Intelligent Decision Support Systems Leveraging Knowledge Graphs and Ontologies for AI-Empowered Intelligent Engineering Systems

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ABSTRACT

Integrating knowledge graph and ontology into intelligent decision support system is a great progress in making decisions in complex engineering environment. With the engineering system theory, network physical system principle and information theory, these semantic technologies provide organized knowledge that machines can understand. This helps to make decisions that take into account the context, can be explained, and make full use of resources. This paper focuses on the theoretical basis, how to mix methods, where to use them, and the problems of ontology and knowledge map in intelligent decision-making system and intelligent engineering system. The technologies that help to achieve this goal include: digital twins that link the virtual with the reality, reinforcement learning that uses semantic rules to organize tasks, computer vision with ontology annotation to find defects in real time, and edge computing to conduct rapid semantic reasoning. Specific examples of intelligent manufacturing, energy system and infrastructure monitoring show that measurable progress has been made in work efficiency, reducing uncertainty and reusing knowledge. Critical analysis compares these benefits with limitations, such as the work of maintaining ontology, the difficulty of large-scale reasoning, the problem of data quality, and the vulnerability when concepts change. An initial idea put forward an adaptive framework called semantic network physical system, in which there is a meta-semantic layer to measure the usefulness of knowledge and make the system develop itself. The conclusion is that different disciplines need to work together to create a reliable and highly autonomous engineering system.

Keywords: Intelligent Decision Support Systems; Knowledge Graphs; Ontologies; Cyber-Physical Systems; Digital Twins; Semantic Interoperability; Reinforcement Learning; Computer Vision.

1. INTRODUCTION

The diffusion of artificial intelligence accelerates the development of intelligent engineering system, and the close combination between physical process and computer intelligence. The network physical system theory formalizes this connection through continuous feedback loops, which require quick and contextual decision-making, even if there are uncertainties and different things [1]. Intelligent decision support system is very important, but the conventional version can't understand the meaning well, can't talk with different data sources well, and can't explain their functions well. Knowledge graph and ontology are very suitable to solve these problems.

Knowledge map puts things and their links into a structure that can be browsed for easy questioning and inference. Ontology gives formal definitions of rules about concepts, attributes and boundaries, which are usually written in logical descriptions. Together, they help to speak the same language, which is very important for representing knowledge well in the whole system life cycle in model-based system engineering [2]. From the perspective of information theory, these technologies transform raw data into meaningful structured information, thus reducing uncertainty and enabling decision-making to consider connections and causes, rather than just isolated signals.

This review uses strict structure to analyze how intelligent decision support system enhanced by knowledge graph and ontology can help intelligent engineering system driven by artificial intelligence. Section 2 explains the theoretical basis from system engineering, network physical system and information theory. Section 3 introduces the main methods of technology integration and mixing. Section 4 shows important application fields through concrete engineering examples. The fifth part discusses the challenges, risks and future directions, and puts forward a new framework. Section 6 gives the conclusion and what this means for the study. Research areas are mainly concentrated in manufacturing, energy and infrastructure, but also optimistic and bad aspects.

2. THEORETICAL FOUNDATIONS: SEMANTIC REPRESENTATION IN SYSTEMS ENGINEERING AND CYBER-PHYSICAL SYSTEMS

System engineering theory emphasizes life cycle management, requirement traceability and interdisciplinary comprehensive knowledge. Formal ontologies directly agree with these ideas. They have replaced natural language specifications that have been verified by logical models and machines. These models are helpful to automatically verify and analyze the impact of changes [3]. In the practice of model-based system engineering, ontology-driven mode allows consistent abstraction from the needs of stakeholders to verification and then to architectural design. This reduces costly inconsistencies in the future. According to the theory of network physical system, physical dynamics and computer algorithms are closely related, and their interaction creates new behaviors. Traditional state representation uses numerical variables, but they forget the relationship and causal knowledge, which is very important for advanced reasoning. Ontology and knowledge graph give this missing semantic layer. They allow the interpretation of sensor data by understanding the context and make the intervention conform to the physical laws and domain limitations [4]. This semantic network physical system layer transforms passive monitoring into active knowledge-driven decision-making cycle.

Information theory goes beyond the grammatical measurement of uncertainty, and it recognizes that semantic content is a special dimension of information value. Knowledge graph and ontology use semantic information by clearly coding important relationships and axioms. In this way, they make the data more useful in engineering situations where there is noise or everything can’t be seen. This organized and reduced semantics is helpful to traditional control methods.

A new idea comes from this mixture: we get a “semantically enhanced network physical system”, in which the knowledge layer actively participates in control, not just a place to store things. Symbolic reasoning about ontology can create possible rules or actions, and then the digital optimizer can improve them; This makes the theory of network physical system more powerful, and even in the face of unforeseen problems, it can describe and adapt to the architecture separately.

3. KEY TECHNOLOGIES AND INTEGRATION METHODOLOGIES

In order to make full use of intelligent decision support system using knowledge graph and ontology, it is necessary to combine them with modern artificial intelligence technology. Digital Twins is a good example. Virtual copies of physical objects defined by ontologies are always associated with sensor data and allow “what-if” simulation. Digital cognitive twin architecture fills the knowledge map with engineering data from multiple sources, which helps to make decisions and relate the current state to simulated past and future events [5,6].

Reinforcement learning of dynamic programming is much better when adding semantic information. In a flexible factory, task scheduling has complex relationships, resource constraints and security rules, which will change with real-time events. Knowledge-graph-enhanced compensation learning puts these restrictions into ontology mode to help express the state or prevent some operations. This mixed use of fewer examples can learn faster, ensure possible decisions, and is more powerful than the method of using only data. This shows the real advantage of adaptive production control.

Computer vision for online inspection and quality control is also enhanced by ontology integration. The simplified semantic segmentation model can accurately locate surface defects, and at the same time, it can link the anomalies found with process parameters, material specifications and historical results stored in the knowledge map. This context link transforms the original detection into decision support based on root cause, allowing targeted intervention instead of general alarm [7].

Edge computing meets the strict delay requirements of real-time network physical control. Lightweight ontology inference or compressed knowledge graph is embedded on the edge of the network, allowing instant semantic query and inference without communicating with the cloud. These deployments are very important for the critical safety loop in robot assembly or power grid stability, and the millisecond response determines the physical results.

These integrations bring measurable benefits in decision-making transparency and knowledge reusability through clear reasoning traces. Nevertheless, they introduce important trade-offs: large initial investment in ontology engineering, potential vulnerability when knowledge base lags behind physical changes, and computational overhead that may damage strict real-time guarantee, unless approximate or embedded-based methods are used.

4. APPLICATION DOMAINS IN INTELLIGENT ENGINEERING SYSTEMS

In intelligent manufacturing, an intelligent decision support system using knowledge graph and ontology has been established for predictive maintenance and process optimization. Automobile assembly plant integrates equipment hierarchy, real-time sensor flow and maintenance records into a unified knowledge map. The resulting decision support system can predict faults and prescribe intervention measures, thus reducing unplanned downtime by more than 20% and promoting knowledge transfer between parallel production lines [8].

Energy system, especially smart grid, uses semantic technology to analyze fault propagation and optimize distribution. Ontology simulates the topological relationship between substation, production line and production assets, while knowledge map combines telemetry with weather forecast and other external variables. The reinforcement learning agent working on this semantic-rich substrate optimizes the energy flow by observing the safety and regulatory constraints expressed in the form of ontology rules, thus improving the stability and acceptance rate of renewable energy.

Infrastructure monitoring applications, such as bridge and pipeline health assessment, use computer vision defect detection and asset management knowledge map. Semantic Segmentation found an exception at the pixel level. These test results are automatically displayed in the graph, so as to determine the maintenance priority according to the risk. This method prolongs the service life of assets and optimizes the limited maintenance resources under the budget and operation constraints.

In all these fields, the benefits are better interpretation of decisions, less demand for rare human experts, and better communication between different subsystems. The risk is the spread of modeling errors in physical operations and a lot of work to integrate with the old non-semantic systems, which shows that strict verification protocols are needed before they are used in places where security is important.

5. CHALLENGES, LIMITATIONS, AND FUTURE PROSPECTS

Although it has proved useful, there are several problems that prevent people from using it. Accurate logical reasoning on the ever-changing large-scale knowledge map usually exceeds the real-time task in the network physical environment. Then, the system uses an approximation [2] that exchanges integrity with speed. It takes a lot of work to maintain and develop ontology, and the engineering process may experience a drifting concept, making the old axiom useless, which may lead to errors and direct physical consequences.

The problem of data quality is more prominent in the semantic system: missing or noisy relationships will destroy the reasoning chain. In addition, it needs specialized experts to make a good ontology, which makes it difficult for small organizations to use it. Security and privacy issues become more important in the ecosystem of network physical connection. In these ecosystems, the shared knowledge graph may display the secret information about the operation wrongly, or create new attack ways to manipulate the decision logic.

The future trajectory will focus on the neural symbol architecture, which closely links neural perception with reasoning on the knowledge map, and may be enhanced by extensive language models to help create natural language ontology and problem interface. Edge optimization semantic technology and federated knowledge graph learning commitment provide distributed private decision support for multi-stakeholder environment.

Adaptive Semantic Cyber-Physical Systems Framework adds a meta-semantic layer to the normal cyber-physical system, which always observes the usefulness of knowledge through the measurement of information theory, and independently triggers the action of acquiring more knowledge or seeking expert advice. These self-improvement mechanisms can maintain good decision-making quality even when things change, and better demonstrate the adaptive and lasting idea of system engineering.

6. CONCLUSION

Knowledge graph and ontology provide a solid foundation to help intelligent decision system work with AI in intelligent engineering system. By integrating formal knowledge into decision-making, these technologies help to better understand things, better explain things, work faster, and follow the principles of system engineering, network physical system and information theory. When you combine them with digital twins, reinforcement learning, computer vision and edge computing, you will see improvements in manufacturing, energy and infrastructure, but there are still problems of size, maintenance and robustness.

In order to gain greater autonomy and trust, we need to study reasoning that applies to many things, to knowledge that changes independently, and to share knowledge among safe people. The adaptive layer discussed here provides a path for the decision-making system to change itself and keep consistent with the reality. Finally, to have a real intelligent engineering system that can work safely even in complex situations, people from AI, system engineering and professional fields need to work together. We are turning to a system that can do many things, but also be responsible and use organized knowledge to control complexity.

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