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ORIGINAL ARTICLE

Chatter detection and suppression in machining processes: a comprehensive analysis

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Abstract
Chatter is a phenomenon that occurs during machining operations, causing vibrations that can negatively impact the quality of the machined surface. Detecting and avoiding chatter is crucial for efficient machining processes. Various strategies have been developed to address this issue, including offline chatter prediction, online chatter detection and suppression, and the use of artificial intelligence (AI) solutions in line with Industry 4.0 trends. However, the topic of chatter detection is partially discussed as a section in some review publications, and it does not appear as a kernel focus. With the addition of the latest development in chatter detection and suppression, conducting a rigorous review of chatter is critical. This work entails tracing analytical chatter detection techniques (stability lobe diagram, Nyquist plot, finite element analysis), experimental chatter detection techniques by using various data acquisition signals and from time–frequency signal processing methods (fast Fourier transform, discrete wavelet transform, hilbert-huang transform, short-time Fourier transform, etc.), as well as the most recent AI techniques (artificial neural network, support vector machine, hidden markov model, fuzzy logic, k-nearest neighbor, etc.). A thorough investigation was conducted to determine the limitations of these various techniques and to provide potential solutions for detecting chattering in machining processes. Moreover, The approaches for suppressing chatter (active + passive) during the machining process will also be thoroughly reviewed in this article.

Keywords Chatter detection · Chatter suppression · Machine tool · Artificial intelligence · Vibration

Abbreviations

AI	Artificial intelligence
SLD	Stability lobe diagram
FEA	Finite element analysis
FFT	Fast Fourier transform
DWT	Discrete wavelet transform
HHT	Hilbert-Huang transform
STFT	Short-time Fourier transform
ANN	Artificial neural network
SVM	Support vector machine
HMM	Hidden Markov model
DOC	Depth of cut
MRR	Material removal rate
OFRL	Open-loop frequency response locus
SDF	Single degree of freedom
TDS	Time-domain simulation
OTF	Oriented transfer function
CNC	Computer numerical control
SFMC	Servo feed motor current
AC	Alternating current
DC	Direct current
TD	Time-domain
FD	Frequency-domain

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TFD	Time-frequency domain
WT	Wavelet transform
PSD	Power spectrum density
CNN	Convolutional neural networks
KNN	K-nearest neighbors
SOM	Self-organizing map
TMD	Tuned mass damper
DVA	Dynamic vibration absorber
SSV	Spindle speed variation
PD	Proportional-derivative
CPU	Central processing unit
GPU	Graphics processing unit
TPU	Tensor processing unit

1 Introduction

Machine tools are critical components in metalworking industries, enabling the production of complex shapes and precise components with high efficiency. However, their operation often results in vibrations, which can lead to a variety of machining issues such as tool wear, tool breakage, machine spindle bearing wear, poor surface finish, decreased product quality, and increased energy consumption. Excessive vibration can lead to inefficiencies in operation, product quality issues, and increased manufacturing costs. Consequently, predicting cutting vibrations is crucial to reducing machine idle time and workpiece material failure costs [1–23]. Vibration in machine tools must be controlled to achieve higher accuracy and productivity. Rigidity and stability are two important characteristics for analyzing the dynamic behavior of machine tools [51]. There are typically three categories of vibrations that arise during machining procedures: (a) free vibrations (b) forced vibrations and (c) self-excited vibrations (chatter). The chatter vibration type is typically the most severe one. The primary cause of self-excited vibrations (Chatter) is the dynamic instability of the cutting [23, 111].

There are two types of chatter (self-excited vibrations): primary chatter and secondary chatter. Primary chatter is induced by tool-to-workpiece friction, thermomechanical processes, or mode coupling. The regeneration of the wavy surface on the workpiece causes secondary chatter. The most harmful vibration is regenerative vibration [7]. The chatter in a machine tool is a highly complicated phenomenon because of the variety of elements that can comprise the dynamic system and its behavior: the cutting tool, the tool holder, the workpiece material, the machine tool structure, and the cutting parameters. Chatter can also occur during milling, turning, drilling, boring, broaching, and grinding, among other metal removal procedures. Chatter has several undesirable consequences, including bad surface quality, inaccuracy, excessive noise, inappropriate tool wear, machine tool failure, decreased material removal rate (MRR), and increased expenses in terms of material removal, Material, and energy impact on the environment, and costs of recycling reprocessing, or dumping non-acceptable final parts to recycling points [100]. Chatter is a serious problem for these reasons. To avoid chatter, workshop machine tool operators typically choose cautious cutting parameters, and in some situations, further manual operations are needed to clear chatter marks left on the object surface. This typical approach almost invariably results in a reduction in output.

Even though the regeneration effect, the fundamental cause of chatter, was discovered and researched very early on, predicting its occurrence remains a major research focus [110]. Most of the study has emphasized preventing regenerating chatter vibrations by either predicting their occurrence or recognizing them as early as possible. Chatter has been studied for many years, with the oldest studies dating back to 1907 [90]. The examination of the chatter phenomenon first focuses mostly on the chatter's stability forecast. Numerous conventional methods, including frequency and time-domain techniques, have been proposed by researchers including Altintas [147, 6], Tlusty [153], and Insperger [139]. The major goal is to build a dynamic model of the cutting system so that the link between the DOC and spindle speed may be determined by the solution of the kinetic equation. Stability lobe diagrams (SLDs), which easily connect the crucial DOC and spindle speed, were developed to better illustrate the link. Because of the aforementioned, using SLDs to reduce chatter is a difficult technological endeavor. Instead, chatter detection has been frequently used for the machining process as sensor technology has advanced due to its advantages of real-time and high precision. If chatter develops during the cutting process, it can be determined with the help of the received sensor signal, and effective methods, like active [153] or passive [139] reduction techniques, can then be applied as early as practical to prevent the beginning of chatter.

There are some outstanding review studies on chatter in milling operations [142, 6–110, 8–139]. However, in other review papers, the topic of chatter detection is just briefly treated as a section and does not appear as a core focus. Furthermore, the existing review articles do not cover several recent chatter detection and suppression strategies.

This research covers different methods for chatter detection, including analytical techniques like the SLD, Nyquist Plot, and FEA. It also explores experimental approaches involving various data acquisition signals and time–frequency signal processing methods such as FFT, DWT, HHT, and STFT. Additionally, it delves into the latest AI techniques like ANN, SVM, HMM, Fuzzy Logic, and KNN. A comprehensive analysis was carried out to identify the limitations of these diverse techniques and propose potential solutions for detecting chatter in machining processes.Furthermore, this article conducts an extensive review of approaches for chatter suppression, which includes both active and passive methods, during the machining process.

2 Detection/prediction techniques of chatter

*Investigation of chatter prediction and detection can be mainly classified into two broad categories, i.e., 1. Analytical techniques 2. Experimental Techniques.*In field A as shown in Fig. 1, the arrow indicates stable revolutions, suitable for milling. The left part of the graph is for turning. The gaps between lobes are relatively small. Hence, instead of pinpointing stable revolutions, adjusting the cutting speed (revolutions) is employed as a method to mitigate chatter. In the lower part of the graph, a curve depicting chatter frequency is observed, and this frequency varies with revolutions. Stable revolutions can be identified based on these variations, constituting a specific series. Optimal cutting speeds (revolutions) for different materials and tools can then be selected by technologists. To generate specific diagrams, measurements of the transfer function at the tool's location (for milling) or the workpiece's location (for turning) are employed in calculations. The procedure for deriving this diagram is elucidated in paper [11].

Table 1 provides a comparison of analytical and experimental techniques for chatter detection in machining, highlighting their key differences in terms of data sources, real-time monitoring, accuracy, adaptability, cost, complexity, and applicability. The choice between these techniques depends on the specific requirements of the machining process and the available resources Fig. 1, shows the details of analytical and experimental methods for predicting and detecting chatter so far in the literature.

Table 1 Comparison of analytical and experimental techniques for chatter detection in machining

Aspect	Analytical techniques	Experimental techniques
Basis of detection	Based on mathematical models, simulations, and theoretical analysis of machining dynamics	Rely on physical measurements, sensors, and actual machining tests
Data requirements	Typically require knowledge of machining parameters, tool, workpiece properties, and dynamic models	Need sensors (vibration, acoustic, force, etc.) and data from the actual machining process
Real-time monitoring	Can provide real-time monitoring and prediction if integrated with CNC or control systems	Primarily used for offline analysis, real-time monitoring can be achieved with advanced sensors and processing
Accuracy and precision	Highly dependent on the quality of the dynamic models and the accuracy of input parameters	Provide accurate and precise results as they are based on actual machining conditions
Early detection	Can often detect chatter at an early stage if the dynamic model is accurate and parameter inputs are correct	Detect chatter as it occurs during actual machining, but early detection depends on sensor sensitivity and sampling rate
Adaptability	Require updating of models and parameters when machining conditions change or new tooling is used	Generally adaptable to different machining scenarios and setups, with minimal model adjustment
Computational resources	Demand computational resources for simulations and modeling, which may be resource-intensive	Requires less computational power during real-time data acquisition but may require processing power for analysis
Cost	Generally less costly once dynamic models are established. Initial development may be expensive	Sensors and data acquisition equipment may have upfront costs, but the overall cost is relatively lower

2.1 Analytical techniques

There are several approaches documented for the analytical predictions of various conditions of chatter stability. The creation of SLD, finite element method/analysis, and Nyquist plots are three of them that are frequently used in the literature and will be discussed here. Due to ease and clarity in identifying stable vs unstable cutting conditions, construction is the most preferred technique among scholars. The SLD can be created using mathematical models for any number of DoF (degrees of freedom) slicing operations.

2.1.1 Stability lobes diagram (SLD)

A stability lobe diagram (SLD) serves as a visual tool in metal cutting processes, primarily aimed at assessing system stability and mitigating chatter vibrations. This graphical representation charts the stability of machining operations with

Table 1 (continued)

Aspect	Analytical techniques	Experimental techniques
Skill and expertise	Require skilled engineers with expertise in dynamic modeling and simulation	Skilled operators are needed for sensor installation, data collection, and analysis
Complexity	Complex and may be challenging to develop, but once established, operation is relatively straightforward	Relatively simple to set up and use, with most complexity in signal analysis and interpretation
Applicability	Suitable for situations where accurate dynamic models and parameter inputs are available	Applicable to a wide range of machining operations with sensor availability
Examples	Stability lobes in cutting diagrams, analytical models like the Regenerative Chatter Model	Sensors like accelerometer or microphone for vibration and acoustic signals, force sensors, and tool-wear monitoring

respect to two critical parameters: spindle speed (or cutting speed) and depth of cut. Tailored to the unique combination of machining parameters, tool geometry, and workpiece material, the SLD assists operators and engineers in pinpointing optimal cutting conditions where the risk of chatter is minimized. By offering a clear understanding of stability characteristics, the diagram aids in refining machining strategies to enhance performance and reduce the likelihood of disruptive vibrations. Creating a stability lobe diagram involves experimenting and analyzing data. Machining tests are performed using various spindle speeds and depths of cut, and the outcomes are then utilized to build the diagram. Computer simulation tools can also be employed to generate these diagrams, taking into account tool, material, and machine specifics. Figure 1, Illustrate the chatter SLD in a machining operation in which the gray area corresponds to unstable cutting conditions that lead to chatter. Chatter's amplitude increases during the cutting process within this region. In contrast, the white area signifies stable cutting conditions, including depth of cut and workpiece or tool revolutions, specifically the cutting speed. Chatter, once initiated, dampens in this region. The boundary separating these two areas is referred to as the chatter stability limit, which is characterized by a consistent chatter amplitude. The graph illustrates that the stable depth of cut experiences significant changes with varying revolutions. Based on SLD, the maximum MRR and the right choice of chatter-free cutting settings can be foreseen prior to the machining operation. In field A as shown in Fig. 1, the arrow indicates stable revolutions, suitable for milling. The left part of the graph is for turning. The gaps between lobes are relatively small. Hence, instead of pinpointing stable revolutions, adjusting the cutting speed (revolutions) is employed as a method to mitigate chatter. In the lower part of the graph, a curve depicting chatter frequency is observed, and this frequency varies with revolutions. Stable revolutions can be identified based on these variations, constituting a specific series. Optimal cutting speeds (revolutions) for different materials and tools can then be selected by technologists. To generate specific diagrams, measurements of the transfer function at the tool's location (for milling) or the workpiece's location (for turning) are employed in calculations. The procedure for deriving this diagram is elucidated in paper [11].

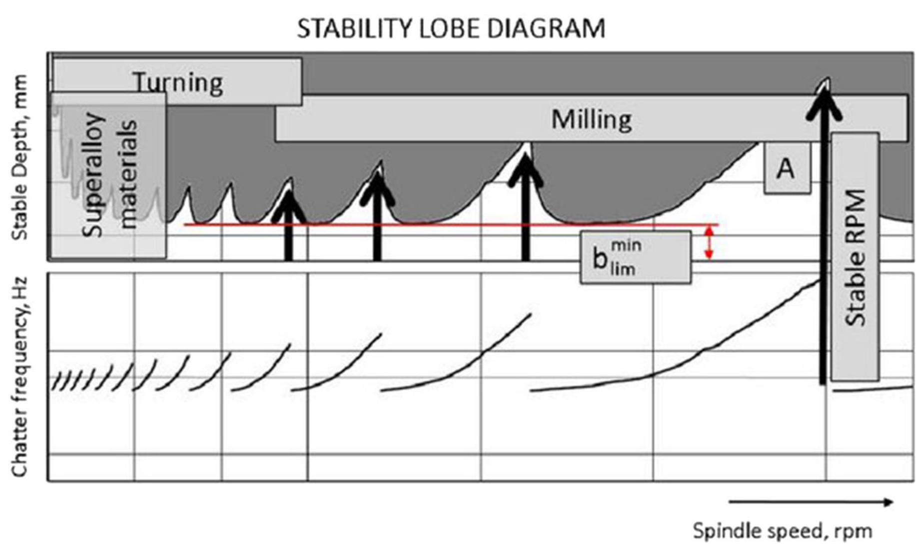


Fig. 1 Illustration of the chatter stability lobe(SLD) in a machining [95]

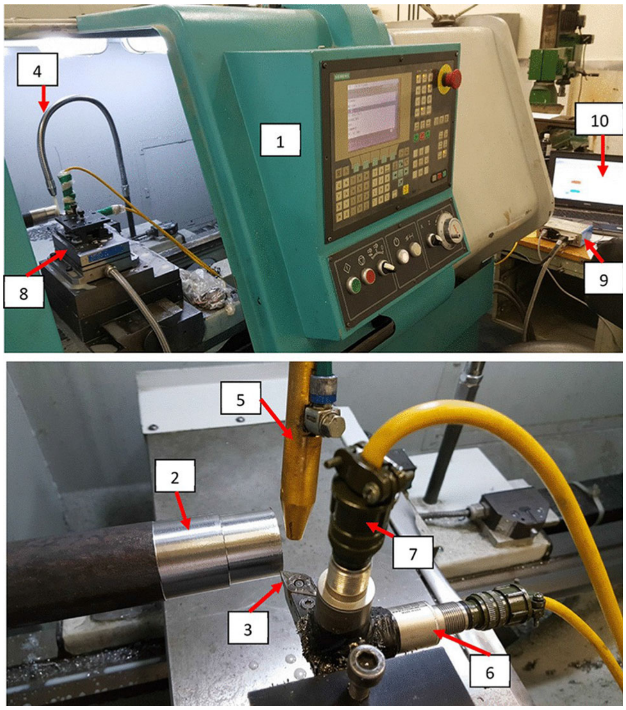


Fig. 2 The machining test setup (1-CNC lathe, 2-workpiece, 3-tool, 4-flood cooling (wet machining) nozzle, 5-MQL nozzle, 6-accelerometer in the feed direction, 7-accelerometer in the cutting direction, 8-dynamometer, 9-charge amplifier, 10-DynoWare software [37]

Meritt [84] described stability conditions using stability charts, allowing chatter to be predicted in terms of process variables like spindle speed and DOC. This was an important addition since, selecting the appropriate process settings, permitted an increase in material removal rate without generating noise. Das and Tobias' [30] linear chatter stability models have taken into account how the dynamic force is affected by the thickness of an immediate, regenerative chip. The whole chip generation process was not included in the stability models offered here. Tlusty's [126]CIRP group discovered that instead of negative dampening of the chip production process, Self-excited vibrations induced by the force–displacement interplay between cutting tools and the cutting operation cause chatter in turning and other operations (Figs. 2, 3).

Various model parameters can be taken into account to complete analytical modeling. The turning tool is modeled in the bulk of these studies as an SDF(Single Degree of Freedom) spring-mass system cutting a stiff material with a cutting force proportional to the process variables. Linear stability analysis, or theory, is the name given to research conducted under such assumptions. To comprehend their impact on chatter stability, the models have taken into account factors such as tool angles and wear. An SDF time delay-differential equation with terms for cubic and quadratic polynomials connected to structural response and cutting force was presented by [91]. Three levels of chatter stability have been predicted by the model: unconditionally stable, conditionally stable, and unstable.

Chatter stability is determined by the width of the cut. Although the cutting process is believed to be stable, The work makes it abundantly evident that the use of linear stability analysis in the industry is constrained by unstable cyclic motions. Chandiramani & Pothala [21] used an oversimplified 2DF model of the cutting instrument to characterize the dynamics of noise. It was found that increasing the cut width led to more instances of the tool departing the cut and greater chatter amplitudes.

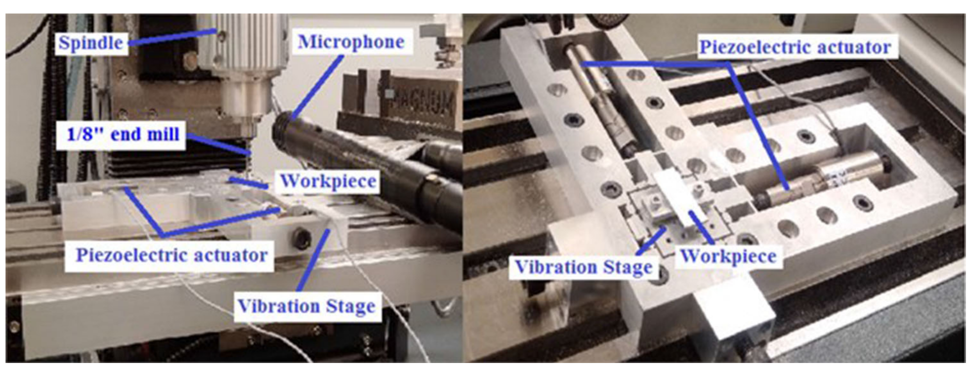
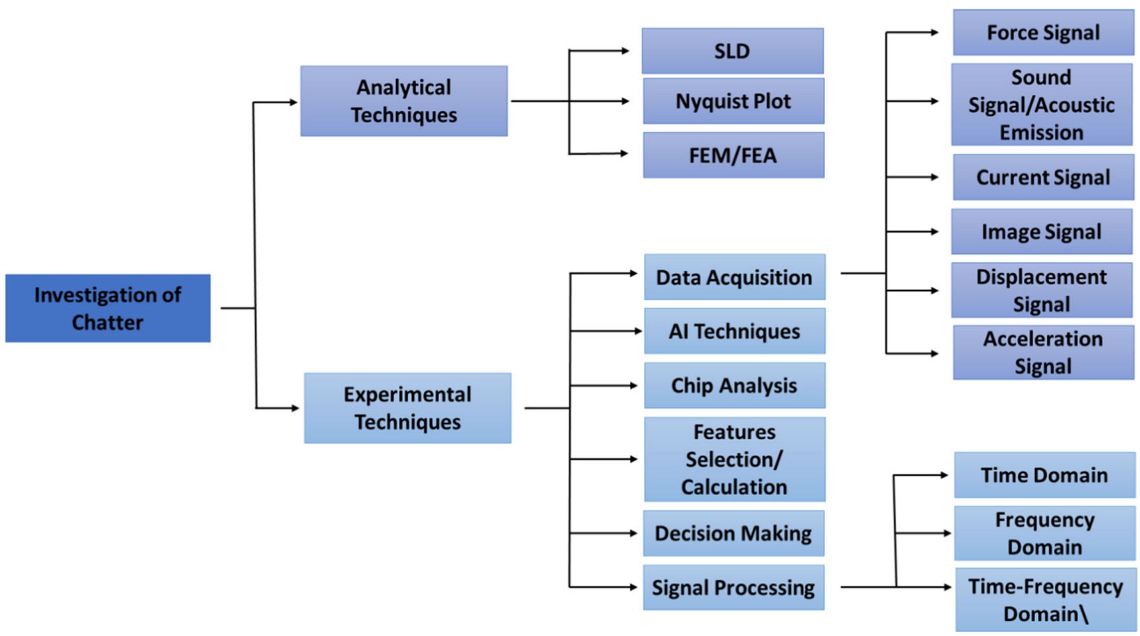


Fig. 3 Experimental setup of vibration assisted micro milling having microphone for sound signal [50]



To comprehend the effects of the cross-transfer function and the cutting force ratio on chatter stability, an analytical model with an SDF and a 2DF was provided by Suzuki et al. [113]. Even when the other circumstances were identical, In the experiment, it was discovered that the critical widths of cut for the clockwise and counterclockwise rotating processes were significantly different. The solutions are the same for analytical models based on SDF and 2DF systems. To study large amplitude motions, Dombovari et al. [32] introduced an SDF model of orthogonal cutting, which was developed as a delay differential–algebraic equation. When evaluating chatter vibration and estimating chatter stability, relatively few researchers have considered the flexibility of the tool and workpiece [22–14]. Moreover, much research on analytical models by taking into account tool-wear and process damping has been done in the past [27–141].

Following an examination of several analytical models and approaches, an analytically calculated SLD was shown to typically depend on the machine tool, work material, and tool form. As a result, it is challenging to implement such an SLD in practice because it varies in different situations. Additionally, due to the employment of a statistical approach to the cutting process, any analysis method used to generate the SLD is unable to evaluate the high stability characteristic at a lesser spindle rate.

2.1.2 Nyquist plots

The SLD serves as a valuable resource for predicting machining stability and gleaning insights from empirical data and cutting experiments. Nevertheless, it comes with notable limitations. SLDs are specific to the conditions and tooling used during their development, which constrains their adaptability to changing machining scenarios, tool wear, or material variations. Furthermore, SLDs are primarily used as tools for post-processing analysis, limiting their ability to make real-time predictions. To overcome these constraints, machining engineers frequently explore alternative analytical techniques, with the Nyquist plot being a commonly chosen alternative. The Nyquist plot offers a more versatile and theoretical approach, making it an appealing choice for real-time stability analysis in machining processes.

Certain scholars studied control theory to forecast chatter by employing Nyquist plots. Nigm [64] suggested an approach based on feedback control theory that is theoretically the same as Merrit [84], however, it has the advantage of considering cutting process dynamics. The analysis technique was strong enough to be applied analytically or graphically and was able to account for all types of regeneration. The Nyquist criterion was applied by the author to gauge stability. The Nyquist criteria demand that the open-loop frequency response locus (OFRL) be plotted, whereas the approach just entails plotting the operational receptance. Plotting the operative receptance is even faster than sketching the OFRL. Additionally, a stability study employing the Nyquist criterion was carried out by Wang and Cleghorn [136].

To forecast stability, Eynian and Altintas [38] modeled the transfer matrix among displacements and cutting forces and then presented an SDF and 3DF turning model. The Nyquist criteria are then used to analytically predict stability. The chatter in orthogonal cutting using the SDF rotating mechanism was expected by modeling the procedure using OTF (oriented transfer function) and t-decomposition forms [129]. By using the Nyquist criteria for OTF and t-decomposition form, the system's stability was further evaluated. The Nyquist analytical method and the TDS (time-domain simulation) method were contrasted.

The limitation of the Nyquist approach to assessing if the cutting circumstances are stable is a downside. Therefore, the TDS technique is better than the Nyquist technique because it compares the width of the cut and cutting speed to provide stable and unstable zones on SLDs. The TDS methodology is a more effective method of analysis and has several distinctive features, such as nonlinear cutting properties.

2.1.3 Finite element analysis (FEA)

The Nyquist plot and the SLD provide valuable insights into machining stability, but they come with distinct limitations. Nyquist plots rely on linearized system analysis, which can be challenging to apply to complex non-linear and time-varying machining dynamics, thereby limiting their predictive accuracy in such situations. Conversely, SLDs, which are based on empirical data, are tailored to specific conditions and tooling, making them less flexible when it comes to accommodating variations in machining scenarios, tool wear, or material properties. Additionally, SLDs are primarily retrospective tools, which constrains their ability to make real-time predictions. To overcome these constraints and achieve a more holistic comprehension of machining stability, engineers frequently employ FEA. FEA provides a numerical simulation methodology that encompasses the entire machining process, taking into consideration variables such as material properties, tool geometry, and dynamic behavior. Through the utilization of FEA, engineers can attain a more profound understanding of the intricate interactions between forces, vibrations, and thermal effects during machining. This approach goes beyond linear analysis and is better equipped to emulate the intricate real-world complexities of machining systems, rendering it a valuable tool for both the prediction and optimization of machining stability. Different strategies for the development of analytical stability analysis have been provided in the literature including FEM/FEA. Wang and Cleghorn [136] used the Nyquist criteria to perform stability analysis on a spinning stepped shaft workpiece using a finite-element beam model. Baker and Rouch [12] used the FEM technique to assess the instability of a machining process utilizing commercial ANSYS software to build a structural model, however, Experiment results did not support the validity of their findings. Without considering the dynamics of the cutting process models, the impact of structural parameters on machine instability was investigated. Instead, the method provided allows for the examination of both cutting tools as well as object flexibility. Using ANSYS software and finite element analysis, Mahdavinejad [81] projected the stability of a turning operation. This FEA model considers the flexibility of the tool, workpiece, and machine structure. Brecher et.al [101] used 3 tetrahedral-shaped solid elements of type SOLID92 for the workpiece when performing a FE model in ANSYS. After considering several geometries, a final workpiece with 35,516 parts was produced. After that, A workpiece was created using FE analysis, and the modal parameters of the stability method were often adjusted to account for workpiece variations during milling. Any FEM model has the limitation of being unable to account for the quality of the interface between the machine tool's contact surface, as these features are difficult to explain numerically. As computing power and technology improve, FEM/FEA approaches are more likely to be used to study futuristic analytical models.

2.2 Experimental techniques

The stability state in offline mode can be predicted using experimental methods, and the chatter commencement in online mode can be detected. These techniques have the potential to create the same machining environment that is not manned. Experimental strategies are classified in Fig. 1 and discussed below in terms of stability prediction and verification procedures (detection) of chatter.

2.2.1 Data acquisition

The first step in detecting chatter is always data collecting. Figure 4 depicts a typical flowchart of the chatter detection process. Before preprocessing with filters to eliminate the unwanted components, the raw signals were first recorded during the cutting process. The frequency spectra were then obtained using FFT. Since the energy ratio was then evaluated as a chatter indicator, its value can be used to gauge the chatter's intensity. Several machining circumstances are also taken into account to acquire the steady and unsteady signals concurrently, including the geometry of the tool [132], rotation of the spindle [57], the DOC [60], and the sample material. Acceleration signals [52–108], force signals

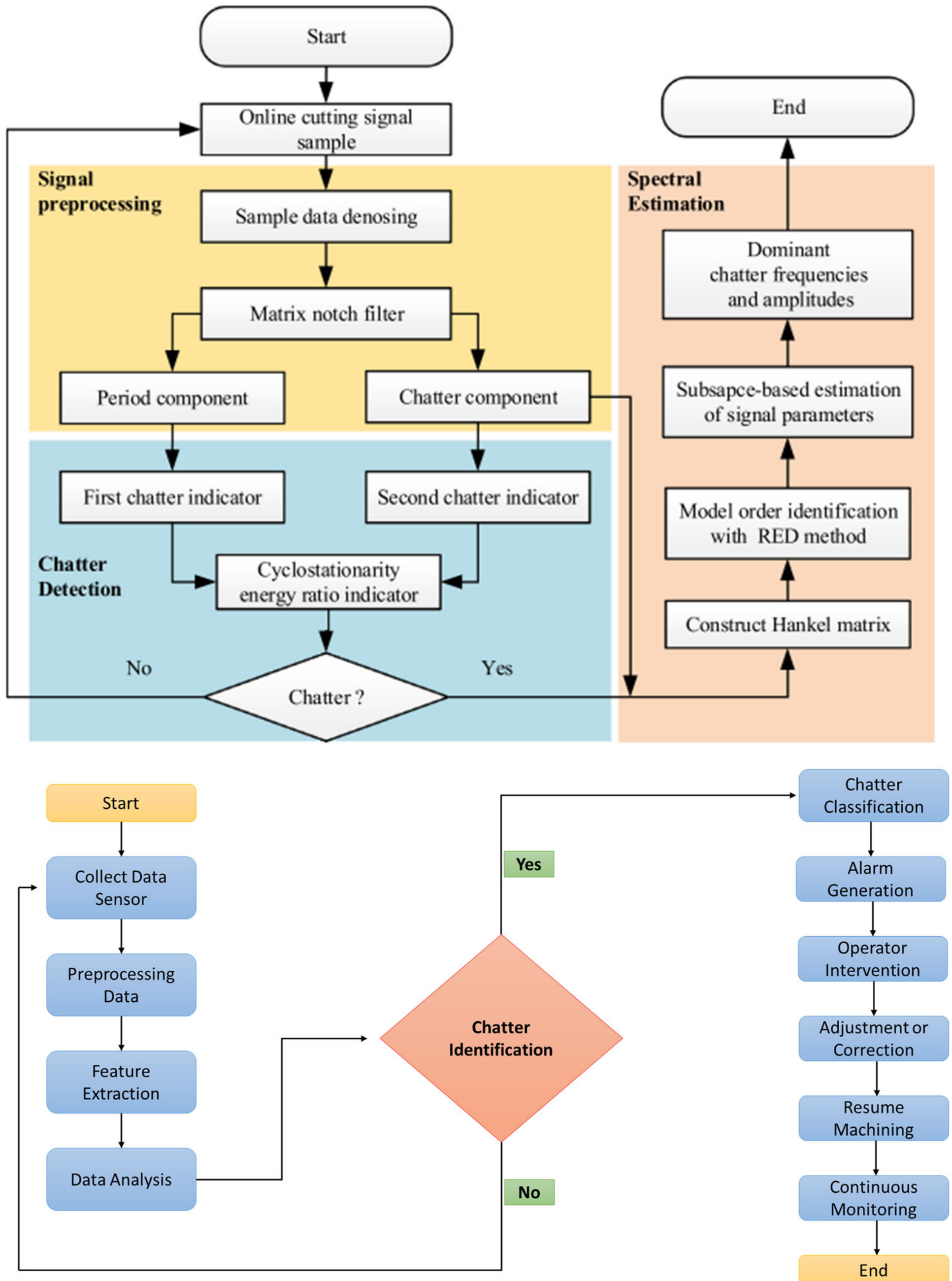


Fig. 4 The chatter detection process flowchart

[60–103], and sound signals [108, 45, 72–105], are the most prevalent sensor signals, and these signals are known to be the most ideal for chatter detection. Different signals used for the detection of chatter include the following: Current signal [83–9], image signal [4, 34, 65, 53, 114], and displacement signal [89–44].

Force signal The force signal has been widely employed to identify chatter. The most common sensors used to obtain the force signal are plate dynamometers [69, 45, 137], and rotating dynamometers [18], which are used. The feed force, feed perpendicular force, and axial force are the three components of cutting force that the plate dynamometer, which is always set up on the workbench, can measure. The torque and cutting force can be measured by the rotating dynamometer, which is typically clamped to the spindle [77, 103]. Fig. 2 illustrates the experimental setup, which includes a dynamometer for measuring the force signal.

Using the acquired force signal, Dunet al. [34], Yang et al. [145], and Li et al. [69] later identified chatter in the milling process. Detection of chatter in boring Wang et al. [137], grinding Gradisek et al. [45], and turning activities Karam and Teti [52], had been completed at the time of writing. The results described that by utilizing the chatter output extracted from the force signal, it is possible to monitor the start of the chatter.

A problem for the industry is that the dynamometer is always more expensive than other sensors. Furthermore, using a spinning dynamometer may limit the alternatives for cutting settings and reduce the rigidity of the cutting system.

Acceleration signal The acceleration signal is captured by an accelerometer as depicted in Fig. 2 during both the machining process and the modal tap test. For machining activities such as milling [4, 134], Although an accelerometer can be placed on the workpiece or the spindle, it is always connected to the tool for turning operations since chatter frequently happens on the tool side [143]. Furthermore, researchers connected the accelerometer to the live center [79]. Shi et al. [108] made a comparison between the acceleration signals acquired concurrently from the spindle and workpiece accelerometers using the same signal processing technique and chatter indications as before. According to experiments, compared to the spindle, the tool's acceleration signal, which is obtained perpendicular to the feed direction, is more chatter-sensitive and is better at identifying chatter than the feed direction under the same conditions.

Because the accelerometer was directly mounted to the workpiece, the acceleration signal it produced was more susceptible to chatter. The method for mounting the accelerometer on the workpiece, however, lacks sufficient strength. Only when the vibration is low may it be utilized for machining without coolant. However, it is more practical to mount the accelerometer on the spindle.

Sound signal To obtain the sound signals, a microphone is required [31, 125]. The machining process is not greatly impacted by the microphone's regular distance from the workpiece. Numerous researchers have employed sound signals to find chatter in a variety of machining operations, including milling [108, 17, 105], grinding [59], and boring [97]. Figure 3 demonstrates the utilization of a microphone to detect the sound signal.

The cutting state is determined using many parameters collected from the acoustic signal, including frequency [65, 42], and variance [106]. The force signal may recognize the change in cutting state before the sound signal [45], The results show that sound signals, like force and acceleration signals, are suitable for chatter detection [125]. Additionally, the microphone has a wider bandwidth than other sensors, making it more versatile in most circumstances [10], except for low-frequency machining.

Current signal For the detection of chatter, current signals are classified into spindle motor current and servo feed motor current (hereby called SFMC). According to Liu et al. [105] analysis of the acceleration signal's performance in comparison to the SFMC signal gathered throughout the grinding process, the current signal is more sensitive to cutting circumstances as compared to the acceleration signal. Liu et al. [42] came to the same conclusion from the turning process.

The current signal's most evident advantage is that it may be acquired from CNC commands without the use of an external sensor [9]. However, because the machining process gathers current signals using alternating current (AC), It must first be converted to direct current (DC). The current signal also has the following issues [124].

Image signal The off-line image signal [4, 34] and the online image signal [53, 114]. are two more ways to partition the picture signal. A microscope is used to gather the offline picture signal, which can be used to determine whether or not chatter occurs intuitively. Many investigators have attempted to employ online image signals to detect chatter, as well as a symbolic experiment design for online picture collection based on machine vision development. Lei and Soshi [65] successfully identified the commencement of chatter in milling and Khalifa et al. [53] identified the same for turning operations, by combining the acquired visual information with the texture analysis approach. Their respective findings demonstrate that by using their techniques, it is possible to accurately identify the surface flaws caused by cutting procedures. However, using an image signal to detect chatter has significant drawbacks. The image's resolution, which directly affects the outcomes of the detection, is the most important component. Generally speaking, the image's resolution should be high, but it also means a high processing expense. As a result, it will take longer to calculate, making it more challenging to identify noise in the early stages of pregnancy. Additionally, the workpiece surface imperfection, camera vibration, and lighting conditions all affect the detected results.

2.2.2 Signal processing

After data collection, signal processing is done to make sense of the signals that the sensors are receiving. Traditional signal processing methods, such as time-domain (TD), frequency-domain (FD), and time–frequency domain (TFD) analysis, are frequently studied. In his assessment of these signal processing methods, Heyns [48] discovered that the estimation of tool wear and chatter mostly relies on the TD and FD approaches. The Wavelet transform (WT), among other TFD techniques, has a higher potential that hasn't yet been fully explored. Time-domain techniques are frequently employed in TCM, according to Zhu et al. [154], however, they do lose some time-domain signal information.

Table 2 Summary of the most common signal processing techniques. [139]

Method		Merits	Limitations	Literature
Time Domain(TD) method	Raw signals Resample Techniques Time series Model	A small calculation	There is no frequency data Bad robustness	[61] [56, 151] [127, 135]
Frequency domain (FD)method	FFT Spectra analysis	Provide frequency information Identify the core of chatter	No time information Poor real-time performance	[79, 26] [125]
Time-frequency domain (TFD)method	STFT DWT HHT	Simultaneously acquire the time and frequency information	Fixed resolution Wavelet fundamental function selection might be challenging Mode mixing problem	[4, 22] [44, 117, 146] [132, 137]

When the WT and Fast Fourier transform (FFT) were examined, it was discovered that the WT's localization and scarcity properties made it far more efficient than the FFT. WT produces time-localized frequency information. In TCM, WT has a high sensitivity to quickly changing tool circumstances. It resists modifications to the working environment.

Table 2 provides a summary of the most popular signal processing techniques. Whether the signal is unfiltered, resampled, or raw can all be used to determine the features of the time-domain approach. Accordingly, the features can be used to determine the cutting status, although they only reflect the signal's temporal domain information. In the case of mutative machining conditions, certain properties could not be valid. To retrieve the frequency information, the frequency-domain approach converts the signal from the TD to the FD. However, without knowing when they first appeared, only the emerging frequencies may be realized. In contrast, the information included in the TFD technique also contains information that is in the FD. For a thorough analysis of signal processing techniques, the author cited [139].

2.2.3 Chip analysis

To ascertain stability parameters and identify chatter occurrences, several researchers have examined the chips produced during a turning operation. However, they think that studying chip development can only reveal chatter-related information after it has already happened. Because of this, this method is unable to foresee when chatter will start.

Tangjitsitcharoen [115, 116] presented a method for monitoring a CNC turning machine while it is in use and detecting cutting states. The technique makes use of the power spectrum density (PSD) of the dynamic cutting force. When the cutting conditions are chatter, broken chip formation, and continuous chip creation, the experimental findings showed three types of PSD patterns. The PSD derived from chatter is greater than that from continuous and broken chip formations. Using a scanning electron microscope (SEM), researchers examined chip top and sectional views and discovered that chips created while turning and thread cutting have the same consistently spaced sharp teeth along the chip's free edge [98]. Following a study of chatter amplitudes, it was discovered that chatter occurs when the chip serration frequency is similar to or an integer multiple of the system's constituent parts' dominant natural frequencies.

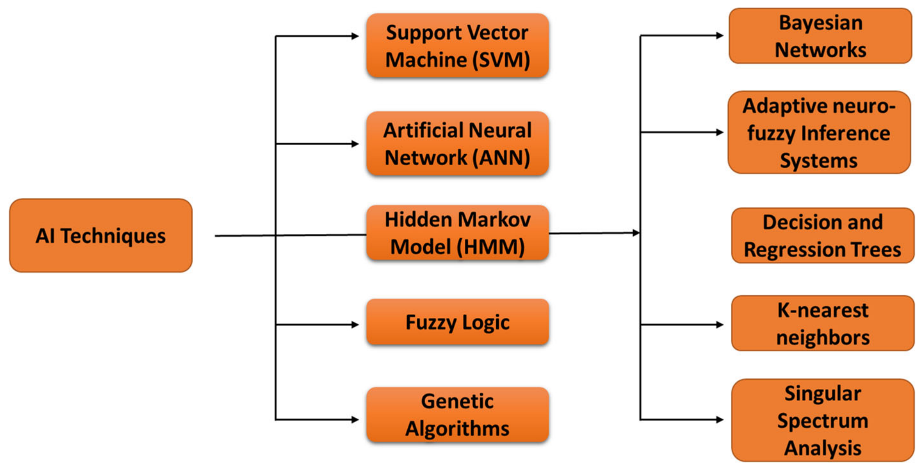
2.2.4 Feature selection

Following the use of various signal processing techniques, feature selection is always carried out. It is a crucial phase in the chatter detection process and serves the aim of choosing the features that are chatter-sensitive. It is possible to determine the corresponding machining state by keeping an eye on changes in these indications. The steps of feature generation and selection can be separated into two categories. First off, not all features are chatter-sensitive, although many features are created using the statistical method or other methods. The selection of characteristics is critical for achieving a compromise between computation performance and classification accuracy in chatter detection. The approach of feature selection is most frequently employed as described by [139].

2.2.5 Classification

Establishing a categorization system is the next stage after choosing the right features, and using this system, the cutting status may be quickly determined. The two categories of classification methods that are most frequently employed are the threshold approach and the intelligent recognition algorithm. For chatter identification, both of these techniques have been widely applied. [139] provides an overview of the major classification schemes.

Fig. 5 Summary of AI techniques used in tool condition monitoring



2.2.6 Artificial intelligence (AI) techniques

Artificial intelligence (AI) is the concept of developing intelligent machines that can emulate human thinking and behavior. Machine learning is an AI application that enables machines to learn from data without being explicitly programmed. With the advancement of AI-based systems, machine tools may be successfully monitored by anticipating tool wear kinds, remaining useful life, and high-quality machining [99]. The summary of AI techniques used in the machine tool condition monitoring is depicted in Fig. 5.

Chatter detection using AI techniques The recurrence of chatter can be predicted and detected by classifying signal properties gleaned from sensory data using AI techniques i.e. artificial neural networks (ANN) [14, 64, 108–118], the Hidden Markov model (HMM) [150], and Fuzzy logic [113–121]. A fuzzy system's decision-making is speedy due to its simplicity, however, choosing the appropriate algorithms for the planned system is challenging. The majority of identification algorithms used in automatic chatter use detection, which depends on deep learning models like CNN, SVM [152], and ANN [117–19]. The ANN technique was shown to be superior and more popular overall than HMM and Fuzzy techniques for its accuracy trainability, increased signal feature prediction, classification, massively parallel structure, speedier adoption, and ANN hardware and software that is commercially available. ANN considerably minimizes the computational time required for simulation studies, pattern identification, and decision-making.

As machine learning has advanced, noise in the cutting process has been identified using ever more intelligent recognition algorithms. Support vector machine (SVM), k-nearest neighbors (KNN) [108], convolution neural networks (CNN) [102, 107], and their variations are some of the regularly used supervised learning algorithms [22]. Additionally, classification systems use unsupervised learning methods such as the self-organizing map algorithm (SOM) [19] and the K-means clustering algorithm (K-means) [34]. SVM is the most extensively used for classification systems because it has the best generalization ability, excellent durability for small data, and an easy computation method.

One of the first experiments to utilize machine learning to recognize chatter was done in the 1990s [123]. In order to understand the properties of the pushing force spectrum while drilling.

adaptively, the author used a neural network. The author of the study [20]created an observer for an actual control system to cut down chatter while filming using ANN. The study [8] used a variety of sensors to identify chatter and developed a number of multi-layered neural networks by incorporating inputs of different signals and cutting parameters to analyze the sensor or combination of sensors that could provide a dependable source of data for monitoring the chatter, but it did not offer any conclusive solutions.

WT and SVM were coupled for the detection of chatter in a study by [146] The feature vector for the SVM classifier was created using the wavelet transform's standard deviation and the signal frequency band's wavelet packet energy ratio. The article [109] presents a novel method for detecting cutting chatter that is based on WT and multiclass SVM.

It is significant to notice that the chatter phenomenon is linked to an increase in vibrational signal amplitude in all of these publications, and that the majority of verification experiments are far from commercial usage.

Advances in artificial intelligence have made it possible for methods like deep learning to automatically retrieve features from input data. The (CNN) is one of the most widely used techniques for converting data into information because It has the ability to analyze raw information and automatically spot data feature representations in a variety of forms [43]. The vibration signal was translated into the time–frequency spectrum in the research [41] to create a deep-learning model for chatter detection. The time–frequency features are extracted by the deep neural network, and the VMD divides the vibration signal into the chatter band. To categorize the features obtained from chatter detection, an SVM is introduced.

A deep neural network is trained to recognize the various chatter stages. By combining CNN and genetic algorithms, the authors of the paper [155] were able to detect chatter on the picture of the machined part. By improving their technique, they were also able to solve the oscillation problem brought on by the employment of genetic algorithms. In the paper [102], a chatter detection method that combines a CNN and a physics-based model is presented. By linking artificial neurons with calibrated weights, they can imitate how the human brain works and forecast a state using CNN.Numerous deep learning techniques have been evaluated in these relatively recent studies, frequently in combination with other techniques, and have generally produced positive outcomes. Although some articles use actual cutting conditions, the majority of studies still use machining parameters that are distant from industrial applications. Nevertheless, it is always obvious that chatter and vibration amplitude have a close relationship. It is challenging to decide whether all these complex techniques are superior to straightforward RMS-level monitoring. Table 3 provides a detailed comparison of various AI techniques employed for chatter detection.

3 Chatter suppression technique

In machining, chatter suppression and control are difficult problems to solve. According to reviews by Abele et al. [1] and Zhu and Liu [153], numerous research initiatives aimed at chatter control have been conducted in recent years. The two fundamental types of chatter suppression techniques are passive and active chatter suppression. Table 4 illustrates the distinctions between active and passive chatter suppression techniques. A summary of chatter suppression techniques for the machining process is shown in Fig. 6 and these techniques will be briefly reviewed in this section.

The passive approach aims to decrease chatter by modifying system behavior. The design of the machine tool can be improved, or extra components that absorb extra energy or interfere with the regenerative effect can be added to alter or modify the system's response [100].

These additional components are capable of damping, minimizing, and controlling chatter and typically have reduced rigidity. Some of the most common passive chatter suppression mechanisms used on machines are vibration absorbers, mass dampers, friction dampers, and tuned dampers. Using vibration cutting, Xiao et al. [143] demonstrated a strategy for reducing chatter vibration. By causing friction during vibration between the inserted plate surface and the wall's inner hole, Marui et al. [82] employed a friction plate in the tool shank's overhang to increase the dampening capacity of the mechanism. The tuned mass damper (TMD) or dynamic vibration absorber (DVA) is one of many passive suppression systems that has been largely used in various applications. Tobias [104], provided a few useful methods for reducing chatter and enhancing process stability by attaching vibration absorbers to different machine tool components.

Wang et al. [140], developed a novel nonlinear TMD that can absorb energy through sliding friction and mass vibration to reduce chatter during the turning process. The innovative nonlinear TMD having a 0.01 mass ratio raised the crucial limiting DOC by 150 to180% in contrast to an undamped system. Using a multi-frequency approach, Otto et al. explored the durability of non-uniform pitch and helical tools and found that these tools can dramatically raise the limiting DOC [93]. Comak and Budak [29] described the reliability of adjustable helix and pitch tools and proposed a realistic way of optimizing pitch angle design to capitalize on stability. Absorbers and dampers are used to reduce chatter by reducing vibration or altering the dampening features of the spindle system [80]. The position of the vibration absorber and the stiffness of its spring were adjusted by Moradi et al. [88] to control chatter. A nonlinear tuned vibration absorber was developed by Habib et al. [47] to reduce chatter. By employing a minimax numerical optimization strategy to enhance the stiffness and damping of several TMD, Yang et al. [144] decreased chatter.

Passive vibration suppression systems provide several advantages, including ease of use, low cost, and the absence of external energy. However, some passive dampers need very exact calibration for excellent operation highly uncertain in the design of machine tools and the cutting operation.

The active approach, as the name suggests, actively eliminates chatter vibrations by continuously observing and diagnosing the turning operation, as well as implementing necessary modifications in the operation. Some studies were able to reduce the regeneration effect by purposefully changing process variables like feed, speed, and DOC. Lin and Hu [72], develop a method for reducing chatter by changing the feed rate and spindle speed. To eliminate the onset of chatter, the cutting tool's rake and clearance angles were modified by Mei et al. [83]. Frumusanu et al. [40] have introduced a turning stability intelligent control system. The cutting force signal was monitored online as part of the procedure. a lag in the feedback control Vibration suppression using a vibration absorber is another option. The temporal delay is usually caused by the fundamental nature of the system's dynamics. It is possible to use a delay to efficiently control the change from chaotic to ordered motion in a system. Olgac and Holm-Hansen [92] developed a delayed resonator to give dynamical systems delayed position feedback control. This

Table 3 Comparison of Various AI Techniques

Aspect	Approach	Data Type	Training Data	Complexity	Strengths	Limitations
Support Vector Machines	Supervised machine learning algorithm that finds a separating hyperplane for classification tasks	Suitable for both numerical and categorical data	Requires labeled data for supervised training	Relatively simple to implement, moderate computational requirements	Suitable for high-dimensional data, can handle non-linearity	May struggle with large datasets. Doesn't provide probability estimates
Artificial Neural Networks	A deep learning model that processes data through interconnected neurons	Suitable for numerical data but can handle various types	Requires labeled data for supervised training	Moderate to high complexity, significant computational resources	Can capture complex patterns and relationships in data	Requires large datasets and computational resources. Prone to overfitting
Hidden Markov Models	The probabilistic model is used to model sequences of observations	Suitable for sequential and time-series data	Requires labeled sequential data with state labels	Moderate complexity requires defining states and transitions	Effective with time-series data, captures state transitions	Makes assumptions about data (Markov property). Rule design can be challenging
Fuzzy Logic	Utilizes fuzzy rules and memberships to handle uncertainty	Suitable for numerical and categorical data with fuzzy logic membership functions	Requires expert-defined fuzzy rules and memberships	Moderate complexity, fuzzy rule and membership design can be complex	Handles uncertainty and vague information well	Does not directly predict chatter, requires significant computation
Genetic Algorithm	Optimization technique inspired by natural selection for parameter tuning	Suitable for numerical data (parameters to optimize)	Requires a defined optimization objective and data	Moderate complexity, computational resources required for optimization	Optimizes machining parameters for chatter avoidance	Sensitive to irrelevant features, performance degrades with increasing data
k-Nearest Neighbors	Instance-based learning algorithm based on similarity to previously observed instances	Suitable for both numerical and categorical data	Requires labeled data for classification	Simple to implement, low computational requirements	Simple and robust for small datasets	Sensitive to outliers and noise. Requires domain expertise
Bayesian Network	Models probabilistic relationships between variables for decision-making	Suitable for various types of data	Requires data for probabilistic modeling	Moderate complexity may require expert knowledge	Represents dependencies and provides probabilistic predictions	Requires signal preprocessing and feature extraction. Does not provide direct classification
Singular Spectrum Analysis	Signal processing technique used for analyzing sensor data	Suitable for time-series data, especially vibration or acoustic signals	Requires time-series sensor data	Moderate complexity, data preprocessing, and feature extraction may be needed	Effective for time-series signal analysis	Requires data for training the ANFIS network

Table 3 (continued)

Aspect	Approach	Data Type	Training Data	Complexity	Strengths	Limitations
Decision &Regression Trees	Decision trees partition data into subsets based on criteria, while regression trees predict numerical values	Suitable for both categorical and numerical data	Requires labeled data with features and target labels	Simple to implement, can be less complex for shallow trees	Provides a visual, interpretable structure for decision-making	Offers interpretability through fuzzy rules and neural network modeling
Adaptive Neuro Fuzzy Inference System (ANFIS)	Integrates fuzzy logic and neural networks for inference and modeling	Suitable for data with vague or uncertain information	Requires data for training the ANFIS network	Complexity depends on the ANFIS architecture and rules	Requires sufficient training data for effective modeling	less suitable for problems with a large number of input variables

Table 4 Difference between Active and Passive Suppression Techniques

Aspect	Active Chatter Suppression	Passive Chatter Suppression
Mechanism	Real-time adjustments during machining, utilizing sensors and control systems	Design and setup modifications, involving tool and workpiece geometry, materials, and damping elements
Timing of Intervention	Real-time adjustments during machining	Implemented before machining begins, with minimal real-time intervention
Productivity Impact	May improve productivity by allowing higher cutting speeds	May limit productivity due to conservative cutting parameters
Equipment & Software	Advanced CNC machines, sensors, and real-time control software	Primarily involves tool and workpiece setup choices
Complexity	Can be complex, requiring skilled operators and specialized equipment	Generally simpler to implement, suitable for a wider range of scenarios
Cost	Typically higher equipment and software costs	More cost-effective, often requiring fewer specialized tools
Applicability	Ideal for high-precision, high-speed machining where chatter can affect part quality	Suitable for various machining operations, with some limitations on cutting parameters

approach provides benefits such as real-time tunability, a wide frequency range, flawless tonal suppression, and ease of control while removing the system's tonal vibrations. Spindle speed variation (SSV) is another method for reducing chatter, in which the spindle speed is continuously altered, disrupting the regenerative effect. By utilizing a disturbance rejecting and stabilizing strategy, Monnin et al. [86, 87] created an active control method based on a piezoelectric stack that increased milling performance. By placing the magnetic actuator at the machine's antinode region, A direct velocity feedback controller was developed by Zaeh et al. [149] and chatter-free MRR was raised. The velocity feedback controller can be applied similarly. A model predictive control method was developed by Li et al. [68] and was successful in reducing chatter. Milling chatter was successfully controlled by Li et al. [70] using a linear matrix inequality-based robust controller. Similar techniques were employed by Wan et al. [133] to reduce chatter by active damping. A magnetic bearing-supported spindle system is also planned. Li et al. [66] also succeeded in controlling chatter by sending back the chatter-related current displacement component through a specially constructed comb filter.

Some encouraging outcomes have been obtained with chatter control, particularly active chatter management.

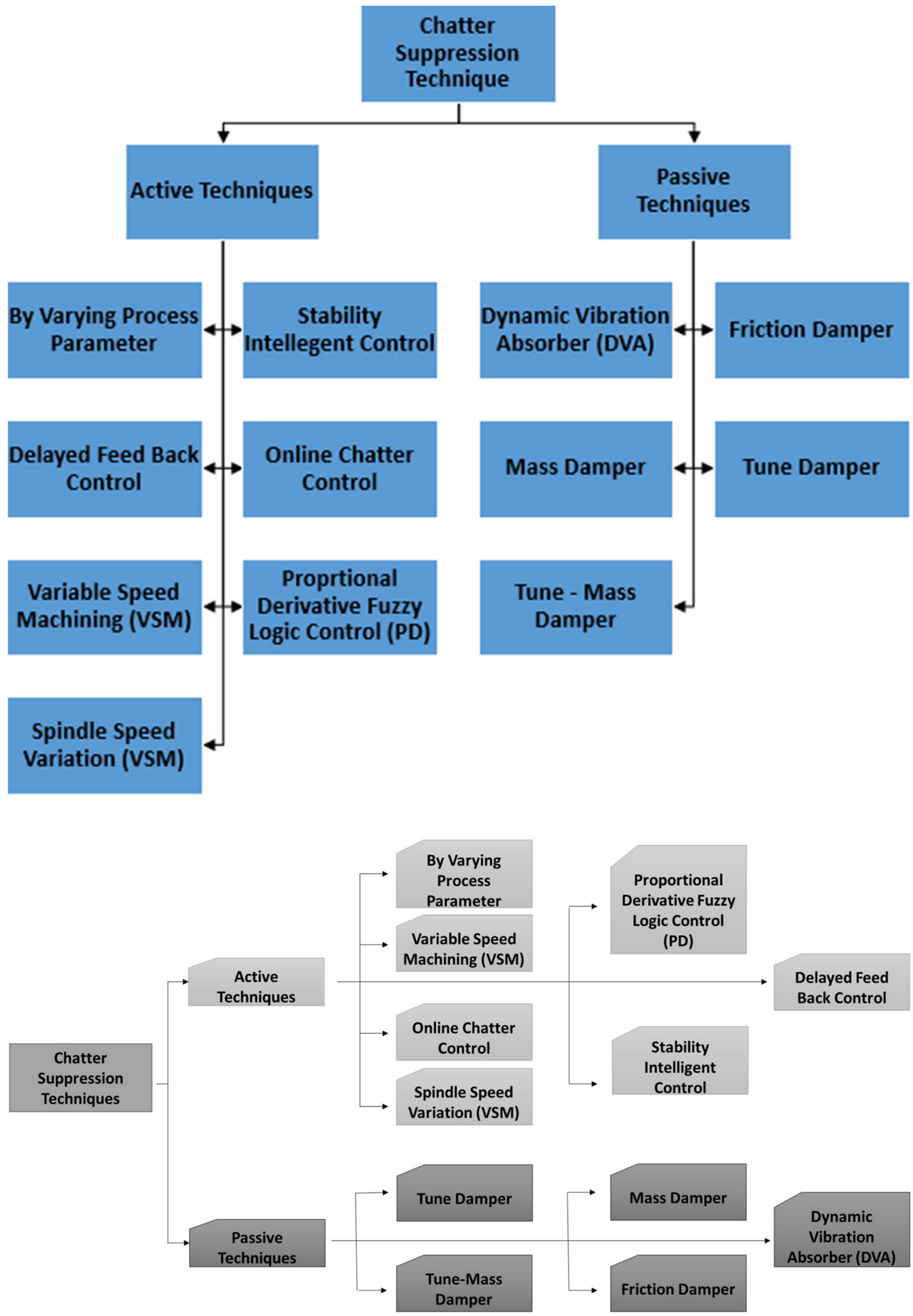


Fig. 6 Summary of chatter suppression techniques for machining process

However, the feedback employed in most studies is the entire vibration behavior of the workpiece system at present or during the preceding tooth passage interval. In this instance, the entire cutting vibration is regulated, and the actuator's control energy is often quite high. As per a recent study [67], displacement difference (the difference between the machine system's displacement responses at the present moment and one tooth passing interval before) is employed as feedback to achieve energy-saving chatter suppression using PD and fuzzy control approaches. It is simpler to develop and use non-model-based control strategies like fuzzy and PD. The results demonstrate that the proven methods not only minimize chatter and increase the maximum (MRR) but also greatly reduce the voltage the actuator needs, allowing for control energy savings.

Recent developments in the field of machining have led to substantial progress in techniques aimed at suppressing chatter during the manufacturing process. This area of study has witnessed considerable research and innovation [33]. emphasizes the significance of carefully choosing machining parameters to maintain stability, prevent chatter, and fulfill the demands for quality and efficiency in the machining of thin-walled SiCp/Al composite workpieces. Another study proposed that increasing the fundamental angular frequency of spindle speed variation tends to be more effective in swiftly mitigating chatter during turning operations [96].A unique approach to addressing chatter is investigated in a study that introduces a diamond turning system assisted by a magnetic field, with the aim of minimizing chatter during the machining of titanium alloys. Empirical evidence from experiments substantiates the efficacy of this magnetic field assistance in suppressing chatter, improving the quality of the machined surfaces, and reducing tool wear [71].In another study, researchers illustrate that a tooling mechanism, capable of adjusting tool angles, significantly enhances the dynamic stability in turning processes. This approach can be readily incorporated into turning machines through straightforward modifications to the tooling mechanism [13].The challenge of dealing with simultaneous chatter during machining is addressed by the researchers. The study investigates parametric tunings for vibration absorbers to enhance stability and introduces a novel tuning criterion, which minimizes the definite integral of the frequency response function while taking into consideration the damping of the absorber's base component [85].

4 Conclusion

The cutting system experiences chatter, which is a self-excited vibration. Extensive research has been done on chatter detection to reveal the cutting state in real time and lessen its effects. This article examines the state of chatter detection research from four perspectives: gathering information, signal processing, choosing features, and classification using conventional analytical and experimental techniques as well as the latest artificial intelligence/machine learning technique. The special focus was to access the ability of AI techniques and challenges for chatter detection. On the other hand, some current issues and prospective solutions are discussed. The following are some findings that can be drawn from the extant literature.

- Although force and acceleration signals are usually considered to be more effective for chatter detection, they are only used in experiments at the moment since dynamometers are expensive and accelerometer installation is technically challenging.
- As a non-stationary phenomenon, chatter is better detected using the time–frequency domain method.
- Features in the FD or TFD may be more vulnerable to chatter since it is characterized by the reassignment of frequency and energy.
- The intelligent recognition system is simpler and user-friendly as compared to the threshold approach, but the resilience and self-adaptability of the latter are far greater.
- Despite the expansion of artificial intelligence (AI) in many areas, the identification of chatter by AI models is still supported by conventional signal processing techniques. In contrast to other fields, researchers do not frequently apply AI approaches to identify chatter phenomena.
- Given the complexity of the existing artificial intelligence models—primarily convolutional or deep neural networks—it is nearly hard for their designers to fully comprehend how they work. However, a machinist can gain a lot from outlining their choices.
- Despite AI models' great capacity to make extremely precise estimates in chatter detection, they nonetheless encounter certain key difficulties: the learning and classification processes requiring a considerable amount of CPU power limits, human knowledge, and time for labeling data, particularly when there are many classes, before training the model; and the lack of transparency due to their inherent natures.
- High-performance computing platforms with graphics processing units (GPUs) and tensor processing units (TPUs), can resolve the computational resource issue during model training.
- Deep learning eliminates the need for extensive trial-and-error by automatically extracting higher-level features and combining feature extraction and classification into a single structure. Deep learning has enhanced the performance of chatter detection just like machine learning models.
- The minimization of chatter is the main goal of chatter research. Prior to suppressing the chatter, it is important to ascertain its nature and evaluate whether it is the cause of the vibration problem. Therefore, techniques for chatter management are frequently employed in conjunction with online chatter detection. Because of this, it is preferable to incorporate both into the machine tool.

Even though chatter detection investigation has progressed significantly, several aspects, including sensor signal selection, real-time signal processing method, feature selection, database formation, and integration of multiple sensors, still require improvement. There is room for chatter detection utilizing AI algorithms that can be aligned with industrial applications with real-time conditions because the majority of research still employs machining parameters that are far from industrial applications. Key challenges and opportunities for future research include improving sensor accessibility and affordability, enhancing signal processing algorithms for greater sensitivity, and integrating multiple sensors for a holistic view of the machining process. Predictive models that anticipate chatter's onset could revolutionize the industry, along with leveraging high-performance computing platforms to overcome computational limitations. Emphasizing synergy between detection and suppression techniques, especially through online systems and adaptive control strategies, holds the potential to greatly enhance machining stability and productivity.

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Declarations

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References

1. Abele, E., Altintas, Y., Brecher, C.: Machine tool spindle units. CIRP Ann. - Manuf. Technol. **59**(2), 781–802 (2010). https://doi.org/10.1016/j.cirp.2010.05.002
2. Ahmadi, K., Ismail, F.: Experimental investigation of process damping nonlinearity in machining chatter. Int. J. Mach. Tools Manuf **50**(11), 1006–1014 (2010). https://doi.org/10.1016/j.ijmachtools.2010.07.002
3. Ahmadi, K., Ismail, F.: Analytical stability lobes including nonlinear process damping effect on machining chatter. Int. J. Mach. Tools Manuf **51**(4), 296–308 (2011). https://doi.org/10.1016/j.ijmachtools.2010.12.008
4. Albertelli, P., Braghieri, L., Torta, M., Monno, M.: Development of a generalized chatter detection methodology for variable speed machining. Mech. Syst. Signal Process. **123**, 26–42 (2019). https://doi.org/10.1016/j.ymssp.2019.01.002
5. Altintas, Y., Eynian, M., Onozuka, H.: Identification of dynamic cutting force coefficients and chatter stability with process damping. CIRP Ann. - Manuf. Technol. **57**(1), 371–374 (2008). https://doi.org/10.1016/j.cirp.2008.03.048
6. Altintas, Y., Stepan, G., Budak, E., Schmitz, T., Kilic, Z.M.: Chatter stability of machining operations. J. Manuf. Sci. Eng. (2020). https://doi.org/10.1115/1.4047391
7. Altintas, Y., Weck, M.: Chatter stability of metal cutting and grinding. CIRP Ann. - Manuf. Technol. **53**(2), 619–642 (2004). https://doi.org/10.1016/S0007-8506(07)60032-8
8. Arriaza, O.V., Tumurkhuyagc, Z., Kim, D.W.: Chatter identification using multiple sensors and multi-layer neural networks. Procedia Manuf. **17**, 150–157 (2018). https://doi.org/10.1016/j.promfg.2018.10.030
9. Aslan, D., Altintas, Y.: On-line chatter detection in milling using drive motor current commands extracted from CNC. Int. J. Mach. Tools Manuf **132**, 64–80 (2018). https://doi.org/10.1016/j.ijmachtools.2018.04.007
10. Axinte, D.A., Gindy, N., Fox, K., Unanue, I.: Process monitoring to assist the workpiece surface quality in machining. Int. J. Mach. Tools Manuf **44**(10), 1091–1108 (2004). https://doi.org/10.1016/j.ijmachtools.2004.02.020
11. Bach, P.: "Vibrace při obrábění. Mach. Tool. **3**, 1–5 (2012)
12. Baker, J.R., Rouch, K.E.: Use of finite element structural models in analyzing machine tool chatter. Finite Elem. Anal. Des. **38**(11), 1029–1046 (2002). https://doi.org/10.1016/S0168-874X(02)00050-1
13. Behrouz, H., Baseri, H., Nourmohammadi, H.: Chatter Suppression in turning by applying a tooling mechanism with the ability to change the tool angles. Results Experimental tests were conducted for the evaluation of the proposed chatter suppression system. vol. 55, no. 4, pp. 93–96, 2023, https://doi.org/10.22060/mej.2023.5172.7490.
14. Benardos, P.G., Mosialos, S., Vosniakos, G.C.: Prediction of workpiece elastic deflections under cutting forces in turning. Robot. Comput. Integr. Manuf. **22**(5–6), 505–514 (2006). https://doi.org/10.1016/j.rcim.2005.12.009
15. Budak, E., Tunc, L.T.: Identification and modeling of process damping in turning and milling using a new approach. CIRP Ann. - Manuf. Technol. **59**(1), 403–408 (2010). https://doi.org/10.1016/j.cirp.2010.03.078
16. Caliskan, H., Kilic, Z.M., Altintas, Y.: On-line energy-based milling chatter detection. J. Manuf. Sci. Eng. Trans. ASME **140**(11), 1–12 (2018). https://doi.org/10.1115/1.4040617
17. Cao, H., Yue, Y., Chen, X., Zhang, X.: Chatter detection in milling process based on synchrosqueezing transform of sound signals. Int. J. Adv. Manuf. Technol. **89**(9–12), 2747–2755 (2017). https://doi.org/10.1007/s00170-016-9660-7
18. Cao, L., Zhang, X., Huang, T., Zhang, X., Ding, H.: An adaptive chatter signal enhancement approach for early fault diagnosis in machining process. Procedia CIRP **82**(July), 308–313 (2019). https://doi.org/10.1016/j.procir.2019.03.273
19. Cao, H., Zhou, K., Chen, X., Zhang, X.: Early chatter detection in end milling based on multi-feature fusion and 3σ criterion. Int. J. Adv. Manuf. Technol. **92**(9–12), 4387–4397 (2017). https://doi.org/10.1007/s00170-017-0476-x
20. Cardi, A.A., Firpi, H.A., Bement, M.T., Liang, S.Y.: Workpiece dynamic analysis and prediction during chatter of turning process. Mech. Syst. Signal Process. **22**(6), 1481–1494 (2008). https://doi.org/10.1016/j.ymssp.2007.11.026
21. Chandiramani, N.K., Pothala, T.: Dynamics of 2-dof regenerative chatter during turning. J. Sound Vib. **290**(1–2), 448–464 (2006). https://doi.org/10.1016/j.jsv.2005.04.012
22. Chen, Y., Li, H., Jing, X., Hou, L., Bu, X.: Intelligent chatter detection using image features and support vector machine. Int. J. Adv. Manuf. Technol. **102**(5–8), 1433–1442 (2019). https://doi.org/10.1007/s00170-018-3190-4
23. Chen, J.F., Lo, S.K., Do, Q.H.: An approach to the classification of cutting vibration on machine tools. Inf (2016). https://doi.org/10.3390/info7010007

24. Chen, C.K., Tsao, Y.M.: A stability analysis of regenerative chatter in turning process without using tailstock. Int. J. Adv. Manuf. Technol. **29**(7–8), 648–654 (2006). https://doi.org/10.1007/s00170-005-2573-5
25. Chen, C.K., Tsao, Y.M.: A stability analysis of turning a tailstock supported flexible work-piece. Int. J. Mach. Tools Manuf **46**(1), 18–25 (2006). https://doi.org/10.1016/j.ijmachtools.2005.04.002
26. Chen, D., Zhang, X., Zhao, H., Ding, H.: Development of a novel online chatter monitoring system for flexible milling process. Mech. Syst. Signal Process. **159**, 107799 (2021). https://doi.org/10.1016/j.ymssp.2021.107799
27. Chiou, Y.S., Chung, E.S., Liang, S.Y.: Analysis of tool wear effect on chatter stability in turning. Int. J. Mech. Sci. **37**(4), 391–404 (1995). https://doi.org/10.1016/0020-7403(94)00070-Z
28. Clancy, B.E., Shin, Y.C.: A comprehensive chatter prediction model for face turning operation including tool wear effect. Int. J. Mach. Tools Manuf **42**(9), 1035–1044 (2002). https://doi.org/10.1016/S0890-6955(02)00036-6
29. Comak, A., Budak, E.: Modeling dynamics and stability of variable pitch and helix milling tools for development of a design method to maximize chatter stability. Precis. Eng. **47**, 459–468 (2017). https://doi.org/10.1016/j.precisioneng.2016.09.021
30. Das, M.K., Tobias, S.A.: The relation between the static and the dynamic cutting of metals. Int. J. Mach. Tool Des. Res. **7**(2), 63–89 (1967). https://doi.org/10.1016/0020-7357(67)90026-1
31. Delio, T., Tlusty, J., Smith, S.: Use of audio signals for chatter detection and control. J. Manuf. Sci. Eng. Trans. ASME **114**(2), 146–157 (1992). https://doi.org/10.1115/1.2899767
32. Dombovari, Z., Barton, D.A.W., Eddie Wilson, R., Stepan, G.: On the global dynamics of chatter in the orthogonal cuttingmodel. Int. J. Non. Linear. Mech. **46**(1), 330–338 (2011). https://doi.org/10.1016/j.ijnonlinmec.2010.09.016
33. Dong, X.W., Li, Z.A., Bian, L., Wang, M., Jin, Z.B., Da Li, Q.: Study on chatter suppression in ultrasonic-assisted grinding of thin-walled workpiece of SiCp/Al composites. Adv. Mech. Eng. **15**(6), 1–9 (2023). https://doi.org/10.1177/16878132231177995
34. Dun, Y., Zhus, L., Yan, B., Wang, S.: A chatter detection method in milling of thin-walled TC4 alloy workpiece based on auto-encoding and hybrid clustering. Mech. Syst. Signal Process. **158**, 1–23 (2021). https://doi.org/10.1016/j.ymssp.2021.107755
35. Elbestawi, M.A., Ismail, F., Du, R., Ullagaddi, B.C.: Modelling machining dynamics including damping in the tool- workpiece interface. J. Manuf. Sci. Eng. Trans. ASME **116**(4), 435–439 (1994). https://doi.org/10.1115/1.2902125
36. Elbestawi, T M. A., Du, S. L. R. X.: Int. J. Maeh.; 32(6):781–796 (1992)
37. Emami, M., Karimipour, A.: Theoretical and experimental study of the chatter vibration in wet and MQL machining conditions in turning process. Precis. Eng. **72**(April), 41–58 (2021). https://doi.org/10.1016/j.precisioneng.2021.04.006
38. Eynian, M., Altintas, Y.: Chatter stability of general turning operations with process damping. J. Manuf. Sci. Eng. **131**(4), 0410051–04100510 (2009). https://doi.org/10.1115/1.3159047
39. Fofana, M.S., Ee, K.C., Jawahir, I.S.: Machining stability in turning operation when cutting with a progressively worn tool insert. Wear **255**(7–12), 1395–1403 (2003). https://doi.org/10.1016/S0043-1648(03)00356-9
40. Frumusanu, G.R., Constantin, I.C., Marinescu, V., Epureanu, A.: Development of a stability intelligent control system for turning. Int. J. Adv. Manuf. Technol. (2013). https://doi.org/10.1007/s00170-012-4074-7
41. Gao, H.N., Shen, D.H., Yu, L., Zhang, W.C.: Identification of cutting chatter through deep learning and classification. Int. J. Simul. Model. **19**(4), 667–677 (2020). https://doi.org/10.2507/IJSIMM19-4-CO16
42. Gao, J., Song, Q., Liu, Z.: Chatter detection and stability region acquisition in thin-walled workpiece milling based on CMWT. Int. J. Adv. Manuf. Technol. **98**(1–4), 699–713 (2018). https://doi.org/10.1007/s00170-018-2306-1
43. Glaeser, A., et al.: Applications of deep learning for fault detection in industrial cold forging. Int. J. Prod. Res. **59**(16), 4826–4835 (2021). https://doi.org/10.1080/00207543.2021.1891318
44. González-Brambila, O., Rubio, E., Jáuregui, J.C., Herrera-Ruiz, G.: Chattering detection in cylindrical grinding processes using the wavelet transform. Int. J. Mach. Tools Manuf **46**(15), 1934–1938 (2006). https://doi.org/10.1016/j.ijmachtools.2006.01.021
45. Gradišek, J., Baus, A., Govekar, E., Klocke, F., Grabec, I.: Automatic chatter detection in grinding. Int. J. Mach. Tools Manuf **43**(14), 1397–1403 (2003). https://doi.org/10.1016/S0890-6955(03)00184-6
46. Gök, F., Orak, S., Sofuoğlu, M.A.: The effect of cutting tool material on chatter vibrations and statistical optimization in turning operations. Soft. Comput. **24**(22), 17319–17331 (2020). https://doi.org/10.1007/s00500-020-05022-3
47. Habib, G., Kerschen, G., Stepan, G.: Chatter mitigation using the nonlinear tuned vibration absorber. Int. J. Non. Linear. Mech. **91**(February), 103–112 (2017). https://doi.org/10.1016/j.ijnonlinmec.2017.02.014
48. Heyns, P.S.: Tool condition monitoring using vibration measurements: a review. Insight Non-Destructive Test. Cond. Monit. **49**(8), 447–450 (2007). https://doi.org/10.1784/insi.2007.49.8.447
49. Ji, Y., et al.: EEMD-based online milling chatter detection by fractal dimension and power spectral entropy. Int. J. Adv. Manuf. Technol. **92**(1–4), 1185–1200 (2017). https://doi.org/10.1007/s00170-017-0183-7
50. Jin, X., Poudel, A.: 712. Experimental study on high frequency chatter attenuation in 2-D vibration assisted micro milling process CM Conventional machining VAM Vibration assisted machining, Mass in and directions, Damping coefficient in and directions, Stiffness in and di. J. Vibroeng.; 17(6):1392–8716 (2015)
51. K. R. Kashyzadeh and M. J. O. Ghorabi, "Study of Chatter Analysis in Turning Tool And Control Methods – A Review," vol. 2, no. 4, pp. 1–5, 2012.
52. Karam, S., Teti, R.: Wavelet transform feature extraction for chip form recognition during carbon steel turning. Procedia CIRP **12**, 97–102 (2013). https://doi.org/10.1016/j.procir.2013.09.018
53. Khalifa, O.O., Densibali, A., Faris, W.: Image processing for chatter identification in machining processes. Int. J. Adv. Manuf. Technol. **31**(5–6), 443–449 (2006). https://doi.org/10.1007/s00170-005-0233-4
54. Kondo, E., Ota, H., Kawai, T.: New method to detect regenerative chatter using spectral analysis, Part 1: basic study on criteria for detection of chatter. J. Manuf. Sci. Eng. Trans. ASME **119**(4), 4–9 (1997)
55. Kotaiah, K.R., Srinivas, J., Babu, K.J., Srinivas, K.: Prediction of optimal cutting states during inward turning: an experimental approach. Mater. Manuf. Process. **25**(6), 432–441 (2010). https://doi.org/10.1080/10426910903229321
56. Kuljanic, E., Sortino, M., Totis, G.: Multisensor approaches for chatter detection in milling. J. Sound Vib. **312**(4–5), 672–693 (2008). https://doi.org/10.1016/j.jsv.2007.11.006
57. Kuljanic, E., Totis, G., Sortino, M.: Development of an intelligent multisensor chatter detection system in milling. Mech. Syst. Signal Process. **23**(5), 1704–1718 (2009). https://doi.org/10.1016/j.ymssp.2009.01.003
58. Kurata, Y., Merdol, S.D., Altintas, Y., Suzuki, N., Shamoto, E.: Chatter stability in turning and milling with in process identified process damping. J. Adv. Mech. Des. Syst. Manuf. **4**(6), 1107–1118 (2010). https://doi.org/10.1299/jamdsm.4.1107

59. Kwak, J.S., Ha, M.K.: Neural network approach for diagnosis of grinding operation by acoustic emission and power signals. J. Mater. Process. Technol. **147**(1), 65–71 (2004). https://doi.org/10.1016/j.jmatprotec.2003.11.016
60. Lajmert, P., Rusinek, R., Kruszynski, B.: Chatter identification in milling of Inconel 625 based on recurrence plot technique and hilbert vibration decomposition. MATEC Web Conf. **148**, 1–5 (2018). https://doi.org/10.1051/matecconf/201814809003
61. Lamraoui, M., Barakat, M., Thomas, M., El Badaoui, M.: Chatter detection in milling machines by neural network classification and feature selection. J. Vib. Control **21**(7), 1251–1266 (2015). https://doi.org/10.1177/1077546313493919
62. Lamraoui, M., Thomas, M., El Badaoui, M.: Cyclostationarity approach for monitoring chatter and tool wear in high speed milling. Mech. Syst. Signal Process. **44**(1–2), 177–198 (2014). https://doi.org/10.1016/j.ymssp.2013.05.001
63. Lange, J.H., Abu-Zahra, N.H.: Tool chatter monitoring in turning operations using wavelet analysis of ultrasound waves. Int. J. Adv. Manuf. Technol. **20**(4), 248–254 (2002). https://doi.org/10.1007/s001700200149
64. Lee, B.Y., Tarng, Y.S., Ma, S.C.: Modeling of the process damping force in chatter vibration. Int. J. Mach. Tools Manuf **35**(7), 951–962 (1995). https://doi.org/10.1016/0890-6955(94)00046-M
65. Lei, N., Soshi, M.: Vision-based system for chatter identification and process optimization in high-speed milling. Int. J. Adv. Manuf. Technol. **89**(9–12), 2757–2769 (2017). https://doi.org/10.1007/s00170-016-9770-2
66. Li, D., Cao, H., Chen, X.: Fuzzy control of milling chatter with piezoelectric actuators embedded to the tool holder. Mech. Syst. Signal Process. **148**(28), 107190 (2021). https://doi.org/10.1016/j.ymssp.2020.107190
67. Li, D., Cao, H., Chen, X.: Displacement difference feedback control of chatter in milling processes. Int. J. Adv. Manuf. Technol. **120**(9–10), 6053–6066 (2022). https://doi.org/10.1007/s00170-022-09128-w
68. Li, D., Cao, H., Zhang, X., Chen, X., Yan, R.: Model predictive control based active chatter control in milling process. Mech. Syst. Signal Process. **128**(28), 266–281 (2019). https://doi.org/10.1016/j.ymssp.2019.03.047
69. Li, K., He, S., Li, B., Liu, H., Mao, X., Shi, C.: A novel online chatter detection method in milling process based on multiscale entropy and gradient tree boosting. Mech. Syst. Signal Process. **135**, 106385 (2020). https://doi.org/10.1016/j.ymssp.2019.106385
70. Li, X., Wan, S., Yuan, J., Yin, Y., Hong, J.: Active suppression of milling chatter with LMI-based robust controller and electromagnetic actuator. J. Mater. Process. Technol. **297**(May), 117238 (2021). https://doi.org/10.1016/j.jmatprotec.2021.117238
71. Li, D., Yip, W.S., Cao, H., Zhang, H., Tang, Y.M., To, S.: "Chatter suppression in diamond turning using magnetic field assistance. J. Mater. Process. Technol. **321**(August), 118150 (2023). https://doi.org/10.1016/j.jmatprotec.2023.118150
72. Lin, S.C., Hu, M.R.: Low vibration control system in turning. Int. J. Mach. Tools Manuf **32**(5), 629–640 (1992). https://doi.org/10.1016/0890-6955(92)90018-C
73. Liu, H., Bo, Q., Zhang, H., Wang, Y.: Analysis of Q-factor's identification ability for thin-walled part flank and mirror milling chatter. Int. J. Adv. Manuf. Technol. **99**(5–8), 1673–1686 (2018). https://doi.org/10.1007/s00170-018-2580-y
74. Liu, H., Chen, Q., Li, B., Mao, X., Mao, K., Peng, F.: On-line chatter detection using servo motor current signal in turning. Sci. China Technol. Sci. **54**(12), 3119–3129 (2011). https://doi.org/10.1007/s11431-011-4595-6
75. Liu, Z., Memon, A.A., Negussie, W., Ketema, H.: Interpreting the sustainable development of human capital and the sheepskin effects in returns to higher education: empirical evidence from Pakistan. Sustain. (2020). https://doi.org/10.3390/su12062393
76. Liu, Y., Wang, X., Lin, J., Zhao, W.: Early chatter detection in gear grinding process using servo feed motor current. Int. J. Adv. Manuf. Technol. **83**(9–12), 1801–1810 (2016). https://doi.org/10.1007/s00170-015-7687-9
77. Liu, Y., Wu, B., Ma, J., Zhang, D.: Chatter identification of the milling process considering dynamics of the thin-walled workpiece. Int. J. Adv. Manuf. Technol. **89**(5–8), 1765–1773 (2017). https://doi.org/10.1007/s00170-016-9190-3
78. Liu, C., Zhu, L., Ni, C.: Chatter detection in milling process based on VMD and energy entropy. Mech. Syst. Signal Process. **105**, 169–182 (2018). https://doi.org/10.1016/j.ymssp.2017.11.046
79. Lu, K., Lian, Z., Gu, F., Liu, H.: Model-based chatter stability prediction and detection for the turning of a flexible workpiece. Mech. Syst. Signal Process. **100**, 814–826 (2018). https://doi.org/10.1016/j.ymssp.2017.08.022
80. Ma, W., Yang, Y., Jin, X.: Chatter suppression in micro-milling using shank-mounted Two-DOF tuned mass damper. Precis. Eng. **72**(May), 144–157 (2021). https://doi.org/10.1016/j.precisioneng.2021.04.017
81. Mahdavinejad, R.: Finite element analysis of machine and workpiece instability in turning. Int. J. Mach. Tools Manuf **45**(7–8), 753–760 (2005). https://doi.org/10.1016/j.ijmachtools.2004.11.017
82. Marui, E., Ema, S., Hashimoto, M., Wakasawa, Y.: Plate insertion as a means to improve the damping capacity of a cutting tool system. Int. J. Mach. Tools Manuf **38**(10–11), 1209–1220 (1998). https://doi.org/10.1016/S0890-6955(98)00001-7
83. Mei, Z., Yang, S., Shi, H., Chang, S., Ehmann, K.F.: Active chatter suppression by on-line variation of the rake and clearance angles in turning- principles and experimental investigations. Int. J. Mach. Tools Manuf **34**(7), 981–990 (1994). https://doi.org/10.1016/0890-6955(94)90029-9
84. Merritt, H.E.: Theory of self-excited machine-tool chatter: Contribution to machine-tool chatter research-1. J. Manuf. Sci. Eng. Trans. ASME **87**(4), 447–454 (1965). https://doi.org/10.1115/1.3670861
85. Mobaraki, M., Ratava, J.: Tuning vibration absorbers to mitigate simultaneous regenerative and mode-coupling chatter. Noise Vib. Worldw. (2023). https://doi.org/10.1177/09574565231179731
86. Monnin, J., Kuster, F., Wegener, K.: Optimal control for chatter mitigation in milling-Part 2: experimental validation. Control. Eng. Pract. **24**(1), 167–175 (2014). https://doi.org/10.1016/j.conengprac.2013.11.011
87. Monnin, J., Kuster, F., Wegener, K.: Optimal control for chatter mitigation in milling-Part 1: modeling and control design. Control. Eng. Pract. **24**(1), 156–166 (2014). https://doi.org/10.1016/j.conengprac.2013.11.010
88. Moradi, H., Bakhtiari-Nejad, F., Movahhedy, M.R., Vossoughi, G.: Stability improvement and regenerative chatter suppression in nonlinear milling process via tunable vibration absorber. J. Sound Vib. **331**(21), 4668–4690 (2012). https://doi.org/10.1016/j.jsv.2012.05.032
89. Moradi, H., Movahhedy, M.R., Vossoughi, G.R.: Robust control strategy for suppression of regenerative chatter in turning. J. Manuf. Process. **11**(2), 55–65 (2009). https://doi.org/10.1016/j.jmapro.2009.06.002
90. Munoa, J., et al.: Chatter suppression techniques in metal cutting. CIRP Ann. - Manuf. Technol. **65**(2), 785–808 (2016). https://doi.org/10.1016/j.cirp.2016.06.004
91. N. H. Hanna, S. A. Tobias (1973) Theory of nonlinear regenerative chatter. Am. Soc. Mech. Eng., no. 73-DET-20
92. Olgac, N., Holm-Hansen, B.T.: A novel active vibration absorption technique: delayed resonator. J. Sound Vib. **176**(1), 93–104 (1994). https://doi.org/10.1006/jsvi.1994.1360

93. Otto, A., Rauh, S., Ihlenfeldt, S., Radons, G.: Stability of milling with non-uniform pitch and variable helix Tools. Int. J. Adv. Manuf. Technol. **89**(9–12), 2613–2625 (2017). https://doi.org/10.1007/s00170-016-9762-2
94. P. Thangavel, V. Selladurai, R. Shanmugam (2006) Application of response surface methodology for predicting flank wear in turning operation. Proc. Inst. Mech. Eng. Part B J. Eng. Manuf. 220(6):997–1003. https://doi.org/10.1243/09544054JEM460SC.
95. P. Bach, M. Poláček, P. Chvojka, J. Drobílek (2014) Dynamic forces in unstable cutting during turning operation. *Manuf. Technol.*; 14(1):3–8. https://doi.org/10.21062/ujep/x.2014/a/1213-2489/mt/14/1/3.
96. Paek, R., Ha, S.H., Ri, S.C.: Optimal determination of spindle speed variation type for the suppression of chatter in turning. Int. J. Adv. Manuf. Technol. **126**(5–6), 2481–2496 (2023). https://doi.org/10.1007/s00170-023-11192-9
97. Pan, J., Liu, Z., Wang, X., Chen, C., Pan, X.: Boring chatter identification by multi-sensor feature fusion and manifold learning. Int. J. Adv. Manuf. Technol. **109**(3–4), 1137–1151 (2020). https://doi.org/10.1007/s00170-020-05611-4
98. Patwari, M.A.U., Nurul Amin, A.K.M., Faris, W., Ishtiyaq, M.H.: Investigations of formation of chatter in a non-wavy surface during thread cutting and turning operations. Adv. Mater. Res. **83–86**, 637–645 (2010). https://doi.org/10.4028/www.scientific.net/AMR.83-86.637
99. Pimenov, D.Y., Bustillo, A., Wojciechowski, S., Sharma, V.S., Gupta, M.K., Kuntoğlu, M.: Artificial intelligence systems for tool condition monitoring in machining: analysis and critical review. J. Intell. Manuf. (2022). https://doi.org/10.1007/s10845-022-01923-2
100. Quintana, G., Ciurana, J.: Chatter in machining processes: a review. Int. J. Mach. Tools Manuf **51**(5), 363–376 (2011). https://doi.org/10.1016/j.ijmachtools.2011.01.001
101. R. Wäsche, "Colloidal processing of metal bonded niobium carbide (NbC-Ni)," *19. Plansee Seminar*. Bundesanstalt fuer Materialforschung und -pruefung (BAM), Berlin, Germany (2017). [Online]. https://opus4.kobv.de/opus4-bam/frontdoor/index/index/docId/40513
102. Rahimi, M.H., Huynh, H.N., Altintas, Y.: On-line chatter detection in milling with hybrid machine learning and physics-based model. CIRP J. Manuf. Sci. Technol. **35**, 25–40 (2021). https://doi.org/10.1016/j.cirpj.2021.05.006
103. Rusinek, R., Lajmert, P., Krzysztof, K., Kruszynski, B., Warminski, J.: Chatter identification methods on the basis of time series measured during titanium superalloy milling. Int. J. Mech. Sci. **99**, 196–207 (2015). https://doi.org/10.1016/j.ijmecsci.2015.05.013
104. S A Tobias, *Machine Tool Vibration: Tobias, S A: 9780216874541: Books*. Blackie, Alberta (1965)
105. Schmitz, T.L.: Chatter recognition by a statistical evaluation of the synchronously sampled audio signal [2]. J. Sound Vib. **262**(3), 721–730 (2003). https://doi.org/10.1016/S0022-460X(03)00119-6
106. Schmitz, T.L., Medicus, K., Dutterer, B.: Exploring once-per-revolution audio signal variance as a chatter indicator. Mach. Sci. Technol. **6**(2), 215–233 (2002). https://doi.org/10.1081/MST-120005957
107. Sener, B., Gudelek, M.U., Ozbayoglu, A.M., Unver, H.O.: "A novel chatter detection method for milling using deep convolution neural networks. Meas. J. Int. Meas. Confed. **182**(March), 109689 (2021). https://doi.org/10.1016/j.measurement.2021.109689
108. Shi, F., Cao, H., Zhang, X., Chen, X.: A reinforced k-nearest neighbors method with application to chatter identification in high-speed milling. IEEE Trans. Ind. Electron. **67**(12), 10844–10855 (2020). https://doi.org/10.1109/TIE.2019.2962465
109. Shi, W., Jia, D.K., Liu, X.L., Yan, F.G., Li, Y.F.: Application of continuous wavelet features and multi-class sphere SVM to chatter prediction. Adv. Mater. Res. **188**, 675–680 (2011). https://doi.org/10.4028/www.scientific.net/AMR.188.675
110. Siddhpura, M., Paurobally, R.: A review of chatter vibration research in turning. Int. J. Mach. Tools Manuf **61**, 27–47 (2012). https://doi.org/10.1016/j.ijmachtools.2012.05.007
111. Siddhpura, M., Paurobally, R.: Experimental investigation of chatter vibrations in facing and turning processes. *Int. J. Mech. Aerospace, Ind. Mechatron. Manuf. Eng.*; 7(6), pp. 84–89 (2013)
112. Sisson, T.R., Kegg, R.L.: An explanation of low-speed chatter effects. J. Manuf. Sci. Eng. Trans. ASME **91**(4), 951–958 (1969). https://doi.org/10.1115/1.3591778
113. Suzuki, N., Nishimura, K., Shamoto, E., Yoshino, K.: Effect of cross transfer function on chatter stability in plunge cutting. J. Adv. Mech. Des. Syst. Manuf. **4**(5), 883–891 (2010). https://doi.org/10.1299/jamdsm.4.883
114. Szydłowski, M., Powałka, B.: Chatter detection algorithm based on machine vision. Int. J. Adv. Manuf. Technol. **62**(5–8), 517–528 (2012). https://doi.org/10.1007/s00170-011-3816-2
115. Tangjitsitcharoen, S.: In-process monitoring and detection of chip formation and chatter for CNC turning. J. Mater. Process. Technol. **209**(10), 4682–4688 (2009). https://doi.org/10.1016/j.jmatprotec.2008.10.054
116. Tangjitsitcharoen, S., Moriwaki, T.: Intelligent monitoring and identification of cutting states of chips and chatter on CNC turning machine. J. Manuf. Process. **10**(1), 40–46 (2008). https://doi.org/10.1016/j.manpro.2008.01.001
117. Tangjitsitcharoen, S., Saksri, T., Ratanakuakangwan, S.: Advance in chatter detection in ball end milling process by utilizing wavelet transform. J. Intell. Manuf. **26**(3), 485–499 (2015). https://doi.org/10.1007/s10845-013-0805-3
118. Tansel, I.N.: Modelling 3-d cutting dynamics with neural networks. Int. J. Mach. Tools Manuf **32**(6), 829–853 (1992)
119. Tansel, I.N., Li, M., Demetgul, M., Bickraj, K., Kaya, B., Ozcelik, B.: Detecting chatter and estimating wear from the torque of end milling signals by using Index Based Reasoner (IBR). Int. J. Adv. Manuf. Technol. **58**(1–4), 109–118 (2012). https://doi.org/10.1007/s00170-010-2838-5
120. Tansel, I.N., Wagiman, A., Tziranis, A.: Recognition of chatter with neural networks. Int. J. Mach. Tools Manuf **31**(4), 539–552 (1991). https://doi.org/10.1016/0890-6955(91)90035-2
121. Tansel, I.N., Wang, X., Chen, P., Yenilmez, A., Ozcelik, B.: Transformations in machining. Part 2. Evaluation of machining quality and detection of chatter in turning by using s-transformation. Int. J. Mach. Tools Manuf **46**(1), 43–50 (2006). https://doi.org/10.1016/j.ijmachtools.2005.04.011
122. Tarng, Y.S., Chen, M.C.: An intelligent sensor for detection of milling chatter. J. Intell. Manuf. **5**(3), 193–200 (1994). https://doi.org/10.1007/BF00123923
123. Tarng, Y.S., Li, T.C., Chen, M.C.: On-line drilling chatter recognition and avoidance using an ART2-A neural network. Int. J. Mach. Tools Manuf **34**(7), 949–957 (1994). https://doi.org/10.1016/0890-6955(94)90027-2
124. Teti, R., Jemielniak, K., O'Donnell, G., Dornfeld, D.: Advanced monitoring of machining operations. CIRP Ann. - Manuf. Technol. **59**(2), 717–739 (2010). https://doi.org/10.1016/j.cirp.2010.05.010
125. Thaler, T., Potočnik, P., Bric, I., Govekar, E.: Chatter detection in band sawing based on discriminant analysis of sound features. Appl. Acoust. **77**, 114–121 (2014). https://doi.org/10.1016/j.apacoust.2012.12.004
126. Tlusty, J., Polacek, M.: The stability of machine tools against self excited vibrations in machining. Int. Res. Prod. Eng. ASME, pp. 465–474 (1963).

127. Tran, M.Q., Liu, M.K., Elsisi, M.: Effective multi-sensor data fusion for chatter detection in milling process. ISA Trans. (2021). https://doi.org/10.1016/j.isatra.2021.07.005
128. Tunç, L.T., Budak, E.: Effect of cutting conditions and tool geometry on process damping in machining. Int. J. Mach. Tools Manuf **57**, 10–19 (2012). https://doi.org/10.1016/j.ijmachtools.2012.01.009
129. Turkes, E., Orak, S., Neseli, S., Yaldiz, S.: Linear analysis of chatter vibration and stability for orthogonal cutting in turning. Int. J. Refract. Met. Hard Mater. **29**(2), 163–169 (2011). https://doi.org/10.1016/j.ijrmhm.2010.10.002
130. Urbikain, G., López De Lacalle, L.N., Campa, F.J., Fernández, A., Elías, A.: Stability prediction in straight turning of a flexible workpiece by collocation method. Int. J. Mach. Tools Manuf **54–55**, 73–81 (2012). https://doi.org/10.1016/j.ijmachtools.2011.11.008
131. Vela-Martínez, L., Jáuregui-Correa, J.C., Rubio-Cerda, E., Herrera-Ruiz, G., Lozano-Guzmán, A.: Analysis of compliance between the cutting tool and the workpiece on the stability of a turning process. Int. J. Mach. Tools Manuf **48**(9), 1054–1062 (2008). https://doi.org/10.1016/j.ijmachtools.2007.10.016
132. Wan, S., Li, X., Chen, W., Hong, J.: Investigation on milling chatter identification at early stage with variance ratio and Hilbert–Huang transform. Int. J. Adv. Manuf. Technol. **95**(9–12), 3563–3573 (2018). https://doi.org/10.1007/s00170-017-1410-y
133. Wan, S., Li, X., Su, W., Yuan, J., Hong, J., Jin, X.: Active damping of milling chatter vibration via a novel spindle system with an integrated electromagnetic actuator. Precis. Eng. **57**(28), 203–210 (2019). https://doi.org/10.1016/j.precisioneng.2019.04.007
134. Wan, S., Li, X., Yin, Y., Hong, J.: Milling chatter detection by multi-feature fusion and adaboost-SVM. Mech. Syst. Signal Process. **156**, 107671 (2021). https://doi.org/10.1016/j.ymssp.2021.107671
135. Wang, Y., Bo, Q., Liu, H., Hu, L., Zhang, H.: Mirror milling chatter identification using Q-factor and SVM. Int. J. Adv. Manuf. Technol. **98**(5–8), 1163–1177 (2018). https://doi.org/10.1007/s00170-018-2318-x
136. Wang, Z.C., Cleghorn, W.L.: Stability analysis of spinning stepped-shaft workpieces in a turning process. J. Sound Vib. **250**(2), 356–367 (2002). https://doi.org/10.1006/jsvi.2001.3725
137. Wang, G., Dong, H., Guo, Y., Ke, Y.: Early chatter identification of robotic boring process using measured force of dynamometer. Int. J. Adv. Manuf. Technol. **94**(1–4), 1243–1252 (2018). https://doi.org/10.1007/s00170-017-0941-6
138. Wang, M., Fei, R.: On-line chatter detection and control in boring based on an electrorheological fluid. Mechatronics **11**(7), 779–792 (2001). https://doi.org/10.1016/S0957-4158(00)00044-1
139. Wang, W.K., Wan, M., Zhang, W.H., Yang, Y.: "Chatter detection methods in the machining processes: a review. J. Manuf. Process. **77**(October), 240–259 (2022). https://doi.org/10.1016/j.jmapro.2022.03.018
140. Wang, M., Zan, T., Yang, Y., Fei, R.: Design and implementation of nonlinear TMD for chatter suppression: an application in turning processes. Int. J. Mach. Tools Manuf **50**(5), 474–479 (2010). https://doi.org/10.1016/j.ijmachtools.2010.01.004
141. Wu, D.W.: A new approach of formulating the transfer function for dynamic cutting processes. J. Manuf. Sci. Eng. Trans. ASME **111**(1), 37–47 (1989). https://doi.org/10.1115/1.3188730
142. Wu, G., Li, G., Pan, W., Raja, I., Wang, X., Ding, S.: A state-of-art review on chatter and geometric errors in thin-wall machining processes. J. Manuf. Process. **68**(March), 454–480 (2021). https://doi.org/10.1016/j.jmapro.2021.05.055
143. Xu, X., Zhou, T., Hu, H., Hu, Y.: Chatter frequency identification and amplitude tracking using short-time difference spectrum analysis. IEEE Trans. Instrum. Meas. **69**(12), 9844–9852 (2020). https://doi.org/10.1109/TIM.2020.3003361
144. Yang, Y., Muñoa, J., Altintas, Y.: Optimization of multiple tuned mass dampers to suppress machine tool chatter. Int. J. Mach. Tools Manuf **50**(9), 834–842 (2010). https://doi.org/10.1016/j.ijmachtools.2010.04.011
145. Yang, K., Wang, G., Dong, Y., Zhang, Q., Sang, L.: Early chatter identification based on an optimized variational mode decomposition. Mech. Syst. Signal Process. **115**, 238–254 (2019). https://doi.org/10.1016/j.ymssp.2018.05.052
146. Yao, Z., Mei, D., Chen, Z.: On-line chatter detection and identification based on wavelet and support vector machine. J. Mater. Process. Technol. **210**(5), 713–719 (2010). https://doi.org/10.1016/j.jmatprotec.2009.11.007
147. Yue, C., Gao, H., Liu, X., Liang, S.Y., Wang, L.: A review of chatter vibration research in milling. Chin. J. Aeronaut. **32**(2), 215–242 (2019). https://doi.org/10.1016/j.cja.2018.11.007
148. Zadeh, L.A.: Fuzzy sets as a basis for a theory of possibility. Fuzzy Sets Syst. **1**(1), 3–28 (1978)
149. Zaeh, M.F., Kleinwort, R., Fagerer, P., Altintas, Y.: Automatic tuning of active vibration control systems using inertial actuators. CIRP Ann. - Manuf. Technol. **66**(1), 365–368 (2017). https://doi.org/10.1016/j.cirp.2017.04.051
150. Zhang, C., Yue, X., Jiang, Y., Zheng, W.: A hybrid approach of ANN and HMM for cutting chatter monitoring. Adv. Mater. Res. **97–101**, 3225–3232 (2010). https://doi.org/10.4028/www.scientific.net/AMR.97-101.3225
151. Zhao, Y., Adjallah, K.H., Sava, A., Wang, Z.: MaxEnt feature-based reliability model method for real-time detection of early chatter in high-speed milling. ISA Trans. **113**, 39–51 (2021). https://doi.org/10.1016/j.isatra.2020.07.022
152. Zheng, Q., Chen, G., Jiao, A.: Chatter detection in milling process based on the combination of wavelet packet transform and PSO-SVM. Int. J. Adv. Manuf. Technol. **120**(1–2), 1237–1251 (2022). https://doi.org/10.1007/s00170-022-08856-3
153. Zhu, L., Liu, C.: Recent progress of chatter prediction, detection and suppression in milling. Mech. Syst. Signal Process. **143**, 106840 (2020). https://doi.org/10.1016/j.ymssp.2020.106840
154. Zhu, K.P., Wong, Y.S., Hong, G.S.: Wavelet analysis of sensor signals for tool condition monitoring: a review and some new results. Int. J. Mach. Tools Manuf **49**(7–8), 537–553 (2009). https://doi.org/10.1016/j.ijmachtools.2009.02.003
155. Zhu, W., Zhuang, J., Guo, B., Teng, W., Wu, F.: An optimized convolutional neural network for chatter detection in the milling of thin-walled parts. Int. J. Adv. Manuf. Technol. **106**(9–10), 3881–3895 (2020). https://doi.org/10.1007/s00170-019-04899-1