Knowledge-Based Engineering Design Supported by a Digital Twin Platform

Sthefan Berwanger[1,2], Henrique Diogo Silva[1,2], António Lucas Soares[1,2], and Cristiano Coutinho[3]

[1] INESC TEC, Porto, Portugal
{sthefan.berwanger, henrique.d.silva, antonio.l.soares}@inesctec.pt
[2] University of Porto, Porto, Portugal
[3] EFACEC, Porto, Portugal
cristiano.coutinho@efacec.com

Abstract. Data generated throughout the product development lifecycle is often unused to its full potential, particularly for improving the engineering design process. Although Knowledge-Based Engineering (KBE) approaches are not new, the Digital Twin (DT) concept is giving new momentum to it, fostering the availability of lifecycle data with the potential to be transformed into new design knowledge. This approach creates an opportunity to research how digital infrastructures and new knowledge-based processes can be articulated to implement more effective KBE approaches. This paper describes how combining a DT-based Digital Platform (DP) with new engineering design processes can improve Knowledge Management (KM) in product design. A case study of a company in the energy sector highlights the challenges and benefits of this approach.

Keywords: Knowledge-Based Engineering · Digital Platform · Digital Twin · Industry 4.0 · Digital Transformation.

1 Introduction

The Industry 4.0 paradigm has promoted the intelligent networking of products and processes along the value chain, enabling more efficient organizational processes that result in innovative customer goods and services. [2,4]. From the technology point of view, Industry 4.0 encompasses developing and integrating emergent and consolidated digital technologies such as the Internet of Things, Cyber-Physical Systems, Artificial Intelligence (AI), Virtual/Augmented Reality, and Cloud Computing.

Within this technological landscape, DT is a concept that builds upon the Industry 4.0 core technologies to be a comprehensive digital representation of a physical system, continuously updated by the data exchange between the counterparts. The DT concept and its technological implementation are closely related to product design and engineering [25]. In a broad approach, recent conceptualizations of the DT of a product encompass the entire product lifecycle data and its integration into a single architecture, fostering the optimization of Product Lifecycle Management (PLM) from design to continuous diagnosis and performance analysis, back to design again.

With data analytical methods becoming widespread for organizations to optimize and integrate manufacturing and business processes, the early and continuous use of KBE methods and solutions is required [6]. The effectiveness of KBE in building Computer-Aided Design (CAD) models [16,17] aligned with the developments of semantic Web technologies have allowed KBE to evolve as complementary to CAD systems [5,14], with authors pointing to data organization and sharing standards such as Resource Description Framework and Web Ontology Language to play a vital role in the future of KBE and KBS. Moreover, the joint and articulated addition of DT technologies with KBE and Knowledge-Based System (KBS) can positively impact product development and the organization's recognition as a leader, enhancing its reputation in the market [13].

This exploratory research aims to describe an organization's challenges in a digital transformation process and the general requirements for developing KBE processes supported by an innovative DT-based DP. The research question guiding the case study is "What are the benefits and problems of implementing a KBE strategy supported by a DT-based DP?". The results emphasize the need for early and continuous use of KBE methods and solutions to enable complete optimization and integration of manufacturing and business processes, with the articulated addition of DT technologies with KBE and KBS positively impacting product development.

The remainder of this paper is structured as follows. Section 2 presents a state-of-the-art overview of related works on KBE and DT. Section 3 describes our view of how a DP provides the core services and the needed interfaces to enable knowledge-based services. In section 4, the research methodology and instruments used to collect data are described, and the research findings concerning engineering processes and optimization proposals are presented. Finally, section 5 concludes the paper and highlights future research.

2 Related work

2.1 Knowledge-Based Engineering

The KBE concept can be synthesized by using KM strategies, tools, and systems to support product design [15]. The goals are to identify relevant knowledge in an organization and to define how to capture, formalize, represent, organize, and store it for better access and sharing. In addition, the ultimate goal is to reduce product development time and costs by automating repetitive and non-creative design tasks and supporting multidisciplinary design optimization in all phases of the design process. The current and most recent notions of KBE relate to the objective of KM in capturing and transmitting knowledge to increase organizational performance. Individual and organizational performance can be improved by preserving and utilizing the assets' present and future knowledge value, including human and automated activities [8]. In sum, KBE is the application of KM to manufacturing design and production. Product design and engineering are inherently knowledge-intensive, requiring structures and processes enabling data and Information Management (IM) to facilitate knowledge extraction and sharing among stakeholders.

2.2 Digital Twin

The most recent concept of DT emerged from [24], defining the DT as a virtual, dynamic model in the virtual world that is entirely consistent with its corresponding physical entity in the real world and can simulate the characteristics of the physical counterpart, behavior, life and performance in a timely fashion. Moreover, [19] defined DT as virtual models of physical objects created digitally to simulate their behaviors in real-world environments. In conclusion, the DT is the digital counterpart of the physical product that aggregates real-time and historical data and information about the product. Furthermore, historical data in this context means that the whole lifecycle of the product is covered. As a step forward in the evolution of the DT concept, [10] builds on previous work that combines DT technologies with semantic models and Data Analytics (DA) tools to suggest a formal description of Cognitive Digital Twin (CDT) as a DT with increased semantic capabilities for detecting the dynamics of virtual model evolution, facilitating the understanding of virtual model inter-relationships, and improving decision-making. These insights can fuel more intelligent product and service behaviors and further develop smart digital product-services systems that can transform customer-supplier relationships and introduce new value propositions [11]. Transformation and integration with business processes become critical to leverage these technologies fully, and KBE provides an approach to this.

2.3 The Role of Digital Twin in KBE

The DT technology is a powerful tool for product development engineers in KBE. The basic DT allows the creation of a digital model of a complex product, simulating and testing several aspects of their designs before they are built, enabling efficient and effective experimental learning. Besides, this reduces the time and cost involved in physical prototyping and allows engineers to identify and address potential problems early in the design process. Advanced DT-centered technologies can further support collaboration and knowledge sharing among engineers and other stakeholders by providing a platform for sharing product data and information, e.g., structural or behavioral design models; data sets from the product operation, or insights from operational data analysis. Such a DT facilitates communication and collaboration across different teams and disciplines, leading to more effective problem-solving and innovation. According to [13], the DT adoption coupled with KBE could lead to partners and the market recognizing organizations as leaders, increasing their reputation. Model-centric design, comprehensive PLM, rapid production of diverse design solutions, and a faster response through a faster knowledge flow were the required skills in this dynamic. In addition, KBE and DT approaches also can help increase knowledge reuse during the engineering phase, which can positively impact the business profits [3].

3 KBE Process Transformation Through DP as Infrastructure

The proliferation of digitalization of business processes has led to the omnipresence of DP in providing digital products and services. The Information Systems (IS) field has long studied DP as digital software systems that act as both innovation and transaction platforms [20,12] by serving as a technological foundation and as a market intermediary [7,9]. In general, a DT can support engineering design processes by: (i) supporting collaboration and coordination of product and process design; (ii) organizing, classifying, and delivering several product design models; (iii) managing the access to data and documents from previous design processes integrated with historical data; and (iv) automating the workflow of some design processes.

With these goals in mind, the DP provides the core services and the needed interfaces to enable knowledge-based services. The DP core provides three main interfaces: (i) user interfaces that allow for the interaction of end-users with all the platform-provided services; (ii) data interfaces for the managing of data; (iii) DT interfaces to establish the bidirectional connections between the platform and the multiple instances of DTs.

By its software nature and modular design, the DP can provide custom sets of foundational tools that, arranged into more complex services, fit the needs of companies and directly interface and be part of business processes. [14] depict a simple KBS as a system capable of receiving inputs, such as customer specifications or product data and processes, and transforming them into outputs, such as CAD models, drawings, processes, or reports, by leveraging product model data from previous configurations, geometries, and engineering knowledge, and external data coming from catalogs of materials descriptions.

Drawing a parallel, a DT can be interpreted as a KBE system: (i) where platform core receives inputs through user interfaces; (ii) which, through the DT interfaces, is capable of accessing historical data from the multiple instances of the DT; (iii) that can leverage data interfaces powered by semantic technologies to interface with multiple external data IS; and (iv) that can interface directly with the organization's business process to deliver the required outputs.

Figure 1 builds on the three KM challenges of knowledge representation, acquisition, and knowledge update [1,23]. These three pillars allow the DP to serve, e.g., as an infrastructure for enterprise customized Machine Learning (ML), DA, and other AI-based services that leverage the existing knowledge to support product design processes better.

Regarding the data architecture, the DT uses ontologies to describe and annotate the domain of knowledge and the rules that constrain it while also leveraging semantic tools, such as knowledge graphs, to semantically link the digital models and allow for the integration of DT models. ML techniques are also crucial for uncovering hidden patterns in the stored knowledge [23]. The several activities and legacy systems that comprise the enterprise's current business processes form the data and information sources that the DP must be able to ingest and manage throughout the entire product's lifecycle. The continuous knowledge update is also a central component of the DP as a KBS. So, this aspect must be part of business processes and strategies.

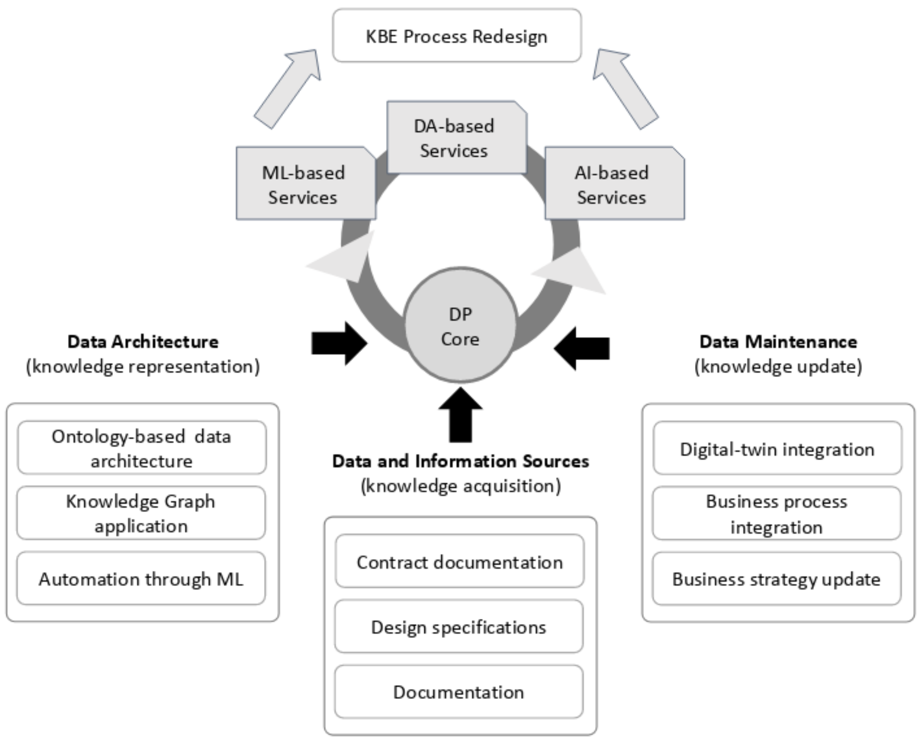

Fig. 1. Interactions between organizational elements and the DP architecture elements.

4 Case Study

4.1 Methodology

The studied company operates in the energy, mobility, and engineering sectors in over 65 countries, whose growth strategy in the international market has been based on the presentation of innovative and quality products. In this case, the product is a Power Transformer (PT), a complex electrical device used in power grids. The relationships between the departments developing the PT are configured as a grid in a matrix structure. It is a sort of organizational administration in which individuals with equivalent skills are pooled for work duties, resulting in more than one manager.

Due to the characteristics of the research, the case study research method was employed to study the context of the engineering process at the company. [21] defined case study research as an empirical inquiry that analyses contemporary phenomena in its real-life setting when the boundaries between phenomenon and context are not readily visible and when numerous data sources are utilized.

The following approach was employed for this work, considering the nature and objectives of the research: (i) establish a research method based on the case study approach; (ii) collect and analyze existing internal documentation; (iii) collect data using focus groups and semi-structured interviews; (iv) analyze the results from the focus group, interviews, and internal documentation; (v) develop improvement proposals for engineering processes and PT design.

4.2 Results and Discussion

This study addresses the research question, "What are the benefits and problems of implementing a KBE strategy supported by a DT-based DP?" As an outcome, we identify and describe the areas where the work contributes.

Current KBE Processes In the PT design phase, it is an acknowledged requirement to optimize the engineering process by implementing the integration of the IS so that data can be retrieved, updated, and stored at specific flow points and milestones to speed up the completion and validation of the requirements, among other documents. In the same way that elements are stored and recovered, the reuse process is hindered due to the dispersion of elements across legacy systems and the lack of any KM strategy. Furthermore, knowledge is not shared correctly among all teams, especially with new members.

The following instruments were considered the most important for promoting and managing tacit knowledge: mentoring programs to encourage senior workers to train juniors through classes, lectures, hands-on activities, and recording from meetings. Furthermore, most customers the organization consulted avoid sharing the data because they consider it sensitive, reserved, and confidential.

The organization's current, complete engineering processes are complex due to the number of activities, dependencies, and stakeholders involved in different stages, from the start of the design of the PT until its delivery and operation at the customer site. For this reason, specific knowledge-intensive tasks were selected according to their business priority to serve as intervention points.

Mapping KBE methodologies KBE requires a KM approach considering various organizational and technical elements, including the industry context, human resources, technological resources, and organizational culture. According to [22], this approach balances an organization's knowledge, resources, and skills with the expertise needed to sell superior products and services to competitors.

The CommonKADS was chosen for implementing KBE supported by the DT platform. Its organization model entails integrating relevant elements and experiences from various sources, including organization theory, business process analysis, and IM, into a coherent and comprehensive package targeted at knowledge orientation in the organization [18]. From this unified view, a detailed organization model was developed to identify challenges and opportunities for a knowledge system implementation and their viability.

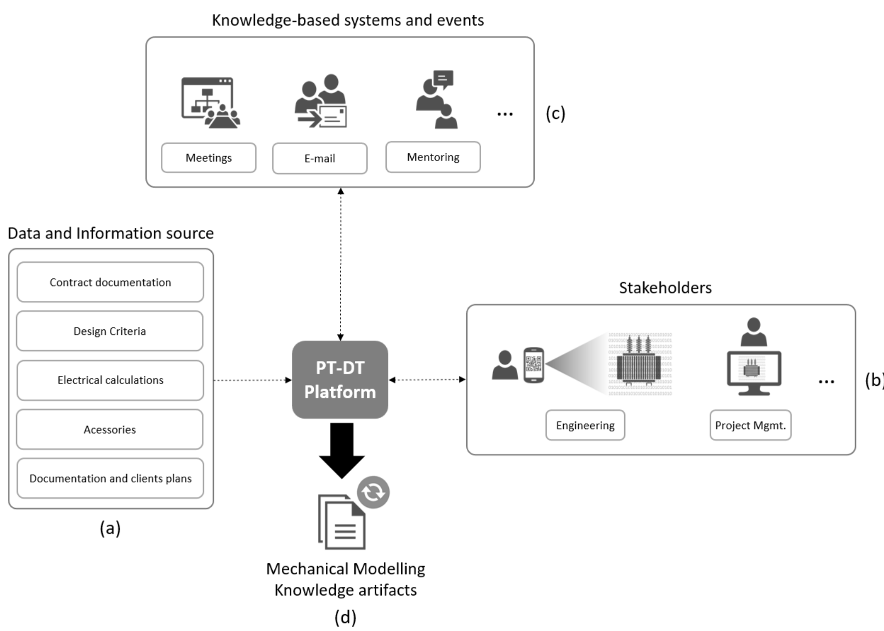

Fig. 2. Redesigned process for mechanical modeling.

The mechanical modeling process is an example of the encountered challenges. It is constantly changing, and a more centralized scenario paired with managing a large amount of information and communication networks is thought to be the goal. New collaborators have a long learning curve regarding the mechanical process. During the training phase, they read the tools' manuals and usually learn by observation and communication with more experienced team members. Much information must be considered, so less experienced designers will have less complex projects allocated to them. Considering these challenges, this task was chosen to be optimized. As presented in figure 2, the redesigned mechanical modeling provides input and storage of data and design information from (a) into the DT. This data is already normalized, cleaned, and organized.

Initial data can be queried in (b) by stakeholders via regular computers or augmented reality techniques. The information may not only be retrieved but edited, deleted, and enriched by team collaboration, with versioning control capability offered by the platform. This data and information can also be read and analyzed in meetings and subsequently enriched with the tacit knowledge generated. In the workplace, this tacit knowledge refers to processes and techniques learned through practical experience and training that are later aggregated into the project knowledge artifacts. Finally, the initial and later enriched data and information are stored in knowledge artifacts as in (d), e.g., as media files by the DT, and periodically updated as new information is added, deleted, or edited.

5 Conclusion

The analyzed company faces many challenges during the different phases of the PT lifecycle. In this exploratory research, we argue that a DP managing the DTs of the PTs can assume the role of KBS for centralizing knowledge-sharing practices and infrastructure to provide customized tools and services that can be integrated into current business processes, enabling innovation in products and services.

The study addresses the research question: “What are the benefits and problems of implementing a KBE strategy supported by a DT-based DP?”.

It is shown that DP as a KBS, through a KBE approach, can support the organization in this process by (i) during the beginning-of-life stage, integrating teams more closely in the development of complex projects to support information flows and collaboration; (ii) for the middle-of-life, provide ML, DA, and AI-powered services for faster and more precise forecasting, such as failure prediction, to foster mode data-driven decision-making processes; and (iii) in the end-of-life, contributes to the long-term reinforcement of its positioning in favor of sustainability while continuing the knowledge updating process that can greatly benefit future design iterations.

Regarding methods of KBE, interactions with the company stakeholders show that the respondents viewed implementing mentoring programs and recording knowledge from meetings through retrievable means. These tools can help teams acquire new knowledge built on pre-existing knowledge, benefiting the product at any stage of its lifecycle. Furthermore, by improving KBE processes, there is an opportunity to improve the culture of actively sharing information with colleagues.

Finally, data sovereignty concerns were also raised, with most customers refusing to share data of the in-use PT, considering it sensitive and confidential. For customers to be willing to share this data, necessary for complete lifecycle optimization, it would be necessary to establish a data disclosure agreement, security requirements, and rigorous data management policies.

While this paper highlights the importance of KM strategies in supporting the success of the KBE approach, this study has several limitations. Future research should focus on exploring methodologies for implementing improved KBE, and the selected criteria for implementing the chosen methodology. Additionally, the technical developments of the vision detailed here can serve as an empirical basis for the CDT literature, as few successful implementation cases of CDT can still be found.

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