Cyber-Physical Systems for Predictive Maintenance Monitoring of Legacy CNC Machine Tools Toward Industry 4.0 Environment

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CNC machine tools are essential equipment in modern industry, and maintaining their operational condition is critical to ensuring production efficiency and product quality. Traditionally, maintenance strategies have relied on corrective and preventive actions. However, predictive maintenance is gaining importance with the advent of new technologies and the Industry 4.0 paradigm. Despite its advantages, the high costs associated with predictive maintenance still limit its widespread adoption. This study proposes a Cyber-Physical System (CPS) model for monitoring CNC machine tools. To this end, critical subsystems and related variables were identified, appropriate sensors were selected, and a hardware monitoring system was designed. Implementing the CPS will enable early fault detection, reducing downtime and maintenance costs.
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Computer Numerical Control (CNC) machines are among the most critical equipment in the manufacturing industry. Their reliability, productivity, and robustness make them integral to industrial operations. A primary goal in modern manufacturing is to enhance productivity and quality by applying strategic maintenance practices—particularly for CNC machines—to improve production rates and product quality [1,2].

CNC machines are complex systems composed of electromechanical and hydraulic components, including mechanically movable parts and precision control systems. Issues such as wear, malfunction, and component failure may occur during manufacturing processes [3,4]. The absence of effective maintenance methodologies often exacerbates these issues. In many industrial settings, the prevailing maintenance approaches are either corrective or preventive, which can lead to unexpected downtimes, loss of productivity, and waste of resources [2,5].

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While appropriate maintenance strategies significantly enhance equipment reliability—and consequently, the entire manufacturing process—predictive maintenance remains challenging to implement, primarily due to its high cost and complexity [2].

The rise of Industry 4.0 and enabling technologies such as sensors, simulation, big data analytics, and artificial intelligence (AI) have begun to transform industrial practices [4,6,7]. Among the most promising applications of these technologies is the deployment of predictive maintenance strategies for CNC machines [2]. Predictive maintenance allows for continuous monitoring of machine components, enabling early fault detection and intervention before failures disrupt operations. This approach is superior to corrective and preventive maintenance as it minimizes idle time and reduces unnecessary interventions and associated costs [8].Despite these advantages, the high investment costs associated with predictive maintenance—such as those required for sensors and data analysis algorithms—have hindered its broader adoption in the manufacturing industry [8]. To make implementation more feasible, it is crucial to identify the most critical machine subsystems and their respective failure modes, focusing monitoring efforts where they are most impactful [2].

However, identifying and defining the variables to be monitored presents challenges, as it requires sensor integration and network connectivity—features not commonly present in legacy CNC machines [9]. These limitations hinder the application of predictive maintenance and make real-time monitoring difficult.

This study aims to identify and define the key variables for implementing predictive maintenance in CNC machines and propose a prototype Cyber-Physical System (CPS) for real-time data acquisition and monitoring.

This article is organized as follows: The current section introduces the context, problem statement, research objectives, and the relevance of the study. Section 2 details the structure of CNC machines, highlights critical components, and describes standard failure modes. Section 3 outlines the hardware development process, including the components used. Section 4 discusses the expected outcomes of the proposed monitoring system. Finally, Section 5 presents concluding remarks and outlines future steps.

CNC Machine Tools

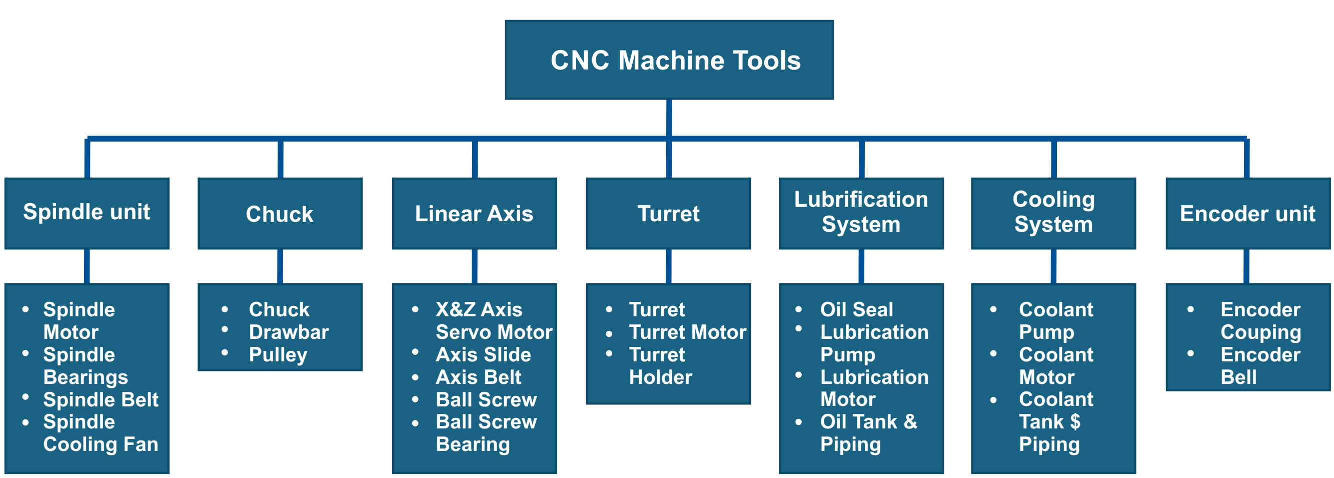
CNC machines are integrated electromechanical and hydraulic systems comprising various interdependent components [4]. While electronic and electrical subsystems may experience sensor failures, relay malfunctions, or blown fuses [2,10–13], these failures are generally less critical than mechanical subsystem failures. In most cases, electronic faults do not directly compromise product quality [8]. Therefore, the maintenance strategy for CNC machines can be optimized by focusing primarily on their mechanical subsystems, which are illustrated and analyzed in Figure 1.

Critical Components

Identifying critical subsystems and their associated failure modes is essential for selecting appropriate sensors for condition monitoring and implementing predictive maintenance strategies. According to Thoppil and colleagues [2], the existing literature provides only a superficial treatment of methods for analyzing the criticality of components in CNC lathes, particularly in prioritizing components for predictive maintenance. A literature review reveals that the monitoring of CNC machine subsystems and components can generally be classified into two categories: the machine tool and the machining process [14].

Within the machine tool category, the primary critical components that require monitoring include the spindle bearings, X- and Z-axis servo motors, ball screw bearings, the turret, the spindle, and the coolant system [2,15]. In the machining process category, monitoring typically focuses on the

Figure 1. CNC machine components.



Source: Thoppil and colleagues (2020) [2].

cutting tool, the machining table, and spindle wear [4,9,14–16].

Table 1 presents the components monitored in each group, their associated failure modes, and the measurable variables that can be used to detect and diagnose failures.

Based on the definition of the components to be monitored and the quantities to be measured, the sensors to be used for monitoring and their placement on the machine can be determined.

Materials and Methods

The methodology is based on identifying the most critical subsystems that can be applied with predictive maintenance to evaluate better solutions and propose a prototype of a CPS integrated with a CNC architecture for real-time data acquisition of the machine and its environment on the shop floor. The architecture model integration is viewed in Figure 2.

Initially, sensors will be installed in locations that do not interfere with the machine's operational workflow. The next step involves collecting data from these sensors and transmitting it to a Programmable Logic Controller (PLC) responsible for initial data processing. In the case of vibration data, a Fourier Transform will be applied to obtain the frequency spectrum and identify characteristic frequency peaks corresponding to specific failure modes. For deformation monitoring, the maximum deformation will be calculated using formulas derived from Mohr's Circle for strain analysis. Once the data is processed, the variables will be transmitted from the PLC to a computer database via industrial wireless communication or Ethernet cable. These values will then be compared with the components' reference values. This analysis process is critical for detecting anomalies and generating actionable insights for predictive maintenance. For example, the system may trigger an alert to notify the operator of abnormal operating conditions, thereby improving process safety and extending the machine's service life.

Hardware Components

Appropriate sensors were selected after identifying the critical subsystems and measurable variables, and a hardware configuration for data acquisition and processing was proposed. Table 2 lists the components suggested for building the system.

Hardware Components

PLC Controller

The XP 340 is a cost-effective programmable logic controller (PLC) featuring a compact design

Table 1. Critical components.

Group	Component	Failure mode	Variable
Machine tool	Spindle bearing	Bearing deformation	Deformation
	X and Z axis servo motor	Bearing wear	Vibration
	Ball screw bearing	Unsmooth operation	Vibration
	Turret	Indexing error	Vibration
	Chuck	Worn out	Vibration
	Cutting fluid	Leakage	Fluid level
Process	Tool	Tool wear	Vibration
	Spindle	Spindle wear	Vibration

Figure 2. Architecture for integration.

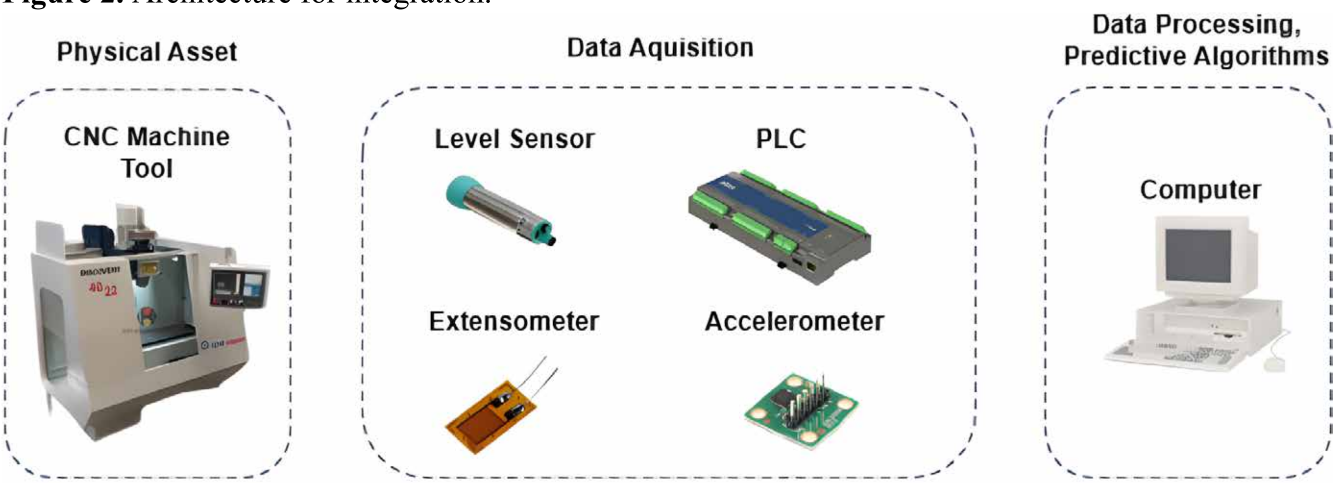


Table 2. Hardware components.

Component	Quantity	Description
Programmable logic controller	1	CLP Altus XP 340
Extensometer	1	CEA-06-250UW-350
Accelerometer	6	Analog Devices ADXL335
Level sensor	1	Pepperl+Fuchs UC4000-30GM-IUR2-V15
Ethernet cable	1	UTP or ScTP, category 5
Connector RJ-45	1	Armored female

and a 32-bit ARM processor. It includes 16 digital inputs, 16 transistor digital outputs, 5 analog voltage/current inputs, 2 three-wire analog inputs, 4 analog outputs, one Ethernet port, and one RS-485 serial port. The device supports a Webserver tool for creating supervisory screens without needing a SCADA system. Additionally, it is compatible with major industrial communication protocols, including MQTT, OPC UA, MODBUS, and PROFINET.

Strain Gauge Sensor

The CEA-06-250UW-350 strain gauge sensor measures mechanical deformation. It operates by varying its electrical resistance when subjected to force. This sensor features compact dimensions, a resistance of 350 ohms, and a tolerance of ±0.3%.

Accelerometer Sensor

Accelerometers are widely employed to measure acceleration or vibration. These devices typically rely on a mass-spring system, where the deformation of a piezoelectric material produces an electric signal proportional to the force applied. The selected Analog Devices ADXL335 operates with a supply voltage of 1.8 to 3.6 V and enables tri-axial (x, y, z) measurement.

Level Sensor

The Pepperl+Fuchs UC4000-30GM-IUR2-V15 ultrasonic level sensor determines fluid levels by calculating the time delay between emitted and received pulses. It offers a measurement range from

350 to 4000 mm, a resolution of 0.5 mm, and an accuracy of ±0.2% of full scale.

Results and Discussion

The proposed cyber-physical system was developed based on the principles outlined in Sections 1 and 2, which enabled the identification of critical subsystems and measurable variables relevant to CNC machine tool performance.

The appropriate sensors were selected based on this foundation, and a hardware prototype for data acquisition and processing was developed. Once implemented, the CPS will enable real-time monitoring of the CNC machine. The collected data will be instrumental in identifying existing faults or potential future failures through predictive algorithms. Monitoring subsystems related to the machine, such as the spindle, motor, and structural components, and tool condition monitoring will ensure greater machine availability and efficiency. Ultimately, this contributes to increased productivity, improved maintenance planning, and higher product quality.

Conclusion

Identifying critical CNC machine subsystems and their failure modes enables the selection of targeted sensors for real-time monitoring. This information significantly contributes to the effective implementation of predictive maintenance, helping to reduce related costs and operational disruptions. The data collected by these sensors can be processed to predict future failures, thereby reducing downtime, minimizing losses, and ensuring consistent product quality.

The proposed hardware will be validated by being deployed on a CNC machine at SENAI CIMATEC's Advanced Manufacturing Plant (PMA). Suitable communication protocols will be defined to integrate the machine, hardware, and management system. Subsequently, sensor-collected data will be processed by the PLC and transmitted to a centralized computer for health condition analysis of the machine components.

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