Leveraging AI and LLM for a Paradigm Shift in the Manufacturing and Logistics Industry

Flavio Tonelli [a)], Marco Mosca [a)] and Antonio Giovannetti [a),b)]

a. DIME, University of Genoa, Via Opera Pia 15a, 1 16145 – Genoa – Italy (Flavio.tonelli@unige.it ,Marco.tullio.mosca@unige.it, antonio.giovannetti@edu.unige.it)

b. Simulation Team, University of Genova, Via Magliotto 2 – Savona – Italy (antonio.giovannetti@simulationteam.com)

Abstract: The manufacturing and logistics industry is experiencing a paradigm shift, marked by a transition from a problem-solving approach to a problem-setting mindset, driven by the integration of Artificial Intelligence (AI) and Large Language Models (LLM). This paper explores the impact of AI and LLM in transforming the world of manufacturing and logistics through two case studies: Manufacturing and Supply Chain and Logistics. Traditional problem-solving approaches in manufacturing have predominantly relied on reactive responses to identified issues. However, with the advent of AI and LLM, manufacturers are now embracing a proactive problem-setting approach. By leveraging AI technologies such as machine learning algorithms and predictive analytics, manufacturers can identify potential bottlenecks, optimize production processes, and enhance overall operational efficiency. LLM enables manufacturers to analyze vast amounts of data, extract valuable insights, and generate innovative solutions to complex manufacturing challenges. Traditional approaches in the domain of supply chain and logistics domain often grappled with uncertainties, such as volatile demand patterns and unforeseen disruptions. Through intelligent algorithms and data-driven decision-making, AI systems can optimize inventory levels, predict demand fluctuations, and dynamically adjust logistics routes in real-time. LLM technologies enhance human-AI interaction by enabling natural language communication, facilitating faster and more accurate decision-making in complex supply chain scenarios. This case study presents real-world applications of AI and LLM in supply chain and logistics, showcasing their role in enhancing operational resilience, minimizing risks, and improving customer satisfaction. By transitioning from a problem-solving to a problem-setting approach, organizations can proactively address challenges, exploit opportunities, and transform their operations. The case studies exemplify the significant impact of AI in achieving operational excellence, cost optimization, and sustainable growth in manufacturing and logistics

Keywords: Artificial Intelligence; Large Language Models; Smart Manufacturing; Logistics; Problem Setting.

I. INTRODUCTION

The manufacturing and logistics environment represents a complex system that can only be studied through a holistic and systematic view of its interactions and processes. The challenges of globalization, sustainability and efficiency force manufacturing companies to constantly innovate and integrate new technologies to select product, process design and engineering strategies to gain or maintain a competitive advantage in the marketplace. In this scenario, the choice of long-term corporate strategy is of paramount importance and has always been made, albeit by different means, by humans (Chakraborty 2011, Rao 2007, Jamwal, et al. 2021). With the advent of Artificial Intelligence, the role of humans not only in tactical operational decisions but also in strategic decisions seems to be changing (Andronie, et al. 2021, Yang, et al. 2021). In recent years, Artificial Intelligence (AI) has become ubiquitous in our daily lives, ranging from personalized digital assistants (Brill, Munoz e Miller 2019) to self-driving cars (Stilgoe 2018). This technology has shown its remarkable capabilities in various fields, such as healthcare (Yu, Beam e Kohane 2018, Jiang, et al. 2017), finance (Buchanan 2019), and transportation (Sadek 2007). However, the use of AI in manufacturing is still in its early stages respect to its potential (Riahi, et al. 2021) In 2020, a Deloitte report estimated that the manufacturing industry generated about 1,812 petabytes (PB) of data each year (Deloitte, 2020). According to the same Report of 93 percent of companies in the manufacturing sector believed that AI would be a key technology to drive growth and that its market would exceed $2 billion by 2025, with an average annual growth of more than 40 percent since 2019. To date, according to the Markets and Markets report, the market has already surpassed $2.3 billion and is projected to reach $16 billion by 2027. Manufacturing industries have only scratched the surface of what AI can offer in terms of improving efficiency, productivity, and quality control. This raises an intriguing question about the potential for AI to revolutionize the manufacturing, logistics and production operations industry and the role of humans inside this complex system.

Artificial Intelligence (AI) has come a long way since its inception, and the latest versions of AI are more advanced than ever before (Saheb e Saheb 2020). With the emergence of Large Language Models (LLMs), such as OpenAI's GPT-3 (Fioridi e Chiaritti 2020), AI is becoming more capable of understanding natural language and generating human-like responses (Chowdhary e Chowdhary 2020). These advancements are particularly exciting because they have the potential to shift the role of humans from problem-solving to problem-setting. By using AI to automate mundane and repetitive tasks, humans can focus on higher-level tasks that require creativity and critical thinking. AI-powered systems enable manufacturers and logistics companies to automate routine tasks, improve efficiency, reduce costs, and enhance overall productivity. AI-based predictive maintenance solutions help manufacturers predict when machinery or equipment is likely to fail (Cao, et al. 2022), enabling them to carry out maintenance proactively, reducing downtime and associated costs. AI can also be used to improve quality control by automatically detecting defects in products as they move along the production line (Sundram e Zeid 2023). AI-powered supply chain management solutions can help manufacturers and logistics companies optimize their supply chains by analyzing vast amounts of data on inventory levels, demand, and supplier performance (Toorajipour, et al. 2021). This paper will explore the potential impact of AI and LLMs on the role of humans in the manufacturing industry through the development of integrated framework of traditional techniques for Operations Management and the use of Artificial Intelligence.

II. PROBLEM SOLVING AND PROBLEM SETTING APPROACHES

Traditionally, problem-solving has been the dominant approach in manufacturing and logistics operations. This approach involves managers and operators identifying problems as they arise and then working to resolve them. However, this reactive approach can lead to a focus on short-term solutions and missed opportunities for long-term improvements. In the context of the emergent sustainable transition, this can result in increased complexity. On the other hand, problem-setting involves identifying potential future problems and working proactively to prevent them from occurring. This approach allows for more strategic decision-making and can result in more efficient and effective operations. Problem setting is the process of identifying a problem or opportunity for improvement within a system or process. In the context of logistics and manufacturing operations, problem setting involves recognizing inefficiencies, bottlenecks, or areas for improvement in the supply chain, production process, or other related systems. problem setting involves a more in-depth analysis of the underlying factors and causes of the problem, which can lead to a redefinition of the problem and the development of more effective solutions.

III. AI AND LLM

Artificial intelligence (AI) is a rapidly growing field of technology that involves the development of computer systems that can perform tasks that typically require human intelligence, such as learning, reasoning, and problem-solving. AI has emerged as a powerful tool for addressing a wide range of real-world problems, from healthcare and finance to transportation and manufacturing. The are a multitude of interpretations of Artificial Intelligence (AI), all of which revolve around the idea of a non-human form of intelligence designed to execute particular functions. In their work from 2016, Russel and Norvig (Russel 2016) conceptualized AI as systems that emulate cognitive processes typically linked with humans tasks, including learning, speech and problem-solving. Today, AI is a rapidly growing field, with applications in a wide range of industries and domains. In healthcare, AI is being used to analyze medical images, diagnose diseases, and develop new treatments. In finance, AI is being used to detect fraud, optimize investments, and automate trading. In transportation, AI is being used to develop autonomous vehicles and optimize logistics operations. Large Language Models (LLMs) are a type of artificial intelligence (AI) system that has been developed to process and generate human-like language. LLMs are trained on vast amounts of text data, enabling them to learn the patterns and structures of language and generate new text that is indistinguishable from human-generated text. Large Language Models (LLMs), such as OpenAI's GPT-3, are a direct evolution of the neural network models known as Transformer. This model was presented in 2017 in an article titled "Attention is All You Need" by Vaswani et al. The Transformer model solved some fundamental problems in deep learning, paving the way for innovation in many fields, including Natural Language Processing (NLP). LLMs, such as GPT-3, are Transformer models trained on huge amounts of text data. They can generate consistent and sometimes surprisingly human-like text. These models can solve a wide range of NLP tasks without the need for task-specific training, a concept known as "zero-shot learning." LLMs offer several advantages. First, they are incredibly versatile. They can be used for a wide range of tasks, from text autocompletion to machine translation, from text summarization to virtual assistance and beyond. Moreover, since LLMs are trained on huge corpora of text, they can generate informed responses on a wide range of topics.

IV. AI AND LLM TO SUPPORT DECISION MAKING

The application of Artificial Intelligence (AI) and Large Language Models (LLM) can play a significant role in shifting the focus from problem-solving to problem-setting in logistics, production, and manufacturing operations. The manufacturing industry is facing the challenge of keeping up with the increasing demand for product customization, while ensuring high quality, cost-effective production and resilience. The integration of Artificial Intelligence (AI) and Large Language Models (LLMs) has the potential to revolutionize manufacturing operations and lead to significant improvements in efficiency, productivity, and quality.

AI and LLM can be used to automate routine tasks and provide real-time insights into operational performance. This can free up human operators to focus on more strategic tasks, such as problem-setting and decision-making. This shift in focus can help companies to identify and address underlying issues and opportunities for improvement in their operations, rather than simply responding to problems as they arise.

Logistics, production, and manufacturing operations generate large volumes of data, which can be difficult and time-consuming for human operators to analyze manually. AI and LLM can help to automate this process, using machine learning algorithms to identify patterns and insights in the data that might be missed by human operators, they can help operators to make more informed and data-driven decisions. Firstly, they can be used to analyze vast amounts of data from various sources, including sensors, production systems, and logistics networks, to identify potential issues and opportunities for improvement. This can help to detect patterns and trends that may not be easily identifiable by human operators alone.

Secondly, AI and LLM can be used to simulate different scenarios and test potential solutions before implementing them in real-world operations. This can help to minimize risks and optimize decision-making, leading to more efficient and effective operations. In this case AI and LLM work as a problem-setting validation process to identify risky scenarios. The role of AI and LLM in logistics, production, and manufacturing operations is to support the shift from problem-solving to problem-setting by providing the tools and insights needed to identify potential future problems and proactively work to prevent them.

Artificial Intelligence (AI) has increasingly been adopted in logistics, production, and manufacturing operations to improve efficiency, optimize processes, and reduce costs. LLMs are capable of a wide range of language-related tasks, including language translation, text summarization, question answering, and conversational interaction. They can also be used for creative writing, generating realistic-sounding dialogue, and even composing music. One of the key features of LLMs is their ability to generate original text that sounds like it was written by a human. They do this by analyzing patterns and structures in the training data, and using this information to generate new text that follows the same patterns.

Examples of large language models include GPT-3 (Generative Pre-trained Transformer 3) developed by OpenAI, BERT (Bidirectional Encoder Representations from Transformers) developed by Google, and T5 (Text-to-Text Transfer Transformer) developed by Google Brain. LLMs have a wide range of potential applications, including natural language processing, chatbots and virtual assistants, content creation, and even education and training. While Large Language Models (LLMs) are primarily designed to process natural language, they may have some applications in logistics, production, and manufacturing operations. For example, LLMs could be used to analyze unstructured data such as text-based customer feedback or product reviews to identify patterns and insights that could inform product design or process improvements.

LLMs could also be used to develop conversational interfaces for customer service or technical support, which could improve the efficiency and effectiveness of these services by providing quick and accurate responses to customer inquiries.

In addition, LLMs could potentially be used for predictive maintenance in manufacturing operations by analyzing data from maintenance logs, sensor readings, and other sources to identify potential issues before they occur. The benefits produced by the transformation of Problem Solving practice to Problem Setting, supported by the use of data analysis and enhanced with AI (and LLM), are extended to more key figures. For example, operations managers would benefit from enhanced monitoring, planning and control capabilities through an integrated network of sensors and actuators, coupled with AI, vastly improving forecasting and decreasing the risk of uncertainty by interacting discursively with the AI itself through the use of LLMs.

With their ability to analyze large amounts of data and detect patterns and trends, these technologies can help creative and innovation practitioners develop new products and identify new business strategies with previously unimaginable precision.

Online and real-time connections (sensors on machines) will power the Digital Twins, while SPC (Statistical Process Control) integrated with AI will enable anticipation of machinery failures, with strong correlation to coefficient of utilization and production rate. Parameters such as increased vibration or energy consumption will allow maintenance to be initiated exactly when needed. The system will be able to be queried and managed not only by technicians, but also by high-level decision makers through the use of AI-based language models. Simplified human interaction with machinery and process (LLM embedded in the Human Machine Interface (HMI)) will significantly simplify the integration of humans and machines resulting in freeing up time to devote to higher level or strategic activities.

This paper proposes an innovative solution based on integration of Large Language Models (LLMs), Digital Twins and Modeling and Simulation in a ChatBot as an intermediary layer between human operators and industrial machines, enhancing efficiency and data processing capabilities. The advent of Artificial Intelligence and Deep Learning Learning, specifically LLMs like GPT-4, provides an unprecedented opportunity to decode the vast volumes of data generated in industrial settings. Traditional human-centric data analysis methods are resource-intensive and have limitations in scale and complexity.

Our study introduces a novel LLM-based chatbot layer in industrial operations to circumvent these limitations. The LLM-chatbot acts as an intelligent interface, capable of interpreting complex data patterns and making strategic operational decisions, relieving the burden on human operators. It decouples extensive knowledge bases and large data volumes from human resources' limitations, enabling a new paradigm of data-driven, automated industrial operations.

The proposed LLM-chatbot layer ensures that machines can effectively utilize the wealth of information while operators focus on higher-level tasks, bridging the gap between the capacity for data analysis and human resources. This integrated approach promises a significant boost in operational efficiency, productivity, and overall industry growth. It provides insights into how AI and ML can be harnessed to drive the next wave of industrial revolution, marking a new era of smart manufacturing.

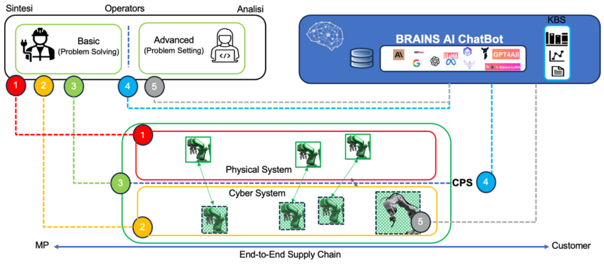

Fig. 1AI ChatBot as the new Layer

Industry 1.0 was characterized by direct human interaction with physical machinery. Human operators worked hands-on with machines, but understanding past and future processes was challenging due to the scarcity of data.

Industry 2.0 introduced digital aspects of the machines. Despite these advancements, the overall vision remained fragmented, with integration of data still a significant challenge.

Industry 3.0 saw the automation of processes, leveraging logical processors and Information Technology (IT). While these processes largely functioned without human interference, there was still a human aspect behind the scene, contributing to decision-making and maintenance.

Industry 4.0 embraced the availability and use of large amounts of data on production sites. With numerous sensors collecting data, decisions on repairs and maintenance became more informed. Predictive maintenance systems even began to implement machine learning to anticipate asset failure and prescribe preventive measures.

Now, with the introduction of an LLM-based chatbot layer, we are transitioning towards Industry 5.0. Here, the Cyber-Physical System is fully integrated. Both structured and unstructured data are processed directly by generative AI that communicates with human operators. This paradigm shift allows operators to focus more on problem setting rather than problem-solving.

The proposed LLM layer, acting as a bridge between the human and machine, interprets and translates vast volumes of complex data into actionable insights. It reduces the cognitive load on human operators by processing and understanding the approximately 80% of company data that is unstructured. This not only streamlines operations but also leverages existing data resources more effectively, converting them into strategic assets.

Therefore, Industry 5.0, bolstered by LLMs, represents a significant shift in how industries operate. It maximizes the potential of AI to process and comprehend extensive amounts of data, freeing human operators to concentrate on higher-level tasks. The dawn of Industry 5.0 signals a new era of smart manufacturing, where data-driven decision-making, proactive problem setting, and high operational efficiency become the new norm.

The incorporation of generative AI, in tandem with simulation models embedded within digital twins, further amplifies the potential of the LLM-chatbot layer. This AI tool leverages the knowledge and needs of the operators, assimilates the massive data derived from various business processes, and generates unique, data-driven insights.

What sets this novel integration apart is its ability to deliver multifaceted solutions that transcend traditional operational boundaries. By processing and understanding a plethora of data from diverse sources, the LLM-chatbot can suggest novel solutions regarding factory layout, process optimization, machinery selection, production planning, and even marketing strategies. This transformative approach allows the AI system to provide recommendations and facilitate decision-making across various aspects of business operations.

The LLM-chatbot's ability to harness the richness of unstructured data and learn from operators' experiences and requirements, ensures that the generated solutions are not only data-driven but also contextually appropriate and operationally feasible. In turn, this leads to an improved alignment between operational practices and strategic business objectives, enhancing overall business performance.

Thus, the introduction of an LLM-chatbot layer in industrial operations represents a paradigm shift, marking the transition to Industry 5.0. It enables businesses to not only automate processes but also intelligently adapt and innovate in response to dynamic operational needs. As such, the LLM-chatbot layer is set to play a pivotal role in the future of smart manufacturing, driving growth, and competitiveness in the industrial sector.

The benefits of the proposed LLM-chatbot layer are vast, particularly when considering the wealth of unstructured data prevalent in industrial settings. It is estimated that up to 80% of all data in companies is unstructured (Balducci & Marinova, 2018; Eberendu, 2018), such as work descriptions, resumes, emails, text documents, presentations, voice recordings, videos, and social media content. Despite substantial efforts, our ability to efficiently capture, structure, and process this data remains limited, thus underutilizing its potential for strategic decision-making and operational improvement.

Incorporating LLMs and modeling and simulation techniques opens up new avenues to fully exploit this unstructured data. These sophisticated models are capable of understanding and generating a wide range of content types, including text, images, and audio files. In an industrial context, this means that valuable insights hidden in unstructured data can now be harnessed effectively. For instance, intricate patterns in operational data can be extracted, performance metrics can be predicted, and potential inefficiencies can be identified.

Furthermore, these models can translate complex, unstructured data into intuitive, actionable insights for operators. This process not only makes the data accessible but also fosters a more informed and proactive approach to decision-making. Ultimately, this enables industries to leverage their existing data more effectively, transforming the vast seas of unstructured data into a strategic asset. The LLM-chatbot layer hence represents not just an advancement in automation but also a breakthrough in data-driven decision-making, offering unprecedented opportunities for enhancing productivity, efficiency, and competitiveness in the industrial sector.

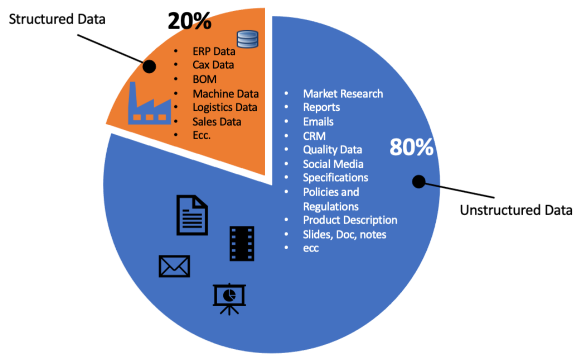

Fig. 2 Data Distribution in companies

V. ARCHITECTURE OF FOUNDATIONS MODELS TO ENABLE PROBLEM SETTING PARADIGM

Foundation Models are pre-trained models built on large-scale data, and they have the potential to serve as the basis for many downstream tasks. These models can be fine-tuned or adapted for specific tasks, making them versatile and efficient for diverse applications. They are called 'foundation' models because they serve as a foundational layer that other models are built on top of.

These models generally follow a transformer-based architecture, similar to LLMs. The transformer architecture is characterized by its use of self-attention mechanisms, which allow the model to weigh the importance of different parts of the input when producing an output. This means that the model is able to consider the entire context of an input when making predictions, leading to more accurate and nuanced results. his design allows for better handling of long-range dependencies in sequential input data, which is particularly useful in natural language processing (NLP) tasks. Transformer models have been adapted for other domains as well, such as computer vision (CV) with the Vision Transformer (ViT) and graph learning (GL) with the Graph Transformer Networks (GTN) (Zhou et al., 2023) The learning methods used for training these models include supervised learning, semi-supervised learning, weakly-supervised learning, self-supervised learning, and reinforcement learning. The specific method used depends on the amount and type of available labeled data, among other factors. n the pre-training phase, the model learns to capture specific attributes, structures, and community information from pre-set tasks. The features learned in this phase can assist in performing the downstream tasks more effectively, and also help in faster convergence of the model. Pretraining tasks can be divided into categories like Mask Language Modeling (MLM), Denoising AutoEncoder (DAE), Replaced Token Detection (RTD), Next Sentence Prediction (NSP), and Sentence Order Prediction (SOP). Now, considering how to apply these concepts to the field of manufacturing and logistics, it's important to note that this application would involve designing the pre-training tasks in a manner that they capture the relevant information for the domain. For instance, in computer vision, human-designed labels like jigsaw puzzles or comparison of various patches from images are used as pretext tasks during pretraining to learn the feature space. the pretext tasks could involve predicting the next step in a manufacturing process, identifying anomalies in production line images, or optimizing routing in a logistics network.

The Authors propose an advanced system capable of improving the management and control of all business processes and information through AI and in particular the use of LLM , Modeling & Simulation and IoT. This system will be able to make operators and decision-makers communicate with different digital and non-digital solutions that are currently unable to find a common integration path within the manufacturing and logistics processes decoupled from the growing complexity.

The collection and preprocessing of IIoT data is the first step of the process through continuous monitoring of the manufacturing plant, collecting data from various sensors. This data is then cleaned and preprocessed, a process which may include handling missing values, attenuating sensor noise, and normalizing data from several sensors to a common scale or other forms of post-processing.

The clean, preprocessed data is then used for modeling and simulation of the digital twin. It represents a detailed simulation of the production plant. The model is updated in real time with new sensor data, allowing you to reflect the current plant status and simulate future plant states under various conditions or decisions.

In parallel with the collection of data in real time, a knowledge base is created which contains structured information on the plant. This information may include technical specifications of the machinery, operating procedures, safety guidelines, etc. This information is stored in a database and can be accessed by the LLM when needed.

All the information managed by the current factory management and departmental systems can be integrated within the knowledge base, providing detailed data on the characteristics of the products, their production methods, their recipes and the relationships with other players involved in their production. as suppliers or contractors. The adoption of an LLM-based system that can access such structured, logically related data allows the development of an intuitive interface for the use of such content as well as for the identification of critical relationships especially if associated with unstructured data that provide information on actors external to the supply chain.

Large Language Model (LLM), such as GPT-3/4, is developed using company-specific documents and data to specifically train its foundation model. This process may involve training the model to understand specific jargon or technical terminology used in the enterprise, or exposure to the types of questions and commands users are likely to provide. This information is stored in a vector database with which the domain-specific fine-tuning of these systems is performed. A Retrieval Augmented Generation (RAG) module can then be integrated to improve performance; the RAG module is, in fact, trained to retrieve relevant documents or information from the company database when the LLM is generating responses, allowing the LLM to provide context, memory (declarative or episodic as appropriate) and more accurate responses and detailed. Furthermore, it is also possible to integrate information deriving from unstructured data, overcoming the need to pre-tag them with meta-data such as emails, documents, images, audio files, videos, presentations, web pages, social media, etc… The description represents an example of what we intend to research, develop and test in the context of this project proposal.

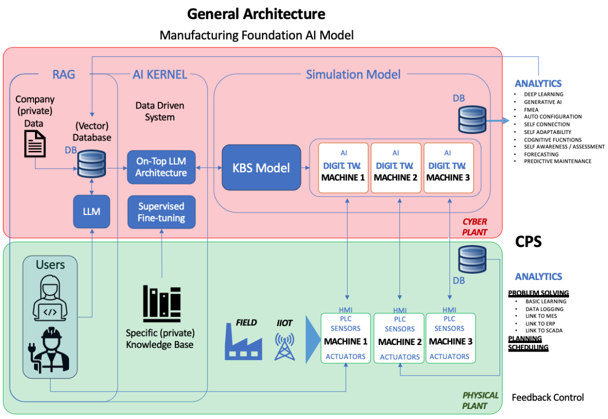

Figure 3. AI Framework

IIoT Data Collection and Preprocessing: The IIoT system continuously monitors the manufacturing plant and collects data from various sensors. This data needs to be cleaned and preprocessed. This could involve tasks such as dealing with missing values, smoothing out sensor noise, and normalizing data from different sensors to a common scale. This is typically done using methods from statistics and signal processing.

Digital Twin Modeling and Simulation: The cleaned and preprocessed sensor data feeds into the digital twin model. This model is a detailed simulation of the manufacturing plant, and is typically created using techniques from system dynamics, control theory, and operations research. It's updated in real time as new sensor data comes in, allowing it to reflect the current state of the plant. The digital twin model can also simulate future states of the plant under various conditions or decisions. This requires sophisticated computational algorithms and high-performance hardware

Knowledge Base Creation: Alongside the real-time data, a knowledge base is created that holds structured information about the plant. This could include technical specifications of the machinery, operation procedures, safety guidelines, etc. This information can be stored in a database and accessed by the LLM when needed.

Large Language Model Fine-tuning: A general-purpose LLM, such as GPT-3, is fine-tuned using company-specific documents and data. This might involve training the model to understand specific jargon or technical terminology used in the company, or exposing it to the types of questions and commands that users are likely to give. The fine-tuning process typically involves supervised learning on a labeled dataset, and may require significant computational resources.

Retrieval Augmented Generation (RAG) Integration: The RAG module is integrated with the LLM to improve its performance. The RAG module is trained to retrieve relevant documents or pieces of information from the company's database when the LLM is generating responses. This allows the LLM to provide more accurate and detailed answers, especially for complex or specialized queries. This is one of the most important elements in the Architecture because through its training it will be possible to interact with an high-level knowledge assistant which is always informed with the current state of situation. It will be possible to make different queries in a multi-model (text, structured data, audio, video) capable of understanding the correlations between different data sources.

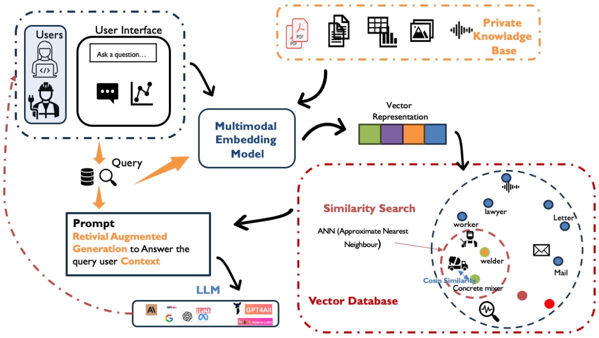

Fig. 4 RAG Module

User Interaction: Users interact with the system through a natural language interface. They can ask questions, issue commands, or request predictions about the state of the plant. The LLM processes these queries, consults the RAG module and the digital twin model as needed, and generates a natural language response.

VI. CASE STUDIES

Predictive Maintenance: AI and LLM can be used to analyze machine data, including sensor readings, maintenance logs, and repair histories, to predict when machines are likely to fail. This can help manufacturers schedule maintenance more efficiently, minimizing downtime and reducing maintenance costs.

Quality Control: AI and LLM can be used to analyze product quality data and identify patterns or anomalies that might indicate issues with the manufacturing process. For example, image recognition algorithms could be used to identify defects in finished products or identify patterns in sensor data that might indicate issues with production equipment.

Supply Chain Optimization: AI and LLM can be used to analyze data from suppliers, production facilities, and distribution networks to optimize the supply chain. This might include optimizing delivery routes, adjusting production schedules to minimize waste, or identifying opportunities to source materials more efficiently.

Inventory Management: AI and LLM can be used to optimize inventory levels and minimize waste. For example, predictive algorithms could be used to identify when certain raw materials are likely to be in high demand, allowing manufacturers to stock up in advance and avoid shortages.

Resource Optimization: AI and LLM can be used to optimize resource allocation, including labor, energy, and raw materials. For example, predictive algorithms could be used to optimize production schedules based on energy usage, or identify opportunities to reduce waste by optimizing material usage.

Internal logistics optimization: significantly improved CU (Utilization Coefficient) and OEE (Overall Equipment Effectiveness), e.g., via AI embedding logic to schedulers, which can further improve batch production priorities in consideration of multiple cascaded objective functions (e.g., minimizing setup time, profit maximization, important Customers priority, ...).

External logistics optimization: GPS integration and route optimization in consideration of multiple cascading objective functions (e.g., booking priority, Important Customers, route minimization, toll minimization, traffic, ...)

Redefinition of Relationship logics: AI associated with LLM can have a huge impact on Relationship management, in literature recognized as major criticality of SCs.

Resource optimization in SDC (Digital Supply Chain): possibility to dynamically reallocate Resources according to continuous variations in the nature of demand, to ensure continuity to the optimum between an agile (upstream material stock, prefers CU of machines) or reactive (downstream finished goods stock, prefers timely delivery to Customer) or hybrid chain. The system will be able to automatically favor distribution points in greatest need, given daily trends, minimizing the bullwhip effect. Especially suitable in case of perishable goods.

VMI (Vendor Managed Inventory) logic optimization: warehouse chains connected to corporate ERPs (Enterprise Resources Planning) that self-manage (orders, shipments and invoicing) on EOQ (Econopic Order Quantity) logics in consideration of seasonality and trends in sales and lead times. All this without requiring Human intervention except at the level of triggers for authorization.

Problem solving/setting in the SC: advanced optimization techniques may be implemented.

Cyber Physical Systems (CPS), hybrid systems that contain in cyberspace a model that reflects the real plant (this model is a simulator that integrates the DTs of individual machines) will provide continuous comparison between the real plant and the simulated plant, hosted on the server and equipped with AI and LLM. The CPS can, within certain limits, make autonomous decisions with a circumstantial approach. In fact, it can project the life of the plant forward in years and anticipate any failure mode, in full accordance with Problem Setting principles.

AI and LLM could be used, for example, to have the Digital Twin produce and maintain an updated FMEA (Failure Mode and Effect Analysis), forming the basis of Problem Setting.

FMEA is a methodology designed to predict and weight the failure or defect modes of a process, product or system, and then analyze their causes and assess their effects. The predictive nature of FMEA makes it ascribable to Problem Setting, rather than Problem Solving, because of its ability to anticipate risks based on the productization of 3 parameters: the probability of occurrence, the severity of the effect, and the possibility of identification through implemented controls. Easy to deduce, then, how DTs and simulators, enhanced with AI and LLM algorithms can, among many other functions, be used to generate FMEA analysis and keep it up-to-date, generating significant impact at the Problem Setting level

Knowledge transfer to the new resources. Greater effectiveness given by validated and consolidated answers in the learning phase; a reduction in the time it takes for operators to enter the production process; the reduction of errors.

VII. CONCLUSIONS

In this paper the Authors introduce an advanced AI-based system that leverages the integration of different technologies such as Modeling & Simulation and IoT through the use of Large Language Models (LLM) to enhance the management and oversight of Manufacturing and logistics processes and information. This system aims to bridge communication between various digital and non-digital solutions, addressing the integration gap present in manufacturing and logistics processes, which are becoming increasingly complex. The processed IIoT data is pivotal in the creation and real-time updating of a digital twin—a detailed virtual representation of the manufacturing plant. This digital twin can provide insights into the current state of the plant and predict future states based on varying conditions or decisions. In tandem with real-time data collection, a comprehensive knowledge base is established. This database encompasses critical information about the plant, including machinery specifications, operational procedures, safety measures, and more. Moreover, it seamlessly integrates data from existing factory management systems, offering a holistic view of product details, production methods, and the interconnected web of suppliers and contractors. LLMs, like GPT-3/4, are tailored to the enterprise by training them on company-specific documents and data. This ensures that the model comprehends the unique jargon and terminology intrinsic to the enterprise. Through fine-tuning and leveraging Retrieval Augmented Generation (RAG) modules, the LLM can pull relevant company data when generating responses, ensuring contextual accuracy. This process also facilitates the integration of various forms of unstructured data, eliminating the need for metadata tagging. By addressing the communication and integration challenges prevalent in today's manufacturing and logistics industries, the proposed system holds the potential to revolutionize the way enterprises operate, offering numerous benefits that span predictive maintenance, quality control, supply chain efficiency, and more.

VIII. REFERENCES

.

[1] Andronie, M., G. Lăzăroiu, M. Latagan, C. Uță, R. Ștefănescu, and M. Cocoșatu. 2021. "Artificial intelligence-based decision-making algorithms, internet of things sensing networks, and deep learning-assisted smart process management in cyber-physical production systems." *Electronics* 10 (20): 2497.

[2] Autor, D., and A. Salomons. 2018. "Is automation labor-displacing? Productivity growth, employment, and the labor share." *National Bureau of Economic Research.*

[3] Balducci, B., & Marinova, D. (2018). Unstructured data in marketing. *Journal of the Academy of Marketing Science*, *46*, 557-590

[4] Brill, T., L. Munoz, and R. Miller. 2019. "Siri, Alexa, and other digital assistants: a study of customer satisfaction with artificial intelligent applications." *Journal of Marketing Management* 35 (15-16): 1401-1436.

[5] Brynjolfsson, E., and A. McAfee. 2014. The second machine age: Work, progress, and prosperity in a time of brilliant technologies. . WW Norton & Company.

[6] Buchanan, Bonnie. 2019. *Artificial intelligence in finance.* Harisportal Hanken.

[7] Cao, Q., C. Zanni-Merk, A. Samet, C. Reich, F.D. B. De Beuvron, A. Beckmann, and C. Giannetti. 2022. "KSPMI: a knowledge-based system for predictive maintenance in industry 4.0." *Ropbotics and Computer-Integrated Manufacturing* 74.

[8] Chakraborty, Shankar. 2011. "Applications of MOORA method for decision making in manufacturing environment." *The International Journal of Advanced Manufacturing Technology* 54: 1155-1166.

[9] Chowdhary, K., and K. R. Chowdhary. 2020. "Natural language processing." *Fundamentals of artificial intelligence* 603-649.

[10] Eberendu, A. C. (2016). Unstructured Data: an overview of the data of Big Data. *International Journal of Computer Trends and Technology*, *38*(1), 46-50.

[11] Fioridi, L., and M. Chiaritti. 2020. "GPT-3: Its nature, scope, limits, and consequences." *Minds and Machines* 30: 681-694.

[12] Frey, C. B., and M. A. Osborne. 2017. "The future of employement: How susceptible are jobs to computerisation?" *Technological forecasting and social change* 114: 254-280.

[13] Gartner. 2017. Applying artificial intelligence to drive business transformation: a Gartner Tren insight report.

[14] Gunst, Carole. 2021. https://www.aspentech.com/en/resources/blog/new-aspentech-research-reveals-the-state-of-industrial-ai.

[15] Jamwal, A., R. Agrawal, M. Sharma, and V. Kumar. 2021. "Review on multi-criteria decision analysis in sustainable manufacturing decision making ." *International Journal of Sustainable Engineering* 14 (3): 202-225.

[16] Jiang, Fei, Yong Jiang, Hui Zhi, Yi Dong, Hao Li, Sufeng Ma, Yilong Wang, Qiang Dong, Haipeng Shen, and Yongjun Wang. 2017. *Artificial intelligence in healthcare: past, present and future.* Vol. 2(4). Stroke and Vascular Neurology.

[17] Markets and Markets . 2022. "Artificial Intelligence in Manufacturing Market by Offering (Hardware, Sofwtare, and Services), Industry, Application, technology (Machine Learning, Natural Language Processing, Context-aware Computing, Computer Vision), & Region (2022-2027)."

[18] Rao, R. V. 2007. Decision Making in the manufacturing environment: using graph theory and fuzzy multiple attribute decision making methods. Vol. 2. London: Springer.

[19] Riahi, Y., T. Saikouk, A. Gunasekaran, and I. Badraoui. 2021. Artificial intelligence application in supply chain. A descriptive bibliometric analysis and future research directions. Vol. 173. Expert Systems with Applications.

[20] Sadek, A. W. 2007. Artificial intelligence applications in transportation. Transportation research circualr.

[21] Saheb, T., and T. Saheb. 2020. "Understanding the development trends of big data technologies: an analysis of patents and the cited scholarly works." *Journal of Big Data* 7(1) (1-26).

[22] Stilgoe, J. 2018. "Machine learning, social learning and the governance of self-driving cars." *Social studies of science* 48 (1): 25-26.

[23] Sundram, S, and A Zeid. 2023. "Artificial Intelligence-Based Smart Quality Inspection for Manufacturing." *Micromachines* 14 (3): 570.

[24] Toorajipour, Reza, Vahid Sohrabpour, Ali Nazarpour, Pejvak Oghazi, and Maria Fischi. 2021. "Aritificial intelligence in supply chain management: A systematic literature review." *Journal of Business Research* 122: 502-517.

[25] Yang, T., X. Yi, S. Lu, K. H. Johansson, and T. Chai. 2021. "Intelligent manufacturing for the process industry driven by industrial artificial intelligence." *Engineering* 7 (9): 1224-1230.

[26] Yu, Kun-Hsing, Andrew L. Beam, and Isaac S. Kohane. 2018. *Artificial Intelligence in healthcare.* Nature Biomedical Engineering.

[27] Zhou, C., Li, Q., Li, C., Yu, J., Liu, Y., Wang, G., ... & Sun, L. (2023). A comprehensive survey on pretrained foundation models: A history from bert to chatgpt. *arXiv preprint arXiv:2302.09419*.