KARMEN: A knowledge graph based proposal to capture expert designer experience and foster expertise transfer.

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Abstract.

[Context] At the cusp of Industry 4.0 and against a backdrop of fierce competition, manufacturing companies must design and manufacture increasingly complex and cost-effective products. Human resources must therefore preserve and maintain their knowledge and the intellectual heritage of their experts.

[Problem] In the next few years, there will be a lack of skilled resources in the manufacturing industry due to retirements. Let's also mention the turnover of consultants working within these companies. It is essential to implement solutions today in order to protect the intellectual heritage of tomorrow. This paper ambition to answer to how can the knowledge of these experts be captured and used, and how knowledge graph could be a suitable tool to achieve this objective.

[Proposal] This article proposes a methodology for implementing **KBE** (**K**nowledge **B**ased **E**ngineering) solutions. This methodology called **KARMEN** (**K**nowledge **A**ccess **R**equest for **M**anufacturing and **E**ngineering by **N**etwork graph) is based on an **FBS** type ontology (**F**unction, **B**ehavior, **S**tructure) as well as on the exploitation of **K**nowledge **G**raphs.

A use case of redesigning a mechanical part for metal additive manufacturing will be presented. Besides, an experimental protocol will be specified to capture the knowledge of business experts within a graph-oriented database built on **Neo4J**.

Finally, it will demonstrate that navigation within a knowledge graph can be a powerful tool for knowledge transfer and support in designing novice profile.

Keywords: Knowledge Management, KBE, Knowledge Graph, Ontology, Neo4J.

1 Introduction

[Context] Knowledge management is essential for the competitiveness of companies operating in the international market[1]. It represents an essential advantage for the preservation of the intellectual heritage of the company in a context where the manufacturing sectors needs to produce faster and at lower cost.

According to Hawisa et al. [2], “Manufacturing companies must have a good knowledge of their products and processes to be competitive. This is increasingly important as products become more complex” [3].

In particular, **KBE** (**K**nowledge **B**ased **E**ngineering) is part of this approach to leverage the knowledge and the expertise of technical experts within the company by focusing on the management of engineering knowledge. Several **KBE** systems are able to exploit process and product engineering knowledge with the goal of reducing the time spent on repetitive tasks, increasing time for creativity and reducing the cost of product development [3].

In this competitive environment, manufacturing industries must produce faster and at lower cost. As noted by Kim et al [4], access to appropriate information at the appropriate time is a crucial issue for companies. It enables the efficient operation of various stakeholder activities, as well as the acquisition of new knowledge that can create value.

[Problem] In the next few years, the manufacturing industry will face a shortage of skilled workers due to retirements. It is important to start implementing solutions to pre-serve the industry's intellectual heritage for the future. The purpose of this paper is to explore how the knowledge of these experts can be captured and utilized, and how a knowledge graph could be a suitable tool to achieve this goal.

[Proposal] In this paper, a new methodology for implementing **KBE** solutions is proposed. This methodology called **KARMEN** (**K**nowledge **A**ccess **R**equest for **M**anufacturing and **E**ngineering by **N**etwork graph) is based on an **FBS** (**F**unction, **B**ehaviour, **S**tructure) type ontology and on the use of **K**nowledge **G**raphs. As noted by Giro et al [5], the **FBS** ontology provides a uniform framework for classifying processes and includes higher level semantics in their representation.

A use case for redesigning a mechanical part for metal additive manufacturing is presented. Besides, an experimental protocol is specified to capture the knowledge of business experts in a graph-oriented database built on **Neo4J** software [6]. This scientific article, investigates how can a **K**nowledge **G**raph be created and proposed to capture and make available complex knowledge from real engineering design activities [7]. The following research question is investigated:

- How can the tacit knowledge of design experts be captured within a Knowledge Graph?

To answer these research question, the authors of this paper, first define the de-sign activities, product lifecycle phase and trace the origins of **KBE**. They explore the use and application of knowledge graphs in engineering design. This allows introducing and explaining the proposed **KARMEN KBE** methodology through four main phases. Lastly, an experimentation is conducted to validate the methodology through a case study of additive manufacturing.

2 Related work

In this section, a review of the related work on design activities and product lifecycle phase, **KBE** methodologies, **K**nowledge **G**raph construction is presented.

2.1 Design activities and Product lifecycle phase.

Design can be considered as a learning process, in which knowledge is collected, synthesized, and organized to achieve an outcome [7-9]. Another viewpoint of design according to **ISO 9000** organization [8], defines design as: "set of processes that transform requirements into specified characteristics or a specification of a product, process, or system." It is impossible to discuss product design without also discussing product lifecycle as they are closely interconnected.

The meaning of term ‘lifecycle’ generally indicates the whole set of phases, which could be recognised as independent stages to be passed followed performed by a product, from ‘its cradle to its grave’. By adopting a well-known model, the product lifecycle can be defined by three main phases [9]:

- **B**eginning **O**f **L**ife (**BOL**).
- **M**iddle-**O**f-**L**ife (**MOL**)
- **E**nd-**O**f-**L**ife (**EOL**)

According to Terzi et al [10], the concepts of product design, manufacturing, repair, and recycling have evolved significantly since the dawn of human civilization. They are now complex and require a significant amount of knowledge to be properly executed. Despite advances in the tools and methods to design and support products, the core principle remains unchanged: identify the customer needs and create a product that meets those needs.

According to Robinson's calculations, engineers spend over 55% of their work time acquiring or sharing knowledge, making the organization and structuring of knowledge a vital aspect of engineering practice [11]. These statistics demonstrate the importance of knowledge management within design activities. The following section focuses on tools for **KBE**.

2.2 KBE methodologies

Various definitions of **KBE** can be found in the literature. For this paper, the selected definition is the one presented by La Rocca [3] as "Knowledge Based Engineering is a technology based on the use of dedicated software tools called **KBE** systems, which are able to capture and systematically reuse product and process engineering knowledge, with the final goal of reducing time and costs of product development by means of the following:

- Automating repetitive and non-creative design tasks.
- Supporting multidisciplinary design optimization at all the stages of the design process".

The core component of the system is the product model, which stores knowledge about the product and the process. Data from external databases are fed into the system. The input to the **KBE** system is usually according to the customer's specifications, and various outputs are produced during processing. The system software is object-oriented, allowing it to perform calculations on demand [12]. According to Verhagen [13] there are a number of **KBE** methods that support the development of **KBE** applications and systems. By far the best known of these is the **MOKA** (**M**ethodology and software tools **O**riented to **K**nowledge-Based Engineering **A**pplications) [14].

This method proposes the implementation of a **KBE** in 6 steps.

- Identify
- Justify
- Capture
- Formalize
- Package
- Activate

The aim of **MOKA** is to provide (i) a 20-25% reduction in the costs and time associated with KBE application development (ii) an efficient methodology to capture and formalize product and process knowledge and (iii) an **IT** tool that supports the capture, representation of knowledge.

The **MOKA** methodology utilizes both an informal and formal model. The informal model utilizes **ICARE** forms, which stands for **I**llustrations, **C**onstraints, **A**ctivities, **R**ules, and **E**ntities. These forms are used to break down and store pieces of knowledge. The formal model uses **MML** (**M**oka **M**odeling **L**anguage, a variation of **UML**) to organize and structure the elements of the informal **ICARE** model. It is an ontological approach that enables the translation of the informal model into a formal model.

However, the **MOKA** methodology encounters the following problems [15]:

- **MOKA** is product-oriented rather than process-oriented.
- **MOKA** focuses solely on supporting the knowledge engineer, not the end-user.
- **MOKA** is unable to account for the maintenance and reusability of knowledge

According to Camara et al [16] it is essential today to propose new methodology of capitalization thanks to the help of AI tools. Artificial intelligence algorithms such as neural networks allow training models to process heterogeneous data and extract new knowledge. These new AI tool opportunities will facilitate knowledge capture and representation throughout the design lifecycle process.

2.3 Knowledge Graphs in Engineering Design

According to Sowa [17] a semantic network or net is a graph structure for representing knowledge in patterns of interconnected nodes and arcs. Sowa identifies six common types of semantic networks, each of which is described below:

- Definitional networks
- Assertional networks
- Implicative networks.
- Executable networks
- Learning networks.
- Hybrid networks.

In the study, the "Definitional networks" type will be used to represent the knowledge graph. Indeed, Huet et al. [18] claim that knowledge graphs break down silos and focus on interactions. It is proposed to use the semantic network to model, store, and represent all product design information and expert resource knowledge. This semantic network will constitute the knowledge graph.

The benefits of using a knowledge graph are numerous. Here are some examples:

- Visualization: A knowledge graph offers a visual representation of the relationships between different entities and concepts, making it easier to understand and explore knowledge.
- Search and navigation: Queries on the graph can extract relevant information and explore the relationships between different elements.
- Implicit knowledge capture: The relationships between entities in the graph can represent implicit knowledge, making it actionable.
- Collaboration and knowledge sharing: A knowledge graph facilitates collaboration and the sharing of knowledge within an organization.

Thus, a user will be able to use the knowledge graph to navigate and search for information. He will also be able to consult his dashboard to access the relevant **KPI**. Queries and data analysis algorithms will be used to enrich the knowledge graph.

2.4 Related work synthesis

The analysis of the related works emphasizes that there is a need and a strong interest in proposing new solutions for capturing, sharing and transfering product lifecycle design knowledge within the enterprise. The knowledge and experience of experienced design engineer is valuable and represents the intellectual heritage of the company. Today, companies lack tools to manage product-related knowledge. Product life cycle information is stored in different software specific to each department in the company. Therefore, it is crucial to keep all the knowledge of the experts, to share it and to pass on to the newly hired designers. In the next chapter of this article, a new method and solution for implementing a **KBE** System called **KARMEN** is proposed.

3 KARMEN KBE proposal

In this section, the proposed **KARMEN** method for capturing, modelling, and sharing the knowledge of an experienced designer, in a knowledge graph is described. A specific use case on redesigning mechanical part for additive manufacturing serves to validate the proposed approach. The **KARMEN** method consists of 4 main phases: Find, Acquire, Model, Exchange. The functional modelling language **IDEF0**. [19], is used to elucidate the **KARMEN** main functions with a well-structured graphical component among boxes, arrows, rules, and diagrams. A box represents a function activity and describes what happens in the function, as shown in (**Fig.1**).

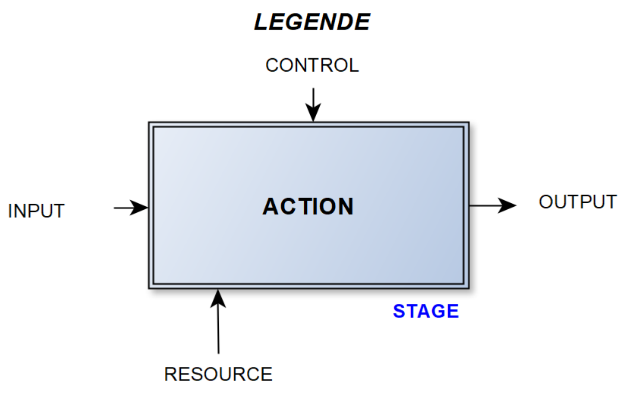

Fig. 1. IDEF0 diagram.

3.1 Additive Manufacturing and use case

The use case deals with additive manufacturing (**Fig.2**). Indeed, it is about redesigning and optimizing a part for additive manufacturing. **A**dditive **M**anufacturing (**AM**) brings new design potential compared with traditional manufacturing [20]. Additive manufacturing is removing the limitations of traditional manufacturing methods, allowing designers to create almost any shape, enabling the use of fully optimized lightweight designs without compromising on performance. **D**esign **F**or **A**dditive **M**anufacturing (**DFAM**) is analogously defined as the design for manufacturability applied to **AM** [21]. It is a design approach that takes into account the characteristics and constraints of additive manufacturing, such as material limitations, mechanical properties, and manufacturing processes, in order to maximize the benefits of this technology. **DFAM** can help reduce costs, minimize waste, and improve the performance of parts produced through additive manufacturing. However, this manufacturing process requires expertise to fully exploit the potential of the additive manufacturing value chain. This expertise and knowledge is often known by only a few experts within the company.

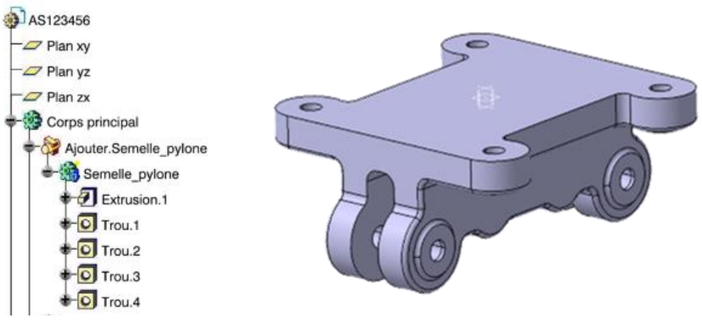

Fig. 2. Part and his CSG tree to redesign for additive manufacturing.

The diagrams below in (**Fig.3**) presents the **KARMEN** methodology. All phases enable knowledge to be captured, structured, formalised and shared chronologically. In the following section, the four steps of the **KARMEN** methodology are described in detail.

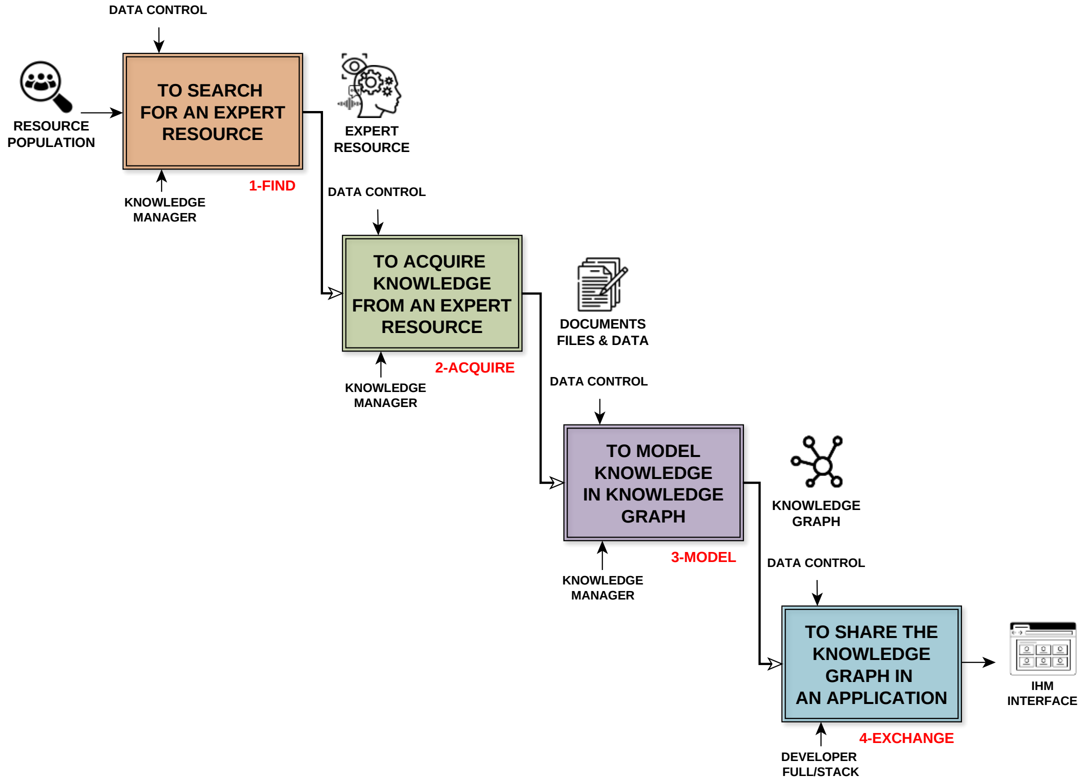

Fig. 3. FAME: The four phases of the KARMEN methodology.

3.2 [MATERIAL AND METHOD] Software used and method.

The **table 1** shows all the software used in **KARMEN** methodology.

Table 1. Documents and software identified within the **KARMEN** methodology.

Software type	Software name	Description
Graph Data Platform	4.4.7	Graph Database
Graph Apps	Neo4j Bloom 2.6.1	Interactive exploration of graph data
Graph Apps	Neo4j - NeoDash 2.2.1	Dashboard Builder
CAD	CATIA V5 R 2013	Mechanical Design
Windows voice recorder	Tape recorder	Record the voice
Data science IDE	Jupyter Notebook / Python 3.9.7	Remote CATIA V5 with Python script
Py2neo library	Py2neo 2021.2.3	Remote Neo4J with Python script
Pycatia library	pycatia 0.5.7	To access the CATIA V5 Automation

3.3 [FIND] Expert designer identification for knowledge capture

This phase consists of finding an expert resource in a technical field. The **K**nowledge **M**anager searches and selects an expert in a database of internal or external resources his or her organisation. This phase requires a current and updated database to identify the competent expert resource. The diagram, (**Fig.3**), describes the scenario for selecting an expert resource. The **U**ser_**S**tory is as follows: As a **K**nowledge **M**anager, I want a search function to identify an expert resource and capture its knowledge.

3.4 [ACQUIRE] Information gathering and expert knowledge

This is a key and important step in capturing the expert's knowledge in a technical field. This phase is called knowledge elicitation or knowledge capitalisation. It involves processes to capture and formalize expertise before its implementation in a system [22]. According to Bareiro et al, knowledge elicitation, is the process of obtaining knowledge from experts [23]. The **K**nowledge **M**anager conducts an interview with the expert to obtain information, knowledge and skill. The **K**nowledge **M**anager uses specific surveys. There are 4 types of surveys available to the **K**nowledge **M**anager:

- **ERS**- [**E**xpert_**R**esource_**S**heet]
- **ICS**- [**I**dea and **C**oncept **S**heet]
- **PCS**- [**P**roduct **C**apitalization **S**heet]
- **PDS**- [**P**roduct **D**ata **S**heet]

The expert has to answer the questions of the various surveys. The **K**nowledge **M**anager writes the expert's answers on the sheets. The knowledge manager uses software to record voice and gaze simultaneously. The voice is recorded and converted to text. All the data and information collected in this way allow the expert's knowledge to be captured. The table (**Tab.2**) describes the essential and necessary sheets required to conduct the interview. The **U**ser_**S**tory is as follows: As a knowledge manager, I want IT support and tools to capture the expert's knowledge in documents and files. Finally, the knowledge manager may ask the expert resource to design or redesign a part accord-ing to specific requirements. In this case, the expert will need to use a CAD software such as **CATIA V5** or 3**DEXPERIENCE**.

Table 2. Table of four sheets to capture the knowledge of expert.

File document	Description task
[**E**xpert_**R**esource_**S**heet]	Capture the experience and skill using a scale of [0, 2, 4, 6, 8] on different items in the **AM** value chain.
[**I**dea_and_**C**oncept_**S**heet]	Representing and illustrating the design concepts
[**P**roduct_**C**apitalization_**S**heet]	Product Capitalization Sheet
[**P**roduct_**D**ata_**S**heet]	Analyzing the Functions, Structure and Behaviors of the Product

3.5 [MODEL] Knowledge Graph Construction and Query execution

This phases consists in gathering all the data collected in the "**Acquiring Knowledge**" phase (**fig.3**) to structure them in a **K**nowledge **G**raph. The data must be organized according to the **FBS** data model, **F**unction, **B**ehaviour, **S**tructure [5].
The **K**nowledge **M**anager has to collect and use all data and surveys to enrich the knowledge graph. The diagram (**Fig.3**) describes the scenario for the knowledge manager to implement the **K**nowledge **G**raph. The **U**ser_**S**tory is as follows: As a **K**nowledge **M**anager, I want to retrieve the documents and survey to create a **K**nowledge **G**raph in the **Neo4J** application.

3.6 [EXCHANGE] Implementation of a data dashboard

This last step allows to exploit the **K**nowledge **G**raph and all the data collected in the previous steps of the **KARMEN** methodology. In this article, the **Neodash** software is used in the **Neo4j** environment. The **Neodash** tool enables the implementation of dashboards from knowledge graph data. The designer can then use this tool as a decision making tool. On this phase there are two user stories. The **U**ser_**S**tories are next: As a full/stack developer, I want to implement a **IHM** to facilitate novice designer tasks and foster knowledge sharing. As a novice designer I want a solution to assist me in my design choices and activities.

4 Results and future work

This section describes the experimental protocol in our study. It successively and exclusively presents the **ACQUIRE** and **MODEL** steps of **KARMEN** methodology. The **FIND** and **EXCHANGE** phases have not been performed.

4.1 [ACQUIRE] Information gathering and expert knowledge

This phase consisted of interviewing the expert to gather information. Below are the details and description.

4.1.1 Participant

A specific expert in **AM** has been identified for the experimental protocol. This choice of expert aligns with the case study of redesigning a part for **A**dditive **M**anufacturing (**DFAM**).

4.1.2 Devices et documents

A specific room was equipped with the necessary equipment to conduct the interview. The room was equipped with a laptop and the necessary software for knowledge capture. The three documents in table (**Tab.3**) such as [**E**xpert_**R**esource_**S**heet], [**I**dea and **C**oncept **S**heet], [**P**roduct **C**apitalization **S**heet] were used. The [**P**roduct **C**apitalization **S**heet] document was not used by the expert. Only the **K**nowledge **M**anager can use it to extract the structure of the **CATIA V5 CAD** model with a specific python script and generate the Structure part of the knowledge tree.

4.1.3 Acquisition activities

The knowledge capture experience was conducted by me as a **K**nowledge **M**anager in a specific experimental room. The table below (**Tab.3**) outlines all tasks of our experimental protocol with their execution times.

Table 3. Table of three sheets to capture the knowledge of expert.

File document	Nb questions	Interview time (mn)
[Expert_Resource_Sheet]	85	45
[Idea_and_Concept_Sheet]	1	5
[Product_Capitalization_Sheet]	5	10

4.2 [MODEL] Knowledge Graph Construction

The **MODEL** phase consisted of retrieving the documents and files collected in the **ACQUIRE** phase to complete and feed the **K**nowledge **G**raph.

4.2.1 Dataset and query execution

In order to prepare the data and feed the knowledge graph, the necessary documents were used and exploited: [**Expert_Resource_Sheet**], [**Idea and Concept Sheet**], [**Product_Capitalization_Sheet**], [**Product_Data_Sheet**]. These documents therefore allowed us to create the nodes and links in our **K**nowledge **G**raph. According to the FBS data model proposed by Gero et al [5] , a **K**nowledge **G**raph has been implemented.

There are also different data models inspired by the FBS model such as the **FBS-PPR** model. However, one has chosen to adapt the FBS model by adding the Resource node. According to Labrousse et al [24] the **FBS-PPR** (**F**unction / **B**ehavior / **S**tructure - **P**rocess / **P**roduct / **R**esource) model consists of deploying the **FBS** model according to three views: the process view, the product view, and the resource view.

Here is the **K**nowledge **G**raph and its structure. There are ten nodes in the **K**nowledge **G**raph which are:

1) **[Product]** in grey colour is the central node of the **FBS-PPR** model.
2) **[Resource]** in orange colour represents the expert resource.
3) **[Process]** in red colour represents the manufacturing process (**AM**).
4) **[Technical Function]** in pink colour represents the technical function.
5) **[Physical Behaviour]** in green colour represents the expected physical behaviour of the product.
6) **[CAD_FILE]** in blue colour represents the product CAD file and links with other product (**CATPart** file). The "New Product" node represents the product redesigned (**DFAM**) by the expert resource.
7) **[Sheet]** in **Purple** colour represents and decomposes product geometry.
8) **[Field]** in **Yellow colour** represents the **AM** value chain.
9) **[Activity]** in **Yellow colour** represents the **AM** value chain.
10) **[Skill]** in **Yellow colour** represents the **AM** value chain.

The links between nodes are: **ADD_BODY**; **BEHAVIOUR_IS**; **FTn**; **FUNCTION_IS**;**HAS_ACTIVITY**;**HAS_BODY**;**HAS_REF**;**HAS_SHEET**;**HAS_SKILL**;**KNOWLEDGE_IN** (Value:[0,2,4,6,8]);**LINK_TO**;**PBn**;**PROCESS_IS**; **REDESIGN_BY**; **REDESIGN_IS; STRUCTURE_IS**.

The documents: [**Expert_Resource_Sheet**], [**Idea and Concept Sheet**], [**Product_Capitalization_Sheet**], [**Product_Data_Sheet**] are directly attached to their nodes: [**ERS**], [**ICS**], [**PCS**] and [**PDS**] (**Fig.4**). When this **K**nowledge **G**raph is complete and fed with datasets including multiple expert resources and their sheets [**ERS**], [**ICS**], and [**PCS**], it will be possible to perform complex queries that will aid the designer. Novice designers will be able to search for parts similar to their design to identify design choices made by experts using powerful data analysis algorithms.

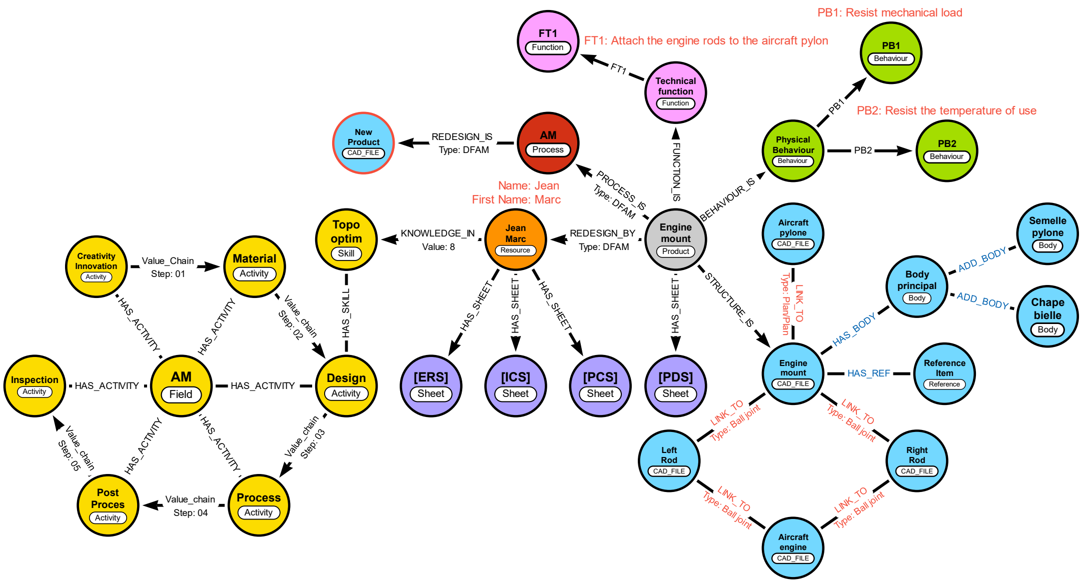

Fig. 1. Knowledge graph of the use case based on the FBS-PPR data model

4.2.2 Data model and graph query

The proposed data model allowed to represent knowledge by structuring data with the data model approach based on the **FBS-PPR** model. The advantages of using a **K**nowledge **G**raph for design activities and knowledge transfer are:

- Clear and structural organization of information
- Easy navigation and information search
- Sharing of knowledge between employees
- Organizing specific mechanical design knowledge in a clear and structured format.
- Documenting efficient processes and practices for mechanical design, allowing for better understanding for new employees or future projects.

The **KARMEN KBE K**nowledge **G**raph allows to identify the skills of the expert resource within the entire Additive Manufacturing value chain. Thanks to **CYPHER** language queries, it is possible to write complex queries in a simple way. As an example, the query below allows to identify Jean's skills within the additive manufacturing value chain :
MATCH (r:Resource {Name: "Jean"})-[:KNOWLEDGE_IN]->(s:Skill) RETURN s)

Knowledge **G**raph makes it possible to capitalise on the design of the existing product and identify the mechanical links and interfaces with other products (For example: what is the structure of my tree in **CAD_FILE,** without opening my **CAD software**). Thanks to the **FBS-PPR** model and its ontology it is possible for a designer to search for information such as technical functions or specific behaviour on the product.
This allows her to make links and correlations with heterogeneous data [4].

Finally, the **K**nowledge **G**raph captures all knowledge and provides access to every step involved in the transformation from the initial product to the redesigned product.

5 Conclusion and Future Work

As a reminder, the research question was to answer the following: How can one capture the tacit knowledge of design experts within a **K**nowledge **G**raph ?
The **KARMEN** methodology was proposed, consisting of four steps: **FAME** (**F**ind, **A**cquire, **M**odel, **E**xchange). This methodology was implemented within the graph-oriented database software **Neo4J**. The use of **Neo4J** offers a computer solution for implementing a structured **K**nowledge **G**raph with a precise data model in which we can perform powerful and complex queries to search for information. This data model is inspired by the **FBS-PPR** data model.
In future work, the proposed model can be enriched by adding other node data. Data such as audio and image were not exploited in this article. In the future, one could exploit artificial intelligence algorithms to extract knowledge and deduce relationships between data, such as inference. Finally, recent query tools such as **ChatGPT3** from **OpenAI** and its **API** will enable us to perform queries directly in natural language, assisting the designer and providing the right information to the right person at the right time.

In conclusion, it is important to acknowledge that the specific aspects related to capturing and representing tacit knowledge have not been addressed in this study. Future research could focus on integrating advanced techniques, such as the use of artificial intelligence algorithms and inference methods, to better handle tacit knowledge within the knowledge graph.

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