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Information Extraction And Knowledge Modeling For Disassembly Processes

German Bluvstein[1]*, Rüdiger Daub[1, 2]

[1]*Technical University of Munich (TUM), Institute for Machine Tools and Industrial Management (iwb), Boltzmannstrasse 15 , Garching near Munich, Germany*
[2]*Fraunhofer Institute for Casting, Composite and Processing Technology (IGCV), Am Technologiezentrum 2, Augsburg, Germany*

Abstract

Disassembly is an important process step of sustainable manufacturing and circular economy strategies. As the cost of disassembly can rise quickly due to its complexity, disassembly planning is necessary to control these costs. An efficient disassembly planning pipeline starts with an efficient knowledge model. However, current disassembly knowledge models often suffer from rigid data structures, insufficient specification of required information, and fragmented data sources. To address these limitations, we propose a five-step concept that combines the analysis of structured information with the analysis of unstructured text-based information by the use of Large Language Models (LLMs). The foundation of this concept is a basic schema for a knowledge graph to accurately represent product structures. This graph is enriched by extracting and interpreting additional process-specific data from a maintenance manual using LLMs. A proposed interactive LLM-based interface allows users to dynamically query, validate, and extend the resulting knowledge graph in real-time. Preliminary implementations demonstrate the feasibility of this approach, bridging the gap between static state-of-the-art disassembly planning models and abstract ontological frameworks.

Keywords: Disassembly; Knowledge Graph; Process Planning; Large Language Models

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* Corresponding author. Tel.: +49 89 289 15542; fax: +49 89 289 15555.
E-mail address: german.bluvstein@iwb.tum.de

1. Introduction

Climate change and resource scarcity increasingly force manufacturing companies to adopt sustainable practices and transition towards circular production systems [1]. In recent years, the rise in End-of-Life (EoL) products underscores the need for effective circular strategies, such as reuse, remanufacturing, and recycling, in advancing sustainable development [2]. Proper management of EoL products contributes to mitigating environmental pollution, reducing resource depletion, and generating economic value [3]. In most circular strategies for EoL products, disassembly is a required initial step. Disassembling a product into its components enables the efficient recovery of reusable resources or the components themselves [4]. Despite their importance, disassembly processes are often costly and complex. Unlike assembly, which follows a defined sequence toward a known final product, disassembly involves uncertainty regarding product condition, resulting in the lack of a consistent terminal state, due to the uncertainty in the quality of targeted components [5]. To address this complexity, a well-informed knowledge model is required to enable structured planning and information management. Currently, disassembly planning experts need to manually prepare the required information to apply established planning methods. This information, including product geometry, joint types, material hazards, and required tools, is typically dispersed across CAD files, bills of materials, technical manuals, and individual expert knowledge [6]. The absence of a consolidated knowledge model typically results in improvised planning and suboptimal decision-making [7]. Recent regulatory initiatives, such as the European Union's Digital Product Passport [8], aim to systematically embed structured product data throughout the lifecycle. This ensures continuous and standardized access to crucial information at the EoL stage. The regulatory highlights the increasing necessity for structured knowledge frameworks supporting circular strategies and therefore disassembly planning. While solutions based on open data principles will significantly enhance transparency and data continuity along the product lifecycle, they will not fully address industrial requirements. Manufacturing companies inherently handle sensitive and proprietary information that cannot be openly shared, necessitating tailored solutions capable of securely integrating internal company data without risking disclosure of critical knowledge. Thus, there is a growing need for structured knowledge frameworks that effectively support both transparency-driven and confidentiality-preserving disassembly planning [9].

Foundational work in disassembly planning has outlined multiple planning phases to handle different planning horizons and uncertainties. Zussman [10] categorized disassembly planning into long-term predictive, short-term predictive, and reactive phases. The long-term phase starts during the product design and considers potential future disassembly requirements without knowing the actual market needs. The short-term phase creates initial disassembly plans when a product is at its EoL stage, without knowing the physical condition of the individual product. Finally, reactive planning occurs at the actual disassembly process, adapting the initial short-term plan to unforeseen issues such as hidden damage, missing parts, or tool failures. This three-phase view, remains relevant in recent research. For instance, Streibel et al. [11] argue that the inefficiency and uncertainty of disassembly can only be overcome with reactive planning that adapts the initially generated disassembly plan with new information.

All phases in disassembly planning require an understanding of the product, process, and available resources which is enabled through a solid knowledge model comprising product structure, materials and conditions, as well as the tools that are used for disassembly. Information deficiency is a bottleneck in disassembly planning, making the creation of a knowledge model for disassembly a manual and error-prone process [12].

2. State of the Art

2.1. Knowledge modeling for disassembly processes

Knowledge models are used to support the planning phases described above. A well-defined knowledge model can represent all the necessary information to describe a disassembly process, enabling the generation of disassembly plans more systematically. Structured knowledge models are therefore essential for consistent and efficient planning [7].

Several approaches for modeling disassembly knowledge exist. Directed graph-based models, such as AND/OR graphs (AOGs), are used to represent all possible disassembly sequences of a product, with nodes as states or subassemblies and edges or arcs as disassembly actions [6]. Precedence graphs show linear task dependencies serving as a basis for sequence generation, where the nodes are process steps and edges are the precedence relationships [13]. Other works, as presented by [14], represent disassembly knowledge in matrix form, e.g., connection matrices or precedence matrices, to encode the disassembly order of parts. Connection matrices show if a component *i* is connected to a component *j*, while precedence matrices show if a component *i* needs to be disassembled before a component *j*. These graph or matrix representations can be input to algorithms to provide a basis for the optimization of disassembly sequences. Another important class of models for the representation of disassembly processes are Petri nets. In particular, Disassembly Petri nets (DPN) provide a formal way to model the dynamic events of disassembly processes. Petri nets' nodes and transitions can represent component states and disassembly actions. Petri-net-based models thereby extend pure graph models by incorporating process timing [15].

While these various modeling approaches have been successful in specific cases, a recurring observation is that knowledge representation is static. This means that additional information can not be added easily [7]. Bicheng and Uptal [7] note that different researchers' models share similar core information, but use different terminologies. For example, it is necessary to encode the connection between parts, what the disassembly precedence is. This suggests an opportunity to unify and reuse disassembly knowledge across methods. Semantic models, such as Knowledge Graphs (KGs), can be one possible approach for this.

A KG uses a network of entities (nodes) and relationships (edges) to represent semantic relations within a domain. In disassembly, a KG provides a linked representation of all disassembly-related information of a product [16]. Unlike a strict sequence graph or matrix, a KG can encode many types of additional relationships (structural, functional, causal) in the same model. For example, Chang et al. [17] proposed a conceptual framework leveraging Industry 4.0 technologies and product family ontologies to facilitate disassembly planning, due to how easy KGs for product information can be extended.

2.2. Information extraction for disassembly processes

Knowledge models require information to be used effectively. This information is extracted from various sources. For disassembly, product design data (e.g., CAD models, bills of materials) and process documentation (e.g., manuals, work instructions) can be used to enrich a knowledge model. Additionally, the analysis of the physical product itself is another strategy to extract information. Recent research has primarily focused on leveraging CAD models to automatically derive disassembly sequences, since geometric and assembly relationships are encoded there [6, 18, 19].

Hansjosten and Fleischer [20] present a method for disassembly sequence graph generation from CAD models of electric motors. As a knowledge model, they use a directed sequence graph developed for the method, where each node corresponds to a specific component and each edge symbolizes the connection between those components. Their method begins with an analysis of the product's CAD model. Central to this analysis are the connections between the various components and component groups, along with their specific characteristics. The connections between parts are extracted through a geometric analysis of the 3D meshes of the CAD file. This is achieved through identifying all contacts and possible movement directions for each part in the assembly. Combining these individual components and connection types into an integrated assembly object yields a knowledge model that can be used for further disassembly planning steps.

Münker and Schmitt [21] developed two approaches for the generation of AOGs from CAD files based on two information types extracted from the CAD file: liaison graphs and moving wedge matrices. The liaison graph is a graph that shows all connections between components in a CAD assembly. Moving wedge matrices indicate feasible collision-free movement for each part. A moving wedge matrix is created for every possible disassembly direction axis. After extracting the information, the authors use a top-down and bottom-up approach to create AOGs. The top-down approach starts with the whole product and disassembles it recursively into sub-assemblies. The bottom-up approach starts with the individual parts and progressively assembles them into larger sub-assemblies. Both approaches lead to AOGs that can be used for further planning, but the bottom-up approach is computationally more efficient. However, the AOGs do not contain any process information and are just a representation of the potential states of the product. Therefore, they need to be supplemented with additional process information, which are not considered in the method.

3. Need for Research

3.1. Knowledge models do not specify what information is required to consistently represent process, product, and resources in disassembly

While knowledge modeling plays a central role in disassembly research, existing approaches often focus on structuring knowledge rather than defining how to populate models with the necessary information. Most frameworks do not specify which attributes are essential to consistently represent product, process, and resource domains, nor do they outline the data sources from which this information should be extracted.

This absence of standardized information requirements leads to inconsistencies and ambiguities in how disassembly knowledge is formalized, especially regarding the interdependencies between domains. Moreover, existing models rarely address the practical step of extracting relevant data, limiting their applicability in industrial settings. Without formalized guidelines for sourcing and structuring disassembly information, the development of consistent and repeatable disassembly process plans remains difficult.

3.2. Information for products, processes, and resources is typically fragmented and requires extraction and consolidation from multiple data sources

Information critical to disassembly planning is frequently dispersed across diverse data formats and documentation types. This distribution reflects the involvement of multiple stakeholders in the product lifecycle, each of whom may generate data independently using varying terminologies, data structures, and levels of detail. The resulting heterogeneity introduces semantic and structural inconsistencies that complicate the processing of information.

Current automated methods for extracting, interpreting, and consolidating this fragmented information remain limited in their capabilities or set strict conditions that cannot be met in practice. The lack of robust, scalable approaches to reconcile disparate data formats and resolve ambiguities impedes the construction of a unified and coherent knowledge base. In particular, data gaps and mismatches between sources pose significant obstacles to effective information retrieval and consistent representation, thereby undermining the effectiveness of model-driven disassembly planning systems.

3.3. The uniformly integrated knowledge needs to be easily accessed and enriched

Effective disassembly planning requires that users can flexibly access and adapt detailed knowledge to suit specific application scenarios, product configurations, or system constraints. However, existing knowledge models often lack mechanisms for dynamic querying, contextual filtering, or continuous enrichment, which significantly limits their practical applicability in industrial settings.

Traditional representations such as directed graphs or Petri nets are inherently static and do not support on-demand exploration or modification of the underlying knowledge structures. While KGs offer a more semantically rich and extensible format, they frequently lack intuitive user interfaces or interactive querying functionalities that would enable domain experts to navigate, augment, or refine the knowledge base without specialized technical expertise. This absence of user-centric interaction capabilities hampers the ability manipulate the knowledge model continuously and restricts the broader adoption of such models in adaptive disassembly planning workflows.

4. Concept

The previously described gaps reveal the absence of a flexible and integrated knowledge modelling framework capable of addressing the complexity and variability inherent in disassembly scenarios. Consequently, there is a pressing need for a structured yet adaptable knowledge model that can accommodate comprehensive product information, incorporate unstructured data sources, and facilitate user-driven, dynamic adaptability.

To bridge these gaps, we propose a five-step concept. Our approach centers around establishing an initial KG generated from CAD-based product data, ensuring a solid foundational representation of product geometry. This initial geometric KG is then systematically enriched with process-related information derived from unstructured textual sources, leveraging the semantic interpretation capabilities of Large Language Models (LLMs). By incorporating an interactive LLM-driven user interface, the proposed knowledge model can dynamically evolve based on contextual requirements and real-time insights, thus ensuring its practical usability and adaptability across diverse disassembly planning applications. An overview of the proposed approach is illustrated in Fig. 1. The concept is demonstrated using an exemplary centrifugal pump also used by Münker and Schmitt [21] for the validation of their method.

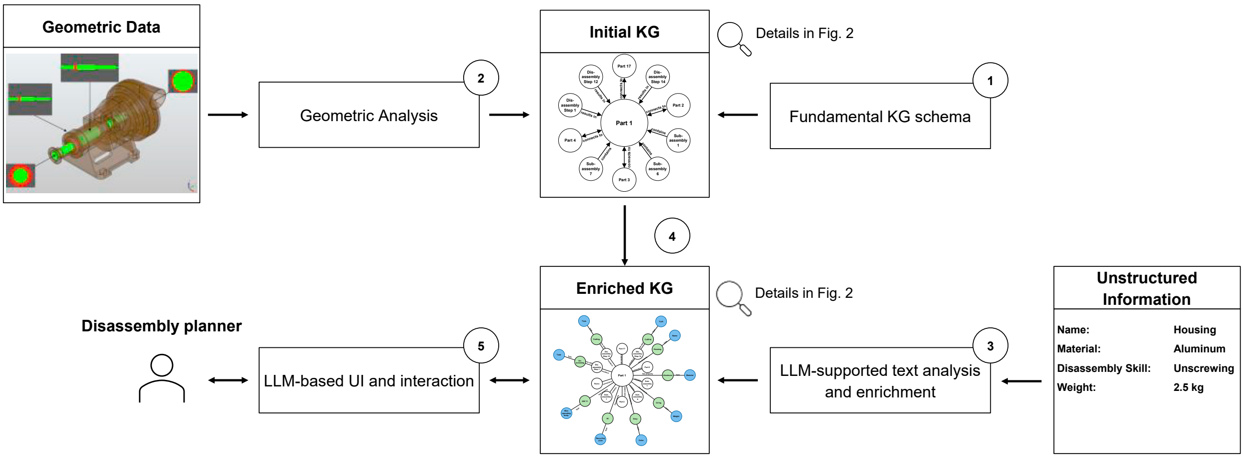

Figure 1: Overview of the proposed concept, exemplified through a centrifugal pump

Step 1 – Fundamental KG schema: The foundation of the proposed concept is a domain-level ontology that provides a lightweight yet structured schema for representing disassembly-relevant knowledge. This ontology defines a class structure along with a set of core relations that describe the modelled entities within the disassembly domain. By establishing a formal vocabulary, the ontology ensures semantic consistency and interoperability across subsequent disassembly planning steps.

The primary purpose of this domain ontology is to serve as a template for the KG, guiding how product, process, and resource information is modeled and integrated. This standardized schema becomes particularly important in later stages when employing LLMs for knowledge extraction and augmentation. It ensures that any LLM-generated additions or modifications adhere to.

Similar approaches have been demonstrated in production-related domains. Bahr et al. [22] define a domain-level ontology to create a KG for failure mode and effects analysis (FMEA), enabling standardized representation and downstream reasoning. There have been several examples of disassembly ontologies [7]. However, they often lack data granularity, structural depth, or practical integration with planning tools. Furthermore, integration with standardized domain models, like the Product-Process-Resource-Skill (PPRS) model [23], should be considered.

To support the demonstration of our concept, we developed a minimal ontology that captures the core structure of an AOG. It defines the classes “Part”, “Subassembly”, and “Disassembly step”, where part instances are grouped into subassemblies, and disassembly steps represent the AND arcs of an AOG. At this stage, the ontology represents disassembly sequences encoded in an AND/OR structure but does not yet specify the semantic or procedural content of disassembly steps, which are introduced in later steps based on geometric and textual data sources. While an initial

KG schema was developed for this demonstration, further research should focus on whether or not existing ontologies can be used as a foundation for this step.

Step 2 – Geometric analysis: The second step involves the extraction and analysis of the product's geometric and structural information, which serves as the foundational layer of the knowledge graph. This step focuses on identifying all relevant component connections and subassemblies, forming the structural basis for subsequent modeling. As discussed in Section 2, several methods for geometric information extraction are already established in the literature and can be leveraged to determine feasible disassembly sequences.

A possible source for geometric and structural information can be CAD files of products. For the demonstration of this step in our concept, we adopted AOG generation method of Münker and Schmitt [21] and combined it with the method proposed by Prasad et al. [24], which extracts geometric information of a product from a STEP file, which is a specific format for CAD files. The extracted information is then mapped onto the schema of Step 1, resulting in an instantiated KG. An isolated node for a single part of the centrifugal pump shown in Fig. 2 on the left. Due to the limited information in the CAD data, the resulting graph conveys only basic structural relationships. Specifically, the CAD file provides no explicit part names or process-related attributes. It can represent only geometric relationships and theoretically possible disassembly steps, without operational context. This example clearly demonstrates the limitations of existing CAD-based disassembly planning methods, highlighting that geometric data alone is insufficient for comprehensive disassembly process planning. The absence of descriptive attributes, semantic identifiers, and procedural context underscores the necessity of incorporating supplementary data sources to extract all necessary information required for practical disassembly knowledge models.

Step 3 – LLM-supported text analysis: The third step focuses on enriching the KG with additional process- and product-related information derived from unstructured, text-based sources. In practical settings, required process-related knowledge, such as disassembly operations, tool requirements, and safety considerations, is typically captured in documents like manuals or work instructions. These documents are not inherently structured in a machine-readable format and thus require semantic interpretation to be integrated into formal knowledge representations.

To address this challenge, an LLM is employed to analyze and extract relevant entities and relationships from these textual sources. LLMs are capable of interpreting contextual semantics and inferring structured information from free-form text, without the need of training. As outlined by Pan et al. [25] in their proposed general framework, the integration of LLMs and KGs represents a synergistic approach that combines the factual precision and relational structure of KGs with the language understanding and generalization capabilities of LLMs. This combination enables the mitigation of typical limitations, such as the incomplete domain coverage of LLMs and the lack of semantic reasoning for undefined information in KGs [25]. In order to further mitigate the limitations of LLMs and enable more deterministic replies, we propose combining the KG schema with a list of standardized process steps. This way, the LLM can be forced to adhere to specific process steps, making the results more comparable.

For demonstration purposes, we used a mock maintenance document for the centrifugal pump previously analyzed in Step 1. This data includes relevant product and process information pertaining to its disassembly and maintenance. The content was processed using an LLM (GPT-4o), which generated the extracted information as structured output required for the KG schema described in Step 1.

Step 4 – Mapping disassembly-relevant information in the KG: In the fourth step, the product-centric KG generated in Step 2 is expanded by integrating the structured, process-related information extracted in Step 3. This integration results in a more comprehensive knowledge model that encapsulates both the physical structure of the product and the associated disassembly processes. By merging product- and process-related knowledge from different and unstructured sources, the graph becomes a more adaptable foundation for disassembly planning.

To facilitate this enhancement, the structured output produced by the LLM is translated into SPARQL queries, which are used to extend the KG in alignment with the schema. This approach allows the dynamic incorporation of disassembly-relevant entities and relationships that go beyond the proposed schema. Instead, the schema evolves according to the contextual interpretation and semantic enrichment performed by the LLM in the preceding step, while adhering to the domain-level ontology.

For demonstration purposes, the unstructured information extracted in Step 3 was used as input to the LLM, which then produced a set of SPARQL update queries aligned with the disassembly ontology schema of the KG. These queries were executed to additional disassembly-related information into the KG. This highlights the potential for interactive, KG augmentation disassembly planning scenarios. A graph enrichment by this approach is exemplified for a single part in Fig. 2 (right side). Compared to the initial knowledge graph instantiated in Step 2, the enriched KG now includes process-related information extracted from the unstructured maintenance file of the centrifugal pump. This additional information is added to the graph as additional properties. Specifically, the enriched graph captures details such as the part name, disassembly tasks, and other product properties. As a result, the graph achieves a greater depth of knowledge, although this enrichment inevitably leads to increased complexity. This comparative example highlights the significant advantage of integrating unstructured textual data through LLM-based semantic analysis. While the initial, geometry-based KG from Step 2 was limited to structural and theoretical information, the enhanced KG in Step 4 provides process-related insights. Despite the synergy of LLMs and knowledge graphs already being demonstrated in other works, further research is required to validate and optimize such methods within real-world industrial environments [25]. In particular, there is a need to investigate approaches that enable interaction between LLMs and knowledge graphs specifically tailored to disassembly planning.

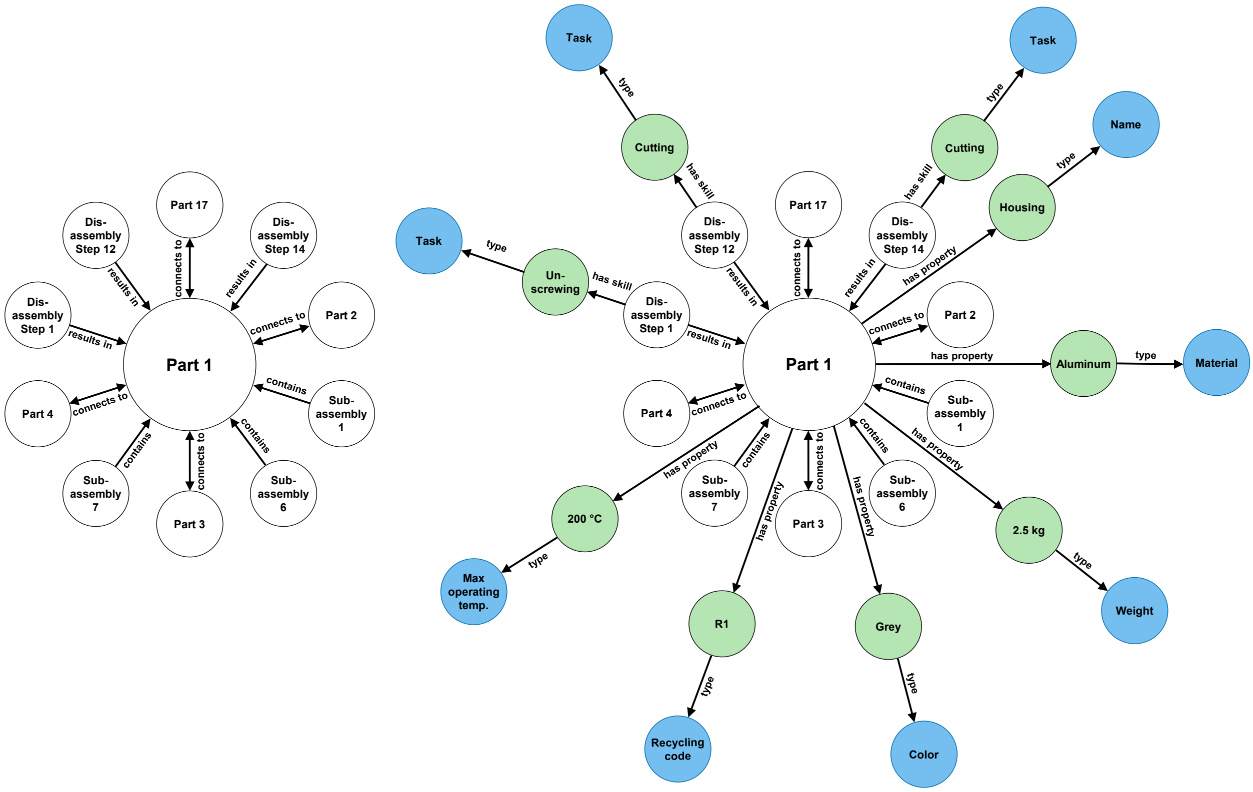

Figure 2: Left: isolated node for a single product part within the initial KG of the centrifugal pump. Right: isolated node for the same product part with enriched information (enriched properties are marked in green and property types in blue)

Step 5 – LLM-based UI and interaction: The final step introduces an interactive user interface powered by an LLM, enabling human users to access, correct, and extend the disassembly knowledge graph as needed. While the structural representation of the product is assumed to be complete, based on geometric analysis in Steps 1 and 2, practical disassembly scenarios often involve planning decisions that extend beyond geometric structure alone. For example, user-specific disassembly goals or updated process knowledge may require adaptation of the disassembly model. Furthermore, expert knowledge can also be an important source of information for disassembly planning. The combined use of an LLM with KG allows a user to input natural language that can interact with the KG. This enables knowledge inherent to the disassembly expert to be systematically added to the KG and knowledge model.

Unlike state-of-the-art planning models, which are effective at identifying feasible sequences but are inherently static, this approach supports dynamic graph refinement, such as providing material information. This means that a user can easily adapt the KG in real time and bridge missing information by themselves, enabling an intuitive way to systematize expert knowledge.

5. Conclusion and Outlook

In this paper, we presented a novel concept aimed at creating flexible and adaptable knowledge models specifically tailored for disassembly process planning. Our proposed approach consists of five steps that integrate the analysis of structured geometric data with the semantic interpretation of unstructured text. Each step has been individually demonstrated through proof-of-concept implementations, illustrating the feasibility of the proposed methodology. However, the integration of these individual steps into a single framework remains a necessary next step for practical application.

Our concept offers significant advantages for industrial applications involving EoL products by providing an adaptable knowledge model. It effectively bridges critical limitations observed in current static models, which require rigidly defined and complete input data. By enabling the enrichment of product-centric knowledge graphs with unstructured, disassembly-related process information, our approach increases the generation and accessibility of disassembly knowledge models.

Nevertheless, the concept proposed in this study also identifies clear objectives for further research. One notable limitation lies in the initial reliance on the geometric completeness of CAD data for constructing the initial KG. In practice, industrial CAD data can be incomplete, inaccurate, or contain discrepancies, posing significant challenges for product assembly analysis. Thus, extending our framework with robust methods for inferring or compensating for missing disassembly information constitutes an important future research direction. Additionally, the proposed user-interface and LLM-driven interaction mechanisms provide an essential pathway to identify and resolve missing information, thereby enabling users to actively enrich and adapt the knowledge graph based on unstructured data and expert input. For this work, a basic structural representation of the product was implemented as an ontology. This served as the schema for the KG. However, existing ontologies in the domain of disassembly process planning should be considered as well. Further work should specifically analyze how existing frameworks can be implemented in this concept in order to achieve a uniform representation of the disassembly process. Specifically, a standardized process step description is needed in this schema to enable deterministic replies of the LLM when it comes to extracted process information from unstructured data. Further research should therefore focus on creating a taxonomy that can be integrated into ontologies.

Finally, the proposed framework's validation in realistic industrial settings remains essential. Future studies should therefore focus on applying and evaluating the concept using authentic industrial datasets and actual disassembly scenarios. Such validation efforts will further demonstrate the adaptability of the proposed method and enable toward its industrial integration and broader adoption.

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