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A Review: Data Collection and Monitoring Systems for CNC Machine Tools in Smart Manufacturing

D. R. Lahore[1], Dr. K. B. Deshmukh[1], Dr. S. A. Sonawane[2]

[1]*Department of Mechanical Engineering, Amrutvahini College of Engineering (AVCOE), SavitribaiPhule Pune University (SPPU),Sangamner, Maharashtra, India*

[2]*Department of Mechanical Engineering, College of Engineering ChhtrapatiSambhajinagar, Maharashtra, India*

E-Mail: dhanshri.lahore@gmail.com, TP: +91-9049009372

Abstract

CNC machine tools are central assets in discrete manufacturing and a foundational element of intelligent manufacturing. This review synthesizes contributions across uploaded sources on data acquisition and monitoring for CNC machine tools with emphasis on standards (e.g., MTConnect, FOCAS), system architectures (edge–cloud CPS), sensing modalities, analytics (signal processing and machine learning), task-level monitoring and scheduling, and operational integration toward “Machine Tool 4.0.” Key findings include: (i) equipment information models based on MTConnect and vendor APIs such as FANUC FOCAS enable uniform, real-time data collection across heterogeneous assets; (ii) hierarchical Petri-net models support robust tracking of machining tasks under uncertainty; (iii) NC program analysis can improve time prediction and preventive maintenance planning; and (iv) prototype implementations validate feasibility using standard development stacks. Persistent challenges include interoperability across controllers, data quality and synchronization, cybersecurity, and the scarcity of open datasets and benchmarks. We outline research directions in semantic interoperability (MTConnect–OPC UA harmonization), edge intelligence, standardized KPIs, and trustworthy AI.

Keywords:*CNC; data acquisition; MTConnect; FOCAS; cyber-physical systems; intelligent manufacturing; Machine Tool 4.0; task monitoring; Petri nets; predictive maintenance*

1. INTRODUCTION

The manufacturing sector is undergoing a paradigm shift from traditional automation to intelligent manufacturing, driven by advances in sensing, networking, and data analytics. CNC machine tools, as the backbone of discrete manufacturing, generate large volumes of operational data that remain underutilized in many workshops. Conventional shop floors often rely on manual logs, isolated controller data, and vendor-specific software, leading to information silos and low transparency.

A robust data collection and monitoring system enables real-time visibility of machine states, process parameters, and production progress. Such systems form the foundation for higher-level applications such as predictive maintenance, adaptive scheduling, digital twins, and closed-loop optimization.

Table 1.Evolution from conventional CNC operation to intelligent manufacturing

Conventional Operation	Digital Monitoring	Smart Shop Floor
Manual Monitoring	Digital Monitoring	CPS-Enabled Smart Shop Floor
Paper Records	MTConnect/FOCAS	Edge & Cloud Processing
Manual Inspection	Real-Time Dashboard	Predictive Maintenance
Basic Control	Local Database	Autonomous Optimization

2. PROBLEM STATEMENT& CHALLENGES

As per the scenario the despite increasing availability of digital interfaces on CNC Controllers, also the no of challenges like Heterogeneous controller protocols across machine vendors - Limited task-level visibility in high-mix, low-volume production - Poor integration of maintenance knowledge into production planning - Lack of standardized data models and benchmarks. These Challenges like to the development of unified, Standards-based data acquisition and monitoring frameworks has been presented in Table 2.

Table 2. Key Challenges in CNC Data Collection

Challenge	Description	Impact
Heterogeneity	Different CNC Vendors use proprietary interfaces	Difficult System integration
Data Silos	Isolated machine-level data	Poor decision making
Uncertainty	Frequent interruptions and changeovers	Inaccurate task prediction
Maintenance gap	Limited use of fault history	Reactive maintenance

3. RESEARCH METHODS

3.1 Smart manufacturing with cyber-physical systems(CPS)

Smart manufacturing combines physical manufacturing methodology with computational intelligence through CPS. The cyber-physical systems based on CNC environment, machines, sensors, networks and software systems interact in real time to enable monitoring, analysis and optimization.

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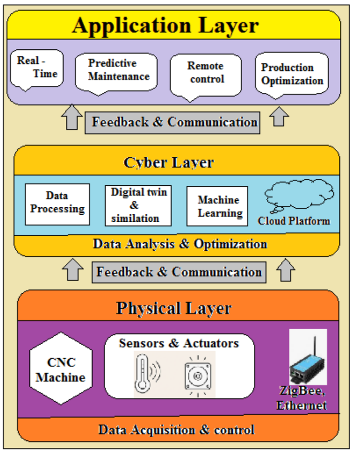

Figure 1. CPS Working Methodology for CNC Machine Tools

3.2 Machine Tool 4.0

Machine tool 4.0 extends industry 4.0 concepts to individual machine tools. A machine tool Acquiescent CNC Machine typically supports: connectivity and standardized communication, self-awareness of operational states and integration with enterprise systems (MES, ERP).

4. RESEARCH METHODS

4.1 MTConnect

MTConnect is an open, read-only communication standard that provides a vendor-neutral data model for manufacturing equipment. It uses HTTP-based communication and represents data in XML/JSON Format, enabling consistent access to machine state, axis positions, spindle speeds, alarms and more.

4.2 FOCAS (FANUC Open CNC API Specification)

FOCAS is a closed-source API provided by FANUC for accessing internal CNC controller data. It enables high-frequency data acquisition of detailed machine parameters such as program executive status, alarms, offsets and counters.

4.3 Hybrid Interoperability Approach

A combination of FOCAS for native controller access with MTConnect for normalized data representation provides a practical solution for different shop floors.

Table 3.Comparison of MTConnect and FOCAS

Aspect	MTConnect	FOCAS
Type	Open Standard	Vendor Specific API (FANUC)
Access	Read only	Read (Limited write capability)
Data model	Standardized, XML/JSON-based	Proprietary
Typical use	Unified monitoring	Detailed controller data

5. System Architecture for CNC Monitoring

5.1 System Architecture

A CNC monitoring system consists of three layers. The first layer is the Data Acquisition layer, which consists of CNC Controllers, Sensors, and Adapters. The second layer consists of a data processing layer, which includes data normalization, buffering, and storage. The last or third layer is an application layer, whichprovides for visualization, analytics, and decision support.

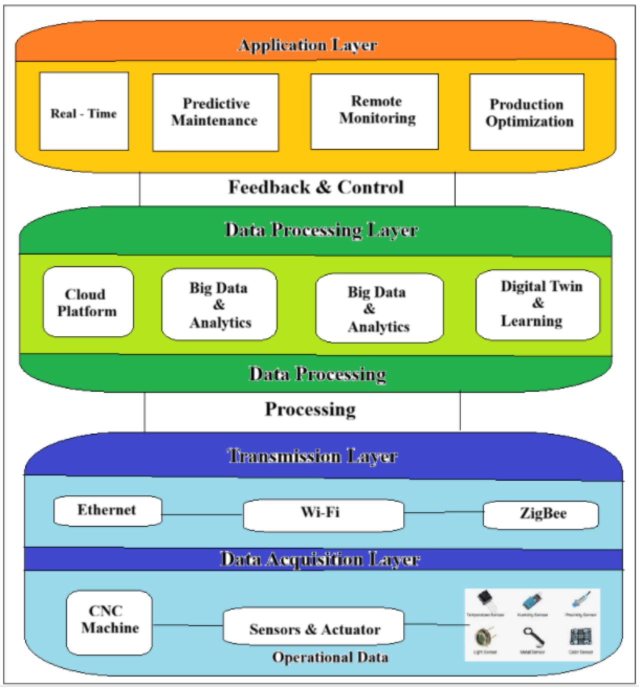

Figure 2. Layered Architecture of a CNC data Acquisition and monitoring system

5.2 Edge-Cloud Deployment

It contains an edge layer that includes real data collection, pre-processing, and low-latency response, as well as another cloud/server layer that contains historical storage, advanced analytics, and cross-machine optimization.

6. Sensors and Data Processing

6.1 Controller-Machine Data

- Machine States (Power on, ready, running)
- Axis Positions and feed rates
- Spindle speed and load.
- Alarm and event logs

6.2 Controller-Machine Data

- Vibration Sensors for spindle and bearing health
- Acoustic emission sensors for tool wear detection

- Force sensors for cutting process monitoring
- Energy meters for power and sustainability analysis

Table 4.Common Sensors used in CNC Monitoring

Sensor Type	Measured Parameter	Application
Vibration	Acceleration	Spindle/Bearing health
Acoustic emission	High-frequency signals	Tool wear detection
Force	Cutting forces	Process stability monitoring
Energy	Power consumption	Energy efficiency

7. Key Performance Indicators (KPIs)

The KPIs derived from CNC Data acquisition and monitoring systems include Overall Equipment Effectiveness (OEE), Mean Time Between Failure (MTBF), and alarm frequency for energy consumption per part.

Table 5.CNC Monitoring KPIs and their Significance

KPI	Description	Benefit
OEE	Overall equipment utilization metric	Productivity Improvement
MTBF	Mean Time Between Failure	Reliability analysis
Energy/part	Energy efficiency indicator	Sustainability improvement

8. Conclusion

The data acquisition and monitoring systems for CNC machine tools are fundamental enablers of smart manufacturing. The standards, such as MTConnect, combined with APIs like FOCAS, provide a practical methodology for interoperable data acquisition. For the advanced analytics, task-level monitoring, and predictive maintenancesignificantly enhance productivity and reliability. Future research should focus on semantic harmonization, edge intelligence, and standardized benchmarks to accelerate adoption.

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