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Framework for Natural Language Processing to Automate Material Flow Simulation in Production System Planning

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Abstract

An increasingly dynamic market environment is enforcing greater changeability and flexibility in production systems. To address this complexity with simulation models, expert knowledge needs to be externalized. Therefore, we propose a framework that converts expert discussions and written documents into textual requirements to create simulation configurations. This automates the manual and time-consuming process of specifying the scenario and instantiating simulation models. We discuss the overall architecture that is able to understand complex technical language and explain the approach that dynamically adapts to new requirements. The natural language processing-based framework promises great potential of a seamless setup up of a-priori evaluations of productions systems to enable a comprehensive deployment of digital twins.

Keywords: Natural Language Processing; Large Language Model; Machine Learning; Production Control; Digital Twin

1. Motivation

The progressive use of artificial intelligence and natural language processing (NLP) creates enormous growth potential and offers the opportunity to significantly increase productivity in any domain [1]. Today, generative artificial intelligence is already being used successfully in many industries. In addition to typical applications like generating appropriate messages for chatbots and evaluating large amounts of data for predictions, generative artificial intelligence is now also being utilized to create images and music. Moreover, it becomes increasingly important in the processing of multimodal input for the extraction of information and e.g. the creation of computer code as with GitHub CoPilot [2, 3].

Transitioning from these more creative applications, the capabilities of generative artificial intelligence extend to industrial settings as well. It is crucial that production systems are designed to be changeable, flexible, responsive, and resilient, given the impact of various internal and external stimuli on KPIs. The objective is to be proactive rather than reactive, by pinpointing pertinent information for simulations from the wealth of requirements, documentation, and descriptions available. In the context of manufacturing, experts face numerous challenges arising from a wide array of information on influencing factors. However, standardized tools like questionnaires, structured interviews, and even lengthy discussions with experts often lead to ambiguous answers [4]. From this context, it becomes clear that NLP, in the form of Large Language Models (LLMs), especially when

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fine-tuned with simulation context and data, stands out as an effective tool for processing this information. LLMs are able to condense extensive descriptions of production processes and states into concise user stories, clear acceptance criteria and suitable restrictions, thus efficiently handling information in a structured manner [6]. However, in contrast to the common isolated solution, a structured integration into a comprehensive system is an important requirement for the comprehensive use of LLMs. Therefore, to allow a long-term utilization of LLMs as part of the standard working tools, a framework is needed that includes LLMs to derive e.g. requirements and user stories from a problem description in a production system context and to identify solution spaces for various tools, in this case digital twins of the material flow realized in form of event-discrete simulation models. This will be an important step towards automatically instantiating simulation studies in digital twins for material flow simulations, aimed at addressing specific issues in the production system.

The remaining paper is organized into five main sections: Section 2 introduces the related work and Section 3 presents a framework for utilizing LLMs for material flow simulation in production system planning. Section 4 discusses a use case and the framework. Section 5 concludes with a summary of the main findings and contributions, along with future research directions.

2. Related Work

To implement LLMs as a tool in the simulation toolbox, an understanding of the role of LLMs with regard to digital twins of the material flow (Section 2.1) is necessary. To include the expert domain knowledge into these digital twins, in Section 2.2 requirements engineering supported with LLMs for simulations as the application domain is introduced.

2.1. NLP in Combination with Digital Twins

Utilizing the technological advancement of generative artificial intelligence in practical applications, as in the context of manufacturing, some approaches start utilizing LLM techniques, e.g. to analyze maintenance logs of past events [19], and to extract latent knowledge from short texts generated by machines to inform about maintenance decisions [4]. Furthermore, [2] focuses on retrieving potential solutions for new problems by searching for analogous issues stored in remote technical assistance reports for troubleshooting. Furthermore, NLP is often used to leverage retrievable central knowledge databases commonly found in manufacturing environments [16]. [17] introduced an LLM -based system for problem-solving management with an integrated content-based recommender engine to enhance knowledge management on the shop floor. In [4] a generic NLP pipeline to incorporate textual information from machine providers to reduce downtime of machines is presented. Another application was introduced by [5], in which LLMs are investigated to generate simulation models for inventory and process control, with the generated simulations being created as Python code. Here, the area of application is not necessarily a material flow based digital twin but rather generating a simple simulation following a description.

However, the approach of utilizing LLMs in the context of simulations has potential beyond e.g. creating code in Python with numerous prompts and thorough code analysis. It can also upgrade and expand existing simulations on various platforms, enhancing their functionality. Moreover, LLMs can aid simulation experts by making the requirements and completion criteria clearer, utilizing implicit knowledge to streamline and perfect the simulation process. [8,10]

The before mentioned approaches focus on the integration of NLP into the production context, the analysis capabilities can be used to uncover patterns. In this paper, we introduce a framework for employing NLP and specifically LLMs to structure problem statements and create user stories and acceptance criteria for designing material flow simulation studies conducted with digital twins. Additionally, with the implementation this framework, it will facilitate the auto-instantiation of simulation studies based on the user stories generated by LLMs. However, before developing such a framework for auto-instantiated digital twins, the system must precisely understand the parameters and its allowed value space required for instantiation of e.g. the material flow. This represents an alternative methodology to the process mining-based approaches, as exemplified in [7], wherein the focus is on the automated generation of simulations through the analysis of event-based data. In contrast, our approach requires an initial seed model that establishes the simulative foundation, whereby changes to the system are processed by the LLM-based Module as requirements for the simulation study.

2.2. NLP for requirements engineering in simulation

Requirements engineering (RE) is the discipline that involves defining, documenting, and maintaining the requirements of a system or project, serving as a critical foundation for successful project development. These requirements need to fulfill four different criteria: clear, complete, traceable, and verifiable. [18]

As nearly every requirement is written in form of natural language, NLP has become an essential tool in requirements engineering, aiding in the automated analysis, interpretation, and management of these requirements [19]. Therefore, a great research interest has emerged in utilizing NLP techniques within the field of requirements engineering, as shown in the surveys e.g. in [19] and [20]. Moreover, [21] has shown that many papers focus on the analysis of requirements followed by the quality assurance and the extraction of requirements. Moreover, [20] demonstrates that LLM assists in structuring the requirements by modeling various use cases in different modelling languages, such as UML or SysML. However only very few approaches focusing on manufacturing can be identified [20]. Furthermore, to the best of the authors knowledge there is no specific approach connecting LLMs and RE with material flow simulations based digital twins. Even though the use of RE in simulations is to some degree similar

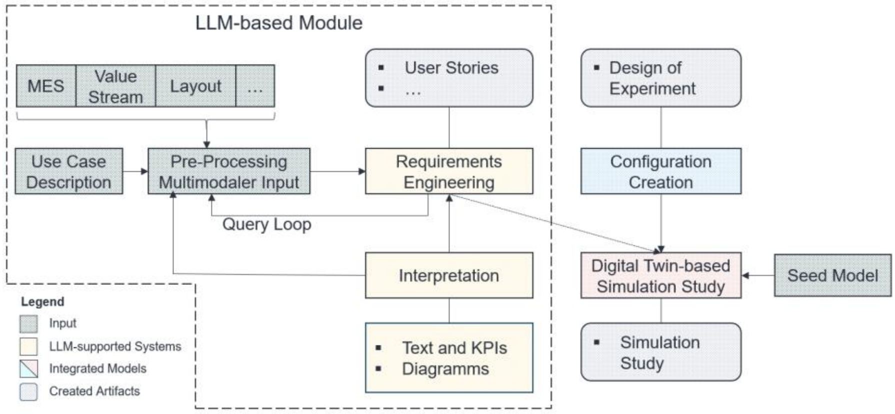

Fig. 1: Structured overview of the framework to incorporate LLMs for the instantiation of digital twins of production systems

to its typical application in general software development, there are distinct specifications that set this domain apart. Requirements for material flow simulations are often tailored to the specific physical layout and processes of a particular site, in contrast to the more abstract and less agile nature of traditional system requirements. [23] Additionally, material flow simulations must frequently, every shift or even every exceptional event, adapt to changes in production or logistics, requiring swift updates to requirements, whereas software system changes are usually planned and executed within a structured development cycle. [23] Therefore, it is necessary to further look into how LLMs are in applied in digital twins today and the opportunities for simulations experts to leverage the ability of RE analytics in context of the dynamic digital twins.

3. Framework to incorporate LLM for the instantiation of digital twins of production systems

This framework incorporates LLMs to identify use cases and solution spaces necessary to auto-instantiated simulation studies of material flow simulations. By utilizing the manifold information dimensions of multimodal data, requirements engineering based specification methodology and the application of material flow based digital twins (hereafter referred to as "digital twins") as shown in Fig. 1, we are able to analyze and formalize the information provided by production planners with respect to simulation studies by using LLMs. The identification of the solution space of parameter sets within the digital twin and the scenarios in the scenario funnel allows different design-of-experiments to be created automatically to perform simulation studies. Thereby, this framework increases efficiency and reduces the time needed to perform simulation studies in different use cases. The main areas oft he framework are introduced in detail in the following.

3.1. Utilizing LLMs to Pre-Process Data to Identify the Objective and the Indications for Simulation Studies

The strength of data-driven technology is based on the fact that a large amount of appropriate data is available and has been comprehensively processed. Here, LLMs are used to seamlessly analyze, structure and formalize multimodal information, whether it's conversational exchanges, text-based best practices or visual data streams, as can be seen in green. This includes the integration of partial production data from Manufacturing Execution Systems (MES) and the consolidation of process maps or Excel files with detailed process landscapes. In addition, LLMs have the ability to sophisticatedly interact with domain experts and simulation experts creating a collaborative space where information gaps are identified and resolved. This interaction is not only in plain text form, but can also include the integration of further information in form of diagrams of value streams and other information provided in e.g. PDF formats, transforming a variety of data into actionable insights.

By leveraging the versatility of LLMs, organizations can transform expert-led conversations and production data into a coherent structure. This process not only serves to record the current state of matters but also creates the conditions for forward-looking modeling and scenario planning. Such capabilities are not only theoretical possible with lots of IT expertise; they are already achievable to a certain degree with publicly available tools. Here, the role of prompt engineering is crucial, as it involves creating queries that guide the LLMs to generate the most relevant and accurate responses.

3.2. Utilizing LLMs to create an Understanding of the Needs of Domain Experts

Moreover, the solution to complex problems in production systems often lies in the effective capture and utilization of expert knowledge. LLMs serve as a channel for externalizing this expertise by processing and putting it into a usable format, such as user stories and acceptance criteria, as integrated in yellow. These models are utilized by supplementing tacit knowledge - filling in the gaps with expert knowledge of what is not said but understood by these experts - and thus creating a comprehensive basis for problem solving.

NLP enhances document analysis by automating the organization, analysis, and interpretation of unstructured data, a capability particularly valuable in the manufacturing industry where extensive documentation and data analysis are crucial. It supports human staff by recognizing patterns, and converting textual data into actionable insights [4]. To enhance precision, LLMs are trained and fine-tuned on domain-specific data, such as manufacturing processes or supply chain logistics. This allows them to comprehend and analyse complex details provided by domain experts, thereby significantly improving the accuracy and relevance of simulation studies. [10] For instance, in a manufacturing context, these artificial intelligence-based models combined with LLM-based model scan precisely predict equipment failures or optimize production schedules based on historical data and expert insights. This shows that LLM-based models, are able to accelerate and streamline processes, leading to operational improvements. [4]

These ability of LLMs also allows for specialized applications in various domains, such as RE, where extensive documents are examined and the information are formulated in a specific grammatical structure, such as in requirements specification. [8] This methodology ensures that requirements documents are both consistent and complete. Here, LLMs are able to identify and categorize key concepts, which facilitates the transformation of informal descriptions into formalized specifications. This process supports traceability by directly linking requirements to design elements, code and test procedures, improving requirements validation by uncovering ambiguities, redundancies and conflicts. [10] Furthermore, LLMs allow stakeholders to interact with requirements documents through natural language queries, enabling a more intuitive experience. [22] In this way, LLMs play a crucial role in streamlining change management of the requirements specification by efficiently identifying and incorporating changes in requirements. [8] In addition, LLMs help in domain analysis by identifying the terminology specific to the domain, which is crucial for accurate understanding and communication within a use case. In project-based application domains, LLMs can be utilized to generate user stories from the requirements that have been communicated by domain experts, bridging the gap between technical specifications and actionable development tasks. It also prioritizes these requirements by analysing and ranking them based on defined criteria, ensuring that development efforts are aligned with business requirements. Finally, LLMs help to condense long requirements documents into concise summaries. [10]

3.3. Utilizing LLMs to describe results of simulation studies

In the field of simulation of complex production systems, the clarity of experimental results is important for effective decision making. In this framework LLMs will also be used to refine the findings from simulation studies into documentations that are tailored to the level of understanding of different stakeholders. The customizability of LLMs ensures that the granularity of the information presented matches the user's technical expertise and information needs and enables an intuitive understanding of the results. In addition, the framework utilizes the capabilities of LLMs to draw conclusions from the experimental data and describes them with a level of refinement that matches the end user's expertise. This process involves not only presenting data, but also transforming it into a coherent synthesis of results that enables stakeholders to understand the implications of the findings in the context of their operational objectives. The documentation of experiments and the generation of actionable recommendations are also part of conducting simulations studies that can be designed by LLMs. By processing experimental protocols, results and contextual data, LLMs systematically produce comprehensive documentation that includes both the methodological approaches used and the resulting findings. The use of LLMs to present the results of simulation studies is a central aspect of the framework, as it goes beyond data reporting and allows an interpretive analysis, where complex results are not only reported, but also contextualized, explained and translated into strategies.

By transferring requirement specifications and the results of the simulation studies through LLMs into the dynamic world of the material flow based digital twins, we can achieve a closed pipeline between the added value of automated processing of necessary information for optimizations and the investigation through simulations in production environments.

3.4. Multi-Model-based Approach to conduct Simulation Studies

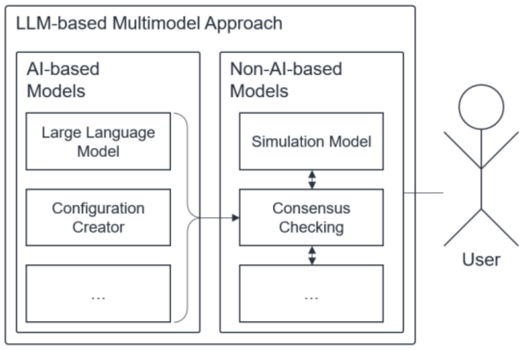

Fig. 2: The framework enables the integration of different models and abilities to further strengthen the added value of digital twins in production systems

Within the proposed framework, the combination of different AI-based, such as LLMs, time series analyses or reinforcement learning for production control, and not-AI-based models, such as digital twins and e.g. a control element to enable human-in-the-loop control systems, are central and enable the pooling of specialized capabilities to solve complex problem domains, as shown in red and blue in Fig 1. Und detailed in Fig. 2. This model integration facilitates the identification of required simulation studies through the systematic combination of empirical data and conclusions drawn from the underlying digital representations. Here, a seed model can be utilized to run simulations of the up-to-date digital twin to create insights of the systems behavior. The analysis process also involves a careful examination of the digital twin's environment and enables the identification of important problem features. This is achieved by synthesizing different data sources and leveraging the strength of the models to arrive at a holistic understanding of the production system challenges. Following problem identification, individual design of experiments are configurated to create a scenario funnel by the domain experts. This includes the targeted adjustment of variables and parameters within the simulation and the parameter space. While the concept of event-discrete simulations is defined with ease, the definition of digital twins is rather broad and diverse [11, 12]. In this framework we define a digital twin, similarly to [13,14], as a digital instantiation of a unique asset with similar properties, conditions and behavior. The instantiation of event-discrete simulations as digital twins through automated update and validation mechanisms enhances validity and extends usability. Hereby, a simulation model is compared with real-world data and adjusted if necessary. [15] By retrospectively creating digital twins, it becomes possible to investigate specific problem statements of the domain expert, such as scenario analysis in production control, optimizing worker loops, fine-tuning parameters, and identifying and resolving gradual stock build-up issues, through in-depth analysis of data of past events. Consequently, optimization through 'one-way' simulations can be handed over to digital twins, which offer a significantly higher level of accuracy, closely mirroring reality. Here, LLMs can help to determine the solution space and thus the corridor of permissible solutions from experts. In addition, the delineation of the experimental design is critical to the integrity of the system's results. By integrating these elements, the framework goes beyond the function of a mere analytical tool; it becomes an important part of the iterative process of knowledge discovery and validation in the field of production system design. The collaboration between human expertise and the extensive knowledge encapsulated in LLMs enhances the investigative process. Humans can interpret the outputs of LLMs, apply contextual understanding, and provide critical feedback, which in turn refines the machine's learning. This synergistic relationship allows for more advanced analyses and the development of innovative digital twins.

4. Case Study to evaluate the Framework

In this section, we delve into a theoretical case study, described in subsection 4.1 and discussed in subsection 4.2, that showcases a possible application of the framework while also addressing real-world challenges. Typical use cases may include managing operational loops, addressing supply shortages to preemptively respond to external triggers before key performance indicators are affected, and analyzing operational issues to derive actionable insights from identified simulation models. In this case study, we focus on the gradual accumulation of inventory. Minor variations in the production process resulted in an unanticipated accumulation of inventory over various production cycles. This slow inventory build-up leads to increased inventory costs, impacting the company's operational efficiency. Here, the introduced framework could be used to identify the root causes, which may include the variation of product mixes and inefficiencies in the production process. By simulating this scenario, it is possible to predict the impact of mitigation strategies on inventory levels.

4.1. The procedure of the framework in this case study

The process begins e.g. with the manufacturing experts detecting an unexpected increase in inventory levels that indicates a potential inefficiency in the production system. A detailed report is created that describes the process of identifying the problem, compares the current operating condition with the desired target condition, and records the sequence of events that led to the observed increase in inventory levels. To get to the root cause of the problem, a team of simulation experts and data scientists analyze historical time series data from the MES. The aim of this analysis is to uncover underlying patterns or anomalies that could explain the increase in stock levels. The system creates in the first step comprehensive reports with charts and KPIs to illustrate the data trends and insights gained over time for the experts to evaluate. The collected data is then integrated with the original problem report, system descriptions and simulation parameters into an LLM-based module. This instantiated system evaluates the information, requests further details if necessary and creates a detailed requirements specification. It also creates user stories and acceptance criteria tailored to the execution of simulation studies for the specific problem. In addition, the recommender system together with the domain expert proposes a solution space and defines a set of parameters that can be investigated by the simulation experts. This proposed solution space is validated together with the domain experts to ensure its relevance and potential effectiveness. The simulation experts then model the production system in the simulation environment and validate it to reflect the actual state as accurately as possible. They use the solution space to experiment with various adjustments, such as changing the sequence of the product mix, optimizing process sequences and adjusting buffer sizes. The aim is to bring the performance of the simulated system into line with the target state. Each simulation run is followed by a thorough analysis of the results, which are documented using KPIs and diagrams to provide a solid basis for future investigations.

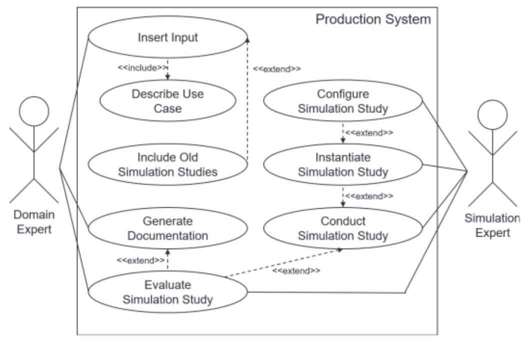

Fig. 3: UML use case diagram of the framework introducing the possible interactions of an implemented framework model.

4.2. Discussion

This case study allows to evaluate the LLM-enhanced framework, which will allow to mitigate pain points associated with traditional inventory management, such as slow response times, inaccurate data interpretation, and suboptimal decision-making. By leveraging LLMs, organizations will benefit from a more dynamic and responsive analytical process. This process facilitates quicker identification of stock level anomalies, more accurate predictions of their potential impacts, and more effective strategies for their resolution.

However, the framework still raises challenges that need to be addressed in future research. One major challenge is the validation of the simulation outcomes against actual production data to ensure the recommended changes will effectively address the identified issues without unintended consequences. Moreover, as the production environment and market conditions evolve, the LLM-based system must continuously adapt and learn, requiring regular updates and recalibrations based on new data and expert feedback. It must also learn to handle extraordinary events and out-of-population scenarios, ensuring resilience through e.g. robust anomaly detection. This ongoing process of validation and adaptation is crucial for maintaining the accuracy, and effectiveness of the LLM-enhanced simulation studies in optimizing inventory management and overall production efficiency.

5. Conclusion and Outlook

The innovative framework integrates LLMs with digital twins and multi-model approaches to transform production system planning. It externalizes expert knowledge by recording conversations and data into structured, formalized formats, filling gaps with implicit knowledge. Diverse models interlink to identify issues through data synthesis and enable scenario-based simulations, driving toward informed experimental designs that validate problem-solving strategies. LLMs customize the final report according to user expertise, creating understandable reports and extracting actionable conclusions from complex simulations. This documentation and recommendation process leverage LLMs for clarity and strategic guidance. Across these facets, the framework represents a synergy of NLP and simulation technologies, redefining problem identification, scenario exploration, and data interpretation within production systems. It enables a new approach for predictive and adaptive planning, ensuring that every step from problem understanding to solution implementation is data-driven, precise, and user-centric.

Future directions of investigation will be focused on the specific auto-instantiation of simulations based on recognized concepts and data drifts. LLMs can be used to build semantic schemata and map with different data sources. In addition, LLMSs can contribute to the description and interpretation of findings during and after the simulation. Finally, this framework will be implemented with an industry partner to evaluate in a real-world setting.

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