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ORIGINAL ARTICLE

A data-driven framework for predicting machining stability: employing simulated data, operational modal analysis, and enhanced transfer learning

Jamie Coble[4] · Matthew Alberts[1] · Sam St. John[1] · Simon Odie[1] · Anahita Khojandi[1] · Bradley Jared[3] · Tony Schmitz[2,3] · Jaydeep Karandikar[2]

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Abstract

Chatter, a self-excited vibration phenomenon, presents a significant challenge in machining operations, particularly in high-speed milling, where it can degrade tool life, reduce material removal efficiency, and compromise workpiece quality. Addressing this challenge requires a reliable predictive model that can accommodate the complex dynamics of various machining scenarios. This study introduces a novel, data-driven approach to predicting machining stability, leveraging over 140,000 simulated datasets and employing advanced techniques such as operational modal analysis (OMA), enhanced transfer learning (TL), and receptance coupling substructure analysis (RCSA). By integrating these methodologies, the framework effectively classifies and predicts chatter across diverse operational modes, achieving robust and accurate outcomes. Our model utilizes a Random Forest (RF) classifier trained with the comprehensive dataset, which demonstrates substantial improvements in both predictive accuracy and robustness. Specifically, the RF model achieved an accuracy rate of 85%, an area under the curve (AUC) of 0.90, and an F1 score of 0.88, underscoring its capability to adapt to varying machining configurations. These results highlight the framework's potential to enhance operational efficiency and machining quality by providing reliable chatter predictions across a broad range of machining parameters. This research thus offers a significant advancement in predictive maintenance for machining processes, enabling more stable and efficient manufacturing operations.

Keywords Transfer learning · Operational modal analysis · Chatter · Stability · Machining dynamics · Receptance coupling · Predictive maintenance

1 Introduction

Effective and accurate machining technology remains a critical component in modern manufacturing, particularly in sectors such as aerospace and automotive, where high precision and stable machining are paramount. The ability to predict and maintain machining stability, especially under high-speed milling (HSM) conditions, is essential to preventing the detrimental effects of chatter, a form of self-excited vibration [1]. Chatter can reduce tool life, lower material removal rates, and degrade the quality of the finished workpiece, posing ongoing challenges in productivity and product reliability [2].

To address these challenges, recent studies have focused on data-driven approaches and machine learning to enhance predictive accuracy. Wang et al. developed transfer learning (TL) models designed to adapt to varying operational conditions in machining [3]. Their work shows that TL can generalize across conditions by leveraging knowledge from pre-trained models, which is particularly useful for tool wear monitoring and chatter prediction under different machining setups. Similarly, Unver and Sener applied advanced TL methods that incorporate traditional frequency and time-domain features, demonstrating the potential for TL to improve tool condition monitoring by adapting to new data distributions [4]. These studies underscore the potential for TL in predictive maintenance applications, where models trained on specific conditions can effectively generalize to other configurations.

Traditional methods have also contributed foundational insights, particularly in the frequency domain and time domain. Early work by Tlusty [5], Tobias [6], and Koenigsberger and Tlusty [7] established theoretical bases for understanding self-excited vibrations in machining, identify-

Extended author information available on the last page of the article

ing the factors that influence chatter onset and progression. Their research laid the groundwork for current predictive approaches, highlighting the need for effective chatter prediction to optimize machining accuracy, tool life, and cutting efficiency [8, 9]. Despite these advances, accurately predicting chatter remains challenging due to the complexity of self-excited and force-induced vibrations [10]. Over the last decade, scholars have increasingly directed their attention toward methods aimed at averting or mitigating chatter, and these approaches fall into distinct categories, including stability prediction, passive control, and active control [11].

In developing predictive models for machining stability, various methods have been proposed, often categorized into frequency domain and time domain approaches. Altintas and Budak introduced a widely used zero-order analytical method for stability prediction in large material removal milling, though its accuracy diminishes with small radial depths of cut [12]. Other methods, such as the semi-discretization approach by Insperger and Stépán, which uses delay differential equations (DDEs) for generating stability lobe diagrams (SLDs), have also been effective but can require extensive computational resources [13]. Moreover, additional chatter prediction approaches have been suggested, including the method by Li and Liu, which derives the SLD through numerical calculations, enabling simulation and acquisition of the cutting process's vibration signal [14]. Schmitz and Smith further refined stability prediction models using frequency response functions (FRFs) and force models, though these methods involve complex data acquisition and pre-process prediction steps [15].

Building on the advancements in TL and predictive maintenance by Wang et al. and Unver and Sener, this study integrates operational modal analysis (OMA), TL, and receptance coupling substructure analysis (RCSA) into a comprehensive, data-driven framework. The proposed approach leverages over 140,000 simulated datasets to predict and classify chatter across diverse operational modes, aiming to improve adaptability and robustness in predictive modeling. This research advances the field of predictive maintenance for machining processes by offering a model that is capable of reliable chatter predictions across a broad range of machining conditions, contributing to more stable and efficient manufacturing operations.

This research introduces OMA through simulated data as a tool to conveniently obtain spindle operational modes across a wide array of machining parameters. The OMA method improves the convergence of the dynamic modal parameter identification, and the omission of modes is avoided [16] & [17]. Combining OMA and simulated machining data facilitates operational mode identification and chatter prediction, enhancing efficiency and safety, especially in high-speed rotating spindles. An issue that still plagues many researchers is the ability to generate vast amounts of machining data, given the time and cost to do so. Alberts et al. have shown that simulated data is a viable way to produce a random forest prediction model around chatter [18].

TL emerged as a solution to establish a prediction model for tool-tip modal parameters, addressing the challenge of predicting under changing machining conditions [19]. Also, chatter caused by tool wear under different processing conditions has a certain similarity, so TL can be applied to tool condition monitoring under different machining conditions [3]. Existing TL models, while innovative, face limitations in prediction accuracy, particularly when machining conditions change. RCSA is a method rooted in the principles of structural dynamics and system substructuring, offering a sophisticated means to comprehend and predict the dynamic interactions between different subcomponents of a machining system, notably the tool and holder assembly. In response, this paper proposes an enhanced TL model based on RCSA theory, which considers multiple connections between the tool and holder, enhancing accuracy in predicting tool-tip dynamics.

Building on research by Wang et al. and that by Unver and Sener, we will leverage work done by Yesilli et al. around TL to analyze a collection of over 140,000 simulated data sets across various operational modes and apply the novel approach by Alberts et al. to analyze and produce a generalizable chatter prediction model across operational modes [3, 4, 18, 20].

The comparative analysis between the following Study 1 and Study 2 is central to this research. By evaluating the performance of the baseline model from [18] against the enhanced model in this paper, we can draw important conclusions about the effectiveness of OMA, TL, and RCSA in improving predictive modeling for machining stability. Specifically, the comparison seeks to answer the following research questions:

- How does the integration of OMA contribute to a deeper understanding of the system's dynamic behavior, and how does it impact the accuracy of the predictive model?
- How does TL enhance the model's ability to generalize to new and unseen machining conditions?
- What are the benefits of incorporating RCSA in understanding and predicting the dynamic interactions within the machining assembly, and how does it influence model accuracy?
- To what extent do these advanced methods reduce the incidence of false negatives, where chatter is not predicted but occurs, compared to the baseline model?
- What is the overall improvement in predictive performance, and how does this translate into practical benefits for industrial machining operations?

The results from these studies are expected to provide clear evidence of the advantages offered by advanced modeling techniques. We hypothesize that Study 2 will demonstrate significant improvements in both the accuracy and robustness of the predictive model, particularly in scenarios where operational conditions vary from those seen during training. These improvements are not just academic; they have direct implications for real-world machining operations. More accurate and reliable chatter predictions can lead to better process control, reduced downtime, improved tool life, and higher-quality machined products.

In conclusion, the structured comparison between Study 1 and Study 2 serves as a critical component of this research. It allows us to rigorously evaluate the potential of OMA, TL, and RCSA in enhancing predictive models for machining stability, ultimately contributing to the development of more effective and reliable manufacturing processes.

2 Data description

This section provides an overview of the data sources, key concepts related to OMA, and the various feature groups derived from OMA, as well as the methods used for estimation and practical considerations.

2.1 Data collection and simulation

At the core of this study is a comprehensive simulated dataset, generated from the model developed by Schmitz and Smith, designed to reflect the range of conditions typically encountered in high-speed milling [15]. The dataset encompasses various operational modes, ensuring a broad representation of potential machining scenarios. This diversity is critical for capturing the range of vibrational dynamics that can occur in actual machining processes, making the dataset a valuable resource for studying chatter phenomena.

The simulation parameters were selected to closely mimic real-world machining dynamics. Emphasis was placed on accurately simulating factors like self-excited and forced vibrations, which are crucial for understanding chatter [20]. The richness and variety of the dataset are key for providing deep insights into the complexities of machining vibrations.

Python was chosen for data management, preprocessing, and analysis, leveraging its robust libraries and computational efficiency. This choice facilitates the handling of the large dataset and supports the implementation of predictive models, thanks to Python's compatibility with machine learning libraries such as Scikit-learn [21].

The data collection and simulation phase is marked by a focused approach to creating a detailed and representative dataset. Python's capabilities enable efficient data management and lay the groundwork for the application of advanced analytical methods, which are elaborated on in the following sections of the paper.

2.2 Operational modal analysis

OMA is a pivotal component in this study, offering a robust framework for extracting modal parameters from the system's output responses under actual operating conditions. Unlike traditional modal analysis that requires the system to be isolated and excited in a controlled environment, OMA operates directly on the system in its operational state, capturing the dynamics as they manifest under actual working conditions. This attribute makes OMA particularly suitable for industrial applications where isolating a system is impractical or impossible.

2.3 System dynamics and modal parameters

The dynamics of a linear time-invariant system can be described by the second-order differential equation of motion:

$$\mathbf{M}\ddot{\mathbf{x}}(t) + \mathbf{C}\dot{\mathbf{x}}(t) + \mathbf{K}\mathbf{x}(t) = \mathbf{f}(t) \tag{1}$$

where

- $\mathbf{M}$ is the mass matrix,
- $\mathbf{C}$ is the damping matrix,
- $\mathbf{K}$ is the stiffness matrix,
- $\mathbf{x}(t)$ is the displacement vector as a function of time t,
- $\mathbf{f}(t)$ is the external force vector [22].

In OMA, the goal is to determine the system's natural frequencies, damping ratios, and mode shapes (ϕ) from the measured response $\mathbf{x}(t)$, without direct knowledge of the excitation force $\mathbf{f}(t)$.

2.4 Natural frequencies and mode shapes

For free vibrations, where no outside force is acting on the system ($\mathbf{f}(t) = \mathbf{0}$), the system's response can be expressed as a sum of modal contributions:

$$\mathbf{x}(t) = \sum_{r=1}^{n} \phi_r q_r(t) \tag{2}$$

where $q_r(t)$ represents the modal coordinates corresponding to the rth mode shape ϕ_r.

Assuming harmonic motion $q_r(t) = Q_r e^{j\omega_r t}$, the characteristic equation is obtained:

$$(-\omega_r^2\mathbf{M} + j\omega_r\mathbf{C} + \mathbf{K})\phi_r = \mathbf{0} \tag{3}$$

Here, ω_r is the rth natural frequency and ϕ_r is the corresponding mode shape [23].

2.5 Damping ratio

The damping ratio ζ_r for the rth mode, a measure of vibration decay, is given by

$$\zeta_r = \frac{c_r}{2\sqrt{k_r m_r}} \tag{4}$$

where c_r, k_r, and m_r are the modal damping, stiffness, and mass, respectively. Alternatively, ζ_r can be derived from the logarithmic decrement or half-power bandwidth in the frequency domain [22].

2.6 Frequency response function

The FRF relates the output $\mathbf{X}(\omega)$ to the input $\mathbf{F}(\omega)$ in the frequency domain:

$$\mathbf{X}(\omega) = \mathbf{H}(\omega)\mathbf{F}(\omega) \tag{5}$$

where the FRF $\mathbf{H}(\omega)$ is defined as

$$\mathbf{H}(\omega) = (\mathbf{K} - \omega^2\mathbf{M} + j\omega\mathbf{C})^{-1} \tag{6}$$

In OMA, the objective is to estimate $\mathbf{H}(\omega)$ from the operational responses and extract the modal parameters without requiring explicit knowledge of $\mathbf{F}(\omega)$ [24].

2.7 Modal parameter estimation in OMA

Several techniques can be used for modal parameter estimation in OMA. Two widely adopted methods are covariance-driven stochastic subspace identification (SSI-COV) and frequency domain decomposition (FDD).

2.7.1 Covariance-driven stochastic subspace identification

The SSI-COV technique involves

1. **Constructing the Hankel matrix**: Arrange the output data into a block Hankel matrix $\mathbf{H}$.

$$\mathbf{H} = \begin{bmatrix} \mathbf{Y}(t) & \mathbf{Y}(t+1) \cdots \mathbf{Y}(t+p-1) \\ \mathbf{Y}(t+1) & \mathbf{Y}(t+2) \cdots \quad \mathbf{Y}(t+p) \end{bmatrix} \tag{7}$$

2. **Singular value decomposition (SVD)**: Perform SVD on $\mathbf{H}$ to obtain

$$\mathbf{H} = \mathbf{U}\Sigma\mathbf{V}^T \tag{8}$$

where Σ contains the singular values, which help determine the system's order.

3. **State-space model construction**: Derive the state-space matrices $\mathbf{A}$ (state transition matrix) and $\mathbf{C}$ (output matrix) from $\mathbf{U}$ and Σ.
4. **Modal parameter extraction**: The eigenvalues λ_r of $\mathbf{A}$ provide the natural frequencies and damping ratios:

$$\lambda_r = e^{(-\zeta_r \omega_{nr} \Delta t + j\omega_{dr} \Delta t)} \tag{9}$$

where ω_{nr} is the natural frequency, ω_{dr} is the damped natural frequency, and Δt is the time step [25].

2.7.2 Frequency domain decomposition

The FDD method begins with estimating the power spectral density (PSD) matrix from the operational response data. Following this, singular value decomposition (SVD) is applied to the PSD matrix at each frequency to extract singular values, which reveal the system's dynamic characteristics. Finally, peak-picking is performed on the singular value spectrum to identify the natural frequencies, with the corresponding singular vectors representing the mode shapes [26].

2.8 Practical considerations

When applying OMA, several factors must be carefully considered to ensure accurate results. Noise sensitivity is a significant concern, as OMA can be particularly sensitive to noise in low-energy modes, often requiring the application of averaging and filtering techniques to improve signal quality. Additionally, selecting the correct model order is crucial to avoid issues of overfitting or underfitting, which can impact the accuracy of the analysis. Finally, the system's response under operational conditions may exhibit non-linearities or non-stationary behaviors, both of which should be accounted for to achieve reliable results.

OMA provides a powerful framework for identifying the dynamic characteristics of a machining system under operational conditions. By leveraging techniques such as SSI-COV and FDD, the natural frequencies, damping ratios, and mode shapes can be accurately estimated, contributing to more reliable predictions of machining stability.

In the context of this research, OMA was systematically applied to the simulated dataset to identify the operational modes intrinsic to the machining process. The process involves the collection of vibration data from the simulated system, followed by sophisticated signal processing techniques to extract the modal parameters. This includes determining natural frequencies, damping ratios, and mode shapes, which are critical in understanding the system's vibrational behavior.

A key advantage of OMA in this study is its ability to provide insights into the system's behavior under different operational conditions without the need for external excitation especially for large datasets [27]. This is particularly beneficial for understanding the conditions that lead to chatter, as it allows for the analysis of the system's response to actual machining forces and conditions. The extracted modal parameters serve as foundational inputs for subsequent predictive modeling and analysis.

Furthermore, OMA's non-intrusive nature allows for the continuous monitoring and analysis of the system, making it an invaluable tool for predictive maintenance and real-time system diagnostics. By enabling the identification of subtle changes in the system's modal parameters, OMA can provide early warnings of potential issues, allowing for timely interventions to prevent the onset of chatter.

In summary, the application of OMA in this study provides a deep understanding of the system's dynamic behavior under actual operational conditions. This understanding is crucial for developing predictive models that are not only accurate but also reflective of the real-world complexities of high-speed milling processes. The integration of OMA with advanced signal processing techniques, all implemented within the Python ecosystem, ensures that the modal analysis is both rigorous and efficient. The insights gained from OMA form a critical part of the foundation for the advanced predictive modeling techniques detailed in the subsequent sections of the paper.

2.9 Transfer learning model development

In this research, TL emerges as a strategic approach to model development and adaptation, addressing the challenge of predictive modeling under varying machining conditions. TL is particularly apt for this study as it allows for the leveraging of knowledge extracted from the extensive simulated dataset, facilitating the application of this knowledge to predict chatter in new and changing scenarios. This approach is particularly valuable when data distributions differ between training and application environments.

2.10 Fundamentals of transfer learning

TL leverages a pre-trained model from a source domain, $\mathcal{D}_S$, characterized by feature space $\mathcal{X}_S$ and distribution $P_S(\mathbf{X})$, to improve performance in a target domain, $\mathcal{D}_T$, with its own feature space $\mathcal{X}_T$ and distribution $P_T(\mathbf{X})$. The goal is to improve the target predictive function $f_T(\mathbf{X})$ where $P_S(\mathbf{X}) \neq P_T(\mathbf{X})$ [28].

2.11 Mathematical framework

The TL process involves two main stages:

- **Pre-training:** The model is first trained on the source domain by minimizing the loss function $L_S(\theta)$:

$$\theta_S = \arg\min_{\theta} L_S(\theta) \tag{10}$$

- **Fine-tuning:** The pre-trained model is then adapted to the target domain by minimizing $L_T(\theta)$, starting from θ_S:

$$\theta_T = \arg\min_{\theta} L_T(\theta; \theta_S) \tag{11}$$

2.12 Application in machining stability prediction

In this study, TL is applied to adapt a Random Forest model trained on simulated machining data (source domain) to extrapolated machining data (target domain). Feature alignment is crucial, ensuring that the model effectively transfers knowledge between the simulated and actual environments.

2.13 Benefits and challenges

The TL framework employed in this study offers several benefits and faces certain challenges. Among its advantages, TL reduces data requirements in the target domain, improves the model's ability to generalize to new conditions, and accelerates model training by beginning from a pre-trained state. However, challenges include potential domain discrepancies that may lead to negative transfer, misalignment of features between source and target domains, and the additional computational costs involved in fine-tuning complex models. The adaptability of the TL framework is especially valuable in machining, where operational conditions can vary widely, making the ability to swiftly adjust to new conditions a critical asset.

The model training process began with a thorough preprocessing of the simulated data. This involved normalization to ensure consistency in scale across different features and the selection of the most predictive features based on their relevance to chatter phenomena. Feature selection was performed meticulously to ensure the model's focus remained on the most informative attributes, reducing the risk of overfitting and improving model interpretability. This was done by utilizing the recursive feature elimination (RFE) process. This method is a cornerstone in our process of choosing features, systematically eliminating the less critical features from our initial extensive collection. The fundamental principle of RFE is its capacity to refine and identify the most influential features, thus enhancing the model's clarity and markedly decreasing the need for computational resources [29].

Following preprocessing, the Random Forest algorithm was employed for model training. This choice was guided by the algorithm's proven track record in handling high-dimensional data and its robustness against overfitting, aiming to leverage the intrinsic advantages of the Random Forest (RF) model. This model is distinguished for its resilience to noise and its adeptness in assessing the significance of features, crucial in improving the analysis's overall applicability [30]. Random Forest, an ensemble learning method that constructs multiple decision trees during training and outputs the mode of the classes (classification) or mean prediction (regression) of the individual trees, provides a balance between accuracy and computational efficiency.

The integration of TL within this framework involved fine-tuning the Random Forest model using a subset of the target domain data. This process ensures that the model, initially trained on the simulated dataset, remains sensitive and adaptive to the nuances of new operational conditions. Model training also involved rigorous cross-validation, particularly k-fold cross-validation, to assess the model's performance and generalizability robustly. This validation approach not only provides insights into the model's accuracy but also helps in identifying any potential biases or variances that could affect its performance in real-world settings.

The TL and model training phase is characterized by a systematic and strategic approach, leveraging the strengths of the Random Forest algorithm and the adaptability of TL. The rigorous preprocessing, feature selection, and cross-validation procedures ensure that the model is both accurate and robust, capable of adapting to new machining conditions while providing reliable chatter predictions.

2.14 Receptance coupling substructure analysis

RCSA forms a crucial pillar in the predictive modeling approach of this study, representing a significant advancement in understanding and predicting dynamic behavior within machining systems [31]. A widely adopted approach involves integrating the experimentally measured dynamics of the machine tool substructure with the analytically modeled dynamics of the tool-holder combination using RCSA [32].

2.15 Fundamentals of RCSA

RCSA is based on the principle that the dynamics of an assembly can be predicted by coupling the FRF of its substructures. The FRF, $\mathbf{H}(\omega)$, represents the relationship between applied force and resulting displacement in the frequency domain:

$$\mathbf{H}(\omega) = (\mathbf{K} - \omega^2\mathbf{M} + j\omega\mathbf{C})^{-1} \tag{12}$$

where $\mathbf{K}$, $\mathbf{M}$, and $\mathbf{C}$ are the stiffness, mass, and damping matrices, respectively.

2.16 RCSA methodology

The RCSA process involves

- **Substructure characterization:** Measure or calculate the FRFs of individual substructures, such as the tool and holder.
- **Receptance coupling:** Combine these FRFs using the dynamic stiffness matrix $\mathbf{D}(\omega)$ to obtain the coupled system's FRF:

$$\mathbf{H}_{AB}(\omega) = \mathbf{H}_A(\omega) + \mathbf{H}_B(\omega) - \mathbf{H}_A(\omega)\mathbf{D}(\omega)\mathbf{H}_B(\omega) \tag{13}$$

2.17 Application in machining

In machining systems, RCSA is used to analyze the dynamics of the tool-holder assembly. By coupling the FRFs of the tool and holder, RCSA helps predict stability limits and potential chatter, critical for optimizing machining performance.

2.18 Benefits and challenges

The RCSA approach offers several benefits and presents certain challenges within the predictive modeling framework. One of its primary advantages is the ability to conduct modular analysis of complex assemblies, enhancing the accuracy of predictions related to system behavior and stability. However, RCSA also requires precise FRF measurements, and its application can be computationally intensive, particularly for large systems. In the context of this research, RCSA provides a nuanced understanding of the tool-holder dynamics, which is crucial given that the complex interactions between the tool and holder significantly impact the system's overall dynamic response and its susceptibility to chatter.

The implementation of RCSA in this study involved the following key steps:

1. Substructure characterization: The dynamic characteristics of individual substructures, namely the tool and holder, were meticulously identified. This involved determining the FRFs of the substructures in isolation, providing a detailed insight into their individual dynamic behaviors.
2. Coupling analysis: The identified substructures were then analytically coupled using RCSA principles. This coupling analysis is based on the concept that the total dynamic behavior of a coupled system can be derived from the individual behaviors of its subcomponents. The process involves the calculation of coupling matrices and the application of RCSA algorithms to predict the dynamic response of the coupled tool-holder system.

3. Modal parameter extraction: Following the coupling analysis, the modal parameters of the coupled system, including natural frequencies, damping ratios, and mode shapes, were extracted. These parameters are crucial in understanding the system's susceptibility to chatter and form the basis for subsequent predictive modeling.
4. Integration with predictive modeling: The modal parameters derived from RCSA were integrated into the TL framework, enhancing the predictive model's ability to accurately forecast tool-tip dynamics under varying operational conditions. This integration ensures that the model's predictions are not only based on historical data but are also grounded in the physical realities of the machining system's dynamic behavior.

The integration of RCSA into the predictive modeling framework marks a significant departure from traditional chatter prediction methods. By considering the multiple connections between the tool and holder, RCSA provides a more comprehensive and accurate prediction of the system's dynamic behavior. This accuracy is crucial for developing reliable chatter predictions, particularly in scenarios where the tool-holder assembly undergoes changes due to varying operational conditions.

RCSA enhances the robustness and reliability of the predictive model by providing a deep understanding of the system's dynamic behavior. The integration of RCSA with the TL model ensures that the predictions are not only data-driven but are also deeply rooted in the physical understanding of the machining system's dynamics. This comprehensive approach significantly advances the capability to predict and mitigate chatter in high-speed milling processes, contributing to enhanced operational efficiency and product quality.

3 Method

The methodology can be seen in Fig. 1 and is outlined below.

3.1 Data preparation

Ensuring that data is correctly prepared and segmented is fundamental to the success of any machine learning project. This section describes the meticulous process undertaken to prepare the 140,000 datasets, ensuring their readiness for effective use in training and validating both the baseline and the new predictive models.

Data cleaning and preprocessing: The first step in preparing the data involved a comprehensive cleaning process to ensure data quality and consistency:

- Handling missing values: Missing data points were identified and appropriately handled, either by imputation using statistical methods or by removing data points where necessary to maintain data integrity.
- Noise reduction: Given the nature of vibration data in machining, noise reduction techniques such as smoothing and filtering were applied to enhance the signal quality, crucial for accurate feature extraction.
- Normalization: Data normalization was performed to scale the numerical values to a standard range. This is particularly important in machine learning to prevent attributes with larger ranges from overpowering those with smaller ranges, ensuring all features contribute equally to the analysis.

Feature engineering: The feature engineering process was designed to identify and select the most relevant attributes from the raw vibration data collected during machining operations. In the data preprocessing phase of this study, a structured approach was adopted to ensure effective feature extraction and transformation.

Fast Fourier transform features: Fast Fourier transform (FFT) features: Custom Python scripts were developed to extract FFT features, capturing the frequency-domain characteristics of the vibration data. This step was essential for identifying critical frequency components that could help discern between stable and unstable machining conditions.

Time-series features: The TSFresh library was utilized for comprehensive time-series feature extraction. This library provides a systematic integration of computational techniques, offering a broad range of statistical and descriptive features that capture the temporal dynamics of the data. The raw data sets were transformed into feature datasets using this combination of TSFresh and FFT methodologies.

OMA features:

- Natural frequencies: These are the frequencies at which the system tends to oscillate in the absence of damping or external forces and are fundamental to understanding system dynamics.
- Damping ratios: This measures the damping characteristics of the system, which describe how oscillations in the system decay after a disturbance.
- Mode shapes: These are the shapes that the system naturally wants to take on while vibrating at each natural frequency. Mode shapes are crucial for understanding the vibration patterns of the system.
- Modal scales: These scales provide a quantitative measure of how much each mode shape contributes to the system's response.

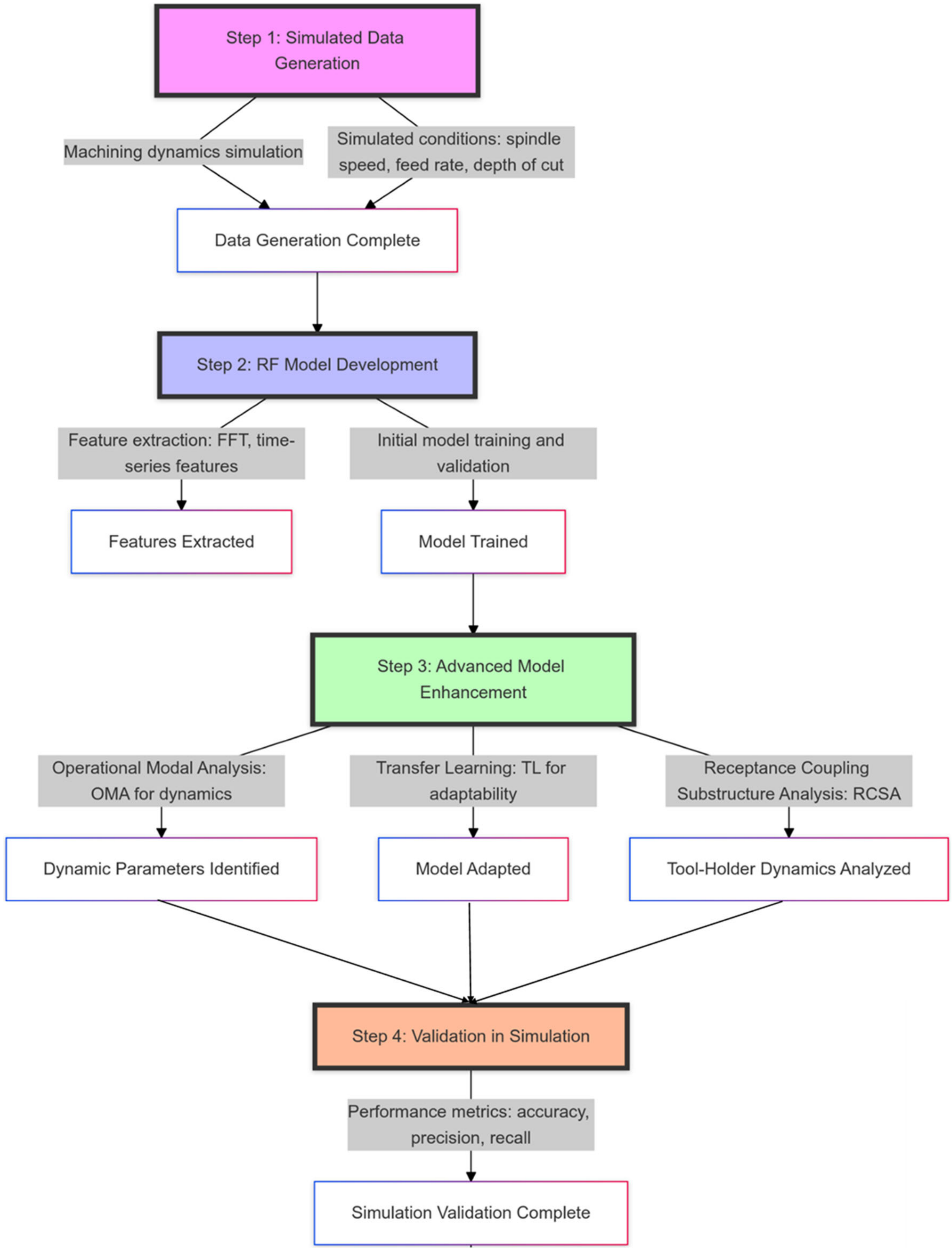

Fig. 1 Methodology flow chart

- Modal assurance criteria (MAC): A statistical measure that compares the similarity of mode shapes. It is used to verify the consistency or changes in modal properties over time or different operational conditions.

RCSA features:

- Frequency response functions: These functions describe how different parts of the system respond to various frequencies of input, used to predict how the entire system will behave.

- Coupling stiffness and mass matrices: These matrices describe how different parts of a machine or structure are connected and interact dynamically. They are crucial for understanding the overall dynamic behavior when different parts are assembled.
- Assembled system FRFs: Once individual FRFs are known, RCSA can be used to predict the FRFs of the assembled system. These are critical for predicting how modifications in the structure (like changing a part or configuration) will affect overall system behavior.
- Dynamic stiffness and compliance: Measures of how much a system deforms under dynamic loads, which can be crucial for assessing system performance under operational conditions.

Feature selection and reduction: Challenges in FFT Interpretation: The analysis revealed challenges in discerning stability and instability from FFT data alone, highlighting the need for a more holistic approach that includes time-series features (refer to figures illustrating stability and instability). RFE: To mitigate the risk of model overfitting due to the extensive number of features (846 in total), the RFE process was employed. RFE systematically reduced the feature set to the 17 most significant features, categorizing them into 10 FFT features and 7 time-series features. This refined selection maintained the model's predictive accuracy while reducing computational overhead.

Finalized feature set: The final selection of features, resulting from RFE, forms the input for the RF classification model. The combination of the FFT and time-series features provides a comprehensive perspective on the vibration data, enabling the RF model to robustly distinguish between stable and unstable conditions. This is in line with the features that were identified by Alberts et al. [18]. These features can be seen in Tables 1 and 2.

The transformation of raw datasets into precisely refined feature sets was achieved through a combination of custom Python scripts and the TSFresh library. This approach ensured that each feature was analyzed for its significance in predicting chatter. The preprocessing phase plays a pivotal role in accurately identifying the markers of stability and instability, as depicted in the figures. This systematic feature extraction and selection process provides a solid analytical foundation for the RF classification model, ensuring robust predictive capability in milling operations.

Data segmentation: To evaluate model performance effectively, the data was segmented into distinct sets for training, validation, and testing. The largest portion, comprising 70% of the data, was allocated to the training set, which was essential for the model to learn the underlying patterns and dynamics associated with chatter. A further 15% of the data was designated as the validation set, used to fine-tune model parameters and to help prevent overfitting by providing an unbiased evaluation of the model fit during the training process. The final 15% was set aside as the testing set, used exclusively to assess the model's performance after training and validation were complete, ensuring an objective measure of its predictive power.

Table 1 FFT features extracted

Feature	Description
Acceleration peak (g)	peak=max(a)
Acceleration RMS (g)	$RMS = \sqrt{(1/n)\sum_{i=1}^{n} ai^2}$
Crest factor	$Crest = X_{peak}/X_{RMS}$
Standard deviation (g)	$\text{std} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \overline{x})^2}$
Velocity RMS (in/s)	$V_{RMS} = \sqrt{A^2/2}$
Displacement RMS (in)	$D_{RMS} = \sqrt{(a/(2 * pi * f)^2)^2}$
Peak frequency (Hz)	Highest peak frequency (Hz)
RMS (g) from 1 to 65 Hz	$RMS_{1-65} = \sqrt{(1/n)\sum_{i=1}^{65} ai^2}$
RMS (g) from 65 to 300 Hz	$RMS_{65-300} = \sqrt{(1/n)\sum_{i=65}^{300} ai^2 r}$
RMS (g) from 300 to 6000 Hz	$RMS_{300-1000} = \sqrt{(1/n)\sum_{i=300}^{1000} ai^2 r}$

Source: FFT features are sourced from Alberts et al. [18]

Cross-validation setup: To further enhance the robustness and reliability of the model evaluation, a k-fold cross-validation setup was employed, specifically to aid in model tuning and selection. This technique involves rotating the training and validation sets through multiple iterations, or folds, to ensure that each data point is used in both training and validation phases. By maximizing the use of available data in this way, the k-fold cross-validation provides a more comprehensive assessment of the model's performance.

This careful preparation and segmentation of the data are critical to the success of the subsequent modeling steps, ensuring that both the baseline and the new models are trained, validated, and tested under optimal conditions. This approach to data management underpins the integrity and validity of the study, laying a solid foundation for the predictive analyses that follow.

3.2 Data sets

Data sets A, B, and C are derived from the same machining tool setup, with variations in cutting depth, rotational speed of the machine tool head and cutting forces of 600, 700, and $800 \times 10^6 N/m^2$. The number of teeth on the cutting head will also include variations for 2, 3, 4, and 6. This results in data sets of A01, A02, A03, A04, B01, B02, B03, B04, C01, C02, C03, and C04. Each set consists of 5000 data files,

Table 2 Time series feature and description

Feature	Description
Ratio value number to time series length	The number of unique values versus the total number of values
Benford correlation	How often a value starts with a certain number, in analytics overwhelmingly a value is most likely to start with a 1
Change quant f-agg "var" False qh 1.0 ql 0.4	Aggregator function of the differences taken over a specific range of upper and lower quartiles
FFT coefficient attr "imag" coeff 55	Fast Fourier Transform of the imaginary part of the data with a coefficient of 55
FFT coefficient attr "imag" coeff 77	Fast Fourier Transform of the imaginary part of the data with a coefficient of 77
Agg linear trend "stderr" len 10 f agg "min"	Linear least squares regression for certain attributes for a certain number of time series data points
Permutation entropy dimension 4 τ 1	Counts the frequency of permutation and returns the appropriate entropy, this is a complexity measure for time series data

Source: Time series features are sourced from Alberts et al. [18]

covering RPM settings ranging from 6000 to 11,000 rpm in 50 rpm increments, with the cutting depth varying from 0.2 to 10 mm in 0.2 mm increments. This breakdown of data sets will be duplicated over 3 different tool modal setups as shown in Table 3. This is meant to showcase how the modal will perform on data from different machines with different modal parameters as indicative of the real world.

3.3 Model evaluation and validation

Evaluating and validating the predictive model is integral to ensuring its efficacy and reliability, particularly in operational settings. This section of the study outlines a varied approach designed to thoroughly assess the model's performance across several metrics and validate its predictive capabilities.

For a robust evaluation, we selected a combination of metrics to comprehensively gauge the model's effectiveness. Accuracy provides a fundamental measure of the model's overall correctness by calculating the ratio of correctly predicted observations to the total observations. Area under the curve (AUC), derived from the receiver operating characteristic (ROC) curve, is a performance metric for classification problems at various threshold settings, representing the model's ability to distinguish between classes; a higher AUC indicates better predictive performance and robustness. The F1 score balances precision and recall, making it particularly valuable in scenarios with an uneven class distribution, as it accounts for both false positives and false negatives; this is especially crucial in our context, where unpredicted chatter events can have severe implications. Finally, precision and recall provide insights into the model's accuracy in identifying positive class instances both among actual positives (recall) and among its total predicted positives (precision), giving a detailed view of the model's detection performance.

To ensure the model's stability and generalizability, k-fold cross-validation was utilized. In this approach, the dataset was split into k smaller subsets or folds. The model was trained on $k-1$ of these folds, with the remaining fold used as a test set. This process was repeated k times, allowing each fold to serve as the test set exactly once. By averaging the results across all k trials, this method provides a more comprehensive understanding of the model's performance across different subsets of data.

The model's predictions were rigorously compared against known outcomes within the extensive simulated dataset to assess its accuracy and reliability. By matching the model's predictions with the established outcomes of the simulated scenarios, we evaluated the precision of the model's chatter detection across various operational settings. Special attention was given to scenarios where operational conditions known to induce chatter were simulated, allowing for a focused analysis of the model's sensitivity and specificity in detecting these critical conditions.

Table 3 Modal parameters

Modal	ω tx	τ tx	ζ tx	ω ty	τ ty	ζ ty
Modal 1	2000*pi rad/s	1e7 N/m	0.05	2000*pi rad/s	1e7 N/m	0.05
Modal 2	1500*pi rad/s	5e6 N/m	0.02	1500*pi rad/s	5e6 N/m	0.02
Modal 3	3000*pi rad/s	2e7 N/m	0.05	3000*pi rad/s	2e7 N/m	0.05

A sensitivity analysis was conducted to examine the influence of various input parameters on the model's predictions. By systematically varying input parameters and observing the corresponding changes in the model's outputs, we identified the most influential factors affecting the model's performance. This analysis of feature importance allowed us to prioritize the most impactful features, guiding further refinement and optimization of the feature selection process.

In conclusion, the model evaluation and validation process adopted in this study is extensive and thorough, designed to ensure that the predictive model not only achieves high accuracy and reliability in theoretical simulations but also performs effectively and efficiently in practical, real-world applications. This comprehensive evaluation approach helps bridge the gap between theoretical research and industrial application, ensuring the model's relevance and utility in enhancing machining operations.

4 Investigation

The primary goal of this research is to develop and validate predictive models for machining stability, focusing on identifying and mitigating chatter during high-speed milling operations. To achieve this, we conducted two distinct studies—referred to as Study 1 and Study 2—each designed to evaluate different approaches to predictive modeling.

Study 1 serves as the baseline for this research. It focuses on evaluating the performance of traditional predictive modeling techniques applied to machining stability. Specifically, Study 1 utilizes a RF model trained exclusively on simulated data, without the integration of advanced methodologies. The purpose of this study is to establish a benchmark for predictive accuracy and robustness when relying on conventional data-driven approaches. By assessing the performance of the baseline model, we can identify its strengths and limitations in predicting chatter under varying operational conditions.

Study 2 introduces advanced methodologies aimed at improving the predictive accuracy and generalization of the model. This study integrates OMA, TL, and RCSA into the predictive modeling framework. The goal of Study 2 is to demonstrate how these advanced techniques can enhance the model's ability to adapt to new machining conditions, improve its robustness, and ultimately provide more reliable predictions of machining stability. OMA is used to extract critical modal parameters from the system's operational response, TL is employed to adapt the model from simulated data to real-world operational conditions, and RCSA is utilized to accurately capture the dynamic interactions within the machining assembly. By comparing the results of Study 2 with those of Study 1, we aim to highlight the benefits of incorporating OMA, TL, and RCSA into the predictive process.

4.1 Study 1: evaluation of original model performance

The objective of this analysis is to assess the predictive performance and robustness of the original RF model across the entire dataset and for each variable type. The RF model was optimized specifically for this dataset by adjusting hyperparameters, including the number of estimators, maximum depth, and splitting criteria. Following optimization, the model was trained on a balanced portion of the dataset, ensuring representation of all modal conditions, cutting forces, and teeth combinations.

For a more granular assessment, the training data was further divided by key variable groups, including modal conditions, cutting forces, and cutting teeth, allowing for an intra-variable performance evaluation. Each subset was independently evaluated using metrics such as accuracy, AUC, F1 score, and other relevant measures. The overall predictive performance of the original model was then validated through k-fold cross-validation applied to the entire dataset, providing a comprehensive measure of model stability. Finally, a benchmark was established by testing the model on the remaining 15% of the dataset, yielding insights into its accuracy and robustness under diverse conditions.

4.2 Study 2: evaluation of the new model with OMA, TL, and RCSA

The objective of this analysis is to demonstrate the effectiveness of the new predictive model, which incorporates OMA, TL, and RCSA, in improving chatter prediction across a range of operational conditions. To enhance the model's predictive capability, new features extracted from OMA and RCSA were added to the original feature set. The new model was then trained on the same training subsets used in Study 1 to allow for a direct comparison with the original model.

For intra-variable performance evaluation, the model's adaptation to changes in each modal condition was assessed using accuracy and AUC metrics. The model's robustness was further evaluated across different cutting force conditions, and its accuracy and adaptability were measured across various cutting teeth configurations. A comprehensive comparative analysis was conducted by examining cross-validation results for both the original and new models across the entire dataset. Finally, statistical significance analysis was performed to quantify the improvements in performance offered by the new model, highlighting its enhanced effectiveness in predicting chatter across diverse machining scenarios.

In both studies, the same comprehensive simulated dataset is used as the primary data source. The dataset undergoes meticulous preparation, involving noise reduction, normalization, and feature extraction, as described in the "Data description" section. For Study 2, additional steps are taken to incorporate operational data and features derived from OMA and RCSA. These features are critical for the fine-tuning of the model through TL, allowing it to leverage pre-existing knowledge from the simulated environment while adapting to real-world conditions.

In Study 1, the RF model is trained exclusively on the simulated data, following traditional machine learning practices. In Study 2, the model undergoes pre-training on the simulated data, followed by fine-tuning on a smaller, domain-specific dataset using TL. This approach allows the model to benefit from both the breadth of the simulated data and the specificity of the operational data, with OMA-derived features providing insights into the system's dynamic behavior and RCSA enhancing the model's understanding of the tool-holder interactions.

Both studies employ k-fold cross-validation to ensure the stability and generalizability of the models. This method involves partitioning the dataset into "k" subsets, training the model on "k-1" subsets, and validating it on the remaining subset. The process is repeated "k" times, with each subset used as a validation set once. This approach provides a comprehensive assessment of the model's performance across different data splits, reducing the likelihood of overfitting.

To facilitate a meaningful comparison between the two studies, a consistent set of evaluation metrics is used. These include accuracy, AUC of the ROC, F1 score, precision, and recall. These metrics are chosen for their ability to capture different aspects of model performance, such as its ability to correctly classify stable and unstable machining conditions, its sensitivity to false positives and false negatives, and its overall predictive power.

5 Results

The investigation progressed through a series of organized studies. Each study elucidated a different aspect of the model's performance and examined the effectiveness of the implemented features.

5.1 Study 1 results—original model

Study 1 focused on evaluating the performance of the original Random Forest model across a newly expanded dataset of 140,000 instances, covering various modal conditions, cutting forces, and cutting teeth configurations. The model was optimized for this dataset by adjusting hyperparameters for better adaptability. As seen in Fig. 2, key performance metrics indicated an overall accuracy of 78%, an AUC of 0.82, and an F1 score of 0.75. While the model showed reasonable effectiveness across the entire dataset, the performance analysis revealed limitations in handling complex scenarios, partic-

Model	Accuracy	AUC	F1 Score
Original	78%	0.82	0.75
OMA/TL/RCSA	85%	0.90	0.88

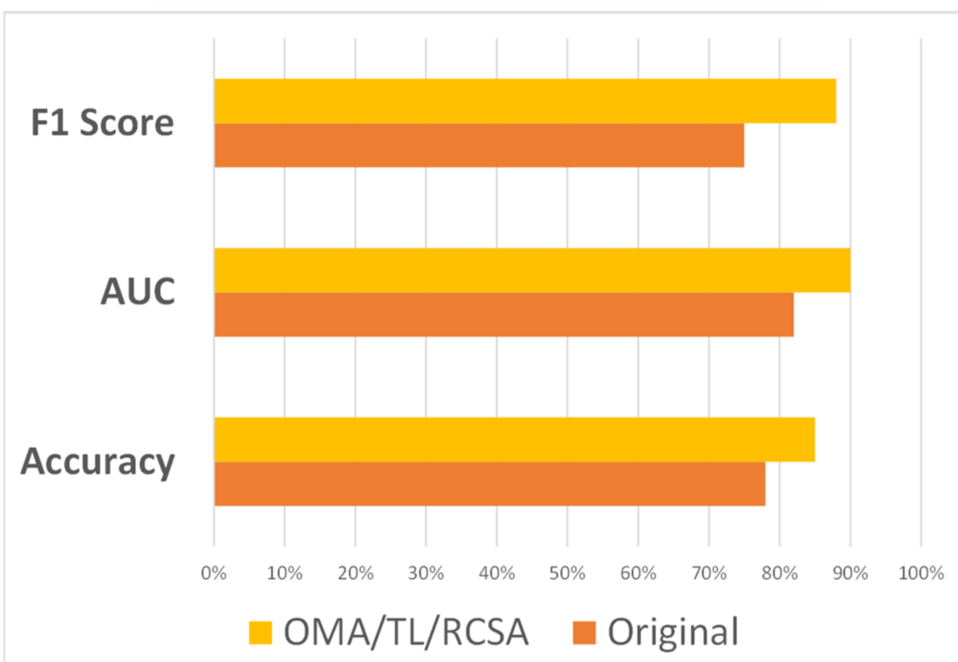

Fig. 2 Original model vs. new OMA/TL/RCSA model

ularly at higher cutting forces and varied modal conditions. The new model demonstrated a superior overall accuracy of 85%, an AUC of 0.90, and an F1 score of 0.88. Notably, it performed exceptionally well in handling complex scenarios across varying modal conditions, cutting forces, and numbers of cutting teeth, reflecting significant improvements in predictive accuracy and robustness. This enhancement is attributed to the model's advanced feature engineering and learning techniques, which effectively captured and analyzed the complexities of machining vibrations.

5.2 Study 2 results

Study 2 delved into the detailed evaluation of the new model, which integrates OMA, TL, and RCSA. The model was rigorously tested against the same extensive dataset of 140,000 data points that was used to evaluate the original model.

This new model demonstrated superior performance metrics overall, including an accuracy of 85%, an AUC of 0.90, and an F1 score of 0.88. The performance was also broken down and analyzed by key variables to gain insights into specific areas of strength and needed improvements:

Modal conditions:

As seen in Fig. 3, the model showed marked improvements in predictive accuracy across different modal conditions (Modal 1, Modal 2, Modal 3). This suggests that the integration of OMA has significantly enhanced the model's sensitivity to variations in operational modes, crucial for predicting machine behavior under different dynamic states.

Cutting force:

Performance analysis across varying cutting forces (600, 700, 800) revealed that the model maintained high accuracy and robustness, even under higher force conditions as seen in Fig. 4. This indicates that the model, bolstered by RCSA, can effectively adapt to and predict changes in machining stability that arise due to variations in applied force.

Cutting teeth:

The analysis by different numbers of cutting teeth (2, 3, 4, 6) showed that the new model effectively handles the complexities introduced by varying teeth configurations (Fig. 5). This is particularly important in scenarios where cutting dynamics significantly influence chatter and machine performance.

6 Discussion

This study successfully demonstrates the significant advantages of integrating operational modal analysis, transfer learning, and receptance coupling substructure analysis into predictive modeling for machining stability. By leveraging a comprehensive dataset of over 140,000 simulated instances, we developed a robust RF model that markedly outperforms

Modal 1	Accuracy	AUC
Original	80%	0.83
OMA/TL/RCSA	88%	0.91

Modal 2	Accuracy	AUC
Original	75%	0.78
OMA/TL/RCSA	86%	0.89

Modal 3	Accuracy	AUC
Original	79%	0.85
OMA/TL/RCSA	81%	0.87

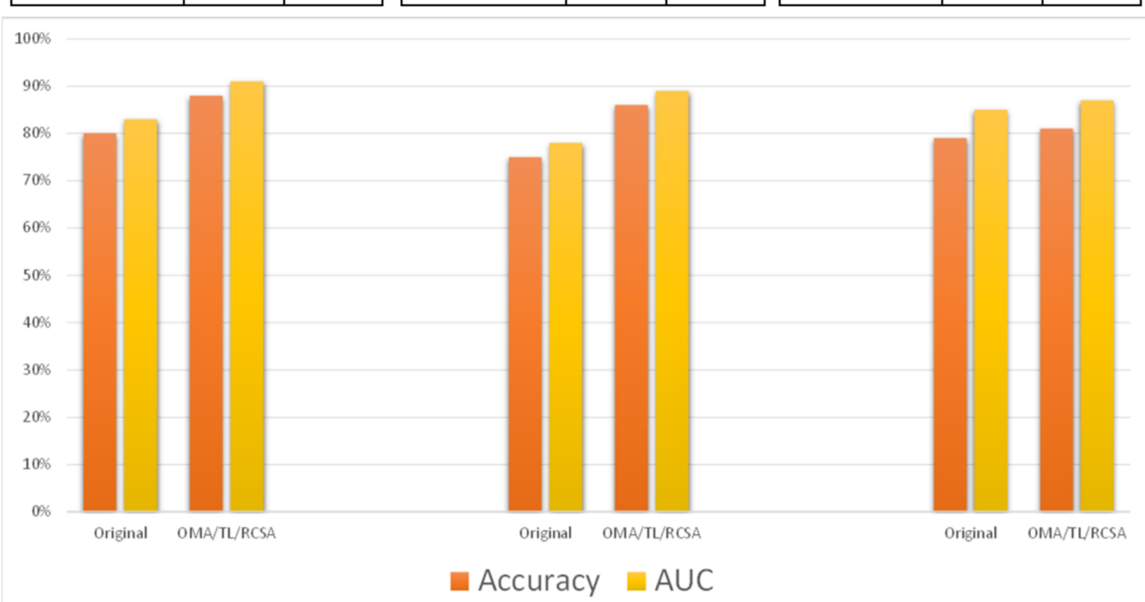

Fig. 3 Modal performance evaluation

Cutting Force 600 N	Accuracy	AUC
Original	77%	0.80
OMA/TL/RCSA	84%	0.84

Cutting Force 700 N	Accuracy	AUC
Original	78%	0.81
OMA/TL/RCSA	85%	0.91

Cutting Force 800 N	Accuracy	AUC
Original	79%	0.84
OMA/TL/RCSA	87%	0.93

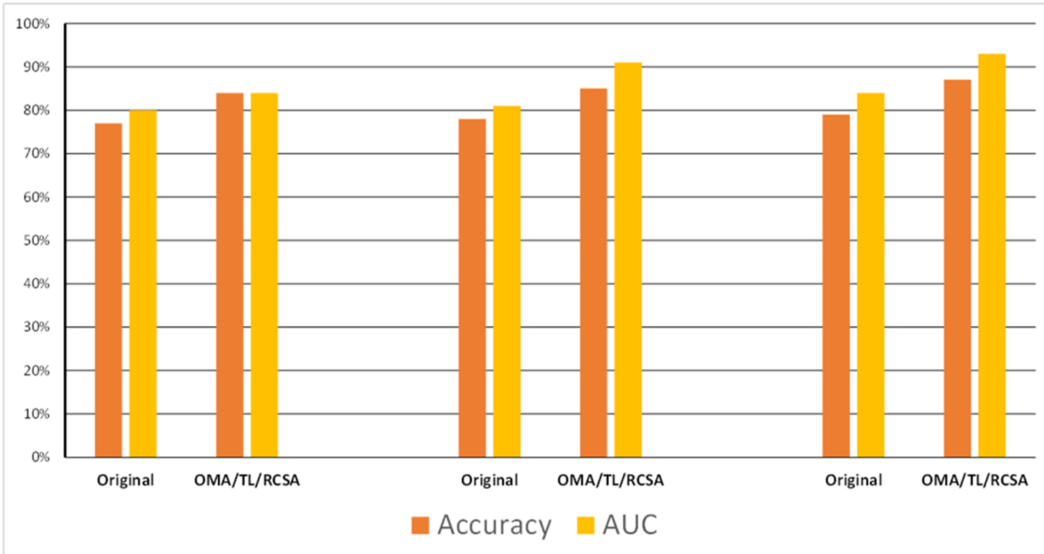

Fig. 4 Cutting force comparison

traditional approaches in predicting and mitigating chatter across diverse machining conditions.

The enhanced model not only achieves higher accuracy, AUC, and F1 scores but also shows exceptional adaptability to varying modal conditions, cutting forces, and numbers of cutting teeth. These improvements highlight the model's ability to capture complex vibrational dynamics that are crucial for ensuring machining stability and quality. The integration of OMA provided deeper insights into the system's operational modes, TL facilitated the model's adaptability to new and changing conditions, and RCSA enhanced the understanding of tool-holder dynamics, all contributing to a more comprehensive and reliable predictive framework.

The implications of these findings are far-reaching, particularly in high-precision industries such as aerospace and automotive manufacturing, where the prevention of chat-

Cutting Teeth 2	Accuracy	AUC
Original	80%	0.85
OMA/TL/RCSA	87%	0.92

Cutting Teeth 3	Accuracy	AUC
Original	76%	0.79
OMA/TL/RCSA	84%	0.88

Cutting Teeth 4	Accuracy	AUC
Original	78%	0.82
OMA/TL/RCSA	85%	0.90

Cutting Teeth 6	Accuracy	AUC
Original	81%	0.86
OMA/TL/RCSA	89%	0.94

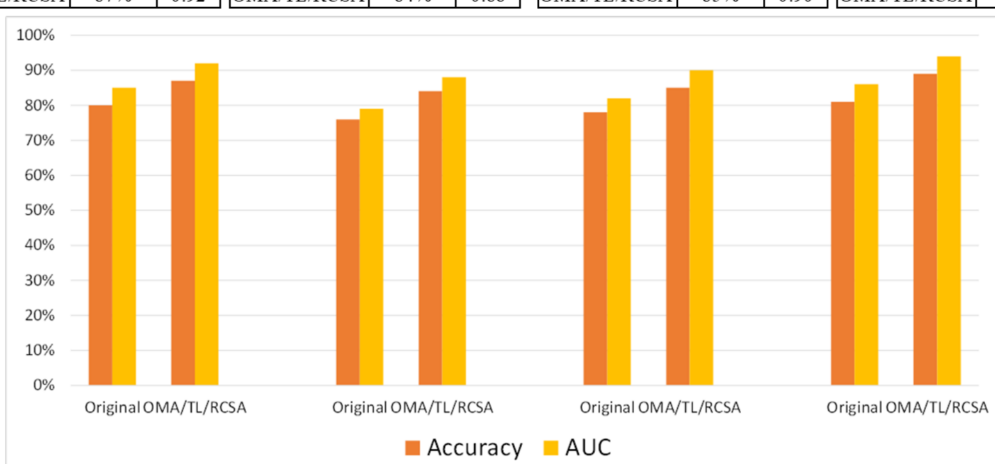

Fig. 5 Cutting teeth comparison

ter can significantly enhance operational efficiency, reduce downtime, and improve product quality. This research not only advances the field of predictive maintenance but also sets the stage for more intelligent and automated manufacturing processes.

However, the complexity and computational demands introduced by these advanced techniques suggest that further research is necessary to optimize and scale the model for real-time applications. Future work should focus on refining these methodologies to reduce computational overhead, enhance scalability, and simplify implementation, making the benefits of this approach accessible to a broader range of industrial applications.

In summary, this study provides a powerful new tool for predicting machining stability, offering significant improvements over existing models. The integration of OMA, TL, and RCSA into predictive analytics represents a substantial step forward in the field, with the potential to transform machining processes and contribute to smarter, more reliable manufacturing systems.

7 Conclusion

The comparative analysis of the original RF model and the enhanced model incorporating OMA, TL, and RCSA highlights the substantial improvements that can be achieved through advanced analytical techniques in machining stability prediction.

The enhanced model consistently outperformed the original RF model across all tested scenarios, including varying modal conditions, cutting forces, and numbers of cutting teeth. The significant increase in overall accuracy, AUC, and F1 score suggests that integrating OMA, TL, and RCSA effectively captures the complex dynamics of machining processes that traditional models might overlook. These improvements are particularly evident under challenging conditions, such as higher cutting forces and diverse operational modes, where the original model's performance typically declined.

OMA's ability to derive detailed modal parameters from the operational state of the system proved crucial in enhancing the model's sensitivity to different vibrational behaviors. This deeper understanding of the system's dynamics allowed for more accurate predictions of chatter, even under varying and unpredictable machining conditions. The application of TL significantly improved the model's adaptability, enabling it to maintain high predictive accuracy despite changes in machining conditions. By transferring knowledge from the extensive simulated datasets to new scenarios, TL ensured that the model remained robust across a wide range of operational parameters.

The incorporation of RCSA provided a more nuanced understanding of the tool-holder dynamics, which are critical in determining the system's overall stability. This method allowed the model to account for the physical interactions within the machining system more effectively, resulting in better predictive performance, especially in scenarios involving variations in the tool-holder assembly.

While the enhanced model shows clear advantages, it also introduces challenges that must be addressed for broader implementation like computational complexity, scalability, and a higher level of domain expertise. The integration of OMA, TL, and RCSA increases the computational demands of the model, which could limit its applicability in real-time monitoring systems where processing speed is crucial. As the model becomes more complex, ensuring its scalability for different industrial applications may require further optimization. Future work should explore methods to reduce computational overhead without sacrificing accuracy. Implementing and interpreting OMA and RCSA require a significant level of domain expertise. To facilitate wider adoption, it may be necessary to develop user-friendly tools or interfaces that abstract some of this complexity while still leveraging the advanced capabilities of these techniques.

The advancements presented in this research have significant implications for the machining industry, particularly in sectors that demand high precision, such as aerospace and automotive manufacturing. The ability to accurately predict and mitigate chatter could lead to substantial improvements in operational efficiency, reduced downtime, and enhanced product quality. Moreover, the model's success in handling diverse operational conditions suggests that it could be effectively adapted to various other machining processes, offering a generalized solution to vibration-related challenges in manufacturing.

Moving forward, research should focus on refining these techniques to enhance their practicality and ease of implementation. Exploring alternative machine learning algorithms that might integrate more seamlessly with OMA and RCSA could further improve the model's performance while reducing computational requirements. Additionally, implementing this model across real-world data would provide valuable insights into its operational effectiveness and help identify areas for further refinement.

In conclusion, the integration of OMA, TL, and RCSA into predictive modeling represents a significant leap forward in the field of machining stability. However, for these advanced techniques to be widely adopted in industrial settings, ongoing research will need to address the challenges of computational demand, scalability, and domain-specific complexity. This study lays the groundwork for future developments that could make these sophisticated models more accessible, practical, and impactful in real-world manufacturing environments.

Author Contributions Conceptualization, creation of data pipeline, and experimentation within data pipeline done by MA. Article writing is done by MA with key contributions for machining from JK, BJ, and TS. Data acquisition for simulated data performed by MA. Review of paper done by JC, BJ, JK, AK, TS, and SS.

Data Availability Machining files and derived data are publicly available.

Code availability Code written in this study is not publicly available.

Declarations

Conflict of interest The authors declare no competing interests.

Ethics approval The authors claim that there are no ethical issues involved in this research.

Consent to participate All the authors consent to participate in this research and contribute to the research.

Consent for publication All the authors consent to publish the research. There are no potential copyright/plagiarism issues involved in this research.

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Authors and Affiliations

Jamie Coble[4] · Matthew Alberts[1] · Sam St. John[1] · Simon Odie[1] · Anahita Khojandi[1] · Bradley Jared[3] · Tony Schmitz[2,3] · Jaydeep Karandikar[2]

✉ Jamie Coble
jamie@utk.edu

Matthew Alberts
malberts@vols.utk.edu

Sam St. John
sstjohn3@vols.utk.edu

Simon Odie
sodie@vols.utk.edu

Anahita Khojandi
khojandi@utk.edu

Bradley Jared
bhjared@utk.edu

Tony Schmitz
tony.schmitz@utk.edu

Jaydeep Karandikar
karandikarjm@ornl.gov

1 Department of Industrial and Systems Engineering, University of Tennessee, 851 Neyland Drive, Knoxville, TN 37996, USA

2 Manufacturing Science Division, Oak Ridge National Laboratory, 1 Bethel Valley Road, Oak Ridge, TN 37830, USA

3 Department of Mechanical, Aerospace, and Biomedical Engineering, University of Tennessee, 1512 Middle Drive, Knoxville, TN 37996, USA

4 Department of Nuclear Engineering, University of Tennessee, 863 Neyland Drive, Knoxville, TN 37996, USA