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| RESEARCH ARTICLE

Utilizing LLM models for advanced automation, manufacturing operations

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| ABSTRACT

With the high rate of digitalization in manufacturing operations, extensive data gathering and local optimization have been made possible; however, the fragmented nature of the decision-making process in manufacturing operations, in the domains of production, quality, and maintenance, still persists. The state-of-the-art automation and artificial intelligence solutions that are currently available in the market are largely specific to the task and do not possess the ability to understand unstructured knowledge, reason across diverse contexts, and provide transparent support for the decision-making process to engineers and operators. The recent advances in large language models (LLMs) open new opportunities to provide cognitive and semantic reasoning capabilities in manufacturing operations. In this paper, a conceptual and design-oriented framework is proposed to utilize large language models (LLMs) to facilitate sophisticated automation in manufacturing operations. The proposed architecture for utilizing LLMs in manufacturing operations considers LLMs as a cognitive orchestration and decision support layer, where enterprise and shop-floor systems, operational context knowledge, and analytical and optimization tools are integrated. The proposed framework has clearly defined functional operational roles for LLMs in manufacturing operations, such as production, quality, and maintenance, and a formalized human-in-the-loop approach to ensure accountability, safety, and regulatory compliance in manufacturing operations, along with governance and validation mechanisms to address the risk of unreliable results from LLMs. The research provides a manufacturing-related architectural perspective for the automation enabled by large language model (LLM) technology, highlighting the role of LLM technology in the facilitation of semantic interoperability, cross-functional coordination, and explicable decision-making. Although the research does not include any validation, the suggested framework provides a basis for the upcoming industrial pilot research and supports the move towards robust and human-centric manufacturing systems, as suggested by the industry 5.0 concept.

| KEYWORDS

Large language models; Smart manufacturing automation; Human-AI collaboration; Manufacturing operations management; Industry 5.0

| ARTICLE INFORMATION

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1. Introduction

Manufacturing operations are in the midst of a fundamental transformation driven by the rapid coalescence of cyber-physical systems, industrial data platforms, and advanced artificial intelligence technologies. While Industry 4.0 initiatives have driven widespread connectivity, sensor-based monitoring, and optimization, the operational intelligence in most manufacturing operations remains significantly fragmented. Core decision processes, such as production rescheduling, quality deviation analysis, and engineering changes, continue to rely on manually coordinated toolsets, expert knowledge, and inflexible rule-based automation. Such fragmentation limits the ability of manufacturing operations to effectively adapt to disruptions, increasing product variety, and geographically distributed operations [1].

The current automation architectures mostly rely on programmable logic controllers, manufacturing execution systems, and optimization or machine learning-based models, which are mostly designed to perform specific tasks or functions. Even though such systems are efficient in supporting localized control and prediction, they do not possess functionality to support cross-context reasoning across heterogeneous operational environments, unstructured engineering knowledge, and explanations of results in a human-understandable fashion. Therefore, manufacturing engineers and planners are still mainly relied upon to integrate knowledge across operational domains, such as design, production, quality, and supply, through manual and time-consuming means [2].

Recent advancements in large language models (LLMs) have provided a new paradigm for the development of intelligent manufacturing automation by incorporating the ability to perform semantic reasoning, natural language interactions, and integrating domain knowledge. Unlike traditional data-driven models, LLMs have the ability to interpret engineering documents, standard operating procedures, maintenance reports, and production reports within a single representational framework. This ability of LLMs makes them a new layer of cognition to be used for decision-making, workflow, and contextual diagnostics in the entire manufacturing lifecycle [3].

Despite the growing interest in the application of large language models (LLMs)-based systems within the domain of enterprises and software, their application to manufacturing operations remains an understudied area. In the existing literature, the focus remains limited to the ways in which the reliability and governance constraints of LLMs could be ensured within the context of industrial automation [4].

Inspired by this research gap, the research in the current paper proposes a manufacturing-centric conceptual framework that seeks to exploit the capabilities of large language models (LLMs) to facilitate the achievement of highly automated systems in manufacturing, quality, and maintenance processes. The originality of the research in the current paper resides in the definition of the operational architecture and the human-LLM collaboration model, which consider LLMs as decision support and orchestration tools, but not as controllers. The research in the current paper follows a conceptual and design research approach, avoiding the use of experimental and operational data to focus on architectural aspects, governance, and research opportunities for intelligent and human-centric manufacturing systems.

2. Literature Review

2.1 AI and automation in manufacturing operations

The applications of artificial intelligence in the manufacturing process have mainly focused on improving the efficiency, reliability, and predictability of the manufacturing system. Previous research has extensively studied the application of machine learning-based methods in production planning and scheduling, predictive maintenance, quality inspection, and optimization of various manufacturing parameters. Supervised and unsupervised learning models have been widely used for pattern recognition in equipment degradation, machine failures, and surface or dimension-related defects in products. At the same time, simulation-based optimization models have been developed for various manufacturing scenarios, including line balancing and optimization in the manufacturing system [5].

Despite their methodological maturity, these approaches are still mostly task-oriented. The majority of AI approaches have been trained for particular, narrow, and well-defined operational objectives, require considerable feature engineering, and require data preparation for each task. As a result, these approaches have limited support for cross-functional decisions, for instance, relating production plans with engineering changes, quality variances, or maintenance constraints. The limited scope of these approaches for addressing manufacturing operations makes it difficult for them to handle dynamic and interconnected manufacturing environments, particularly for multi-site production scenarios [6].

2.2 Knowledge-driven and decision-support systems in manufacturing

To overcome the limitations of data-driven models, various studies have investigated knowledge-based systems and decision support systems in manufacturing operations. In the past, expert systems and rule-based systems were proposed to utilize domain knowledge in process planning, problem-solving, and machine diagnostics. Recently, manufacturing knowledge graphs were proposed to describe the associations between products, processes, and resources [7][8].

Even though these systems facilitate the traceability and formalization of engineering knowledge, they often require significant modeling and maintenance costs. The acquisition of knowledge still relies on manual processes and requires continuous expert support to ensure the alignment of rule bases and ontologies with the ever-changing shop floor practices. In addition, the integration of structured knowledge models and real-time operational data is usually poor, and the support offered to the decision-making process is fragmented and does not extend effectively to other departments such as production, quality, maintenance, and supply coordination [9].

2.3 Natural language interfaces and conversational systems for industrial environments

Several research studies have proposed conversational agents and natural language interfaces to improve access to manufacturing information systems. These solutions enable operators and engineers to interact with machine status, production performance, or maintenance data by means of specific intents and dialogue flows. Even though conversational interfaces improve the usability and accessibility of operational information, they remain mainly dependent on static templates and rule-based interaction patterns [10].

In addition, conversational interfaces are restricted to specific decision-making scenarios and cannot support complex operational interpretation, such as identifying multiple causes of production problems or explaining trade-offs between alternative scheduling strategies. Therefore, conversational interfaces remain mainly used as information retrieval tools rather than decision support in manufacturing operations.

2.4 LLM models and their emerging industrial relevance

Current advancements in large language models (LLMs) have revealed strong reasoning over unstructured text, generation of structured data, and orchestration of tasks within an enterprise domain. Initial industrial applications of LLMs have focused on software development, document automation, analysis of business processes, and orchestration of enterprise tasks. These results demonstrate the potential of LLMs to aggregate heterogeneous data and provide explanations that are understandable to non-technical users [11].

The domain of manufacturing adds another layer of complexity due to safety-critical processes, hard real-time constraints, and strong coupling with physical assets. In most existing studies, which are focused on large language models (LLMs), little is said about the possibility of integrating LLMs with manufacturing execution systems, engineering information systems, or operational control systems. In addition, the operational role of LLMs in production, quality, or maintenance decision-making is not clearly defined [12].

2.5 Critical gaps in existing literature

The literature reviewed has identified three major gaps, namely, the lack of end-to-end architectural models that incorporate LLMs as functional components in manufacturing automation systems, the lack of a well-structured framework that describes the role of LLMs in facilitating various cross-functional activities in the manufacturing domain, and the lack of research on governance and reliability issues, including decision validation, traceability, and mitigation of incorrect results provided by LLMs, among others. These gaps highlight the need for developing a conceptual framework that describes the role of LLMs in the context of manufacturing automation and human-centric decision-making.

3. Methodology (Conceptual Framework and Research Design)

This investigation uses the design science-oriented approach of research methodology in order to conceptualize the role of large language models in advanced manufacturing automation. Design science is pertinent in this investigation since it is not geared toward empirical validation but rather toward the formulation of an architectural artifact that is theoretically informed and deployable in order to fill in the gap in the current state of the art in manufacturing automation. The research process follows three sequential stages: (i) problem identification based on limitations observed in current AI-enabled manufacturing operations, (ii) conceptual artifact design in the form of an LLM-enabled operational architecture, and (iii) theoretical validation through consistency with established manufacturing automation and human–machine collaboration principles.

In addition, manufacturing operations have been modeled as a socio-technical system where production engineers, planners, quality engineers, and maintenance specialists interact with enterprise and shop floor information systems to implement coordinated decisions. Accordingly, in the proposed framework, technical integration and organizational interaction mechanisms are considered.

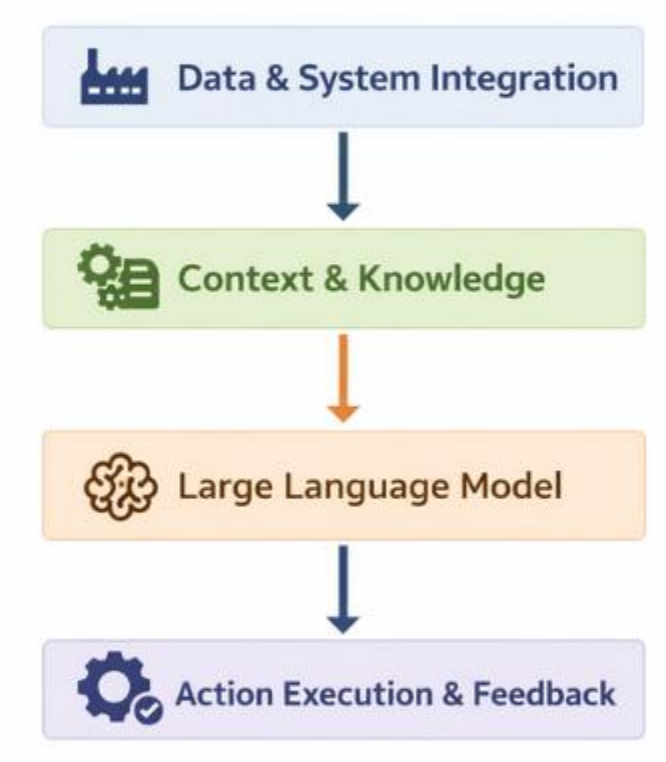

Fig 1. workflow for the proposed LLM-enabled manufacturing

A simple and single-column workflow for the proposed LLM-based manufacturing automation framework is presented in the figure. The manufacturing data, derived from enterprise and system sources, is first integrated within the Data and System Integration layer and subsequently contextualized within the Context and Knowledge layer. The decision-support is achieved through contextual reasoning within the Large Language Model, and the validated results are executed through action execution and feedback within the Action Execution and Feedback layer.

3.1 Conceptual architecture for LLM-enabled manufacturing automation

The proposed framework has an organizational structure based on a layered operational architecture with four tightly coupled layers.

The first layer is the data and system integration layer, integrating various manufacturing information systems, including manufacturing execution systems, enterprise resource planning systems, product lifecycle management systems, quality management systems, computerized maintenance management systems, and industrial data platforms, as well as simulation and digital twin environments, which provide analytical and predictive tools. The purpose of this layer is to provide access, using standardized interfaces, for higher-level reasoning components to both structured and unstructured operational information.

The second layer is the context modeling and operational knowledge layer. In this layer, engineering documents, standard operating procedures, work instructions, process constraints, equipment specifications, production records, maintenance records, and others are synthesized in a machine-readable and semantically structured way, which aims at reducing the fragmentation that exists between engineering knowledge and real-time operational data, which is the current constraint in decision transparency.

The third level represents the reasoning and orchestration level for large language models (LLMs). In this level, it is not considered as a controller on its own but as a cognitive orchestration component to interpret context, integrate heterogeneous system information, and generate decision recommendations along with their associated justifications. The LLM is operated within a set of constrained prompts and output to guarantee compatibility with industrial workflows and downstream systems.

The fourth layer makes up the action execution and feedback layer. This layer is said to interface with established planning engines, maintenance processes, quality escalation processes, as well as communication systems. Decisions that are approved are executed through traditional operational systems, whereas the feedback from the execution process is constantly fed back to the contextual knowledge layer.

3.2 Functional operational roles of LLMs

In the proposed architecture, four functional operational roles for large language models (LLMs) are delineated. First, an operational query and diagnosis agent helps engineers and operators to interpret production deviations, equipment alarms, and quality non-conformances through contextual operational knowledge. Second, a planning and rescheduling assistant helps with short-term and mid-term production planning by interpreting constraints, resource availability, and engineering changes. Third, a quality and compliance reasoning assistant helps with deviation analysis, corrective action formulation, and regulatory traceability. Fourth, a maintenance and asset intelligence assistant helps with fault interpretation, maintenance prioritization, and work order planning.

These roles are intentionally aligned with core manufacturing operational functions to enable cross-functional coordination rather than isolated task automation.

3.3 Human–LLM collaborative operating model

In addition, an in-loop mechanism of human oversight is integrated in the framework. All the recommendations generated by the large language models are subject to role-based validation before execution. In this framework, it is clearly defined how the decision suggestion, decision approval, and decision execution are carried out. This is the basis of the human-centric manufacturing paradigm in which large language models are used in assisting the cognitive workload.

3.4 Governance, validation, and safety mechanisms

To manage the operational risks, the framework includes governance features such as structured prompts, rule-based validation layers, verification of constraints in accordance with the operational policies, and audit logging. Output validation ensures that the outputs are within the defined boundaries and the engineering constraints. The traceability features include the context inputs, the reasoning outputs, and the approval.

3.5 Evaluation logic without empirical experimentation

As this is a conceptual study, the proposed framework is judged using qualitative design criteria. The qualitative design criteria include operational transparency, integrability with existing manufacturing systems, scalability to various domains of operation, support for human-centric decision workflows, and readiness for governance in safety-critical manufacturing systems. These qualitative design criteria form a structured basis for future validation and politization of this proposed framework.

4. Discussion

The proposed LLM-based operational framework has the potential to bring about significant changes in the way manufacturing organizations manage their operations, address disruptions, and manage cross-functional decision-making processes. The proposed framework differs from other conventional automation solutions, which often focus on localized optimization or control, by emphasizing system-level thinking with respect to production, quality, and maintenance operations. The proposed framework has the potential to reduce the time taken by engineers and planners to interact with various forms of operational data and engineering knowledge by using a unified semantic interface, provided by large language models, and thus can be particularly beneficial for improving the responsiveness and stability of dynamic production environments, such as high-mix, low-volume production systems.

From the perspective of ecosystems, large language models (LLMs) can be viewed as the cognitive integration layer in the architecture of smart manufacturing systems, in addition to the already available digital twins, optimization platforms, and predictive analytics solutions. Digital twins provide the quantitative predictions and forecasting capabilities, while machine learning models provide localized predictions. Similarly, LLMs provide the semantic reasoning and contextual interpretation capabilities across different domains. This integration allows manufacturing systems to move from the level of individual analytical tools to the level of integrated and explainable operational intelligence. By facilitating the interoperability between engineering documentation, real-time production information, and enterprise systems, LLMs can facilitate more consistent decision-making across different organizations.

This framework is consistent with the evolution from Industry 4.0 to Industry 5.0 by specifically promoting the concept of human-centered manufacturing operations. Instead of replacing the expertise of humans, the framework of large language models (LLMs) is designed to be a collaborative decision-maker that can enhance the understanding of the operator and the engineer. This can be particularly important for mitigating the cognitive burden on the engineers and the operator, yet still holding the human accountable for safety and compliance-driven decisions. This collaborative approach can be particularly important in the context of manufacturing operations where the interpretation of trade-offs by the expert is critical.

The organizational implications of operations supported by large language models (LLMs) are also significant. Manufacturing engineers, planners, and quality specialists have the opportunity to move beyond their current focus on manual information aggregation to a future focus on validating system recommendations, improving system constraints, and managing escalation, as opposed to routine coordination. This has the opportunity to increase the productivity of the existing workforce while also creating a new need for capabilities in system governance, data management, and human–AI interaction management.

Despite these potential benefits, several technical and ethical challenges remain. The potential for incorrect and/or misleading information due to model hallucinations, incomplete context, and/or biased training data represents a major concern in safety-critical manufacturing environments. Further, the integration of proprietary engineering information and knowledge within the large language model pipelines creates several concerns related to information confidentiality, intellectual property rights, and regulatory compliance. Over-reliance on automated reasoning systems can lead to decreased situational awareness, which must be mitigated.

This particular study is limited in that it is conceptually oriented with no empirical validation. The proposed framework does not quantify improvements in performance or operational risks. Future studies need to focus on industrial pilot implementations, methodologies for fine-tuning in specific domains, and benchmarking studies that evaluate decision quality, speed of response, and adoption potential. These studies are necessary to validate the viability of LLM-based automation in manufacturing operations.

5. Conclusion

In this paper, the authors propose a conceptual framework for the deployment of large language models in the context of manufacturing, which enables the achievement of advanced automation in the operations of the manufacturing system. By conceptualizing the deployment of LLMs as a cognitive orchestration and decision support system, the proposed architecture addresses the fundamental limitations associated with data-driven and rule-based automation systems. In the proposed framework, the heterogeneous data associated with the operations of the system is integrated in an effective manner.

The main contribution of this study is the determination of a structured operational architecture along with a human-LLM collaboration model that includes mechanisms for governance, validation, and traceability in order to ensure the reliability of the system in safety-critical manufacturing environments. In this way, the current paper contributes to the knowledge regarding the integration of large language models (LLMs), in the capacity of complementary intelligence components, in smart manufacturing environments with the aid of digital twins and optimization engines.

From a strategic point of view, the suggested framework enables the shift towards a human-centric and resilient manufacturing system in line with the Industry 5.0 philosophy. In spite of the fact that the study is still in a conceptual phase and cannot be validated empirically, it provides a groundwork for upcoming industrial pilot studies, large language model development in specific domains, and quantitative analysis of the operational impact, thus paving a pathway for a research roadmap to be followed for the development of next-generation intelligent manufacturing automation.

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