Optimization of cutting depth parameters to achieve stability in the machining process

Oybek Tuyboyov[1*], *Zayniddin* Muxiddinov[1], *Shamiliddin* Sirojidinov[1], *Mahliyo* Aliyeva[1], and *Nasillo* Urinov[2]

[1]Tashkent State Technical University, Tashkent, Uzbekistan
[2]Bukhara State Technical University, Bukhara, Uzbekistan

Abstract. The study investigates the effects of cutting depth on machining outcomes through experimental analysis, numerical simulations, and advanced monitoring techniques. Key findings highlight the role of cutting depth in governing cutting forces, heat generation, and vibration behavior, with implications for tool wear and machining precision. The integration of digital twin technology, stability prediction tools, and real-time monitoring systems, such as piezoresistive sensors and vibration analysis, enables optimization of machining conditions for improved productivity and reliability. Results demonstrate that achieving an optimal balance between material removal rates and process stability is crucial for sustainable and efficient machining. Furthermore, this research underscores the importance of considering material properties, tool geometry, and machine rigidity in parameter optimization. The proposed strategies and insights contribute to advancing precision machining practices and enhancing industrial applications.

1 Introduction

The depth of cut in machining processes [1] is a critical parameter influencing surface quality, machining efficiency [2], and vibration dynamics [3]. Its optimization is essential for achieving the desired outcomes across diverse machining operations. Cutting depth [4] directly affects surface roughness and precision. In precision machining, smaller cutting depths [5] often enhance surface quality by minimizing irregularities. For instance, experiments have demonstrated that shallow depths of cut lead to smoother surfaces in high-precision operations [6]. Contrary to the assumption that maximizing depth of cut always reduces machining time, studies suggest the existence of an optimal depth that balances efficiency and quality. In rough turning [7], for instance, excessive depths may lead to increased tool wear and diminished output quality. Identifying and adhering to this optimal range is vital for sustainable machining practices. The depth of cut also governs the stability of the machining process by influencing vibration behavior. Shallow cuts typically reduce regenerative vibrations in high-speed operations [8] but can amplify forced vibrations,

* Corresponding author: oybektuyboyov85@gmail.com

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affecting both stability and surface integrity. These dynamic characteristics underscore the importance of tailoring cutting depth to the specific machining context.

While cutting depth is a pivotal factor, its influence cannot be isolated from other critical parameters such as tool material [9], workpiece properties, and machine rigidity. These elements collectively determine machining outcomes, necessitating a holistic approach to process optimization [10]. Recent advancements in numerical modeling and real-time monitoring have significantly enhanced the understanding of machining stability and surface quality. Techniques such as the differential quadrature method and machine learning have enabled precise predictions of stability limits and optimal parameters. Additionally, innovations like digital twin technology allow adaptive control of machining conditions, ensuring consistent quality in complex operations.

Cutting depth is a fundamental parameter in machining processes, significantly influencing force generation, heat distribution, material removal rates, and overall machining stability. Its optimization is crucial for enhancing efficiency, precision, and product quality. This section systematically explores the effects of cutting depth on key machining outcomes and highlights strategies for achieving an optimal balance between material removal efficiency and process stability. The cutting depth directly affects the magnitude of cutting forces due to its impact on the cutting area and width. Understanding these dynamics is essential for optimizing cutting parameters to maintain process stability and tool integrity. Heat generation in machining is closely tied to cutting depth [11]. Deeper cuts result in greater friction and deformation in the cutting zone, increasing heat generation. This, in turn, affects residual stress distribution, particularly in thin-walled parts [12], where deeper cuts can lead to stress concentrations beneath the surface. Such stresses may cause machining deformation and compromise dimensional accuracy, underscoring the need to balance cutting depth with heat dissipation strategies to ensure machining precision. While deeper cuts enhance productivity by removing larger volumes of material, excessive depths can adversely affect surface quality, stability, and tool wear. Achieving an optimal depth is therefore essential for balancing efficiency with process reliability. Chatter, a dynamic instability in machining processes, is heavily influenced by cutting depth.

Stability prediction tools [13], such as stability lobe diagrams and analytical models, play a pivotal role in identifying chatter-free operational conditions. These tools help optimize axial and radial depths of cut, ensuring stable material removal while maximizing efficiency. Recent advancements in stability prediction leverage techniques such as neural networks, semi-discretization methods, and particle swarm optimization. Neural networks predict [14] limiting axial depths based on machining parameters, while stability charts generated via semi-discretization help visualize optimal cutting conditions. Optimization techniques, including Kriging and particle swarm methods [15], further refine cutting parameter selection to enhance stability and productivity. Despite advancements in modeling and optimization, challenges remain in addressing dynamic interactions, particularly in high-speed and precision machining contexts [16]. The interplay between cutting dynamics, heat distribution, and material properties introduces complexities that require robust data-driven approaches.

2 Methods

The methodology for this study incorporates experimental investigations, virtual simulations, and advanced analytical tools to explore the interplay between CNC machine capabilities, machining parameters, and material characteristics. Virtual simulation technologies, such as SolidWorks-based systems [17], are employed to create risk-free environments for students to interact with CNC machines. These simulations provide a comprehensive understanding of machine structures and operations while reducing material waste and ensuring safety during practical training sessions. The impact of this approach on student learning outcomes, engagement, and skill development is systematically assessed. Experimental studies are conducted on CNC turning machines to analyze geometric inaccuracies, including linear positional deviations and squareness errors. The methodology involves regular inspections and calibrations, supported by precision measurement tools, to quantify deviations and assess their impact on product quality.

This process helps identify key factors contributing to errors and establishes a framework for maintaining CNC machine reliability. To optimize machining conditions, the study integrates digital twins for real-time data-driven adjustments. By simulating machining scenarios and evaluating experimental data, this approach achieves significant improvements in productivity, such as reduced machining times and production costs. The digital twin framework is validated through comparisons with traditional optimization methods, highlighting its effectiveness in real-world applications.

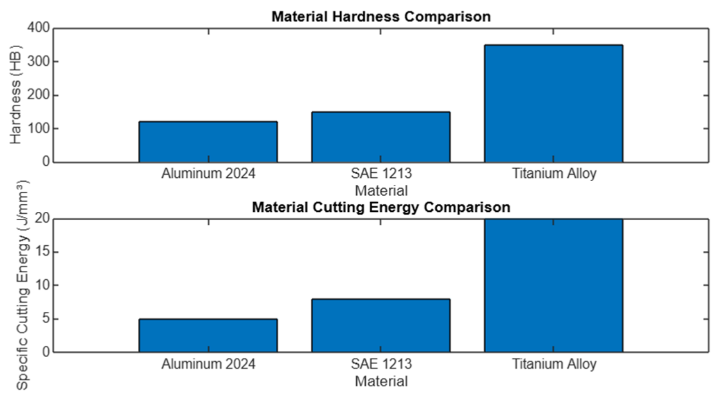

Fig. 1. Material Hardness Comparison and Energy Requirements for Machining Different Materials.

Figure 1 indicates a material's resistance to deformation. Titanium alloys exhibit high hardness (350 HB), making them suitable for demanding applications like aerospace but challenging to machine. Aluminum 2024 (120 HB) and SAE 1213 (150 HB) are softer and easier to machine, reflecting their lower hardness values. SCE measures the energy required to remove a unit volume of material during machining. Titanium alloys have high SCE (20 J/mm^3), attributed to their toughness and strength. In contrast, Aluminum 2024 and SAE 1213 have lower SCE values (5 J/mm^3 and 8 J/mm^3), indicating easier machinability.

Tool life (Figure 2) decreases with increasing edge radius due to higher cutting forces and heat generation at larger edge sizes. This plot illustrates how maintaining an optimal edge radius (e.g., ~0.2 mm) maximizes tool longevity while minimizing wear and energy consumption. Efficiency decreases as the side cutting edge angle increases due to greater material resistance and cutting forces. Lower angles (closer to 0°) promote smoother cutting, whereas higher angles (~90°) are less efficient but might improve specific applications requiring heavy cutting.

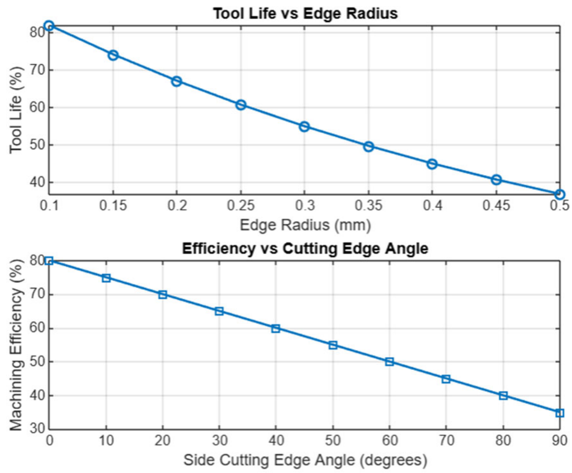

Fig. 2. Tool life and efficiency, effect of side cutting edge angle on efficiency.

Cutting force (Figure 3) increases with the engagement angle due to greater tool-material contact. This relationship highlights the need to optimize engagement angles to balance cutting force and machining precision. Peaks in force can lead to tool deflection and reduced accuracy. As engagement angle increases, the tool wear area expands linearly due to prolonged contact and higher friction at the cutting interface. This demonstrates the trade-off between machining depth and tool life, suggesting a need to minimize excessive engagement. Material Type Plots emphasize the machinability of materials, where higher hardness and specific cutting energy indicate greater resistance to machining. Such insights are critical in material selection. Cutting Tool Geometry Plots focus on optimizing tool design (e.g., edge radius and cutting angle) for better performance, longevity, and efficiency. Workpiece Geometry Plots explore the interaction between tool and workpiece, showing how parameters like engagement angle influence cutting forces and wear, which directly impact machining quality and cost.

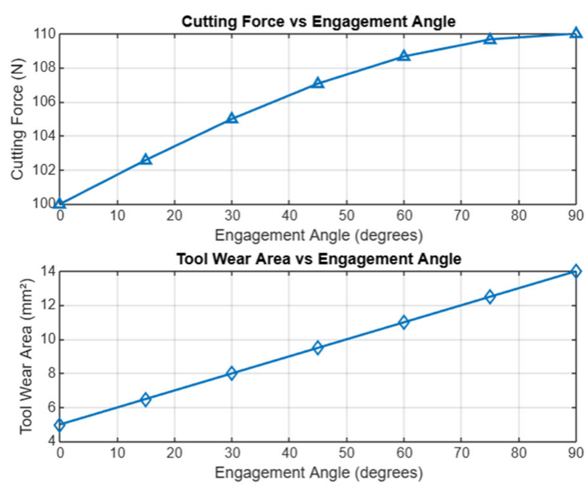

Fig. 3. Cutting dynamics and wear, tool wear progression with engagement area.

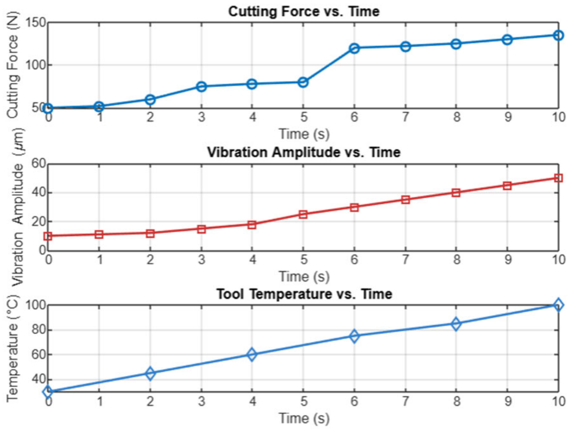

Fig. 4. Integration of sensors for real-time monitoring.

Figure 4 is Cutting Force versus Time which is a critical parameter in machining, reflecting the interaction between the cutting tool and the workpiece. Changes in cutting force overtime indicate tool wear (increasing force suggests a worn-out or dull tool). Material inconsistencies (harder material zones cause higher forces). Changes in machining parameters (e.g., feed rate, depth of cut). Monitoring this parameter ensures machining processes are stable, improves tool life, and avoids part defects.

Second plot in Figure 4 depicts Vibration Amplitude versus Time. Vibration amplitude is directly related to the stability of the machining process and the health of the cutting tool. Increased vibration amplitude over time signals Tool wear or breakage. Instability in the machining setup (e.g., loose fixtures, improper cutting parameters). Excessive vibrations degrade surface quality, reduce tool life, and increase noise levels. Monitoring helps in detecting and addressing instability early, improving product quality.

The third plot in Figure 4 is Tool Temperature versus Time. Temperature rise in the cutting zone affects tool wear, material properties, and surface finish. High temperatures can cause thermal softening of the cutting tool, leading to faster wear. Alter material microstructure, compromising workpiece quality. Real-time temperature monitoring ensures the cutting process operates within optimal temperature ranges. Tool coatings or coolants are effectively utilized to reduce thermal impact.

3 Results

Figure 5 below illustrates how the vibration signal varies over time. The x-axis represents time (in seconds), and the y-axis shows the amplitude of the signal. The signal consists of sinusoidal components (representing vibration frequencies) and random noise (simulating real-world disturbances). Time-domain analysis is fundamental in signal processing to observe transient behaviors and overall signal patterns, often used as a preliminary step before frequency analysis.

This plot is derived from the Fast Fourier Transform (FFT) of the time-domain signal. The x-axis shows frequency (in Hertz), and the y-axis displays amplitude (scaled by the FFT operation). The peaks in the spectrum correspond to the dominant frequencies present in the vibration signal. In this case, frequencies at 100 Hz and 500 Hz indicate the main vibration sources. Frequency-domain analysis is critical for identifying vibration modes, resonance frequencies, and irregularities in systems like milling operations. These plots are crucial in machining studies, as they help correlate vibration signals with cutting forces, enabling real-time monitoring and predictive maintenance in manufacturing systems.

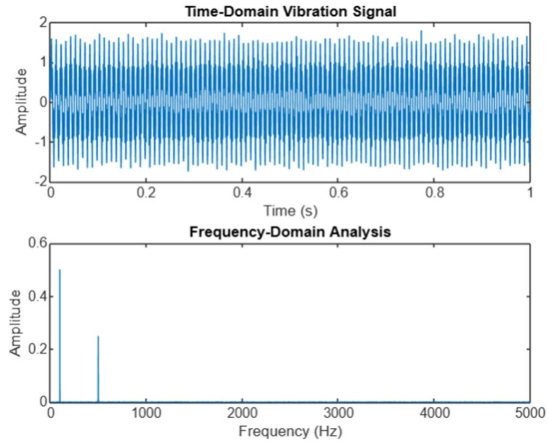

Fig. 5. Time-domain vibration signal and frequency-domain spectrum.

Figure 6 demonstrates the fundamental operating principle of a piezoresistive transducer. The x-axis represents the applied force (in Newtons), while the y-axis shows the resulting resistance (in Ohms). The resistance decreases linearly with increasing force due to the piezoresistive effect, where mechanical deformation causes a proportional change in the material's electrical resistance. This relationship is critical for force-sensing applications, as it forms the basis for converting mechanical input into an electrical signal that can be measured and analyzed. The second plot depicts the electrical response of a piezoresistive transducer integrated into a Wheatstone bridge circuit. The x-axis shows the applied force (in Newtons), and the y-axis shows the output voltage (in Volts).

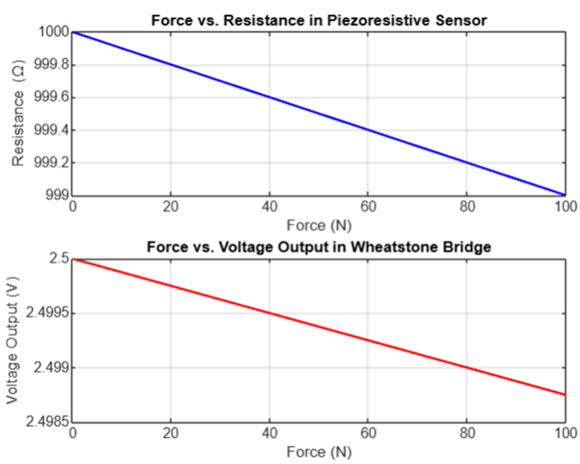

Fig. 6. Relationship between applied force and resistance and voltage output of a wheatstone bridge versus applied force.

The voltage output increases with force because the Wheatstone bridge becomes increasingly unbalanced as resistance changes. This output can be calibrated to accurately measure applied forces. These plots provide a comprehensive understanding of how piezoresistive transducers function, making them a reliable and economical choice for SMEs in cutting-force monitoring and other applications.

Figure 7 represents the gradual wear of a cutting tool during machining, with the x-axis showing time (in seconds) and the y-axis displaying the tool wear (in millimeters). The progression combines linear growth (representing continuous material loss) and sinusoidal fluctuations (capturing transient effects such as vibrations or cutting force variations). Random noise simulates environmental disturbances. Monitoring tool wear is crucial for determining when a tool needs replacement, ensuring machining stability, and avoiding poor surface finishes or catastrophic failures. Tool wear follows well-established physical principles, including abrasive and adhesive wear mechanisms influenced by cutting speed, temperature, and material properties.

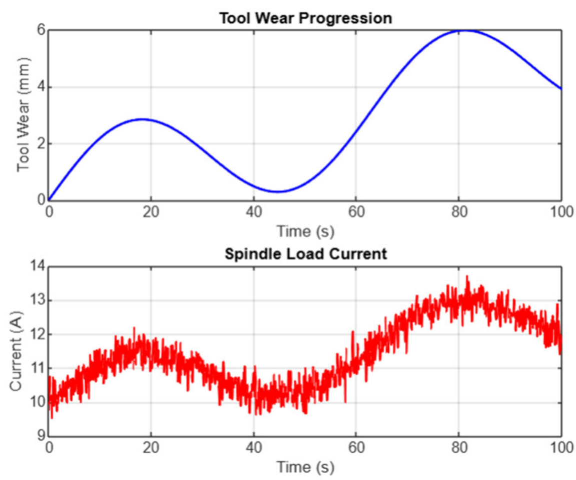

Fig. 7. Tool wear over time and spindle load variations over time.

The second plot shows changes in spindle-load current as a function of time. The x-axis is time (in seconds), while the y-axis indicates spindle load (in Amperes). The load increases as the tool wears, reflecting greater resistance during cutting due to increased contact area and friction. Random variations represent fluctuations in cutting conditions or material inconsistencies. Spindle load monitoring is an indirect method for assessing tool wear and cutting force. It is a cost-effective, real-time solution widely used in automated tool condition monitoring (TCM) systems to enhance operational reliability and reduce downtime. These plots illustrate critical aspects of real-time monitoring techniques that use intelligent tools and sensors, showcasing how dynamic feedback can optimize machining processes in industrial settings.

Figure 8 shows how vibration signals, consisting of low-frequency cutting forces and high-frequency noise, behave over time. The x-axis represents time (in seconds), and the y-axis shows amplitude. The original noisy signal (blue) combines machine vibrations and tool-induced forces. After applying Kalman filtering, the filtered signal (red) retains the cutting force while suppressing noise. Time-domain signal processing is essential for monitoring dynamic processes and identifying real cutting forces during machining. The second plot visualizes the cutting force component alone (low-frequency sinusoidal signal). The x-axis represents time, and the y-axis represents amplitude.

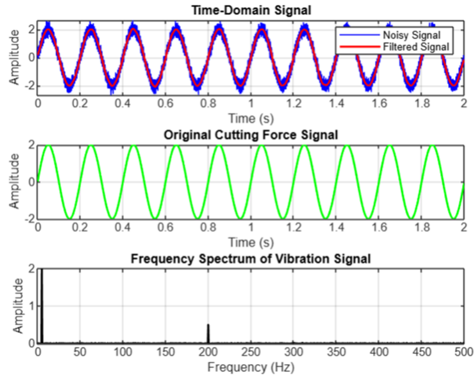

Fig. 8. Noisy Signal and Filtered Signal in Time Domain, Original Cutting Force Signal and Frequency Spectrum of Vibration Signal.

Cutting forces are extracted by isolating low-frequency components using signal processing techniques. Accurate identification of this signal is crucial for analyzing machining efficiency and tool stability. The third plot depicts the frequency distribution of the vibration signal. The x-axis represents frequency (in Hertz), and the y-axis represents amplitude. Peaks in the low-frequency range correspond to cutting forces, while high-frequency components represent noise. Frequency separation methods (like FFT) enable clear identification of the force signal, crucial for advanced monitoring and optimization techniques.

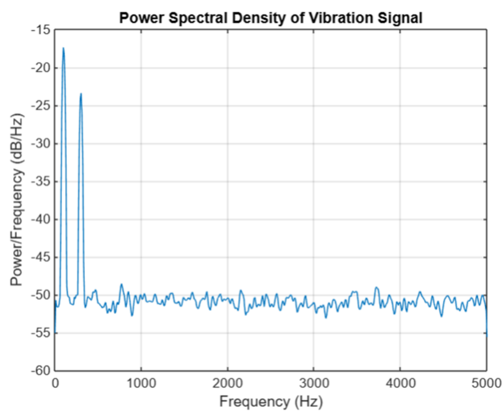

Fig. 9. Power Spectral Density (PSD) of Vibration Signal for Tool Wear Detection.

The PSD in Figure 9 represents the distribution of signal power across different frequency components. It is expressed in units of power per Hz. In tool wear detection, PSD helps isolate frequencies that correspond to cutting vibrations. Changes in these frequencies and their amplitudes indicate tool wear progression. As tools wear out, their vibration profiles change due to increased cutting resistance and surface irregularities. Higher amplitude vibrations (evident as peaks in PSD at certain frequencies). Shifting or broadening of frequency bands due to unstable cutting dynamics. These frequency-domain features serve as reliable indices for assessing tool health. Vibrations are recorded using accelerometers during machining. PSD is computed using techniques such as Welch's method. This involves segmenting the signal, applying a window function (e.g., Hamming), performing an FFT on each segment, and averaging the results to reduce noise Increased PSD magnitudes at specific frequencies correlate with tool degradation, helping predict wear progression and plan timely interventions. This analysis provides an invaluable tool for monitoring and maintaining cutting tools in advanced manufacturing processes, especially under high-speed or precision machining conditions.

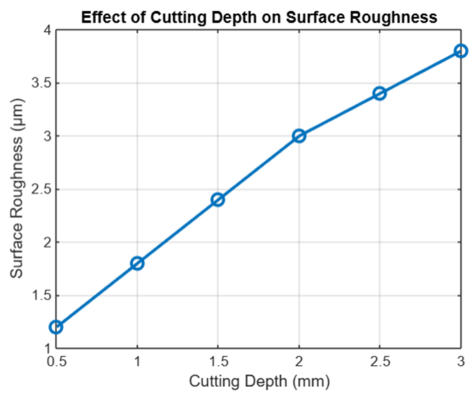

Fig. 10. Effect of Cutting Depth on Surface Roughness.

Figure 10 demonstrates the relationship between cutting depth and surface roughness in machining processes such as milling or turning. Cutting depth refers to the thickness of the material layer removed by the cutting tool in a single pass. As cutting depth increases, the tool engages more material, leading to higher cutting forces, greater tool wear, and increased vibrations in the machining process. Surface roughness is a measure of the texture of the machined surface, usually quantified in microns. A rougher surface typically results from increased cutting forces and vibrations that disturb the tool-workpiece interaction, leading to an uneven surface.

As cutting depth increases, surface roughness tends to worsen. This is because the tool experiences greater resistance from the workpiece, leading to higher vibrations, instability, and increased wear, all of which contribute to poorer surface finishes. The plot typically shows a positive correlation: higher cutting depths result in higher surface roughness, especially if other machining parameters (like cutting speed or feed rate) are held constant. Maintaining a balance in cutting parameters is critical. While deeper cuts may improve productivity, they tend to degrade surface quality unless compensated by adjustments to feed rates or cutting speeds. Understanding this trade-off helps in optimizing machining parameters to achieve the desired balance between productivity and surface finish. This plot provides insight into how machining parameters should be carefully adjusted to optimize both the performance and quality of the finished part.

4 Discussion

The depth of cut has emerged as a multifaceted parameter in machining processes, profoundly influencing surface quality, tool wear, and process stability. The results of this study highlight the intricate balance required to optimize machining parameters, particularly depth of cut, to achieve desired outcomes without compromising efficiency or precision.

The findings confirm that smaller depths of cut enhance surface finish by reducing irregularities. However, this benefit diminishes in operations where shallow cuts lead to forced vibrations, affecting surface integrity. The interplay between cutting depth and vibration dynamics, as shown in Figures 3 and 5, underscores the importance of stability prediction tools like stability lobe diagrams and FFT analysis. By identifying chatter-free operational zones, these tools allow precise adjustments, reducing the risk of surface degradation and tool wear.

The results (e.g., Figures 2 and 3) reveal a direct correlation between cutting depth, heat generation, and tool wear. Deeper cuts generate higher friction and thermal loads, accelerating tool wear and impacting the dimensional accuracy of machined components. These findings validate the need for real-time monitoring systems, such as those demonstrated in Figure 4, which effectively track cutting force, vibration amplitude, and temperature. Such systems enable timely interventions, mitigating the adverse effects of excessive heat on tool and workpiece integrity.

5 Conclusion

Deeper cuts increase material removal rates, offering higher productivity but at the expense of stability and surface quality. This trade-off, evident in Figures 2 and 10, highlights the necessity of finding an optimal depth of cut tailored to specific material and operational constraints. For instance, softer materials such as Aluminum 2024 exhibited lower specific cutting energy and higher machinability, as demonstrated in Figure 1. These insights emphasize material-specific optimization for maximizing efficiency while preserving tool longevity.

Advanced tools and methodologies, including neural networks and digital twins, have proven effective in addressing the challenges associated with dynamic interactions during machining. As shown in Figure 6, integrating sensor-based systems with analytical models offers precise control over cutting parameters, ensuring consistent machining quality. Furthermore, filtering techniques like Kalman filtering, depicted in Figure 8, enhance the accuracy of signal processing, allowing for better interpretation of cutting dynamics and real-time adjustments.

Despite these advancements, challenges persist in optimizing machining conditions for high-speed and precision contexts. Dynamic interactions between cutting depth, material properties, and thermal effects remain complex, necessitating further research into data-driven approaches. Future studies could explore the integration of machine learning with stability prediction tools to refine parameter selection and enhance process adaptability.

The results reaffirm the pivotal role of cutting depth in determining machining outcomes. By leveraging modern tools and real-time monitoring systems, it is possible to achieve an optimal balance between efficiency, precision, and tool longevity. These findings provide a foundation for developing more sustainable and reliable machining practices, paving the way for enhanced productivity in industrial settings.

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