Data Acquisition and Communication in CNC Machine Tools for PdM

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Abstract: In addition to the traditional requirements of quality and productivity, new production paradigms also demand fault prognosis and diagnosis capabilities that classical maintenance methods do not provide. In this scenario, the application of predictive maintenance emerges as a viable alternative. Predictive maintenance is a technique that uses monitoring systems to analyze the condition of assets, based on data collected from sensors, to prevent or avoid failures. By estimating the future condition of machine components, maintenance costs can be reduced, operating time can be increased, and maintenance tasks can be optimized.
Despite these advantages, the technique is not yet widely adopted within the manufacturing sector because it requires sensing and data processing resources that make its implementation costly. To facilitate the implementation of this technique in the manufacturing sector, a low-cost hardware for data acquisition was proposed. Based on the system's components, an architecture for communicating the collected data and an application model were proposed, which allow for the visualization of this data and serve as a basis for implementing predictive algorithms for fault detection and anomaly prediction.
After implementation on a demonstration machine, the system is expected to be capable of collecting machine data in real-time, enabling the identification of faults and anomalies, thereby reducing downtime and costs. This adds benefits to various organizational levels, such as at the operational level, through the reduction of unplanned stops and increased safety. In the maintenance and process sector, it facilitates a transition from preventive to proactive methods. In terms of strategic results, it leads to the reduction of operational costs and an increase in the reliability and predictability of production.
Keywords: CNC machine tools. Predictive maintenance. MQTT. Monitoring systems.

1. Introduction

The manufacturing industry represents a highly relevant sector for the economic development of many countries (Haraguchi, Cheng, and Smeets, 2017 [1]), becoming a target of research, development, and innovation (RDI) actions aimed at strengthening the competitiveness of both companies and countries in the segment. The incentive to adopt new technologies, along with new production demands, transforms traditional manufacturing into smart manufacturing, evolving from mass production to customized production (Qianzhe et al., 2019 [2]).

(Monostori et al., 2016 [3]) explain that smart manufacturing is a paradigm that optimizes resource allocation, featuring real-time analysis, intelligence, refinement, and agile perception of the real-time status of the market and customers. This means that processes are constantly monitored by sensors and connected systems that apply artificial intelligence and machine learning algorithms to learn from the collected data, analyzing data in real-time, which enables the early detection of failures, the automatic adjustment of production parameters, and the continuous improvement of process and product quality control. In this way, smart manufacturing reduces waste, costs, and increases operational efficiency.

This new paradigm demands from production systems not only the traditional requirements of quality and productivity but also requirements for fault prognosis and diagnosis. In this context, traditional maintenance processes become insufficient as they are not capable of detecting failures in advance, thus favoring the application of predictive maintenance.

Predictive maintenance (PdM) uses condition-based monitoring systems that identify significant fluctuations and variations in variables and signals based on sensor data, to prevent or avoid failures (Vanraj et al., 2016 [4]). This means that the future behavior/condition of machine components can be approximated, which will help to optimize maintenance tasks (Lee et al., 2019 [5]) that can be performed before failures occur, during periods of inactivity, or lower equipment demand.

Therefore, the implementation of PdM is a vital requirement for the manufacturing sector, where increasing productivity and product quality are constant objectives. These advantages can be of great value for an important piece of manufacturing equipment, the CNC machine tool. Dependent on the CNC's operational conditions, the production rate and the quality of processed products are directly affected by improvements in the machine's operational conditions. Thus, increasing the reliability of this equipment can bring great benefits to the sector.

However, despite its advantages, the manufacturing industry has been discouraged from implementing such maintenance practices due to the high associated investment. Predictive maintenance requires additional expenses, such as sensors and the development of computational algorithms for data analysis (Thoppil, Vasu, & Rao, 2019 [6]). To facilitate the implementation of PdM in the manufacturing sector, a low-cost hardware for data acquisition, a communication architecture for the collected data, and an application model for analyzing this data will be proposed.

This work is organized as follows: This section presented an introduction addressing the context, the problem description, the research objectives, and a justification for the topic's relevance. The second section will describe the components and procedures used for the construction of the hardware, propose a communication architecture model for integration between the hardware's constituent devices, and an application model for processing and visualizing the collected data. The third section will discuss the expected results from the method's implementation. Finally, the fourth section will provide final considerations on the method's implementation and the next steps.

2. Methodology

To develop the proposed method, the critical components to be monitored were first identified through a literature review. These include: the condition of the machining tool, as monitored by (Hesser and Bernd, 2019 [7]), (Goodall et al., 2020 [8]), (Zhu, 2018 [9]), or (Qianzhe et al., 2019 [2]) and (Ramírez et al., 2020 [10]). The spindle bearing, by (Lee et al., 2019 [5]) and (Thoppil et al., 2020 [11]). The servomotors for the x and z axes, the ball screw bearing, the turret, the spindle, and the coolant, by (Thoppil et al., 2020 [11]). The model was proposed for a ROMI Discovery 4022 vertical machining center, shown in Figure 01.

Figure 1. ROMI Discovery 4022 vertical machining center.

For the equipment in question, the tool, the spindle, and the spindle motor will be monitored. Based on the components to be monitored, the sensors could be defined and a hardware for monitoring could be proposed. Based on the elements that constitute the system, the protocols for the integration of all entities could be defined. Then, an application for processing and visualizing the collected data was proposed.

2.1. Hardware for Data Acquisition

Based on the components to be monitored, the sensors and devices for the construction of the hardware responsible for acquiring data from the machine tool were defined. These elements can be seen in Table 01.

Table 1. Hardware Components

Component	Quantity
Altus XP 340 PLC	1
Allen-Bradley 1606 XLE Power Supply	1
Altus PH-3500 Multifunction Meter	1
BALLUFF BCM R15E-002-DI00, 5-S4 Condition Monitoring Sensor	2
Altus ET2 – 0800 Switch	1
TURCK TBEN-L5-8IOL IO-Link Master Module	1
Current Transformer	3

The table presents the elements used for the construction of the system. Each element has a specific function, which are:

Power Meter – For measuring the current, power, and voltage data of the spindle motor, a power meter can be used (in this case, an Altus PH-3500) which has as its main features: a 16-column by 4-line liquid crystal display (LCD), capable of displaying up to 64 characters on the screen, a built-in Ethernet interface, and support for MQTT.

Programmable Logic Controller (PLC) - For the proposed system, the Altus XP 340 programmable logic controller was used as a communication interface. Its main features include: low cost, compact design, a 32-bit ARM processor, 16 inputs, 16 digital transistor outputs, 5 V/I analog inputs, 2 three-wire analog inputs, 4 analog outputs, 1 Ethernet port, 1 RS-485 serial port, and support for a web server tool that allows the creation of supervision screens without the use of Supervisory Control and Data Acquisition (SCADA) systems. Additionally, the PLC is compatible with major communication protocols, including MQTT, OPC UA, MODBUS, PROFINET, among others.

Vibration Sensor – For monitoring the vibrations of the tool and the spindle, the BALLUFF BCM R15E-002-DI00, 5-S4 condition monitoring sensor was used. Its main features are: an operating voltage of 24Vdc, operating current < 15 mA, vibration measurement in the time domain with a frequency range of 2…1800 Hz (±10 %), 2…2500 Hz (±3 dB), contact temperature with a measurement range of -25...+70 °C, and an IO-Link communication interface.

Switch – To allow communication via Ethernet between the various connected devices, a switch can be used. The Altus ET2 – 0800 was chosen, which features: 8 fast Ethernet ports, a 448 kb memory buffer, and an IP30 protection rating.

Power Supply – The devices that are part of the hardware require a constant 24 V supply. For this, a power supply with such capacity must be used; the chosen one was the Allen Bradley 1606 – XL power supply.

RS-232 to USB Serial Converter – As the machine's data output is of the RS-232 type, an RS-232 to USB serial converter can be used so that the CNC command data can be transmitted to the PLC.

IO-Link Master Module – To enable communication between the BALLUFF condition monitoring sensor and the Altus PLC, the TURCK TBEN-L5-8IOL IO-Link master module must be used. Its features include: an operating voltage of 24 Vdc, operating current < 300 mA, and it operates with PROFINET, EtherNet/IP, and Modbus TCP Server protocols.

Current Transformer (CT) – For the power meter to be used for measuring the motor's data, current transformers must be used. This is because the power meter has a current measurement range limited to 10 A, while the spindle motor's current is 25 A.

From the definition of the hardware and the knowledge of the protocols supported by each component, a communication architecture for the acquisition, processing, and visualization of the collected data could be proposed.

2.2. Communication

Based on criteria such as latency, reliability, availability, scalability, interoperability, ease of implementation, and cost, a three-layer communication architecture was proposed. They are:

2.2.1. Data Acquisition Layer

This is the direct interface with the physical process. It is divided into three fronts:

CNC Data Collection: Data will be collected via an RS-232 to USB converter cable. A computer will act as an intermediary, physically connecting to the CNC through the USB converter to read the serial data and then use a script to publish this information on the local network via the MQTT protocol. In this way, the Altus XP 340 PLC can subscribe to the corresponding

MQTT topic and receive the CNC data over the Ethernet network, integrating it efficiently with the rest of the monitoring system.

Electrical Data Collection: Electrical data will be collected by the power meter, connected directly to the Altus ET2-0800 Switch via an Ethernet cable. The following protocols can be used:

- **MQTT (Recommended for Analysis):** The power meter can act as an MQTT client, publishing data asynchronously to a broker.
- **Modbus TCP (Recommended for Control):** The PLC can act as a Modbus master and query the power meter at regular intervals to obtain real-time data for control logic or local interlocking.

- **Vibration and Temperature Data Collection:** Vibration data will be collected by the Balluff BCM Sensor with an IO-Link interface. The sensor is connected via a standard IO-Link cable to the TURCK TBEN-L5-8IOL IO-Link Master Module. The sensor communicates with the master via IO-Link. The IO-Link Master, in turn, connects to the Altus ET2-0800 Switch via an Ethernet cable.

2.2.2. Communication and Local Processing Layer

In this layer, the data is concentrated in the PLC and processed locally. It has the following structure:

Local Network: The Altus ET2-0800 Switch creates the local Fast network, interconnecting the PLC, the IO-Link Master, and the Power Meter.

Communication with the IO-Link Master:

- **Protocol:** PROFINET. The Altus XP 340 PLC will act as the PROFINET Controller, and the TURCK IO-Link Master as the PROFINET Device. This is a high-performance, deterministic communication, ideal for obtaining vibration and temperature data with low latency.

Data Aggregation in the PLC:

- The PLC receives vibration/temperature data from the IO-Link Master via PROFINET.
- The PLC receives electrical data from the Power Meter (via Modbus TCP or by subscribing to a local MQTT topic).

- The PLC receives command data from the CNC over the Ethernet network.

Edge Processing: The PLC can perform pre-processing to carry out several functions, such as synchronization, temporal alignment of data from different sources, calculation of simple indicators, issuing alerts, generating immediate alarms, and local supervision. The embedded web server tool in the PLC can be used to create simple supervision screens, accessible by any browser on the local network, for quick diagnostics without the need for a SCADA system.

2.2.3. Supervision and Analysis Layer

This layer is responsible for transforming raw data into intelligence for predictive maintenance. It is composed of:

- **Gateway to the Cloud:** The Altus XP 340 PLC acts as the gateway. After aggregating and synchronizing the data, it prepares it for sending.
- **Sending Protocol:** MQTT is the protocol for communication with the cloud/corporate systems. It is lightweight, secure, and efficient in networks with possible instability. The PLC must format the data from all sources into a single message.
- **Destination Infrastructure:**
  - **MQTT Broker:** The PLC will publish this message to a specific topic in an MQTT Broker. This broker can be on a local server or on a cloud service.
  - **Consumers:** Various systems can subscribe to this topic to receive real-time data, such as Databases, Analysis Platforms, and Dashboards.

With the definition of the communication architecture, an application model for the consumption and visualization of data can be established.

2.3. Data Processing and Visualization

An application was proposed to consume and process the collected data, allowing for the visualization of the machine's behavior in real-time. The application has the following structure:

2.3.1. Data Source: MQTT Broker

The application architecture integrates with the communication architecture. The Altus XP 340 PLC publishes a consolidated message to a topic in the MQTT Broker, which is the entry point for all real-time data.

Ingestion and Storage: Telegraf + InfluxDB

To move data from the broker to the database efficiently, Telegraf is used:

Telegraf: is a lightweight collection agent, part of the InfluxDB ecosystem. Telegraf is configured to subscribe to the MQTT topic where the PLC publishes the data. It collects each message, converts it to the optimized InfluxDB format, and inserts it into the database in real-time.

InfluxDB: it will contain buckets (like databases) for the raw machine data and for the results generated by the analysis platform.

2.3.2 Analysis and Intelligence

The analysis platform interacts with InfluxDB in a continuous cycle that has the following structure:

Data Reading: a Python script queries InfluxDB to obtain historical data that can be used to train Machine Learning models. It can also query recent data to make real-time predictions.

Insight Generation: The model processes the data and generates new information, such as a machine Health Index, anomaly detection, and failure prediction.

Recording the Results: the script writes these new insights back into InfluxDB, in a separate bucket.

2.3.3 Visualization Layer: Grafana

Grafana can be used as a visualization tool, as it has native and high-performance integration with InfluxDB. It connects to InfluxDB and allows for the creation of interactive dashboards. The proposed model allows for real-time monitoring of the asset, facilitating the analysis of indicators and the creation of predictions about the machine's health.

3. Results and Discussion

The proposed method was based on establishing the critical variables to be monitored in a CNC machine tool to propose a hardware for monitoring and communicating this data. A communication architecture was developed to integrate the connected devices, enabling the development of an application that allows for real-time monitoring of the asset, in addition to the possibility of using the collected data to create an operational history that can be used for building and training machine learning algorithms for failure prediction and anomaly detection.

After the hardware implementation, it will be possible to monitor the process in real-time, providing data for more assertive decision-making regarding operational and maintenance aspects. This culminates in benefits such as a reduction in the number of unplanned downtimes, a reduction in operating costs, an increase in overall equipment effectiveness, and greater reliability and predictability of production.

4. Conclusion

The development of a low-cost methodology for monitoring CNC machine tools that allows for the application of predictive maintenance techniques is of great value to the manufacturing sector. The results obtained impacted various organizational levels, such as the operational level, through the reduction of unplanned downtimes and increased safety. In the maintenance and process sector, it facilitates a transition from preventive to proactive maintenance methods. In strategic results, it leads to a reduction in operational costs and an increase in the reliability and predictability of production.

The next steps consist of validating the method, which will occur with its implementation on a demonstration machine located at the Advanced Manufacturing Plant (PMA) of SENAI CIMATEC. For this, the hardware will be installed on the machine, and based on the collected data, the application responsible for monitoring and failure prediction can be developed.

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