Sensors and Materials, Vol. 38, No. 6 (2026) 3685–3700
MYU Tokyo

S & M 4528

Sensor-assisted Intelligent Manufacturing Execution System Architecture for Digital Transformation, Intelligent Decision-making, and Enterprise Performance Enhancement

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(Received June 4, 2026; accepted June 16, 2026)

Keywords: large language models, multi-modal collaborative processing, manufacturing execution systems, sensor-assisted manufacturing, automated report generation, industrial IoT, smart manufacturing

Conventional manufacturing execution system (MES) reporting systems often suffer from fragmented sensor data management, labor-intensive report preparation, delayed decision-making, and limited capability for the intelligent interpretation of heterogeneous manufacturing information. Therefore, the objective of this study is to develop a sensor-assisted MES framework integrating large language models (LLMs) and multi-modal collaborative processing (MCP) to improve manufacturing information transparency, report generation efficiency, and intelligent operational decision-making. In this study, we propose a sensor-assisted MES framework integrating LLMs with MCP to accelerate digital transformation and improve intelligent decision-making in smart manufacturing environments. Conventional MES reporting processes often rely on manual data collection, fragmented information analysis, and delayed operational feedback, which reduce management responsiveness and limit enterprise operational performance. By combining advanced natural language processing, heterogeneous sensor data fusion, and Industrial Internet of Things (IIoT)-based monitoring, the proposed LLM+MCP framework enables the automated extraction, analysis, visualization, and synthesis of manufacturing information into intelligent executive reports. The framework integrates multiple sensing modalities, including time-series production signals, equipment operation records, process parameters, tabular manufacturing data, and unstructured operational logs, thereby supporting real-time monitoring, anomaly identification, and adaptive management decisions. Through the designed intelligent reporting and sensing architecture, manufacturing managers can rapidly obtain operational insights and optimize production scheduling, resource allocation, and quality control strategies. Experimental results demonstrate that the proposed system achieves more than 90% reduction in report generation time, including reductions from 60 to 5 min for daily reports, 180 to 15 min for weekly reports, and 480 to 30 min for monthly reports, while maintaining 99.9% system availability and stable response latency ranging from 5 to 60 s.

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https://doi.org/10.18494/SAM6465

ISSN 0914-4935
https://myukk.org/

From the results, we can confirm that the proposed sensor-integrated LLM+MCP framework effectively enhances manufacturing information transparency, accelerates enterprise digital transformation, improves intelligent decision-making mechanisms, and ultimately strengthens operational efficiency, management responsiveness, and overall enterprise performance in smart manufacturing systems. Although challenges remain regarding heterogeneous sensing-data quality, data consistency, and the reliability of AI-generated content, the proposed framework addresses these issues through multi-modal sensing integration, structured data preprocessing, and low-rank adaptation (LoRA)-based domain adaptation, thereby improving the robustness and practicality of intelligent manufacturing analytics.

1. Introduction

Manufacturing execution systems (MESs) play an essential role in modern smart manufacturing by connecting enterprise-level management with shop-floor production operations. With the rapid advancement of Industrial Internet of Things (IIoT) technologies and intelligent sensing systems, manufacturing environments continuously generate large volumes of heterogeneous sensing data, including equipment operation records, production parameters, process logs, quality inspection information, and time-series sensor signals.(1–3) These sensing data sources provide important information for production monitoring, process optimization, predictive maintenance, and operational decision-making. However, conventional MES platforms still rely heavily on the manual report generation and human interpretation of manufacturing data, resulting in significant delays, inconsistent report quality, and reduced responsiveness in industrial environments.(4,5) Consequently, improving the efficiency of sensor-based manufacturing information processing has become an important issue in intelligent manufacturing systems because real-time sensing analytics and automated information interpretation directly affect operational responsiveness, production coordination, management decision quality, and overall enterprise performance in digitally transformed manufacturing environments.

In recent years, large language models (LLMs) such as Generative Pre-trained Transformer (GPT), Bidirectional Encoder Representations from Transformers (BERT), and Large Language Model Meta AI (LLaMA) have demonstrated remarkable capabilities in natural language understanding, automated summarization, and intelligent content generation.(6–9) Owing to their strong contextual reasoning and semantic analysis abilities, LLMs have gradually attracted attention in industrial applications, including manufacturing analytics, industrial knowledge management, and automated documentation.(10,11) In smart manufacturing environments, LLMs can assist in converting large-scale sensor-derived production data into readable and structured operational reports, thereby reducing the burden of manual data analysis while simultaneously supporting intelligent operational assessment, management coordination, and data-driven decision-making processes in modern manufacturing enterprises. Nevertheless, directly applying general-purpose LLMs to manufacturing systems remains challenging because industrial data often involve heterogeneous sensing information, domain-specific terminology, and real-time operational constraints.[12] In addition, the full-scale retraining of LLMs typically requires substantial computational resources and high training costs, limiting practical deployment in industrial systems.[13]

To address these limitations, multi-modal collaborative processing (MCP) has emerged as an effective approach for integrating heterogeneous manufacturing information from multiple sensing modalities.[14] MCP enables the simultaneous processing of structured production records, unstructured textual logs, visual information, and time-series sensor signals, thereby improving the completeness and reliability of manufacturing analytics. In industrial environments, multi-modal sensing integration has been widely applied to quality monitoring, predictive maintenance, intelligent inspection, and process optimization because it provides more comprehensive operational awareness than single-source data analysis.[15] By combining multi-modal sensing data with intelligent language generation, manufacturing systems can achieve more efficient report generation, anomaly identification, and real-time operational feedback, thereby accelerating enterprise digital transformation and enabling more adaptive and intelligent manufacturing management mechanisms. However, computational efficiency and scalability remain important challenges for multi-modal fusion frameworks in large-scale manufacturing applications. Therefore, we propose a sensor-assisted MES framework integrating LLMs with MCP for intelligent automated report generation. The primary objective of this study is to develop and validate a sensor-assisted intelligent MES framework capable of integrating heterogeneous industrial sensing information, automated language generation, and multi-modal collaborative processing for real-time manufacturing analytics and report generation. In addition, we aim to improve operational responsiveness, reduce report preparation effort, and enhance intelligent decision-making capability in smart manufacturing environments.

The proposed framework combines advanced natural language processing, multi-modal sensing data fusion, and low-rank adaptation (LoRA)-based model optimization to improve report generation efficiency while maintaining computational scalability. The system integrates heterogeneous sensing information, including process parameters, equipment operation records, production metrics, and time-series manufacturing data, and automatically transforms these data into structured executive reports. Through the proposed LLM+MCP architecture, report generation time can be significantly reduced while supporting real-time industrial monitoring and decision-making. To validate the practical effectiveness of the proposed framework, a three-month deployment was conducted in a real manufacturing environment. Experimental results demonstrate that the proposed system achieves more than 90% reduction in report generation time while maintaining high system availability and stable response performance. In addition, the framework demonstrates strong scalability and computational efficiency through LoRA-based fine-tuning and modular multi-modal processing strategies. These results confirm that the proposed sensor-integrated LLM+MCP framework provides an effective and scalable solution for MES digital transformation, intelligent sensing applications, and smart manufacturing systems. Furthermore, the proposed architecture improves operational transparency, accelerates management response efficiency, enhances data-driven decision-making capability, and ultimately contributes to enterprise operational performance and manufacturing competitiveness.

2. Methodology

2.1 System architecture

The proposed sensor-assisted LLM+MCP framework was designed to improve automated report generation and intelligent operational management in MESs by integrating intelligent language generation with heterogeneous industrial sensing information. Through the incorporation of real-time sensing technologies and IIoT-based monitoring mechanisms, the proposed architecture enables continuous manufacturing data acquisition, adaptive information analysis, and sensor-driven decision support for smart manufacturing environments. As shown in Fig. 1, the proposed architecture consists of multiple interconnected modules that support sensor data acquisition, data preprocessing, multi-modal fusion, intelligent report generation, and visualization output for smart manufacturing applications. The first module focuses on data ingestion and preprocessing. The framework connects to MES databases and industrial sensing systems through standardized interfaces, including Java Database Connectivity and Open Database Connectivity protocols, to collect heterogeneous manufacturing information. The acquired data include production parameters, equipment operation records, work orders, process routing information, time-series sensor signals, environmental sensing information, equipment-status monitoring data, quality inspection records, and unstructured operational logs. To further illustrate the heterogeneous sensing integration mechanism in the proposed MES environment, an additional sensor-assisted data acquisition framework is presented in Fig. 2.

The sensing architecture integrates multiple industrial sensing modules, including equipment-status sensors, environmental monitoring units, process-parameter sensing systems, barcode and RFID tracking devices, and production-line operational monitoring sensors. In the industrial sensing layer, multiple sensing devices were deployed to continuously monitor manufacturing conditions and production activities. Equipment-status monitoring was achieved using current, vibration, and rotational speed sensors to capture machine operating conditions and detect abnormal equipment behavior. Environmental monitoring units incorporated temperature, humidity, and airborne particle sensors to evaluate workplace environmental stability and production quality conditions. Process-parameter sensing modules collected manufacturing variables such as pressure, flow rate, cycle time, and production throughput through industrial instrumentation installed on production equipment. In addition, RFID readers and barcode

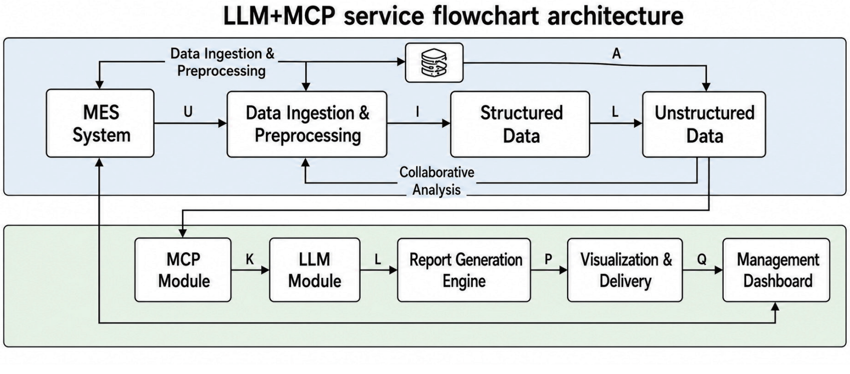

Fig. 1. (Color online) LLM+MCP service flowchart architecture

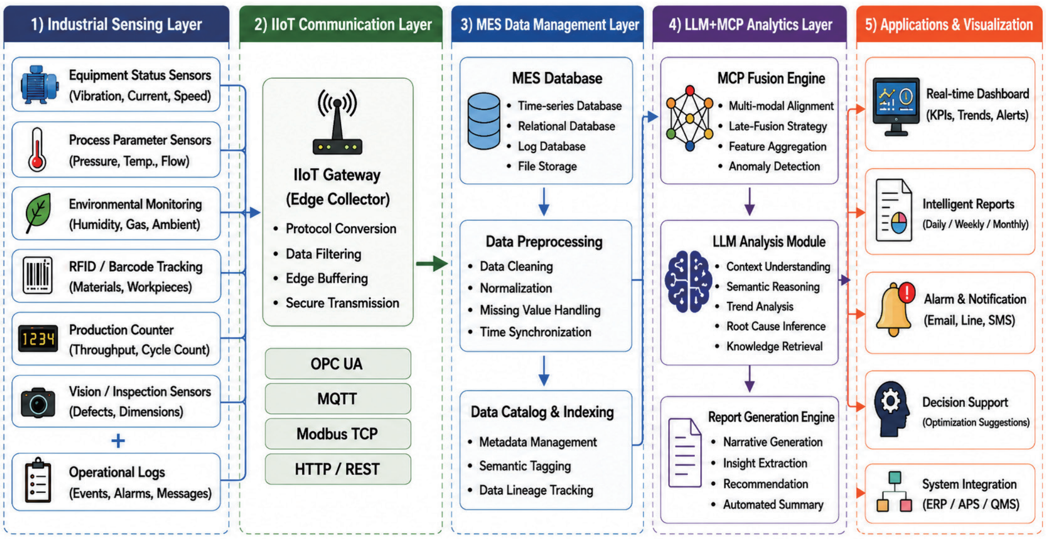

Fig. 2. (Color online) Sensor-assisted industrial data acquisition and intelligent sensing framework for the proposed LLM+MCP-assisted MES architecture. The framework integrates industrial sensors, RFID/barcode tracking, process monitoring, and IIoT communication for real-time manufacturing data collection and intelligent operational analysis.

scanners were employed for material tracking, workpiece identification, and production traceability. Machine-vision inspection devices equipped with industrial cameras were used to monitor product dimensions, surface defects, and assembly quality. The acquired sensing data were transmitted through OPC UA, MQTT, Modbus TCP, and HTTP/REST communication protocols via IIoT gateways and subsequently stored in the MES database for intelligent analysis and report generation. These heterogeneous sensing devices provide the real-time manufacturing information required for anomaly detection, production monitoring, process optimization, and decision support within the proposed LLM+MCP framework.

Through IIoT communication interfaces, the acquired sensing information is continuously transmitted to the MES database and subsequently processed by the LLM+MCP analytical framework. This sensor-integrated mechanism improves real-time manufacturing visibility, enhances operational synchronization capability, and supports intelligent manufacturing decision-making in practical industrial environments. These heterogeneous sensing data are continuously collected through interconnected industrial sensing modules and IIoT communication interfaces to support real-time manufacturing visibility and intelligent operational monitoring. Parallel preprocessing pipelines are adopted to normalize and synchronize multi-source sensing data, thereby reducing computational bottlenecks and improving real-time processing capability. Through this design, the system can efficiently manage large-scale industrial sensing information generated in smart manufacturing environments, thereby improving manufacturing information transparency, accelerating enterprise digital transformation, and enhancing the responsiveness of operational management systems. The second module is the LLM intelligence core, which utilizes the LLaMA foundation model combined with LoRA-based fine-tuning techniques.

The model was trained using approximately 15000 instruction-response pairs extracted from 5000 historical manufacturing reports to enhance domain-specific language understanding and report generation capability. LoRA represents weight updates as low-rank matrices, reducing fine-tuning computational complexity from $O(n^2)$ to $O(rn)$, where $r << n$, allowing fast domain-specific adaptation on limited resources. Here, n denotes the dimension of the original model weight matrix, while r represents the low-rank dimension used in LoRA, where r is much smaller than n $(r << n)$. The matrices A and B are low-rank trainable matrices used to approximate the weight update ΔW. Specifically, ΔW denotes the change applied to the original model weights during fine-tuning. By representing the weight update as the product of two low-rank matrices, the number of trainable parameters can be significantly reduced while preserving model adaptation capability. The LLM module automatically interprets manufacturing sensing data and converts operational information into structured executive summaries, analytical descriptions, and management-oriented operational insights. By integrating intelligent language reasoning with sensor-derived manufacturing analytics, the framework supports rapid operational assessment, anomaly interpretation, and data-driven decision-making processes for enterprise management. Compared with conventional manual analysis, the proposed approach significantly improves processing efficiency while maintaining semantic consistency and report readability.

The third module performs MCP for sensor-integrated manufacturing analytics. In this framework, structured production records, time-series sensor signals, tabular process metrics, and unstructured textual logs are processed independently before final information fusion. A late-fusion strategy is employed to improve scalability, computational efficiency, and operational flexibility in large-scale manufacturing environments. Through multi-modal sensing integration and collaborative information analysis, the proposed MCP mechanism enhances production coordination capability, operational monitoring accuracy, and manufacturing process optimization. In addition, the framework integrates visualization engines to transform sensing information into graphical representations, thereby supporting the intuitive interpretation of manufacturing performance and process deviations. This modular processing mechanism allows heterogeneous sensing data to be analyzed simultaneously while maintaining efficient computational performance in large-scale manufacturing environments. Figure 3 further illustrates the operational workflow of the proposed LLM+MCP framework. The workflow includes industrial sensing data acquisition, data preprocessing, multi-modal information

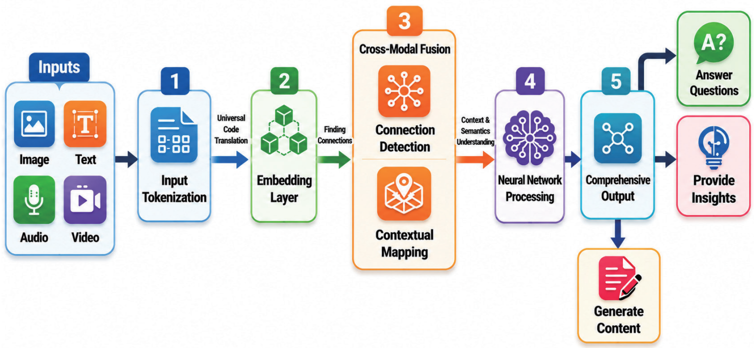

Fig. 3. (Color online) Multimodal LLM work in six simple steps.

analysis, intelligent language generation, report visualization, and MES integration. Through the integration of heterogeneous sensor-derived manufacturing information and automated language processing, the proposed framework enables efficient real-time report generation and operational decision support in smart manufacturing environments.

The fourth module integrates the proposed framework with the MES platform and automated report generation system. Standardized application programming interfaces (APIs) are utilized to support low-latency communication between manufacturing databases, sensing systems, and the LLM+MCP architecture. Through real-time sensor data acquisition and intelligent report synthesis, the framework can automatically generate operational reports for production monitoring, process evaluation, and anomaly analysis. The generated reports are subsequently delivered to the MES dashboard to support intelligent manufacturing management and industrial decision-making. The final module focuses on visualization and output presentation. The generated reports integrate textual summaries, sensor-derived process analyses, and graphical visualizations into a unified dashboard interface. By combining intelligent sensing analysis with automated natural language generation, the proposed framework enhances operational transparency, improves manufacturing data interpretation efficiency, accelerates intelligent decision-making processes, and supports enterprise-level operational optimization in smart factory environments. Consequently, the proposed architecture contributes to improved manufacturing responsiveness, management efficiency, and overall enterprise operational performance.

2.2 Algorithmic complexity and computational efficiency

To improve the computational efficiency of sensor-assisted manufacturing analytics, the proposed framework adopts LoRA-based model optimization and modular multi-modal processing strategies. In the LoRA fine-tuning mechanism, LoRA decomposes the weight update ΔW into the product of two low-rank matrices, $A \in \mathbb{R}^{d\times r}$ and $B \in \mathbb{R}^{r\times k}$, such that $\Delta W = BA$, where $r << \min(d, k)$, as shown in Eq. (1). This reduces the number of trainable parameters from $d \times k$ to $d \times r + r \times k$. When $d \approx k \approx n$, the full-model fine-tuning complexity of $O(n^2)$ is reduced to $O(rn)$, cutting training time and memory usage by more than 90%.

$$W_{new} = W_{original} + \Delta W = W_{original} + BA \tag{1}$$

In terms of computational complexity, $O(n^2)$ represents the computational cost associated with conventional full-parameter optimization, whereas $O(rn)$ corresponds to the reduced complexity achieved by the LoRA approach. Because the low-rank dimension r is substantially smaller than n, the computational and memory requirements are considerably reduced. This approach enables efficient domain-specific training of the LLM while maintaining high report generation quality. Consequently, the proposed system can be deployed in practical industrial environments without requiring excessive computational resources. The MCP framework employs a late-fusion strategy to independently process heterogeneous sensing information, independently processing time-series data, tabular metrics, and LLM-generated text. The algorithmic complexity for each modality is approximately $O(m)$, where m is the number of data points. The final fusion complexity is $O(k)$, where k is the total output size. Since k is typically much smaller than the total input size, MCP achieves linear time scalability and maintains computational efficiency. This design significantly improves scalability and reduces processing latency in industrial applications involving large-scale sensing data streams. In addition, the inference latency of the proposed LLM+MCP framework was optimized for near real-time MES reporting applications. Experimental observations indicate that report generation response times range from approximately 5 to 60 s depending on report complexity and sensing data volume. The integration of parallel data preprocessing, modular sensor fusion, and LoRA-based model optimization enables the framework to maintain stable response performance while supporting continuous industrial sensing and operational monitoring.

2.3 Experimental design

To evaluate the practical performance of the proposed sensor-assisted LLM+MCP framework, a three-month deployment experiment was conducted in a real manufacturing environment. The experimental setup consisted of two operational scenarios, including a conventional manual report generation process and the proposed automated report generation framework. The deployment experiment was conducted in a real manufacturing environment involving production planning, material tracking, assembly operations, process inspection, and packaging activities. The facility utilized an MES platform integrated with industrial sensing devices, RFID/barcode tracking systems, and IIoT communication infrastructure for operational monitoring and data collection. Owing to industrial confidentiality agreements and production-information security requirements, photographs and identifying information of the manufacturing site cannot be publicly disclosed. Nevertheless, all experimental data reported in this study were collected during the actual three-month industrial deployment of the proposed framework under normal production conditions. The deployment was performed without interrupting normal manufacturing operations, allowing the proposed framework to be evaluated under practical industrial conditions.

The manufacturing environment continuously generated heterogeneous sensing information, including equipment operation data, process parameters, production records, and time-series industrial monitoring signals. During the three-month deployment period, sensing data were continuously acquired from multiple production-line sensing devices. The monitored variables included equipment current consumption, machine vibration levels, operating speed, environmental temperature and humidity, process pressure, production cycle time, production throughput, RFID-based material tracking information, barcode identification records, and machine-vision inspection results. These sensing data streams were synchronized through the IIoT communication infrastructure and automatically transferred to the MES platform for subsequent preprocessing, multi-modal fusion, and intelligent report generation. During the experiment, the proposed framework automatically collected and processed manufacturing sensing data from the MES platform and associated industrial monitoring systems. The acquired sensing information was subsequently analyzed through the LLM+MCP architecture to generate structured operational reports. Evaluation metrics included report generation time, report quality consistency, system response performance, computational resource utilization, and operational scalability. In addition, system availability and response latency were monitored to assess the reliability of the proposed framework under continuous industrial sensing conditions. Through the integration of intelligent sensing analysis, multi-modal data fusion, and automated natural language generation, the proposed methodology provides an efficient solution for real-time manufacturing information processing and intelligent MES report generation.

3. System Architecture, Methodology, and Mathematical Models

3.1 Report generation time

Figure 4 further visualizes the comparison between conventional manual report generation and the proposed sensor-assisted LLM+MCP framework. The proposed system significantly reduces operational latency for daily, weekly, and monthly reporting tasks through automated sensing-data analysis, LoRA-based lightweight optimization, and modular multi-modal processing. The substantial reduction in report generation latency demonstrates the effectiveness of intelligent sensing integration and automated manufacturing information interpretation in practical industrial environments. Table 1 demonstrates that the proposed sensor-assisted LLM+MCP framework significantly reduced report preparation time compared with the conventional manual reporting process. The preparation time for daily reports decreased from 60 to 5 min, whereas weekly reports were reduced from 180 to 15 min. In addition, the processing time required for monthly reports decreased from 480 to 30 min. These results correspond to time-saving improvements exceeding 90% for all reporting tasks. The substantial

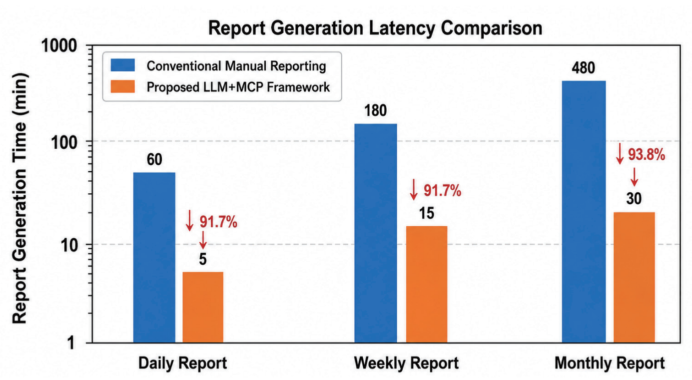

Fig. 4. (Color online) Comparison of report generation times between manual reporting and the proposed LLM+MCP framework for daily, weekly, and monthly manufacturing reports.

Table 1
Comparison of report generation times.

Report type	Control (min)	Experimental (min)	Time savings (%)
Daily	60	5	91.67
Weekly	180	15	91.67
Monthly	480	30	93.75

reduction in report generation latency is primarily attributed to the computational efficiency of LoRA-based lightweight fine-tuning and the modular parallel processing capability provided by the MCP architecture. Through the integration of heterogeneous manufacturing sensing information, real-time data preprocessing, and intelligent language generation, the proposed framework effectively accelerates manufacturing information processing and improves operational responsiveness in smart manufacturing environments. Furthermore, the rapid generation of executive reports enhances management efficiency and supports enterprise digital transformation by enabling faster sensor-driven decision-making and operational coordination.

3.2 Report quality and objective metrics

The quality evaluation results shown in Table 2 indicate that the proposed LLM+MCP framework substantially improved the overall quality of manufacturing reports compared with conventional manually generated reports. Blind expert evaluations demonstrated improvements exceeding 20% across all evaluation dimensions, including content accuracy, structural coherence, visual presentation, and analytical insight. Specifically, the proposed framework achieved improvements of 22.2% in content accuracy, 33.8% in structural coherence, 47.5% in visual presentation, and 30.8% in analytical insight. In addition, the framework achieved a ROUGE-L score of 0.78, confirming a high degree of semantic consistency and structural alignment with expert-generated manufacturing reports. These results demonstrate that the proposed sensor-assisted framework not only improves automated report generation efficiency but also enhances the readability, interpretability, and practical utility of manufacturing information. Through the intelligent integration of sensor-derived production data and automated analytical summarization, the framework supports more effective operational evaluation and management decision-making in MES environments. Consequently, the proposed system contributes to improved operational transparency, manufacturing coordination capability, and enterprise management performance.

3.3 Objective evaluation of report quality

The proposed framework demonstrated stable operational performance and high computational efficiency during continuous industrial deployment. Experimental observations indicate that the system maintained 99.9% operational availability, while the response time for report generation typically ranged from 5 to 60 s depending on report complexity and sensing

Table 2
Report quality evaluation.

Quality dimension	Manual score	LLM+MCP score	Improvement (%)
Content Accuracy	7.2	8.8	22.2
Structural Coherence	6.8	9.1	33.8
Visual Presentation	5.9	8.7	47.5
Analytical Insight	6.5	8.5	30.8

Note: Quality scores were obtained through blind expert evaluations conducted by five manufacturing-management specialists. Reported values represent the mean scores across all evaluators.

data volume. Owing to the lightweight parameter adaptation mechanism provided by LoRA and the modular parallel computation strategy of MCP, the framework effectively balances computational workloads without requiring additional hardware resources. The proposed architecture therefore supports scalable deployment in practical manufacturing environments while maintaining stable sensing-analysis performance and low operational latency. Moreover, the integration of sensor-assisted manufacturing analytics with intelligent report synthesis improves real-time monitoring capability and strengthens adaptive operational management in MES environments. These characteristics demonstrate the practical feasibility of integrating the proposed framework into enterprise-level smart manufacturing systems and further support digital transformation and intelligent operational optimization.

3.4 Case study: automated report for work order B220-20250828006-0005

To demonstrate the practical capability of the proposed framework in a real manufacturing scenario, a case study was conducted using Work Order B220-20250828006-0005. The automatically generated report shown in Fig. 5 successfully identified that the production order

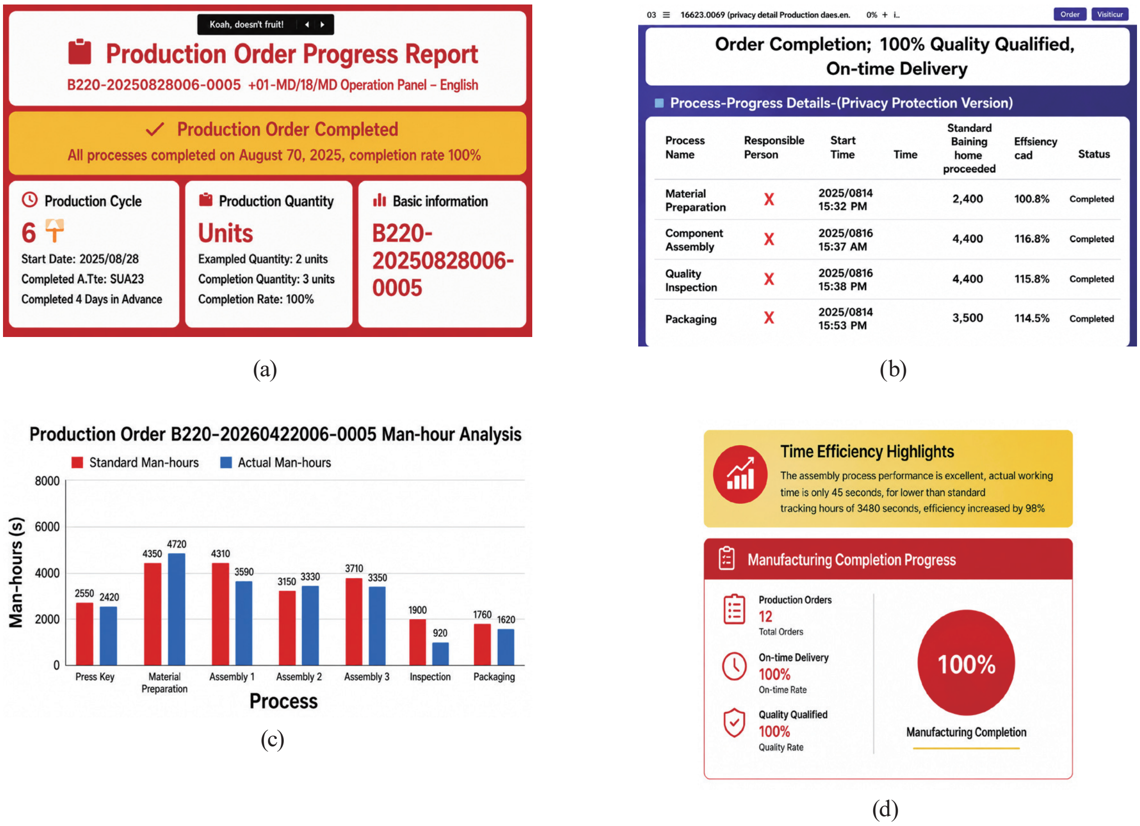

Fig. 5. (Color online) Visualization of an automatically generated work-order report obtained from the actual industrial deployment experiment. (a) Production-order progress dashboard, (b) privacy-protected process monitoring interface, (c) standard versus actual man-hour analysis chart, and (d) manufacturing completion and efficiency visualization dashboard.

was completed four days ahead of schedule and accurately determined the primary contributing factor for the performance improvement. To protect proprietary manufacturing information and operational confidentiality, the selected process names and personnel-related identifiers shown in Fig. 5 were anonymized and replaced with generic labels for presentation purposes. The visualization therefore serves as a privacy-protected representation of the actual deployment results while preserving the operational characteristics and analytical outcomes of the original manufacturing data. Figure 5 shows the production order progress dashboard [Fig. 5(a)], the privacy-protected process monitoring interface [Fig. 5(b)], the participant and workflow management interface (not shown here), the production flow chart of manufacturing procedures (not shown here), the standard versus actual man-hour analysis chart [Fig. 5(c)], and the manufacturing completion and efficiency visualization dashboard [Fig. 5(d)]. The process-monitoring interface includes representative manufacturing stages, namely, Material Preparation, Component Assembly, Quality Inspection, and Packaging, which are presented using privacy-protected generic process labels.

The generated analysis indicated that "The assembly process was exceptionally efficient, with an actual time of only 43 s compared with the standard of 3480 s," corresponding to approximately 99% efficiency improvement. The automatically generated report also integrates sensor-derived manufacturing information with graphical visualization analysis, including a bar chart comparing standard and actual process times. This visual representation enables managers to rapidly identify production deviations, process bottlenecks, and operational optimization opportunities. Through the integration of intelligent sensing analysis, automated language interpretation, and visualization-based decision support, the proposed framework assists enterprise managers in improving production scheduling, workflow coordination, resource allocation, and performance evaluation. In addition, the proposed LLM+MCP framework demonstrates strong capability in real-time manufacturing data integration, anomaly detection, and operational intelligence generation within MES environments. These results confirm that the proposed sensor-assisted architecture can effectively support intelligent manufacturing management and contribute to enhanced operational efficiency and enterprise performance. Figure 5 shows the automatically generated MES report visualization for Work Order B220-20250828006-0005, showing standard versus actual process times. The assembly process achieved 99% efficiency improvement (43 s vs 3480 s), enabling early task completion.

The visualization highlights efficiency deviations and provides actionable insights for scheduling and production optimization. The data presented in Fig. 4 and Table 1 were collected from the three-month industrial deployment experiment described in Sect. 2.3. All the performance data presented in Figs. 4 and 5 and Tables 1 and 2 were obtained from the authors' three-month industrial deployment of the proposed framework. No external datasets or previously published data were used. Report generation time was measured directly from the system logs by recording the elapsed time between report-generation initiation and report completion. For comparison, the conventional manual reporting process was evaluated using the same reporting tasks performed by manufacturing personnel under normal operational conditions. Report quality was evaluated through blind assessments conducted by five manufacturing-management experts. The experts independently scored each report according to four criteria, namely, content accuracy, structural coherence, visual presentation, and analytical insight, using a ten-point evaluation scale. The final scores reported in Table 2 represent the average values across all expert evaluations. These procedures ensured the consistency, fairness, and reproducibility of the reported performance results.

3.5 System performance

The proposed sensor-assisted LLM+MCP framework achieved stable operational performance during continuous deployment in practical manufacturing environments. Experimental results indicate that the system maintained 99.9% operational availability, with response times ranging from approximately 5 to 10 s for routine reports and from 30 to 60 s for more complex analytical reports. These results demonstrate that the proposed architecture exhibits strong scalability, efficient resource utilization capability, and stable real-time sensing-analysis performance. Through the integration of LoRA-based lightweight optimization, MCP modular processing, and intelligent sensor data fusion, the framework effectively reduces computational burden while maintaining high report generation quality and operational reliability. Furthermore, the proposed system improves manufacturing information transparency, accelerates intelligent decision-making processes, and enhances enterprise operational responsiveness. These characteristics collectively demonstrate the practical potential of the proposed LLM+MCP framework for supporting MES digital transformation, intelligent manufacturing management, and enterprise performance enhancement in smart factory environments.

3.6 Comparison with existing automated report generation frameworks

To further evaluate the novelty of the proposed framework, a comparison was conducted with representative automated report-generation approaches reported in the manufacturing and industrial-information literature. Most existing automated reporting systems primarily focus on database-driven report generation or rule-based information summarization. Although these approaches can reduce manual reporting effort, they often lack heterogeneous sensor integration, multi-modal data fusion capability, and intelligent language-generation functionality. In contrast, the proposed sensor-assisted LLM+MCP framework integrates real-time industrial sensing information, including equipment-status monitoring, process-parameter sensing, RFID/barcode tracking, machine-vision inspection, and IIoT communication data. Furthermore, the framework combines LoRA-optimized LLMs with multi-modal collaborative processing to automatically generate management-oriented reports and operational insights. This capability extends beyond conventional template-based reporting systems by enabling the intelligent interpretation of manufacturing events, anomaly identification, and adaptive decision support. Therefore, compared with existing automated reporting approaches, the proposed framework provides enhanced sensing-data utilization, greater analytical flexibility, stronger scalability for heterogeneous industrial environments, and improved support for intelligent manufacturing management.

4. Discussion and Analysis

4.1 Technical contributions

In this study, we propose a sensor-assisted MES framework integrating LLMs, MCP, and LoRA-based lightweight fine-tuning for intelligent automated report generation in smart manufacturing environments. By combining IIoT-based sensing technologies with intelligent language processing, the proposed framework enables the efficient integration of heterogeneous manufacturing information, including process parameters, equipment operation records, and time-series sensor signals. One major contribution of this research is the integration of LoRA fine-tuning with multi-modal late-fusion processing in MES applications. Compared with conventional full-parameter LLM training, LoRA significantly reduces computational complexity and hardware requirements while maintaining high-quality language generation capability. In addition, the proposed MCP architecture independently processes structured production records, sensing signals, and operational logs before performing collaborative fusion, thereby improving scalability and parallel processing efficiency in manufacturing environments. Another important contribution is the transformation of sensor-assisted MES systems from traditional monitoring platforms into intelligent decision-support systems. Through real-time sensing analysis, automated report generation, and visualization-based operational interpretation, the proposed framework supports adaptive production coordination, process optimization, and manufacturing performance evaluation. These characteristics demonstrate the potential of integrating intelligent sensing technologies with enterprise digital transformation and operational management systems.

4.2 Practical implications

The experimental results demonstrate that the proposed LLM+MCP framework provides substantial practical value for intelligent manufacturing applications. The reduction in report generation time by more than 90% significantly decreases the workload associated with conventional manual reporting processes, allowing managers to focus more on operational planning and strategic decision-making. Through automated sensing-data analysis and intelligent report synthesis, the framework improves manufacturing information transparency and operational responsiveness in smart factory environments. The proposed architecture also enhances management decision quality through the continuous integration of sensor-derived manufacturing information. By combining intelligent sensing analytics with visualization-based reporting, managers can rapidly identify production abnormalities, evaluate process efficiency, and optimize production scheduling and workflow coordination. Furthermore, the lightweight LoRA optimization and modular MCP architecture enable deployment without requiring extensive hardware resources, making the framework suitable for various manufacturing systems. This characteristic is particularly beneficial for small and medium-sized enterprises (SMEs), which often face limitations in digital infrastructure and computational resources.

Through efficient sensor-assisted manufacturing analytics and automated reporting mechanisms, SMEs can improve operational efficiency, manufacturing visibility, and enterprise management capability while supporting digital transformation and enterprise performance enhancement.

5. Limitations and Future Work

Although the proposed framework demonstrates promising performance, several limitations and future research directions should be considered. First, the reliability of heterogeneous manufacturing sensing data remains an important factor affecting report quality and analytical accuracy. In addition, LLM-generated outputs may occasionally produce hallucination phenomena when interpreting complex industrial scenarios. Although cross-referencing generated content with manufacturing databases improves reliability, it also increases computational overhead. Second, future work will focus on integrating edge computing and digital twin technologies to further reduce response latency and improve real-time operational monitoring capability. The incorporation of edge intelligence may support more adaptive manufacturing management and predictive operational optimization in dynamic industrial environments. Third, the current framework mainly relies on supervised fine-tuning using historical manufacturing reports. In future studies, we will therefore investigate Reinforcement Learning from Human Feedback to improve long-term adaptability and contextual reasoning capability in real manufacturing environments. In addition, future integration with enterprise resource planning, predictive maintenance, and intelligent scheduling systems may further strengthen enterprise-wide operational coordination and intelligent manufacturing performance.

Another important research direction involves the integration of emerging sensing technologies and advanced sensing materials into the proposed framework. Future smart manufacturing environments are expected to incorporate next-generation industrial sensors, including flexible sensors, self-powered sensing devices, intelligent machine-vision systems, and AI-enabled edge sensors capable of performing local data analysis. In addition, advances in sensing materials, such as nanostructured materials, functional thin films, and high-sensitivity semiconductor sensing materials, may further improve sensing accuracy, environmental robustness, and real-time monitoring capability. The proposed LLM+MCP architecture provides a scalable platform for integrating these future sensing technologies by supporting heterogeneous sensor fusion, the intelligent interpretation of sensing data, and adaptive decision-making. Therefore, in future studies, we may investigate how novel sensor designs and advanced sensing materials can be incorporated into the framework to enhance predictive maintenance, process optimization, quality inspection, and autonomous manufacturing management in next-generation smart factories.

6. Conclusions

In this study, we proposed a sensor-assisted MES framework integrating LLMs and MCP for intelligent automated report generation in smart manufacturing environments. By combining heterogeneous sensor data, IIoT-based monitoring technologies, intelligent language generation, and visualization-driven analysis, the proposed framework effectively improves manufacturing information processing efficiency and operational decision-making capability. The integration of real-time sensing analytics with automated report synthesis enables manufacturing managers to rapidly obtain operational insights, identify production abnormalities, and optimize workflow coordination and resource allocation in practical industrial environments. Experimental results demonstrated that the proposed system reduced the report generation time by more than 90% while maintaining 99.9% system availability and stable response performance. In addition, the integration of LoRA-based lightweight optimization and MCP modular processing significantly improved computational efficiency, scalability, and deployment flexibility for practical industrial applications without requiring excessive hardware resources. The generated reports and visualization dashboards also enhanced operational transparency, anomaly identification capability, production scheduling efficiency, and enterprise management responsiveness. Overall, the proposed framework demonstrates strong potential for supporting MES digital transformation, intelligent manufacturing management, and enterprise performance enhancement in future smart factory environments. Future work will focus on integrating edge computing, digital twin technologies, and adaptive intelligent learning mechanisms to further improve real-time operational analysis and autonomous manufacturing decision-making capability.

Acknowledgments

This work was supported by Summit-Tech Resource Corp. and by projects under Nos. NSTC 113-2221-E-390-011 and NSTC 114-2622-E-390-001.

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