Article

Machining Stability Categorization and Prediction Using Process Model Guided Machine Learning

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Abstract: The time-domain dynamic process model is used to generate data and guides the stability criteria for machine learning, saving the experimental costs for a number of required data for the metal process. Fourier transformation of vibration data simulated using a dynamic process model generates the feature lists including multiple frequencies and amplitudes at each process condition. The feature lists for milling stability are analyzed for training the machine learning algorithm. The amplitude and frequency distributions may change according to the dynamic pattern of the machining stability. The vibration patterns are grouped into stable, chatter, and boundary conditions by performing data training using support vector machines and gradient tree boosting. In the high-speed milling of Al6061-T6 with 6000 to 18,000 RPM and variations of axial and radial depths of cuts, 2400 data sets of the time domain data were trained and tested. Actual experimental tests are carried out for new process conditions with the range of 9890 to 28,470 RPM and 989 to 2847 mm/min. The experimental stability outcomes are compared with predictions from the algorithms. Stability is accurately predicted over new conditions with around 0.9 prediction accuracy, which means the methodology can be used to predict, categorize, and monitor stability in end milling processes.

Keywords: stability pattern recognition; machine learning; dynamic modeling; chatter

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1. Introduction

Chatter is one of the significant issues in metal processing and is still a bottleneck to maximize the process under a tightened quality requirement in modern manufacturing industries. Researchers previously tried to predict the chatter phenomenon by using analytical solutions and to monitor it using the vibration amplitude threshold and Fourier transformation method. Recently, machine learning has been applied to manufacturing processes to classify process errors and to improve quality and productivity.

Many researchers advanced the mechanics and dynamics of milling processes from one-directional vibration modes to multiple directional ones. After the first chatter stability laws in the frequency domain [1,2], Sridhar proposed two coupled, delayed differential equations with time-varying coefficients, and Minis and Yanushevsky formulated the first analytical solution of milling stability using Floquet's theory [3,4]. Altintas and Budak developed a general and closed solution of milling stability in the frequency domain [5,6]. Insperger et al. presented a semi-discrete time-domain stability solution of milling operations [7]. Davies et al. proposed added stability lobes [8] for low radial immersion and Olgac et al. formulated a stability solution for simultaneous machining [9]. Ko and Altintas proposed dynamic models for plunge milling processes [10,11], and Ko formulated a time-domain model with tool wear effect affecting stability [12]. In addition, researchers also worked on the Finite Element Method (FEM) and process conditions to prevent tool breakages [13,14].

Recently, as computing speed is significantly increased, machine learning has been a critical approach for monitoring and predicting processes over a wide range of possible conditions. Cherukuri et al. [15] worked on the artificial neural network of turning stability by using a physics-based analytical stability limit. In this article, experimental tests

were not presented for stability validation, and simulation was performed with 1000 to 4000 RPMs and cutting depths up to 2.5 mm. Yao et al. [16] extracted two features from experimental acceleration signals using wavelet transformation and applied support vector machine (SVM) to classify the chatter problem. Feature classification was performed up to 1120 RPM and cutting depths 1 mm. Wan et al. [17] proposed Adaboost-SVM using 16 features extracted from experimental data to enhance the accuracy and reliability of chatter identification. The test conditions are 2700 to 5700 RPM and cutting depths are up to 8 mm. Kvinevskiy et al. [18] proposed chatter classification using experimental audio data without a manual threshold. The test cases conditions are from 4200 to 6700 RPM. Cao et al. [19] propose the self-organizing map (SOM) neural network for early chatter detection. The test condition was fixed at 9600 RPM and cutting depth up to 10 mm. Oleagaa et al. [20] worked on a regression tree for the prediction of chatter frequency less than 100 Hz for heavy-duty milling machines up to 1000 RPM. Saravanamurugan et al. [21] used discrete wavelet transformation (DWT) to extract features from sensor signals and classified the features into stable, transition, and chatter using SVM. The boring process was classified with the ranges of 180 to 1000 RPM and 0.5 to 1 mm cutting depth. Pan al. [22] used multi-sensor data for chatter tests and applied SVM for classification with high accuracy. Their cutting parameters ranged from 180 to 220 RPM and 0.4 to 1.0 mm cutting depths. Tran et al. [23] trained a time-frequency image of the force signal and applied a convolutional neural network (CNN) model to identify the chatter. The cutting conditions are 2250 to 6000 RPM, up to 1.4 mm cutting depth at a fixed feed rate of 150 mm/min. Chen et al. [24] categorized micro-milling stability by training short-time Fourier transformation (STFT) images through SVM. The cutting speed is from 10,000 to 16,000 RPM with 0.015 to 0.14 mm cutting depths.

Performing machine learning over a wide range of process conditions requires many sample data due to the combinational effect of process conditions. So far, machine learning has been performed for limited ranges of process conditions, such as fixed variation of radial depth of cut or spindle rpm due to experimental costs and computation time. Thus, this article proposes simulation structure and algorithm to use data sets from the time domain dynamics model to significantly reduce experimental costs over the wide range of process conditions such as axial depth of cut 1.3 mm to 3.4 mm, the radial depths of cut 2.5 mm to 7.5 mm, spindle RPM 6000 to 28,470 RPM, and feed rates 600 to 2847 mm/min. Process conditions can be extended and classified depending on machine specification and stability boundary. After simulated data are arranged into feature lists, stability variation is trained by using machine learning algorithms. The trained algorithm can categorize machining vibrations as self-excited vibration, forced vibration, and boundary or transition status. SVM and gradient boosting algorithms are applied for training the data. The normalized amplitudes and frequency arrays from simulated Fast Fourier Transformation (FFT) are rearranged for training the machine learning algorithm. The algorithm is tested in new data sets with more than 90% prediction accuracy and experimentally compared in chatter and stable-cutting conditions. Section 2 addresses a time-domain process model, which generates data sets for feature elements; Section 3 presents stability classification and validation using support vector classification and gradient tree boosting; and Section 4 discusses the results and finally concludes the contribution in the Conclusion. The proposed methodology uses the distribution pattern of vibration frequencies and amplitudes to evaluate stability. Dynamic model-guided data analytics with 2400 sets of data generated in less than 10 min reduces the cost of experimental data for milling chatter prediction for wide ranges of process conditions.

2. Generation of Data Sets for Feature Elements Using Time-Domain Process Model

In this article, simulation data are arranged into feature lists to train machine learning to reduce the experimental cost. If the operation parameters are given, the trained algorithm based on the time-domain dynamic process model can categorize milling stability. Based on traditional chatter theories, the stability lobes are estimated as boundaries composed

of RPM and axial cutting depth as shown in Figure 1 [10]. In previous research regarding stability training, machine learning was performed for a limited range of process conditions. In this study, time-domain data are generated with the variances of RPM, feed rates, and axial depths of cuts according to the variation of radial depths of cut.

Figure 1. Stability lobes from zero-order stability equation (Roeders 760, radial depth of cut = 3 mm, Feed per tooth = 0.05 mm, modal parameters indicated in Table 1). (a) Impulse response test. (b) An example of stability lobes.

Table 1. Tested modal parameters of the solid end mill.

X Directional Mode	Modal Frequencies (Hz)	Damping Ratio	Stiffnesses (N/m)
1	4788	0.013	17,319,060
2	4350	0.013	85,984,251
3	2094	0.050	29,565,946
4	1044	0.025	67,967,391
Y Directional Mode			
1	4781	0.012	18,451,192
2	4344	0.015	71,005,842
3	1044	0.027	57,201,135
4	1925	0.043	39,730,944

For this study, Section 2 addresses the time-domain dynamic model structure and its connection to machine learning execution. In this article, a chatter vibration model uses a mechanistic approach for macro-scale milling processes considering the regenerative effect on uncut chip thickness and time effectiveness. Researchers may use other models if the models can reflect the regenerative effect of milling dynamics in uncut chip variations and rotational motions with high frequency [25]. In the case of using commercial FEM software, the simulation time may take one day for one condition even without regenerative effects [26].

The dynamic process model generates 2400 sets of simulation data, which are transferred to the gradient tree boosting and support vector machines.

The vectors $(\vec{\tau}, \vec{n}, \vec{b}, \vec{T}_c)$ for differential cutting forces at the tool edge element are developed in Figure 2. The differential force vectors are obtained based on the unit vectors $(\vec{n}, \vec{T}_c)$:

$$dF_n(i, j, k) = K_n T(\varnothing, \theta_{hl}) \vec{n} dA_c, dF_f(i, j, k) = K_f K_n T(\varnothing, \theta_{hl}) \vec{T}_c dA_c \quad (1)$$

where $dA_c = h(\varphi) \cos \alpha_r (\Delta a / \cos \theta_{hl})$.

$$T(\varphi, \theta_{hl}) = \begin{bmatrix} \cos \varphi \cos \theta_{hl} & -\sin \varphi & \cos \varphi \sin \theta_{hl} \\ \sin \varphi \cos \theta_{hl} & \cos \varphi & \sin \varphi \sin \theta_{hl} \\ -\sin \theta_{hl} & 0 & \cos \theta_{hl} \end{bmatrix} \quad (2)$$

Figure 2. End milling and unit vectors on the end mill.

dF_n and dF_f are converted into dF_x , dF_y , and dF_z in Cartesian coordinates using transformation matrix $T(\varphi, \theta_{hl})$ composed of local helix angle (θ_{hl}) and cutting-edge angular location (φ).

$$\begin{aligned} dF_x(i, j, k) &= [K_n(\cos \alpha_r \cos \varphi \cos \theta_{hl} + \sin \alpha_r \sin \varphi) \\ &+ K_n K_f \cos \theta_c \left(\sin \alpha_r \frac{1}{f_2} \cos \varphi \cos \theta_{hl} - \frac{1}{f_2} \cos \alpha_r \sin \varphi - \frac{f_1}{f_2} \cos \alpha_r \cos \varphi \sin \theta_{hl} \right) \\ &+ K_n K_f \sin \theta_c \left(-\frac{f_1}{f_2} \sin \varphi + \frac{1}{f_2} \cos \varphi \sin \theta_{hl} \right)] dA_c \\ dF_y(i, j, k) &= [K_n(\cos \alpha_r \sin \varphi \cos \theta_{hl} - \sin \alpha_r \cos \varphi) \\ &+ K_n K_f \cos \theta_c \left(\sin \alpha_r \frac{1}{f_2} \sin \varphi \cos \theta_{hl} + \frac{1}{f_2} \cos \alpha_r \cos \varphi - \frac{f_1}{f_2} \cos \alpha_r \sin \varphi \sin \theta_{hl} \right) \\ &+ K_n K_f \sin \theta_c \left(\frac{f_1}{f_2} \cos \varphi + \frac{1}{f_2} \sin \varphi \sin \theta_{hl} \right)] dA_c \\ dF_z(i, j, k) &= [-K_n \sin \theta_{hl} \cos \alpha_r + K_n K_f \cos \theta_c \left(-\sin \alpha_r \frac{1}{f_2} \sin \theta_{hl} - \frac{f_1}{f_2} \cos \alpha_r \cos \theta_{hl} \right) \\ &+ K_n K_f \sin \theta_c \frac{1}{f_2} \cos \theta_{hl}] dA_c \end{aligned} \quad (3)$$

The force coefficients (K_n , K_f , and θ_c) are identified using a mechanistic approach [27]. For example, the coefficients of Al 6061-T6 are calculated as $K_n = 1157 \text{ N/mm}^2$, $K_f = 0.613$, and $\theta_c = 0.56$.

Finally, the total forces sum up the elemental forces considering the cutter engagement with workpiece.

$$F(j) = \sum_i \sum_k dF(i, j, k) \quad (4)$$

The tool center position (X_c , Y_c) is estimated using feed and runout (R_r) in Equation (5).

$$\begin{Bmatrix} X_c(t) \\ Y_c(t) \end{Bmatrix} = \begin{Bmatrix} feed_x t + R_r \sin(\varphi) \\ feed_y t + R_r \cos(\varphi) \end{Bmatrix} + \begin{Bmatrix} x(t) \\ y(t) \end{Bmatrix} \quad (5)$$

The transfer function (Φ) is identified from the impulse response test at the tool tip, and lateral vibration displacements (x, y) is calculated as follows:

$$\begin{Bmatrix} x(t) \\ y(t) \end{Bmatrix} = \begin{bmatrix} \Phi_{xx} & \Phi_{xy} \\ \Phi_{yx} & \Phi_{yy} \end{bmatrix} \begin{Bmatrix} F_x(t) \\ F_y(t) \end{Bmatrix} \quad (6)$$

where the following is the case:

$$\Phi_{ab}(s) = \frac{\Delta a}{F_b} = \sum_{h=1}^{N_h} \frac{w_{nh}^2/k_h}{s^2 + 2\zeta_h w_{nh}s + w_{nh}^2} \quad (7)$$

where N_h is the total number of modes, h represents each mode, and w_{nh} , k_h , and ζ_h are the natural frequency, modal stiffness, and damping ratio, respectively.

The tested solid carbide end mill has two flutes, a diameter of 10 mm, a rake angle of 10° , a helix angle of 30° , and a runout of $5 \mu\text{m}$. The modal parameter of the tested tooling is listed in Table 1. The modal parameters are obtained from real and imaginary parts of transfer functions identified from impact hammer tests.

Machining configuration information is sent to the time domain process simulation with variations of process conditions as illustrated in Figure 3. The cutting forces excite the tooling structure, which shifts the tool center's position (X_c, Y_c). Accordingly, dynamic uncut chip thickness is estimated, and forces are updated in the time loop. The time-domain data are updated with a fourth Runge–Kutta integration at each incremental time interval during the rotation of a cutting tool. The time-varying cutting forces, including tool displacements, are simulated and processed according to the variations of process conditions.

Figure 3. The algorithm to generate data sets for feature elements with variations of process conditions.

Figure 4 shows the overall data flow used to train the machine learning algorithm such as SVM and gradient tree boosting. The time-domain dynamic process model generates

the process outputs such as force, displacement, etc. The feature generation algorithm extracts FFT data of the outputs and sorts out the maximum frequencies and amplitudes with operation frequencies and cutting depths. Accordingly, machine learning is executed to match features with targets.

Figure 4. Feature and target generation.

3. Stability Classification and Validation Using Support Vector Classification and Gradient Tree Boosting

Various machine learning methods, including support vector classification (SVC) with linear and RBF kernels and gradient tree boosting, are applied to classify feature lists composed of simulation data from the time domain dynamic model. Support vector machines are one of the supervised machine learning methods, and SVM classifiers employ a kernel to define linear and non-linear hyper-plane for separations of classes. In this article, linear and radial basis function (RBF) kernels are used for SVM. Gradient tree boosting is one of the machine learning methods for regression and classification tasks, which use typically decision trees [28]. The gradient tree boosting approach has been applied for classifying stable and chatter conditions.

Firstly, the data generated from the time-domain model are processed and the frequency components are rearranged by normalizing the amplitudes according to the order of maximum amplitude.

Feature lists are composed of operation frequency (kHz), axial depth of cut, radial depth of cut, force frequencies with eight components, and normalized amplitudes with seven elements normalized over the first one sorted according to the amplitude of each frequency. The three targets are 0: stable, 1: boundary, and 2: chatter vibrations, respectively.

Figure 5 illustrates the time domain simulation's output to produce the training data. Lateral vibrations in X, Y directions are dominant in the end milling process; thus, only F_x and F_y are extracted even though F_z can be obtained. While Figure 5a shows stable processes possessing a pattern where the harmonics of major operating frequencies are dominant, Figure 5b illustrates another pattern of distribution of frequencies and amplitudes that are different due to tool vibration modes with around 4.8 kHz. The cutting forces are simulated using the process model, and FFT is performed for extracting the frequencies and amplitudes as a part of feature elements.

Figure 5. Examples of predicted force data and FFT (radial depth of cut = 3 mm, feed rate = 700 mm/min, Al6061-T6). (a) Simulated forces and FFT for RPM 7000, axial depth of cut 1.5 mm. (b) Simulated forces and FFT for RPM 7000, axial depth of cut 7.5 mm.

Using the algorithm in Figure 3, 2400 sets of process conditions were simulated with the ranges of the axial depth of cut 1.3 mm to 3.4 mm, the radial depths of cut 2.5 mm to 7.5 mm, spindle RPM 6000 to 18,000 RPM, and feed rates 600 to 1800 mm/min. The total number of cutting conditions is 2400. The time-domain simulation with 20 cutter rotations for each condition can generate the total feature data set of (2400, 18) and the target set of (2400). Eighteen feature elements are formed considering cutting conditions, operation frequencies, and frequency components from the FFT of the time-domain output. The generation of the complete data sets takes less than 10 min, which is considered quite efficient compared to experimental time and cost. The data lists are divided into training and test sets with the ratio of 0.8 to 0.2.

The support vector machines and gradient tree boosting are trained using the training data sets for stability classifications. The support vector machine parameters such as the penalty parameter of the error term (C) and the parameter for non-linear hyperplanes (γ) are determined when the ten-fold validation prediction accuracy is maximized by using iterative comparisons. The predicted and original targets are compared as in the confusion matrix for the trained test sets of data using SVM (linear kernel $C = 90$), as in Figure 6. The predicted and original targets were compared as in the confusion matrix for the trained test sets of data using SVM (RBF kernel $C = 55$, $\gamma = 1$), as in Figure 7.

Support vector classification with linear function (SVC, $C = 90$, kernel = 'linear') shows ten-fold cross-validation score of 0.908, prediction score of 0.917 for test data, and RBF SVC ($C = 55$, $\gamma = 1$) outputs ten-fold linear cross-validation score of 0.897 and prediction score 0.912 for test data.

Figure 6. Confusion matrix for trained and test data with SVM (linear kernel C = 90). (a) Confusion matrix for trained data. (b) Confusion matrix for test data.

Figure 7. Confusion matrix for trained and test data with SVM (RBF kernel C = 55). (a) Confusion matrix for trained data. (b) Confusion matrix for test data.

The variables of gradient boosting classifier have been tuned by comparing ten-fold validation accuracy according to the variable set of ($n_estimators = 36$, $max_depth = 20$, $random_state = 1$). The variables are tuned when the ten-fold validation prediction accuracy is maximized. The gradient tree boosting method was applied to train the data, and the ten-fold cross-validation shows an accuracy of 0.913. The prediction accuracy for test data is 0.912. The predicted and original targets were compared as in the confusion matrix for the trained test sets of data using the gradient boosting classifier, as in Figure 8. The gradient boosting classifier demonstrates better accuracy than SVC with linear and RBF kernels based on the ten-fold cross-validation score, the prediction accuracy for test data, and the confusion matrix.

Gradient tree boosting is successfully trained and applied to recognize stability patterns according to the feature list. The feature importances were sorted for this stability pattern recognition by running a gradient tree boosting algorithm, as shown in Figure 9. In the case of the unstable cutting, the amplitudes of non-harmonics of the operating frequencies are not arranged in regular descending order as frequencies increase in this study. It is shown that the algorithm can categorize stability using operation frequencies and the variations of the arrays of frequency components.

Figure 8. Confusion matrix for trained and test data with gradient tree boosting ($n_{\text{estimators}} = 36$, $\text{max_depth} = 20$, $\text{random_state} = 1$). (a) Confusion matrix for trained data. (b) Confusion matrix for test data.

Figure 9. Feature importances with gradient tree boosting, 18 features (o_f: operation frequency; adoc: axial depth of cut; rdoc: radial depth of cut; f1 to f8: frequency components according to the magnitudes of the amplitudes; amp2 to amp8: highest to lowest amplitude ratio, normalized over amp1).

While traditional chatter theory presents stability lobes in terms of axial depths of cuts and RPM, as illustrated in Figure 1, the trained pattern for frequency component arrangements can tell the process stability for different combinations of axial and radial depths, RPM, and feed rates. As shown in feature importances, frequency component patterns are good enough to classify chatter stability. The differences in frequency order distinguish stable and chatter conditions. ‘amp7’ is affected by chatter frequency amplitudes, and ‘f2’ to ‘f8’ are arranged by the stability pattern.

The surface of the boundary condition is the transitory area between stable and chatter and may look clean with minor marks, as shown in Figure 10a. The surface mark pattern may be different depending on the vibration mode. The surface of the stable milling is shown in Figure 10b as an example.

Figure 10. Boundary condition with minor chatter marks and stable condition. (a) Boundary condition with minor marks on the surface (RPM 11,500, feed 1150 mm/min, radial depth of cut 3 mm, and axial depth of cut 2 mm). (b) Stable cut (RPM 9500, feed 950 mm/min, radial depth of cut 3 mm, and axial depth of cut 2 mm).

The experimental cutting conditions are selected outside the ranges of trained and test data. The experimental surfaces tell the stability of the process as in Figure 11 and gradient boosting is also used to categorize the stability pattern of the given conditions as in Table 2. In the milled surface illustrated in Figure 11a, the stable process appears, and the trained algorithm also predicts the stable process with the feature data as in Table 2 (N = 1). As shown in Figure 11b, the chatter happened, showing a rough surface. The stability for the conditions is also predicted as chatter using the presented algorithm.

Figure 11. Stable machined surface and chatter surface. (a) Stable cut (RPM 28,500, feed 2850 mm/min, radial depth of cut 2 mm, and axial depth of cut 4 mm). (b) Unstable cut (RPM 19,400, feed 1940 mm/min, radial depth of cut 2 mm, and axial depth of cut 4 mm).

Table 2. Feature and target predicted with gradient tree boosting radial depth of cut (2 mm) and axial depth of cut (4 mm).

N	RPM	Feed Rate (mm/min)	Feature Data	Prediction Using Gradient Tree Boosting and Feature Data
1	28,500	2850	[0.475000 4.000000 2.000000 0.952381 1.904762 2.857143 0.476190 3.809524 1.428571 4.761905 2.380952 0.574279 0.195333 0.150367 0.105525 0.104575 0.074296 0.043728]	1 Stable
2	19,400	1940	[0.323333 4.000000 2.000000 0.647249 1.294498 1.941748 0.323625 2.588997 0.970874 3.236246 5.469256 0.575251 0.193802 0.119335 0.107485 0.086229 0.081963 0.050962]	2 Chatter

The other process conditions with spindle RPMs (from 19,000 to 28,470 RPM) and feed rates listed in Table 3, much different from the trained data range (up to 18,000 RPM), were experimentally tested. As shown in Table 3, the trained machine learning algorithm categorizes stability accurately, matching the experimental outcome of stability for six experimental conditions.

Table 3. Experimental stability tests with the radial depth of cut (3 mm) and axial depth of cut (3 mm). The tested RPM from 19,000 to 25,892 and feed rates from 1900 to 2847 mm/min outside of the trained boundary.

N	RPM	Feed Rate (mm/min)	Prediction Using Machine Learning (Gradient Tree Boosting)	Experimental Stability
1	19,000	1900	Chatter	Chatter marks on the surface
2	20,465	2046	Stable	Stable
3	21,961	2196	Chatter	Chatter marks on the surface
4	23,927	2392	Stable	Stable
5	25,892	2589	Chatter	Chatter marks on the surface
6	28,470	2847	Stable	Stable

Additional tests were performed with variations of process conditions and some of them are shown in Table 4.

Table 4. Additional chatter stability tests.

N	RPM	Feed Rate (mm/min)	Radial Depth of Cut (mm)	Axial Depth of Cut (mm)	Prediction Using Machine Learning (Gradient Tree Boosting)	Experimental Stability
1	9890	989	2	2	Stable	Stable
2	20,420	2042	2	4	Stable	Stable
3	21,820	2182	2	4	Chatter	Chatter marks on the surface
4	25,874	2587	2	4	Chatter	Chatter marks on the surface
5	28,496	2849	2	4	Stable	Stable
6	23,710	2371	3	2.5	Stable	Stable
7	25,863	2586	3	2.5	Chatter	Chatter marks on the surface
8	17,300	1384	0.5	7	Stable	Stable
9	18,230	1458	0.5	7	Stable	Stable

4. Discussion

In the high-speed milling of Al6061-T6 with 6000 to 18,000 RPM and variations of axial and radial depths of cuts for end mill with two flutes and 10 mm diameter, 2400 data sets of the time domain data were trained and tested. Rather than using the threshold of maximum amplitude, the algorithm analyzes the changing pattern of the frequency component array to recognize chatter stability. The machine learning algorithm with the proposed methodology demonstrates that the stability prediction accuracy can reach around 0.9.

Actual experimental tests were carried out for new process conditions (9890 to 28,470 RPM and 989 to 2847 mm/min) much different from trained conditions. The experimental stability outcomes are compared with predictions from the algorithms. Stability is accurately predicted over new conditions with around 0.9 prediction accuracy, which means that the methodology can be used to predict, categorize, and monitor the stability in end milling processes.

SVM with a linear kernel may have a limitation for non-linear stability problems. Thus, the SVMs with RBF kernel and gradient tree boosting are recommended. SVM and gradient tree boosting were compared and gradient tree boosting indicated a slightly better accuracy

in the presented studies. The article suggests the structure to use simulation data for training machine learning for stability categorization over a wide range of process conditions.

Tool wear may affect cutting forces and process damping. A time-domain solution can include the process damping according to tool wear. However, tool wear gradually changes, and when a certain amount of tool wear is induced, the machinist changes the old tool with a new tool. If the tool wear profile is provided, stability can be simulated with process damping as the author's previous article handled the tool wear effect on stability [15], where new data can be generated in this case. Tool wear is another complex phenomenon that will be further investigated apart from this study.

5. Conclusions

This study investigates how machine learning can be trained using simulated time-domain data to categorize end-milling chatter stability over a wide range of process conditions. The time-domain simulation model replaces actual experimental tests for training machine learning algorithms in order to reduce experimental costs for a large number of combinational cutting parameters. Rather than using the threshold of maximum amplitude of chatter frequencies, the proposed methodology uses the distribution pattern of maximum vibration frequencies and amplitudes to evaluate the stability pattern. Accordingly, the pattern is trained using a machine learning algorithm using support vector machines and gradient tree boosting to categorize stability, as described in Figure 4. Even though both algorithms show high accuracy around 0.9, gradient tree boosting demonstrates better accuracy than the support vector machine.

Rather than using a number of experimental data for data analytics, a simulation model for milling chatter effectively replaced experimental data for machine learning. It is proved that dynamic model-guided data analytics can reduce the cost of experimental data for milling chatter prediction. Even without large amounts of experimental data, if the prediction data of the physical model are trained, machine learning can be used to categorize the system's stability over many potential combinations of process conditions.

In the future, the methodology will be extended in robotic manufacturing processes often facing chatter issues and integrated with a controller communication module to monitor and control milling processes. Sensor data from process monitoring will be categorized using the proposed algorithm, and process and system dynamic parameters will be identified in conjunction with the process model by applying machine learning.

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Nomenclature

θ_{hl}	local helix angle
α_r	rake angle of cutting edge
θ_h	helix angle
φ_p	pitch angle
$F_n(i, j, k)$	normal pressure force
$F_f(i, j, k)$	frictional force
$\vec{\tau}$	unit vector tangent to the cutter edge
$\vec{n}$	unit vector normal to rake face
$\vec{b}$	unit vector on the rake surface and perpendicular to the cutter edge
$\vec{T}_c$	chip flow vector
N_f	the number of flutes

Δa	length of edge element along the radial direction.
N_a	total disk number
θ	rotation angle of the cutter
$T(\varphi)$	transformation matrix
φ_c	flute spacing angle
h_c	uncut chip thickness
K_n	normal cutting force coefficients
K_f	frictional cutting force coefficients
θ_c	chip flow angle
R_r	radial runout

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