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Enhancing sustainability in manufacturing through cognitive digital twins powered by generative artificial intelligence

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Abstract

The rise of Industry 4.0 has brought new advancements in manufacturing, with a focus on integrating digital technologies to optimise processes and increase sustainability. Cognitive Digital Twins (CDTs) are emerging as a powerful paradigm in this area. They leverage advanced analytics, artificial intelligence (AI), and machine learning to create dynamic, real-time representations of physical manufacturing systems. This paper explores how CDTs can improve sustainability within the manufacturing sector. It proposes integrating generative artificial intelligence (GenAI) into the platforms that operate these digital twins to grant them cognitive capabilities. The work introduces a method for mapping and integrating energy consumption data to an Internet of Things (IoT) platform that includes the digital twin and a generative AI language model, such as ChatGPT. This proposed approach serves as a stepping stone towards unlocking the full potential of CDTs. It empowers manufacturers to achieve higher levels of sustainability and environmental responsibility.

Keywords: ChatGPT; Cognitive manufacturing; digital twin; generative artificial intelligence; Internet of Things; sustainable manufacturing;

1. Introduction

In the quest for increased flexibility and adaptability in manufacturing systems, various manufacturing paradigms continue to provide numerous solutions, leveraging technological advancements to achieve necessary tactical and strategic changes. It is undeniable that bio-inspired approaches have contributed to problem-solving in manufacturing. Examples of these systems include Holonic Manufacturing Systems (HMS) and Biological Manufacturing Systems (BMS). A widely-used term nowadays is 'intelligent manufacturing', derived from the characteristic of 'intelligence' primarily observed in humans and some animals before being programmed into machines as Artificial Intelligence (AI). Currently, the application of AI in manufacturing is centred on 'learning' from available data to identify patterns and assist in decision-making. As such, in a natural progression, 'learning' is usually followed by 'cognition', 'meta-learning' and even 'meta-cognition'. Therefore, in a natural evolution of manufacturing systems, 'cognitive' manufacturing is expected to be a step forward following the current 'intelligent' manufacturing.

As a concept, the *Cognitive Factory* was envisioned in literature as in [1, 2] with the aim of changing the factory from being 'deterministic', i.e., relying primarily on off-line programming to become 'dynamic', i.e., on-line instructions are generated as a result of processing and reasoning on-line observed data. The objectives back then were [3]:

- To increase knowledge transparency between systems
- To ensure the connectivity between humans and machines
- Upgrading manufacturing systems to more adaptive ones
- Facilitating autonomous planning procedures.

One important point to notice here is that these objectives have not endured any radical change as it is currently aimed to transfer manufacturing to the era of Industry 5.0, which fundamentally empowers human-machine interaction by enabling further interoperability between systems, and thus, further knowledge-sharing. The other point relates to the means of enabling cognitive manufacturing in the light of less advanced information and communication technologies, which translates into decreased data availability, less computational power and longer time for results validation.

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Generative Artificial Intelligence (GenAI) is a game-changer that promises a significant transformation in the way tasks are accomplished. When delving into the field of cognitive manufacturing, there is a need to define “Cognitive Artificial Intelligence” (CogAI) and ”Generative Artificial Intelligence” [4]. CogAI aims to mimic human thought processes and interact with the world in a similar manner by focusing on understanding experiences and utilising knowledge for decision-making [4]. On the other hand, GenAI aims to create new ideas, solutions, and processes [4]. Some experts in the scientific community perceive CogAI as a completely different field from GenAI. However, in this work, we align with the opinion expressed by the Stanford Institute for Human-Centered Artificial Intelligence (HAI), which states that GenAI systems can model high-level cognitive phenomena such as natural language and image understanding. AI generative models produce responses that are similar to neurobiological representations found in humans and animals [5].

As sustainable manufacturing is now positioned in the policy of manufacturing companies due to consumers’ preference for sustainably manufactured products and governmental laws and incentives, cognitive manufacturing systems need to be designed in correspondence to these new requirements. On the other hand, the industrial Internet of Things (IIoT), Cyber-Physical systems technology in addition to enhanced computational capabilities enables the construction of cognitive manufacturing systems. Motivated by these facts, this work aims to present a novel framework for integrating large language models in manufacturing systems to empower Cognitive Digital Twins (CDTs) GenAI for the aim of enhancing the system’s sustainability and making decisions informed by this demand. The remainder of this paper is as follows: Section 2 presents the work on cognitive manufacturing in general, and the work on CDTs, in particular. Section 3 proposes an approach for building CDTs. A case study is introduced in Section 4 as an exemplary application of the proposed approach. Finally, Section 5 concludes the paper.

2. Related work

In 2010, Zaeh et al [6] interpreted the term “cognition” in the factory as the act of equipping machines with cognitive capabilities which help to expand their abilities. Currently, with the increased emphasis on human involvement, Elmaraghy et al [7, 8] define a manufacturing paradigm called Adaptive Cognitive Manufacturing Systems (ACMS), where the concept of ‘cognitive adaptability’ arises as a theoretical system feature enabled by utilising elements of artificial and hybrid human-machine intelligence including sensing, perception, prediction, planning and autonomous decision making. In this context, the provided dynamic adaptability supports social and economic sustainability [7]

Sharma and Gupta [9] analysed the role of CDTs in sustainable development in the context of Industry 5.0 using the TOE-HOT framework, which allows for covering the influence of the technological, environmental and human aspects on sustainability. Focusing on the maintenance aspect, D’Amico et al [10] reviewed the literature on CDT with the aim of developing digital twins (DT) and further advancing the maintenance management to create a structured DT or a CDT, where the authors highlighted the future DT’s contribution to implementing sustainability evaluation. Savić et al [11] believe that one way of managing limited resources is achievable through the development of an abstract domain-neutral architecture of a CDT. Sustainability in this work is expressed in terms of the ability to provide a holistic view of the system in addition to resource reuse. Unal et al [12] showcased the use of CDTs in the Horizon project COGNITWIN (Cognitive Plants Through Proactive Self-Learning Hybrid Digital Twins) which involves the development of CDTs to achieve the targets of reduced energy consumption and real-time condition monitoring. The development of a cognitive digital twin implemented in a steel pipe manufacturing factory resulted in a 10% decrease in energy consumption of the production line and a reduction in carbon footprint.

Kalaboukas et al [13] used CDTs as fundamental components for building a circular supply chain. For this purpose, they identified three essential aspects for cognition to be realised: reasoning services, simulation and prediction services and optimisation models and services. A reference model for data governance is introduced in [14] emphasising sustainability (social, economic and environmental) as the main driver of the CDT decision-making, whether it is acting autonomously or supporting the human operator by giving recommendations.

Following a review of the literature on GenAI, Rane et al [15] believe that GenAI (ChatGPT in particular) may play a role in reducing energy consumption due to the language model’s ability to judge the data coming from sensors and production processes. By conducting a qualitative study that received a significant number of responses, Panigrahi et al [16] believe that AI chatbots (which essentially use generative AI techniques) can improve the performance of supply chains leading to better sustainable supply chain performance. On the other hand, Ghobakhloo et al [17] expressed concerns about the influence of some technologies such as GenAI and cognitive computing on social values as there is neither a guarantee for ensuring human centrality, nor a legislative framework that takes that into account.

To summarise and identify the research gap:

- The research work on activating CDTs in manufacturing systems is growing and several architectures/frameworks are being introduced.
- No previous approach to integrating generative AI in the CDT model has been proposed.
- The proposed architectures do not offer hands-on tools to practitioners in order to implement CDTs.

Therefore, the current work aims to address these gaps by proposing the inclusion of GenAI engines (such as ChatGPT) to support the cognitive capabilities of digital twins. The next section outlines the proposed approach.

3. An approach for building cognitive digital twins

The approach proposed in this work treats a CDT as a traditional DT connected to GenAI. This connection allows the DT to evolve into a CDT. The amalgamation process occurs on a platform that provides the necessary infrastructure to facilitate this evolution.

3.1. Establishing a suitable platform

The targeted platform in this research's vision has to be able to host the digital twin model or to be able to communicate with it securely and reliably. On the other hand, for DT to be realised, a bidirectional data exchange with its counterpart needs to be established. Thus, a paramount aspect/feature to be provided by the platform is flexible communication with both physical and digital entities. Both DT and CDT may require considerable computational capabilities depending on the complexity of the digital model (and the level of detail included in it) and the data analytics required by the end user/beneficiary. Hence, the targeted platform has to provide the necessary data storage (especially reading from and writing to various databases), and the computational power needed to handle large volumes of data and run complex simulations.

The platform should be scalable to accommodate the growing needs of the manufacturing environment. It should be flexible enough to adapt to evolving requirements, including adding new sensors, machines, or production lines, as well as integrating with emerging technologies. In the search for a suitable platform, the cost factor can be considered as well. This can be broken down into licensing fees, infrastructure costs, and implementation expenses while delivering value and return on investment for manufacturing organisations. Examples of the platforms that fulfil the aforementioned demands are Node-Red[1] and TIA IoT[2].

3.2. Development of traditional DT

The process of developing a DT is not in the scope of this work. A variety of approaches have been proposed in the academic literature and industrial practice to building DTs. The current work agrees with [18] in terms of the use of model-based systems engineering (MBSE). CDTs can predict the behaviour of systems based on various scenarios and inputs. By integrating MBSE techniques, more accurate models that capture the intricacies of the system, enabling better prediction of performance, failures, and potential optimisations can be created.

On the other hand, CDTs can be connected to real-world systems, providing real-time monitoring and control capabilities. By integrating MBSE techniques, system operators can ensure that the digital twin accurately reflects the behaviour of the physical system, allowing for effective monitoring, diagnosis of issues, and proactive maintenance.

[1] https://nodered.org/about/
[2] https://tia-platform.com/en

3.3. Integration of cognitive capabilities

As theorised, CDT goes beyond the basic representation of a physical object and incorporates advanced cognitive capabilities. It can harness technologies such as artificial intelligence (AI) and machine learning to enable higher-level cognitive functions. A cognitive digital twin can reason, learn, make predictions, and interact with users in a more intelligent and human-like manner. It can process complex data, adapt to changing conditions, and provide insights, recommendations, and contextual understanding.

As GenAI is becoming more affordable and reachable through a number of large language models (e.g., Google Gemini, Google Bard and ChatGPT), many researchers have proposed approaches and methods to use GenAI to advance the manufacturing industry. It has been noticed that GenAI demonstrated many cognitive capabilities such as the comprehension of language with the ability to address the semantics of language at some point, memory in terms of understanding contexts and following up on the same topic, in addition to demonstrating logical reactions to inputted data. As a result, the question that arises is "how to integrate GenAI in manufacturing systems?".

System integrators/designers do not necessarily have the expertise required to develop large GenAI models nor the time to generate/collect data and then train the models. Meanwhile, the market for generative AI is changing and new competitors are entering the market. With the competition becoming more fierce, prices are expected to become more reasonable with bundles targeting manufacturers as their needs are not the same as normal personal needs. Technically speaking, communication with language models can be established through Application Programming Interfaces (APIs) provided by the mother company to use them in a variety of applications, such as chatbots. Consequently, manufacturers and system designers have the opportunity to experiment with the applicability and usefulness of GenAI. They can explore and test how GenAI can be applied in their specific manufacturing processes or system designs. By conducting experiments, the feasibility, advantages, and potential benefits of integrating GenAI into their operations can be tested. This experimental approach allows for a practical evaluation of GenAI's capabilities and its potential impact on manufacturing and system design.
To showcase the implementation of the approach above, a case study is introduced in the following section.

4. Case study

4.1. Description

A production line for widgets, involving four distinct processes is being developed for an industrial partner. These manufacturing processes are:

1. Cutting: Raw materials are cut into individual pieces. (Processing Time: 2-5 minutes)

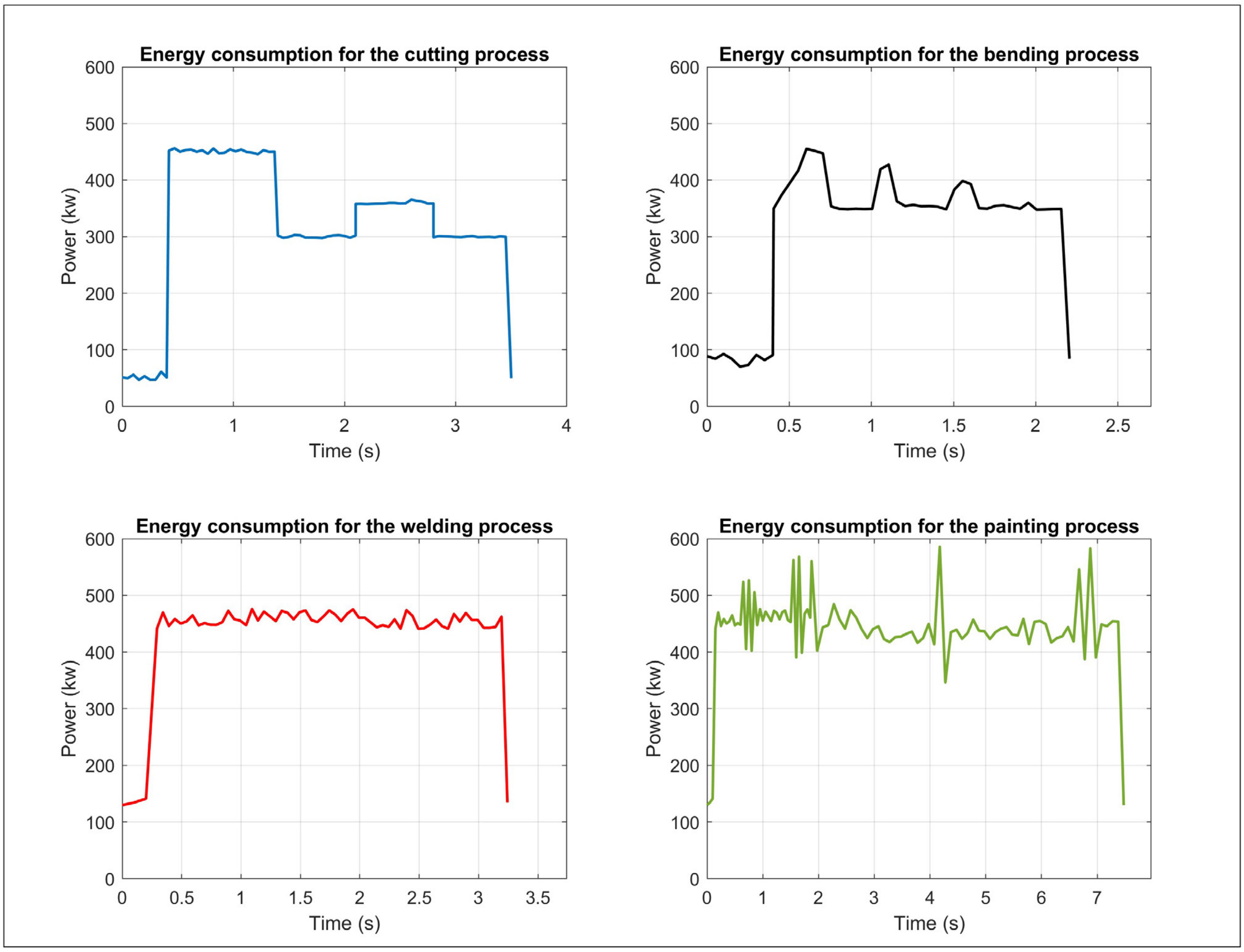

Fig. 1. A sample of transmitted energy consumption data

2. Bending: The cut pieces are bent into the desired shape. (Processing Time: 1-3 minutes)
3. Welding: The bent pieces are welded together. (Processing Time: 3-5 minutes)
4. Painting: The welded widgets are painted. (Processing Time: 5-10 minutes)

Energy consumption was recorded by using IoT sensors. An example of captured energy consumption data is shown in Figure 1.

4.2. Implementation

As explained in 3 and according to the MBSE, the development of a CDT starts by creating a traditional CDT, which is meant to be at the process level in this case using the Discrete Event Simulation (DES). This method can be used to predict and control energy consumption while the manufacturing system is being developed (early life cycle phases), as explained in [19]. DT is developed using the SymPi Python library[3] under the assumptions that new raw materials arrive at the cutting station every 1-2 minutes, and each process has a buffer with a capacity of 5 units except for the Painting which has no buffer due to drying constraints. Similar to the work implemented in [20], Python shell nodes are used to exchange input and output with Python scripts using the Python shell node [4].

The platform chosen to host the digital twin is Node-Red (NR) due to its ecosystem that allows the use of a variety of programming languages (e.g., Java and Python) and communication protocols. Moreover, a graphical user interface (GUI) can be created so that the user can interact with the created code and its outcomes. The developed graphical code is shown in Figure 2. Another important feature of NR is the possibility of using IoT communication protocols such as MQTT (Message Queuing Telemetry Transport) and OPC UA (Open Platform Communications Unified Architecture). In this work, as the installed sensors use OPC UA, the OPC UA client node was used in the code. The received data is written to a CSV file so that it can be sent to the GenAI engine.

[3] `https://simpy.readthedocs.io/en/latest/`

[4] https://flows.nodered.org/node/node-red-contrib-pythonshell

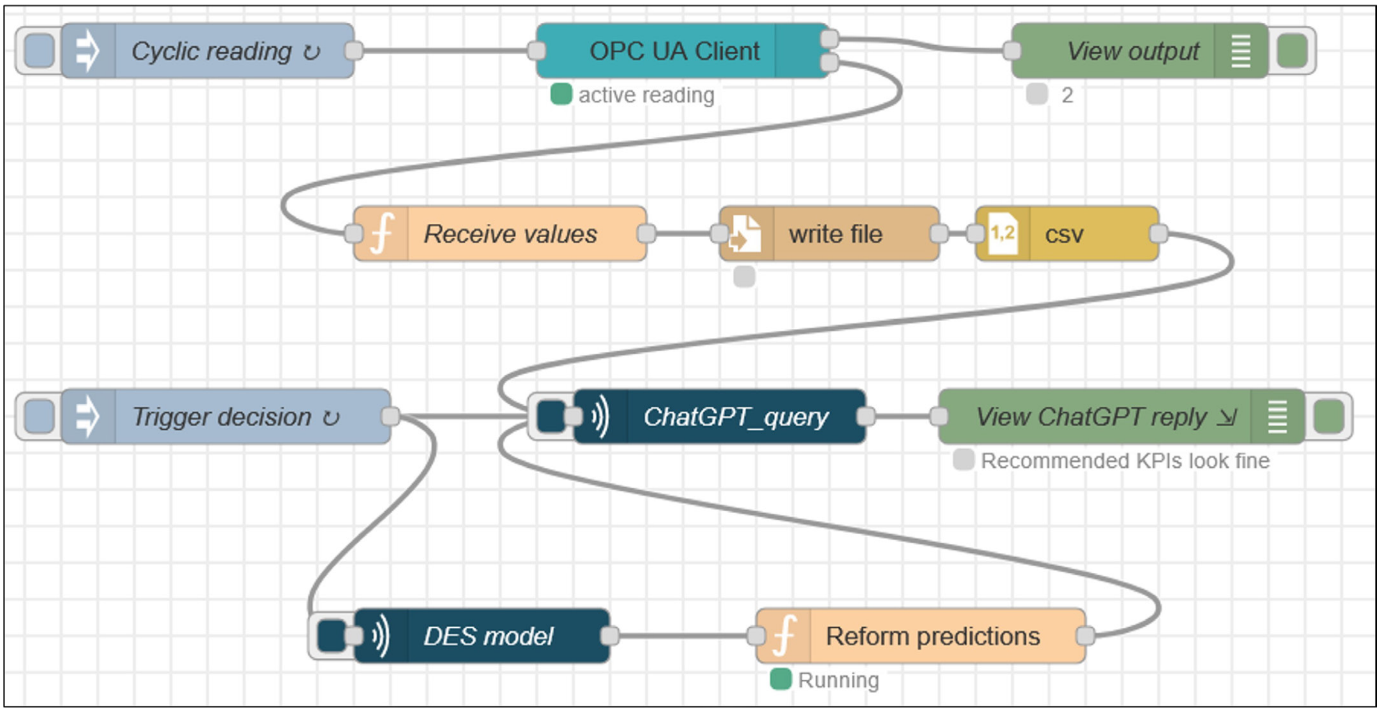

Fig. 2. The graphical code on the Node-Red platform

There are many GenAI engines in the market now. ChatGPT was chosen due to its popularity and the availability of a ChatGPT API. To enable this API, 'openai' Python library is needed in addition to a security key generated on the ChatGPT account. The current work tests the communication with ChatGPT and how to improve the quality of its responses. By writing the data and storing it in a CSV file, it is attempted to create a context that helps the engine better perceive inputted data.

4.3. Testing scenarios and result

Some Key Performance Indicators (KPIs) were programmed in the Python script (called by the Python node in the code) such as the maximum and minimum allowed cycle times for each process, and the maximum allowed energy consumption. Currently, the response is received on the Command Prompt (cmd) on the Windows operating system or Terminal on Linux, although it is possible to design a dashboard, but this will be implemented in an extended future work. The decision-making is triggered every 10 minutes. This in-progress work aims to exemplify three scenarios as a starting point to develop the introduced concept. These scenarios are as follows:

- Scenario A: where manufacturing processes run smoothly in agreement with the defined virtual model (DES) and the corresponding energy consumption.
- Scenario B: where cycle times, and thus, energy consumption show unexpected changes. However, these changes are not statistically significant.
- Scenario C: where the energy consumption behaviour changes significantly.

The response of the language model to Scenario A is shown in Figure 3 referring to the fact that operations are behaving normally. For Scenario B, the response shown in Figure 4 includes a recommendation to optimise energy consumption as the deviation is noticeable. More emphasis is included in the response to Scenario C (Figure 5), where it is recommended to check the process parameters and the efficiency of the equipment.

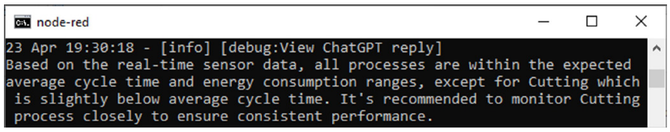

Fig. 3. The response of the language model (Scenario A)

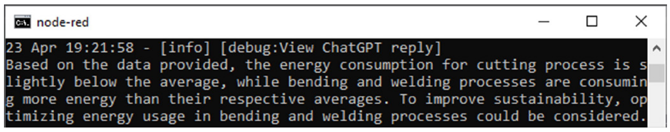

Fig. 4. The response of the language model (Scenario B)

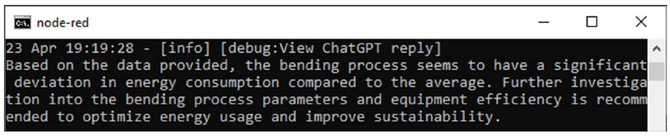

Fig. 5. The response of the language model (Scenario C)

4.4. Limitations

The current work did not examine all the potential cognitive capabilities that GenAI can offer to support CDTs, but a portion of that as the focus for the time being is to test the functionality and the architecture that can support it. Furthermore, the visualisation in order to get user interaction and test further cognitive responses is not implemented.

As a proof of concept, ChatGPT is tested but there are other engines such as Google Gemini whose responses can be compared to determine the best contexts in which each engine can better perform. Inputs to ChatGPT are not yet optimised in terms of the query format and wording, which requires a different set of experiments.

5. Conclusion

Traditional digital twins mainly focus on simulating the behaviour of physical assets. CDTs are gaining traction in the manufacturing sector due to their capabilities which are growing day after day thanks to Industry 4.0 technologies such IoT and Artificial Intelligence. This paper contributes to the advancement of CDTs by proposing to use GenAI as a means for gaining additional cognitive capabilities. Against this background, an approach for combining GenAI with traditional digital twins on a suitable platform is proposed. ChatGPT, an example of GenAI, is connected to the DES digital twin of a production facility using the Node-Red platform to test functionality. Logical responses could be obtained from ChatGPT using inputted data provided by the IoT server.

Future work will be extended to examine the performance of other Generative Artificial engines and compare the outcomes. In addition, further cognition characteristics will be systematically evaluated.

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