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Knowledge-based feedback of product information into product design

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Abstract

This paper introduces a knowledge-based feedback system for product design, using XML and CSV files to integrate product usage data. Through data mining, this data is combined with existing knowledge to support design teams. The knowledge base, created using methods like rule-based systems, Bayesian networks, neural networks, and knowledge graphs, supports decision-making. The knowledge graph, implemented in Neo4j, is characterized by integrating diverse knowledge sources. The concept was validated using simulated data from 3D printers, demonstrating its effectiveness, and anticipates customer needs and optimizes product generations, fostering the creation of customized products.

Keywords: Knowledge-based feedback; product design; product information; knowledge graph; product life cycle management

1. Introduction

As a consequence of the increasing digitalization and automation that characterize Industry 4.0, the number of machines and processes that generate substantial quantities of data is rising [1, 2]. Nevertheless, the intrinsic value of this data is contingent upon its integration with knowledge that facilitates efficient utilization and well-founded decision-making [3]. Knowledge-based systems occupy a pivotal position in this regard, as they are capable of analyzing data and transforming it into usable knowledge. This renders them invaluable assistance systems for a plethora of applications, including process control and decision support [4].

In the context of product development, knowledge-based systems can facilitate the generation of valuable insights through the utilization of product data [2]. Such systems facilitate the incorporation of data from subsequent product life stages, including utilization and recycling, into the development process. This enables the avoidance of errors inherited from earlier product generations and the optimization of requirements in a targeted manner [5]. The efficient retrieval and structuring of this knowledge result in reduced development times and enhanced future product adaptation [6].

The objective of this paper is to develop a conceptual framework for the knowledge-based feedback of product information into product development. To this end, a data mining process is implemented with the objective of generating knowledge from returned data and integrating it into a central knowledge base and this knowledge base is designed to support decision-making in product development through the use of suitable query methods [3]. The concept presented has the potential to enhance the efficiency of product development, secure competitive advantages and achieve greater customer satisfaction over the long term [2].

In the following sections of this paper, the background that led to the development of the knowledge-based feedback is highlighted. Subsequently, the concept itself is explained. A practical validation is presented, followed by a reflection of the result and future perspectives.

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2. State of the Art

This section equips the reader with a background and the potential of knowledge-based systems in product design.

2.1 Background

Products go through different phases in their life cycle, from product design to recycling [7]. These phases are represented in the product life cycle [8]. Data, information, and knowledge are generated in all phases of the product lifecycle and in all cross-functional processes. Today, even simpler products generate large amounts of data from multiple sources during their lifecycle, and this trend is growing [8]. The efficient use and management of this information and knowledge is an ongoing challenge with great potential for cost and time savings as well as quality improvements [8].

The Product Lifecycle Management (PLM) concept was developed with the aim of mapping all phases of the product lifecycle [3]. What PLM systems have in common is that they centrally plan, structure and manage product and process-relevant data from different phases of the product lifecycle [7]. The product life cycle defines the framework for the life phases of products, and controls the collection, storage and analysis of this data. However, in the midst of these processes, it becomes clear that pure data management alone is not enough. This is where knowledge-based systems come into play, using the interplay of data and expert knowledge to make informed decisions and solve complex problems [9].

The idea of knowledge-based systems is to store and present this knowledge in a user-friendly, formal and well-documented way so that it can be used in a repeatable and comprehensible way when required [9].

According to Bock et al [10], knowledge is not only the basis for a company's competitive advantage, but also the most important factor for the value of a company. The knowledge of employees influences the innovation process and the quality and accuracy of this process [10].

Knowledge-based systems consist of two components, the knowledge base and the interference engine [2]. In the knowledge base, knowledge and data are structured in formal semantics, e.g. in the form of rules, facts, axioms, definitions and statements [11]. The interference engine is the knowledge processing component. The interference engine is applied to the knowledge base in order to solve problems and find new knowledge [2].

Sources of data and knowledge include generated sensor data, existing databases, books or subject-specific human experts [3]. One challenge is that this data and the knowledge behind is often available in different formats, such as GPS coordinates, temperatures, pressure values, vibrations and repair reports [3].

Knowledge-based systems differ in the methods on which they are built and operate, such as rule-based systems, Bayesian networks, neural networks or knowledge graphs. What these knowledge-based methods and systems have in common is that they simulate intelligent thinking and action in a specific area by representing and processing knowledge [3].

In recent years, the processing of knowledge through knowledge graphs has received increased attention [12]. Their underlying structure enables an improved understanding and optimized interpretation of knowledge, both for humans and machines [12].

Due to the rapidly increasing use and spread of the term "knowledge graph", Ehrlinger et al [11] have attempted to find a standardized definition for it. They define knowledge graphs as follows: "A knowledge graph acquires and integrates information into an ontology and applies a reasoner to derive new knowledge."

Knowledge graphs consist of objects and relationships. The nodes of the graph are the objects and the vectors between the nodes represent the relationships [11]. A distinction is made between two types of knowledge graphs: RDFs based on triples and labeled property graphs [13].

RDF stands for Resource Description Framework and refers to a triple-based structure developed by the World Wide Web Consortium (W3C) [13]. An RDF graph always consists of a structure of subject, object and predicate, which is referred to as a "triple" [13].

In labeled property graphs, the objects (nodes) and relationships (vectors) also have internal structures [13]. This means that special knowledge about the objects or relationships can be stored within the nodes and vectors. Objects can have different labels that assign the objects to specific categories [13].

2.2 Potentials of knowledge-based systems in product design

Knowledge based systems improve the processing of knowledge in the individual phases of the product life cycle. One phase that can particularly benefit from this is the product design phase. The product design process is characterized by a series of information processing decision processes [14].

The costs for product design are low compared to the other costs that a product incurs during its life cycle. However, around 75% of production costs are caused by decisions made during product design [15]. This phenomenon is also known as "front loading". This means, the costs of a product are largely determined in the development phase, as the fundamental decisions that influence the entire product life cycle are made at this stage [15]. Due to this front loading, product design offers particularly great potential for reducing costs.

The feedback of product information from the later phases into product design is therefore already a central component of the PLM concept. However, the state of the art shows that there is still a significant gap between the actual status and target status of existing PLM systems [3].

PLM systems manage reports, CAD files, technical drawings and simulation data during the design process. This has the disadvantage that other product lifecycle phases such as product use and recycling are not sufficiently taken into account. Design knowledge is not reused efficiently and the effects on later product life phases are not sufficiently analyzed [2]. This is why feeding data and knowledge from earlier phases back into the product design process holds great potential, for example for optimizing future product generations.

3. Knowledge feedback into product design

The specific potentials of knowledge-based systems in product design, that have been carved out in the state of the art, motivate this paper which proposes a novel concept of knowledge-based feedback of product information into product design. In the following, the first subsection describes the concept overview whereas the second subsection presents the concept implementation via a Knowledge Graph.

3.1 Concept Overview

Development times are getting shorter and shorter, products are becoming more complex and diverse, the number of variants is increasing and there is a shortage of qualified personnel. The more efficiently knowledge can be processed the better development teams can meet these challenges.

For this reason, a concept was developed for the knowledge-based feedback of product data into the product creation. It enables the structuring, easy retrievability and thus availability of the required knowledge. Such a knowledge-based system is able to provide valuable decision-making aids and make the development process more efficient.

The concept has been developed for products that are constantly being improved or further developed and that are manufactured in large quantities. Large-scale production involves considerable effort and have great potential for knowledge acquisition. Small improvements can have a major impact due to the large number of units produced.

It is also important that the products have a high intensity of use or a long service life. If the amount of data obtained is too small, no significant conclusions can be drawn from the data.

Complex products with high quality requirements (e.g., turbines, production machines, etc.) are often already equipped with sensors for condition monitoring. The traceability of this data is therefore comparatively inexpensive, as there is no need to install expensive new sensors.

Figure 1 shows a general concept structure that can be implemented using various knowledge-based methods.

The first step is to generate the data during product use. Data and information from various sources can be recorded here. Previous knowledge from product design can be used here to select which parameters are to be fed back. Sources for the product data can be, for example, sensor values, customer feedback, maintenance and repair reports and customer information. To ensure the traceability of the data, the source (e.g., a sensor number) and the date of recording are always recorded. The recorded data and information are then fed back into the product design phase.

In preprocessing, the returned data and information is converted into a standardized format that is suitable for the data mining process.

After preprocessing, the data is analyzed in a data mining process. The aim is to generate information from the data and knowledge from the information, e.g. through recognition of patterns.

The information and knowledge from product use are then combined with the previous knowledge from product design to form a knowledge base.

The knowledge base is then available to the product developers and knowledge engineers. The knowledge base can be accessed by knowledge discovery methods, query methods and knowledge representation methods can be applied to the knowledge base. The query method makes the knowledge available to the product developers and the knowledge base can be analyzed and validated via this interface. The knowledge can be used to support the product design process.

Knowledge discovery methods can also be applied to the knowledge base to generate new knowledge. Through linking knowledge creates new knowledge. This knowledge can be discovered and then either added to the knowledge base itself or used to improve the structure or composition of the knowledge base.

An important task of knowledge management is knowledge representation. Knowledge representation is a kind of filter to present knowledge clearly and to clarify key aspects. Knowledge can be represented by a graphical structure or by diagrams such as pie charts or bar charts.

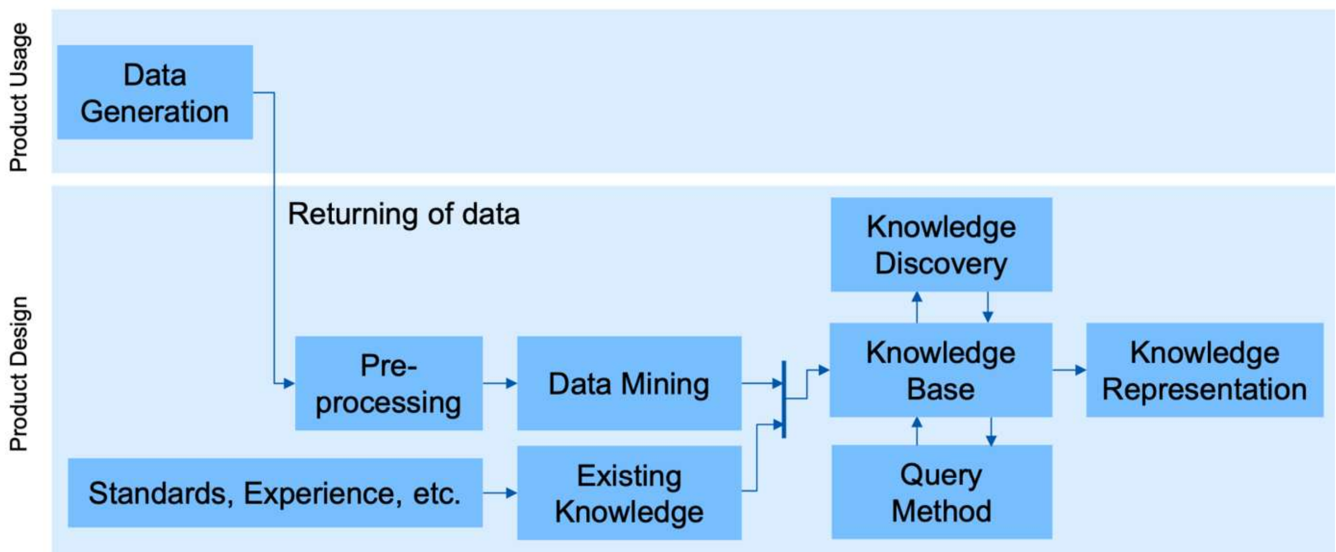

Figure 1 – Structure of the developed concept

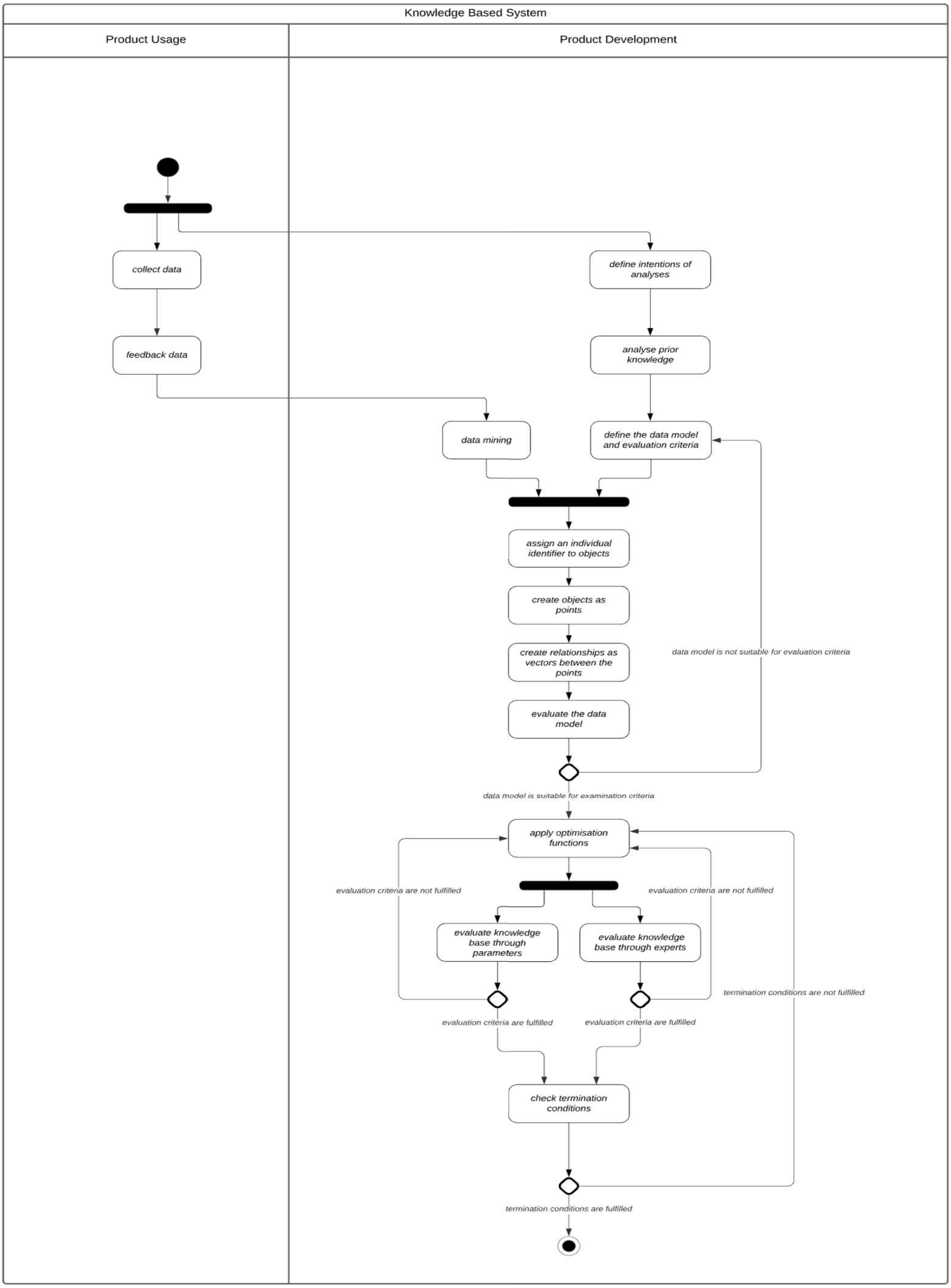

Figure 2 – Activity diagram of the developed concept for knowledge graphs

3.2 Knowledge-based feedback of product information via Knowledge Graph

Knowledge graphs have a large number of use cases and are characterized by a high degree of flexibility with regard to adaptation to other use cases. This makes them a particularly suitable method for managing knowledge in a complex phase such as the product design process. During product use, data from a wide variety of sources is generated in many different forms. Knowledge graphs prove to be particularly advantageous when combining a wide range of different forms of knowledge and can therefore be used throughout the entire development process.

Graph databases have good scalability and can also handle large amounts of data in the petabyte range [16]. A knowledge graph would therefore also be suitable as a knowledge-based system for the entire development process.

A key advantage over other methods is the ability to add existing knowledge from product design or previous product lines.

The activity diagram in Figure 2 shows the concept developed on the basis of the usage of knowledge graphs.

The process starts with the collection of data during product use and the definition of test criteria during product design. The examination criteria describe the use case and define the objective of the knowledge analysis. For example, the development team can determine that it wants to examine the products for their fulfillment of the requirements. This is followed by an analysis of the prior knowledge in order to generate knowledge that can be integrated into the knowledge base.

A data model and evaluation criteria are then defined. The data model describes the structure of the graph. It defines which types of nodes and relationships exist and which internal structures these nodes and relationships have. The evaluation criteria define which conditions the knowledge graph must fulfill in order to be suitable for processing the knowledge.

The data collected during product design is analyzed in a data mining process and then fed back into product design.

It is not advisable to integrate all measured values separately into the knowledge base, as the knowledge contained in the values is of interest to the product developer and not a single individual value. The amount of data from different sensors over a longer period of time is too large to justify an overview of individual values. Therefore, the data mining process is a key factor in generating knowledge from data.

The knowledge gained from the product data and the existing prior knowledge from product design are combined and individual identifiers are created to ensure that all data can be clearly traced and assigned.

In the next steps, all objects are first implemented as points and all relationships as vectors. The points and vectors are created based on the schema defined in the data model.

The data model is then evaluated using the evaluation criteria. If the data model is not suitable for investigating the examination criteria, a new data model is extended or defined and the process starts again. If the data model is suitable for examining the examination criteria, the graph is optimized in the next step.

In this phase, optimization functions are used to identify and add missing relationships and nodes. In the optimization phase the knowledge base is analyzed so that newly discovered knowledge can also be added to the knowledge base.

In the next step, the graph is evaluated by parameters and experts. If the evaluation is successful, the termination condition is checked. The termination condition must be defined and specifies the point at which further searching and linking of newly knowledge no longer generates any added value, but instead leads to unnecessary redundancies.

If the termination condition is fulfilled, this results in a comprehensive, evaluated knowledge graph that serves as a knowledge base. The knowledge graph can now be used to support decision-making and knowledge generation in product design.

The knowledge graph is constructed here according to the top-down approach. With this approach experts use their prior knowledge and experience to determine the structure of the graph and then fill it with the data obtained.

To ensure the traceability of data sources, each piece of information must always be clearly assigned to a source. A clear assignment of information to its respective sources ensures that data that has been falsified by defective sensors is not included in the decision-making process. This reduces the risk of misinterpretation of data and enables an objective evaluation of sensor data.

4. Validation

To validate the developed knowledge graph concept, a prototypical implementation was conducted using simulated data from 3D printers.

The simulation is based on an FDM (Fused Deposition Modeling) 3D printer, which produces three-dimensional workpieces layer by layer using CAD data [17]. Data generated during the printer's operation, such as print bed temperature and print speed, was incorporated into the knowledge graph. The primary focus of this implementation is to manage and link the printer's operational data with specific performance requirements. Furthermore, the knowledge graph integrates prior knowledge about materials, components, and locations, enriching the data network and enabling more informed decisions.

Beyond 3D printer data, additional nodes and relationships were modeled to represent customers, requirements, locations, and environmental conditions. This data model forms the foundation for the prototype implementation. Neo4j (version 1.5.9) was chosen as the platform for its robustness, open-source nature, and user-friendly interface, as well as for its support of the LPG (Labeled Property Graph) model [16]. Neo4j's Cypher query language allows efficient data processing, and its Python interface enables seamless integration of data into the graph structure.

To construct the knowledge graph, a CSV file containing product data was imported through the Python interface. Nodes were created from the data, and semantic relationships between data nodes were established to reflect real-world connections. This setup enabled the concept to evaluate printer usage data against performance requirements, identify trends, and anticipate customer needs based on location information. Additionally, the knowledge graph assisted in component selection, and its structure facilitated the identification of potential conflicts between product properties and requirements.

The knowledge base's utility as a tool for decision support and knowledge retrieval was also validated. New insights derived from linked data within the graph were successfully integrated into the knowledge base, expanding its usefulness. For validation, a use case was developed under simulated conditions with randomly generated and carefully crafted data that included specific dependencies relevant to the concept. While this prototype demonstrates the concept's potential, further testing with real data and in real-world conditions will be required to fully validate its capabilities.

The implementation of the knowledge graph proves its fundamental suitability as the basis of a knowledge-based system. In particular, the integration and linking of prior knowledge and product usage data distinguishes the concept from knowledge-based methods. The prototype implementation shows that knowledge graphs have the potential to support the entire product design process and to integrate product usage data.

5. Conclusion

This paper presents a conceptual framework for integrating knowledge-based feedback into product development processes through the utilization of a knowledge graph, which offers the potential for enhanced efficiency and decision support. The implementation of the concept demonstrated both potential and the need for further development to address identified challenges.

A significant area for future investigation is the updating of the knowledge base with regard to time dependencies, such as standards and customer requirements, which are subject to constant change and must therefore be made available for optimal decision-making and the implementation of automatic updating could serve to reduce the considerable manual effort currently involved [12]. Further potential exists for integrating the knowledge system into existing PDM and PLM systems, which are used intensively in practice. Such an extension would serve to enhance the system's overall acceptance and user-friendliness.

Furthermore, the expansion of the system to encompass disparate product lines and product life phases, with a particular focus on the product recycling phase, holds considerable promise. The incorporation of a diverse array of product data and sources across multiple product generations has the potential to bridge knowledge gaps and uncover novel synergies that can inform and enhance product development. In particular, linking data from seemingly independent areas (such as 3D printing and drones) could enable interesting conclusions to be drawn through a company-wide knowledge system.

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