Development of A Cyber Physical System For Conventional Machines in Smart Factories

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Abstract

In this study, the successful development of a Cyber-Physical System (CPS) tailored for four conventional machines in a real manufacturing environment was presented. Each machine was equipped with multiple sensors to monitor key operational parameters and ensure comprehensive data acquisition. The collected data is processed and visualized through an intuitive smart dashboard that can be accessed via a server computer and a web-based application. The proposed system allows for real-time monitoring, analysis, and report generation, including the automated calculation of Overall Equipment Effectiveness (OEE) and Overall Line Effectiveness (OLE) for operational efficiency. Besides, the CPS proactively identifies and mitigates potential errors, and enhances system reliability by implementing data thresholding techniques. Furthermore, the architecture can support predictive maintenance by analyzing trends and anomalies in sensor data. It paves the way for minimized downtime and cost savings. The CPS represents a significant advancement in digitizing conventional machines and manufacturing processes, contributing to increased efficiency, transparency, and scalability in line with the Industry 4.0 era.

Key Words: IoT; Cyber Physical System; Smart Factory; Industry 4.0; Digital Transformation; Digitalization; OEE.

1 Introduction

CPSs integrate the physical and digital worlds by embedding sensors, actuators, and software into industrial equipment, and allow precise monitoring and control. This integration fosters predictive maintenance that reduces downtime and optimizes resource utilization. By enabling seamless communication between devices, machines, and systems, the Internet of Things (IoT) plays a critical role in smart factories. Through IoT connectivity, real-time data is collected and shared across networks and helps enhance operational efficiency and decision-making. Together, IoT and CPS enable advanced automation, flexibility, and scalability, which are fundamental to Industry 4.0. By leveraging these technologies, smart factories can achieve unprecedented levels of productivity and innovation (Dornho¨fer et al. [10]; Averyanov et al. [2]). CPSs have found applications across a wide range of industries. In healthcare, CPS is utilized to enhance patient care and streamline medical procedures (Hemalatha et al. [13]; Rosado et al. [24]). Agriculture has benefited from CPS through innovations in precision farming and resource management (Hamzah et al. [12]). In transportation, CPS improves safety and efficiency by integrating intelligent systems(Wang and Liu [31]). Furthermore, CPS is a key enabler in smart city initiatives and drives sustainable urban development (Hemalatha et al. [14]). It also plays a role in water sustainability by monitoring and managing resources effectively (Cui [8]). CPS supports supply chain management and aids in the development of strategic policies across various sectors (Tonelli et al. [28]; Cheong and Lee [5]). Many studies have highlighted the vulnerability of CPS to external cyber-attacks, which can disrupt industries and lead to financial losses (Jamaludin and Rohani [17]). Besides, in (Oks et al. [23]), the authors present a novel categorization of industrial CPS across 10 sections, 32 areas, and 246 fields, and offer insights into future research directions to enhance Industry 4.0 applications. The others explore the defining characteristics, design methodologies, current state of the art, applications, challenges, and opportunities for addressing complex problems in the field of CPS (Lozano and Vijayan [21]). In (Habib and Chimsom I [11]), the authors highlight CPS's evolution toward intelligent, decision-making systems, their applications in smart cities, manufacturing, and supply chains, and the challenges of cybersecurity, real-time control, and interoperability that must be addressed for future advancements. The integration of digitization, Industry 4.0, the IoT, machine learning, and artificial intelligence is transforming the roles of plant operators and maintenance technicians. In (Wittenberg [33]), these advancements over the decades, current industry demands, and key research areas are examined. In ([1]), the authors investigate the interoperability challenges and integration of Digital Twins (DTs) within edge-enabled CPS in the context of Industry 4.0/5.0. The study identifies 77 interoperability challenges and proposes a framework with six levels—technical, syntactic, semantic, pragmatic, dynamic, and organizational—to help practitioners effectively adopt and use interconnected DTs in CPS. The CPSs Co-Simulator (CPS-Sim), a framework that integrates Matlab/Simulink for physical system simulation and QualNet (or OMNeT++) for communication network simulation is introduced. The key innovation lies in synchronizing these simulators with different time management methods, effectively demonstrated through a distributed clock synchronization algorithm in wireless sensor networks (Suzuki et al. [27]). Integrating CPS with IoT and Artificial Intelligence (AI) enables smart decision-making, and drives innovations in process optimization and customization. The researchers explore the integration of AI with CPS through Representation Learning (RepL) and emphasize its potential to extract meaningful abstractions from noisy sensor data and discrete system states. The study examines contemporary RepL methodologies applied to time-series data generated by CPS. A three-tank system as a case study to evaluate their strengths, limitations, and conditions for practical deployment in CPS contexts is used (Steude et al. [26]). The IoT holds a vital role in transforming traditional factories into smart factories in Industry 4.0. It enables predictive maintenance, energy optimization, and enhanced workplace safety through interconnected devices and sensors. Existing IoT connectivity solutions, highlighted IoT applications, technical challenges, and explored emerging technologies in smart factories are reviewed. They consist of predictive maintenance, asset tracking, inventory management, supply chain optimization, and so on (Ding et al. [9]; Soori et al. [25]; Cherif and Frikha [6]). In this paper, a CPS was successfully developed for two conventional milling machines and two conventional turning machines. The system collects and processes data from these machines, displaying it on a smart dashboard. Key performance metrics such as OEE and OLE are automatically calculated, providing valuable insights into operational efficiency. Four distinct Programmable Logic Controllers (PLCs) were integrated to manage the machines and ensure seamless data communication. By applying data thresholding techniques, the system effectively detects and prevents potential errors in order to enhance reliability. This CPS demonstrates a robust solution for digitizing conventional machines and aligning them with Industry 4.0 standards.

2 Literature Review

The field of industrial automation leverages CPS to optimize production processes and equipment performance. In (Hoffmann et al. [15]), the authors present a concept for the development, commercialization, operation, and maintenance of industrial CPSs in modern production, and highlight the challenges and opportunities for advancing both research and industrial practice. It defines the components and technological aspects of industrial CPS, compares them with traditional systems, and discusses key challenges and solutions to ensure the long-term sustainability of these systems. CPSs can transform technologies that bridge the physical and virtual worlds to create innovative applications and processes while dissolving traditional boundaries. The authors explore how CPS and IoT can drive a paradigm shift in manufacturing systems, optimize strategies, and introduce new applications, services, and data-driven business models (Kim and Park [19]). In (Chugh and Taqa [7]), the authors explore the role of Industry 4.0 technologies, including CPS and IoT, in transforming manufacturing through automation, real-time data exchange, and interconnected systems. By integrating physical components with software and communication networks, these technologies enhance decision-making, predictive maintenance, traceability, and production optimization. The proposed system is demonstrated through examples and a real-world case study. To increase productivity without the high costs of new machinery, the authors propose digitizing traditional machines by integrating motor controllers and sensors to collect and transmit data. This approach enhances the machining process by improving surface quality, reducing tool wear, and minimizing the risk of failure (Nguyen et al. [22]). In (Briatore and Braggio [3]), the research explores how Industry 4.0 technologies like IoT, DTs, and CPSs can revolutionize maintenance through predictive and prescriptive maintenance. By integrating these technologies into the Maintenance 4.0 framework, the study emphasizes resilience and environmental sustainability and proposes a six-step roadmap that begins with small-scale pilot projects to generate valuable results. The research explores the integration of Cloud Manufacturing and CPS through the use of OPC Unified Architecture (OPC UA) as a communication protocol to enable seamless data exchange and interoperability. The proposed hybrid architecture addresses challenges such as real-time monitoring, adaptive control, and efficient data management, and provides a pathway for optimizing manufacturing processes, and enhances real-time capabilities using cloud resources(Ji and Xu [18]). Besides, in (Va´squez-Capacho [30]), the authors introduce V-nets, a new formalism designed to address diagnosis challenges in CPS and industrial processes. V-nets are proposed as a reliable tool for managing fault detection and improving supervisory control in scenarios where traditional formal models of Discrete Event Systems (DES) fall short. The collaborative processes and model-based technologies used to develop a prototype Cyber-Physical Production System for USB sticks are detailed in (Zamfirescu and Neghina˘ [36]). It emphasizes co-simulation technology to enhance fidelity, enable independent subsystem validation, and facilitate structured dialogue between specialized teams. In the metallurgical industry, fused magnesia smelting for fused magnesium furnaces (FMF) is an energy-intensive process with high temperatures and complex dynamics. This process makes it challenging to measure and model the energy consumption per ton (ECPT) accurately. The paper introduces a CPS-based embedded optimal operational control system integrating advanced algorithms, industrial cloud computing, and wireless communication, successfully applied to ten FMF production lines in China. This integration significantly reduces the ECPT (you Chai et al. [35]). Cyber-physical production systems (CPPS), which link physical and digital components, serve as the backbone for these smart factories. It enables real-time management, adaptive processes, and optimization through global cooperation and innovation (Hozdic´ [16]). In (Torres et al. [29]), The authors focus on developing SmartBoxes using low-cost hardware like Raspberry Pi and industrial platforms such as NI CompactRIO, and employing OPC-UA and MQTT protocols for real-time data collection, processing, and integration. These SmartBoxes facilitate seamless interaction between supervisory systems and physical assets. And, a study presents a CPS-based thermal error compensator for CNC machine tools that are designed on an embedded system to rapidly collect sensor data, predict thermal errors, and communicate with CNC systems and cloud platforms (Lou et al. [20]). Applied to a CNC machine tool, the result demonstrates effective performance under various machining conditions. In the competitive manufacturing landscape, companies are integrating advanced technologies to enhance processes and productivity and align with Industry 4.0 principles. The research examines the transformation process of a factory producing spherical bushels. They utilize FlexSim software to create a production simulation platform for real-time management of production, supply, and logistics via Material Requirement Planning (MRP) and CPPS. The simulation optimized by using a load-capacity adjustment method. It improves equipment occupancy rates, demonstrates significant efficiency gains, and lays the groundwork for a future digital twin of the company (Chakroun et al. [4]). In (Williams et al. [32]), the authors present the implementation of DT of Cyber-Physiscal Tormach CNC machines, which replicates physical manufacturing operations by generating tool path positional values along the X, Y, and Z axes. The DT uses the MTConnect communication protocol to collect and store data in standardized XML and JSON formats for analysis. Validation was carried out by simulating and manufacturing a coin geometry on a real CNC machine. The results show a high correlation between the DT and real system. By integrating supervisory control and data acquisition (SCADA), edge computing, and cloud computing to monitor and analyze data streams from CNC machines and sensors, in (Yang et al. [34]) the authors propose a new data analysis framework for CPS. The framework employs signal smoothing and anomaly pattern detection techniques to identify and store significant patterns in the data stream. These patterns can then be used for further analysis and applications within CPS.

3 Research Methodology

In this project, four new control boxes for four machines were built. Each machine was equipped with a PLC controller from a different brand because, in reality, the company is using a wide variety of PLCs from different manufacturers and generations. A central server simultaneously connects to all four PLCs to collect data and store it in a shared database. A smart dashboard to show critical values that need to be monitored and provide alerts when sensor signals indicate that the equipment is about to operate abnormally was developed. Two important indicators calculated and displayed on the dashboard are OEE and OLE. Among them, Overall Equipment Efficiency (OEE) is a critical indicator, calculated as follows:

$$OEE = A \times P \times Q \quad (1)$$

where: A = Run Time / Planned Production Time. This measures how much time the production line was running as planned.
P = (Ideal Cycle Time × Total Count) / Run Time. This assesses whether the line is running at its maximum speed or capacity.
Q = Good Count / Total Count. This evaluates the proportion of defect-free products.

Planned Production Time and Ideal Cycle Time are predefined values that can be set in advance. Total Count represents the total number of products produced. Good Count refers to the quantity of products meeting quality standards. Both Total Count and Good Count are manually recorded. Consequently, Run Time is the only variable that requires automatic measurement during production. To address this, the authors propose capturing this value by transmitting an on/off signal to the data center whenever the machine starts or stops. With accurate information on machine start and stop times, Run Time can be calculated efficiently and reliably. Besides, OLE is a metric used to evaluate the performance and efficiency of an entire production line. It is similar to OEE but focuses on the performance of multiple machines or stations working together in a line. OLE was also calculated and displayed in this project. Based on actual production needs, three parameters (Capacity Utilization, First Pass Yield, and Scrap Rate) are also calculated using formulas (2), (3), and (4) and displayed. Where:

Capacity Utilization = Actual output / Maximum possible output (2)

First pass yield = (the number of units successfully produced without rework) / (the total number of units entering the process) (3)

Scrap rate = the amount of scrap / the total amount of output (4)

By equipping inverters, display screens, and sensors, the two traditional milling machines have been digitized as follows:

- The system for controlling spindle speed in milling machines has been enhanced by integrating a 3-phase inverter. It allows precise speed adjustments for optimal machining performance, product quality, and tool life. Additionally, the authors propose using optical sensors to record spindle speed data with high accuracy and enable analysis to identify and address factors affecting tool life and surface quality.

- Monitoring coolant parameters is essential for efficient milling machine operations. The coolant helps manage temperature, clear abrasive particles, and maintain machining quality. By using ultrasonic and thermal sensors, the developed CPS can automate the collection of coolant level and temperature data, enable better maintenance planning, and address issues such as low density, insufficient coolant levels, or overheating.
- In production, electric energy consumption during system operation is a crucial factor that can be calculated using wattage and spindle torque. Through torque value inspection, the operator can assess the compatibility between the feed rate, spindle speed, and the material properties of the workpiece. This process helps prevent tool breakage or wear during machining and ensures accuracy by enabling corrective actions for tool wear. Similarly, the digitization of two traditional lathes integrates sensors, control systems, and visualization tools with the following enhancements:
- Spindle speed monitoring: an optical sensor has been installed to record high-precision spindle speed data for real-time analysis. This enables optimization of machining processes and enhances tool life.
- Temperature monitoring: two temperature sensors measure spindle and motor temperature that provide critical insights to prevent overheating, ensure operational stability, and help condition-based maintenance planning.
- Energy efficiency monitoring: a current sensor is utilized to monitor the machine's power consumption that supports efficient energy management and early fault detection through monitoring the abnormal changes in current.
- Precision control system: a three-phase variable frequency drive (VFD) replaced traditional contactor-based motor control to allow step-less control and precise speed adjustments for enhancing machining accuracy, product quality, and tool life. A three-tier light tower provides real-time operational status updates, improves situational awareness, and ensures machine safety.
- Monitoring operations and observing graphical data: A Human-Machine Interface (HMI) has been installed to provide intuitive control and monitor operational parameters that can improve productivity and interaction between operators and machines.

This digitization establishes a foundation for cyber-physical integration in advanced manufacturing systems. Based on practical working experience, key indicators that directly affect product quality, machine failure, and tool breakage—such as spindle speed and coolant temperature—have been set with thresholds to notify operators before issues occur. Critical data is stored and analyzed, and reports can be easily generated to facilitate the management process. To easily monitor the dashboard in the areas inside and outside the company, a web-based application with a control flow as shown in Figure 1 was developed.

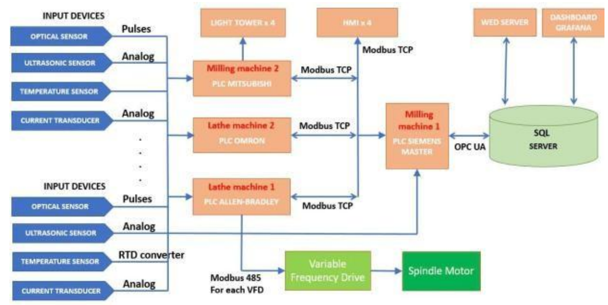

Figure 1: Connection diagram and transmission protocol of devices in the CPS system.

The diagram illustrates a system where various input devices, such as optical sensors, ultrasonic sensors, temperature sensors, and current transducers, provide essential data to multiple PLCs, including Siemens, Mitsubishi, Omron, and Allen-Bradley. Each sensor serves a specific purpose: optical sensors measure the spindle motor's speed, ultrasonic sensors monitor the coolant water level, temperature sensors track both the spindle motor's temperature and the coolant water's temperature, and current transducers measure the total current consumption of the machine. The Siemens PLC acts as the master, consolidating data from other stations and transmitting it to an SQL server using OPC UA for further processing. This data supports web-based monitoring and dashboard visualization via Grafana. Additionally, at each station, the PLCs control spindle motors using Variable Frequency Drives (VFD) via Modbus 485, with all configurations and operations at each machine being managed through the HMI. Furthermore, the spindle motor's torque is calculated based on the current measured from the VFD to enable precise motor management and system optimization. This setup integrates data acquisition, control, and visualization for efficient industrial automation.

4 Results and Discussion

Figure 2 depicts the actual CPS system with four traditional machines (02 milling and 02 turning) connected and transmitting data to the server computer. The inverters, sensors, light towers, and control cabinets integrated into each machine are all operating as planned. The entire system was operated simultaneously to test connectivity and the seamless flow of data. Additionally, to ensure the accuracy of OEE and OLE values, the CPS was continuously operated for several days.

For the milling machines, four sensors are installed at suitable locations as below:

- An optical sensor is mounted on the gearbox of the main motor to measure spindle speed.
- A temperature sensor is positioned in the coolant reservoir to monitor coolant temperature.
- An ultrasonic sensor is also installed in the coolant reservoir to measure the coolant level.
- A current sensor is placed on the power line within the machine's electrical cabinet to track its current consumption.

Similarly, the digitization of two traditional lathes includes the installation of four sensors, control systems, and visualization tools with the configuration as follows:

- **Spindle speed monitoring:** An optical sensor is installed inside the headstock to record high-precision spindle rotational speed data for real-time analysis.
- **Spindle motor temperature monitoring:** A temperature sensor is mounted on the spindle motor housing to measure its temperature.
- **Spindle temperature monitoring:** Another temperature sensor is installed within the headstock to measure the spindle temperature.
- **Energy efficiency monitoring:** A current sensor is located in the electrical cabinet to track the lathe's power consumption and energy usage.

Additionally, a three-color light tower is mounted at the top of the machines to indicate its operational status. The data collected from these sensors is processed and displayed on the HMI which is mounted on the control panel. This HMI interface allows operators to monitor machine parameters and adjust control settings flexibly. The spindle speed is managed by a VFD located in the electrical cabinet and can be modified either through the HMI or the dashboard. This digitization establishes a foundation for cyber-physical integration in advanced manufacturing systems.

Figure 2: CPS system.

A professionally designed smart dashboard includes a general page summarizing the statistics of all four machines (Figure 3). On the General Page, which displays the overall statistics for all machines, the top part features graphs of the statistical values: OLE, Capacity Utilization, First Pass Yield, and Scrap Rate. The bottom part shows the key values of these parameters for each machine. Additionally, the OLE value of the whole system consisting of 4 machines is also calculated and displayed.

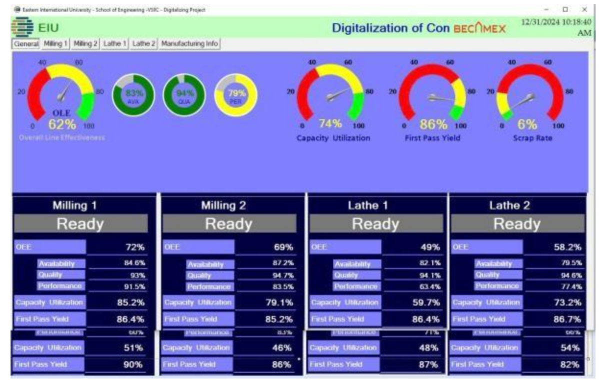

Figure 3: General page – Smart Dashboard on the server machine.

Each machine also has its own dedicated page displaying data from sensors, statistics, and warnings to alert operators about potential errors (Figure 4). The current basic awareness consists of Excessively High Coolant Temperature, Low Coolant Level, Abnormal Spindle Torque, and Excessively High Spindle Temperature. The displayed data for each machine are Machine operating status (Run/Idle/Error), OEE, Name of operator, Sensor data, power consumption (in watts and currency), warning messages, and statistics of specific data. On the left side of the interface, the machine's image is displayed along with the manufacturer's name and model. Below this, the operator's information is shown, including the name and photo. The system tracks data about the primary operator, the machine they are using, and their working hours. This information helps to visually identify the current operator and review operation history. The system includes a feature to change the operator by double-clicking the "Change Operator" option. This allows another operator to use the machine with permission and records each operator's operating time. As a result, any issues caused by operators can be traced back through the stored database. All data collected from the 4 machines are stored and can be exported according to the storage time when needed.

Figure 4: The user interface of the milling machine with the warning message "Abnormal Spindle Torque"

The web-based interface of the system is displayed as shown in Figure 5. Through this interface on the web-based application, operators can remotely monitor the operational status of the entire CPS system. A mobile application is currently being developed to facilitate monitoring.

Figure 5: Smart Dashboard on the web application.

The result of the project is a favorable first step toward developing predictive maintenance modes as well as creating an automated production plan to optimize the production planning process. This is a basic, typical CPS system that includes the following functions:

- **Sensors:** Collect data from the physical environment.
- **Control Systems:** Process data collected from sensors and make decisions or commands to control physical devices.
- **Communication Network:** Connect sensors, control devices, and computers or servers to transmit data between components in the system. This network may include both wireless and wired protocols.
- **Computing and Software Processing:** Process and analyze data from sensors, and provide functions such as real-time analysis, forecasting, optimization, and automatic decision-making.
- **Actuators and Physical Devices:** Execute physical actions based on control commands from the system.
- **User Interface:** Allow operators to monitor, supervise, and control the system.
- **Safety:** Prevent damage or accidents.
- **Data Integration and Analytics:** Integrate data from various sources and use analytical algorithms to extract useful information, optimize system performance, and support decision-making.

5 Conclusions

In this paper, the successful development of a CPS designed to integrate four conventional machining tools is presented. The system effectively collects and visualizes data through a smart dashboard, and generates reports and alerts for potential risks that could impact the equipment. The alerts are based on data analysis from various sensors to ensure timely responses to anomalies. The CPS not only enhances real-time monitoring and operational reliability but also serves as a foundational step toward transforming traditional manufacturing systems into smart factories. The proposed system is full of functions that a standard CPS needs. By adopting this system, manufacturers can align with Industry 4.0 objectives so that they can achieve higher efficiency, improved decision-making, and greater adaptability to the demands of modern production environments.

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