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Manufacturing Knowledge Graph: A Connectivism to Answer Production Problems Query With Knowledge Reuse

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ABSTRACT Manufacturing knowledge (MK) is enjoying a "new golden age" in the academic domain, marked by vast reuse to support product-related production problems (PPs) solving decision making for manufacturing enterprises in the industry sector. However, the practice of MK reuse and research is fragmented and insufficient, which cannot be mature to provide a systemic solution for that a decision-maker has to consider the involving issues: how MK can be used earlier and rightly; what kind of practical problems can be solved? In order to answer those interconnecting issues, this paper firstly proposes a connectivism framework to clarify the compressive relationship of problem-to-problem, knowledge-to-knowledge and problem-to-knowledge with knowledge integration, knowledge matching, and problem-solving layers. Then, based on the framework, an ontology-based MK graph (MKG) is constructed with a unified MK-filter to collect and integrate multifactor and multilevel MK, and a graph-oriented meta-knowledge model (MKM) is proposed to represent the details between the knowledge entities (i.e., concept and instance), which also shows the contribution to knowledge reasoning. After that, driven by a structure temporal query (i.e., 5W2H), a semantics-based knowledge computation is developed to compute the intrinsic term similarity (IS) and relational term similarity (RS) between two knowledge entities in the MKG. Finally, a case study is taken to demonstrate the effectiveness and performance of the proposed methods.

INDEX TERMS Production problems (PPs), manufacturing knowledge (MK), manufacturing knowledge graph (MKG).

I. INTRODUCTION

The philosophy of continuous improvement for manufacturing enterprises is never out of fashion to solve PPs during the product lifecycle and the new generation information techniques-based knowledge reuse to planning and answer problems query has received attention in the industry and academic domain. The National Institute of Standards and Technology (2017) has defined MK as a phrase with vast meanings, which may include knowledge on the effects of material properties decisions, machine and process capabilities or understanding the unintended consequences of design decisions on manufacturing [1]. A survey conclude that MK has been reused in the whole processes of product lifecycle management [2] and product design knowledge reuse percentage averages a 28% for manufacturing application [3].The Defense Acquisition University(2011) proposes that the acquisition, operation and support of product could account for 60-80% of the product life cycle cost [4]. These claims highlight that the marginal value of more MK reused by enterprises is the decrease in production cost of product lifecycle, and the increase in effective production time, efficiency and profit permitted by a smaller amount of production problem-solving time. However, from the angle of systematic view of PPs solving with MK, a lack of connective vision among problem solvers has limited the availability of industry-mature solutions.

So, the question still needs to be answered: how to use MK, timely, in the product life cycle, to provide a more mature and accurate solution of decision-making for problems solving? While, previous researches have tried to identify the chance in exploring the knowledge reuse for

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decision making. Technically, W3C, as a technical standard institution, has made great foundation to describe and represent knowledge language standards, such as semantic networks [5], resource description framework (RDF) [6] and Web Ontology Language(OWL) [7], [8]. Davis *et al.* [9] directly answered the question what knowledge representation is with definition terms of five roles: surrogate, a set of ontological commitments, a fragmentary theory of intelligent reasoning, a medium for efficient computation and a medium for human expression. Kim *et al.* [10] proposed a knowledge mapping model to capture and represent manufacturing organizational knowledge. Xie *et al.* [11], taking advantage of concise descriptions for entities that usually may be easily ignored, studied the a RL (representation learning) method for knowledge graph(KG).

Currently, knowledge graph is one of the state-of-the-art technologies to improve search engine capabilities and enhance the quality and experience of users' search in the field of information retrieval [12] and the some famous knowledge graphs have been created, such as YAGO [13], DBpedia [14], Freebase [15] and the Google knowledge graph [16]. To efficiently work with previewing and ingesting RDF/semantic data, a plugin named Neosemantic was created, by Barassa, to import RDFS/OWL ontology into the graphics database Neo4j [17]. To remedy the obstacle of finding too many or too few relevant answers from triple-pattern queries driven by natural language processing, Arnaout and Elbassuoni [18] proposed a general framework for effective searching of RDF knowledge graphs and studied the constants of augmenting the relaxed queries by turning them into a set of keywords and combining the results of relaxed queries with a ranking model. By modeling the data and knowledge as an RDF graph model, Song *et al.* [19] proposed TR Discover, a natural language interface translating questions into executable queries for answer retrieval.

Coming to the manufacturing industry application of Zhou et al. has devoted great attention on graph-based knowledge reuse to support knowledge-driven decision-making in new product development [20] and digital twin manufacturing cell towards intelligent manufacturing [21]. Li *et al.* [22] presented a structured heterogeneous CAM models based on process knowledge graph to describe the CAD models and NC processes in a unified way to guide the data mapping and exchange, which provides an easy rule-based reasoning for obtaining implicit semantics and enriches the unity of the process knowledge graph. Ruiz *et al.* [23] study the knowledge reuse integrating the collaboration from multi-experts knowledge with the Transferable Belief Model (TBM) to support collaborative decision making in industrial maintenance management.

In the view of problem-solving, more attention has paid on knowledge management, but ignored the enterprise system-level issues. While, there is significant research effort devoted to those obstacles met during the product lifecycle. Several fundamental studies pay more attention on hackling and modeling the mess of problems including where they come [24], [25]: an event-based production activity chain model was built to actively plan and monitor in the shop floor [26], how they can be managed and solved in the supply chain [27], [28] and what the problem solving cost is [29]. Camarillo *et al.* [30] focused on the manufacturing problems solving and proposed a multi-agent system with integrated the 8D to define problem, PFMEA to analyze problem, CBR to reason and PLM to manage problem. And the feasibility of system architecture was validated in two different manufacturing plants.

Obviously, all the above forerunner researches have important significance. Nevertheless, they only focus on a certain domain model-based problems and do not address the applicability and versatility in the whole manufacturing sector, and few works have dedicated to the issue of expression and classification of MK and PPs at the same time, which may the reason of the availability of MK reuse is low, but in the R&D and design phase [31]. Meanwhile, scarcely any study involves PPs query issue, due to there is a lack of manufacturing domain knowledge graph. Thanks to the pros and cons of pioneer researches, this paper proposes a novel connectivism reference framework of MK reuse driven question query for decision making in problem-solving process. To answer the problem query, the main goal of this framework is to help querists find the most related MK and making right decision for givens problems. For this goal, an ontology-based MKG is constructed with a unified MK-filter to capture and integrate multifactor and multilevel knowledge hidden in manufacturing enterprises. In addition, a meta-knowledge model (MKM) is employed not only to detail the MK term in graph and description, but also to help distinguishing term entity semantics in the process of knowledge matching and computation. Further, a score function to evaluate entity semantic matching in the solution recommendation is developed, which contains the similarity of the intrinsic term similarity (IS) and relational term similarity (RS) between two knowledge entities in the MKG.

The rest of this paper is organized as follows: Section 2 clarifies the related definitions and proposes a connectivism framework. Section 3 the describes the whole process of ontology-based MKG construction. Section 4 explores the knowledge matching and computation. A demonstration case is taken in section 5 as a point to illustrate and evaluate the above models and methods. Finally, conclusion and future work are discussed in the section 6.

II. A FRAMEWORK OF CONNECTIVISM

A. DEFINITIONS

Due to the complexity of production processes and the chaos of standardization and formalization to knowledge, the amount of knowledge reuse is low. To better understand PPs and MK, some related terms are clarified first.

Definition 1: Production problems (PPs): refer to the gap between the target state and resulting state or bottlenecks appearing in certain step of product lifecycle for actual production and operation of a manufacturing enterprise, such as product unreasonable design, quality defects, production line unbalancing and so on. Through solving these problems, product quality and enterprises efficiency can be increased, so as to decrease product cost and achieve more profits for enterprises.

Definition 2: Problem-domain knowledge (PDK): a kind of objective and rational MK, which plays a cruel role in helping problem solvers better understand the context and domain criteria, e.g. with a fixed feed rate, the cutting speed is faster and the roughness is lower. In most case, it refers to product-related standards, material, processing knowledge and so on.

Definition 3: Problem-solving knowledge (PSK): a kind of subjective and practical MK, which consists of specific problem solving methods and strategies with providing a concrete executable logic and steps, e.g. TRIZ/DFSS for product design problems, value stream mapping (VSM) for manufacturing wastes, six Sigma for quality control barriers, design of experiment (DOE) for parameter optimization, 5S for Gemba Kaizen and so on.

Definition 4: Problem-evaluating knowledge (PEK): a kind of assessing MK, which gives a total judgment of evaluation form the aspects of problem-solving feasibility, quality, efficiency, processing time and cost, e.g. business model canvas and SWOT for economic efficiency, measurement system analysis (MSA) for quality stability and system repeatability and reproducibility.

Definition 5: Past-production problems (P-PPs): broadly defined, is a kind of MK able to solve new problem based on the solutions of similar past problems solving cases. And it is formally represented and stored in the manufacturing enterprises case base. Fortunately, based on the cooperation, we have access to the enough industry cases from Haier (one of largest white-goods manufacturer in China), Jereh (a global high-end petroleum equipment manufacturer), Shaanxi Beiren (a package printing equipment manufacturer), Xian XD (a large switchgear manufacturer).

B. A CONNECTIVISM FRAMEWORK OF MK REUSE

Connectivism is an integrated theory that explains knowledge, across internet technologies in modern society, is connected, distributed and changing. This theory, originally, proposed by Siemens to emphasize the role of social and cultural context in how and where learning occurs [32], developed and applied to the massive open online courses, where anyone could enroll online [33].

For problem-solvers in manufacturing enterprises, however, the connectivism can be represented as a graph theory to describe the relations (edge) between problem-to-problem, knowledge-to-knowledge and problem-to-knowledge and those entities (vertex) in the process of problem-based knowledge matching. A common scenario in the entire problems solving process, thanks to the problem complexity (such as randomness, messy or cluster), a holistic problem-solving solutions cannot be right extracted from the formless knowledge bases, except from a view of connectivism. Ultimately, like a ripple, the effects coming from a certain problem would transmit to the whole production processes, which would restrict shortening the lead times and improving production capacities.

Based on these connectivistic theory and production dilemma, we have to consider the question: how can those PPs be right located, described solved with right people in right context and time using right solutions consisting of right MK and the right evaluating criteria. Therefore, a connectivism framework of MK reuse is proposed as shown in the Fig. 1.

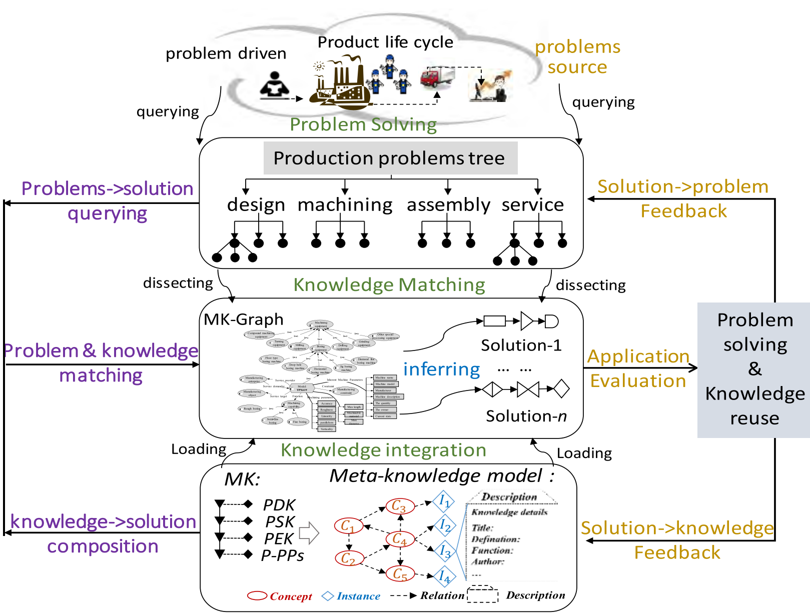

FIGURE 1. A connectivism framework of MK reuse.

This framework contains three layers: the bottom layer is the knowledge integration and fusion space, where knowledge base integrated not only various knowledge but also the past problems solved plays the role of case resource. The intermediary layer is knowledge navigation and matching space, where suitable knowledge matching strategies are employed to recommend appropriate knowledge to decision-maker for problem solving. The top layer is problems solving space, which simulates an interactive interface inputting problem querying and outputting solutions between this framework and problem-solvers.

1) KNOWLEDGE INTEGRATION LAYER

As a think tank of this framework, one of the goals of the knowledge integration layer is to gather heterogeneous knowledge including those production truth, information and principles from academic study, industry investigation, practical observation or engineering experiment, and then convert into P-PPs, PSK, PDK and PEK. The other one goal is to provide those knowledge resources to form problem-solving solution of meeting the enterprise's problem query thorough the knowledge matching.

2) KNOWLEDGE MATCHING LAYER

Driven by the problem query from the real world, the main goal of knowledge matching is to get pertinent knowledge for problem-solvers. It takes the advantage of the relationship between knowledge points (including of the knowledge entities of P-PPs, PSK, PDK and PEK), and avoids the isolation of knowledge in the process of solving problems, which emphasizes the character of connectivism framework and also highlights the efficiency, accuracy and comprehensiveness of knowledge matching.

3) PROBLEMS SOLVING LAYER

As the interface between this framework and real manufacturing environment, the problems solving layer plays the role of communication between problem query and ideal final solutions for problem-solvers in manufacturing enterprises. In this scenario, supported by knowledge matching, an ideal final solution, driven by problem query, can be easily recommended to a problem solver, which solution is composed of knowledge including of P-PPs, PSK, PDK and PEK from the knowledge integration.

This framework is an extendable framework, where knowledge and problem nodes are constantly updated and evolved that those nodes can be added, deleted, revised and checked in the whole resource space. Meanwhile, the integration of problems and knowledge is foundation of resource space construction (i.e., production problem space and knowledge space) and problem querying from production sites is the core driving force of knowledge navigation in knowledge matching space. So, this paper focuses on the knowledge and problem matching techniques, which can promote enterprise problem solving ability, efficiency and viability. In the next section, on the basis of connectivism theory, an ontology based MKG is built to drive this framework with three layers.

III. MKG CONSTRUCTION

Let us take a scenario: a mechanic wants to locate a certain wrench from his office, so he can straightforwardly find it since he has almost all the knowledge and information about it. It is a sort of graph set in his mind about his office. However, in a manufacturing enterprise, due to the high dimensionality and complexity of MK, a mechanic struggles in executing knowledge points simply in his mind. What is worse, it severely hinders knowledge sharing correct and causes knowledge reuse efficiency and effect low. Owing to the representation of an object can contain its relationships to other objects, the form of graph to represent MK is a practical choice. However, to develop solutions from a connectivisitc vision of problem solving framework, it is crucial to know what type of content (i.e., knowledge) will fill the framework, and how this content may be connected.

To answer those questions, this paper employs a knowledge graph method based on ontology to (1) define term of MK as explicit formal specifications; (2) transfer certain aspects of knowledge points into graphical form that is easily understandable and reusable. (3) Thus, every bit of MK exists within a subject can be deciphered and this helps a mechanic easily to create some predictions and modifications in decision-making.

A. MANUFACTURING KNOWLEDGE FILTER

For the reason MK may be mined from production practices, crawled through internet or created by academia, the structures of knowledge may be the unstructured expertise and effort, structured case and knowledge base or semi-structured sensor data [34]. And all that picture-symbolic-virtual-textual knowledge, emphasized by Guerra and Young, may be the type of explicit, tacit and implicit [35].

To address that nature complexity and technical simplification of MK, a domain-specific knowledge filter is proposed to reduce redundancy and help improve classification performance of MK, which works as an accurate pre-processing for knowledge, not just for integrating hardware-software sensor data [36] previously developed in our lab.

Definition 6: MK-filter is broadly defined as a kind of computer-aided knowledge structuralization mediator that firstly observes inputting MK including structured, unstructured and semi-structured, from production environment, then merges the inputted knowledge through embedded methodologies and protocols, and finally output the unified knowledge format. Thus, MK-filter can be formalized as:

$$MK - filter ::= < id, type, vTime, Pro, Cap, unit, Lib > \tag{1}$$

where the properties of MK-Filter, respectively, describe the Unique Resource Identifiers (id), merging type, valid operation time, mapping protocols, capability, operation units and history library.

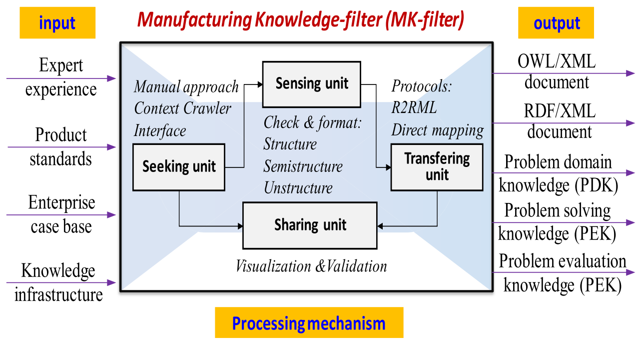

FIGURE 2. The diagram of MK-filter.

As the Fig. 2 shown, the MK-Filter have four units, i.e., seeking unit, sensing unit, transferring unit and sharing unit. Seeking unit actively absorbs heterogeneous MK with the manual approach, context crawler and interface. Here, the manual approach is proposed to curate the unstructured (e.g., expert experience) and semi-structured (e.g., electronic drawings, proce's-verbal) MK by an open or closed group experts with a character of smaller volume but higher precision. Interface approach is used to import and express customized mappings from relational knowledge bases to structured base. Meanwhile, the context crawler works as a MK extension tool that extracts massive knowledge terms from knowledge infrastructure with the character of large volume but low precision.

Sensing unit is a pre-treatment step and main goal is to separate redundancy and noise from inputted knowledge package based on certain criteria and properties, and further synthesizes the collected heterogeneous knowledge into a standard and customized mapping format. It should be pointed out that due to the temporal context, it is necessary to ensure that manufacturing knowledge product-related is reliable and current during the process of constructing solutions. For example, the international standards on bonded abrasive products-safety rules (ISO 525:1999) is abolished now and cannot be used to guide production [37].

Transferring unit follows the knowledge transferring language and protocols (e.g., the R2RML: RDB to RDF mapping language [38], the direct mapping of relational data to RDF language [39] and JDBC: Java database connectivity, which are recommended by the W3C) to transfer the knowledge format form the existing model to a target vocabulary of the user's choice. According to the recommendation, a RDF triple can be viewed as a triple with three fields: $<$ subject, predicate, object $>$ described with URIs or literals, which has great potential for identification and interpretation of knowledge term [18]. Thus, the whole set of RDF MK entities can be viewed as a label graph, which also is named RDF MK graph. A mature exchanging tool of R2RML is D2RQ, which provides an access to mapping relation data structure to graphical data, and can be available at *http://d2rq.org*.

Sharing unit plays the role of MK management and application, such as knowledge visualization, validation storage (including history events). Usually, the management function can be expressed as a computer aided software applications or web service, which can be packaged and shared with interface. Therefore, it produces easy access to inputting heterogeneous knowledge into the filter for mapping and the converted knowledge can be further displayed to custodians and users.

Thanks to the mature HTML language, it is easy to develop a web Application to filter knowledge. In addition, to complement the whole filtering processes of MK, the curated (a closed group of experts), collaborative (an open group of volunteers including on-site staff and experts) and automated approaches (ML and NPL techniques, such as web crawler) have also been introduced to extract and codify heterologous knowledge in this paper.

With the help of MK-filter, the structured, unstructured and semi structured MK hidden in production environment can be captured and normalized, and further makes the bedrock for MKG construction.

B. MANUFACTURING KNOWLEDGE REPRESENTATION

After the filtering process, the variables of MK have been classified as PDK, PSK, PEK and P-PPs with the aid of knowledge filter. So, there necessarily needs a unified MK representation model before next steps of knowledge matching and computation. And some knowledge model to store and manage various types of knowledge have been tried, but most ignoring the description details of concepts and instances related to a manufacturing information.

Here, motivated by a previously proposed knowledge map conceptual model [10] and representation learning method [11], as Fig. 3 shown, this paper employs a graph-oriented meta-knowledge model (MKM) to represent knowledge terms with a formal, explicit, non-redundant and unambiguous representation, whose main strengths is to represent term set as diagram to express the relationships between knowledge entities (referring to concepts and instance) and that entities are detailed with concise description. Further, two definitions introduced can interpret the model.

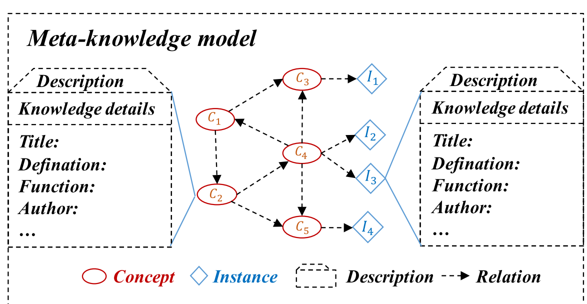

FIGURE 3. Meta-knowledge description model.

1) GRAPH-BASED REPRESENTATION

Entities that may be concepts or instances are the graph-based representation for knowledge terms, which can be directly represented as connecting vertices with linking edges in MKG. This kind of representation is the same as the most existing operations on the low-dimensional, which only focuses on semantic relations of entities and ignores the concise descriptions for entities.

2) DESCRIPTION-BASED REPRESENTATION

Deeply, to descript the term entity for efficient knowledge capturing, matching, computing and sharing accurately, a specification named description-based representation is introduced to detail entities with concise descriptions for knowledge term in the form of text, table, chart, diagram, etc.

Technically, aiming at semantics representing MK term in the form of computer readable graph composed of entities, many artificial intelligence approaches have been proposed and utilized, for instance, description logics [9], [40], semantic networks [5]. And the more current methods are the W3C Resource Description Framework (RDF) [6] and Web Ontology Language (OWL) [41], which has traction for linking concept as the interlinking knowledge and data on the web in the relational form.

In this paper, we will loosely follow OWL standard to promote the canonicalization of MK variables. Specifically, OWL ontology is designed to play a role of making machine-interpretable definitions of basic entities and relations among them in domain with a set of formal description: KO= < concept, instance, literals, datatype, property>, corresponding to a set of design criteria<clarity, coherence, extendibility, minimal encoding bias, minimal commitment> [42]. Here, concept defines the classes within the ontology; instances denotes the object individuals; literals represent concrete data values; datatype defines the types that these values can have; property comprises object property and data property. An object property (owl: ObjectProperty) defines a relationship between two individuals (instances, members), as in, "FishboneDiagram part_of Diagram", where "FishboneDiagram" and "Diagram" refer to specific instances of the corresponding classes, not to the classes themselves. A data property (owl: DatatypeProperty) specifies a relationship between an individual and a literal (integer, double, float, string, boolean, etc.), for example, "FishboneDiagran" is composed with 6 causing factors containing man, machine, material, method, measurement and environment, and the detail description profile is also available at *http://58.206.100.146/fishbone/* (the address of Fish Bone web APP in our lab). On the basis of two kind of property, the proposed MKM based on OWL is feasible to construct with the protégé tool.

C. ONTOLOGY BASED MKG CONSTRUCTING

As shown in Fig. 4, a MKG based on ontology has constructed by an innovative MK-filter and unified meta-knowledge description model to integrate and express manufacturing knowledge term entities. And in the view of top to bottom, the steps of integration of heterogeneous knowledge are generalized as the following: (1) according to the domain knowledge ontology dimension theory, constructing the knowledge entity, including concept and instance, connecting schema (2) to import the inherent terms and relations from enterprise past problem-solving case information base (i.e., Haier-GZ fridge quality control case, XD tool Manage base, Beiren printing machine assembly outsourced library) through the designed MK-filter and extract hidden knowledge buried in production environment or academic database according to knowledge category, competence and feature. (3) building the MKG based on domain ontology via the unified structured knowledge filter and representation model heterogeneous knowledge entities, which can be explained with knowledge schema, description and graph to express the terms and relationship among them in the MKG. Contrarily, from bottom-up, the built ontology based MKG can also provide an approach to extending terms form production environment or pruning and completing the redundancy and incompleteness of domain terms in the existing knowledge bases with the description logics. For example, the "sameAs", "equivalentClass" and "equivalentPreperty" axioms can be included to assert identity of the term of fishbone graph, which can also be referenced as either cause-effect graph or Ishikawa graph because of an instance having more than one name for a term.

Addition to the ontology based semantic approaches, during the whole processes of MKG construction, some related approaches and tools have been used to complement. For instances, to interoperate the MKG, the W3C Direct Mapping of Relational Data to RDF and R2RML mapping language support a standard for RDB to RDF transformation. And the Neosemantics plugin was used to import RDFS/OWL ontology into a graph database-Neo4j [17], which can be used to compute knowledge semantics similarity in the graph base. In addition, in the protégé tool, the Description Logic Reasoner is employed to verify the consistency and hierarchy of MK and the Graphviz is used as graph visualization tool, but the owl query language for the limited usability, temporal feature, etc. And a temporal pattern query based on structured ontology language will be detailed in the next section.

IV. KNOWLEDGE MATCHING AND NAVIGATION

A. TEMPORAL PATTERN QUERY BASED ON STRUCTURED ONTOLOGY LANGUAGE

A problem querying is to MKG as a pump is to reservoir, which provides the driving force of knowledge matching from solutions of problem-solving to manufacturing difficulties for decision makers. After the interview with 400 workers (effective 389) from cooperative enterprises, we conclude that most querying patterns they proposed to search answer from knowledge bases can be summarized as the so-called "5w2h" query patterns. Those patterns have shown the great success in finding the clues to solve problems of production efficiency, product quality, waste and cost, brainstorming for invention, data collecting in industry and

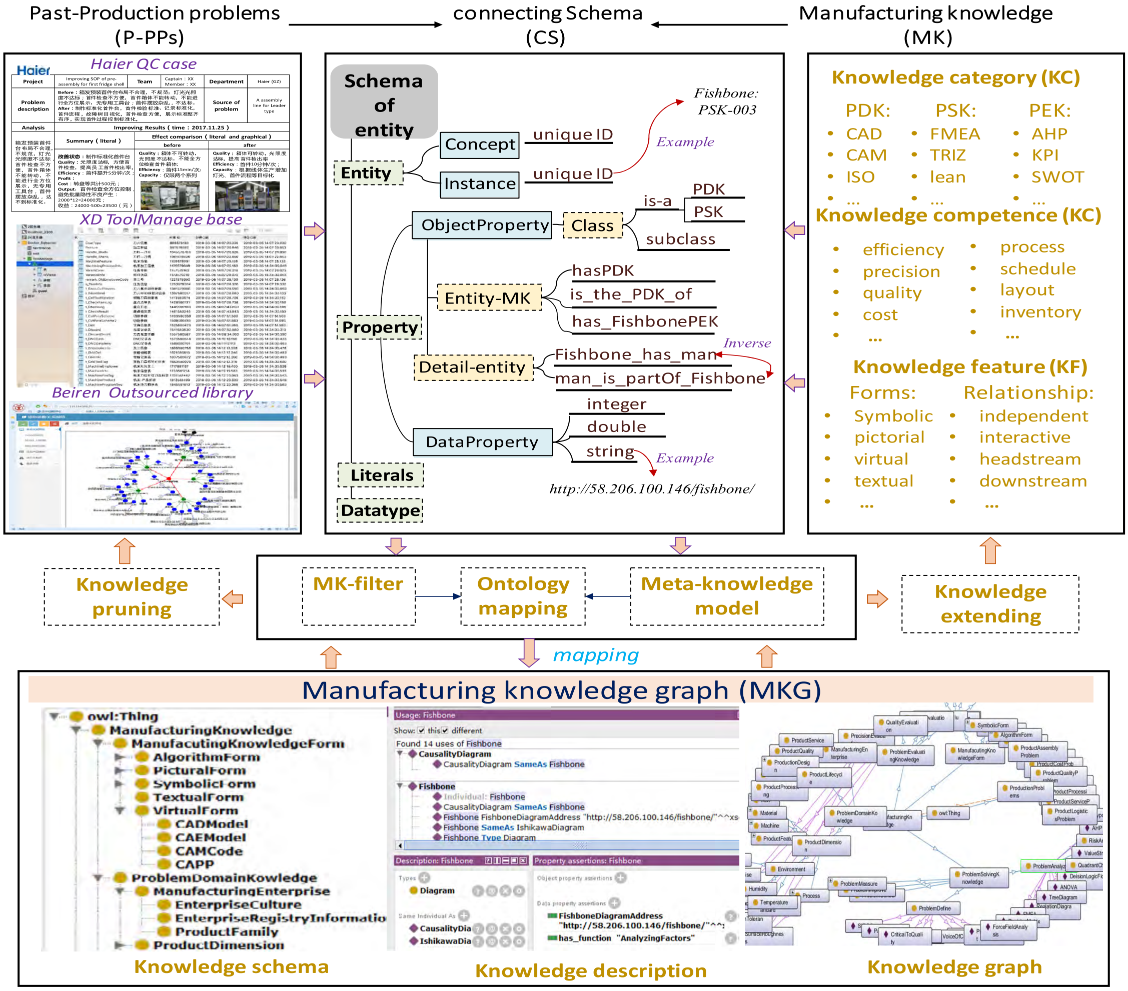

FIGURE 4. Graphic detail of ontology based MKG.

other fields [43], [44]. The world's most famous pattern query website is the wikiHow *(https://www.wikihow.com)*, where one can query with structured pattern "how to".

Meanwhile, due to the reason that knowledge has lifespan, it inspires us that obsolete MK may not be the right choice to a present problem when decision making. So, it needs to consider that temporal question to knowledge matching cues for temporal relations of querying, which cannot be efficiently handled by the owl query language in the protégé. Lastly, combining a temporal query method and the structure ontology query language SPAROL-ST [45], as Fig. 5 shown, this paper classify the "5w2h" query patterns into two kinds: "Wh*"(i.e., who, where, what, when and why) pattern and "How" (how to and how much) pattern to cope with the temporal query questions. A question can be decomposed as general sub-question and a temporal sub-question with a SINGAN, and Allen introduced 13 temporal SIGNAL [46] (such as before, during, last, etc.). There are three key steps in the question decomposition, (1) the first is to locate the temporal SIGNAL, (2) the second is to extract the query words (Wh*, How) and (3) the third is to answering the simple

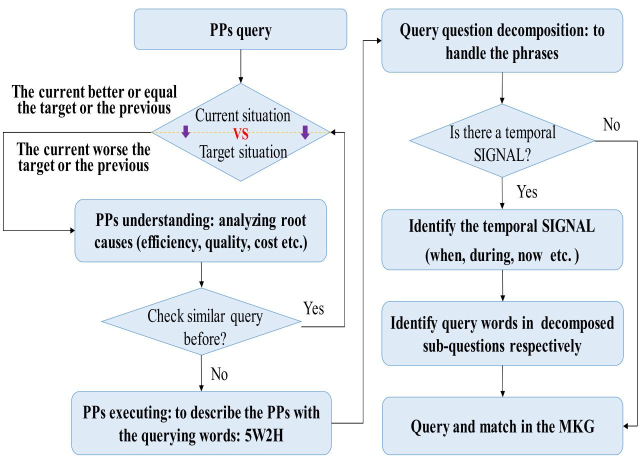

FIGURE 5. The implement logic of temporal pattern query.

sub-question. For example, along with its semantics, the RDF graph based pattern query "how to improve the part surface roughness during the cutting process?" can be expressed as Table 1:

TABLE 1. Decomposition of pattern querying questions.

Wh* and how* is the querying question word and t_i is the question tokens. The temporal constrain is the fragment after the SIGNAL word.
Expected input: How to … SIGNAL $t_{1 \ldots} t_m$? **Question pattern:** How to do… during $t_{1 \ldots} t_m$? **E.g.:** how to improve the part surface roughness during the cutting process? **Sub-question 1:** how to improve the surface roughness of part? **Sub-question 2:** when is the process of part cutting?
$(?\,how, improve, surface\ \ roughness) \leftarrow (?\,how, improve,$ $cutting\ \ surface\ \ roughness) \cap (?\,SIGNAL, process\ \ of,$ $part\ \ cutiing)[?\,t], T_a \le ?\,t \le T_b$ Here, the T_a and T_b mean the starting and ending points of part cutting. Thus, it provides a temporal clue for exploring the certain MK with the time features.

B. KNOWLEDGE-PROBLEM MATCHING

Driven by the structured query, it is clear that matching relative MK to PPs is becoming more unambiguous based on the constructed MKG, which can be easily represented as RDF graph. Absolutely, it is convinced that the crux of problem solving with knowledge reuse, in the matching process, is being able to (1) find all relation instances instead of the limited predefined relations (2) and recognize the shortest relation path between related entities (i.e., MK and PPs terms), which can be abstracted as a connecting schema (CS) triple (MK, relation, PPs) to express how can a knowledge point quickly navigate to a certain problem or how can a problem rightly find the optimal cure.

$$CS ::=< MK, relation, PPs > \tag{2}$$

The rationale for categorization of knowledge matching relation is based on the main constraint conditions and inferring strategies of knowledge entities, which are vital factors, determining problem solving solutions. Strategy is inferring direction and rule of knowledge matching and how to apply them, while the constraint predefined some actions or conditions for those inferring strategies.

$$relation ::=< strategy > \otimes < constraint > \tag{3}$$

According to the MK matching triple, the matching strategy can be bidirectional transferring of both well-established entities, i.e., the knowledge-driven navigation and problem-driven navigation.

In knowledge-driven navigation, the emphasis lies on gathering more product-related information and knowledge, and use of this knowledge as the basis for further inferring and navigation. The knowledge in this strategy that is used is mostly PDK on how to manufacture a customer-satisfied product in the whole product lifecycle process. For example, coming to face processing of part, matching strategy can follow the domain rule: (1) datum design-bottom fixing-side gripping-top milling (2) rough milling-semi finishing milling-finishing milling, under certain constraint conditions of operators, machines and cutting tool parameters. It also needs to be pointed out that knowledge-driven navigation strategy has clustering and hierarchical attribute as shown by the purple arrow in the Fig.6, which is convenient for recommending and predicting knowledge entities in the MK graph.

In the problem-driven navigation, the emphasis lies on more problem-related phenomena and characters, which results in a highly defined problem on an abstract or specified level to find and focus on fewer alternative knowledge points.

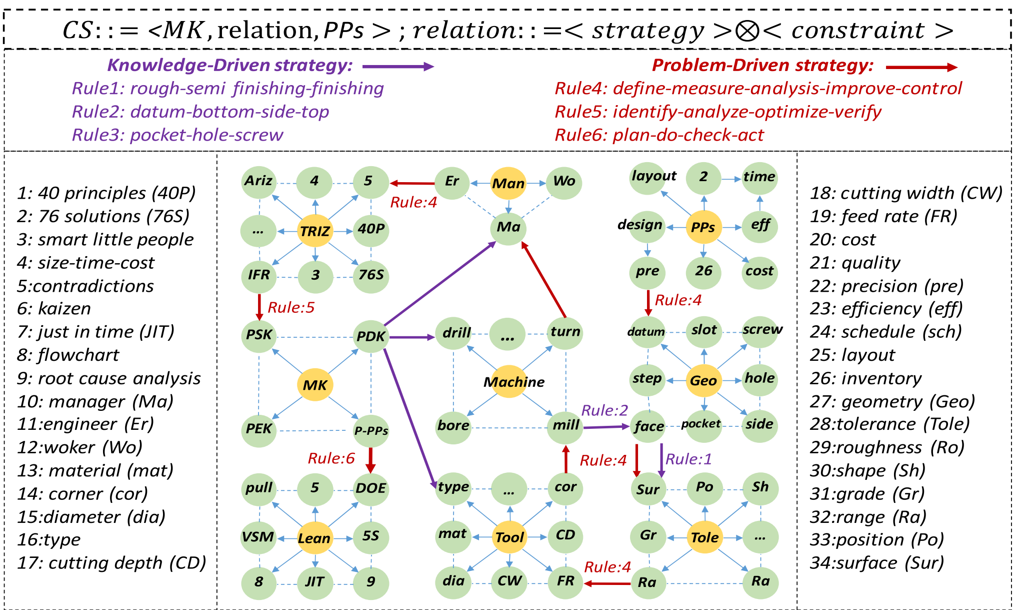

FIGURE 6. Graphic detail of MK matching.

This does not mean the quality of the matching solution is lower. The knowledge used in this strategy is mostly PSK and P-PPs, which has shown great success in the former cases or extracted and summarized from the former cases. For example, to solve the product accuracy defects by the DOE (Design of Experiment) to choose the optimal parameters, problem-driven strategy can follow the continuous solving rules: (1) define defect-measure actuality-analyze factor-improve solution-control improvement (2) plan-do-check-act. It can also get that the problem-driven navigation strategy has stream attribute as shown by the red arrow in the Fig.6, which pulls the right knowledge to a problem.

In addition, the constraint conations are predefined to check or restrict knowledge matching and navigation, such as the disjoint axioms separate certain knowledge sets (i.e., PDK, PSK and PEK) in the distinct classes and enable concept matching within boundaries of entire knowledge graph. while the instance matching constraint aims at avoiding mismatching graph node, the example is that SPC (Statistical Process Control) born to process quality monitor and control based on statistical methods, should be applied to a certain number of samples, but a single piece or small batch order for the current personalized customization situation.

C. SEMANTICS BASED KNOWLEDGE COMPUTATION

To support knowledge matching and satisfy problem semantic query, semantic based knowledge term similarity computation is an alternative. However, the most existing similarity measurement models focus on designing and improving the algorithm accuracy and ignores the distinction between concept and instance and both regarded as entities in the computer and information domain [11], such as statistical regression [47], [48], graph embedding [49], etc. And the most famous low-dimensional continuous vector model-TransE [50] performs well in 1-to-1 relations, while it has issues for tackling 1-to-N, N-to-1 and N-to-N relations. Especially in the domain of industry, MK term entities have more detail descriptions to refine application scenario; for instance, the hole and shaft assembly knowledge is detailed by the diameter, tight assembly fit, clearance fit etc., which may be brief descriptions or standards manuals document.

According to the designed meta-knowledge MKM to express knowledge triples and detail descriptions, we developed an algorithm, named meta-knowledge algorithm (MKA), motivated by a previously proposed methods named ASMOV [51] for knowledge semantic computation, which can compute the similarity of entities from the neighborhood of nodes or from the existence of paths between nodes in the MKG. Primarily, as the Fig. 7 shown, a score function is proposed to evaluate entity matching in the solution recommendation procedure, which contains the similarity of the sets of descriptions to the term entities and the relative graphical relations among the knowledge term entities in the whole MKG. We name the former item intrinsic similarity (IS) and the later one relational similarity (RS). The knowledge semantic computing process is iterative, where an

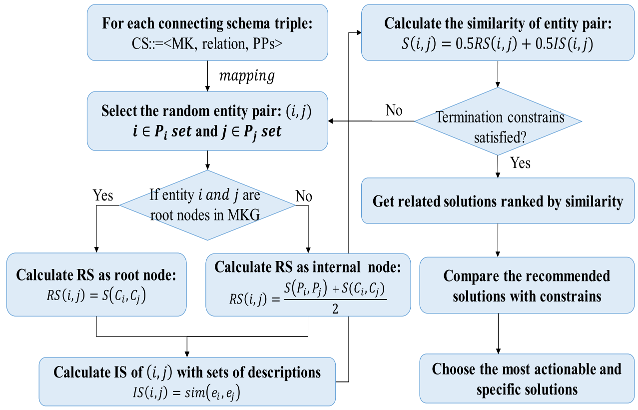

FIGURE 7. The implement logic of knowledge computation.

n1 × n2 term similarity matrix is calculated in sequence, and represents the similarity of term $i \in P_i = \{p_1, p_2, \cdots p_i\}$ to term $j \in P_j = \{p_1, p_2, \cdots p_j\}$. Finally, the $S(i, j)$ is composed of the intrinsic similarity $IS(i, j)$ and the relation similarity $RS(i, j)$ as the following:

$$S(i, j) = 0.5RS(i, j) + 0.5IS(i, j) \tag{4}$$

Because MKG is a hierarchical directed acyclic graph, it means that some knowledge has more impact than others because they are more fundamental. So it is necessary to compute the similarity between the parents and children of the entities, which validates the direction of knowledge navigation (i.e., problem-driven and knowledge-driven). Further, the relational similarity $RS(i, j)$ is computed by determining the similarity between the sets of terms (P_i, P_j) that are the parents of the i and j, and the similarity between the sets of terms (C_i, C_j) that are the children i and j. Here, the similarity $S(P_i, P_j)$ and $S(C_i, C_j)$ are also calculated by the cosine similarity and belong to [0, 1].

$$RS(i, j) = \begin{cases} \dfrac{S(P_i, P_j) + S(C_i, C_j)}{2} & (Internalnode) \\ S(C_i, C_j) & (Rootnode) \end{cases} \tag{5}$$

$IS(i, j)$ is taken as the cosine similarity of the sets of descriptions assigned to term i and j. Here, the cosine similarity is chosen because it works well in representing structural equivalence with high stability in measuring consistency [52]. Given the two vector of attributes, e_i and e_j, the $\cos(\theta)$ is represented using a dot product and magnitude as:

$$IS(i, j) = sim(e_i, e_j) = con(\theta) = \frac{1}{s \times t} \sum \frac{\overrightarrow{l_s} \cdot \overrightarrow{l_t}}{\left\| \overrightarrow{l_s} \right\| \left\| \overrightarrow{l_t} \right\|} \tag{6}$$

where $\overrightarrow{l_s}$ and $\overrightarrow{l_t}$ are components of vector e_i and e_j respectively; the number of description labels to term i is s, the number of description labels to term j is t.

V. APPLICATION CASE AND EVALUATION

On the basis above, a specific MKG platform for PPs solving with MK-driven in the product lifecycle was built based on the Java language and database SQL 2016 on the hardware Huawei Fusion-server RH2288 with a four Xeon E7-4809 v4 @ 2.1GHz and 600GB RAM, Windows Server 2012. All the MK entities focused on the mentioned domain of white-goods, high-end petroleum equipment, package printing equipment and switchgear, and the last trained MKG contains 4568 nodes (46%PDK, 39%PSK, 15%PEK) connecting in 12658 relations.

A. EVALUATION

1) EXPLORING QUERY PATTERNS WITH SIGNAL

To evaluate how the platform based on MKG performs, experiment comparisons, set up by the domain experts and engineers, were implemented to demonstrate the performance of the proposed knowledge matching methods between the PPs query patterns of with temporal signal and without temporal signal. And the performance comparisons indexes were chosen as the following four items:

F1-measure query length is introduced to explore the influence of question length on the answers accuracy. It has to be pointed out that the designed query patterns of with temporal signal, in this paper, it not only keeps an eye on knowledge semantics, but also lifespan of knowledge. As the Fig.8 (a) shown that the best performance of with temporal signal get from a query of averaged 9.3 words and without temporal signal appears in a query of averaged 5.6 words. Although the query length of without temporal signal is less than with temporal signal, the platform precision of with temporal signal is higher (0.79 VS 0.65 on average).

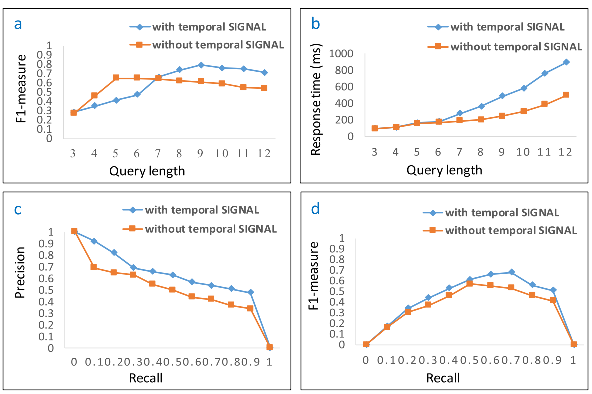

FIGURE 8. Driven by query approach: Performance comparison of (a) F1-measure and (b) response time with different query length, exploring (c) recall-precision and (d) recall-F1 measure.

Response time is statistical data to demonstrate the inferring performance of our developed algorithm driven by this temporal query patterns, which pays attention on calculating the similarity of both knowledge entities and description details. As the Fig.8 (b) shown that the response time of with temporal signal is relatively longer when the query length exceeds the averaged 6 words, which means that temporal signal causes. However, every coin has two sides that the gradient of F1-measure value begins increasing bigger at the point of averaged 6 words, which is the most concerned issue for an inquirer.

Precision-recall usually used in the information retrieval is to assess the fidelity of true positives item in the all actually retrieved items (i.e., false positives and true positives) and the recall is a measure of completeness of true positives item in the items that should to be rightly retrieved (i.e., false positives and false negatives). Meanwhile, F1-measure is a weighted harmonic mean of precision and recall, which gives an integrated evaluation to the information retrieval [53]. Fig.8 (c) shows the precision-recall curves and (d) presents the F1 measure-recall curves. Through the curves, our designed with temporal signal query pattern outperformed the without temporal signal query pattern in both precision and F1-measure due to designed query patterns driven by the SPAROL-ST language can be better understood and search with better accuracy.

Unavoidably, it is necessary to point out that this platform, driven by query patterns, failed to work well under a few query situations, such as query length is smaller than averaged 3 words or exceeds averaged 12 words. The reason may be that the former situation is short of extracting key words under the proposed patterns, while the latter situation is hard to capturing right key words for the redundancy, which need to be explored deeper in the future.

2) COMPARISON WITH PRA

To improve the performance of the proposed graph-based approach named MKA in this paper, the best way is to compare with the other state-of-the-art-approach. Here, a traditional graphical PageRank algorithm (PRA) [54] was chosen as the control object. And the comparison performances were measured by two indexes. Mean reciprocal rank (MRR) evaluates the generated recommendation lists, in terms of the rank where the intended songs appear, and this metric is quite sensitive to the rank values and as a sharp decay [53]. *MRR* can be calculated as:

$$MRR = \frac{1}{|C|}\sum_{c \in C}\frac{1}{rank(c)} \tag{7}$$

where C means the total retrieved set, $|C|$ is the number of relevant entity triples, $rank(c) = 1$ decides a retrieved result is relevant and zero otherwise.

Secondly, $HR@n$ indicates whether if the described items appear on the generated recommendation lists (presence) and how many times they appear (frequency)within top-n recommended items [55].

$$Hit@n = \frac{1}{|C|}\sum_{c \in C}\left(\delta\left(rank(c) \leq n\right)\right) \tag{8}$$

where δ is the indicator function, n means the top-n recommended items.

Using 50 test query question within length between 3 and 12 words, this paper selected the MRR and *Hit@10* as the comparison indexes between the traditional *PRA* and the

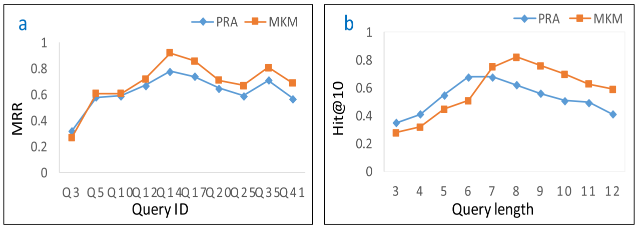

FIGURE 9. performance comparison between *PRA* and *MKM* (a) *MRR* and (b) *Hit@10*.

Problems Brief

➢ **The manufacturing enterprise**

Enterprise B is a producer of package printing equipment in China. There are 1000+ employees (161 R&D personnel), working with 42 high precision machines, five assembly lines and outputting 48 kinds printing machines. To enter the international market from 2016, the enterprise urgently wants to improve the performance of products.

➢ **Production problems (PPs)**

Roller assembly accuracy is one of the main factors determining the product performance of uniformity of ink layer and the correct conduction of paper. Take the DL250 machine as a point, the production problems can be described as:

- what is the cause and effect of the low accuracy of roller assembly ?
- how to improve the roller assembly accuracy?

FIGURE 10. Problem brief for a manufacturing enterprise.

approach(MKA) proposed in this paper, which are two common ranking metrics in recommender system. As the Fig.9 (a) shown that the MRR performance of MKA is better than *PRA*, but the query 3 among the 50 test queries. After in-depth analysis, it can be drawn that the number query 3 is too short to be recommended relevant items and both the MRR values of PRA and MKA are smaller (0.32 and 0.27), which can also be proved by the *Hit@10* performance. On the other hand, from the Fig.9 (b), we can know that *Hit@10* value of MKA begins increasing bigger than that value of PRA at the point of averaged 7 words. Notice that the best performance of *Hit@10* for MKA is at the range of 7 and 9 and all the values are bigger than 0.75, which can provide an optimal query question length for an inquirer. So, the approach proposed in this paper makes sense.

B. A CASE STUDY

A case of improvement of coaxiality error in roller assembly of printing machine has used as an industrial application to show how can MKG support the problem-solvers make a right decision for PPs solving (roller assembly accuracy improvement) during the assembly process.

To answer the problem shown in the Fig 10, a knowledge platform based on MKG is built to recommend the most relevant knowledge and tools driven by the problem query. According to the query words (what and how), temporal signal (2016) and key words (roller assembly etc.) on problems, the most feasible solutions composed of relevant knowledge terms and detail descriptions are figured out by the ranking similarity score of each knowledge entity shown in the Fig 11. Specifically, MK is shared among the problem solvers helping decision-making and the problem is solved as the following steps. Firstly, according to problem appearances like the roller assemble tolerance is beyond the upper and lower control lines, the problem-solvers could analyze and measure root causes and query and

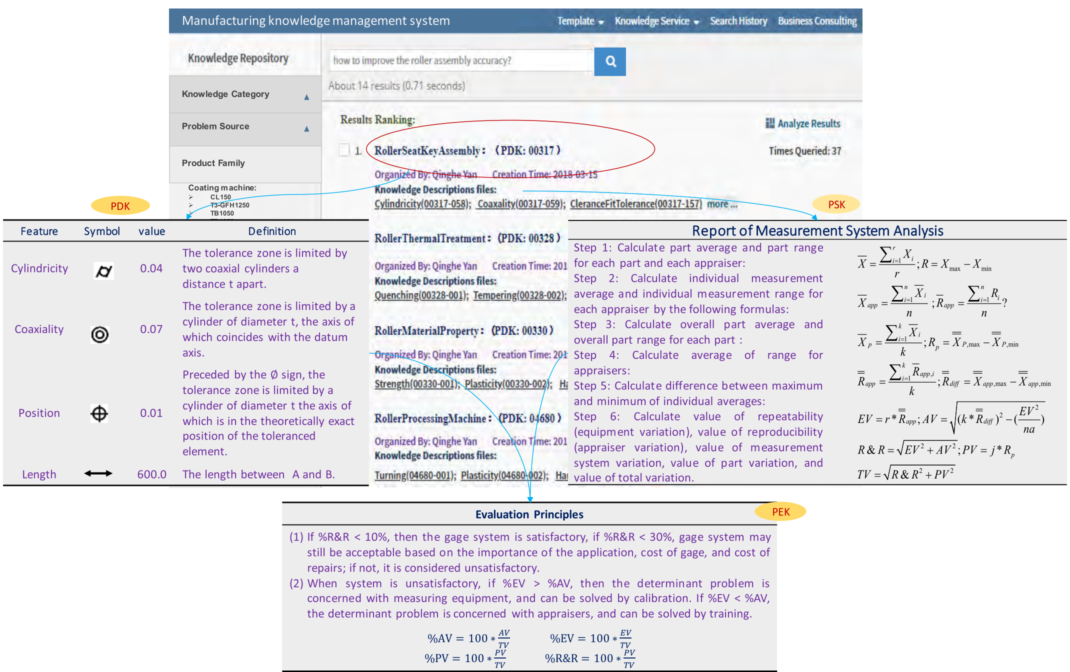

FIGURE 11. A case of PPs solving with MKG based platform.

TABLE 2. The indicators of computational details with MGK platform.

Genre	Indicator	Formula	Specifics
Personnel Skills	searching time	$p_1 = \frac{Time_{sea}}{Time_{pro}}$	$Time_{sea}$: *MK searching time* $Time_{pro}$: *whole improvement time*
	training pass rate	$p_2 = \frac{Pass_{num}}{Train_{num}}$	$Pass_{num}$: *number of trainees* $Train_{num}$: *number of total training*
Technology Innovation	technology promotion	$p_3 = \frac{Succe_{num}}{Exten_{num}}$	$Succe_{num}$: *number of successful technological promotion* $Exten_{num}$: *total number of successful technological promotion*
	patent	$p_4 = Pro_{pat}$	Pro_{pat}: *probability of innovative patent applications*
Quality	product percent of pass	$p_5 = \frac{Quality_{num}}{Check_{num}}$	$Quality_{num}$: *number of qualified product inspection* $Check_{num}$: *Total number of product sample inspection*
Benefits	benefits	$P_6 = \frac{Savings \times P_{suc}}{Cost \times T_{com}}$	P_{suc}: *probability of success for improvement project* (P_3) T_{com}: *time to completion of a whole project* (*week*)

get the recommended PDK: RollerSeatKeyAssembly (such as geometry and position knowledge: cylindricity, coaxality, CleranceFitTolerance, etc.); MaterialProperty (such as strength, plasticity, hardness, toughness, fatigue strength); ThermalTreatment (such as quenching, tempering, annealing, etc.); ProcessingMachine (such as turning, welding, drilling, milling, cutting tool, etc.) and RollerAssembler (such as seniority, skill, gender, education, etc.). Secondly, measured and compared with those PDK enterprise standard and criteria using PSK (such as Prato Chart, MSA, SIPOC, etc.), problem-solvers confirm that roller radial deformation is the true defect, which is caused by the stress and strain factors in the former thermal treatment process. To optimize the current thermal parameters, a relevant DOE, also as a point of PSK, is selected to find the ideal parameter solution of quenching temperature, time and tempering temperature (1275°, 8min, 560°) with an orthogonal table L9(34). Lastly, to verify the continuous improvement of roller radial run-out (from 0.04 to 0.02 mm), a PEK point R&R analysis is recommended to evaluate the gauge repeatability and reproducibility (6.7%) of improving process, which is satisfactory.

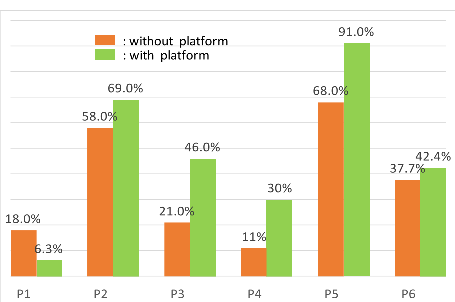

FIGURE 12. Benefits for package printing machine production process with MGK platform.

Extending to the whole production processes of package printing machine, a comparison and the benefits of using MKG platform are illustrated by the following perspectives as shown in the Fig 12: improving personnel skills (i.e., P1: knowledge searching time and P2: pass rate of skills training), technology innovation (i.e., P3: technology promotion and P4: patent application), quality (i.e., P5: percent of product pass) and benefits (i.e., P6: Pareto priority index). And the indicators computational details can refer to the table 2 in appendix.

VI. CONCLUSION AND FUTURE WORK

In this paper, a three-layer framework reference model of PPs solving with MK is proposed, which can help solver making right decision in right time with right knowledge. Specially, the main contribution of our work can be concluded as the following: (1) an Ontology-based MKG is constructed with a unified MK-filter to collect and integrate multifactor and multilevel manufacturing knowledge. And a graph-oriented meta-knowledge model (MKM) is proposed to detail the MK term in concept, instance description, which can accurately distinguish the knowledge entity semantics. (2) during the process of knowledge matching and navigation, a score function to evaluate entity semantic matching in the solution recommendation is developed, which contains the similarity of the intrinsic term similarity (IS) and relational term similarity (RS) between two knowledge entities in the MKG and out performs the traditional PRA approach. (3) taking into account the knowledge entity lifespan property, the problem query patterns with the temporal signals, starting with traditional query words "5w2h", is explored.

For future work, we plan to (1) explore the flexibility of query length based on a natural language query semantic knowledge graph constructing in manufacturing sector,

(2) further investigate the knowledge relation extraction and matching methods, (3) explore the application and learning fields.

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