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An Interaction Engine and Question Refactor Method in Question Answering for Knowledge-Driven Process Planning

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ABSTRACT

Process planning is the intermediate stage between product design and product production. In the ever-evolving landscape of manufacturing, the optimization of process planning plays a key role in ensuring efficiency, cost-effectiveness and overall productivity. Traditional process planning methods often rely on predefined rules and expert knowledge, along with process engineers' experiences, which are tacit and unstructured, existing in their minds. Weak optimal results and resource inefficiencies come in accordance with inefficient knowledge reuse. Existing research work has developed systematic knowledge modeling for process planning and constructed a process knowledge graph (PKG), based on which fundamental question answering (QA) has been performed. But there is the single round strategy in the process of QA over knowledge graph (QAKG). Process planners' questions may be not parsed and they don't have chance to implement or even don't know what to implement. We propose an interactive QAKG framework containing the question refactor method for process planning. The interaction engine will be triggered when the input question can't be parsed to query statement for target entities. Candidate intermediate entities are searched and listed for specifying. The initial question will be refactored after integrated with the entities selected by users. The methodology is implemented by taking the process data of CPU cooler from a manufacturing enterprise. Results show the method could promote the intelligence of knowledge-driven process planning as well as the level of knowledge acquiring and sharing.

Keywords: Process planning, Knowledge graph, Question answering, Intelligent interaction

INTRODUCTION

The transformation of manufacturing to intelligence drives the revolution of product life cycles such as design, machining and maintenance, as well as for process planning (Zhang et al., 2020; Lu et al., 2020). A series of activities needs to be decided to determine the time, cost, tools and production quality during the process planning, which is regarded as the intermediate stage between product design and manufacturing (Harabin and Behandish, 2022; Xiao et al., 2023; Zhang et al., 2022a). Intelligent manufacturing involves a series of complex processes, including many interrelated steps and dependencies, which become assets in the form of knowledge for manufacturing enterprises. It is required that characteristics and relationships of the manufacturing process knowledge need to be fully considered, accurately expressed and utilized during the knowledge-driven process planning.

Traditional process planning methods often rely on predefined rules and expert knowledge, as well as the experience of engineers, which are tacit and unstructured in the minds of engineers, making it difficult to share and reuse knowledge (Wen et al., 2023a). Depending on technologists' experience, skills, and intuition, it's labor-intensive and time-consuming to make process decisions during the knowledge-driven process planning. What's more, senior engineers would adhere to their own preferences, ignoring the updating of process knowledge in the enterprise and the field. The above defects hinder the generation of optimal process planning results.

Knowledge graph is an important research direction of cognitive intelligence in AI, and it is an effective tool for knowledge management (Chen et al., 2020; Wen et al., 2023b). In the research of process planning, knowledge graph satisfies the storage and organization form of process knowledge, and provides great support for the sharing and reuse of process knowledge (Wen and Wang, 2021). Combining knowledge graph and process planning is one of the important bases of intelligent manufacturing (Xiao et al., 2023). Process knowledge graph (PKG) has been widely studied and applied, and has achieved good results (Guo et al., 2022; Zhang et al., 2022; Zhou et al., 2022).

Current researches have proposed knowledge retrieval methods based on corresponding knowledge bases to support knowledge-driven process planning (Zhang et al., 2020; Xu et al. 2017). From the PKG and its structure, process knowledge is researched and reused, by methods like case-based reasoning (Dong et al., 2022), inference algorithms (Qian et al., 2021), similarity computing (He and Jiang, 2019). Question answering over knowledge graph (KGQA) system parses the questions raised by users, generates structured queries, and then retrieves and deduces the corresponding entity answers in knowledge graph (Xiong et al., 2021; Qiu et al., 2021), which is also considered by the research on process planning (Wen et al., 2023a; Kumar et al., 2016; Liu et al., 2021).

General retrieval methods have fixed limitations on the retrieval requirements input. QAKG system has the ability to understand the query in the form of natural language, representing more intelligence for knowledge reuse. However, most QAKG s just provide assist in the single round and lack interaction with users. When the input question could not be understood, the QA round would end. The system can't ask for more information while the user has no way to supplement or even doesn't know what information to supplement. So it is necessary to set the feedback engine for the lacking entity that is indispensable when searching with complex relationships. In the scenario of process planning, such interaction is needed for enterprise with a low level of knowledge reusing, which will be improved with highly structured process knowledge already organized in PKG.

Based on the previous work by Wen et al. (2023a), this paper proposes an interactive QA framework (see Figure 1) for knowledge-driven process planning based on PKG. There is an interaction engine introduced in the framework. The input question not parsed successfully in the regular route will trigger the interaction engine and be refactored. By the proposed question refactor method, candidate entities are retrieved for specifying to clarify the initial question and the search path will be complete. The manufacturing process data of CPU coolers is utilized to implement the QAKG system containing interaction engine along with the question refactor method. The proposed framework is proved to be helpful for the intelligence of QAKG during the knowledge-driven process planning.

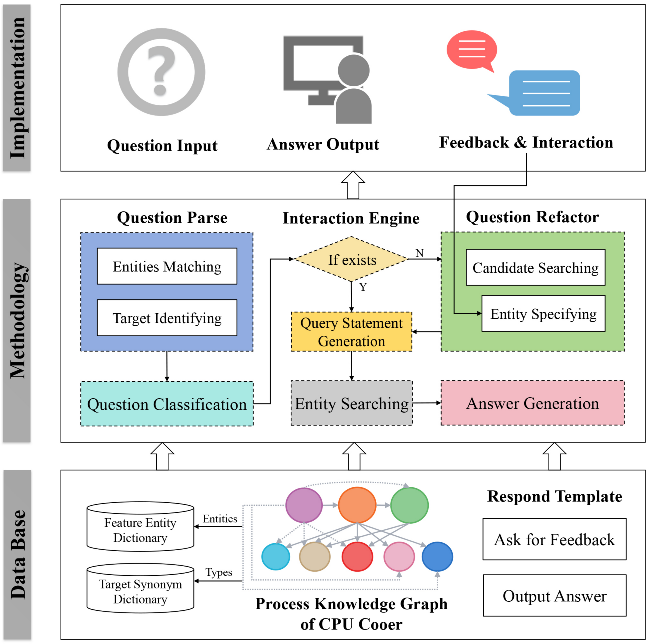

Figure 1: The framework of interactive KGQA.

The rest of this article is structured as follows: The second part introduces the method proposed. In this part, PKG constructed in the previous work is introduced and the principle of propose of the KGQA is reviewed. Then the proposed method is implemented in the third part. The fourth part summarizes the whole article.

METHDOLOGY

Previous work has constructed the PKG based on the domain ontology for process knowledge, which defines concepts and relationships of process knowledge and makes formal representation (Wen et al., 2023a). And a question answering approach over PKG is presented to support process planning. For more intelligent process of question answering by achieving interaction between human and system, a question refactor method is proposed, which can refactor searching path by the selection feedback after providing candidate entities.

THE PKG AND QAKG APPROACH

There are 8 types of entities represented by nodes, together with 15 types of relationships represented by edges, forming the structure of PKG (see Figure 2). Sequence of processes plays a vital role in process planning, dominated by which a workpiece is machined. Each process involves a series of operating procedures to achieve the processing task. In addition, there are corresponding machine tools (like punch press, stock cutter, CNC machine, etc), general appliances (like rubber basket, thermometer, fixture, etc), chemicals (like acid degreasing agent, antioxidant, nitric acid, etc), points of attention and working hours for each process. Meanwhile, some operating procedures involve specific general appliances and chemicals.

Relationships among entities are listed in Table 1. Combined with Figure 2, we can see that the relationships $r_{12}, r_{13}, r_{14}, r_{15}$ are represented by dotted arrows, which means indirect relationships. Exactly the set of operating procedures of a certain process is not unique. It is noted that some processes have more than one set of operating procedures, each corresponding to a certain workpiece. Similarly, different workpieces may have different corresponding entities belonging to other 5 types under the same process. So it is necessary to set these indirect relationships in order to clarify the condition between the direct relationships, which is also required by the searching function.

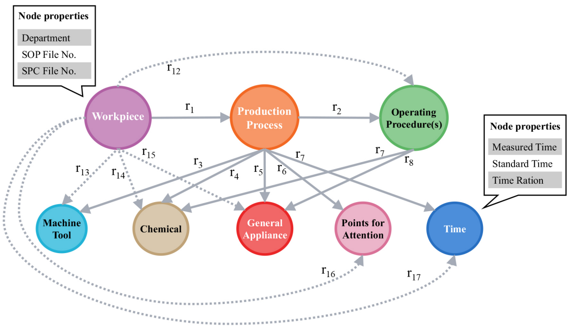

Figure 2: The structure of PKG containing nodes and edges.

Table 1. Relationships in the PKG.

Relation	Type	Name
r1	process#	No. # Process
r2	pcprocessed_follow(#)	Processed following (No. #) operating procedures in the process
r3	pcprocessed_by	Processed by the machine tool in the process
r4	pcprocessed_using	Processed using the chemical in the process

(Continued)

Table 1. Continued

Relation	Type	Name
r5	pcprocessed_with	Processed with the general appliance in the process
r6	pcpay_attention_to	Points of attention in the process
r7	pctime	Process hours
r8	operated_using	Operating procedure(s) using the chemical
r9	operated_with	Operating procedure(s) with the general appliance
r12	wpprocessed_follow(#)	The workpiece is processed following (No. #) operating procedures
r13	wpprocessed_by	The workpiece is processed by the machine tool
r14	wpprocessed_using	The workpiece is processed using the chemical
r15	wpprocessed_with	The workpiece is processed with the chemical
r16	wppay_attention_to	Points of attention in the process
r17	wptime	Process hours concerning the workpiece

To assist process planners and support highly specialized process planning in different scenarios, queries for process knowledge and corresponding answers need to be understood and retrieved respectively. The flow chart of question answering is shown in Figure 3. First, all nouns of entities are listed by their types and stored into the feature dictionary, which is then transformed into the AC tree by the Aho-Corasick algorithm (Aho and Corasick, 1975). Meanwhile, a synonym dictionary is designed containing the target words, which may exist in questions asked by users. Next, the feature entities are detected and attached with types through the AC tree and the target word is identified as the entity type. Then feature entities and the target are integrated and the type of question is classified.

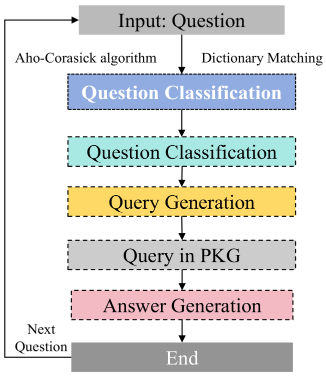

Figure 3: The flow chart of question answering over PKG.

The query statement is generated with entities filled based on a meta path-based searching path (Yu et al., 2014). One-hop and multi-hop path are designed to search the target entity. As shown in Figure 4, the Cypher query statement of the one-hop path is

"MATCH (m:Workpiece)-[r]->(n:ProductionProcesses)

where m.name = 'entity' return m.name, r.name, n.name ORDER BY r.name"

And the Cypher query statement of the multi-hop path is

"MATCH (m:Workpiece)–>(n:ProductionProcesses) -[r:pcprocessed_follow]->
(p:OperatingProcedures)

where m.name = 'entity' and n.name = 'entity' AND (m:Workpiece)–>
(p:OperatingProcedures) return m.name, n.name, p.name"

We can see that sequential relationships could be devoted to multi-hop path. The main relationship that works is "pcprocessed_follow", but the constraint that the workpiece must have relation with returned operating procedures is indispensable. Otherwise, there are several sets of operating procedures returned.

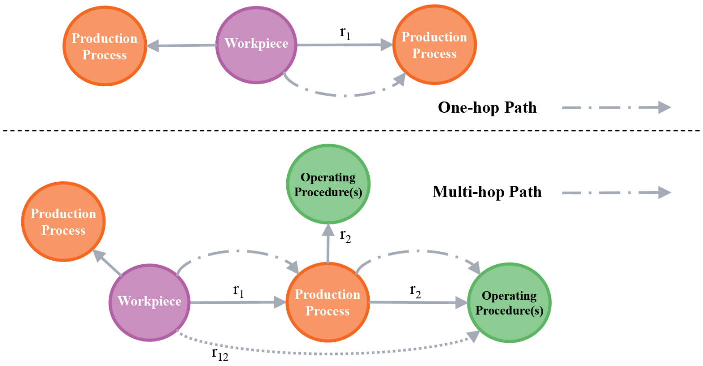

Figure 4: Examples of one-hop path and multi-hop path design.

The current QAKG approach has some shortcomings like that it could perform limited types of question answer. For example, process planners wonder the operating procedures of the certain process of a workpiece. But they wouldn't mention the workpiece. The search path needs to be designed just over the relationship r2. There might be several sets of operating procedures returned, which would be confusing for process planners. As the single-round QA ends, they need to re-enter more complete questions. So it is necessary to add the interaction engine to perform multi-round QA for indispensable entities, which is beneficial to planners and the efficiency of process planning. Here comes the interactive QA in the next subsection.

INTERACTIVE KGQA FOR PROCESS PLANNING

Question refactor method and interaction engine are proposed and introduced into the mentioned QAKG. Facing the question types that need additional feature entities, it is more efficient to generate feedback consisting of necessary candidate entities. Interactive QA aims to obtain more information and capture complete intentions of users. When obtaining specific feature entities selected by users from candidates, the search path and answer become more precise due to the more detailed constraints. Also, the QA process could return to the stage that provides the candidates and wait for another detailed information.

As mentioned before, a certain process may have different sets of operating procedures depending on the related workpiece, so as chemicals, general appliances, points for attention and working hours. So we concentrate on types of questions over the relationship r_2, r_4, r_5, r_6, r_7. Similarly, take the question type over the relationship r_2 as an example, namely, asking for operating procedures of a certain process. The workpiece processed, relationship r_1 and r_{12} are supposed to assist searching. The transition of search path is shown in Figure 5. With the question refactor method, the search path could be determined until the workpiece is specified from candidates.

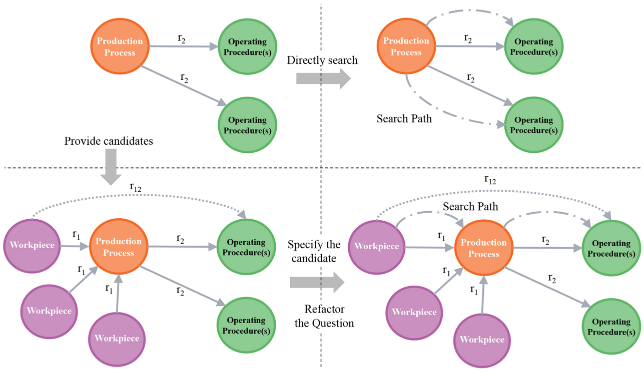

Figure 5: Examples of transition of search path.

The flow chart of question answering containing interaction engine is shown in Figure 6. Due to the new type of questions which are parsed out uncertain search path, there is an interaction engine after query generation, on which the Cypher may not exist as lacking indispensable entities. So the question refactor method is performed and query statement for candidate entities is generated. For example, when the initial question is "operating procedures of the process", the query statement for candidate entities is generated on the relationship r1 and shown as follows

"MATCH (m:Workpiece)–>(n:ProductionProcesses)
where n.name = 'entity' return m.name, n.name"

Entities searched are workpieces involving the process specified in the question, which are to be listed as candidates for specifying. When specified, the entity is inserted into the initial question and the newly generated question will be processed in the same way. When finishing answer generation, it will still ask for other entities to start with next question refactor. There is another option to end this round of QA.

We give instructions on how the interactive KGQA containing interaction engine and question refactor method works in this subsection. With the generated query statement, the entities searched will be returned based on the PKG to respond to the input question in the form of corresponding direct targets and related recommending targets, involving process planning-related knowledge, which can be devoted to the question-oriented process knowledge reuse.

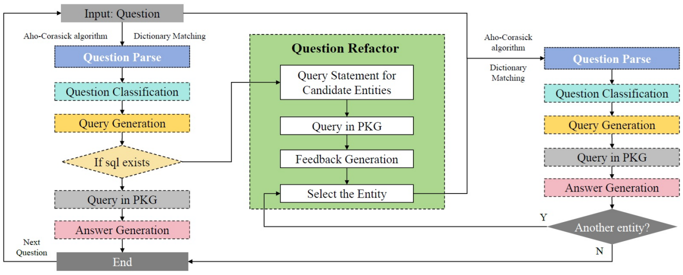

Figure 6: The flowchart of the interactive KGQA.

IMPLEMENTATION

Process data concerning the manufacturing process of CPU cooler from a manufacturing enterprise is used to construct the PKG, which is applied to knowledge-driven process planning. After data processing, structured process knowledge is imported into Neo4j graph database (see Figure 7) by the py2neo package coded in Python 3.9. There are 476 nodes in 8 types of entities and 2872 edges in 15 types of relationships.

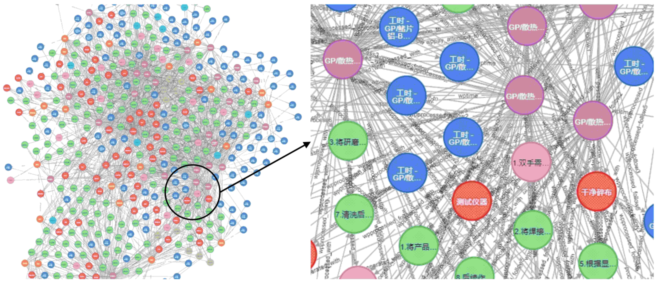

Figure 7: Partial schematic diagram of the PKG.

According to process planning scenario of CPU cooler and the structure of the PKG, there are 8 types of questions with the one-hop search path and 9 types of questions with multi-hop research path. And 5 types of questions to be answered by the interactive method are listed in Table 2. An example of implementation of interactive QA over PKG is shown in Figure 8.

Table 2. Types of questions concerning interaction.

Question definition	Explanation
productionprocesses_operatingprocedures	Operating procedures of the process
productionprocesses_pointsforattention	Points for attention of the process
productionprocesses_chemicals	Chemicals used in the process
productionprocesses_generalappliances	General appliances used in the process
productionprocesses_time	Working hours of the process

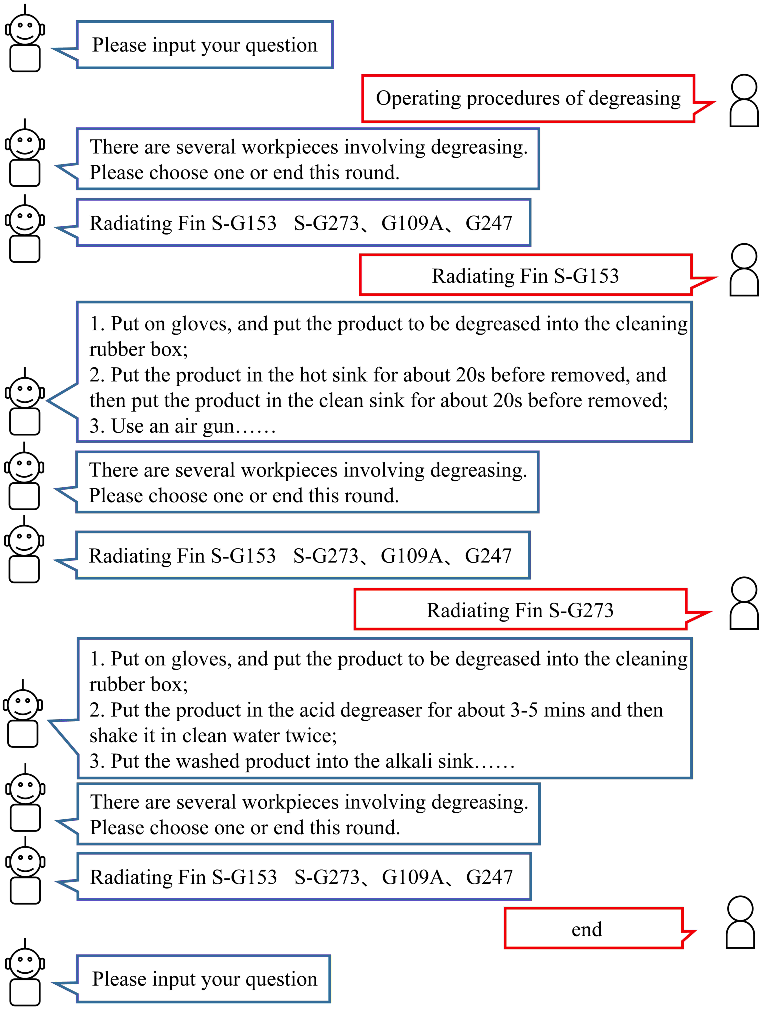

Figure 8: An example of implementation of interactive QA over PKG.

CONCLUSION

PKG provides semantic framework for the optimized storage and representation of process knowledge and its relationship to each other. KGQA is able to offer a rapid, simple and intelligent way for knowledge acquiring and sharing. The interactive KGQA framework proposed achieves the interaction between human and machine linked with PKG. With the interaction engine, question refactor method can be utilized for process planners to select intermediate entities from candidates searched in PKG to refactor the question. The implementation of the framework proposed shows the effectiveness on promoting the intelligence of knowledge-driven process planning and convenience of planners.

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