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Intelligent Diagnostics and Performance Optimization of Machine Tool Through Integrated Vibration and Modal Assessment for Industry 4.0

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Keywords：natural frequency, modal shape, vibration monitoring, impact hammer test, intelligent diagnosis system

ABSTRACT

Precision machining is often suffers by dynamic errors, vibrations, and thermal distortions that detrimentally affect accuracy and increase machining time. To address these issues, the present study proposes a systematic methodology integrating Finite Element Analysis (FEA), Experimental Modal Analysis (EMA), and a real-time Prediction Diagnosis Performance System (PDPS) to evaluate dynamic behavior and compensate for errors in CNC machine. Experimentally validated with impact hammer tests, achieving less than 1.5% error in the first three natural frequencies. Real-time vibration signals were acquired under different clamping conditions and analyzed using RMS (root mean square) and PCA (principal component analysis) techniques for identifying abnormal patterns. PDPS was established to be more than 90% accurate in detecting eccentric clamping and vibration anomalies, enabling proactive maintenance and reducing machine downtime. The study facilitates the development of intelligent machine tool systems and supports Industry 4.0 targets through the adoption of virtual modeling, real-time monitoring, and intelligent control.

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INTRODUCTION

Post-process testing is the foundation of traditional quality assurance, while modern techniques emphasize real-time monitoring via vibration analysis and monitoring. This improves productivity in a competitive industry by enabling intelligent pre-diagnosis, lowering manual labor, and guaranteeing product standards while cutting down on machining time and expenses. Considering the growing need for semiconductors, optics, and aviation, ultra-precision alongside micro-fabrication facilities has acquired important value (Corbett, McKeown et al. 2000). To enhance productivity and quality in machining operations, strategies have been devised and applied across different stages of design and manufacturing, including machine tool design, product design, process planning, and process control (Altintas 1992). Each machine tool technology includes the following elements: the drive servo (including spindle and feed drives), the machine tool structure, the workpiece, and the cutting process. This investigation asserts that grasping the interplay between these machine tool components and the cutting process is indispensable for advancing advancements in efficiency and quality in machining. Machine tool failures caused by misalignment during installation and expansion due to heat during operations are typically unforeseen at the machine phase of design. Notwithstanding ongoing attempts, there is still a lack of successful ways to predict such errors while resorting to experimentation. So the proposed machine simulator's practical use for accurate machining will be possible after all equipment errors have been controlled, ensuring they have no impact on part reliability. Notably, a complex matter of mathematical and thermal error compensating is not addressed here but has garnered plenty of interest from other investigators (Koren 1994, Gao, Ibaraki et al. 2023). Dynamical investigation comprises the evaluation of the force of cutting for determining the dynamic motion quality of the manufacturing equipment. At present, standard

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methods to interaction evaluation contain the single-frequency method(Wei et al. 2021),the multi-frequency technique(Stepan 2013), the time-domain form finite simulation method(Bayly, Halley et al. 2003), and the discrete method(Li, Zhang et al. 2013).Tool wear monitoring has garnered considerable interest among researchers in recent times (Franco-Gasca, Ghosh, Ravi et al. 2007). (Sun, Tsung et al. 2007) Effectively carried out fault detection on an enormous rotational machine utilizing algorithms for classification. (Scheffer and Heyns 2004) established a manufacturing condition surveillance system incorporating neural networks and noise from vibration in an interrupted cutting circumstance during the turning procedure of aluminum alloy objects. Several investigations (Yuan and Ni 1998, Ramesh, Mannan et al. 2000, Ramesh, Mannan et al. 2000, Newman, Allen et al. 2003) have investigated previous attempts focused on strengthening cutting quality via error mitigation in serial kinematic machines (SKMs). Motor fault-current relationships are investigated by (Marques, Martins et al. 2013) using PCA to extract features from abnormal signals. The research focuses on problems with the rotors and stator short circuits. Validation by experiment confirms the effectiveness of motor current sensing for recognizing faults. (Jiang, Han et al. 2020) introduce MCSA for gearbox fault identification, employing PCA and Ads for feature extraction and current signal processing, respectively. PCA-SVM provides outstanding precision in time-domain anomaly prediction, while PCA-AdaBoost/SVM excels in frequency-domain anomaly identification. (Chen, Ye et al. 2017) established a bearing fault prediction model utilizing EWT and the KPCA method. Screening with seven unusual circumstances gives a recognition rate of 98.8% for single abnormalities and 98.4% for composite abnormalities. (Shi, Guo et al. 2020) integrates recursive neural network (RNN) and principal component evaluation (PCA) for gear fault diagnosis, solving early low-fault signal identification problems. Investigations provide a detection method with less than 17% error rate, exhibiting high precision.(Wang and Yang 2020) utilizes a neural network and PCA for gearbox fault identification while solving difficulties with initial weak fault signal identification.. (Hamadache, Lee et al. 2015) suggest employing the rotation speed for Bearing Fault Diagnosis (BFD), outperforming conventional methods depending on noise and current signals. Improved analysis using PCA yields a 20% higher diagnostic success rate when compared to standard PCA and 30% over-speed changing speed situations. (Wang, Ritou et al. 2020) establishes a smart manufacturing technique incorporating unstructured machine learning techniques with the Gaussian mixture. Milling data collected from four simulations of machines are used to develop and implement the mathematical framework, showing little deviation between anticipated and real outcomes. (Zhang, Jiang et al. 2017) Integrates FCA and SVM with VMD and PCA to analyze asymmetrical failure data of rotating machinery. PCA collects features, while SVM train and evaluates the algorithm using the fault data as repetitions. (Goyal, Dhami et al. 2020) Evaluates bearing life by adopting bailout line spectrum parameters. PCA extracts features in order to decrease signal complexity. Both the ANN and SVM models exhibit accuracies of 98.3% and 97.2%, accordingly, for prediction. (Soualhi, Medjaher et al. 2014) integrates HHT, SVM, and SVR for bearing deterioration surveillance, diagnosis, and prediction, revealing strong diagnosis efficiency. (Dong, Sun et al. 2014) employ EMD to break down bearing vibration signals into IMFs. PCA extracts features and reduces dimensionality, followed by fault prediction using SVM training. Utilizes EEMD for processing cutting vibration signals and obtain IMFs. PCA compresses data, whereas ICA divides signals into independent groups. The method effectively extracts energy efficiency characteristics while cutting. The technique effectively recognizes and identifies faults in experimental gadgets. PCA and correlation vector machine (RVM) are combined by (Zhu, Chen et al. 2021) to assess reliability. In order to train RVM to predict the mixing index and probability density function (PDF) for equipment reliability calculations, PCA extracts important features. Experiments on aero-engine bearings verify the high accuracy of failure time prediction. This study aims to improve machining quality and effectiveness by focusing on accurate error prediction. It is related to important problems in precision machining and machine tool fault identification. While there have been improvements in error detection, problems like setup misalignment and thermal expansion during operation are yet to be addressed. FEA and EMA are employed in this study to investigate the dynamic response of a horizontal turning machine, with an emphasis on natural frequency and mode shape detection flow chat shows in Figure 1.

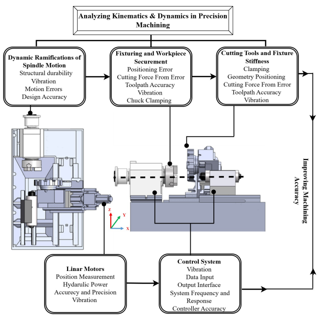


Fig 1. Analyzing kinematic and dynamic precision machine

Computational accuracy and reliability are obtained by adaptive mesh refinement and verification by impact hammer testing. Additionally, errors can be located and corrected immediately through a PDPS, making the machine tool operate more smoothly and precisely. These advancements result in reduced machining time and cost, and increased productivity to achieve the strict precision manufacturing standards. The proposed plan provides for real-time prediction and mitigation of vibrations-induced errors, resulting in improved surface finish and size accuracy of the machined components. The use of PDPS helps to predetermine when the machinery is to be maintained, saves downtime, and prolongs the life of machine tools. The suggested method provides a solid platform for optimizing machining operations, which is crucial in industries like aerospace, automotive, and precision engineering, where high efficiency and quality are of great concern, Figure 2 shows the working flow for experiment planning.

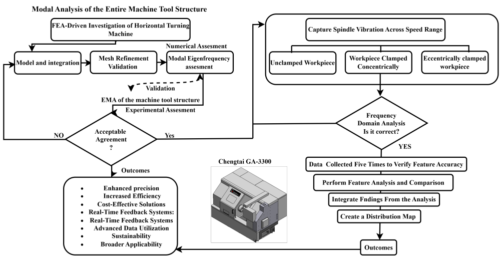


Fig 2. Flow chart of experiment planning

FEA-Driven Investigation of Horizontal Turning Machine

Initially, geometric models of the horizontal turning machine are generated using CAD software and then imported into an FEA algorithm. The material properties for the machine tool components are designated according to the standards outlined in [72]. Tetrahedral meshing is used for the primary machine tool structure, whilst hexahedral meshing is implemented for minor components, selected according to their shape and stress distribution properties, CAD model shown in Figure 3. A following FEA simulation is performed to ascertain the inherent Eigen frequencies of the system, altering machine tool settings, and generating a comprehensive dataset including various tool configurations.

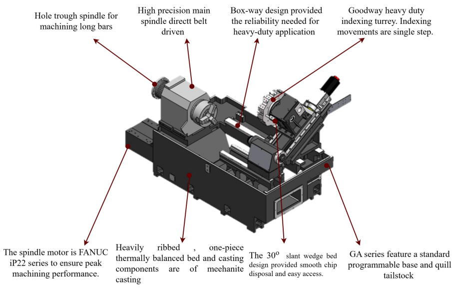


Fig 3. GoodwayGA-3300 machine model

Model and integration

Model development and evaluation are crucial in studies of horizontal turning machines. This investigation entails the development of a finite element model of the turning process with CAD software, then imported into FEA algorithm for advanced simulation where material attributes are allocated to the components. Grey cast iron is used for the majority of components because of its reduced density compared to structural steel and its cost-effectiveness. The assembly process entails placing the model into the X, Y, and Z coordinate planes for precise analysis. This material selection reflects that of the physical machine, whereby grey cast iron is used for substantial components to reduce structural weight. The tool turret and head chuck are designated with structural steel (SS) characteristics, as shown in Table 1.

Table 1. Material specification

Property	Structural Steel	Grey cast iron
Density (Kg/m^3)	7850	7200
Young's Modulus (Pa)	$2*10^{11}$	$1.1*10^{11}$
Poisson's Ratio	0.3	0.28

The experiment carried out on the Goodway GA-3300 machining center. The Goodway series CNC lathes provide exceptional cutting performance and machining precision. This lathe excel at compound processing for turning and milling operations because they combine high horsepower, a strong structure, and a large servo positioning turret the specification of prototype shown in Table 2.

Table 2. Specification of prototype model

<table>
<tr><td colspan="2">Gearbox Spindle</td><td colspan="3">Feed axis</td></tr>
<tr><td>Spindle Transmission Mode</td><td>Direct belt drive</td><td rowspan="2">Travel</td><td>X</td><td>200 mm</td></tr>
<tr><td>Transformer</td><td>3000 rpm</td><td>Y</td><td>150 mm</td></tr>
<tr><td>Spindle motor power</td><td>18.5kW</td><td colspan="2">Feed rate</td><td>4800 mm/min</td></tr>
<tr><td>Maximum workpiece diameter that can be clamped</td><td>Φ105 mm</td><td rowspan="2">Stroke speed</td><td>X</td><td>20 m/min</td></tr>
<tr><td colspan="2">Shaft (universal)</td><td>Y</td><td>24 m/min</td></tr>
<tr><td rowspan="2">Shaft motor</td><td rowspan="2">AC Servo motor1.0Kw</td><td colspan="2">Positioning accuracy</td><td>0.015 mm</td></tr>
<tr><td colspan="2">Reproducibility</td><td>± 0.003 mm</td></tr>
<tr><td colspan="5">Machine size</td></tr>
<tr><td colspan="2">Machine body size (with chip remover) Width x Depth x Height</td><td colspan="3">4,160 x 1,980 x 1,910(mm)</td></tr>
</table>

Mesh Refinement Validation

Adaptive methods are the key to putting FEA into engineering practice to make cost-effective, timely, and quality-based decisions. Structural analysis entails physical and simulation modeling simplifications, which introduce two predominant types of errors: discretization and physical modeling errors.

Discretization errors can be controlled systematically, whereas physical modeling errors are based on judgment by experienced people. Effective FEA involves a trade-off between accuracy and computational requirements in terms of processing time, hardware, software, and analyst skill

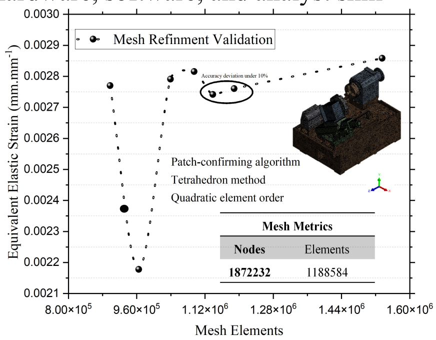


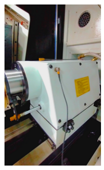
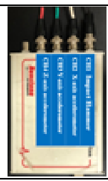
Fig 4. Mesh refinement validation

Figure 4 confirms mesh refinement, with increased errors in adaptive grids compared to uniform ones. First-order accuracy was verified at coarse–fine interfaces.Grid-independence tests using eight meshes demonstrated that finer grids enhanced deformation and stress accuracy.

Natural frequency and mode shaper analysis of the machine tool structure

This section defines the analytical and EMA conducted to ascertain the modal characteristics of the machine tool. The validation of the suggested approach is presented, along with an analysis of the impact of the whole machine structure on its dynamic behavior. All trials were performed on a single machine tool. The modal study concentrated on assessing natural frequencies and mode shapes, finding resonance occurrences, and offering insights for design alterations to enhance structural stability and operational performance. A initial modal analysis is performed on the static machine to ascertain its free vibration modes, which are influenced by mass, stiffness, and component distribution, while disregarding damping and external loads. The motion equation is simplified, and the study encompasses a frequency range of 0 to 500 Hz, assessing the first five natural frequencies. Experimental validation is conducted by an impact hammer test, an economical technique for determining natural frequencies. A rubber-tipped hammer activates the machine, and vibration responses are captured using a three-axis accelerometer. Data is gathered using a SCADAS unit linked to NOVIAN software, which delivers frequency response functions (FRF) to record the machine's dynamic reaction, experimental equipment. The recorded FRF is analyzed using ME ‘scope software to compare modal frequencies and mode shapes with those produced by FEA code. A total of 96 data points were measured, and the findings were examined using curve fitting and modal shape assessment to verify the correctness of the modal parameters. Table 3 shown the experiment setup.

Table 3. Model experiment analysis setup with specification

Equipment	Impact hammer	Accelerometer	SCADAS devices	Data Acquisition Device
Physical				
Technical	Tip Configuration: Grey-9912 Extender: None	Axis Sensitivity X-axis: 103.9 mV/g Y-axis:104. Z-axis:104.	Four input channels and one output channel.	Software compatibility ME SCOPE
Function	Imparts a controlled impulse force to the structure for excitation.	Determines the vibration at many locations on the structure electrical signal that is proportionate to the acceleration	The SCADAS unit conditions input signals and acquires real-time data.	ME scope software visualizes mode forms, extracts modal parameters, and validates data via curve fitting.

RESULTS AND DISCUSSION

Modal investigation of the GA-3300 CNC turning machine is conducted using FEA code to ascertain its inherent frequencies and mode shapes. The first five modes are examined shown in Figure 5 (a), emphasizing the impact of vibration on critical machine components such the axle, tailstock, and headstock. These modes are recognized as possible contributors to machining errors resulting from resonance. Experimental validation is performed with an impact hammer test, with response data gathered from 96 locations on the machine. The recorded FRF signals were analyzed using ME scope software for modal form assessment, mode shape shown in Figure 5 (b) (Chan, Reddy et al. 2023). A strong correlation was seen between the analytical and experimental findings, with errors of 0.7%, 1.2%, and 0.2% for the first three modes.

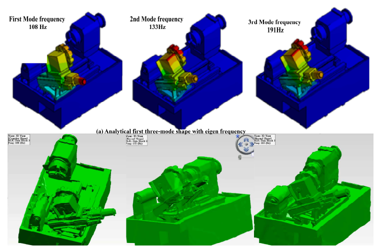


Fig 5. Eigen frequency (a) Analytical mode shape (b) Experimental mode shape (Chan, Reddy et al. 2023)

The findings validate the precision of the CAD model in replicating the machine's dynamic behavior, with errors remaining comfortably within the acceptable 10% level shows in Figure 6.

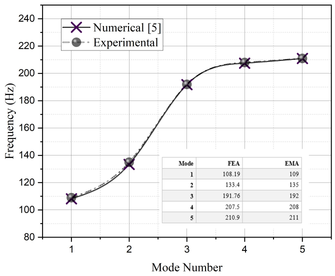


Fig 6. Experimental validation

To assess the impact of modal shapes on machine tool dynamics, analytical mode forms are juxtaposed with those derived via EMA using the Modal Assurance Criterion (MAC). The MAC measures the squared correlation between two modal vectors, with values ranging from 0 to 1. Auto-MAC assesses the consistency of extracted mode forms, where off-diagonal terms approaching zero indicate correctness, while Cross-MAC compares modes obtained from various procedures or situations shown in Figure 7. The results from EMA and Operational Modal Analysis (OMA) tests confirm the dependability of the indicated mode shapes, however significant variations in higher modes are seen owing to differing worktable circumstances.

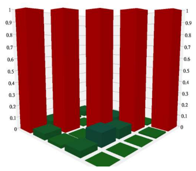


Fig 7. MAC values of different mode shape

Modal vibration study reveals movement in lower modes, in contrast to pronounced vibrations in higher modes, underscoring the influence of the operational condition on modal behavior. The validated model is applicable for further optimization and analysis of machine performance. Investigation presents a comprehensive method for improving the performance and stability of high-precision CNC machine tools using sophisticated analytical and experimental methodologies. The study employs FEA methods, integrating static rigidity analysis, modal testing, and multi scale lattice optimization to tackle ground-borne vibration and noise issues.

Frequency Domain Analysis and RMS Data Analysis

This study provides a practical framework for detecting and managing dynamic imbalances that cause machining errors by implementing the eccentric locking mechanism and evaluating vibration signals under various clamping situations. Implement the eccentric locking mechanism, commence by drilling drilling three threaded holes with M10x12mm dimensions within the central 1/4 circle region of the end face of the initially clamped component shown in Figure 8.

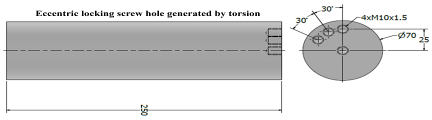


Fig 8. Clamped component

Subsequently, affix screws and washers securely within these apertures to intentionally introduce eccentricity. This deliberate manipulation induces dynamic imbalance and vibration upon clamping, thereby altering the signal characteristics. Detailed specifications regarding the size and placement of the locking positions can be referenced in Figure 8.The experimental protocol entails signal acquisition at intervals of 250 rpm for subsequent analysis, under three distinct clamping states: (a) Unclamped workpiece, (b) Clamped workpiece without eccentricity, and (c) Clamped workpiece with eccentricity, as delineated Subsequently, install the eccentric fixture onto the lathe spindle. Noteworthy is the stipulation that in this investigation, the spindle cannot be clamped without an object present, as depicted in Figure 9(a). Furthermore, when a circular round bar is situated, the workpiece fails to achieve eccentricity, as demonstrated in Figure 9(b). Finally, to achieve the clamped and eccentric state, three (10x12) mm screws and gaskets are fitted, as depicted in Figure 9(c).

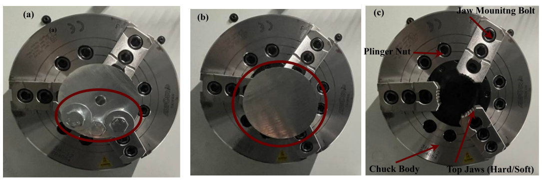


Fig 9. Clamping vibration test conditions for the spindle (a) Clamped work piece without eccentricity (b) Clamped work piece with eccentricity(c) Unclamped Workpiece on Spindle

Table 4. Experimental parameters

State	Speed (rpm)							
Idling	250	500	750	1000	1250	1500	1750	2000
Regular	250	500	750	1000	1250	1500	1750	2000
Eccentric	250	500	750	1000	1250	1500	1750	2000

Experimental procedure followed in this research facilitated efficient detection and visualization of the dynamic behavior of the machine tool using both time and frequency domain analyses. Frequency-domain analysis, which is based on system transfer functions, provides a graphical means of describing linear system dynamics and supplements the shortcomings of time-domain techniques. According to Chen et al. (2020), the acceleration signals are measured for gear chatter identification, associating vibration levels with gear quality and machining accuracy. In this research, vibration data were transformed into spectral form by using FFT, and consistent frequency responses were observed. For a spindle speed of 1000 rpm, the prevailing frequency noticed is 16.67 Hz, as shown in Figure 10(a, b).

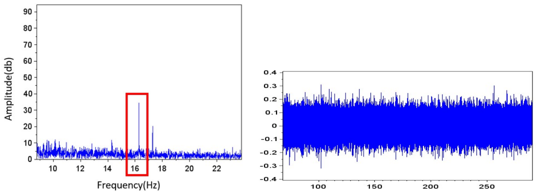


Fig 10. Frequency domain analysis (a)Frequency domain (b) Time domain

It is difficult to differentiate peak values in the time domain; therefore, RMS is utilized to derive maximum, effective, and average vibration values for the sake of easier comparison using line plots. Eccentricity in clamped workpieces can be a function of changing spindle speed as opposed to being inherent. The frequency-domain signal is transformed into RMS to observe, compare, and analyze the differences shows in Figure 11.

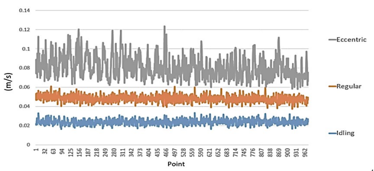


Fig 11. Spindle speed 1000 rpm RMS analysis

The combination of frequency domain and RMS analysis allows for accurate vibration monitoring under varied clamping conditions, which aids in the optimization of operational parameters to enhance machining quality and reduce energy consumption. These insights help with predictive maintenance, reducing downtime and prolonging machine tool life, as well as driving the design of innovative clamping fixtures for increased stability.

Precision Boost: Error Compensation Machine Tool (ECTM)

CNC machining systems are favored for their flexibility, efficiency, and precision. Five-axis machines offer superior control of tool workpiece positioning, enhancing accuracy and reducing interference. However, increased axis complexity directly affects control precision and product quality, making error detection and compensation essential. Error recognition requires precise design and manufacturing but involves high costs. In contrast, error compensation offers a cost-effective alternative to improve accuracy post-production. By analyzing signal distribution maps, spindle health can be monitored and maintenance optimized to meet stringent performance standards. Figure 12 shown the three phase of error compensation machine tool.

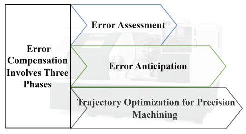


Fig 12 Error compensation phase machine tool

Turning machine error compensation includes offline and online techniques; the first one modifies future operations according to measured errors, whereas the second one compensates for errors in real time without repeatability assumptions. Online compensation is a cost-effective and flexible approach, which has been extensively researched to improve machining accuracy.

Error Assessment

Machine tool errors from assembly misalignment and thermal expansion pose significant challenges in the design phase. Without experimental validation, predictive models remain limited, making error compensation essential for achieving cutting accuracy. Geometric and thermal error mitigation thus remains a critical focus in machining research (Shiraishi, Kume et al. 1988, Kiridena and Ferreira 1991). At the start of machining a new part, a preliminary cleaning cut is usually used to correct any form errors in the mounted workpiece. Forced machine vibrations, caused by periodic forces from unbalanced machine components or a noisy cutting environment, are unpredictable during the early stages of machine or part design (Chen, Ulsoy et al. 1998). However, these effects can be mitigated by using balanced dynamic components and vibration isolation techniques. Precision in measurement and prediction is critical, as it directly influences system accuracy. The method entails identifying and characterizing machining errors, selecting measurement methods and devices, performing error measurements, and predicting errors directly or using an error model.

Error assessment machine tools utilizing prediction diagnosis performance system (PDPS)

Online error prediction involves measuring errors without interrupting the machining process, resulting in continuous measurement data. As (Zhan-Qiang, Venuvinod et al. 1998) point out, this approach provides practical solutions for real-time measurement and quality control. However, the lack of dedicated probes prevents widespread use in machining operations. (Chan, Jian et al. 2021) Emphasize on intelligent diagnosis of small machine tools in tech-driven sectors. Real-time monitoring of temperature, spindle current, and vibration allows proactive maintenance. A miniature health monitoring app facilitates in online machine health tracking and trend analysis to facilitate subsequent maintenance. In this experiment, data was collected using a Chengtai GA-3300. PDPS accelerometer, a current sensor, and a spindle eccentric fixture specification are shown in Table 5.

Table 5. Acceleration gauge specifications

Dynamic Range	±40g
Sensitivity	**250 mV/g**

Each clamping state will be systematically examined across eight different speeds and experimental parameters explained in Table 4.
The accelerometer is unable to weigh more than 10% of the measured object. Workpiece material, frequency range, dynamic range, environmental conditions, and three-axis measurements are accelerometer selection criteria. Bolt fixation is best for accelerometers in permanent installations because it requires drilling holes in the workpiece. Fixation and magnetic adsorption have different properties, as shown in Table 6.

Table 6. Characteristic Comparison of 3 Accelerator

Install Way	Operating temperature	Repeatability	Installation time	Bandwidth range	maximum amplitude
Bolt	1000	Excellent	long	Width (1.0) Reference	extremely high
Adhesive	80	excellent	Short	Width (0.9)	high
Beeswax	40	good	short	Width (0.9)	Low ($100ms^2$)
Magnet	150	good	Extremely short	second width (0.8)	middle ($2000ms^2$)
Double sided tape	95	good	short	second width (0.8)	middle
Probe type		Inferior	Extremely short	Extremely narrow (0.07)	

Thermocouples are used as temperature sensors in this experiment because they can measure temperatures over a wide range with little voltage fluctuations caused by changes in temperature. In Table 7, shown thermocouple's essential specs.

Table 7. Temperature sensor specification table

Dynamic Range	0 − 300℃
Sensitivity	33.3 mV/℃

Various workpieces were mounted on the spindle of the Chengtai GA-3300 lathe, and data was collected both when they were clamped and unclamped mounted workpiece design shows in Figure 13. The experiment included scenarios where the workpiece was held without eccentricity and clamped with eccentricity, with various vibration signal data collected for subsequent processing and analysis.

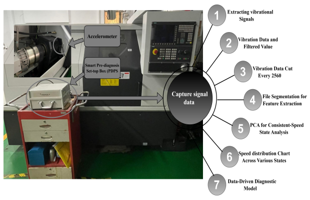


Fig 13. Data collection and analysis, vibration signal
Figure 13 shown the flow chart of data collection and analysis vibration signal processing. Vibration signals were collected with signal acquisition software in five clamping conditions at every spindle speed to evaluate tool condition. Contemporary manufacturing depends on computerized monitoring systems for fault diagnosis and tool presence confirmation. This research utilizes PCA and a real-time PDPS to categorize tool states founded on vibration and acoustic signals with 100% surface roughness classification accuracy. Experimental findings demonstrate that PDPS surpasses conventional methodologies in tool tracking and health monitoring, with distribution maps illustrating clear signal separation under clamping conditions at constant speeds. So, to establish a standard health model to judge whether the vibration is close to a general state or approaching an abnormal state shows in Figure 14.

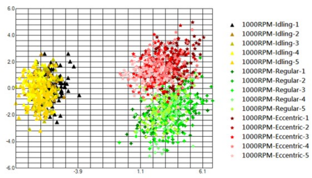


Fig 14. Distribution diagram of each clamping state of the spindle speed 1000 rpm

Establishment of Health Diagnosis Model and Simulation Diagnosis

Case I

From the PCA and comparison results of the same rotating speed and different clamping States, it is clear that a 1000-rpm distribution map has good judgment ability for the health diagnosis method. In addition, the PCA results combined with the Gaussian mixture model (GMM) module through the modeling program, the intelligent prediction, and a diagnosis system are used to establish the diagnosis model and warning line, applied to the real-time monitoring software for health diagnosis. The monitoring results show that the machine is in an unclamped condition, meaning no workpiece is mounted on the spindle. This baseline condition represents the machine's natural vibration response without any external mass or imbalance, and the monitoring value remains below the warning line, indicating that the system is "normal," shown in Figure 15 (a). When the monitoring results are compared with the model data by PCA, the results are slightly offset from the model data, and the distribution status similarities are as high as 90% in the distribution map shown in Figure 15 (b). Case II

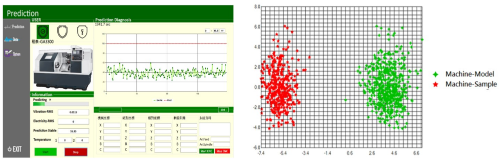


Fig 15. Interface of health diagnosis results (Idling)
(a) Interface of health diagnosis(b) Diagnosis Results

Case II

Real-time monitoring of clamping a non-eccentricity condition and clamping an eccentricity condition shall be combined and compared. Non-eccentricity is set to normal, and eccentricity to abnormal. The results of the eccentricity condition indicate a large or abnormal spindle vibration above the warning line shown in Figure 16(a). PCA can identify a severe abnormality of the data distribution when shown in Figure 16 (b), the eccentricity data is compared to the non-eccentricity data. Abnormal conditions are identified in advance through health diagnosis, parameter adjustment, or maintenance to avoid unnecessary cost waste caused by workpiece scrapping due to continuous processing.

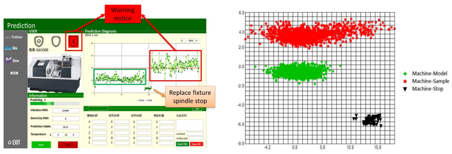


Fig 16. PCA distribution (a) Interface of health diagnosis b) Diagnosis results

Advancing from present obstacles to future prospects

This section ends by discussing how the difficulties identified in the review might direct future studies of machine tools. The two primary directions of future trends are incremental innovation, which focuses on incremental enhancements and long-term viability and disruptive innovation, which involves high-risk research for possible innovations in technology. Figure 17 shown three main areas of investigation here discussed: modelling strategies before done by Chan et al. (Chan, Reddy et al. 2023) with utilized of FEM for same machine model; hardware, from technique design to the practical execution of new detecting, activation, and interaction technological advances.

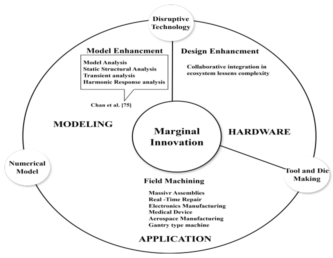


Fig 17. Advancing from present obstacles to future prospects

Modeling

(Chan, Reddy et al. 2023) Utilized the same model Chengtai GA-3300 for FEM to improve CNC machine tools' accuracy and productivity by analysing machining operations and machine structures. Under real-world conditions, stress and deformation analysis can extend machine life and improve performance. This study focuses on applying FEM to analyse and optimize CNC machine tool operations and structures. Using a virtual model of a CNC turning machine, vibrations were analyzed, and experimental validation confirmed frequencies Spatial position analysis and rigidity tests were performed, leading to topology optimization for improved design. Comparison between old and new models showed a 1.5% increase in the first three modal frequencies. Collaborative investigation into simulation is facing difficulties due to a rise of interest in model-free techniques. These approaches utilize artificial intelligence to learn machine tool behavior by analyzing datasets and predict its behavior appropriately. Numerous researchers (Chan, Ullah et al. 2023, Chan, Li et al. 2024) have offered an evaluation of the operational abilities of a high-precision machine tool through analysis of its virtual counterpart built with CAD. Utilizing the FEA software, comprehensive static and modal analyses were carried out in order to determine the tool's static bending and stiffness.

Hardware

In the context of Industry 4.0, intelligent manufacturing can be greatly improved by integrating machine learning algorithms into CNC control systems. Real-time tool wear estimation based on sensor feedback and data-driven models allows for predictive maintenance, minimizing unplanned downtime and improving process reliability. Proactive detection of wear not only protects surface quality and dimensional accuracy but also increases tool life and reduces operational costs. Rather than viewing CNC machines as end-use devices, next-generation systems must be designed as high-performance, open platforms with capabilities for adaptive diagnostics and automatic compensation in the face of changing operating conditions.

Application

Integrating IoT with advanced CNC machines enables real-time monitoring and control. Empirical studies show that maximizing stiffness, dynamic response, acceleration, and energy efficiency is key to optimal lathe performance, especially in precision-driven sectors like aerospace and medical manufacturing. Future applications are expected in high-value processing, surgery, and extreme environments, with the medical field showing strong potential for parallel machine tool adoption in the coming decade (Kobler, Nuelle et al. 2016).

CONCLUSION

This study confirmed the movement of a horizontal CNC lathe using FEA and EMA together to achieve accuracy and precision. The suggested Prediction Diagnosis Performance System (PDPS) provides the capability of real-time vibration detection and compensation, which improves accuracy and stability in machining. An eccentric locking device was used to create imbalance conditions, which helped analyses spindle vibration with different clamping conditions. Principal Component Analysis (PCA) on frequency-domain and RMS-converted signals successfully discriminated clamping conditions with more than 80% accuracy, constituting the foundation of a robust health monitoring model. This system is in favor of predictive maintenance as it allows early identification of spindle anomalies, minimizes downtime, and enhances process efficiency. The proposed approaches align with the objectives of Industry 4.0, offering an effective solution for intelligent and flexible machining. We will incorporate AI algorithms in the future to enhance predictive diagnostics and render it beneficial for other forms of high-precision manufacturing.

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