Chatter in Manufacturing System – Prediction and Detection

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Chatter is a phenomenon that periodically occurs in machining systems. Its occurrence in machining processes excites the tool and other elements of the machining system, creating „chatter marks“ on the workpiece surface, which affects the quality of the machined surface and dimensional accuracy. An increased noise level is another indicator of the presence of chatter. These consequences have driven researchers and global companies to develop machining systems or software for their programming, aiming at the prediction, detection, and suppression of chatter in machining systems. A large number of mathematical models and software solutions have been developed and published in leading international journals. The topic of this paper is a review of the current state of research on chatter, with an emphasis on the methods and techniques for chatter prediction and detection in machining systems.

Key Words: *chatter, stability lobes, regenerative effect, process damping, wavelets, support vector, detection*

1. INTRODUCTION

Chatter in machining processes first emerged at the beginning of the last century and was, at that time, considered the most delicate problem faced by mechanical engineers in designing machining technologies and manufacturing parts [1]. Several decades later, the importance of machine tool rigidity was highlighted as a key factor influencing the occurrence of chatter in machining systems [2].

Chatter in a machining system manifests as either self-excited or forced oscillations, resulting from the interaction between the cutting tool and the workpiece during machining. It stems from various chatter models in machining systems and is observed through undesirable acoustic effects (high-frequency noise), visible chatter marks on machined surfaces (wavy or serrated textures), and a significant reduction in machi-ning quality and dimensional accuracy. Additionally, chatter negatively impacts tool life (accelerated tool wear), process productivity, and the energy efficiency of the machining system. These challenges have driven research efforts in chatter analysis, aiming for a better understanding of its initiation and development, and consequently, the advancement of methods for predicting, detecting, and suppressing chatter in machining systems.

The prediction domain involves determining, in advance, the conditions under which chatter will occur. Mathematical modeling, stability analysis of the machining system, and simulation-based predictions of system behavior are some of the approaches in this domain. The results provide accurate identification of stable and unstable regions in the frequency domain and the determination of critical parameters (spindle speed, depth of cut, rigidity, etc.) under various influencing factors, such as machining system stiffness, tool geometry, and machining process parameters.

Detection refers to the identification and monitoring of chatter occurrence in real-time during

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machining, often using sensors (such as accelerometers, dynamometers, and microphones) and signal analysis techniques (e.g., time-domain and frequency-domain analysis, entropy analysis). The objective of detection is the early identification of initial chatter indicators and the monitoring of oscillation amplitude and frequency development in recorded signals. A major challenge in chatter detection lies in signal noise interference, which complicates tracking, as well as the speed and efficiency required for real-time signal processing.

Chatter suppression techniques include active and passive methods to reduce or eliminate unwanted oscillations. Active methods utilize adaptive systems (e.g., active dampers), while passive methods involve optimizing system rigidity, damping vibrations through additional materials, and structural modifications. The results are reflected in increased cutting process stability, improved surface finish quality, and reduced tool wear. A potential challenge in achieving the desired outcomes is the high cost of implementing active systems and the need for precise adjustment of machining process parameters.

The complex nature of chatter and numerous influencing factors require an integrated approach that encompasses signal analysis, mathematical modeling, experimental methods, and the development of intelligent algorithms for chatter prediction, detection, and suppression in machining systems. Similar conclusions were reached by Arnold [3], one of the pioneers in the study of this phenomenon. He stated that chatter originates from forces generated during the cutting process rather than external forces.

Other pioneers in studying this phenomenon include Tobias, Fishwick, and Polacek [4, 5], who identified the presence of vibrations in machining due to wave modulation and their regeneration on the machined surface. Under conditions of finite stiffness, the feedback phenomenon transforms current vibrations into larger amplitude vibrations in the subsequent cycle. Around the same period, Tobias [2] and Merritt [6] developed the fundamental differential equations of machining dynamics, distinguishing different modeling approaches for chatter in machining systems. These analytical models contributed to the development of simulation environments for chatter prediction.

The advancement of computing technology has enabled the recording of signals using sensors during machining processes. This has facilitated real-time process monitoring by measuring various physical quantities. By analyzing and interpreting extracted signal segments, conditions are created for the development of models for monitoring the machining system during operation [7–10].

This paper presents a review of the available literature, with a focus on chatter prediction and detection in machining systems. Chapter 2 describes chatter models in machining systems. Chapter 3 discusses chatter prediction techniques, while Chapter 4 presents techniques for chatter detection based on sensor signals recorded during machining. Chapter 5 provides the conclusion and an overview of potential directions for future research.

2. MODELS OF CHATTER

This chapter provides an overview of the fundamental chatter models that arise in machining processes.

Mode coupling represents a form of self-excited vibration that occurs in systems with at least two orthogonal degrees of oscillatory freedom, where vibrations in these directions must be phase-shifted [11]. This phenomenon arises when vibrations in different directions begin to influence each other through cutting forces, which cause displacement of the tool tip. This effect is particularly pronounced in processes such as milling, turning, and drilling, especially in systems with reduced stiffness, such as robotic manufacturing processes.

Figure 1 illustrates a milling tool model that oscillates in two mutually perpendicular directions, x and y, during the cutting process.

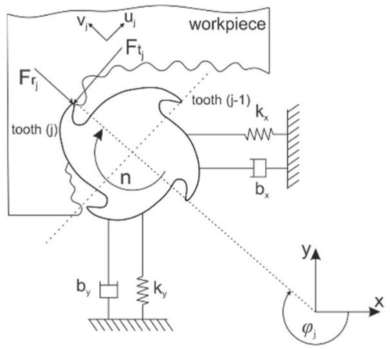

Figure 1 - Tool oscillation in two mutually perpendicular directions, adapted from [12]

The mathematical model that describes mode coupling is based on the fundamental differential equations of motion for the tool tip in the considered directions shown in Fig. 1, as given in Eq. (1)[11 - 13]:

$$m_x\ddot{x} + b_x\dot{x} + k_x x = F_x(t)$$
$$m_y\ddot{y} + b_y\dot{y} + k_y y = F_y(t) \quad (1)$$

Where are m_x, m_Y mass, b_x, b_y damping coefficients, k_x, k_y stiffness coefficients, x, y displacements, $\dot{x}, \dot{y}$ velocities, $\ddot{x}, \ddot{y}$ accelerations, F_x, F_y cutting forces in the considered directions. In literature and practice, the derived form of these equations is most commonly used, as shown in Eq.(2):

$$\ddot{x} + 2\zeta_x\omega_{nx}\dot{x} + \omega_{nx}{}^2 x = \frac{\omega_{nx}{}^2}{k_x}F_x(t)$$

$$\ddot{y} + 2\zeta_y\omega_{ny}\dot{y} + \omega_{ny}{}^2 y = \frac{\omega_{ny}{}^2}{k_y}F_y(t) \qquad (2)$$

Where are ζ_x, ζ_Y damping ratio, ω_{nx}, ω_{ny} natural frequencies in the considered directions.

By solving the system of differential equations, the values of the unknown quantities in the considered directions can be determined, while ensuring the correct application of boundary conditions, which vary from case to case.

The regenerative effect is a mechanism of chatter formation in machining processes, arising from the interaction between the cutting tool and the workpiece. Under conditions of reduced stiffness in the tool-workpiece system, displacement occurs, leading to variations in the chip thickness. This variation results in the formation of a wavy machined surface. When the tool passes over the previously machined surface in the next cycle, the chip thickness variations increase. This further amplifies surface irregularities, making it progressively rougher and increasing the intensity of cutting forces.

A study conducted by Merritt [6], later confirmed by Altintas and Weck [13], examined the dynamics of the cutting process using a turning system with a single degree of freedom. Figure 2a schematically illustrates the turning of a disk with a width a, which is smaller than the width of the cutting tool.

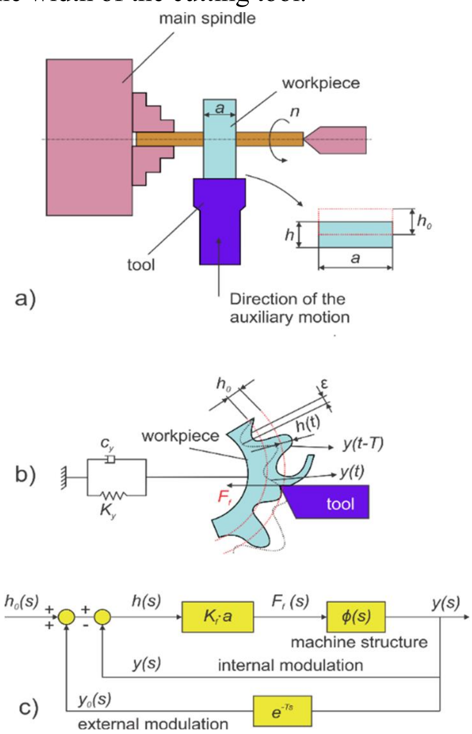

Figure 2 - Regenerative effect in a single degree of freedom system, adapted from [14]

During the machining of the disk shown in Fig. 2a, the parting tool moves transversely in a straight line relative to the axis of the main motion, corresponding to the orthogonal cutting mechanism. The main cutting force F_t (the tangential component of the cutting force) is collinear with the cutting speed, while the penetration resistance F_r (the radial component of the cutting force) is collinear with the feed motion of the tool. In a chatter-free cutting process (an absolutely rigid system), these two cutting force components are calculated as a linear function of the cutting width a and the feed f [6, 14], which corresponds to the static chip thickness h_0. Equation (3) presents the formulation of the tangential and radial cutting forces.

$$F_t = K_t a h_0$$

$$F_r = K_r a h_0 \qquad (3)$$

In the case of orthogonal cutting with chatter, as shown in Fig. 2b, the machining system can be considered as a single degree of freedom oscillatory system along the y-axis. After the first revolution of the workpiece and the tool's penetration into the material, wave modulation appears on the machined surface of the workpiece. As the tool gradually penetrates the material, the regeneration of the wavy surface occurs. In this case, the amplitude of tool oscillations along the y-axis gradually increases. The general expression for the dynamically varying chip thickness Eq.(4), which results from the regeneration of the wavy surface, is presented in [6, 12–17].

$$h(t) = f_t \cdot sin(\phi) \cdot sin(\kappa) + v_{j,0}(t-T) - v_j(t) \qquad (4)$$

Where are f_t feed per tooth, $h(t)$ dynamic chip thickness between two consecutive tool passes t and $t-T$, where t is the observed moment in time, and T is the rotation period of the workpiece in turning or the rotation period of the tool in milling. The block diagram of the regenerative effect with internal and external modulation is shown in Fig. 2c. The input signal $h_0(s)$ represents the initial excitation of the system or the wavy machined surface. Internal modulation constitutes the feedback loop that includes the output signal $y(s)$, which is feedback into the system through the modulation of the machine structure $\phi(s)$. This block describes the dynamic properties of the tool-workpiece system, including its stiffness, damping, and natural frequencies. The cutting coefficients represent the influence of physical cutting parameters, such as the cutting force coefficient K_f and the depth of cut a, which determine the magnitude of the cutting force $F_f(s)$. The feedback mechanism provides the output signal $y(s)$, which represents the vibrations or deformations of the system during cutting. It is feedback into the system through the delay function e^{-Ts} and directly affects the chip thickness $h(s)$. This results in a change in the cross-section of the chip in subsequent cutting cycles, leading to the accumulation of vibrations.

Process damping refers to the dissipation of energy caused by the interference between the tool's flank face and the machined surface of the workpiece during relative vibrations between the tool and the workpiece [18]. The influence of damping in the machining process increases at low spindle speeds due to the occurrence of phase shift, which increases the number of waveforms on the machined surface, further amplifying the slope of the wavy surface.

Figure 3 illustrates the motion of the tool in contact with the wavy machined surface during the cutting process. An angle γ can be observed between the tool's flank face and the tangent to the machined surface, which affects the amount of energy dissipated through friction and plastic deformation. The minimum and maximum values of angle γ depend on the vibration amplitude and the relative motion between the tool and the workpiece.

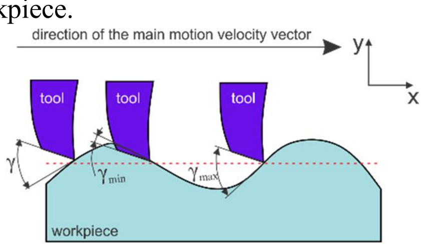

Figure 3 - Illustration of different tool phases during orthogonal cutting with process damping, adapted[14]

Greater wave slope (more pronounced contact, γ_{min}) leads to increased damping, which results in an increase in the normal force perpendicular to the tool's direction of motion. Conversely, when the relief angle is larger (no contact, γ_{max}), the normal force decreases. Since the force variation follows a sinusoidal path, is phase-shifted by 90° relative to displacement, and has an opposite sign to the cutting speed, it is considered a viscous damping force. The process damping force F_d in y direction, can be expressed as a function of velocity $\dot{y}$, width of chip b, cutting velocity v and constant C.

$$F_d = C\frac{b}{v}\dot{y} \tag{5}$$

Since the wavy surface has a sinusoidal nature, the damping effect will be greater for shorter oscillation wavelengths λ, as the slope of the sinusoidal surface increases, i.e., the angle γ decreases, and there is a greater number of angle variations γ.

In Eq. (6), the formulation for the wavelength is given:

$$\lambda = \frac{v}{f} \tag{6}$$

The wavelength equation shows that lower cutting speeds or higher vibration frequencies f result in shorter wavelengths, thereby increasing process damping.

The effect of increased damping, in turn, leads to a reduction in vibrations during machining (process stability) and, consequently, an improvement in surface quality. From a practical standpoint, process damping enables machining at greater depths of cut at low spindle speeds, which will be demonstrated through the stability diagram.

3. PREDICTION OF CHATTER

The primary goal of chatter prediction is to identify stable and unstable operating regions of the machining system to ensure a high level of accuracy and productivity. This analysis is based on a combination of experimental, analytical, and numerical methods, providing a comprehensive insight into the dynamics of the machining process.

Chatter prediction is traditionally divided into two key approaches: experimental construction of stability lobes and analytical methods. Stability lobes are graphical representations that clearly define stable and unstable machining regions, while analytical methods enable the construction of these maps based on mathematical models and theoretical assumptions. Figure 4 presents a stability lobes of a machining system.

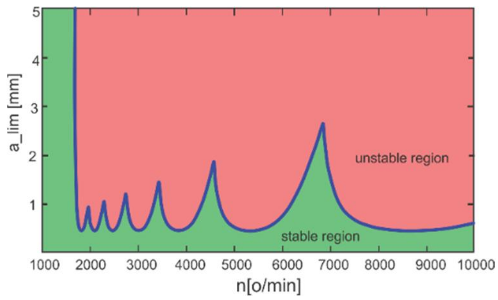

Figure 4 - Example of stability lobe of manufacturing system [15]

3.1 Experimental procedure for creating a stability lobe

The stability lobe represents the relationship between the critical depth of cut and spindle speed, distinguishing between stable and unstable operating regions of the machining system. The critical depth of cut is the depth at which chatter occurs.

In the milling process, inclined planes are machined using a single tool on the same material, at different spindle speeds, with a full tool engagement angle, and at the same feed rate for each machined slot. The moment indicating the onset of chatter is identified by inferior surface quality and increased noise levels during machining. Measurements are conducted after machining, during which the slot length l and surface roughness i.e. its arithmetical mean value R_a. Roughness is measured on the slot's frontal surface.When it exceeds the threshold corresponding to a finely machined surface($i.e. R_a = 1.6\,\mu m$), the length of that part of the slot is measured, and the critical depth of cut is determined using the tangent of the anglea_{lim}.Figure 5 shows a plate with machined slots. A cross-section of one slot is also provided, with defined dimensions that are measured after conducting the experiments.

Equation (7) presents the formulation for calculating the critical depth of cut for a given spindle speed:

$$a_{lim} = l_{lim} \cdot tan\,\beta \tag{7}$$

Where isβsteep slope angle. Once the series of experiments is completed, the measured values of the critical depths of cut are plotted on a diagram corresponding to the spindle speeds at which they were obtained. After plotting all points, a curve is drawn, as shown in Fig. 4, which separates the stable and unstable operating regions of the machining system.

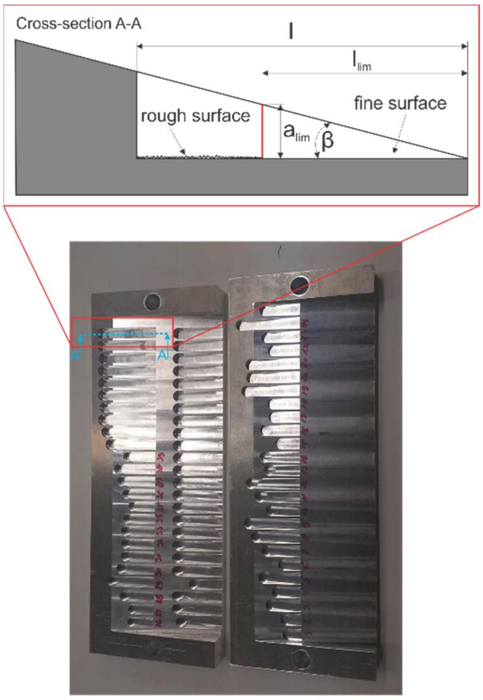

Figure 5 - Machining of slots on a steep plane with the cross-section of a single slot, adapted [15]

Experimentally obtained stability maps provide the most accurate indication of the dynamic stability of the machining system under measured conditions. However, a drawback of this technique is the large number of required experiments, which is time-consuming. If there is a change in tool overhang length, tool or workpiece material, clamping method, etc, the dynamic characteristics of the machining system also change, making the obtained stability map no longer applicable. The experimental determination of a stability map for turning follows a similar approach. Instead of an inclined plane, the experiment is conducted on a pre-machined conical surface. In addition to the large number of experiments, another drawback is that the number of prepared cones must match the number of experiments. The arithmetical mean roughness height $R_a$is measured on the machined cylindrical surface. After machining, changes in surface quality are identified, and the length of the cylindrical surface segment that meets the acceptable roughness value is measuredR_a. In Eq. (8), the formulation for calculating the critical depth of cut in turning is given:

$$a_{lim} = l_{lim} \cdot tan\frac{\beta}{2} \tag{8}$$

Figure 6 presents the experimental setup for determining the experimental stability map of the machining system for turning.

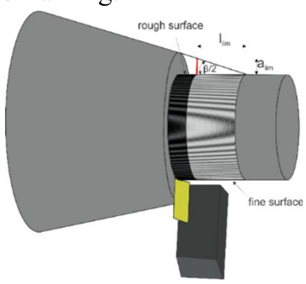

Figure 6 - Machining of a cone for determining the critical depth of cut

3.2 Analytical procedure for creating a stability map

The creation of stability maps for a machining system using analytical methods requires mathematical modeling of its dynamics. The first step in this process is determining the frequency characteristics of the system in two mutually perpendicular directions, which is achieved through Experimental Modal Analysis (EMA). This subsection presents the mathematical modeling of the stability of a CNC (computer numerically controlled) milling machine.

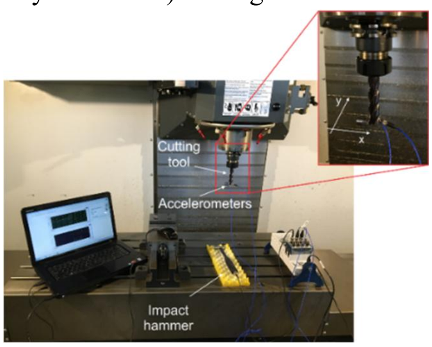

Figure 7 - Experimental setup for determining frequency characteristics using EMA, adapted [12]

Figure 7 shows the experimental setup for performing EMA in the x and y directions.

The experimental setup for EMA consists of a computer, an accelerometer for measuring acceeration, an impact hammer for applying excitation force, and a module for A/D signal conversion. Fast Fourier Transform (FFT) is applied to the time-domain excitation and response signals to generate Frequency Response Functions (FRF) by taking their ratio. From the FRF, the frequency characteristics such as phase, amplitude, and its real and imaginary components are extracted, which are necessary for the next phase of analysis. Additionally, coherence diagrams are determined, which serve as a quality check for the conducted experiment. The transfer function matrix $\Phi(j\omega)$identified in the tool-workpiece contact zone is represented in matrix form (9) [11]:

$$[\Phi(iw)] = \begin{bmatrix} \Phi_{xx}(j\omega) & \Phi_{xy}(j\omega) \\ \Phi_{yx}(j\omega) & \Phi_{yy}(j\omega) \end{bmatrix} \tag{9}$$

Where are$\Phi_{xx}(j\omega)$ i $\Phi_{yy}(j\omega)$direct transfer functions, $\Phi_{xy}(j\omega)$ и $\Phi_{yx}(j\omega)$cross transfer functions.The fundamental expressions for cutting forces Eq.(3), based on the mechanistic model, can be rewritten in matrix form after incorporating the expression for dynamic chip thickness:

$$\{F(t)\} = \frac{1}{2}\alpha K_t [A_0]\{\Delta(t)\} \tag{10}$$

It has a non-trivial solution if its determinant is equal to zero:

$$det\left[[I] - \frac{1}{2}K_t\alpha\left(1 - e^{-j\omega_c T}\right)[A_0][\Phi(j\omega_c)]\right] = 0 \tag{11}$$

Equation (11) represents the characteristic equation of the closed-loop milling process. For simpler notation, the oriented transfer function matrix is introduced as:

$$\Phi_0(j\omega_c) = \begin{bmatrix} \Phi_{0xx}(j\omega_c) & \Phi_{0xy}(j\omega_c) \\ \Phi_{0yx}(j\omega_c) & \Phi_{0yy}(j\omega_c) \end{bmatrix}$$

$$\Phi_{0xx}(j\omega_c) = \alpha_{xx}\Phi_{xx}(j\omega_c) + \alpha_{xy}\Phi_{yx}(j\omega_c)$$

$$\Phi_{0xy}(j\omega_c) = \alpha_{xx}\Phi_{xy}(j\omega_c) + \alpha_{xy}\Phi_{yy}(j\omega_c)$$

$$\Phi_{0xx}(j\omega_c) = \alpha_{yx}\Phi_{xx}(j\omega_c) + \alpha_{yy}\Phi_{yx}(j\omega_c)$$

$$\Phi_{0xy}(j\omega_c) = \alpha_{yx}\Phi_{xy}(j\omega_c) + \alpha_{yy}\Phi_{yy}(j\omega_c) \tag{12}$$

and characteristic equation:

$$\Lambda = -\frac{N}{4\pi}aK_t\left(1 - e^{-j\omega_c T}\right) \tag{13}$$

From Eqs. (12) and (13), we obtain:

$$Det\ |\,[I] + \Lambda\Phi_0(j\omega_c)]\,| = 0 \tag{14}$$

The characteristic Eq. (14) is easily solved for a given natural frequency ω_c, specific cutting forces K_t, K_r,tool engagement angle$\phi_{st}, \phi_{ex}$and the structure's transfer functions, where the characteristic equation takes the form:

$$\Lambda = \Lambda_{R_e} + j\Lambda_{I_m} \tag{15}$$

Bysubstitutinge$^{-j\omega_c T}$ $= cos\omega_c T - jsin\omega_c T$into Eq. (13), the critical depth of cut at the natural chatter frequency $\omega_c$is obtained:

$$a_{lim} == -\frac{2\pi}{NK_t}\left[\frac{\Lambda_{R_e}(1-cos\omega_c T)+\Lambda_{Im}sin\omega_c T}{(1-cos\omega_c T)} + j\frac{\Lambda_{I_m}(1-cos\omega_c T)-\Lambda_{R_e}sin\omega_c T}{(1-cos\omega_c T)}\right] \tag{16}$$

Since$a_{lim}$is a real number, the imaginary part of Eq. (16) cannot appear in the further solution

$$\Lambda_{I_m}(1 - cos\omega_c T) - \Lambda_{R_e}sin\omega_c T = 0 \tag{17}$$

$$\kappa = \frac{\Lambda_{Im}}{\Lambda_{R_e}} = \frac{sin\omega_c T}{1-cos\omega_c T} \tag{18}$$

By substituting Eq. (18) into Eq. (16), the final value of the critical depth of cut for chatter-free machining is obtained:

$$a_{lim} = -\frac{2\pi\Lambda_{R_e}}{NK_t}(1 + \kappa^2) \tag{19}$$

For a given chatter frequencyω_c,the chatter limit, expressed in terms of the critical milling depth, can be directly determined from Eq. (19). The corresponding spindle speeds can be determined as follows:

$$\kappa = tan(\psi) = \frac{cos\left(\frac{\omega_c T}{2}\right)}{sin\left(\frac{\omega_c T}{2}\right)} = tan\left[\frac{\pi}{2} - \frac{\omega_c T}{2}\right] \tag{20}$$

The phase shift of the natural frequency is:

$$\psi = tan^{-1}(\kappa) \tag{21}$$

While the phase shift between internal and external modulation is:

$$\varepsilon = \pi - 2\psi \tag{22}$$

Ifthe number of waves (k) formed within the tool engagement angle is an integer, then:

$$w_c T = \varepsilon + 2k\pi \tag{23}$$

At the same time, the phase shift must be considered(ψ)real and imaginary part$\left(\Lambda_{R_e}, \Lambda_{I_m}\right)$of natural frequency. The spindle speed is determined simply based on the tooth entry period into the cut [11]:

$$T = \frac{1}{\omega_c}(\varepsilon + 2k\pi) \Rightarrow n = \frac{6\ 0}{NT} \tag{24}$$

The previously derived methodology must be implemented in an appropriate software package, such as MATLAB or Python. The number of waves (N) in the stability lobes as one of the input parameters of the program and represents the number of loop iterations required to generate a single wave on the stability map. Figure 8 presents the stability lobe obtained analytically using the previously described methodology.

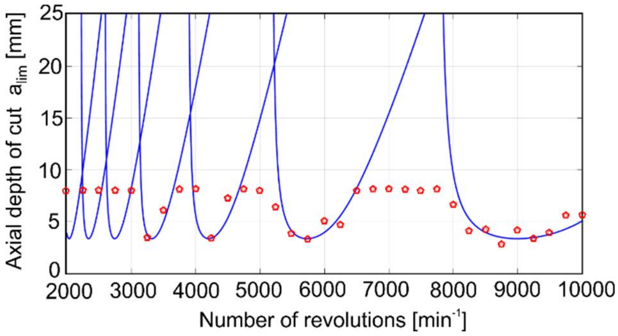

Figure 8 - Stability lobe obtained by the analytical method, adapted [15]

4. DETECTION OF CHATTER EVELOPMENT

This chapter presents chatter detection techniques based on the analysis of various types of sensor signals collected during the machining process. Digitized signals are suitable for analysis in both the time and frequency domains. Figure 9 proposes the structure of a signal processing system.

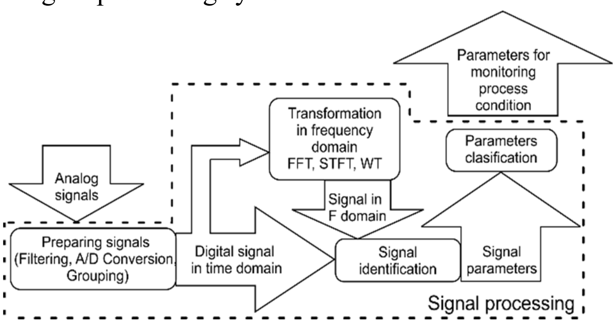

Figure 9 - Flow diagram of signal processing, adapted [19]

Analog signals collected from sensors are first filtered and converted into a digital format, making them suitable for further analysis, which can be performed in either the time domain or the frequency domain using various techniques. By identifying characteristic parts of the signal and extracting relevant signal parameters, the condition of the machining system during the process can be assessed, which is one of the key elements of machining system monitoring.

4.1 Sensor subsystem

Sensors are an essential component of modern machining systems, which have integrated monitoring algorithms within their control units. Their role is to measure the values of relevant physical quantities and, together with the control system, monitor the general condition of machine elements and the machining process status. The most commonly used sensors include dynamometers, accelerometers, acoustic sensors, and microphones. Table 1 provides an overview of these sensors, along with their applications, characteristics, and capabilities in the monitoring domain of the machining system:

Table 1. Sensors and their characteristics

Sensor	Measuring value	Application/Characteristics /Capabilities
Dynamometer	Force $[N]$	Analysis of machining system stability. Detection of chatter onset. Optimization of cutting parameters.
Accelerometer	Acceleration$\left[\frac{m}{s^2}\right]$	Detection of chatter onset. Monitoring tool condition and detecting damage. Analysis of the dynamic characteristics of the machining process.
Acoustic sensor	Wave frequency $[Hz]$	Detection of tool breakage. Real-time process monitoring. Identification of irregularities in the cutting process.
Microphone	Decibels $[db]$	Monitoring acoustic signals during cutting. Fast detection of chatter based on acoustic characteristics. Low-cost solutions for machining process analysis.

4.2 Signal transformation from the time domain to the frequency domain

The transformation of a signal from the time domain to the frequency domain involves applying the Fast Fourier Transform (FFT) to the time-domain signal. The FFT formulation is an algorithm that calculates the discrete Fourier transform for a sequence of N samples [20]:

$$X[k] = \sum_{n=0}^{N-1} x[n]\, e^{-j\frac{2\pi}{N}kn}, k = 0, 1, 2 \ldots, N-1 \quad (25)$$

Where are$x[n]$a sequence of discrete samples in the time domain, $X[k]$a sequence of discrete samples in the frequency domain, $e^{-j\frac{2\pi}{N}kn}$Fourier basis for frequency$k$.The Short-Time Fourier Transform (STFT) divides the signal into small time segments, applying the Fourier transform to each segment, thus providing a time-frequency representation. However, it has limited resolution due to the fixed window length. Wavelet transform uses variable windows, allowing for better time resolution for high frequencies and better frequency resolution for low frequencies, making it suitable for analyzing nonlinear signals. Figure 10 shows the hierarchical tree of the decomposed signal.

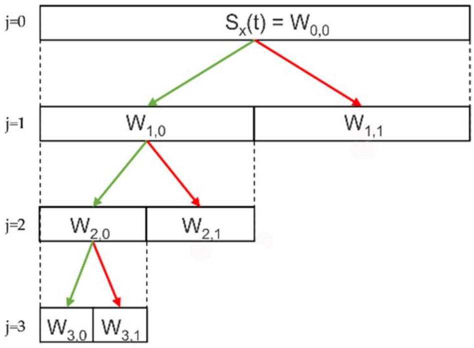

Figure 10 - Signal decomposition using wavelets[21]

Structure of the decomposed signal$S_x(t) = W_{j,i}$ consists of detail vectors*(i=1)*and approximation vectors *(i=0)*.The detail vectors contain high-frequency components, while the approximation vectors contain low-frequency amplitudes of the original signal being decomposed. The levels of the decomposed signal are represented by j.

The S-transform combines the advantages of STFT and wavelet transform, providing a time-frequency representation with windows that automatically adjust depending on the frequency. This ensures high precision in analyzing localized time-frequency characteristics of the signal. Figure 11 shows the spectrogram illustrating the gradual increase in the oscillation amplitude of a point on the turning tool. Acceleration was measured during the machining process of the internal conical surface. The sudden increase in the amplitude spectrum indicates that the excitation frequency has reached the natural frequency, meaning that chatter has occurred during the machining process.

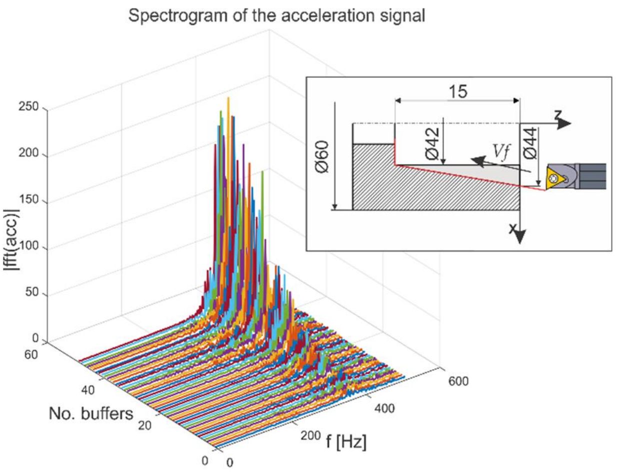

Figure 11 - Spectrogram of the acceleration signal of a point on the turning tool

4.3 Extraction of signal parameters in the time domain

Signal analysis in the time domain involves calculating various statistical characteristics over the extracted segments of the signal. Table 2 presents the characteristics most commonly applied for signal analysis, and thus, for assessing the condition of the machining system.

Table 2. Statistical characteristics of the signal in the time domain [22, 23]

Formulation	Statistical feature
$x_m = \frac{1}{n}\sum_{i=1}^{n} x_i$	Mean value
$x_{std} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - x_m)^2}$	Standard deviation
$x_{rms} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i)^2}$	Root mean square (RMS) value
$x_p = max(\lvert x_i \rvert)$	Pik
$x_{ske} = \frac{\sum_{i=1}^{n}(x_i - x_m)^3}{(n-1)\cdot {x_{std}}^3}$	Skewness
$x_{kur} = \frac{\sum_{i=1}^{n}(x_i - x_m)^4}{(n-1)\cdot {x_{std}}^4}$	Kurtosis
$CF = \frac{x_p}{x_{rms}}$	Crest factor
$CLF = \frac{x_p}{\left(\sqrt{\frac{1}{n}\sum_{i=1}^{n}\lvert x_i \rvert}\right)^2}$	Clearance factor
$SF = \frac{x_{rms}}{\frac{1}{n}\sum_{i=1}^{n}\lvert x_i \rvert}$	Shape factor
$IF = \frac{x_p}{\frac{1}{n}\sum_{i=1}^{n}\lvert x_i \rvert}$	Impulse factor
$CV = \frac{x_{std}}{x_m}$	Coefficient of variation

The parameter x_i in the previous table represents the current value of the sample, while the parameter n represents the number of samples within the considered signal segment (buffer).

The values of the obtained statistical parameters are graphically presented depending on the time or segment in which they were identified. The selection of appropriate statistical characteristics should allow the identification of a threshold in the signal, which will separate the stable region from the unstable region of the machining system during the machining process.

Figure 12 clearly shows the jump in the coefficient of variation when transitioning from the stable to the unstable region.

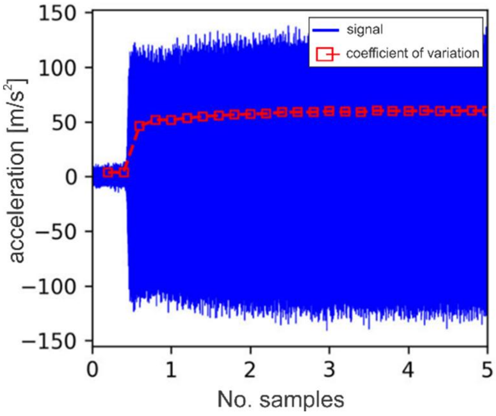

Figure 12 - Defining the threshold using the coefficient of variation (CV) [24]

4.4 Extraction of signal parameters in the frequency domain

Signal analysis in the frequency domain involves applying statistical characteristics to the signal spectrum. Table 3 presents the statistical characteristics and their formulations for frequency domain signal analysis [22, 23, 25, 26].

Table 3. Statistical characteristics of the signal in the frequency domain [30]

Formulation	Statistical feature
$MSF = \frac{\sum_{j=1}^{m} f_j^2 S(f_j)}{\sum_{j=1}^{m} S(f_j)}$	Mean square frequency
$\rho = \frac{\sum_{j=1}^{n} \cos(2\pi f_j \triangle t) S(f_j)}{\sum_{j=1}^{n} S(f_j)}$	Autocorrelation function in one step
$FC = \frac{\sum_{j=1}^{n} f_j S(f_j)}{\sum_{j=1}^{n} S(f_j)}$	Center of frequency
$FV = \frac{\sum_{j=1}^{m} (f_j - FC)^2 S(f_j)}{\sum_{j=1}^{m} S(f_j)}$	Standard frequency

The parameter f_j in the previous table represents the current frequency value, while the parameter $S(f_j)$ represents the amplitude spectrum value for the considered frequency.

4.5 Classification of signal parameters

The purpose of signal parameter classification using algorithms such as Support Vector Machines (SVM) and Artificial Neural Networks (ANN) is to efficiently identify and differentiate between various states of a system, process, or signal based on their characteristics. Specifically, in the context of chatter detection, it is used to:

- Identification of patterns in the data – Algorithms like SVM and ANN can extract complex correlations between input and output signal parameters and system state classes;
- State classification – Based on the input characteristics of the signal, the models can determine which state class the signal belongs to;
- Automation and accuracy improvement – Unlike traditional methods that require manual analysis, machine learning automates the process and allows for high classification accuracy, even under complex conditions;
- Real-time application – These algorithms can operate in real time, enabling quick identification and response to undesirable states;
- Reduction in data processing complexity – By using SVM and ANN algorithms, the number of required input parameters can be reduced, retaining only the most relevant signal features for classification;

4.5.1 Support vector machine

Support Vector Machine (SVM) is a supervised machine learning algorithm used for classification and regression. The principle of SVM is based on finding the hyperplane that best separates data from different classes or predicts the values of the target variable. The support vectors are the data points that are closest to the hyperplane separating them. The main goal of SVM is to determine the maximum margin between the classes in order to achieve the best generalization of the data classes. Figure 13 illustrates the classification of two data groups using SVM.

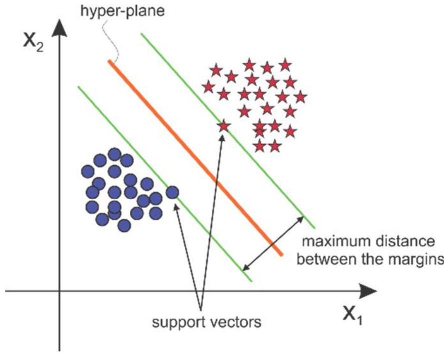

Figure 13 - Illustrated representation of feature classification using SVM SVM-a [25, 27]

To achieve better generalization, different types of Kernel functions are used, which allow SVM to work efficiently with nonlinear data. A commonly used kernel in SVM is the RBF kernel (Radial Basis Function), which is used to map data into an infinite-dimensional space using the Gaussian function. It is capable of efficiently modeling complex nonlinear relationships between data [22, 23, 27 - 29].

The parameter of the RBF kernel that affects the performance of the selected classification model is the width of the Gaussian distribution (γ). Another parameter considered is C, which controls the balance between maximizing the margin and minimizing classification errors in the chosen data set.

For the selected set of features determined over a segment of the signal, a value is assigned that describes the system's state. Stable and unstable operation modes are most commonly classified, with values 0 and 1 assigned, respectively [22, 23, 27 - 29].

The algorithm is trained based on the input features and output values, which are assigned based on the system's state estimation.

The advantages of the SVM algorithm include its high accuracy in classifying data and its ability to generalize to unseen data due to the maximum margin between classes. Disadvantages are evident in the complexity of hyperparameter tuning and high computational demands with large datasets. Furthermore, the SVM algorithm is never used alone for chatter detection; it is always combined with additional tools for signal feature extraction and hyperparameter optimization to achieve maximum classification accuracy and efficiency.

4.5.2 Artificial Neural Networks

Artificial Neural Networks (ANNs) are deep learning algorithms. In the context of chatter detection, they are used for classifying signal segments into two or more classes. Machine learning techniques such as convolutional neural networks, deep convolutional neural networks, and RBF networks utilize extracted signal parameters from both the time and frequency domains to determine whether the process is stable or unstable at the output [30 - 35].

The proposed methodology for chatter detection is shown in Figure 14. As part of this methodology, the recorded signals must be filtered first, and then certain parameters are calculated over the extracted signal segment. The selection of relevant signal parameters is determined using the relative entropy method, which detects changes in the signal distribution.

Afterward, 40% of the selected features are randomly chosen for training the artificial neural network model, while the remaining features are used for model validation. The trained network model provides an output indicating whether the signal is stable or if chatter (unstable) is present.

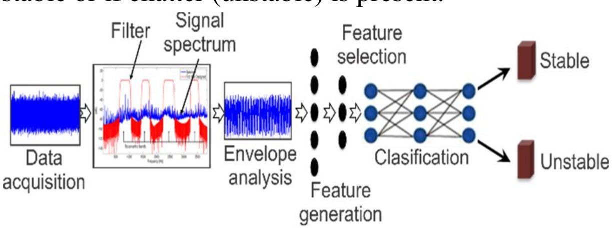

Figure 14 - Architecture of the model for chatter detection using ANN, adapted from [33]

Artificial neural networks have the ability to model complex, nonlinear relationships in data, making them highly suitable for chatter detection in unstable machining processes. Additionally, they can automatically extract relevant features from signals, reducing the need for manual data processing.

The drawbacks of artificial neural networks include the requirement for a large amount of data for effective training and the need for various data preprocessing techniques, which can reduce their ability to correctly classify new data. Furthermore, due to the complex structure of the model, it is often difficult to understand how the network makes decisions and which features have the greatest impact on the results.

4. CONCLUSION

This paper presents an overview of the current state of research in the field of chatter prediction and detection problems in machining systems.

When it comes to chatter prediction, potential research can focus on the development of simulation environments, which closely model real working conditions. Both the graphical representation in the form of stability maps and the analytical calculation of the critical frequencies of the machining system can significantly contribute to improving conditions for avoiding chatter in machining processes.

The integration of chatter detection systems with the machine tool control unit would represent a significant improvement in machining operations in terms of monitoring.

5. ACKNOWLEDGMENTS

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REFERENCES

[1] Taylor FW. On the art of cutting metals, *Transactions of ASME*, 28: p. 31–248404, 1907.

[2] Tobias SA, ed. *Machine Tool Vibration*, Blackie & Son Limited, 1965.

[3] Arnold RN. The mechanism of tool vibration in the cutting of steel, in Proc. *Institution of Mechanical Engineers,* Vol. 154, pp. 261–284, 1946.

[4] Tobias SA, Fishwick W. The chatter of lathe tools under orthogonal cutting conditions, *Transactions of the ASME,* Vol. 80, pp. 1079–1088, 1958.

[5] Tlusty J, Polacek M. The stability of machine tools against self-excited vibrations in machining., In Proc.

International Research in Production Engineering Conference, Pittsburgh, PA, USA, ASME: New York, USA, pp. 465–474, 1963.

[6] Merritt HE, Theory of self-excited machine–tool chatter, *Transactions of ASME*,Vol. 87, pp. 447–454, 1965.

[7] Quintana G, Ciurana J. Chatter in machining processes: A review, *International Journal of Machine Tools & Manufacture*, Vol. 51, pp. 363–376, 2011.

[8] Wang W. K, Wan M, Zhang W. H, Yang Y. Chatter detection methods in the machining processes: A review, *Journal of Manufacturing Processes*, Vol. 77, pp. 240–259, 2022.

[9] Siddhpura M, Paurobally R. A review of chatter vibration research in turning, *International Journal of Machine Tools and Manufacture*, Vol. 61, pp. 27-47, 2012.

[10] Navarro-Devia JH, Chen Z, Dao DV, Li H. Chatter detection in milling processes—a review on signal processing and condition classification, *The International Journal of Advanced Manufacturing Technology*, Vol. 125, pp. 3943–3980, 2023.

[11] Altintas Y. *Manufacturing automation: Metal cutting mechanics, Machine tool vibrations, and CNC design*, Second Edition, University of British Columbia, 2012.

[12] Vorkapic N, Slavkovic N, Kokotovic B, Zivanovic S, Dimic Z. Implementation of a cutting forces model through virtual simulation of machining process. *The International Journal of Advanced Manufacturing Technology*, Vol. 135, pp. 3085–3099, 2024.

[13] Altintas Y, Weck M. Chatter stability of metal cutting and grinding, *CIRP annals,* Vol. 53, No.2, pp. 619-642, 2004.

[14] Otto A, Rauh S, Kolouch M, Radons G. Extension of Tlusty′s law for the identification of chatter stability lobes in multi-dimensional cutting processes, *International Journal of Machine Tools and Manufacture*, Vol. 82, pp. 50-58, 2014.

[15] Košarac A, Šikuljak L, Šalipurević M, Mlađenović C, Zeljković M. Prediction of self-excited vibrations occurance during aluminium alloy AL 7075 milling, in proc. *18th International Symposium INFOTEH-JAHORINA (INFOTEH),* East Sarajevo, Bosnia and Herzegovina, pp. 1-6, 2019.

[16] Fu Z, Zhang X, Wang X, Yang W. Analytical modeling of chatter vibration in orthogonal cutting using a predictive force model, *International Journal of Mechanical Sciences*, Vol. 88, pp. 145-153, 2014.

[17] Das MK, Tobias SA. The Relation Between the Static and the Dynamic Cutting of Metals, *International Journal of Machine Tool Design and Research,* Vol. 7, No. 2, pp. 63–68, 1967.

[18] Ahmadi K, Altintas Y. Identification of Machining Process Damping Using Output-Only Modal Analysis, *Journal of Manufacturing Science and Engineering,* Vol. 136, No 5, article 051017, 2014.

[19] Teti R, Jemielniak K, O'Donnell G, Dornfeld D. Advanced monitoring of machining operations. *CIRP annals*, Vol. *59, No.*2, pp. 717-739, 2010.

[20] Chen Y, Li H, Jing X, Hou L, Bu X. Intelligent chatter detection using image features and support vector machine, *The International Journal of Advanced Manufacturing Technology*, Vol. 102, pp. 1433-1442, 2019.

[21] Vorkapić N, Kokotović B, Živanović S. Standard deviation and spectral analisys for chatter detection using wavelet transform packet, in Proc. *6th International Conference "Mechanical Engineering in the 21st Century – MASING 2023",* Niš, Serbia, 14-15 December 2023.

[22] Zheng Q, Chen G, Jiao A. Chatter detection in milling process based on the combination of wavelet packet transform and PSO-SVM, *The International Journal of Advanced Manufacturing Technology*, Vol. 120, No.1-2, pp. 1237-1251, 2022.

[23] Vorkapić N, Kokotović B, Živanović S. Comparison of signal features from time and frequency domain for chatter detection, in Proc. *39th International Conference on Production Engineering of Serbia*, Novi Sad, Serbia, pp. 42-47, 26-27 October 2023.

[24] Ye J, Feng P, Xu C, Ma Y, Huang S. A novel approach for chatter online monitoring using coefficient of variation in machining process, *The International Journal of Advanced Manufacturing Technology,* Vol. 96, pp. 287-297, 2018.

[25] Yesilli M. C, Khasawneh F. A, Otto A. On transfer learning for chatter detection in turning using wavelet packet transform and ensemble empirical mode decomposition, *CIRP Journal of Manufacturing Science and Technology*, Vol. 28, pp. 118-135, 2020.

[26] Pan J, Liu Z, Wang X, Chen C, Pan X. Boring chatter identification by multi-sensor feature fusion and manifold learning, *The International Journal of Advanced Manufacturing Technology*, Vol. 109, pp. 1137-1151, 2020.

[27] Vorkapić N, Momcilovic B, Kokotović B, Živanović S. Chatter detection using support vector machine, *in Proc 7th International Scientific Conference on Mechanical Engineering Technologies and Applications COMETa2024*, pp. 90- 97, East Sarajevo-Jahorina, RS, B&H, 14.-16. November 2024.

[28] Yao Z, Mei D, Chen Z. On-line chatter detection and identification based on wavelet and support vector machine, *Journal of Materials Processing Technology*, Vol. 210, No. 5, pp. 713-719, 2010.

[29] Wang Y, Bo Q, Liu H, Hu L, Zhang H. Mirror milling chatter identification using Q-factor and SVM, *The International Journal of Advanced Manufacturing Technology*, Vol. 98, pp.1163-1177, 2018.

[30] Petrović M, Miljković Z, Babić B. Veštačka inteligencija u koncepcijskom projektovanju inteligentnih tehnoloških sistema – pregled stanja u oblasti istraživanja, *Tehnika,* Vol. 68, No. 5, pp. 873-885, 2013.

[31] Cherukuri H, Perez-Bernabeu E, Selles MA, Schmitz TL. A neural network approach for chatter prediction in turning, *Procedia Manufacturing*, Vol. 34, pp. 885-892, 2019.

[32] Kounta CAKA, Arnaud L, Kamsu-Foguem B, Tangara F. Review of AI-based methods for chatter detection in machining based on bibliometric analysis, *The International Journal of Advanced Manufacturing Technology*, Vol. 122, No. 5, pp. 2161-2186, 2022.

[33] Lamraoui M, Barakat M, Thomas M, Badaoui ME. Chatter detection in milling machines by neural network classification and feature selection, *Journal* of Vibration and Control, Vol. 21, No. 7, pp. 1251-1266, 2015.

[34] Sener B, Gudelek MU, Ozbayoglu MU, Unver HO. A novel chatter detection method for milling using deep convolution neural networks, *Measurement,* Vol. 182, article 109689, 2021.

[35] Cao H, Zhou V, Chen X, Zhang X. Early chatter detection in end milling based on multi-feature fusion and 3σ criterion, *The International Journal of Advanced Manufacturing Technology*, Vol. 92, pp. 4387-4397, 2017.

REZIME

PODRHTAVANJE U OBRADNOM SISTEMU – PREDIKCIJA I DETEKCIJA

Podrhtavanje (eng. chatter) predstavlja fenomen koji se periodično pojavljuje u obradnom sistemu. Njegova pojava u procesima obrade utiče na pobudu alata i drugih elemenata obradnog sistema, stvarajući tako „brazde“ (eng. chatter marks) na površini materijala obratka, što utiče na kvalitet obrađene površine i tačnost mera. Povišeni nivo buke tom prilikom samo je još jedan od pokazatelja na prisustvo podrhtavanja. Sve ove posledice navele su istraživače i svetske kompanije ka razvoju obradnih sistema ili softvera za njihovo programiranje, u cilju predikcije, detekcije i potiskivanja podrhtavanja iz obradnog sistema. Razvijen je veliki broj matematičkih modela i softvera koji su publikovani u svetski izabranim časopisima. Tema ovog rada je pregled trenutnog stanja u oblasti istraživanja podrhtavanja sa akcentom na pregled metoda i tehnika za predikciju i detekciju podrhtavanja u obradnom sistemu.

Ključne reči: *podrhtavanje, karte stabilnosti, regenerativni efekat, procesno prigušenje, vejvleti, support vector, detekcija*