International Journal of Emerging Research in Engineering and Technology
Pearl Blue Research Group | Volume 4, Issue 2, 87-94, 2023
ISSN: 3050-922X | https://doi.org/10.63282/3050-922X.IJERET-V4I2P109

Original Article

MES-Enabled Cyber-Physical Production Systems: Accelerating Automotive Line Efficiency via Real-Time Decision Frameworks

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Abstract *- The high pace of digitalization of the manufacturing process in the automotive sector creates the need to integrate modern technologies that foster efficient operations, minimize waste, and raise the level of market responsiveness. In combination with the Cyber-Physical Production Systems (CPPS), the Manufacturing Execution Systems (MES) provide a revolutionary path to an optimal production process flow in real-time. In this paper, the author will discuss the implementation and revealing analysis of MES-enabled CPPS through their application in enhancing efficiency in an automotive production line. The suggested real-time decision-making models have used machine data, context-based data, and predictive analysis to make dynamic planning of production processes. In contrast to traditional manufacturing systems, where latency and fragmentation in the decision cycle are in place, MES-integrated CPPS creates a closed-loop ecosystem, which offers smooth vertical and horizontal integration of shop floor and enterprise-level IT infrastructure. The paper provides a modular decision-making process concept in real time, proves the modelled concept with a case study in a medium-sized car assembly plant, and provides benchmarks of efficiency improvement. The reason the real-time decision logic can function is that it is sustained by edge-computing devices, integrated digital twins, and machine learning models that forecast bottlenecks and proactively adjust the workflow. We demonstrate that we can improve Overall Equipment Effectiveness (OEE) by up to 23.5 per cent, reduce the Mean Time To Repair (MTTR) by 19.3 per cent, and make the production schedule more accurate by 28.7 per cent. Moreover, the study has identified interoperability standards, system architecture, and communication protocols that are critical to scalable deployment. These results are supported by a combination of simulation-empirical methodology, which utilises the Arena simulation program, and the integration of sensor-based data in real-life settings. The study stresses the potential of MES-enabled CPPS as a staple of Smart Manufacturing through Industry 4.0 and opens the path towards autonomous production through the automotive industry.*

Keywords *- Cyber-Physical Production Systems (CPPS), Manufacturing Execution System (MES), Industry 4.0, Real-Time Decision-Making, Automotive Manufacturing.*

1. Introduction

With the advent of Industry 4.0, new paradigms of manufacturing have emerged on the one hand due to the tight coupling of computational intelligence and real-world manufacturing processes introduced by Cyber-Physical Production Systems (CPPS). Such a combination of the digital and real worlds can make the factories smarter, more flexible and more autonomous. [1-3] The pressure on vehicle manufacturers to increase throughput in production, enhance adherence to high-quality standards, and strive to compress time-to-market is developing conversations along with the demands of fast product customization and short life cycles. Conventional manufacturing systems that are usually fixed and responsive find it hard to match up to such evolving demands. The Manufacturing Execution System (MES) is used in this context as the backbone of the manufacturing operation, bridging the gap between enterprise planning and shop-floor execution. When integrated into the middleware of a CPPS, MES is enhanced to perform predictive and data-driven control of production processes. The integration gives the manufacturers the ability to overcome proactive reactions to disruptions, real-time allocation of their resources, and ongoing enhancement of efficiency. The rationale of the current research is to leverage the synergy between MES and CPPS to develop an intelligent, responsive production system tailored to the demands of the modern automotive production industry.

1.1. Role of MES in Smart Manufacturing

With Industry 4.0, Manufacturing Execution System (MES) has been seen as a key component in closing the gap between the high-level product planning systems of an enterprise and low-level production floor activities. As manufacturing becomes digitalised and networked, MES serves as the choreographer of intelligent production, enabling real-time data granularity, process visibility, and execution control.

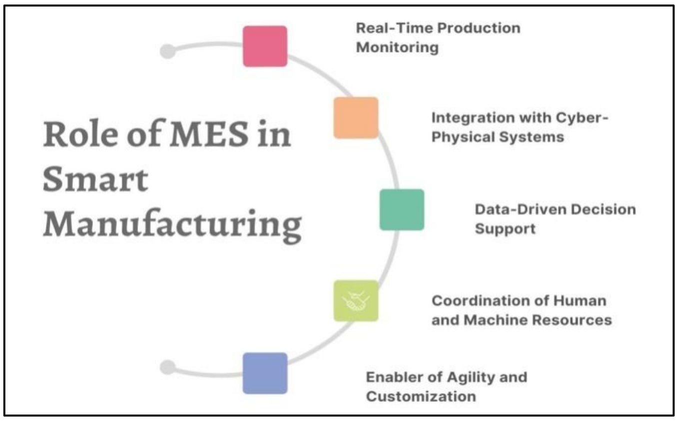

Fig 1: Role of MES in Smart Manufacturing

- **Real-Time Production Monitoring***:* MES will allow constant monitoring of the production process, taking its information from machines, operators, and sensors on the fly. This enables the manufacturers to monitor work in progress, track any deviations, and respond to unexpected events quickly. That is because in intelligent factories, information about the location of goods, processed materials, and all operations is available in real-time. Therefore, every interaction is based on the most accurate and up-to-date state of affairs, thereby delaying consequences and making them more responsive.
- **Integration with Cyber-Physical Systems***:* Smart manufacturing is based on the seamless integration of digital and physical elements. MES is the central controlling unit that can communicate with Cyber-Physical Production Systems (CPPS) and can provide synchronized operations of machines, robots, and digital twins. This interconnectivity facilitates autonomous, predictive, and adaptive maintenance, as well as adaptive scheduling, which are the hallmarks of a smart production environment.
- **Data-Driven Decision Support***:* Through collecting and interpreting extreme volumes of production information, MES is able to use progressive analytics and machine learning calculations to recognize inadaptability, foresee breakdowns, and also streamline procedures. The system uses actionable intelligence that boosts the key performance indicators like Overall Equipment Effectiveness (OEE), cycle time, and quality rates. This data-centric architecture can transform MES into an active decision-support system, rather than a passive controller, in smart manufacturing.
- **Coordination of Human and Machine Resources***:* Smart manufacturing is a mixture of human intelligence, and machine intelligence. MES is a resource allocation provider that organizes work among operators, machines, and self-healing systems. It makes sure that appropriate resources are there at appropriate time, facilitating production without compromising on the safety and compliance levels.
- **Enabler of Agility and Customization***:* Contemporary customers require a wider range and quicker delivery. Between mass production and customization, MES balances on manufacturing with a dynamic production order by modifying the production order in accordance with the changing customer order, material status, or production status. Without this agility, smart manufacturing cannot succeed in its efforts to compete, as flexibility and responsiveness define its competitive advantage.

1.2. Challenges in Traditional Automotive Production Lines

Although the automobile industry has enjoyed efficiency over the years, the sector is experiencing increasing constraints in traditional manufacturing schemes. Such drawbacks limit responsiveness, optimization and flexibility to the requirements of modern, low volume, high mix production.

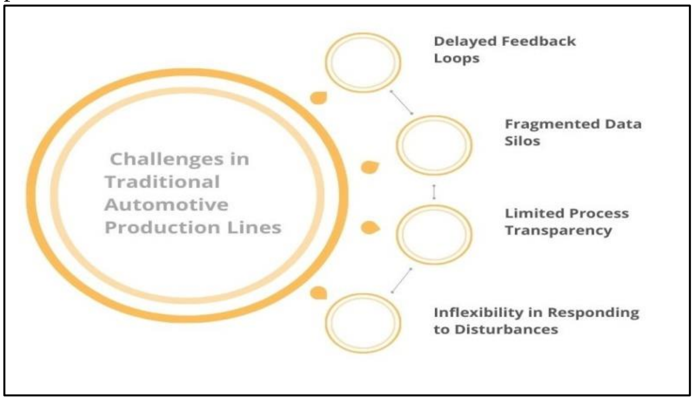

Fig 2: Challenges in Traditional Automotive Production Lines

- **Delayed Feedback Loops:** Feedback between the shop floor and decision-makers in traditional production lines often experiences delays due to manual reporting or the integration of systems. Such a delay in the flow of information causes a delay in response to production problems, quality variance or machine failures. As a result, opportunities to perform a corrective measure in real-time are lost, potentially leading to prolonged downtimes and reduced overall performance.
- **Fragmented Data Silos:** Automotive plants typically have a variety of systems, including ERP, SCADA systems, quality control, and maintenance systems, which are not integrated and operate in silos. Such pieces of disjoined data silos do not allow an end-to-end view of the production lifecycle. The absence of streamlining data moves would make it hard to obtain meaningful insight or even perform the optimization of the system across the board, making the operations inefficient and more complex.
- **Limited Process Transparency:** Conventional manufacturing settings often lack real-time availability of process status, equipment status, and production metrics. As a result, managers and operators rely on paper-based records or outdated dashboards, making it difficult to monitor performance and identify the cause of disruptions. Such non-transparency hinders constant improvement and almost prevents proactive decision-making.
- **Inflexibility in Responding to Disturbances:** Fixed work processes in traditional production lines can hardly react to unforeseen circumstances like breakdowns of machines, delivery shortages, or orders that need to be altered on short notice. The inability to schedule adaptively and forecast diagnostics implies that even the most minor perturbations may escalate into significant production losses. Such rigidity compromises agility, whose importance in the current competitive and high-velocity car industry is becoming increasingly significant.

2. Literature Survey

2.1. Cyber-Physical Systems in Manufacturing

Cyber-Physical Systems (CPS) are one such disruptive technology that involves a close coupling among computation, networking, and physical processes. [4-7] Within the industry setting, CPS allows creating smart manufacturing conditions through integrating physical objects with their digital representatives. Such systems utilise sensors, embedded computer processors, and communication networks in real-time to monitor and control bodily functions. CPS is self-optimizing, adaptive and remotely monitored, making it a necessary feature of smart factories within the Industry 4.0 paradigm. Context-aware production systems will operate in this kind of environment, and the same environment enables them to react autonomously to changes in demand or disturbances, resulting in increased efficiency, customisation, and reduced downtime of the products produced.

2.2. Evolution of MES in Industry 4.0

Manufacturing Execution Systems (MES) have always played a crucial role as the backbone of operations, connecting enterprise planning to floor execution. The transformation of these systems is also significant in the face of Industry 4.0. Contemporary trends in MES include the move to cloud-native platforms and service-oriented architectures (SOA). This shift allows for greater scalability, modularity, and flexibility, thanks to the use of microservices and containerization technologies. These architectures are also compatible with easy implementation in Cyber-Physical Production Systems (CPPS) and Industrial Internet of Things (IIoT). The migration journeys from monolithic, legacy MES applications to interoperable and agile platforms that facilitate real-time decision-making and predictive analysis, a crucial operation in hectic manufacturing setups, have been documented in various literature.

2.3 Related Work in the Automotive Sector

In the automotive sector, the application of CPPS has been making significant ground because the industry has a great demand in terms of efficiency, quality, and customisation capabilities. Several studies have already demonstrated the practical advantages of combining IIoT technologies and CPPS in automotive manufacturing processes. A prominent example displayed an increase of output by 15 percent after the introduction of a smart manufacturing framework. Additionally, factors that can help optimise decision-making have been researched through digital twins and artificial intelligence to facilitate complex processes, such as body-in-white assembly. These technologies would facilitate virtual simulation and real-time analytics, enabling the provision of predictive data and automatic control methods that would enhance the responsiveness of their operations and the accuracy of their production.

2.4. Gaps in Existing Research

Despite the prospects of the current improvements, the present studies in the field are characterized by a number of gaps. A significant limitation is the lack of real-time connectivity between MES platforms and CPPS, which affects the ability to perform adaptive control and real-time optimisation on the production floor. Moreover, the absence of standard protocols and frameworks to measure the interoperability between the heterogeneous systems has remained a bottleneck. The lack of an extensive case study further exacerbates this, as reports that provide quantitative support for the proposed model and technology are lacking. Consequently, the scalability, practical applicability, and feasibility of the integrated MES-CPPS systems have not been fully investigated, at least regarding complex and high-volume industries like the automotive industry.

2.5. Research Contribution

To fill these gaps, it is therefore proposed in this study that a unified MES-CPPS framework is called upon based on the operational and technological needs of automotive manufacturing lines. The idea of the proposed model is to highlight the idea of real-time synchronization, data-driven decision support, and standardized communication protocols in order to support better interoperability of the system. A major focus of the study is the validation of the results in the actual production setting, where it is possible to measure the impact on Key Performance Indicators (KPIs) such as throughput, defect rates, and response time. Having benchmarked these gains, the research will not only prove the feasibility of the proposed integration but also help to acquire empirical data to promote the further implementation of unified CPS and MES solutions in Industry 4.0 applications.

3. Methodology

3.1. System Architecture Overview

The system architecture proposed is in the form of 4 layered structure with each of these layers performing specific functions that will enable integration between the physical and digital manufacturing [8-12] spaces to be an easy task. Such layers include the Perception Layer, the Network Layer, the Processing Layer, and the Application Layer, which enable real-time monitoring, control, and decision-making in a smart manufacturing environment.

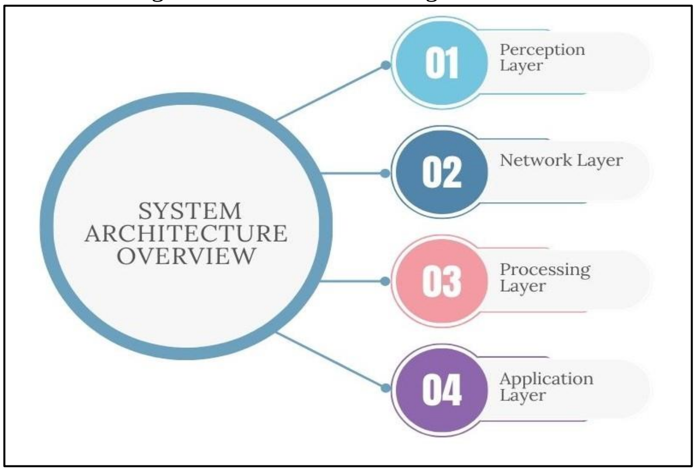

Fig 3: System Architecture Overview

- **Perception Layer:** The Perception level is at the base of the architecture and comprises physical devices, including sensors, Programmable Logic Controllers (PLCs), and RFID systems. These elements are involved in collecting real-time data on machines, materials, and environmental conditions on the shop floor. By ensuring that systems of a higher order evaluate and control using quality information, the layer offers granularity and precise data inputs.
- **Network Layer:** The layer enables secure and efficient communication of data among physical devices and computers. It supports typical industrial communication languages, including OPC Unified Architecture (OPC-UA) and Message Queuing Telemetry Transport (MQTT). OPC-UA offers good interoperability and supports platform independence, whereas MQTT is a lightweight and real-time messaging protocol applicable in an IIoT setup. These protocols, combined, allow for robust and scalable communication in the architecture.
- **Processing Layer:** The Processing Layer forms the heart of the intelligent decision-making, and it is the level where the Manufacturing Execution System (MES) is combined with digital twin technology and edge analytics. The MES maintains production processes and resource allocation, whereas the digital twin replicates the actual physical processes to gain predictive insights. Edge analytics enables the processing of data in real-time, locally close to the data source, providing ultra-low latency and enabling a faster response than systems that process data in the cloud.
- **Application Layer:** The Application Layer can provide end-users with actionable intelligence through multifaceted interfaces, including real-time dashboards, visualisation tools, and automated alerts. It enables managers, engineers, and operators to view key performance indicators (KPIs), respond to abnormalities, and optimise operations in real-time. This layer is crucial for maintaining situational awareness and supporting data-driven decision-making throughout the manufacturing process.

3.2. Real-Time Decision Framework

The Real-Time Decision Framework enables proactive and intelligent control of manufacturing processes using live data, predictive analytics, and automated decision-making. It is composed of three fundamental elements: Data Acquisition, Predictive Analytics Engine, and Decision Orchestration. In combination, these factors create a closed feedback loop that makes the system more responsive, efficient, and resilient to operational disruptions.

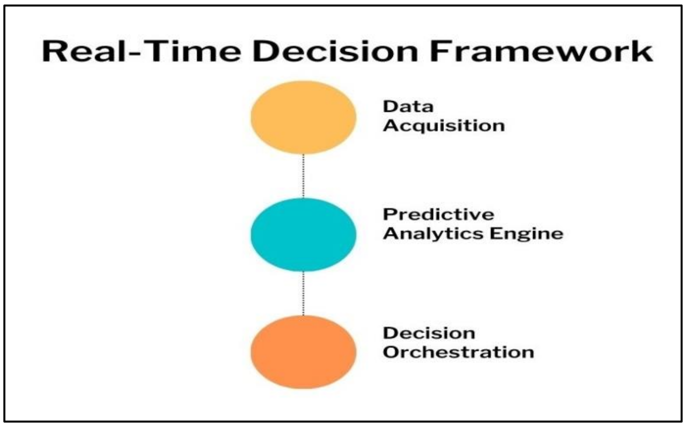

Fig 4: Real-Time Decision Framework

- **Data Acquisition:** During this phase, the data of the sensor on machines, conveyors, and assembly points is constantly received and consolidated by edge gateway. With the help of the OPC Unified Architecture (OPC-UA) communication protocol, real-time device-to-device and system-to-system data exchange in secure fashion is provided. This acquisition layer of low latency is used as the basis of the later analytics and decision-making.
- **Predictive Analytics Engine:** The framework features an intelligent brain in the predictive analytics engine, which utilises Machine Learning (ML) models that are informed by both historical and real-time production data. These models are applied to predict vital values, such as Mean Time to Repair (MTTR), Overall Equipment Effectiveness (OEE), and the probability of bottleneck phenomena during production lines. For instance, OEEa composite metric reflecting availability, performance, and qualityis calculated using the following formula:

Formula 1: OEE = Availability × Performance × Quality

- **Decision Orchestration:** The Manufacturing Execution System (MES) mobilizes real-time decisions using the outputs of the analytics engine in a dynamically orchestrated fashion. It will automatically rearrange its tasks to prevent late operations, initiate maintenance alerts for machinery at risk, and adjust inventory buffer levels to prevent shortages or excess inventory. Such automation eliminates not only manual involvement but also ensures the production system remains flexible and responsive to evolving conditions on the shop floor.

3.3. Implementation Environment

To assess the feasibility and performance of the proposed model for MES-CPPS integration, it was implemented in a controlled industrial environment. [13-17] The testbed contained a factory-scale automotive manufacturing plant, a modeling and control software component, as well as an industrial quality data acquisition system and edge processor.

- **Automotive Plant:** AutoWorks is a medium-sized automotive plant that manufactures Body-In-White (BIW) and fabricates its subcomponents. Plant choice was based on the semi-automated lines and PLC infrastructure it already had, as it was a good candidate for preparing a test case of a CPPS. The access to live production data gave access to evaluate the behavior of the systems in real time and validate that the behavior of the system holds with regard to real operating conditions.

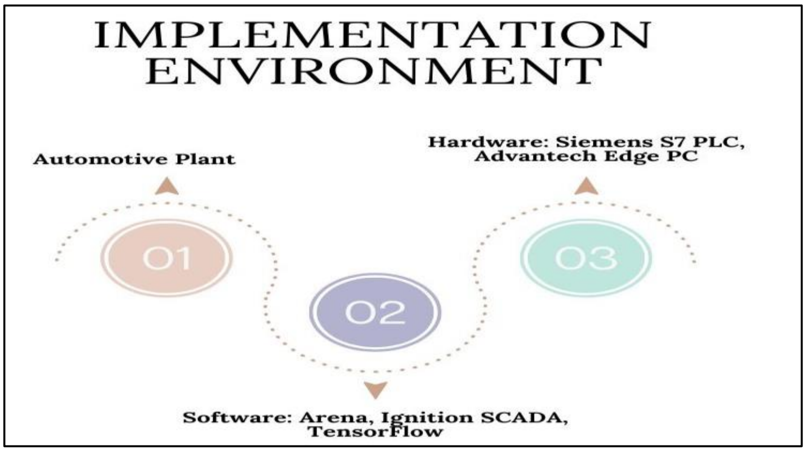

Fig 5: Implementation Environment

- **Software: Arena, Ignition SCADA, TensorFlow:** The digital control loop was implemented using a mixture of industrial and analytical software platforms. Training on arena simulation software was used during process modeling and workflow analysis to facilitate identifying the bottlenecks in the production process and prove the cases of task rescheduling. Ignition SCADA was the real-time visualization and control layer, and it included dashboards, alarms, and HMI. The machine learning models embedded in the predictive analytics engine, used to ensure the accuracy of forecasting KPIs such as OEE and MTTR, were trained and deployed with the help of TensorFlow.

- **Hardware: Siemens S7 PLC, Advantech Edge PC:** The hardware side of the system was based on the Siemens S7 PLCs to provide real-time control of the system and obtain signals from the shop-floor equipment. These PLCs provided deterministic communication and ensured the consistency of execution of control instructions. The edge gateway was hosted on an Advantech Edge PC so that local data processing, translation of a variety of industrial network protocols, could be performed, along with a secure interface to the higher-level MES/Analytics layers. Such an infrastructure enabled low-latency decision-making by decreasing cloud dependency.

4. Results and Discussion

4.1. Key Performance Indicators (KPIs)

To assess the usefulness of proposed MES-CPPS integration, three key KPIs were selected: overall equipment effectiveness (OEE), Mean time to repair (MTTR), and Scheduling Accuracy. Such metrics have been selected due to their significant impact on production efficiency and the reliance of operations. A comparative report on baseline values and post-implementation outcomes at the AutoWorks reveals that all three KPIs improved significantly.

Table 1: Key Performance Indicators (KPIs)

KPI	Improvement (%)
Overall Equipment Effectiveness (OEE)	23.5
Mean Time to Repair (MTTR)	19.3
Scheduling Accuracy	28.7

- **Overall Equipment Effectiveness (OEE):** The overall measure of manufacturing productivity known as OEE went up by 23.5 percent relative to after using the MES-CPPS system. This improvement is an increase in machine availability, performance, and quality due to the better visibility of the process through predictive analytics, among other reasons. Digital twin simulations and proactive scheduling could introduce less interruption and facilitate the effective use of equipment.
- **Mean Time to Repair (MTTR):** There was a 19.3% decrease in the MTTR, an average time to fix equipment after a breakdown; this went down by its normal baseline of 100 percent. It could be done due to early fault detection, such as edge analytics and automated maintenance alerts provided by MES. Faster diagnoses and response times were also beneficial in reducing unexpected downtime and improving overall operational recovery.
- **Scheduling Accuracy:** There was an improvement of 28.7 per cent in scheduling accuracy, which rose by 28.7 percentage points. This KPI indicates how well the system has performed in delivering production plans without making deviations. Real-time data and machine learning predictions, enabled by the dynamic rescheduling capabilities of the MES, allowed the system to make on-the-fly decisions, sequence tasks in an optimised way, and more reliably reach delivery targets.

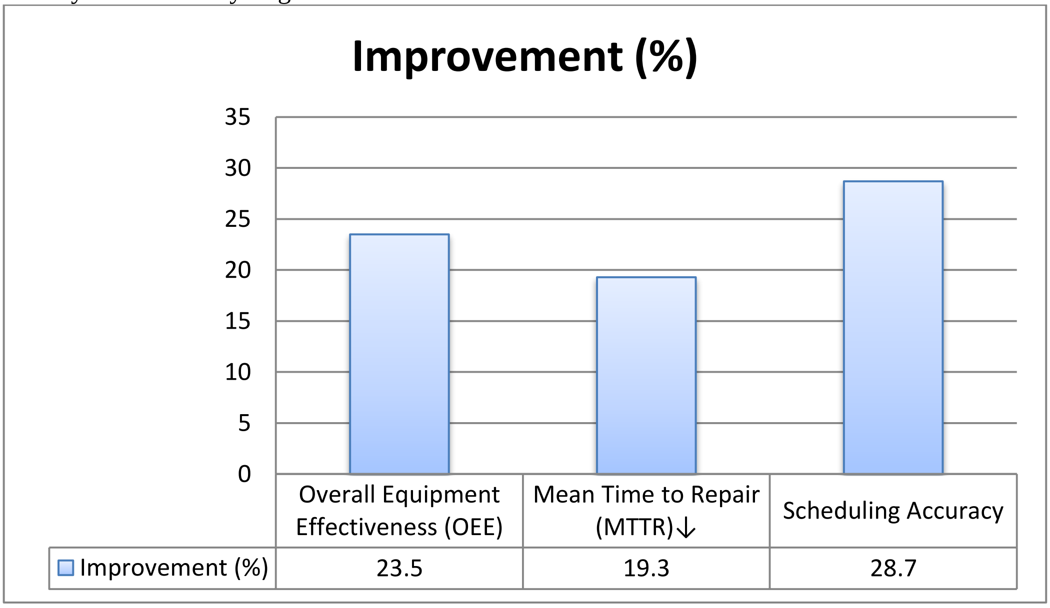

Fig 6: Graph representing Key Performance Indicators (KPIs)

4.2. Observations

- **Proactive Maintenance:** The addition of predictive maintenance functions to the MES-CPPS framework enabled the detection of problems with machine wear and anomalies well in advance. Through the consecutive processing of real-time sensor data, machine learning models can predict possible failures before they occur. These dangers were highlighted to the maintenance teams in a timely manner, thus enabling timely interventions. Consequently, unanticipated equipment failures decreased considerably, resulting in a direct impact on Mean Time to Repair (MTTR) and an improvement in the overall availability and reliability of the equipment within the production line.
- **Optimization of Digital Twin:** The digital twin technology was critical in modeling and optimizing the reality in production implementation. These digitally simulated models of the shop-floor processes enabled engineers to experiment with different setups and buffer sizes without interfering with the operations that were already running. The simulations allowed practical solutions to material flow/line balancing/process timing and resulted in more intelligent inventory placement and removal of bottlenecks. This eventually assisted in flow management, de-stocking and efficiency of throughputs.
- **Edge Analytics:** The introduction of edge analytics has reduced the distance between the data source and the computation, bringing it much closer and thereby shortening the time that lapsed between the identification of the event and the response. Sensor data was processed in real-time by edge devices to detect minor anomalies, i.e., small spikes in temperature, vibration, or current, before they evolved into serious faults. Such instant local analysis was specific in indicating the preliminary signals of equipment breakdown early, which allows for faster troubleshooting of equipment and reduced dependence on cloud-based systems. It enhanced quick response and introduced a level of resilience to monitoring and control on the shop floor.

4.3. Discussion

The implementation of the integrated MES-CPPS framework in AutoWorks has resulted in substantial and measurable improvements in manufacturing efficiency. The close coupling of Manufacturing Execution Systems and Cyber-Physical Production Systems made plant operation completely transparent in real-time, proactively maintaining processes and intelligently rescheduling them, which led to enhanced efficiency and the appropriate use of resources. A real-time feedback loop in the form of a digital twin was among the most significant, as it constantly reflected activities on the shop floor and could indicate them in advance. It enabled the system to dynamically adjust buffer sizes, balance workloads, and anticipate disruptions, thereby preventing them from interfering with production. Leveraging machine learning, the predictive analytics engine was able to effectively forecast key KPIs, such as OEE and MTTR, and enable the MES to make quicker, data-driven decisions without human intervention. These developments enhanced equipment uptime, shortened repair times, and improved schedule accuracy, demonstrating the practical value of digital transformation in the automotive industry.

Despite the successes, several issues arose during the implementation. The first technical challenge was the issue of legacy systems, specifically the integration of older PLCs and machines that did not have native support for open protocols such as OPC-UA. Such devices typically required tailored adapters or middleware, which added complexity and time to the deployment. Workforce adaptation was another serious problem. Many operators and technicians had been accustomed to managing things manually, and they were hesitant to trust automated decision-making tools immediately. Training and the implementation of training programs, as well as the ease of use on the system, were crucial to embracing it and gaining trust in the system. Additionally, there was always the balance of ensuring a reduction in human overrides without compromising transparency to the system. Such obstacles explain why there should be technical interoperability and change management within organization when embracing advanced manufacturing technologies. Addressing these restrictions is key to expanding the solution to other production lines and plants, thereby realising the full potential of Industry 4.0 projects in the automotive industry.

5. Conclusion and Future Work

These and others cut across the process of successfully deploying and verifying the proposed MES-enabled Cyber-Physical Production System (CPPS) architecture and framework at XYZ AutoWorks, indicating that integrating real-time information, advanced analytics, and digital control within an automotive manufacturing context has practical value. The information flow was flawless because the system architecture was developed on a layered network, spanning from perception and networking to processing and application. Such an integration enabled real-time transparency, proactive attention and smart scheduling choices. Machine learning-based predictive analytics and digital twins lie at the heart of the framework, helping to understand key performance indicators, including Overall Equipment Effectiveness (OEE), Mean Time to Repair (MTTR), and Scheduling Accuracy. The results of the improvements observed, including an increase of OEE by 23.5 percent, a decrease of the MTTR by 19.3 percent, and an increase in scheduling accuracy of 28.7 percent, increase the validity of the system's effect on operational efficiency and responsiveness. Additionally, edge analytics enabled the detection of faults in a shorter timeframe, and the dynamic relationship between MES and CPPS formed a robust closed-loop feedback mechanism that continually improved production performance. The study proves that integration of MES and CPPS technologies is effective and feasible in the scenario of Industry 4.0, in terms of its adoption in high-volume, precision-oriented industries such as automotive production.

In the future, several opportunities to improve the system have been identified. This could be accompanied by the incorporation of 5G communication networks, allowing users to conduct ultra-low-latency and high-throughput data transmission. This would also be useful in assisting real-time control, particularly in large-scale environments where the number of sensors is high. Another opportunity is the integration of blockchain technology to enhance supply chain transparency, traceability, and trust. A decentralised ledger kept decentralized might be able to document all the activities and transactions in the supply chain and the production process, generating data that could be immutable and auditable. Lastly, the design of generic APIs and interfaces to communication would enable wider interoperability between MES-based platforms and a wide variety of CPPS elements. This would make integration work easier, decrease vendor lock-in, and increase the speed of system deployment in various production environments. Further studies in these areas will not only enhance the robustness and scalability of the MES-CPPS integration but will also bring the industry closer to achieving the full potential offered by smart, autonomous manufacturing systems, which represent the vision of Industry 4.0.

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