Artificial Intelligence Cyber Physical System Platform for Industry 4.0

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Abstract. Cyber-physical systems (CPSs) are the essential element in the implementation of Industry 4.0. These systems are catalysed by pooling physical and topological components. Computer vision-based artificial intelligence models in CPSs enable innovative applications in smart manufacturing, transport, and agriculture. Computer vision technology and Artificial Intelligence are applied to monitor and analyse CPS's operation process and status to achieve operational excellence through productivity improvement and energy optimisation. This paper proposes the system architecture of the Artificial Intelligence Cyber-Physical System Platform for Smart Manufacturing Systems. The system architecture integrates computational algorithms, communication networks, and physical processes. A CPS in the smart factory involves the integration of a mechatronic device with a control system and networked systems for advanced control, monitoring, and interaction. The proposed platform implementation approach provides a versatile and dynamic solution for CPS in the manufacturing industry. This paper presents the motivation, status, and implementation of the Instrumentation and Measurement of a CPS for Industry 4.0 using an AI Cyber-Physical System Platform.

Keywords: Cyber-physical systems · Computer vision · Artificial intelligence · Smart manufacturing

1 Introduction

Cyber-physical systems (CPSs) are socio-technical systems with a transdisciplinary engineering approach, integrate electronics, mechanics, software, and other technical components. CPS utilize the integrated Systems Modeling approach to provide a cohesive design theory along with associated design, analysis, and simulation tools. Enabling Technologies like Artificial intelligence (AI) and Computer Vision (CV) applications in CPSs have solved real-time interaction challenges and system efficiency issues in dynamic environments. Evolution of CPSs involves tightly integrating physical objects with computational resources for continuous coordination. CPS integrate sensing, computation, control, and

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networking to automate processes, improve efficiency, and achieve smart systems. They use customizable computer-based control loops combining off-the-shelf components to monitor and control physical processes. Rapid research and development in CPS has powered the digital transformation of physical objects and infrastructures into more efficient and intelligent ones.

CPSs find application in vital sectors like dynamic and proactive traffic safety, healthcare, factory and process control. Dietmar et al. [1] proposed traffic flow simulation studies to focus on modelling cyber-physical environments, transportation system processes and the information technology for applying CPSs to on-road transport systems. W. An et al. [2] propose agriculture cyber-physical systems (ACPSs) architecture to achieve precision agriculture. B. Et-Taibi et al. [3] introduced Information and communication technology (ICT) for the optimal usage of resources to achieve better crop yields in Smart Agriculture (SA) Cyber-physical Systems. D. P. F. Moller et al. [1] models the requirements of cyber-physical systems for on-road transport. Yao et al. [4] analyzed CPS-based smart manufacturing-based Internet of Things (IoT), Internet of Services (IoS), and Internet of People (IoP).They proposed a reference architecture for CPS-based manufacturing containing Physical manufacturing resources, Communication networks and Cyber manufacturing services. Thomas et al. [5] emphasized the need for CPS design to develop assembly worker competence. Oks et al. [6] Industrial Cyber-Physical Systems (CPS) refer to the amalgamation of physical and cyber systems employed in manufacturing and smart product contexts, facilitating the provision of pertinent data for value generation. Dafflon et al. [7] reviewed that the success of Industry 4.0 in manufacturing is dependent on key components, including the human component (HC), cyber component (CC), and physical component (PC). Standardizing the interfaces between components such as HC-CC, CC-PC, and HC-PC is necessary to ensure success.

Computer Vision technologies closely integrate cyber and physical systems, allowing for real-time physical systems detection, monitoring, and control. Zhang B et al. [8] introduced an architectural framework for a computer vision-based method tailored for sensing construction sites, intended for application in Cyber-Physical Systems (CPS). Shiquan Ling et al. [9] proposed a human-cyber-physical system (HCPS) framework that uses computer vision tech to monitor the assembly cell system. Athanasios et al. [10] reviewed the deep learning schemes for computer vision to achieve substantial performance in various visual understanding tasks. This article presents the significance of four deep learning models used in computer vision problems: Convolutional Neural Networks, Deep Belief Networks, Deep Boltzmann Machines, and Stacked Autoencoders. Yizhong et al. [11] propose a collaborative resource-batch size optimization configuration method for distributed deep learning systems to optimize AI models' training accuracy and resource cost. Pivoto et al. [12]reviewed the main CPS reference architecture models for Industry 4.0 (5C Architecture, RAMI 4.0, and IIRA), their correlation and interoperability, and common emerging and legacy technologies, protocols and standards. Kannengiesser et al. [13] propose a multi-level method for modelling CPS that involves creating viewpoints and views based on the ISO/IEC/IEEE 42010:2011 standard. Oyesola et al. [14] propose an architectural framework model integrating the manufacturing proposition into a structure. The goal is to promote the manufacturing of customized, smart, and automated mechanical and electronic devices that efficiently utilize integrated Internet networks. Lee et al. proposed a 5-level architecture to guide CPS implementation, improving product quality and system reliability by incorporating intelligent and robust manufacturing equipment [15]. Guzman et al. [16] presented a manufacturing system architecture that integrates agile production, lean manufacturing, statistical approaches, and intelligent modules to optimize manufacturing processes while minimizing errors. All the reference architectures provide a technology-neutral starting point for Artificial Intelligence Cyber Physical System Platform using 7-layer architetcures.

2 Cyber-Physical Systems in Manufacturing

CPS utilizes sensors, actuators, and networked communication to merge the physical and digital worlds and enhance efficiency, safety, and automation in industrial systems. A well-integrated CPS enhances the efficiency, productivity, and safety of manufacturing processes. Integration of AI and computer vision with CPS creates new interdisciplinary opportunities in science and technology. Advanced Computer Vision algorithms improve CPS's real-time interaction and automation efficiency for physical systems and dynamic environments. CPS, a core concept in Industry 4.0, involves the seamless integration of physical processes with computational systems. This integration enhances real-time control and monitoring capabilities. A typical CPS consists of three main components Physical device, Control layer and Computational layer. In physical devices, sensors and actuators are crucial for acquiring real-time data about the physical world and publishing it to the control layer. On the other hand, the control layer is responsible for making decisions on how to control the device. It processes data from sensors and sends commands to actuators. The computational layer provides the necessary computational resources required by the control layer, which may include processors, memory, and storage devices. "Fig. 1" illustrates the essential CPS components in manufacturing. Mechatronic systems are physical devices of CPS. CPS physical devices encompass a diverse range of hardware components. Significant components of CPS physical devices include sensing/controlling physical components, mechanical arrangements, Embedded systems, Control systems software and communication devices. The Cyber core acts as the computational layer within CPS, enabling data simplification, examination, and manipulation between CPS devices and other technologies. The Cyber core encompasses software for data acquisition, processing, storage, analysis, resource management, real-time control, and decision-making. Additionally, it includes operating systems, embedded computing, high-performance computing, and intelligent data analytics. This paper presents a recommendation for the components comprising the Artificial Intelligence Cyber-Physical System Platform tailored for industrial manufacturing.

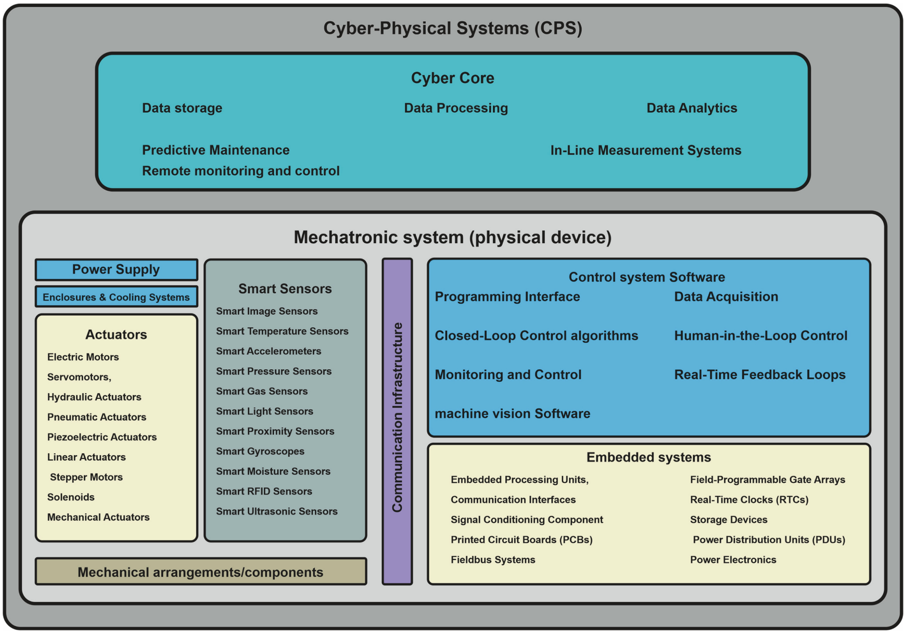

Fig. 1. Cyber-Physical Systems Components

3 Artificial Intelligence Cyber-Physical System Platform

Establishing a robust Cyber-Physical System platform is crucial for the manufacturing industry to remain globally competitive and drive digital transformation. This platform is pivotal in facilitating significant technological advancements and relocations within the industry. This framework has a 7-layer architecture as shown in "Fig. 2". These layers are the CPS Service Configurator, Service Provider, Acquisition layer, logger, publisher, and presentation layer.

3.1 Service Configurator Layer

CPS's physical components encompass sensors, actuators, and PLCs - the primary data-capturing modules in manufacturing. In a cyber-physical system, the live feed of data sources includes various smart sensors, such as those for temperature, pressure, gas, light, moisture, proximity, RFID, ultrasonic, level indicators, and image capture, among others. Mechatronics systems and robots, equipped with sensors and actuators, play a crucial role in the manufacturing industry. These systems generate a large volume of data that can be used to guide decision-making. The data can be used to optimize the manufacturing process, allowing for customized orders to be fulfilled and manufacturing specifications to be adjusted to meet changing standards. The sensors generate heterogeneous data transmitted to embedded systems for further analysis. This service configuration layer provides a platform for configuring and validating the control logic in the embedded system and simulating it. This layer includes a programming interface for the control system to configure the required hardware, digital and analog I/O signals, and the control strategy. Additionally, it features a Machine vision and AI/ML configurator that enables the configuration of computer vision-logic, machine learning, and artificial intelligence algorithms to process vision data.

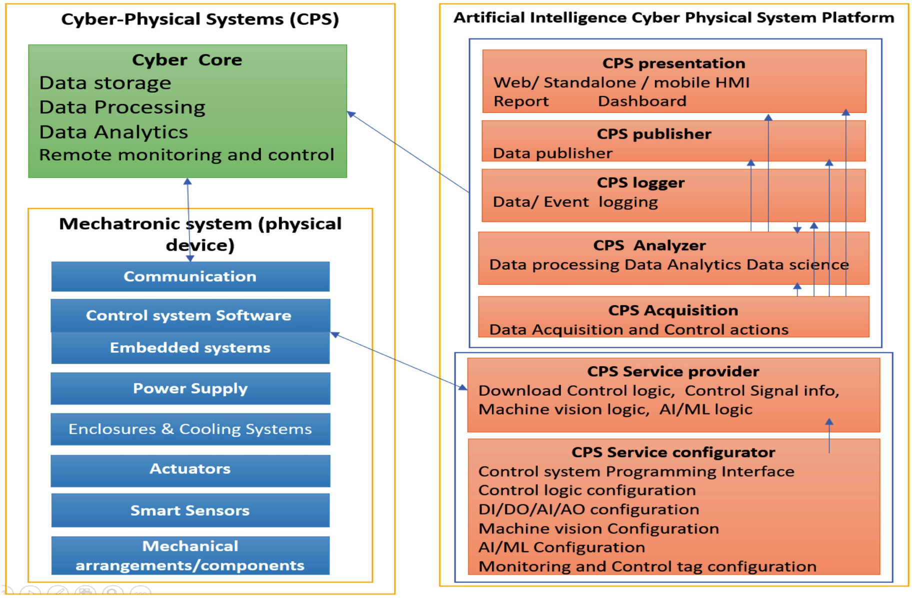

Fig. 2. Layerd Architecture

3.2 Service Provider Layer

Embedded systems are essential in CPS as the computational backbone connecting the physical and digital worlds.They are scalable, redundant industrial controllers for fast processing control loops and efficient IO scans to acquire /control field signals. An AI-based Machine vision algorithm running in the embedded system allows the system to be intelligent, adaptive, and capable of autonomous decision-making. The service provider layer downloads control algorithms, IO scan field signal configurations and AI-based machine vision algorithms from the service configurator layer. Embedded systems process sensor data according to this configuration, make real-time decisions, and control actuators for CPS to interact and respond to surroundings.

3.3 Acquisition Layer

CPS also includes scalable and flexible data acquisition software with a Human-machine interface and Data logger in the cyber core. This acquisition layer acquires real-time data from the CPS physical device. It provides data to other layers like logger, publisher and presentation in the cyber core to enable real-time monitoring, analysis, and control. In CPS, real-time data acquisition is essential for timely decision-making and management. Data from physical devices is transmitted to the digital world using wired or wireless communication protocols such as Modbus, MQTT, CoAP, or other industry-standard communication protocols. Network protocols, such as TCP/IP and Ethernet, ensure seamless data transfer and synchronization. This cyber core bottom layer employs a standardized data model interface to handle data transmitted and received by various subsystems within the framework. This interface establishes dependable, scalable, flexible, consistent, and secure data models to ensure interoperability for real-time processes. Secure communication protocols and encryption methods ensure the confidentiality and integrity of data during acquisition. The acquisition layer utilizes standardized interfaces and communication protocols to facilitate interoperability with other components of the CPS.

3.4 Analyzer Layer

The cyber core is a crucial component of CPS that enables precise control and optimization of the system by utilizing advanced algorithms, real-time data processing, and adaptive control strategies. The analysis layer derives insights, makes informed decisions, and optimizes the system's performance. The cyber core facilitates collecting, storing, managing, and analysing extensive data from CPS sensors. This data is vital for optimising system performance, detecting anomalies, and making informed decisions. The cyber core also empowers CPS with predictive maintenance capabilities, allowing them to anticipate potential failures and schedule proactive maintenance, reducing downtime and improving system reliability.

Data analysis in CPS involves processing and interpreting the data collected from the acquisition layer. Preprocessing and standardisation techniques ensure consistency in analysis. Descriptive statistics parameters such as mean, median, and standard deviation are used to determine the central tendency and variability of the collected data to summarise data. Time series analysis techniques are employed to discern patterns and trends within data across successive intervals. It is commonly used for forecasting future events based on historical data. Machine learning techniques are applied to predict system behaviour and anomalies. Optimization algorithms enhance process efficiency based on data analysis.

3.5 Logger Layer

The logger layer plays a pivotal role in enabling the effective operation of CPS. This data storage layer's demands increase for real-time data access, scalability, security, and privacy. CPS physical device data volumes can overgrow as systems expand and collect more data. In the framework, accurate, consistent, and unaltered data is readily accessible to different users through a standardized interface. Data loggers efficiently scale to handle increasing data volumes and store acquired data while safeguarding sensitive information from breaches. The processing of extensive data from sensor actuators is crucial for facilitating rapid insights in real-time, batch, or remote control operations.

3.6 Publisher Layer

The cyber core publisher layer enables CPS to integrate and collaborate with other systems, enabling data sharing, coordinated actions, and interconnected operations. The publisher layer feeds data to the analytics layer and control systems. The communication components within this platform facilitate straightforward access, monitoring, and analysis of CPS physical devices while offering adaptable resource management. The data provider interface in the platform transmits the processed information to the appropriate CPS components, including the service provider layer, data analytics layer, and Presentation layer. This layer serves as a connection between the physical device and the cyber core. Data publishing standards using topic hierarchies help categorize and manage data streams based on their origin, type, or location within the CPS.

3.7 Presentation Layer

The cyber core provides user interfaces and interaction platforms that enable humans to monitor, control, and interact with CPS. The presentation layer transforms raw data into meaningful visual representations, facilitating comprehension, analysis, and decision-making. HMIs range from simple displays and control panels to advanced visualization tools and augmented reality systems. Visual analytics provide functions of descriptive and inferential statistics with analytical chart generation. It helps to create analytical models in graphic mode. Time-series charts enable users to track trends and changes in data over time. Digital Twin and 3D models are used to understand the CPS dynamics. Numerical values, text, images, and other data formats are used to monitor real-time data and set control logic parameters. Data visualization enables CPS to make informed decisions based on real-time data analysis, historical trends, and machine learning techniques. This data is valuable for trend analysis, anomaly detection, and predictive maintenance.

4 Implementation Approach of AI Cyber-Physical System Platform in a Manufacturing Industry

The manufacturing industry has taken the first step towards digitalization by implementing a PLC system and SCADA technology based on the layered architecture proposed by Industry 3.0. The objective is to reduce the need for operator intervention in the manufacturing process. This implemented architecture consists of Field sensors, Smart Electronics/Control Systems, Data acquisition, Data processing, Data storage, Data provider and Data visualization. Industry 3.0 Automation solution includes a Controller, Control system configurator, Web SCADA HMI, Reports and Expert system. This industrial automation transforms manufacturing operations, achieving greater efficiency, productivity, and quality control and enhancing employee skills and engagement.

Second-level digitalization for implementing Industry 4.0 involves a strategic and phased approach to integrate digital technologies, data-driven processes, and automation into manufacturing and industrial operations. Industry 4.0 aims to virtualize and modularize production processes using smart electronic devices, cloud computing, edge computing, IoT, DigitalTwin and industrial robots. 'Fig. 3" shows the AI Cyber-Physical System Platform's primary building blocks: Service Configurator, Application Services, Analyzer, Logger, and Visualizer, integrated for supporting instrumentation and measurement in Industry 4.0.

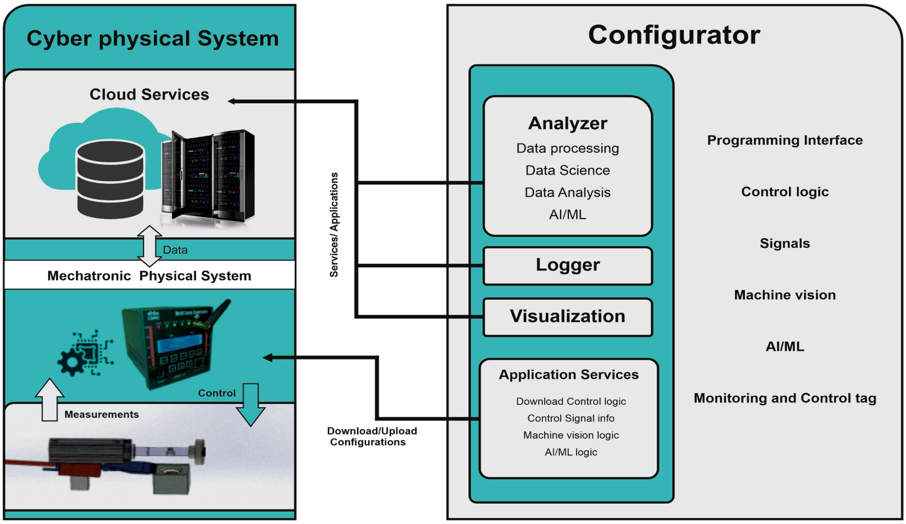

Fig. 3. AI Cyber-Physical System Platform

The AI Cyber-Physical System Platform utilizes the Service Configurator to facilitate the configuration of sensors, actuators, and control algorithm logic to the embedded system of CPS. Configurators provide the configuration of sensors to measure relevant physical parameters and Configure actuators to execute desired actions based on control signals. Control algorithm logic includes proportional-integral-derivative (PID) controllers, model predictive controllers, fuzzy logic controllers, or other advanced control strategies. The Configurator sets sensor calibration, sampling rates, and data acquisition parameters. Define actuator parameters, including response times, operating ranges, and safety limits. The machine vision configurator with an algorithm library readily available in the Platform Service Configurator layer allows the configuration of computer vision and ML/AI logic necessary for CPSs. This AI algorithm is applied to optimize control strategies in CPS. After the configuration of control logic and signal information, they can be downloaded and executed in the embedded system by the Application Service running in the Platform. The embedded system measures sensor data and controls the actuators for physical processes. This automation streamlines the production process and optimizes resource utilization. Computer vision and ML/AI logic are downloaded and executed in the embedded system to control the machine vision process. This adaptive control logic allows the system to adjust its behaviour in response to changing conditions. Embedded systems processe the measured data from the sensors and provide insights into the various aspects of the physical process.

The cloud core in CPS is responsible for managing and analyzing the data generated by the physical system, using cloud services provided by the platform. The data acquisition service collects data from the physical device, pre-processes it, and provide it to storage, analytics, and visualization services. Using the AI Cyber-Physical System Platform, we can evaluate production decisions based on analytics performed at the Cloud core in the CPS. This platform provide tools and libraries to accelerate the development of CPS. Simulating CPS behavior prior to deployment is advantageous, as it aids in early identification and resolution of issues during the development lifecycle.

5 Advantages of the System

AI Cyber-Physical System Platforms offer improved efficiency, productivity, safety, and security to manufacturing industries. These platforms combine digital systems with sensors and actuators to enable real-time monitoring and control of physical processes. This enables immediate response to changing conditions, resulting in increased efficiency. CPS platforms optimize resource allocation using data analytics and optimization algorithms, leading to cost savings, improved resource efficiency, and reduced waste.

6 Challenges

Integrating Cyber-Physical Systems (CPS) into existing industrial infrastructure can be challenging due to legacy systems, data compatibility issues, and cybersecurity concerns. A CPS only applies to the manufacturing industry if the plant is appropriately automated using a challenging computerized system and fully operational and calibrated instruments. However, implementing a CPS in manufacturing poses significant challenges due to the heterogeneity of manufacturing equipment, data security, privacy concerns, and a need for more standardization in the platform. It is crucial to cultivate a proficient workforce with cybersecurity, data analytics, and industrial automation expertise to operate, maintain, and manage CPS for successful implementation and adoption. Integrating standardized communication protocols, robust cybersecurity frameworks, and skilled workforce training programs can enable an intelligent, connected, and efficient future of manufacturing.

To tackle the challenges associated with integrating legacy systems, we recommend implementing a middleware communication module and creating a custom interface to facilitate data exchange and interoperability between legacy and CPS systems. Employing data transformation and normalization techniques for data structure and meaning inconsistencies is essential. Follow industry standards like OPC UA (Open Platform Communications Unified Architecture). Adequate training and upskilling initiatives are necessary to safeguard an organization's cyber networks. Engaging in partnerships with educational institutions and training providers to create tailored programs addressing CPS requirements can yield valuable outcomes. Providing comprehensive training for employees is necessary to defend against potential threats.

7 Conclusion

Our paper proposes a versatile platform that can potentially transform the manufacturing industries. Introducing Cyber-Physical Systems can be a game-changer in the era of Industry 4.0. The CPS technology can drive innovation, increase productivity, and enable new levels of intelligence and autonomy in various industrial sectors. The proposed AI Cyber-Physical System Platform integrates digital intelligence, such as real-time monitoring, predictive maintenance, and flexible production systems with physical processes. By connecting remote modules, digitizing and centralizing data, and analyzing production data, the platform can optimize and enhance the production process. The digital transformation of manufacturing industries using the proposed platform can contribute to cost efficiency in terms of development time, resources, and overall project costs.

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