Knowledge Graphs and Intelligent Engineering Systems: Theoretical Integration and Applications in Industrial Decision-Making

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ABSTRACT

Knowledge graph is a structured representation of domain entities, their attributes and their relationships, coded as a labeled directed graph. They have become the main way to integrate different and scattered knowledge into intelligent engineering systems. Different from the statistical machine learning model in which knowledge is hidden in its parameters, knowledge graph shows the reasons, classifications and process relationships in a way that can be understood by machine and human experts. This is why they are very good at being the semantic basis of industrial decision-making. This review focuses on knowledge graphics technology and how to apply them to intelligent engineering systems using network physical system (CPS), system engineering and information theory. She said that the knowledge map is a semantic compatibility layer, which allows the representation of statistical learning to be connected with the ontology in the engineering field. We analyze four transformation paths that artificial intelligence enhanced by knowledge graph promotes the development of manufacturing industry: from production knowledge enclosed in isolated data islands to semantically integrated knowledge, from reactive fault response to ontology-driven predictive diagnosis, from isolated machine control to knowledge-based autonomous operation, from independent subsystems to unified network physical ecosystem based on ontology. We have studied the application of fault detection based on knowledge graph-guided reasoning, knowledge-based digital twin manufacturing cell, intelligent process optimization based on ontology constraint learning and man-machine collaborative decision support. We use industry use cases and written frameworks. We have studied some thorny problems, such as the bottleneck of knowledge acquisition, the decay of temporary knowledge, and extensible reasoning under incomplete graphics. We also discussed the future things, such as automatic knowledge graph construction, neural symbol integration and cognitive digital twins. A new idea is to regard the completeness of knowledge graph as a measurable thing, and it depends on each application, rather than a perfect goal that can never be achieved.

Keywords: Knowledge Graphs; Ontology; Industrial Decision-Making; Cyber-Physical Systems; Digital Twin; Neuro-Symbolic Integration; Fault Diagnosis; Intelligent Manufacturing.

1. INTRODUCTION

Intelligent engineering systems accumulate knowledge from two fundamentally different sources: operational data streams generated by physical processes and sensors, and structured domain knowledge—engineering principles, failure taxonomies, process constraints, maintenance protocols—that experienced practitioners encode over decades of practice. Statistical machine learning methods are very good at finding hidden patterns in the first data, but they can't explain or reason the second data alone: the deep neural network trained on the vibration spectrum can learn to identify the bearing fault signal compared with normal operation, but it can't explain why the signal means bearing fault, nor can it relate this conclusion to maintenance plan, spare parts inventory or production plan that should be triggered by diagnosis. Knowledge map directly solves this problem. As a structural representation of domain things (machines, components, failure modes, process parameters, maintenance operations) and their types and directions, knowledge maps encode the reasons and process knowledge implied in statistical models. They provide a basis for inference, interpretation and reasoning between different fields, and neither the original data nor the learned parameters can do this alone [1,2].

The theoretical reason of knowledge maps in intelligent engineering system is not only their practical use as a place to store information. From the point of view of CPS theory, the computing and physical parts of a network physical system have no common semantic representation of the things they control, which cannot well transform sensor observations into useful decisions for engineering, nor can it correctly spread the consequences of decisions throughout the system [3]. Knowledge graph gives this common semantic layer: they form a formal model of engineering field, in which the computational process of network part and the observable things of physical part are represented as connecting nodes in the graph, which makes reasoning between the two layers better than if each layer is separate. From the perspective of information theory, knowledge graph can be used as a channel of prior knowledge, which can reduce the uncertainty of statistical calculation by giving structural restrictions on physically possible relationships-this is a regularization that cannot be obtained only by training data, which directly improves the sample efficiency and the reliability of AI system decision-making [4].

The rest of this article is as follows. In the second part, the theoretical basis of knowledge graph enhancing intelligent engineering system is established. Section 3 analyzes four transformation paths. Section 4 focuses on the application of fault diagnosis, digital twin cell manufacturing, process optimization and man-machine decision support. The fifth section discusses the challenges and opportunities. End of section 6.

2. THE THEORETICAL FOUNDATION OF ARTIFICIAL INTELLIGENCE AND INTELLIGENT ENGINEERING SYSTEMS

2.1 The Connotation and Characteristics of Intelligent Engineering Systems

In the knowledge graph paradigm, the intelligent engineering system is described as a CPS, its network layer maintains a clear and constantly updated physical domain graph structure model, and its statistical inference engine uses the graph as a semantic reference to verify and explain the learned inferences [3, 5]. Three characteristics make these systems different from traditional intelligent systems that use data. First of all, they have ontological basis: the contents discovered by statistical model (such as detected faults, predicted faults and suggested operations) are associated with nodes in domain ontology, and their relationship shows causal knowledge in engineering. This will transform the incomprehensible statistical results into clear engineering decisions. Then, they have a multi-hop relational reasoning: because the knowledge graph links things with different types of links, the automatic reasoning machine can follow the reasoning chain, which goes through several steps-for example, from the abnormal sensor to the state of the room, then the failure mode, then the maintenance operation, and then the production impact-which is impossible for a simple classifier. Thirdly, they have semantic interoperability: when the things and relationships of two subsystems are based on a common ontology vocabulary, different subsystems in the engineering ecosystem can exchange information in a consistent way. This allows coordination among subsystems required by CPS at the ecosystem level, but pure statistical models-each with its own implicit feature space-cannot be provided structurally [3].

2.2 The Theoretical Logic of Artificial Intelligence Empowering Engineering Systems

The theoretical logic to explain how knowledge map can help intelligent engineering system can be understood in two ways: information thought and engineering thought. In terms of information, knowledge graph limits the possibility that AI model can be found: if AI model is associated with knowledge graph, it can't be concluded that it violates graph rules, which makes the search easier and improves the way of learning the model in few examples and how to keep it good even with different data [4]. This connection is realized by a method called knowledge-graph embedding, which converts the things and links in the graph into small numbers, so that the model can learn the gradient, keep the shape of the graph, and use neural networks [2]. In engineering, knowledge graph helps to understand the source of decision-making in CPS system: every decision can trace the basic ideas and engineering rules in the graph, which gives clues that cannot be provided by a single statistical model [1,5].

The integration of knowledge map and statistical learning framework (sometimes called neural symbol integration) is the technical mechanism to realize these theoretical advantages. When the convolutional neural network for classifying vibration spectrum is enhanced by the fault pattern knowledge graph, the graph limits its classification results to physically possible fault categories, and the improved system provides more reliable diagnosis by using the known properties and use history records of the room, which is less than the driving data of neurons alone, and an isolated neural network cannot do it except that it provides an explanation for each diagnosis that can be tracked in the graph [4].

3. THE TRANSFORMATION PATH OF INTELLIGENT ENGINEERING SYSTEMS MODE DRIVEN BY ARTIFICIAL INTELLIGENCE

3.1 Transition from Standardized Production to Personalized and Flexible Manufacturing

Standardized production uses fixed process knowledge in design. Personalized and flexible manufacturing needs process knowledge that can adapt to different products, materials and working conditions at any time. Knowledge graph helps this transformation by providing a dynamic and modifiable semantic model of production domain, in which new product configuration is represented as an extension of graph without redesigning the whole process specification [6]. A systematic review of knowledge maps in manufacturing and production confirms that knowledge fusion (integrating information from different sources such as engineering standards, operation databases and expert rules into a unified semantic representation) is the main application of knowledge maps in manufacturing industry today, precisely because it solves the semantic integration problem that prevents flexible manufacturing systems from dynamically combining knowledge from different sources [6]. This fusion function is very important for customized manufacturing, in which product customization creates a new combination of process parameters, tool configuration and quality requirements, which cannot be fully covered by existing knowledge sources.

3.2 Transition from Reactive Response to Proactive Prediction and Optimization

Knowledge graph-guided reasoning allows you to proactively predict failures. It uses multi-step chain reasoning (multi-hop inference chains) that link the patterns of the sensors that show the first signs of the (early-indicator sensor patterns) - even if these patterns don't tell you yet what kind of outage is going to happen - to the types of outages (failure modes) and to the states of the components These patterns, along with known component properties and the operational context, are most likely to announce. A knowledge graph that contains the chain of causes since the surface degradation of a bearing.(bearing surface degradation) up to bearing blocking (bearing seizure) through the change in the frequency of vibration Vibration frequency shift and lubrication failure (lubrication failure), which is filled with special parameters for each component from the engineering documents This enables an AI system to reason ahead of time on this chain instead of detecting only the last event [5, 7]. The knowledge-driven digital twin manufacturing cell architecture demonstrates this proactive capability in concrete terms. It puts domain knowledge graphs in a digital twin framework, so that the twin simulation is guided by ontological process constraints instead of purely data-driven models. This allows proactive optimization decisions - such as parameter adjustments, maintenance scheduling, or reconfiguration planning - to be made that are both based on the operational data learned and verified with the engineering principles of the domain [5].

3.3 Transition from Manual Operation to Autonomous Intelligent Control

Autonomous control requires that decisions made by artificial intelligence can be verified by using safety rules and operational restrictions without manual processing. Knowledge graphs are helpful for this check: they represent axioms as graphs for rules, safety boundaries and work instructions. Before performing an action, you can check it by automatically browsing the graph. Therefore, autonomous controllers can use structured knowledge to verify their decisions, rather than just using rewards or training data to know what to do [4, 5]. The knowledge-based digital shadow architecture for machining process shows how it works: the shadow knowledge base contains the relationship between process parameters, tool wear rate and surface quality. Before sending the order, we will check whether the proposed changes conform to the rules. This provides security based on ontology, which cannot be provided by statistical model alone [7].

3.4 Transition from Isolated Systems to Integrated Cyber-Physical Ecosystems

Ecosystem-level integration of heterogeneous CPS components—sensors, controllers, schedulers, maintenance systems, logistics modules—requires a shared semantic vocabulary in which each component's state and decisions can be expressed and understood by other components. Knowledge graphs provide this shared vocabulary through common ontologies: when the fault diagnosis subsystem, the maintenance scheduling subsystem, and the production planning subsystem all share a common ontological representation of machine states, failure modes, and maintenance actions, they can communicate and coordinate in semantically well-defined terms rather than through ad hoc message passing that requires bilateral translation at every subsystem interface [1, 3]. We extend the existing transformation framework, and propose that we should not only evaluate the integration at the ecosystem level through system connectivity, but also evaluate it through ontology coverage-express the proportion of communication events between subsystems in terms fully covered by ontology vocabulary of shared knowledge graph-and regard ontology incompleteness as an engineering defect that can be measured and corrected during system design, rather than the inevitable result of heterogeneous integration.

4. APPLICATIONS OF ARTIFICIAL INTELLIGENCE IN INTELLIGENT ENGINEERING SYSTEMS

4.1 Application in Intelligent Fault Diagnosis and Predictive Maintenance

Knowledge map-guided fault diagnosis is better than statistical method to find faults, which we can see from two aspects. First of all, the chart shows the relationship between faults and symptoms, which reduces false positives because it says the results must match the component type, history and sensor. Statistical methods can't do this because they don't know these connections. Then, the chart can be reasoned: it starts with symptoms, goes through intermediate causes, and reaches the real cause, even if there are not many examples to learn. This is because charts use engineering rules, not just statistics [2,4]. For faults in electrical systems, it is obvious that these graphical methods are superior to statistical methods, especially when there are multiple faults at the same time and the symptoms are mixed, simple methods cannot solve them [1].

4.2 Application in Intelligent Process Optimization and Quality Control

The architecture of knowledge-driven digital twin manufacturing cell demonstrates how to use knowledge map to improve manufacturing. It combines knowledge map, tells manufacturing rules, what parts can do, quality requirements, and the optimizer with digital twin simulation engine and learning machine. This provides a system that learns from working data, abides by manufacturing rules, and keeps pace with digital twins [5]. This architecture is very important, because it can link quality with optimization: because the influence of parameters on quality is written in the diagram as a causal relationship, not just a link to learn but not understand, it can provide parameter suggestions, which are good for data and verified by quality rules. This avoids the problem that the optimizer only looks at numbers, and can find settings that run on numbers, but it breaks the quality rules that we have not learned. The knowledge-based digital shadow system for machining shows this point well: the parameter hints given by shadow always conform to the quality rules, while the irregular hints sometimes violate them [7].

4.3 Application in Intelligent Human-Machine Collaboration and Operational Efficiency Enhancement

Knowledge map helps humans and machines work together to make engineering decisions. They provide a common way to understand why AI makes some suggestions. They convert the numbers of statistical models into steps that engineers can view, verify and use their knowledge to make changes [4]. This is very important for maintenance and planning. When an engineer receives a maintenance suggestion based on the knowledge map, it will be displayed as a path in the fault-cause-maintenance ontology, with sensor evidence and verification. An engineer can judge whether it is correct by using his judgment, instead of accepting or rejecting it like a black box. Research shows that the interpretation of knowledge map helps experts to trust artificial intelligence more than statistical methods, because knowledge map uses words that engineers know, and the numbers used in statistical data do not always correspond to the real reasons [4]. Operational efficiency gains from this enhanced trust and collaboration translate directly into reduced override rates for valid AI recommendations, higher utilization of AI-generated scheduling and maintenance plans, and faster adoption of AI-assisted process improvements.

5. CHALLENGES AND PROSPECTS OF ARTIFICIAL INTELLIGENCE EMPOWERING INTELLIGENT ENGINEERING SYSTEMS

5.1 Current Main Challenges

Four challenges are that the practice of knowledge map in intelligent engineering system is very important at present. First of all, knowledge acquisition-the process of filling the knowledge map of a field with accurate, complete and up-to-date engineering knowledge-is still a time-consuming and arduous work, which requires a lot of help from experts in this field, and also needs to extract information from engineering documents, standards and maintenance records. The systematic study of knowledge map of manufacturing industry shows that the empirical research on automatic knowledge acquisition and industrial application has not been fully developed compared with theory and construction work [6]. Secondly, the decline of temporary knowledge is a structural problem: when parts age, process conditions change and product requirements change, the engineering knowledge put into graphics becomes more and more inaccurate, but most of the recorded manufacturing knowledge graphics architecture has no systematic rules to find and update outdated information [5]. Third, scalable automated reasoning over large, incomplete knowledge graphs remains computationally demanding: industrial knowledge graphs encoding entire production ecosystems span millions of entities and relationships, and exact logical reasoning over such graphs at the latency required for real-time control is generally infeasible with current reasoners, forcing reliance on approximate methods whose error bounds are not always well characterized for engineering-critical decisions [1, 2]. Fourth, knowledge graph incompleteness—the fact that no engineering knowledge graph fully covers all the causal relationships relevant to all decisions the system may be asked to make—creates systematic gaps that can cause knowledge-graph-guided AI to produce confidently incorrect recommendations when queried about relationships not encoded in the graph [2].

5.2 Prospects for Future Development Trends

Three trajectories appear most promising. Automated knowledge graph construction from engineering text corpora—exploiting advances in information extraction, relation classification, and entity linking applied to technical manuals, maintenance records, and standards documents—offers a path toward reducing the manual expert burden of knowledge acquisition to the validation rather than the creation of graph content, though the reliability of automated extraction from technical documents remains a research frontier requiring domain-specific evaluation [1, 2]. Neural symbol integration architecture directly puts the structure of knowledge graph into neural network calculation, instead of connecting the separately trained neural network to the separately maintained graph, which promises to eliminate the alignment cost of the next graph while maintaining the gradient learning advantage of neural architecture, and is the most active frontier in the research of AI engineering knowledge graph today [4]. Starting from the extension of ontology coverage proposed in Section 3.4, we also suggest that the integrity of knowledge map should be regarded as quantifiable application-specific engineering requirements, and the coverage threshold should be defined according to decision-making categories (such as coverage requirements used in software testing), instead of being an asymmetric ideal, so as to provide a design specification, and the construction of knowledge map can measure and certify key applications before deployment.

6. CONCLUSION

This review regards the knowledge map as the semantic bottom layer, and links the pattern recognition ability of statistical AI with the engineering knowledge in intelligent CPS, based on the analysis of CPS theory, system engineering and information theory. The great theoretical idea is that knowledge graph is used as a semantic interoperability layer (to help the coordination between subsystems), as a priori knowledge channel to limit reasoning (to improve the reliability and robustness of statistical models), and as an explanation substrate (to provide reasons for artificial intelligence suggestions that can be followed in graphs). Among the four transformation paths we studied, knowledge graph is still the bridge between data-driven learning and domain verification decision-making. Specific examples include knowledge-driven digital twin manufacturing cells, ontology-constrained process optimization and multi-hop fault mode reasoning. The application in fault diagnosis, process optimization and man-machine cooperation shows the value of this bridge in different engineering fields. However, there are some problems such as knowledge acquisition, temporary attenuation, extensible reasoning and incomplete graphics. These problems are the engineering frontiers that need to be solved in order to use knowledge graphics enhanced AI for large-scale security industry deployment. A new way to treat the integrity of knowledge map as something that can be specified and tested is to treat the specific steps of knowledge map engineering with the rigor required by the industry.

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