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## RESEARCH ARTICLE

# LLM-Enhanced Human–Machine Interaction for Adaptive Decision-Making in Dynamic Manufacturing Process Environments

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**ABSTRACT** Modern production systems generate vast amounts of process data that hold valuable insights for optimizing manufacturing processes. However, production personnel often face the challenge of interpreting this information, especially when dealing with unexpected anomalies or when insights beyond standard reports are required. This challenge arises both from the complex data structures in which the data is provided, and the lack of analytical expertise. This research introduces an approach that leverages Large Language Models (LLMs) to facilitate natural language queries and flexible data visualization, allowing production personnel to interact effortlessly with complex datasets. Tested on process data from an industrial extrusion process that has been enhanced using data augmentation techniques, the proposed concept demonstrates the capability to retrieve relevant data and present tailored visualizations based on simple user prompts. The results demonstrate that LLM-driven data exploration can support production personnel and help overcome the challenges described, which arise from the complex nature of manufacturing data and the specialized domain knowledge required. Future work will concentrate on improving accuracy, robustness, and further integration of domain-specific knowledge, aiming to provide a more reliable and accessible tool for various industrial environments.

**INDEX TERMS** Industry 4.0, manufacturing, large language models (LLMs), data-driven decision-making, real-time sensor data, natural language queries, production process optimization, anomaly detection, data visualization, shop floor analytics.

## I. INTRODUCTION

The manufacturing industry is undergoing a transformation driven by the integration of advanced information and cyber-physical systems, collectively referred to as Industry 4.0 [1]. Consequently, the amount of new technologies and devices that collect vast amounts of data from manufacturing processes and machines is increasing [2]. This

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evolution within Industry 4.0 has accelerated the adoption of data-driven optimization of manufacturing processes. Advanced sensor networks and real-time analytics form the backbone of smarter, more responsive operations. Processes and underlying dependencies have become more visible and traceable through the availability and increased tracking of manufacturing process data [3]. Based on the collected manufacturing process data, valuable insights into production processes can be generated by the application of so-called process mining techniques. Besides giving insights into

the processes, process mining can be used to optimize manufacturing processes by evaluating the performance, detecting anomalies, and provide suggestions for improvement and support in decision-making. The techniques applied to achieve those goals reach from data (pre-)processing, data analysis, including the utilization of Artificial Intelligence (AI) and Machine Learning (ML), to the representation and display of the analysis results. Whereas classical approaches from Statistical Process Control (SPC) face the challenge of handling large amounts of data, process mining allows for the analysis and determination of complex dependencies in Big Data applications that are ubiquitous in the era of Industry 4.0.

Those data-centric approaches, however, introduce the challenge of managing and interpreting complex production data sets with multiple connections, layers and attributes collected from diverse sources [4]. While the vast amounts of data generated in modern production environments present a significant opportunity to enhance decision-making processes [3] this potential often remains untapped since the operational personnel, which is central to day-to-day decision-making, is usually not trained as data analyst [5]. Routine operations may be guided by standard reports and established procedures. However, atypical events demand a more nuanced and flexible understanding of the data and processes [6]. Those complex, investigative tasks lie outside the scope of the responsibilities of production personnel, leaving them ill-equipped to navigate intricate datasets effectively [5].

The need for stronger analytical capabilities becomes particularly relevant when the production environment deviates from its expected norms, such as during process anomalies or unforeseen downtime. Under these circumstances, timely data-driven error analysis is crucial, as delays can lead directly to costly losses in productivity and revenue [7]. To minimize disruptions and restore normal operations quickly, employees must be able to identify and address the underlying issues without undue delay [8].

The skill gaps that are present in the manufacturing environment create a barrier to informed and timely decision-making, underscoring the pressing need for intuitive, user-friendly analytical tools. Such tools can empower personnel to interpret and act upon critical data insights without requiring extensive technical training [9].

Within this context, the role of Human-Machine interaction (HMI) becomes increasingly prominent. Whereas first approaches of Industry 4.0 focused solely on the chances and opportunities generated by the collection and analysis of big amounts of data, more recent developments take into account more human-centered and socially relevant technologies. The goal is to create a bigger picture within the possibilities of human and global resources. By positioning human operators at the intersection of data, machinery, and decision-making processes, HMI seeks to facilitate a more intuitive and productive relationship between people

and the complex systems they oversee [10]. Traditional approaches to HMI, however, are not necessarily designed to provide easy or convenient access to reports and insights during unexpected situations, especially for shop floor, or manufacturing employees with no background in data analysis, often leaving them overwhelmed by the immense data streams integral to modern manufacturing and without a clear path to actionable insight [11].

Addressing these challenges requires not only tools that can interpret and organize data effectively but also architectures that facilitate seamless integration and communication between systems. A critical enabler for such architectures is IoT middleware, which standardizes and streamlines the collection of real-time data from machines and systems. The Unified Namespace (UNS) is an example of an architecture that can build upon such middleware to provide a centralized, ‘single source of truth’ for heterogeneous manufacturing data streams [12], [13]. By consolidating real-time data into a unified view, the UNS eliminates silos, enhances data accessibility, and supports advanced applications, such as real-time optimization and predictive analytics [13].

Building on these foundations, recent advancements in Large Language Models present new opportunities for enhancing this by enabling natural language interactions and simplifying complex data queries [14]. Integrating LLMs could offer a substantial improvement by allowing operators to interact with the system through natural language queries [15]. For instance, an operator can simply ask about production process data or request specific data visualizations. This capability empowers operators to tailor visualizations to their immediate needs in unexpected situations when needed, reducing cognitive load and fostering a more intuitive interaction between humans and machines [9].

While LLMs have shown considerable promise in general applications, a gap remains in adapting these models to meet the specific demands of industrial environments within this context [14], [16]. Three key issues stand out that the paper aims to address. First, the heterogeneity of manufacturing data, ranging from sensor outputs and machine logs to multi-domain attributes, complicates integration [17]. Second, most LLMs lack the deep, domain-specific knowledge needed to reason about intricate industrial processes [18]. Finally, production personnel, despite their operational expertise, often have limited data analysis or visualization skills, making actionable insights difficult to attain in cases when they need to generate visualizations or insights that go beyond the standard reports configured beforehand, such as during unexpected events or deviations that require ad hoc, context-sensitive analysis. [5].

To address the challenges mentioned above, this paper introduces an LLM-enhanced technical concept for processing and visualizing real-time sensor data for an extrusion process illustrated with a use case focused on anomaly detection, with continuously collected data preprocessed and stored for immediate retrieval. While machine data is

currently stored locally in a database, the architecture is extensible and designed to integrate with IoT middleware and UNS frameworks for future scalability. By enabling flexible, user-friendly data queries and visualizations, the solution aims at empowering production personnel to manage processes proactively and respond swiftly to unexpected issues. The findings highlight the potential of LLMs to enhance HMI, making it more intuitive in the advent of deviation from the standard processes.

The paper is structured as follows: first, it reviews the state of the art in human-machine interaction, the application of LLMs in manufacturing, and the role of Unified Namespace architectures. Then, it details the proposed system's architecture and functionalities. Finally, it presents testing results of the system, followed by conclusions and future directions.

## II. STATE OF THE ART

### A. HUMAN MACHINE INTERACTION

Human-Machine Interaction, hereafter used to refer to the broader concept of how humans interact with machines rather than physical interfaces, can be categorized into three key domains according to the HMI taxonomy defined in [15]: Human, focusing on operator roles, skills, and cognitive demands; Machine, addressing technology and data visualization; and Interaction, which bridges humans and machines through user interfaces and collaborative workflows. These domains are interdependent, with the Interaction domain acting as a mediator between the technical capabilities of the Machine and the cognitive requirements of the Human. This taxonomy underscores the need for tools that adapt to user's needs, reduce cognitive load, and provide intuitive access to complex data. State-of-the-art technologies currently implemented in factories for HMI include Supervisory Control and Data Acquisition (SCADA) systems, Manufacturing Execution Systems (MES), and Industrial Internet of Things (IIoT) platforms. SCADA and MES are widely used for real-time monitoring and control of production processes, while IIoT platforms enable the collection and analysis of data from interconnected devices and sensors [19]. These systems excel in gathering and visualizing vast amounts of operational data, but are often limited by their reliance on predefined queries, static dashboards, and the need for technical expertise to interact with the data [20]. To elevate HMI beyond these limitations, technologies such as Big Data analytics, Artificial Intelligence, and more recently, Large Language Models are being explored for integration into manufacturing processes [9]. Specifically, integrating LLMs with existing HMI systems can address significant shortcomings by enabling operators to interact with data using natural language, eliminating the need for traditional search-and-retrieve workflows. Although natural language querying has been previously explored, existing implementations rely on predefined queries rather than leveraging the advanced capabilities of LLMs [21]. This capability would not only enhance access to real-time monitoring and data analysis,

but also reduce dependence on domain specialists, fostering more efficient decision-making and improved productivity in complex industrial environments [22]. In the context of self-service or citizen analytics, this shift also empowers users to autonomously explore data and generate insights, reducing dependency on data scientists or IT specialists. Citizen analytics hereby refers to enabling all users within an organization, regardless of their technical expertise, to access and analyze data, supporting broader decision-making capabilities [23]. Modern self-service platforms, when integrated with machine learning models, enable users to perform advanced analytics on their own, democratizing data access and fostering a more data-driven culture across manufacturing environments [24].

### B. LARGE LANGUAGE MODELS IN MANUFACTURING

The advent of Large Language Models like ChatGPT and LLAMA represents a significant advancement in Artificial Intelligence, particularly in natural language processing. Their ability to process large volumes of text, learn patterns, and generate coherent responses has led to their adoption in tasks like data analysis, content creation, and interactive support systems [25]. While LLMs are already being applied in areas like predictive maintenance and anomaly detection, there remain gaps in their utilization for more interactive applications within the manufacturing sector [26].

Case studies have already demonstrated the potential of LLMs in manufacturing environments. GPT-4, for instance, can generate design specifications from textual inputs, optimize designs for manufacturability, and create both machine-readable and human-readable manufacturing instructions [27]. In additive manufacturing, ChatGPT simplifies interactions with complex datasets and suggests real-time process adjustments, making advanced methods like 3D printing more accessible through user-friendly interfaces [28].

Large Language Models are increasingly being integrated into process mining to improve the automation and understanding of business processes. LLMs can fulfill various tasks, including generating explanations for process executions [29], deriving process models from textual descriptions [30], and answering questions about processes [31]. The integration of LLMs into process mining aims to improve the accessibility and efficiency of business process management tasks by enabling more intuitive interaction with systems and the automation of analysis. The ability of LLMs to process both textual and visual information enables them to learn and apply domain-specific knowledge about processes, allowing them to serve as valuable tools for analyzing and managing business processes.

All applications mentioned above illustrate how LLMs enhance HMI by streamlining workflows and reducing the need for domain-specific expertise. Furthermore, such capabilities reduce cognitive load and improve decision-making efficiency [22]. Despite their potential, deploying

LLMs in manufacturing requires addressing challenges such as domain-specific data training, real-time processing, and ensuring interpretability and trust to meet industrial reliability standards [18]. Foundational LLMs may have limited utility without customization to the specific and dynamic knowledge required in manufacturing [32]. Concerns about information accuracy and the potential for “hallucinated” answers, plausible but incorrect responses, pose serious implications in industrial settings [33].

To address these issues, techniques such as domain-specific fine-tuning, chain-of-thought prompting, and retrieval-augmented generation have been proposed to enhance LLM performance in industrial applications [32]. However, a gap remains in the practical implementation of these approaches within real-world manufacturing systems for data analysis. The technical concept introduced in this paper addresses this gap by integrating agents with LLM-driven orchestration, enabling LLMs to interact seamlessly with other systems and databases to provide more comprehensive and actionable solutions [25].

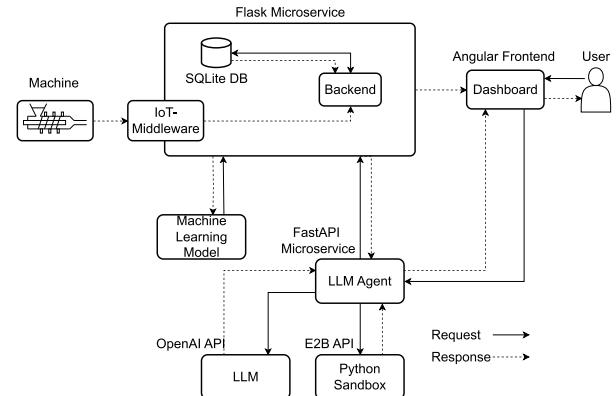
### C. UNIFIED NAMESPACES

Unified Namespace is increasingly recognized as a foundational architectural principle in Industry 4.0, providing a “single source of truth” that consolidates real-time data streams from diverse sensors, devices, and platforms into a unified, context-rich layer [12], [13]. This event-driven, publish/subscribe architecture, often implemented using MQTT, moves away from traditional point-to-point integrations, which can quickly become overly complex as systems scale [34]. Instead, UNS centralizes data, bundling information from various sources, such as sensor readings and product-specific details, into a cohesive namespace. This reduces system complexity, eliminates data silos, and supports more transparent and efficient communication across manufacturing operations [13], [35].

The result is improved interoperability, enabling seamless integration of systems, better decision-making, predictive maintenance, and real-time optimization of manufacturing processes. Through its ability to streamline and contextualize information flows, UNS fosters a resilient and adaptive production environment capable of meeting the demands of modern manufacturing [12]. Moreover, as LLMs integrate into HMI workflows, they rely on timely and consistent data streams. Here, Unified Namespaces ensure that such data is both accessible and contextualized, enabling the LLM to deliver accurate insights.

### III. METHODOLOGY

To address the gaps and challenges identified, this study proposes and implements an initial technical concept, as illustrated in Fig. 1, which integrates LLM capabilities to support manufacturing plant employees. By combining a robust data infrastructure with advanced language models, the proposed approach aims to enhance data accessibility,



**FIGURE 1.** Architecture of dashboard and integrated LLM-module.

facilitate informed decision-making, and improve overall operational efficiency.

The architecture comprises a backend that collects data from different sensors and shop-floors and stores it in a database and is compatible with UNS. An anomaly detection algorithm, in this case a machine learning model, processes this sensor data and records any detected anomalies into the database. A configured LLM module is connected to the backend, utilizing the relational database to respond to user inquiries about the data. Finally, the output generated by the LLM is presented to the user through the front-end interface. This integration enables users to interact with the system using natural language, enhancing usability and facilitating more intuitive access to complex datasets.

### A. BACK-END INFRASTRUCTURE

The backend architecture for integrating LLM functionalities is built on Flask. Flask is a lightweight WSGI web application framework often used for developing simple to complex web applications and APIs with a minimalistic approach [36]. The presented approach is utilizing the Flask API functionalities to define access points to the database and data analytics such as anomaly detection as well as predefined statistics and key performance indicators.

The API structure is split into three different components, enabling an efficient and use-case-independent data and information flow. The database access routes contain setter and getter methods. The setter methods handle all sensory information from the different machines on the shop floor, ensuring data integrity before writing into the database. The getter methods handle all queries to the database, including the requests submitted by the LLM. The analytical routes contain predefined functionalities for gaining insights about the production process. Those can be used by the machine operator to quickly detect anomalies like unscheduled machine downtimes or anomalies within single sensors. In addition, key performance indicators are calculated and prepared to be visualized on the frontend. The sockets (implemented with socket.io [37]) allow bi-directional communication between the backend and the frontend. This is

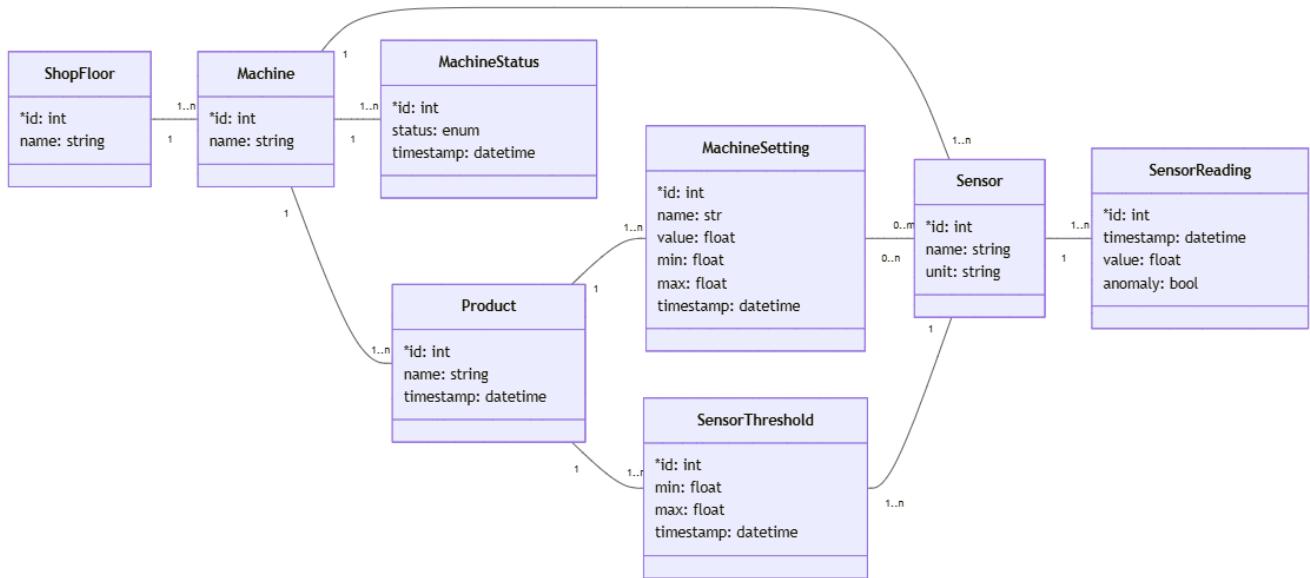


FIGURE 2. Unified shop floor data model.

essential for displaying information about anomalies to the machine operator in real time, triggered by the machine learning model in the background. Furthermore, they are used for updating visualized information in data-efficient matters. Central to this setup is the possibility to utilize UNS. Through UNS, data from heterogeneous IoT protocols (e.g., MQTT, OPC UA, Profinet) can be consistently represented, making it easier to integrate and manage diverse shop floor information. Within the scope of the project, the database is implemented in SQLite. It is integrated directly in the shared file system of the Docker environment, allowing access from the backend routes as well as the LLM agent. The communication to the database is implemented in a way that allows easy adaptation to other relational database management systems.

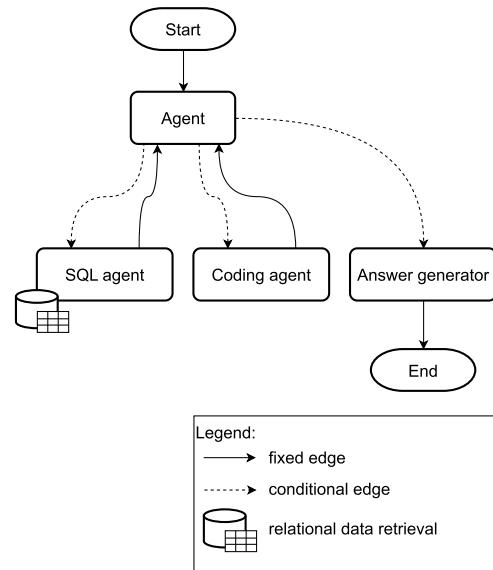
The database architecture is derived from the ISA 95 common object model for physical assets [38]. The data structure presented in Fig. 2 models the hierarchical relationships and attributes of a manufacturing shop floor system. At the highest abstraction level, a “ShopFloor” entity organizes one or more machines (Machine), each equipped with multiple sensors (Sensor) for data collection and monitoring. Each machine is associated with its operational states (MachineStatus), e.g. running, idle or malfunction. The products the machine manufactures (Product), and the settings applied during production (MachineSetting). Sensors record observations (SensorReading), which can be evaluated against predefined operational thresholds (SensorThreshold). These thresholds establish acceptable ranges for sensor data to detect anomalies and ensure quality control. The structure supports traceability by linking products to their production settings, sensor data, and operational conditions. With this facilitating performance optimization and anomaly detection. By organizing these entities and their relationships, the model provides a robust framework for analyzing

production systems, ensuring transparency, and supporting decision-making processes in manufacturing environments. The developed architecture focuses on low complexity while simultaneously maintaining the possibility to map all relevant information for shop floor monitoring and controlling throughout.

### B. LLM AGENT

A modular system architecture is proposed that efficiently processes natural language queries using specialized agents executed via the langgraph [39] and langchain [40] library and OpenAIs GPT-4o-mini model [41]. Central to this architecture is an orchestrating agent that interprets user queries and delegates tasks to two downstream agents: the SQL-Agent and the Coding-Agent. This multi-agent system (Fig. 3) approach is inspired by the multi-agent pattern introduced in [42]. The outputs from these agents are consolidated by an answer generator to produce user-friendly responses.

When a user submits a natural language query, the orchestrating agent analyzes it to determine the required operations. Depending on the query, it activates the SQL-Agent for data retrieval from relational databases, the Coding-Agent for data processing, computations, or visualizations, or both agents if multiple functionalities are needed. Each answer of the SQL- or Coding-Agent is evaluated by the orchestrating agent to determine if the user request was fulfilled or if another activation is necessary. The SQL-Agent manages all interactions with the relational database, listing available tables, extracting table schema, validating SQL queries, and executing them to retrieve the requested data. The different methods to retrieve data from the database are implemented as tools within a toolbox that the SQL-Agent may use. The system-prompt of the agent is designed as a chain-of-thought



**FIGURE 3.** State diagram of the LLM assistant.

prompt. The SQL-Agent calls one of the tools, observes the output and then plans the next step. Additionally, the agent is instructed to not create any SQL queries that modify the data within the database (e.g. INSERT, UPDATE, DELETE ...). A customizable prompt-parameter limits the maximum amount of rows retrieved to not exceed the finite context-length of the LLM. This ensures efficient and reliable data retrieval while maintaining data integrity. The Coding-Agent handles data processing and generates computations or visualizations based on the user's query. It translates queries into executable code, which runs in a secure sandbox environment to ensure system safety. The created visualizations can be systematically retrieved from the sandbox and sent to the frontend. Future enhancements will include improved error handling to increase robustness. After the agents complete their tasks, the orchestrating agent forwards the results to the answer generator, which formats the outputs into coherent, user-friendly responses. These may include natural language summaries, numerical results, or visualizations like graphs and charts, tailored to enhance the user experience. The system workflow is streamlined: the user submits a query; the orchestrating agent interprets it and activates the necessary agents; the agents perform their tasks; and the answer generator compiles and delivers the final response. This architecture is designed for flexibility and adaptability, with the orchestrating agent dynamically routing tasks based on query requirements, enhancing scalability and reliability. By integrating specialized agents with orchestration and response capabilities, the system provides an end-to-end solution for handling natural language queries. It is suitable for applications in decision support, data analysis, and visualization, efficiently addressing complex queries in a user-friendly manner. This contributes to the advancement of intelligent query processing systems by bridging the

gap between natural language inputs and sophisticated data operations.

### C. FRONT-END

The frontend architecture ensuring high flexibility on user and process interaction is built in Angular 17 [43]. The components are divided into traditional predefined shop floor insights extended by the proposed LLM integration. While the traditional components allow a quick overview of the current production on shop floor or machine level, implementing the variety of all analysis that different machine operators need depending on the variety of possible unexpected situations is impossible [44]. Thus, the proposed LLM is integrated to close this gap. Following the principles presented in the HMI-taxonomy, the interaction between the machine and the operator must be kept as intuitive and easy as possible while maintaining a high flexibility and user adaptation. Therefore, a chat-like interface is utilized, offering a familiar interaction environment for the user. The LLM approach presented empowers the tool for queries to the database in natural language. Any text-based question can be asked, in regard to general information about the shop floor, its machines, specific sensory, products, and also analysis of time-based occurrences, e.g. once an anomaly is being detected. The tool does not only provide text-based feedback, but also offers visualizations. In future development the content adaptation to specific users can be further extended by allowing to add analyses provided by the LLM interface to the users' default view. The LLM is not limited to retrieving information from the backend via the backends API. Ensuring certain prompt validation, it can also be utilized for active process control by the operator within throughout the same chat-like interface. Therefore, a highly flexible interface between the machine operator and the shop floor is provided.

### IV. RESULTS

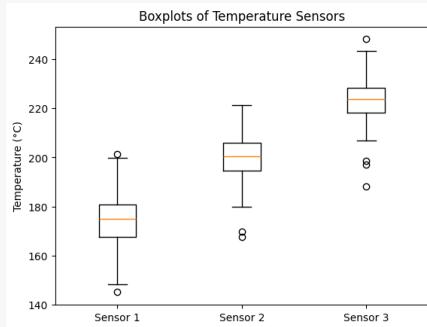
To evaluate the developed technical concept, a synthetic use case was generated. The simulated behavior is derived from an industrial dataset containing sensor readings of an extrusion process. A data generator simulates a single shop floor that contains two machines. Each of the machines has 3 temperature and pressure sensors, resulting in 12 sensors total. The sensors are sampled every second. At the point of testing the system, the database contained roughly 8 hours of data, resulting in 280224 sensor readings. With this approach, a realistic and relevant testing environment is created. In Fig. 4 is an exemplary user input and the respective response of the assistant. The user is asking the bot to visualize the latest 100 values of specific sensors into box plots. With the received information, the user can quickly determine what the typical ranges of the sensors are and how many outliers there were within the last 100 values. The answer shows that the assistant is able to retrieve specific data from the database and then visualize this based on a simple user input. Additionally, the assistant not only creates the



Please visualize the last 100 values of each of the temperature sensors 1,2,3 in individual boxplots.

AI

The last 100 temperature readings for each of the three sensors have been retrieved and visualized in individual boxplots. The values for Temperature Sensor 1 range from approximately 145.11 to 201.40, while Sensor 2's values range from about 167.50 to 221.41. Temperature Sensor 3 shows values between approximately 188.22 and 248.12. Each boxplot effectively illustrates the distribution and variability of the readings for the respective sensors. If you need any further analysis or details regarding the visualizations, please let me know!



**FIGURE 4.** Example input prompt and result from assistant.

boxplot, but also provides a short description of what can be seen in the visualization.

To understand how the assistant is solving this task, the steps that are taken by the assistant are visualized with a UML sequence diagram in Fig. 5. The experiment is tracked using LangSmith [45].

The system is triggered when the user sends the message. Based on the user message, the agent first determines that data needs to be retrieved from the database and calls the SQL-Agent. The SQL-Agent analyses the message and first retrieves all available table names from the database. Next, the structure of the relevant tables is retrieved. Finally, the SQL-Agent creates three SQL queries (listing 1) to retrieve the data.

The SQL queries are executed on the database and the data is passed back to the orchestration agent, which determines to call the Coding-Agent next. The user message and the retrieved data is passed to the Coding-Agent. Based on this the agent writes code (listing 2) that visualizes the data in three boxplots.

```

1 SELECT value timestamp
2 FROM sensor_reading
3 WHERE sensor_id = 1
4 ORDER BY timestamp
5 DESC LIMIT 100;
6
7 SELECT value timestamp
8 FROM sensor_reading
9 WHERE sensor_id = 2
10 ORDER BY timestamp
11 DESC LIMIT 100;
12
13 SELECT value timestamp
14 FROM sensor_reading
15 WHERE sensor_id = 3
16 ORDER BY timestamp
17 DESC LIMIT 100;
```

**Listing 1.** SQL queries created by SQL-Agent.

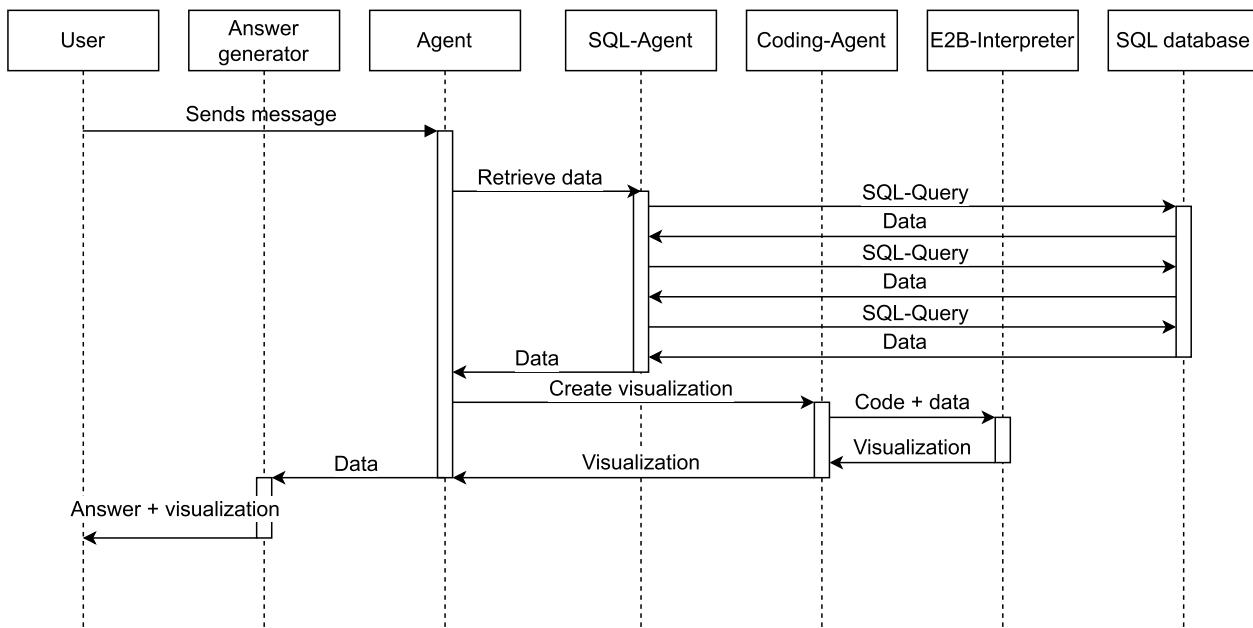
```

1 import matplotlib.pyplot as plt
2
3 # Temperature readings for each sensor
4 sensor_1 = [<placeholder data>]
5 sensor_2 = [<placeholder data>]
6 sensor_3 = [<placeholder data>]
7
8 # Create boxplots
9 data = [sensor_1, sensor_2, sensor_3]
10 plt.boxplot(data, labels=['Sensor 1', 'Sensor 2',
11 'Sensor 3'])
11 plt.title('Boxplots of Temperature Sensors')
12 plt.ylabel('Temperature (C)')
13 plt.show()
```

**Listing 2.** Python code written by Coding-Agent.

The code is then executed in a secure sandbox. The results are then passed back to the Coding-Agent. If no error occurred during the execution, the results are passed to the Orchestration-Agent. The Orchestration-Agent determined that all the needed information was collected by the called agents and therefore decides to have the answer generator write an answer based on the output of the agents. Once the answer is generated it is passed to the user. This example demonstrates that the proposed system can not only retrieve the correct data, but also process it and create the correct visualization based on the user command. By combining a flexible data retrieval agent and an accurate Coding-Agent, the system offers a simple to use and interactive tool for analyzing machine data.

Additionally to this example, 10 prompts (Appendix A) were used to systematically test the data retrieval through the system. In Appendix A are prompts used to test the system, answers from the system and the SQL-query used by the agent to retrieve the information. In 8 out of 10 cases the system created the correct SQL-query and retrieved the correct data. Overall it can be observed that the underlying SQL-Agent is capable of creating complex SQL-queries with multiple join- and group-operations and complex calculations. In the 4th prompt, the system did calculate the average and maximum values for the two machines, but did not distinguish between temperature and pressure. Therefore the result is incorrect. In the 8-th prompt,



**FIGURE 5.** Agent workflow with example input prompt.

the system only retrieved the first 100 readings and not 1000 readings as instructed in the prompt. These results show that the LLM-Agent is already able to perform complex data retrieval tasks and create meaningful insights. At the same time, the reliability of the system must be increased to ensure the correct data is retrieved to be applicable in a decision-making process.

Addressing the challenges defined in the introduction, the structured database design ensures that the heterogeneity of manufacturing data is seamlessly integrated, allowing the LLM to reason about domain-specific relationships inherent in the manufacturing process. The agentic architecture of the LLM further streamlines the processing of complex queries, enabling accurate and context-aware responses. Most importantly, the system showed its capabilities in interpreting natural language, allowing bypassing the need for advanced technical knowledge or predefined report templates to query data or create data visualizations. While initial qualitative evidence highlights the system's utility, future work will focus on quantitative validation through user studies to solidify its practical impact.

## V. INDUSTRIAL IMPLICATIONS

In this research, a first proof of concept for an LLM-based system for manufacturing process data was presented. The proof of concept was conducted using augmented data from an extrusion process, serving as a representative example for the dynamic manufacturing process environment. With the proposed solution, it is shown that the system allows for an effortless analysis and visualization of complex production process data. However, for the successful implementation in

the real-world manufacturing environment, further steps are required.

Firstly, the accuracy and performance of the system, including ML model and an LLM agent, must be further evaluated to ensure it meets the specific requirements of the manufacturing process. Secondly, the system must be fine-tuned on relevant data that accurately represent the manufacturing process. Additionally, the system must be integrated into the manufacturing environment and be able to communicate with other systems and equipment. To ensure the successful implementation of the proposed solution in manufacturing environments, it is essential to have a comprehensive understanding of the manufacturing process and the specific tasks that the model will be performing. It is also important to have a team of experts who can continuously monitor and improve the model's performance to ensure it remains effective and efficient.

The potential challenges in scaling the proposed solution include the need for allocating computational resources, data protection, and fine-tuning the system for specific use cases. However, the expected benefits for production personnel are significant, including the ability to automate tasks, improve accuracy and efficiency, and reduce costs. Therefore, despite the challenges, the potential benefits of scaling LLM-based solutions make it an attractive option for manufacturing organizations.

The proposed system can be adapted to different manufacturing sectors by fine-tuning the system on specific domain-specific data and knowledge. For example, for the automotive sector, the system can be fine-tuned on data related to car manufacturing processes, vehicle components, and assembly line operations. Similarly, for the electronics

sector, the system can be fine-tuned on data related to electronic components, circuit design, and manufacturing processes. Moreover, the system helps to automate various tasks such as quality control checks, predictive maintenance, and supply chain management. It also assists in identifying potential issues in real-time, thereby reducing downtime and improving operational efficiency. Furthermore, the system helps to improve the accuracy and consistency of tasks such as testing and documentation. This leads to better quality control and, ultimately, to reduce costs and increase productivity. In summary, the proposed system has the potential to improve productivity, quality control, and operational efficiency. Its adaptability to different sectors makes it a versatile tool that can be customized to meet specific industry needs.

## VI. CONCLUSION

This research presented and tested an LLM-enhanced technical concept designed to simplify the retrieval, processing, and visualization of real-time sensor data in a manufacturing context. By integrating a modular multi-agent system and a unified data structure, the proposed solution shows its potential in enabling users without data analysis skills to query complex shop floor data and create visualizations through natural language input. The system demonstrated the capability to address a wide range of queries, from basic statistics to generating tailored visualizations, substantially reducing the need for specialized analytics expertise on the shop floor.

The synthetic test scenario, derived from an extrusion process dataset, provided an initial proof of concept. In these trials, the LLM-driven assistant generated largely accurate SQL queries, retrieved relevant sensor data, and delivered meaningful graphical outputs with limited user intervention. Furthermore, the tool demonstrated its ability to empower shop floor and manufacturing employees to gain valuable data insights, specifically for the use in unexpected manufacturing process deviations, by enabling intuitive natural language interaction with complex datasets. This flexibility enhances decision-making under dynamic and unplanned production conditions, bridging the gap between data complexity and operator expertise.

While the results are promising, the system's reliability must be enhanced to ensure consistent accuracy and relevance. The occasional inaccuracies that emerged highlight a need for further refinement, including enhanced domain adaptation, fine-tuning, and improved error-handling strategies. The application of process mining could help to enhance the process understanding of the system through process discovery techniques.

Overall, this approach represents a step toward more intuitive and responsive human-machine interactions in industrial settings. However, future work should investigate scalability, robustness, and the integration of more domain-specific knowledge before applying this solution reliably to diverse, real-world production environments.

## APPENDIX A SHOP FLOOR DATA PROMPTS, ANSWERS, AND SQL QUERIES

**0. Prompt:** What is the current status of each machine on the shop floor?

**Answer: Correct**

- Machine A: running
- Machine B: running

Both machines are primarily in a “running” state, although Machine B has had instances of being “idle” or “maintenance.”

**SQL Query:**

```

1 SELECT m.name, ms.status
2 FROM machine m
3 JOIN machine_status ms
4 ON m.id = ms.machine_id
5 ORDER BY ms.timestamp DESC
6 LIMIT 100;

```

**1. Prompt:** List the minimum and maximum thresholds for all sensors attached to each machine.

**Answer: Correct**

- **Machine A:**

- Temperature\_1: Min: 150.0, Max: 200.0
- Pressure\_1: Min: 1.0, Max: 2.0

- **Machine B:**

- Pressure\_4: Min: 3.0, Max: 4.0

**SQL Query:**

```

1 SELECT m.name AS machine_name,
2       s.name AS sensor_name,
3       st.min AS min_threshold,
4       st.max AS max_threshold
5 FROM machine m
6 JOIN sensor s ON m.id = s.machine_id
7 JOIN sensor_threshold st ON s.id = st.sensor_id
8 ORDER BY m.name, s.name;

```

**2. Prompt:** Identify all sensors that have recorded anomalies in their last 100 readings.

**Answer: Correct**

- Temperature\_1
- Pressure\_2
- Pressure\_3

**SQL Query:**

```

1 SELECT s.id, s.name
2 FROM sensor s
3 JOIN (
4     SELECT sensor_id
5     FROM sensor_reading
6     WHERE anomaly = TRUE
7     ORDER BY timestamp DESC
8     LIMIT 100
9 ) sr ON s.id = sr.sensor_id
10 GROUP BY s.id, s.name;

```

**3. Prompt:** Which machines are assigned to produce which products?

**Answer: Correct**

- Machine A: Product X
- Machine B: Product Y

**SQL Query:**

```

1 SELECT m.name AS machine_name,
2       p.name AS product_name
3 FROM machine m
4 JOIN product p ON m.id = p.machine_id
5 ORDER BY m.name;

```

**4. Prompt:** Show the average, minimum, and maximum values recorded by all sensors in the last 100 readings.

**Answer: Incorrect**

The assistant failed to distinguish between temperature and pressure sensors.

**SQL Query:**

```

1 SELECT s.machine_id,
2       AVG(sr.value) AS average_value,
3       MIN(sr.value) AS min_value,
4       MAX(sr.value) AS max_value
5 FROM sensor_reading sr
6 JOIN sensor s ON sr.sensor_id = s.id
7 GROUP BY s.machine_id;

```

**5. Prompt:** What are the current settings for each machine for all active products?

**Answer: Correct**

- Machine A (Product X):

- Temperature: 200.0
- Pressure: 1.5

**SQL Query:**

```

1 SELECT m.name AS machine_name,
2       ms.name AS setting_name,
3       ms.value
4 FROM machine m
5 JOIN machine_setting ms ON m.id = ms.machine_id
6 WHERE ms.value IS NOT NULL;

```

**6. Prompt:** Find sensors where the last 100 readings exceeded their thresholds.

**Answer: Correct**

- Pressure\_6: 4.11 (Threshold: 3.0-4.0)
- Temperature\_5: 230.57 (Threshold: 175.0-225.0)

**SQL Query:**

```

1 SELECT s.id, s.name, sr.value, st.min, st.max
2 FROM sensor_reading sr
3 JOIN sensor s ON sr.sensor_id = s.id
4 JOIN sensor_threshold st ON s.id = st.sensor_id
5 WHERE sr.value < st.min OR sr.value > st.max
6 ORDER BY sr.timestamp DESC
7 LIMIT 100;

```

**7. Prompt:** Retrieve the total number of anomalies recorded in the last 500 readings.

**Answer: Correct**

- Total anomalies: 18

**SQL Query:**

```

1 SELECT COUNT(*) AS total_anomalies
2 FROM sensor_reading
3 WHERE anomaly = TRUE
4 ORDER BY timestamp DESC
5 LIMIT 500;

```

**8. Prompt:** Which sensors have recorded values outside their thresholds most frequently in the last 1000 readings?

**Answer: Incorrect**

The assistant retrieved data but failed to filter 1000 readings.

**SQL Query:**

```

1 SELECT s.name, COUNT(sr.id) AS out_of_threshold_count
2 FROM sensor_reading sr
3 JOIN sensor s ON sr.sensor_id = s.id
4 JOIN sensor_threshold st ON s.id = st.sensor_id
5 WHERE sr.value < st.min OR sr.value > st.max
6 GROUP BY s.id
7 ORDER BY out_of_threshold_count DESC
8 LIMIT 100;

```

**9. Prompt:** Calculate the percentage of sensor readings marked as anomalies in the last 1500 readings for each machine.

**Answer: Correct**

- Machine A: 6.19%
- Machine B: 5.33%

**SQL Query:**

```

1 SELECT m.id AS machine_id, m.name AS machine_name,
2 (SUM(CASE WHEN sr.anomaly THEN 1 ELSE 0 END) * 100.0 /
3 COUNT(*)) AS anomaly_percentage
4 FROM machine m
5 JOIN sensor s ON m.id = s.machine_id
6 JOIN (
7   SELECT sensor_id, anomaly
8   FROM sensor_reading
9   ORDER BY timestamp DESC
10  LIMIT 1500
11 ) sr ON s.id = sr.sensor_id
11 GROUP BY m.id, m.name;

```

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