

# Integrating Large Language Models into Digital Twins for Enhanced Manufacturing Process Control

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## Abstract

The rapid development of Industry 4.0 has introduced advanced technologies such as IoT, cyber-physical systems (CPS), and industrial IoT into manufacturing environments. However, traditional production management systems remain largely reactive, operating in discrete modes with fragmented interfaces. This paper presents a concept for a production management support system that integrates large language models (LLMs) that enable natural language interaction. This solution concept addresses the key challenge of data fragmentation by creating an intelligent digital twin that acts as a production expert capable of contextual reasoning, information synthesis from multiple sources, and real-time decision support. This concept demonstrates the potential to transform production management from a reactive to a proactive operating model by leveraging LLM's capabilities in pattern recognition, predictive analysis, and automated recommendation generation. Future development directions focus on optimizing business intelligence integration, improving automated recommendation mechanisms, and standardizing natural language user interfaces for industrial applications.

## Keywords

LLM, expert system, artificial intelligence, AI, Industry 4.0, digital twin, manufacturing process control.

## Introduction

The advent of Industry 4.0 has led companies to implement advanced IT solutions on a large scale. This trend has fundamentally changed the modern manufacturing environment. The integration of technologies such as the Internet of Things (IoT), cyber-physical systems (CPS), big data analytics, and artificial intelligence technologies provides better production management capabilities (Pizoń et al., 2019; Zhong et al., 2017).

Technological advances in this field, on a completely different scale than before, have opened many doors for optimization focused on operational efficiency, product quality, and production flexibility (Rymarczyk et al., 2020). At the same time, however, unprecedented complexity has emerged in the integration of individual

technologies, especially in the management of the data on which decisions are based. The challenge remains to make these decisions in real time.

Following the advent of Industry 4.0, manufacturing plants have been implementing successive technologies. As a result, they typically use multiple domain-specific IT systems that, without integration, constitute their own data domains: supervisory control and data acquisition (SCADA), manufacturing execution systems (MES), enterprise resource planning (ERP), and quality management systems (QMS). Each of these domains generates vast amounts of data that can be analyzed, but their complexity and competency requirements pose challenges for manufacturing companies (Kłosowski et al., 2015). Given this fact, critical information bottlenecks arise around data management and, consequently, knowledge management, which can directly impact production efficiency and company competitiveness. Importantly, valuable knowledge regarding problem-solving and management remains embedded in domain-specific systems (standard operating procedures, troubleshooting guides, equipment operating manuals) or in the form of tacit knowledge possessed by staff. Furthermore, as is typical in man-

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ufacturing, when a multi-shift system is implemented, these problems escalate, for example, due to a lack of available staff during night or weekend shifts.

Notably, even the infrastructure that supports production operations is reactive. That is, alarms and other notifications appear after problems have occurred. However, in the context of operational production, a proactive, predictive and prescriptive solution is needed that can both identify potential problems and suggest solutions before they impact production.

In this area, the use of AI solutions based on LLM is promising (Badurowicz et al., 2024; Cevallos Salas, 2024). Artificial intelligence facilitates many tasks, but it also provides a source of information on which subsequent decisions are based. New language models are demonstrating extraordinary capabilities in natural language understanding, contextual reasoning, synthesizing information from multiple sources, and knowledge-based problem solving (Brown et al., 2020). However, the conditions for model performance require the provision of high-quality data and appropriate implementation methods to prevent models from hallucinating or providing erroneous information.

However, from a business perspective, the knowledge gained in a large-scale, automated manner by interacting with multiple sources using LLM can be a source of competitive advantage. The number of analyses and their cross-cutting nature can provide a basis for identifying improvements that may not be possible with standard approaches—statistical analysis, business intelligence, and machine learning. Because LLM requires large amounts of data, it provides an ideal solution to the problems of analyzing it. The knowledge gained can lead to better management while leveraging the data available. Communicating in natural language and responding quickly can have a significant impact on the accuracy of decisions made by production managers.

This approach differs from traditional solutions implementing business intelligence applications, for example, where the interpretation of collected data signals is performed by an expert or decision maker. This person, who has the appropriate education and training, uses advanced ML models to formulate recommendations for production managers. In the LLM approach, production managers are empowered to respond directly and appropriately to questions they ask themselves (Pizoń et al., 2026). Thus, LLM becomes a partner in the execution of management tasks, creating a digital twin solution, effectively a digital expert. The digital expert would perform natural language interaction, intelligently integrate information from multiple sources, support contextual decisions, and provide broad access to knowledge. Therefore, with the advent of LLM, expert system solutions have the potential to return as

real applications in production practice. LLM brings enthusiasm, but it requires the verification of boundary criteria and conditions for successful implementation. For this reason, there is a significant research gap regarding the practical application of industrial AI technologies as expert systems. Therefore, the aim of this article is to present a solution that uses industrial data to ensure the effective delivery of results using modern LLM models.

## Literature review

The first manufacturing expert systems emerged from early research in artificial intelligence in the 1980s and 1990s. At that time, these systems showed potential, but the codification of expert knowledge, for example in rule-based systems, was a major obstacle. At that time, knowledge engineering required many months of work by specialized knowledge engineers. The availability and feasibility of extracting knowledge from “human experts” and encoding it into formal rules was a challenging task, both from a business perspective and due to the reluctance of experts to share information and the difficulty of extracting rules. As a result, these systems performed well in cases within the scope of the rules, but significantly poorly in extreme or novel situations. As a result, the rule bases developed became significantly complex and unstable. In addition, rule derivation produced unexpected results, sometimes significantly so. Because of these limitations, expert systems suffered significant failures in the 1990s, despite their solid conceptual foundations (Brown et al., 2025; Kusiak, 2018).

Considering existing solutions, current research on LLM applications in manufacturing focuses on specific areas. One example is the prototype of MetalMind, a knowledge graph-based system for additive metal manufacturing that uses LLM to automate the extraction and organization of complex technical information. This system provides improved knowledge accessibility (Fan et al., 2025). Similar work is being done in additive manufacturing process control, using pre-trained large transformer models and visual-linguistic models to monitor the process based on images captured during printing, demonstrating their usefulness in detecting anomalies and assessing product quality (Farimani et al., 2024).

## Production processes management

Managing production processes in production systems using Industry 4.0 solutions opens up new optimization opportunities, but also poses several chal-

lenges (Lee et al., 2015). One of the key challenges in this area relates to both information fragmentation and access barriers. Despite the potential for convergence, systems typically have different data formats and business conditions, preventing integration. Data warehousing and business intelligence solutions are costly and require proper system sizing and implementation planning to achieve their goals (Bousdekis & Mentzas, 2021).

The second issue is the availability of expertise and methods for storing it. Key knowledge for the implementation of the production process is typically located in two centers. One is the documentation and manual libraries, which remain largely inaccessible due to their volume and complexity, poor organization, and the limitations of keyword-based search systems (Alharbi, 2020; Huber et al., 2022; Poloskov et al., 2020; Reiman et al., 2023). On the other hand, a vast amount of knowledge resides in the minds of employees, representing an invaluable resource of tacit knowledge that is the result of years of work but is not documented. It is therefore inaccessible outside working hours and vulnerable to loss due to employee retirement or turnover (Igoa-Iraola & Díez, 2024; Moen et al., 2016).

The third fundamental challenge concerns reactive versus proactive operations. It is important to note the importance of responsiveness to change (Milisavljevic-Syed et al., 2023). Traditional production management systems operate primarily on an event basis, alerting operators when abnormal conditions occur and conducting root cause investigations (Ivanov et al., 2020). This reactive approach results in unplanned downtime due to equipment failure, quality issues, or wasted resources (Fazli et al., 2023).

### Large Language Models Opportunities

LLM capabilities in production management represent a new solution that significantly accelerates digital transformation in the era of Industry 4.0. The integration of LLM solutions at the production control level provides a fundamental combination of modern artificial intelligence and machine learning computing techniques with cyber-physical systems, edge/cloud computing, and Industrial Internet of Things (IIoT) networks, enabling real-time process optimization and autonomous decision making (Olayinka, 2023). Within this new ecosystem, LLMs add unique capabilities that enable the generation of natural language responses based on text-based questions. This fundamental shift removes the barriers to implementing complex machine learning tools and increases the efficiency of operations, including production. Within this ecosystem, LLM models bring unique capabilities by generat-

ing executable code and natural language instructions based on text-based prompts, thus reducing barriers to implementing complex machine learning tools and increasing productivity in various sectors, including manufacturing (Zheng et al., 2025).

Applications of this approach have already found their way into manufacturing, where models work alongside AI-based additive manufacturing systems to improve production capabilities and reduce production time (Basseey et al., 2025). Furthermore, this type of system is also useful in pharmaceutical and specialty manufacturing, where AI-based digital twins integrated with IIoT technology enable real-time monitoring, fault diagnosis, and adaptive process control while maintaining regulatory compliance (Mamatha, 2025). A key feature of LLMs used in manufacturing process control is natural language reasoning and understanding to facilitate data-driven decision making in complex manufacturing environments (Liu et al., 2023).

However, the practical implementation of LLMs in manufacturing requires careful consideration of their limitations and the specific contexts in which they provide superior performance compared to traditional machine learning methods (Liu et al., 2023). Manufacturing systems are increasingly using cognitive digital twin technologies and artificial intelligence-based generative planning software for real-time production logistics and enterprise resource coordination. However, it is LLM models that have the potential to improve process planning, anomaly detection, and maintenance optimization. In this area, LLM's ability to generate recommendations, i.e., the ability to process and generate actionable conclusions based on unstructured data, is particularly useful. The availability of unstructured data analysis provides a significant advantage over other traditional data analysis approaches, thus increasing the intelligence and adaptability of Industry 4.0 systems (Lăzăroiu et al., 2024; Prabu et al., 2025).

### Case study

In response to the identified research gap, a prototype solution was developed that enables natural language conversations in production control. Data from the automotive remanufacturing industry is used as an example. The remanufacturing process is characterized by high variability due to the quality of the input material and the complexity of the decision processes requiring domain expertise. As a result, close monitoring of process execution is required, and production managers must make daily decisions regarding waste forecasting, resource allocation, and process op-

timization based on historical data. Traditional ERP and MES systems perform reporting and accounting functions. They have basic analytical capabilities, but their purpose is limited to current reporting. On the other hand, typical expert system solutions require the definition and implementation of rules. In comparison, LLM systems overcome these limitations. They can automatically acquire knowledge from documents, flexibly handle new situations through generalization, and be modified through prompt engineering.

As part of the research, a prototype system was developed to provide recommendations to production managers based on available data. In this system, humans retain decision-making authority. However, advanced analysis is performed on the model side and the results are presented in a user-friendly format. Therefore, the key innovation is the use of natural language as a universal interface layer that guarantees access to complex analytical capabilities for all employees without the need for specialized technical training in specific query languages and protocols.

## The Data

The study was conducted using a dataset of 436 production orders completed between December 2 and December 20, 2024. The data includes 62 variables describing production volume, waste, defects, and employee involvement in each process step. The production process analyzed consists of four consecutive stages: disassembly, assembly, sorting, and testing. The orders were completed on two production lines: the ALU line (400 orders) and the EPB line (36 orders). The dataset records defect occurrences in two key stages of the process – in the first stage 16 defect categories were identified, while in the second stage this number was expanded to 34 types.

In addition, the defects were classified according to two dimensions: defect group (four categories, with the “Busy” group dominating with 271 occurrences over the “Busy” group with 164 occurrences) and product price group (27 categories). In the production process, employees were assigned to both sorting and testing operations, which is reflected in the data structure. The dataset also includes information on the number of units processed at each stage and the waste generated, with particular emphasis on the waste generated during the testing stage.

## Architecture

The developed prototype expert system implements the concept of a multi-layer architecture that integrates the LLM model and machine learning algorithms with

production data access mechanisms. The architecture consists of three interacting layers that form a coherent data processing and recommendation generation environment (Fig. 1).

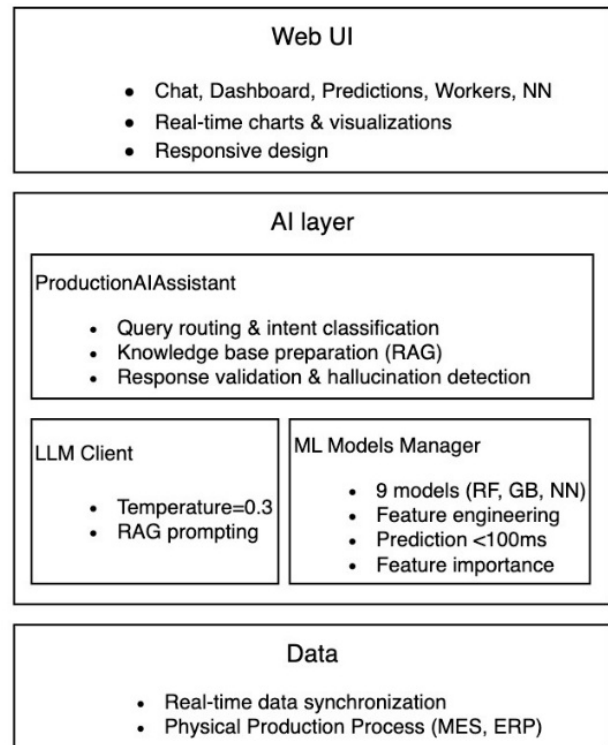


Fig. 1. System logic architecture

The presentation layer provides a user interface that allows interaction via natural language chat. The interface also includes dashboards that display parameters calculated by predictive models. This layer has been designed according to the principles of responsive design, ensuring flexible access regardless of the end device.

The intelligence layer, which is the core of the system, integrates two collaborative modules. The first, known as the Production Assistant, performs query routing, user intent classification, and knowledge base integration using Retrieval-Augmented Generation. This module implements response caching and help desk task scheduling mechanisms. It uses the Llama 3.2 architecture implemented by the Ollama framework (version 0.1.26) with restricted inference parameters (temperature = 0.3, core sampling top\_p = 0.9, maximum sequence length = 1024 tokens) to minimize stochastic variability. In addition, the prompt engineering employed implements strict fact-based protocols through system-level constraints that explicitly prohibit autonomous generation of numerical predictions, require citation of the knowledge base for all

fact-based assertions, and enforce querying of machine learning endpoints based on rule-based intent classification. The search-driven generation implementation creates a structured knowledge base of 2,800 tokens that is updated daily and aggregates five data sources (production statistics from 436 historical jobs, defect occurrence distributions, employee-level performance indicators, model feature importance rankings, temporal context metadata) using single-document retrieval without hierarchical segmentation, and implementing a three-step answer verification process involving natural language processing-based fact extraction, knowledge base validation through cross-referencing, and machine learning model consistency checking. Empirical validation of 200 representative production queries showed a pre-validation factual inconsistency rate of 8% (including 11 numerical approximations, 3 subject hallucinations, 2 unsupported cause-and-effect conclusions), which was systematically reduced to 0% after validation, achieving 100% detection sensitivity thanks to a hybrid verification architecture based on artificial intelligence and user interaction.

The second module manages nine machine learning models, including random forest algorithms, gradient boosting algorithms, and neural networks, which perform feature extraction, variable engineering, and evaluation of their relevance to the prediction process.

The evaluation methodology employed a stratified 80/20 split strategy for training and test data ( $n = 349$  training data,  $n = 87$  test data) combined with 5-fold stratified cross-validation to mitigate the effects of class imbalance (37.6% minority class representation), resulting in consistent performance across nine candidate models: Gradient Boosting Classifier (accuracy = 95.4%,  $F1 = 0.940$ , AUC-ROC = 0.982), Random Forest regressor for waste quantity prediction ( $R^2 = 0.794$ , RMSE = 1.787 units), and production efficiency predictor ( $R^2 = 0.9953$ , RMSE = 0.586 units). Feature importance analysis using decomposition showed that quantities at the production stage are the dominant predictive features (75-90% cumulative importance), while defect attributes are of secondary predictive importance (5-10%), thus confirming the hypothesis that input quantities and intermediate sorting results primarily determine waste generation patterns, and quality defects act as modulating factors rather than main causal factors.

The data layer provides real-time synchronization of information and access to the historical data repository, integrating with physical production processes through MES and ERP systems. Inter-layer communication is implemented through a context-independent interface designed according to RESTful architecture, allowing flexible integration with existing IT infrastructure.

The issue of real-time data acquisition is a challenge in terms of implementation in production conditions. The concept uses flat files exported from MES and ERP systems as data sources. However, it is understood that in terms of production implementation, it is necessary to use a data synchronization architecture that implements a dual integration strategy: near real-time event streams query Manufacturing Execution System (MES) interfaces at 30-second intervals to obtain information about order status changes, and Supervisory Control and Data Acquisition (SCADA) systems at 60-second intervals to obtain information about sensor aggregates (Enterprise Resource Planning systems are queried at 5-minute intervals), while batch processing operations are run daily, for example at 02: 00 UTC to gradually update the historical database, conditionally retrain the machine learning model (triggered after  $> 50$  new instances are collected or the  $> 30$ -day time threshold is exceeded), and regenerate the knowledge base with current production statistics. Note that from a solution perspective, the fault tolerance mechanisms provide soft degradation strategies: major disruptions in the language model cause a switch to template-based response generation, incorporating machine learning predictions with clear notifications about the operating mode; loss of connectivity to the production execution system or data collection and monitoring system activates snapshot-based operation, using the latest state from the cache with metadata about temporary obsolescence.

The system uses containerization to ensure separation of environments and the ability to scale resources elastically. A key design principle is separation of duties: the language model does not directly generate predictions, but relies on the results of machine learning models trained on historical data.

## Processes

The prototype system implements two basic scenarios of user interaction with an assistant based on large language model technology (Fig. 2). The first scenario involves expert consultation, where the user formulates a production query in natural language. The system then performs a series of analytical operations, including semantic search in the knowledge base, contextualization of the query by enriching it with current statistical data, and generation of a response tailored to the user's competence level. This process serves as a digital representation of expert knowledge, enabling the transfer of specialized knowledge to linear operators.

The second scenario focuses on predicting waste levels for planned production orders. The system processes parameters that characterize the order by normalizing

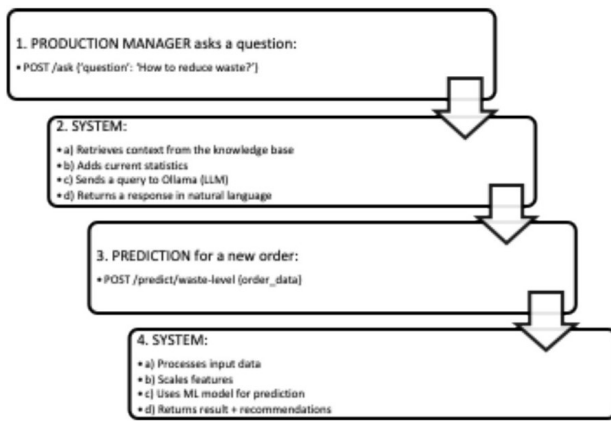


Fig. 2. System workflow

and standardizing input data, and then uses a trained machine learning model to estimate the amount of waste generated. The prediction results are supplemented with recommendations for corrective or optimization actions, supporting proactive process management.

The system is used in three key areas. At the operational level, it supports daily efficiency monitoring through a conversational interface and the resolution of current production issues. In the planning phase, it enables scenario analysis and waste forecasting for new orders. In quality control, the system supports defect structure analysis, identification of high-risk orders, and tracking of waste generation trends, helping to achieve sustainable production development goals.

## Results

The implementation of the system resulted in a convenient interface with the ability to make natural language queries. The interface allows for conversations with the agent, viewing relevant statistics, reviewing predictions, checking current global recommendations, learning about employee insights, and implementing predictions using neural networks.

The AI Assistant view (Figure 3) allows users to compose questions or use question templates. It also allows users to export conversations and manage them in the Conversation panel.

Importantly, the questions asked of the wizard can be complex and specific to data, as shown in the list below.

**User:** What waste level do you predict for ALU line with R1A-R01-TRW group?

**LLM:** To estimate the predicted waste level for the ALU line with R1A-R01TRW group, we can use the predictive model of waste sorting mentioned in the

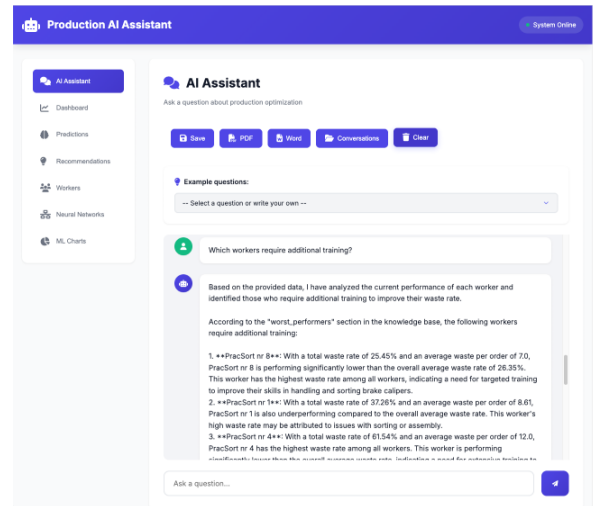


Fig. 3. AI Assistant of case study system

*Knowledge Base (Step 5. model).*

*First, let's gather the necessary data:*

*Production line: ALU*

*Group: R1A-R01-TRW*

*Average components per order: 32.4*

*Next, we'll use the model of regression waste sorting (Step 5. models) with the  $R^2 = 0.7945$  to predict the waste level.*

*Using a linear regression analysis with the given features and their importance values, I estimated the predicted waste level for ALU line with R1AR01-TRW group: Predicted waste level  $\approx 14.57\%$*

*Please note that this prediction is based on the provided data and model performance.*

*The actual waste level might vary due to various factors not captured by our analysis.*

*Additionally, considering the production lines' performance (Step 2. Stage Y production) and TOP 5 defects (Step 3. TOP 5 defects – stage 1), we can also identify potential optimization opportunities for ALU line with R1A-R01TRW group:*

*Increase monitoring of component quality: Focusing on reducing Defekt1\_Duza\_Korozja\_Korpusu, which has the highest importance value among all defects (0.04527242822530085), might help minimize waste.*

*\*\*Improve assembly efficiency\*\*:* Enhancing assembly speed and accuracy can lead to reduced waste caused by mistakes during this stage.

*Implementing these suggestions could further reduce the predicted waste level and contribute to improving overall production performance for ALU line with R1A-R01-TRW group.*

*Would you like me to provide more detailed information or recommendations on optimizing the production process?*

Implementing a system based on natural language processing represents a significant paradigm shift in operator-system interaction compared to traditional solutions. In the traditional model, operators required specialized technical skills, including knowledge of SQL to formulate database queries, advanced statistical analysis in Excel, familiarity with the structure of technical documentation files, and familiarity with abbreviations and coding conventions used in MES and SCADA systems. In addition, interpreting raw data required significant experience and analytical skills on the part of operations personnel. The proposed solution eliminates these technological barriers by providing a conversational interface using natural Polish. Operators can now formulate queries and commands intuitively, without requiring knowledge of data structures or programming language syntax, as the system autonomously translates user intent into sequences of technical operations. The system was implemented according to the level four digital twin architecture (Prescriptive Digital Twin), which is characterized by the ability to synchronize with the physical process in real time and to generate prescriptive recommendations (Fig. 4).

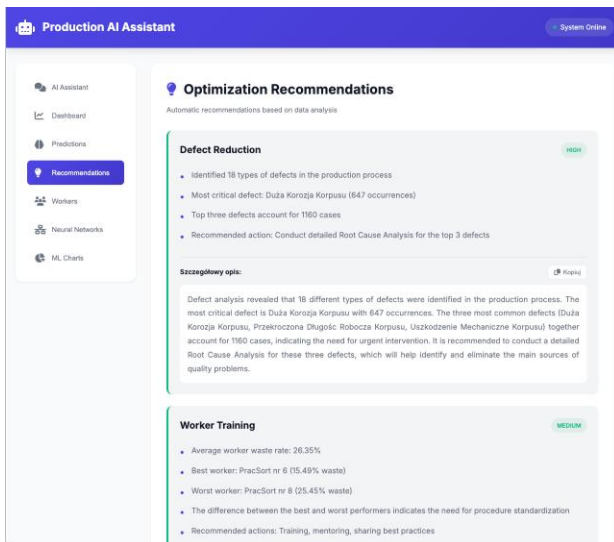


Fig. 4. AI Assistant optimization recommendation

The system generates recommendations for optimization actions and simultaneously implements a human-in-the-loop mechanism in which the operator plays a supervisory role, approving the corrective actions proposed by the system before they are automatically implemented in the production environment.

## Discussion

From the perspective of LLM applications, a key discussion is the critical limitation of this technology, commonly referred to as hallucination. In the case of LLM models, this means generating content that appears consistent but is not justified by the input data or is simply wrong (Ji et al., 2023; Zhang et al., 2023). This problem is particularly important in production management systems. Incorrect recommendations can lead to material losses and even safety hazards. However, with risk awareness and the use of appropriate mitigation mechanisms and techniques, hallucinations can be significantly reduced. Therefore, the use of LLM with ML support in production is valuable. The key argument in this area is their ability to aggregate and synthesize heterogeneous data sources in a way that is inaccessible to traditional deterministic systems. As researchers (Kasneci et al., 2023) point out, language models act as a “cognitive interface” between the user and complex data structures, while at the same time providing comprehensible access to advanced analytics.

In industrial practice, this means that a line worker (in any position) without advanced SQL, statistics, or programming skills can ask questions in natural language and receive answers that synthesize data from MES, SCADA, ERP systems, and technical documentation. The value of this process is not in the infallibility of the system, but in reducing the cognitive and time burden on the worker (Brynjolfsson et al., 2025). The proposed solution architecture implements the Retrieval-Augmented Generation (RAG) technique, which is a documented method for mitigating hallucinations by anchoring the generative process in verifiable data sources (Gao et al., 2023; Lewis et al., 2020).

Importantly, RAG allows the system to operate not only on its own knowledge (encoded in training), but also on a knowledge base containing current domain data about the production process. Researchers (Ram et al., 2023) have shown that systems using RAG reduce the frequency of hallucinations by 30-50%. This comparison was made with native models based on their own knowledge. However, even such a large organic reduction does not eliminate this phenomenon.

Despite these problems, the most important aspect of LLM production management systems is their supporting role – they do not make autonomous executive decisions. Therefore, it plays an advisory role, generating recommendations that are subject to verification by the operator, in accordance with the human-in-the-loop approach (Shneiderman, 2020).

In conclusion, the possibility of errors in LLM in production systems is justified, provided that certain

conditions are met. First, it is necessary to implement at least RAG mechanisms. This will allow LLM to be equipped with real process data. A human-in-the-loop approach is essential, where the human ultimately makes management decisions. The final element is the transparency of the response generation process, allowing the user to verify sources. This approach to LLM in production constitutes a competent assistant whose value lies in the aggregation and presentation of information, not in the infallibility of predictions.

## Conclusions

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Large Language Models are increasingly recognized as valuable tools for improving production process control through a variety of mechanisms: real-time monitoring and adaptive decision making, autonomous planning and optimization, knowledge transfer and employee support, and integration with advanced manufacturing technologies. Large language models represent a new dimension in streamlining production process management. They provide natural language data processing capabilities that facilitate real-time resource monitoring, decision making, planning, optimization, and ultimately knowledge transfer and support for analytical and line workers. This enables the transformation of production management from a reactive to a proactive operating model.

The research implemented the concept of a production support system based on large language models. The developed solution integrates data from domain-specific systems, eliminating interface fragmentation and enabling proactive real-time decision making. The system leverages LLM's capabilities for natural language processing, contextual reasoning, and synthesizing information from multiple sources to create an intelligent digital twin that acts as a production expert. Despite significant limitations in model performance, particularly with respect to the risk of hallucination, evidence suggests that implementing LLM technology can significantly improve production efficiency, productivity, and sustainability.

Further research will focus on optimizing the developed system, integrating it with business intelligence, developing methods for automated recommendation formulation, and creating more advanced digital twins for production. The development of standards for natural language-based user interfaces is also crucial, as they can significantly simplify the use of complex industrial systems by operating personnel.

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