A Case Study on the Software-Defined Manufacturing for AI-based Autonomous Manufacturing

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***Abstract*—Recent advances are shifting manufacturing from automation toward fully autonomous, AI-driven systems. Achieving AI-based autonomous manufacturing demands seamless, real-virtual integration across all process stages, extending beyond individual machine control. This study introduces a software-defined manufacturing framework that combines integrated process control with virtual commissioning to enable such end-to-end coordination. We apply this methodology to an automotive manufacturing process, demonstrating its effectiveness through a case study. In the last, future Software-Defined Manufacturing research issues for the AI-based autonomous manufacturing are summarized.**

***Index Terms*—Software-Defined Manufacturing (SDM), AI-based Autonomous Manufacturing, Virtual Commissioning (VC), Digital Twin (DT), Integrated Process Control**

I. Introduction

In the era of next-generation manufacturing, the industrial landscape is undergoing a rapid transformation from traditional automation toward Artificial Intelligence (AI)-based autonomous production. While conventional industrial automation systems have played a pivotal role in achieving high-speed mass production, they are increasingly constrained by the growing demand for product variety and customization. To overcome the inherent inflexibility of traditional manufacturing, industry trends are shifting toward highly adaptable production systems. This evolution involves the adoption of flexible manufacturing systems, which integrate automated machinery with advanced control architectures to efficiently manage diverse product lines. The incorporation of robotics, AI, and the Internet of Things (IoT) further enhances system adaptability, enabling rapid reconfiguration and on-demand customization in response to dynamic market requirements.

The realization of AI-enabled autonomous manufacturing hinges on three key capabilities: real-time data acquisition, integrated control across the entire production process, and simulation-driven prediction and optimization. Software-Defined Manufacturing (SDM) has emerged as a critical foundation for these capabilities, enabling software-based specification, orchestration, and optimization of manufacturing operations [1], [2]. Unlike traditional hardware-centric systems, SDM shifts the control paradigm toward software-driven adaptability, facilitating intelligent, reconfigurable, and autonomous manufacturing environments. Through the convergence of information technology (IT) and operational technology (OT), SDM aims to enhance efficiency, productivity, and quality while minimizing human intervention. Within the SDM paradigm, Digital Twin (DT) and Virtual Commissioning (VC) technologies have gained prominence as essential enablers [3], [4].

A DT is a high-fidelity digital replica of a physical manufacturing system, encapsulating its equipment, processes, products, and operating environment. This digital representation is continuously synchronized with its physical counterpart through real-time data acquisition from sensors, control systems, and production databases, ensuring that the virtual model accurately reflects the current factory state. Once established, the DT enables systematic variation of environmental and operational parameters, such as machine operating conditions, production schedules, or material properties to perform extensive simulations and predictive analyses. These capabilities allow the evaluation of system performance, identification of potential bottlenecks, and validation of optimization strategies under diverse scenarios, all without disrupting actual operations. By leveraging DTs, AI algorithms can execute large-scale simulations and learning processes under conditions closely approximating real-world scenarios.

VC complements this by providing a methodology for validating and optimizing control logic, such as programmable logic controller (PLC) code, within the DT environment. This approach allows exhaustive testing prior to physical deployment, thereby reducing commissioning time and mitigating operational risks. In the context of SDM, where frequent software-driven reconfiguration is common, VC serves as a vital safeguard to ensure system stability and functional integrity.

This paper investigates the role of SDM as a core methodology for enabling AI-based autonomous manufacturing and proposes a real–virtual integrated framework to demonstrate its applicability. The proposed approach is applied to an automotive production process, leveraging DT and VC technologies to validate AI-generated control logic without interrupting ongoing production. The results highlight tangible benefits, including reduced commissioning time, enhanced production flexibility, and data-driven process optimization.

II. Research Background

A. Autonomous Manufacturing

Autonomous manufacturing represents an evolution beyond the Industry 4.0 smart factory, wherein production systems autonomously perceive, evaluate, and control their operational states with minimal human intervention [5]. It is founded on the convergence of advanced technologies, including artificial intelligence (AI), DT, robotics, and sophisticated software and control architectures. This integration supports the transition from traditional mass production to multi-product, small-batch manufacturing and mass personalization, enabling rapid adaptation to fluctuating market demands and frequent product design changes. While early research efforts predominantly addressed automation of isolated processes, recent studies have increasingly focused on the application of AI to dynamic scheduling and holistic optimization across entire production lines [6]. Achieving the envisioned paradigm of mass personalization will require continued progress in self-organizing manufacturing systems (SOMS) and the development of human-centered AI models capable of continuous learning and adaptation to support human operators [7].

A significant trend is the shift from centralized control architectures toward a decentralized autonomous manufacturing paradigm. In this model, individual production entities communicate and collaborate to respond autonomously to unpredictable situations [5]. Such a distributed approach directly aligns with the resilience principles central to the Industry 5.0 vision. Ultimately, autonomous manufacturing aims to empower systems to make optimal, independent decisions, thereby redefining efficiency, adaptability, and responsiveness in modern industrial operations [5], [6]. Furthermore, ongoing advancement in DT technologies remains essential, particularly in providing concrete, domain-specific use cases that demonstrate clear and measurable benefits in practical settings [8].

B. Virtual Commissioning

VC is an advanced manufacturing methodology in which a virtual representation of a physical production system is created and simulated to test, validate, and optimize control logic, processes, and operational sequences prior to the installation or modification of physical equipment [9]. Its growing importance is closely tied to the increasing complexity and automation of modern manufacturing [3]. The primary objective of VC is to minimize production downtime by enabling virtual validation and optimization, thereby avoiding prolonged line shutdowns during the integration of new equipment or process designs. By verifying operational processes and ensuring compatibility between new equipment and existing PLCs, VC significantly reduces troubleshooting time during on-site

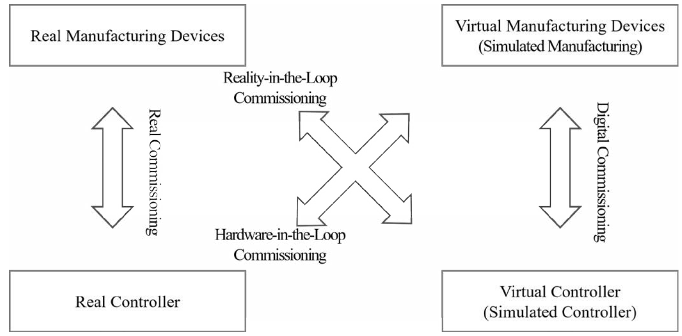

Fig. 1. Commissioning configurations of a manufacturing system [10]

commissioning. Furthermore, VC facilitates pre-production simulations to evaluate equipment utilization, predict production capacity, and estimate output potential based on variables such as production load, workforce availability, and equipment configuration.

Commissioning in manufacturing systems can generally be categorized into four configurations as illustrated in Fig.1 [10]:

- **Real Commissioning**: A real manufacturing system operates with a physical hardware controller and manufacturing devices.
- **Virtual (Hardware-in-the-Loop) Commissioning**: A simulated manufacturing system operates with a real hardware controller and virtual manufacturing devices.
- **Reality-in-the-Loop Commissioning**: A physical manufacturing system operates with a simulated (virtual) controller and real manufacturing devices.
- **Digital Commissioning**: A simulated manufacturing system operates with both the simulated controller and virtual manufacturing devices.

Originally focused on verifying PLC control logic, VC has evolved into a core methodology for validating and integrating models across the entire system lifecycle, including robotics, collaborative automation systems, and DT environments [4], [10]–[13]. This evolution underscores its growing role as an enabling technology for autonomous manufacturing systems.

Despite these advantages, several limitations of VC have been noted in the literature. The complexity and cost associated with high-fidelity model development remain significant barriers to widespread adoption, particularly for small and medium-sized enterprises [3], [9]. The effectiveness of VC depends on access to high-quality, consistent, and accurate data. However, manufacturers often struggle to collect and store massive volumes of disorganized historical data from diverse equipment, and require extensive machine learning expertise. A significant and often unresolved issue is the integration of VC solutions with existing legacy enterprise systems, such as Manufacturing Execution Systems (MES) and Enterprise Resource Planning (ERP), as well as other diverse technologies on the factory floor [7].

C. Software-Defined Manufacturing

SDM represents a transformative paradigm in industrial automation, drawing conceptual inspiration from software-defined networking [1]. Fundamentally, SDM seeks to decouple control software from its underlying hardware through an abstraction layer [14], [15]. This architectural shift is designed to maximize manufacturing system flexibility and reconfigurability, enabling rapid adaptation to dynamic production demands. By facilitating hardware-independent software design, SDM promotes reusability and adaptability, reducing the engineering effort required for future production changes.

The implementation of SDM leverages a suite of advanced technologies to create a flexible, intelligent manufacturing environment. AI and machine learning (ML) enable real-time data analytics, predictive maintenance, quality monitoring, and process optimization. DT technology supports virtual simulation, testing, and validation of manufacturing processes prior to physical deployment, facilitating rapid reconfiguration. Robotics automate physical operations, while IoT sensors provide real-time equipment and process monitoring. These capabilities are supported by robust connectivity, scalable cloud infrastructures with edge computing, integrated MES, advanced control software, and comprehensive cybersecurity measures.

A key enabler of SDM is the adoption of virtualized PLCs, which execute control logic on commercial off-the-shelf (COTS) servers rather than dedicated hardware [14]. This approach enables integrated operation of controllers from multiple vendors on a unified platform, eliminating hardware dependency and improving resource utilization.

The flexibility inherent in SDM extends to rapid and dynamic system reconfiguration [16]. By abstracting control functions into software, manufacturers can adapt production lines to new product variations or process changes with minimal physical intervention. New functions and modules can be introduced during ongoing operations without halting production. This adaptability is reinforced by real-time operating systems and advanced virtualization technologies, which optimize performance for mission-critical control applications while allowing multiple applications to run independently on a single platform [1].

Ongoing research in SDM explores integration with cloud-based control, simulation-driven configuration, and data-centric optimization methodologies. These developments aim to enable fully automated system configuration and optimization, pushing the boundaries of autonomous, highly adaptable manufacturing [15].

III. Proposed Archtecture

A. The real-virtual integrated system framework

The real–virtual integrated system framework proposed in this study for AI-based autonomous manufacturing is organized into a three-layer architecture: the Service Layer, the Virtual Layer, and the Physical Layer. The design adheres to the principles of software-defined manufacturing (SDM) by clearly decoupling hardware from software and enabling organic interaction among layers to achieve end-to-end system autonomy. The proposed framework is illustrated in Fig. 2.

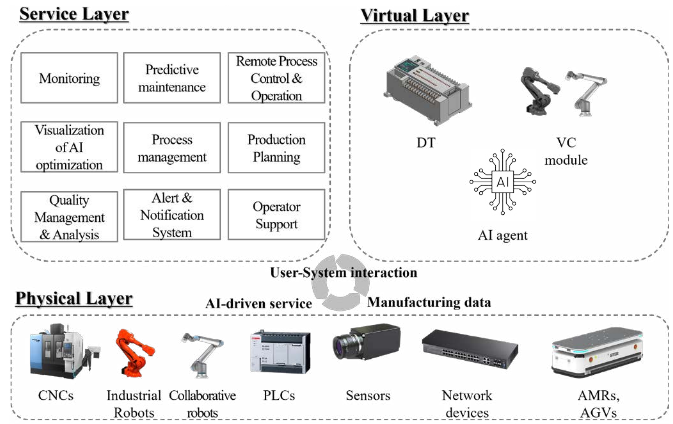

Fig. 2. Real-virtual integrated system framewor

- **Physical Layer**: This layer comprises all physical assets within the manufacturing environment, including CNC machines, industrial robots, collaborative robots, PLCs, and a variety of sensors deployed on the shop floor. The Physical Layer executes production tasks according to control commands issued from the Virtual Layer, while continuously generating real-time status data for feedback to higher layers.
- **Virtual Layer**: Serving as the system's intelligence core, this layer integrates three primary components: the DT, the AI Agent, and the VC module. The DT operates as a real-time virtual replica of the Physical Layer, capturing equipment states, process flows, and environmental conditions. The AI Agent leverages this environment to learn from operational data and derive optimal control policies. Before deployment, the VC module validates these AI-generated policies within the DT environment, ensuring both safety and efficiency prior to execution in the Physical Layer.
- **Service Layer**: This layer manages human–system interaction and provides high-level application services. Key functionalities include process monitoring, predictive maintenance, visualization of AI-generated optimization results, and approval workflows for their deployment. Through these services, operators can effectively oversee, configure, and supervise the manufacturing process.

B. The Data flow

The data flow within the proposed real–virtual integrated framework operates in a closed-loop process consisting of five sequential stages: collect, synchronize, analyze and learn, verify, and apply, as illustrated in Fig. 3.

In the collect stage, sensor and equipment data from the Physical Layer are transmitted in real time to the Virtual Layer via standard industrial communication protocols, such as OPC Unified Architecture (OPC-UA). The DT receives this data to

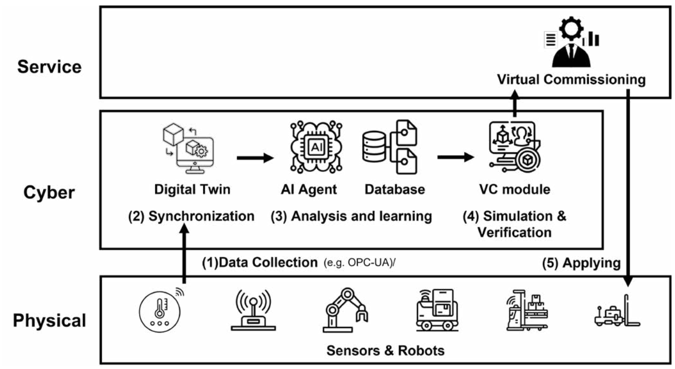

Fig. 3. Data flow of proposed architecture

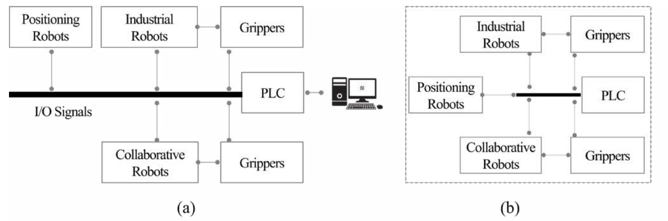

Fig. 4. The I/O mapping of the manufacturing process (a) Physical I/O mapping (b)Virtual I/O mapping

maintain continuous synchronization with the physical factory. A virtual model of the manufacturing cell is generated and updated to reflect any proposed modifications to the physical station, ensuring that the DT remains an accurate and high-fidelity representation of the shop floor.

In the analyze and learn stage, the AI Agent processes both real-time and historical data from the DT to detect operational issues, such as reduced productivity, process bottlenecks, and abnormal equipment behavior. Leveraging predictive analytics, the AI Agent forecasts potential system performance trends, equipment failures, and production slowdowns, enabling proactive intervention. Based on these insights, it learns and formulates optimal control policies, which may include robot motion paths, work sequences, and process parameter adjustments. The DT model itself is continuously refined based on feedback from AI-driven analysis, ensuring higher fidelity to the physical system.

In the simulation and verify stage, the generated control policy is transferred to the VC module, where it undergoes extensive simulation-based validation. Thousands of virtual execution cycles are performed to check for potential issues such as equipment collisions, excessive cycle times, or process instability.

In the apply stage, only the control policies that have passed VC validation are deployed to the PLCs and robot controllers in the Physical Layer. Deployment requires explicit approval from the Service Layer, which provides a clearly defined and streamlined approval workflow. This process enhances system reliability and reduces the likelihood of human error. A rapid rollback mechanism is also incorporated to restore the system to a safe, previously validated state in the event of unforeseen issues following deployment.

Through this cyclical feedback process, the SDM-based framework iteratively improves its operational performance, adaptability, and overall efficiency. Moreover, the proposed architecture offers several notable advantages. By enabling early validation and optimization of control policies in the virtual domain, it significantly reduces commissioning time and minimizes unplanned downtime. The clear separation of hardware and software facilitates rapid reconfiguration of production lines, supporting multi-product and small-batch manufacturing with minimal physical intervention. The integration of AI-driven analysis with DT and VC enhances decision-making accuracy, while the closed-loop feedback ensures continuous system learning and self-optimization. From an operational point, these capabilities lead to improved resource utilization, higher production flexibility, and more resilient manufacturing systems capable of responding effectively to dynamic market demands.

IV. Experimental Case Study

A. Application of the Proposed Framework

This study demonstrates the applicability of the proposed real–virtual integrated framework through a case study involving the automotive Body-in-White (BIW) assembly process. The BIW stage is one of the major phases in automotive manufacturing. The complete assembly process begins with the stamping of sheet metal into body panels, which are subsequently joined during the BIW stage to form the vehicle's rigid, unpainted body shell. The assembled body then proceeds to the paint shop for multi-layer coating and protective treatments, followed by the General Assembly stage, where the engine, chassis, interior, electronics, and other components are installed. The process concludes with comprehensive quality control and inspection to ensure compliance with performance and safety standards.

Within the BIW stage, the metal body structure, essentially the vehicle's structural skeleton, is constructed from individual stamped components. The assembly process is highly automated, involving coordinated sequences of robotic operations to achieve the required precision, structural integrity, and durability. Due to frequent product changeovers in modern automotive manufacturing, flexibility in BIW operations has become a critical requirement.

In this case study, a DT was developed for the BIW door assembly cell. The DT includes multiple industrial robots, collaborative robots, positioning robots, and a PLCs. All robots are six-axis articulated manipulators, designed for high-precision welding and handling tasks. Fig.4(a) presents the I/O mapping of the Physical Layer, while Fig.4(b) depicts its corresponding virtual replica used for VC. All robot movements are controlled through PLCs, and the configuration allows the results verified virtually through VC to be applied to actual manufacturing processes.

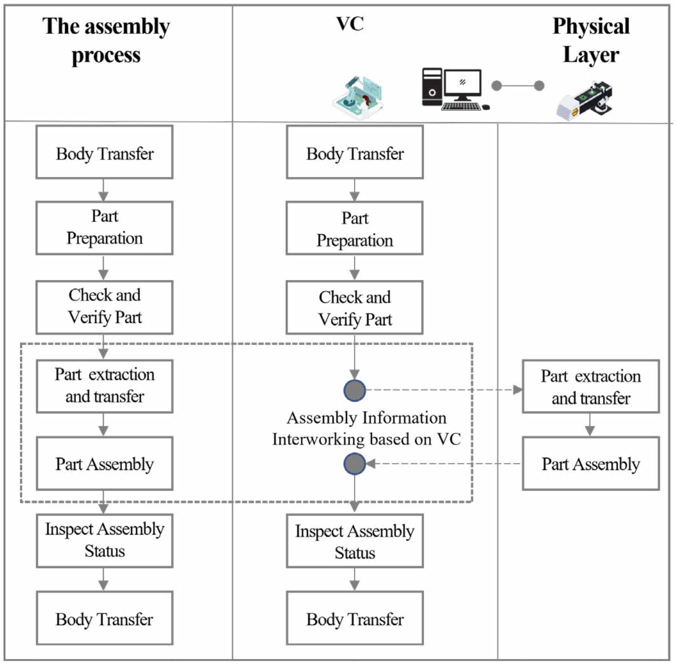

Fig. 5. The assembly process of door in BIW

B. Scenario of the Door Assembly Process

We consider a scenario in which the three-axis points and robot paths for the BIW door assembly are modified to accommodate the production of two different vehicle types. Fig. 5 illustrates the sequence of the BIW door assembly process. Upon arrival of the vehicle body at the assembly cell, industrial robots prepare various parts required for installation and perform defect checks on the prepared components. The correct parts are selected from the available materials, assembled onto the vehicle body, and subsequently inspected to ensure assembly quality. Even in the same assembly process, the robots in the actual physical layer must change their movements to assemble different car types. This sequence varies according to vehicle type, necessitating distinct robot motion commands and process parameters for each variant.

The VC environment replicates this process and interfaces with the Physical Layer, represented by a pilot test line. The pilot test line is configured to emulate the actual production environment while utilizing a minimal set of essential equipment. Robot task generation, modification, and process control are managed within the VC environment, as depicted in Fig. 6.

Fig.6(a) illustrates the AI-driven process for robot code generation and optimization within the VC, including simulation-based verification and iterative refinement. Once the optimized robot task code is finalized, it is transmitted to the Physical Layer for execution. The updated code is tested in the pilot line environment, as shown in Fig.6(b). If previously undetected errors occur during testing, the corresponding robot tasks are revised within the VC environment and re-deployed to the Physical Layer.

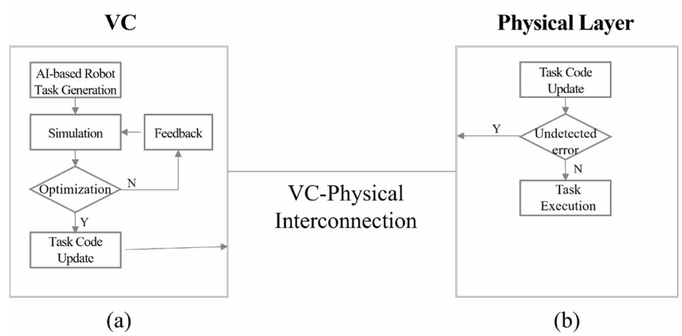

Fig. 6. Robot Task Generation and Update between VC and Physical Layer: (a) AI-based Code Generation and Optimization in VC, (b) Robot Task Execution in the Physical Layer

V. Discussion

This study proposed a real–virtual integrated system framework based on SDM for AI-enabled autonomous manufacturing, emphasizing seamless integration between virtual and physical environments. The framework was validated through an experimental case study involving the BIW door assembly process. The approach demonstrated effective integration of virtual and physical layers for AI-driven robot task generation, optimization, and execution, without interrupting the actual production line.

While the proposed framework marks progress toward practical AI-based autonomous manufacturing, it has several limitations. The current implementation was restricted to a specific process within the BIW stage, limiting generalizability to other production scenarios. Furthermore, although the VC environment accurately replicated the target process, its application was confined to a pilot test line. This restricted the evaluation of VC scalability and complexity when applied to full-scale, multi-line production environments.

Advancing AI-based autonomous manufacturing will require the development of high-performance AI control algorithms capable of handling and optimizing complex production processes in real time. In the SDM context, AI must evolve beyond data analysis to deliver autonomous decision-making and execution capabilities. This includes real-time prediction of factors affecting productivity and automatic generation of optimal policies, such as robot trajectories and process sequences. For effective human–machine collaboration, research into explainable AI (XAI) techniques is necessary to make AI-driven decisions transparent to human operators, along with the development of intuitive human–machine interfaces. Where AI anticipates potential equipment failures and autonomously reconfigures or recovers processes Self-healing systems also represent an important research direction.

In addition, the adoption of standardization technologies and open architectures will be critical to ensuring seamless interoperability among diverse manufacturing systems and solutions. Ultra–high-fidelity digital twin models, capable of reflecting even minute changes in physical systems, must be developed and efficiently updated. Finally, robust cybersecurity mechanisms are essential to safeguard networked manufacturing environments, complementing self-healing capabilities to ensure operational stability in the face of unpredictable disruptions.

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