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Knowledge Graph for Low Carbon Power and Energy Systems

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ABSTRACT

Knowledge graph, originated from Semantic Web technology, is an emerging technology in the field of artificial intelligence (AI). As miscellaneous data and knowledge accumulate in power and energy system sections, an expert system with cognitive competence based on knowledge graph technologies can assist complex decision-making and quick response in relevant knowledge-intensive tasks. This study introduces the basic concept, key research progress and prospects of knowledge graphs, and their applications in low carbon power and energy systems.

Keywords: power and energy systems, knowledge graph, knowledge representation, knowledge extraction, semantic web technology, neural network

1. INTRODUCTION

The carbon reduction targets articulated by the Paris Agreement make it imperative for countries to make significant changes to their power and energy systems to reduce CO2 emissions. One major approach is to integrate and increase the capacity of renewable energy sources.

However, there are multiple challenges in the adoption of renewable energy in power and energy systems. In addition to the well-known instability issue of renewable energy sources, which can lead to frequency and voltage deviations when they are integrated into the grid [1], decision-making in renewable-integrated systems often requires interdisciplinary knowledge and heterogeneous data inputs, such as location-related time-series-type weather or environmental information, land availability, technology-specific cost and market information, technical constraints for different technologies, and demographic information. The rapid development and future needs of distributed energy systems have also fostered the demand for intelligent decision support systems with advanced data management to cope with broad, complex, and multi-dimensional information and to provide rapid response and support automated knowledge formation in the era of big data [2].

To address the challenges, knowledge graphs are widely used as data frameworks for power and energy systems in recent years. The idea of graphical knowledge representation can be traced back to 1956 [3], but it was not until 2012 when the concept of knowledge graph was promoted by Google search engine that it gained great popularity [4]. Fig. 1 shows the fundamental idea and aspects of knowledge graph and its applications to power and energy systems.

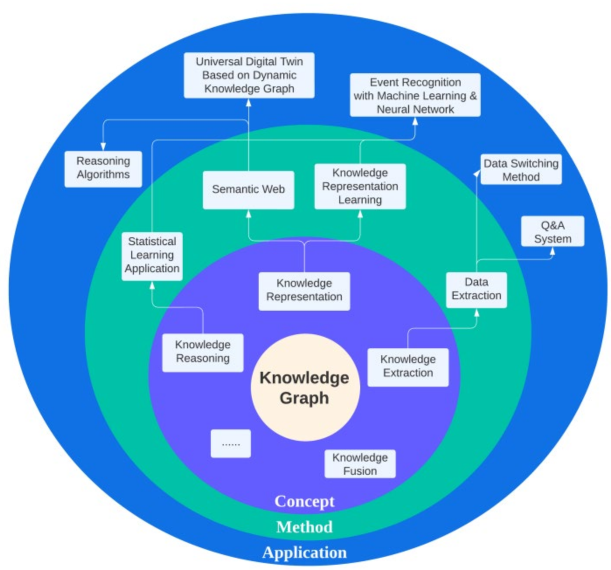

Fig. 1 Knowledge graph concept, method and application on power and energy systems

This paper will review the basic concepts, key research progress and prospects of knowledge graph, and demonstrate their applications to low carbon power and energy systems. The article structure is as follows. Section 2 introduces basic concepts and methods of knowledge graph. Section 3 presents the research progress in knowledge graph application for power and energy systems. Conclusions are discussed in Section 4.

2. CONCEPTS AND METHODS OF KNOWLEDGE GRAPH

2.1 Basic Concepts

Knowledge graph integrates multiple technical genes in the field of AI, including semantic technology, neural network, big data, and natural language processing. The origin of knowledge can be traced back to the semantic web (will be explained in the next subsection) [5]. By storing information semantically, the information silos due to domain and context differences and language ambiguity can be broken down, to increase cross-domain interoperability.

As a systematic knowledge engineering project, knowledge graph has several technical branches, including knowledge representation and knowledge extraction.

2.2 Knowledge representation and reasoning

Knowledge representation is the process to map entities and relations in the real world to that in a representation space. Mainstream knowledge representation methods can be categorized into symbolic and vectorial ones.

A symbolic representation method, also called Semantic Web technology, expresses relationships as edges and entities as nodes to construct a directed knowledge web. The core structure of the Semantic Web is called ontology. An ontology contains hierarchical concepts and relations, which are described with (entity, statement, entity) schema, and restricted by certain logic and deduction rules. Fig. 2 shows an ontology example.

A number of ontology languages have been established. As the basis of most languages, Extensible Markup Language expresses human knowledge in a machine-interpretable form. The Resource Description Framework is a more sophisticated framework, and further extended the Web Ontology Language (OWL). Further, HemiT [6] is developed as an inference engine, which is capable of knowledge reasoning on top of OWL ontologies.

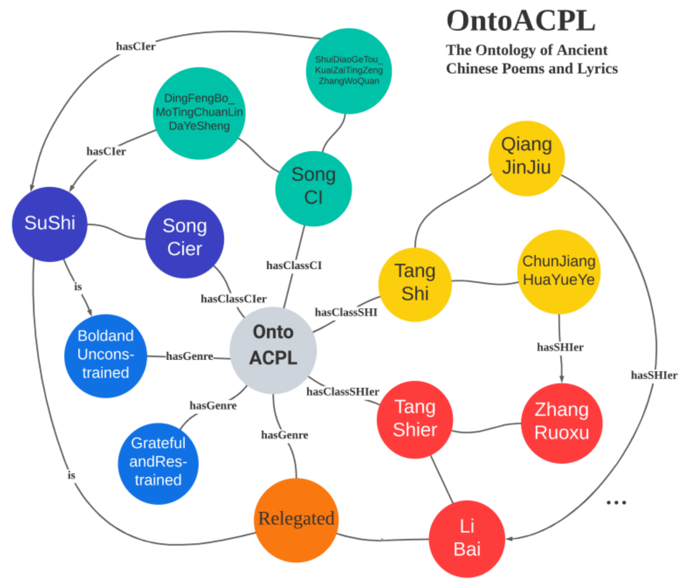

Fig. 2 An ontology example.

The issue of a vectorial representation, or Knowledge Representation Learning (KRL), is to construct a one-to-one mapping relationship between entities and relations with a low-dimensional space [7]. For example, TransE [8] represents entities and relations with a d-dimensional vector triple (h, r, t) (head, relation, tail; h, r, t $\in R^d$), and measures the plausibility of facts with scoring function as

$$f_r(h,t) = ||h + r - t||_{L_1/L_2} \tag{1}$$

Using vector triples, a machine learning model such as Graph Neural Network (GNN), can undertake implicit reasoning and deduction with sufficient data input.

2.3 Knowledge extraction and fusion

The aim of knowledge extraction is to acquire knowledge from unstructured text and other sources, either structured or semi-structured [7]. The main steps of knowledge extraction include completing the knowledge graph, discovering the entities and extracting the relations. Knowledge fusion aims to integrate different knowledge graphs.

In terms of knowledge fusion, one approach to achieve knowledge fusion is through ontology combination, where different ontologies are brought together. Once entities and relationships with the same connotations are identified, different ontologies can be fused together by further making node connections.

To date, knowledge graph technology has been widely employed in many fields. A paper jointly published by Google, Microsoft, IBM, Facebook, and eBay [9] includes representative examples, such as a search engine and a question-answering system. In addition, knowledge graph has also been used to build recommender systems, to enhance Natural Language Processing (NLP) and accelerate scientific research [10].

3. APPLICATION OF KNOWLEDGE GRAPH

Power and energy system consists of components at different levels, such as power stations, generation, conversion and electrical facilities, and circuit equipment. These elements together form an enormous Web of Things, which is naturally suitable for knowledge graph representation.

Based on its graphical structure and machine-interpretability, a knowledge graph is also expected to solve the challenge of difficult fast-response knowledge-aware decision-making brought about by heterogeneous data and numerous factors to be considered in the energy system. What is more, a dynamic knowledge graph is also capable of incorporating real-time data into computing systems and facilitates an intelligent dispatch of highly unstable renewable energy resources.

Data of power systems dispatching is characterized by various types, large quantities, and high speed. Therefore, an appropriate knowledge graph for the system should be multi-layer and cross-domain. The layers can include a physical layer as the core to simulate the grid topology, a layer of data that updates real-time operation information, and an advanced application layer providing external technical support such as load forecasting [11].

3.1 Data extraction and utilization

The ability to handle heterogeneous data is crucial in the construction of the knowledge graph in the power system. Fu et al. [12] proposed a data-switching method, using the N-Gram model, to address the problems of long switching time, unsatisfactory accuracy, and low information utilization. Tang et al. [13] developed a power engineering-oriented intelligent question-answering (IQA) system, which can provide intuitive visualization for users to make different kinds of power engineering data understandable, using Natural Language Processing (NLP) and ontology model-based reasoning algorithms. Further, Wu et al. [14] developed an automatic grid knowledge extraction model using Python by exploring the data storage model of Neo4j around the dynamic nature of models and the inherent data complexity of the grid.

3.2 Knowledge graph with statistical reasoning for deep analysis

Knowledge graph with the ability of statistical computation has also been also realized, with the goal of solving deep and complex logical reasoning problems, particularly for the task of event recognition. Tian et al. [15] proposed an event knowledge graph with vectorial representation that allows knowledge automatically extracted from O&M reports and represented properly. This knowledge graph system made implicit semantic syntax of the power and energy system machine-interpretable and performs well in event extraction and detection. By integrating deep learning, Yang et al. [16] managed to increase the accuracy of monitoring event recognition based on an improved algorithm of Graph Sample and Aggregate (GraphSAGE). They used GraphSAGE to conduct representation learning to generate event alarm vectors and trained the alarm vectors based on related events using Gated Recurrent Unit, verified the effectiveness and improved the accuracy of event recognition.

3.3 Dynamic knowledge graph based on ontologies

In a typical renewable energy system, the key issue is to decide the installed capacities and operation scheduling of different kinds of energy sources. However, when it comes to distributed renewable energy system, a variety of heterogeneous data, whether from environmental parameters and emissions to marketing environments and policies or from historical data to large time series of real-time data are rooted in energy models, making manual decision-making a challenging task. Dynamic data management and intelligent decision-support is therefore required to assist a smooth operation of the future energy system.

In 2019, Devanand et al. [17] proposed an ontology-based energy management system. The proposed OntoPowSys ontology was based on the syntax of the Description Logic and is implemented by the OWL2 language. Our previous work also extended this ontology framework by incorporating an Energy Storage System selection component [18] and building a dynamic knowledge graph in the system of The World Avatar (TWA) project [19]. With intelligent operating agents on the graph, TWA is capable to simulate changes in different scenarios without manual interference in the so called "parallel worlds". For example, conducting a calculation of the optimal energy storage placement the electricity network on the Jurong Island. Further, we are currently constructing a knowledge graph of hybrid renewable energy system (the multi-ontology design is shown in Fig. 3) based on one of our previous work [20], with the goal to serves as a knowledge-aware optimization model for the design and operation of future hybrid renewable energy systems.

4. CONCLUSIONS AND PROSPECTS

Knowledge graph is an emerging AI technology with the ability of integrating heterogeneous data and analyzing complex scenarios. Knowledge graph applications for power and energy systems including data extraction and utilization, statistical reasoning for deep

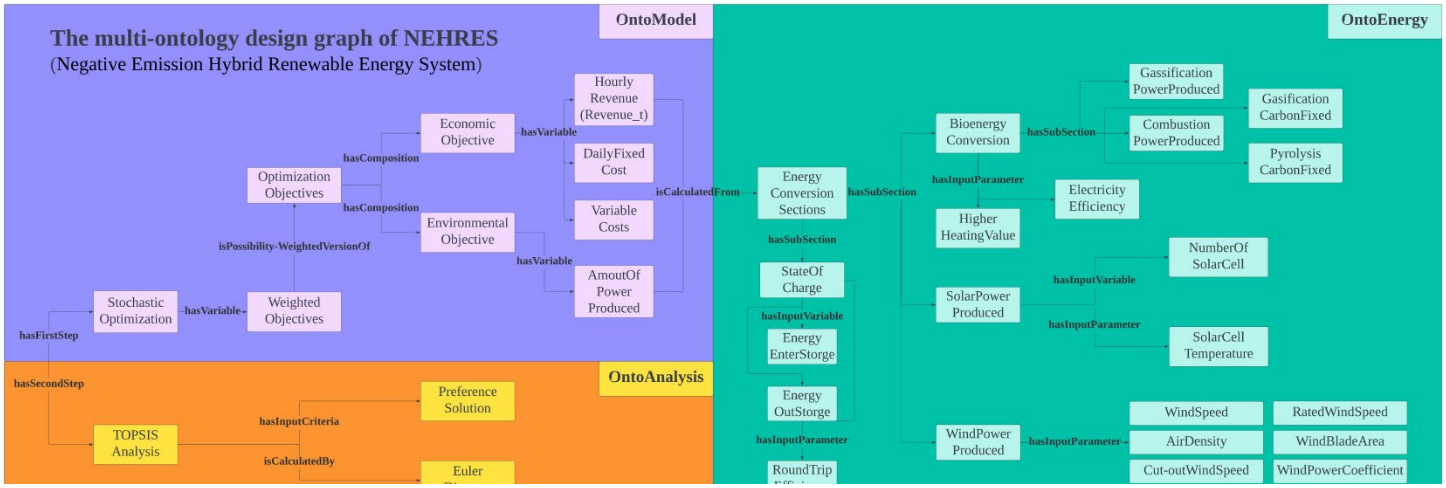

Fig. 3 Ontology design for NEHRES knowledge graph

analysis, and dynamic knowledge graph based on ontologies have been reviewed in this article.

Based on the current research progress, the following directions for the development of knowledge graph in the power and energy system context can be further explored in the future:

On the one hand, with ongoing advancement of vectorial knowledge representation method, integration of knowledge graph with neural networks such as GNN, can significantly improve the model performances for implicit knowledge reasoning and cross-domain model computing. Multi-modal-knowledge graphs can be built for power and energy systems to approach mechanism based analysis in complex scenarios.

On the other hand, universal knowledge graph building standards are necessary to be established, in order to simplify knowledge fusion for different knowledge graphs. Studies of power and energy system knowledge graph shared many homogeneous scenarios, such as power dispatching and event recognition. Knowledge graph technology is instinctively advantaged for integrating different methods with the same paradigm. The implement of universal knowledge graph building standards will promote cross-task interoperability and significantly reduce the labor of repetitive work.

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