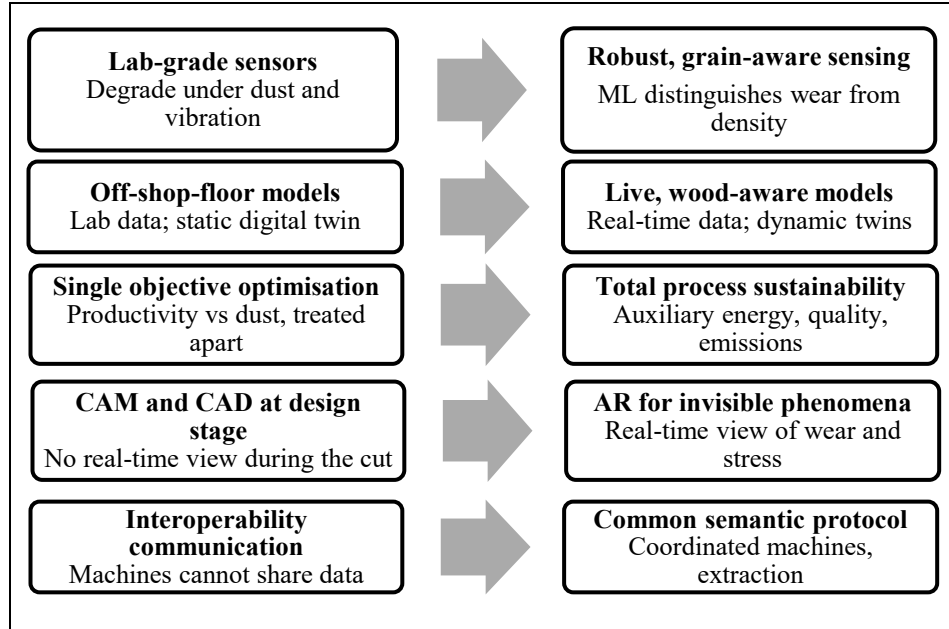


Fig. 5 – Research gaps in CNC wood machining for Industry 5.0.

Islam *et al.* (2025) argue that Industry 5.0 returns the human operator to the center of the picture. The literature on how operators interact with AI-driven decisions is, however, thin. Holograms are already used at the design stage (Fewella, 2025), but real-time visualization of phenomena that are otherwise invisible to the operator, microscopic tool wear and internal thermal stress in particular, has barely been studied. AR-assisted systems that translate complex sensor streams into intuitive visual cues are an obvious next step for human-machine collaboration research.

Hardware sensors degrade quickly in this environment, which is part of why the research has shifted to soft sensors: AI-based virtual sensors that infer the state of the cutting edge from spindle power and motor-load signatures. The weakness of this approach today is that the validated ML models cannot reliably tell the difference between a load rise caused by tool wear, and one caused by a denser part of the board. The result is false-positive tool-replacement alerts and stochastic decisions that the operator eventually learns to ignore.

Interoperability is a separate problem. Yazici *et al.* (2023) discuss communications in the abstract, but on the shop floor machines from different manufacturers cannot exchange data semantically. Industry 5.0 needs a common protocol so that, for example, the extraction system can modulate its fan speed in response to the active CNC program and minimize cross-machine energy use.

6. Conclusions

The 2020–2025 literature shows the wood processing industry moving from the rigid automation associated with Industry 4.0 toward the more operator-centered view of Industry 5.0. The first conclusion of this review is methodology. CNC process efficiency can no longer be evaluated on technical parameters alone; it has to be assessed within a wider frame that includes sustainability and human–machine collaboration.

AI and edge computing currently appear to be the only practical way to account for the intrinsic variability of wood, since its anisotropy exceeds what classical analytical models can predict. The most important technical step in the next phase is the move from static digital twins to dynamic ones that can be self-correct in real time. Without that step, large reductions in waste and energy consumption are unlikely. The review also argues that modern sustainability, in the total-process sense used here, requires a balance between cutting quality, fine dust emissions, and the collateral energy use of the supporting infrastructure. That balance is not delivered by the fragmented optimization approaches of previous decades.

On the human side, the operator's role moves from button-pusher to strategic supervisor, supported by AR overlays and prescriptive maintenance. These tools improve safety by detecting risks that are otherwise invisible, including thermal stress and microscopic tool wear inferred from soft sensors. They offer a low-cost path to AI uptake in regions such as Romania where adoption is far below the EU average. The open question for soft sensors is whether they can reliably distinguish a load increase caused by a hard knot from one caused by a worn edge; until that is solved, the operator still has to remain in the loop. Looking further out, the field will increasingly depend on machine interoperability and ecological traceability, with real-time digital product passports as the natural artefact for embedding wood manufacturing into a circular economy.

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O SINTEZĂ CRITICĂ A CERCETĂRII ÎN PRELUCRAREA CNC A LEMNULUI ÎN ERA INDUSTRIEI 5.0

(Rezumat)

Această lucrare analizează cercetările privind prelucrarea CNC a lemnului publicate între 2020 și 2025, explorând modul de alegere a parametrilor de aşchiere astfel încât calitatea suprafeţei, consumul de energie, uzura sculelor şi impactul asupra mediului să fie echilibrate. Anizotropia, higroscopicitatea şi variabilitatea biologică a lemnului îl fac atât de diferit, chiar şi pentru aceeaşi specie sau pentru aceeaşi placă. Au apărut două schimbări clare. Lucrările de optimizare se deplasează de la experimente cu un singur factor la metode multi-obiectiv construite pe reţele neuronale, algoritmi genetici şi

scheme hibride de inteligență artificială. În paralel, edge computing și mentenanța predictivă aduc luarea deciziilor în timp real la nivelul mașinii în sine. De asemenea, ies în evidență două lacune: puține studii testează senzori și modele de inteligență artificială în condiții de praf și vibrații ridicate, iar gemenii digitali existenți rămân statici și ignoră tensiunile interne, nodurile și neregularitățile fibrei dezvăluite în timpul aşchierii. Lucrarea se încheie pledând pentru o perspectivă totală asupra sustenabilității, optimizând simultan calitatea suprafeței, emisiile de praf, consumul de energie auxiliară și durata de viață a sculelor.