Minireview Article

A Review of Research and Applications of Knowledge Graphs in the Power Sector

ABSTRACT

With the rapid development of science and technology, power system has become the lifeblood of modern society, An increasingly large power system complicates the management, operation, and maintenance of the grid. In order to effectively use a large number of operating data and prior knowledge of power system, the knowledge graph is introduced into the field of power systems.

This paper introduces the research and application of knowledge graph in power system and emphasizes the importance of knowledge graphs in addressing the increasing complexity of power systems and the rising demand for intelligence, the knowledge graph integrates heterogeneous data in a structured way, which helps to improve the technical level of power system management and control, especially in fault diagnosis, equipment monitoring and market transactions. This paper first introduces the basic concept, construction method and main application scenarios of knowledge graph in power system, including data management, equipment operation and maintenance, power system operation management and decision support, Through specific examples, such as a question-answering system for identifying defects in power equipment based on knowledge graphs, the identification method of transmission line missing bolts, intelligent planning of distribution network, etc., the paper shows knowledge graph can effectively improve the operation efficiency and management level of power system. Finally, the paper looks forward to the future development trend of knowledge graph in power system, points out its broad application prospects in smart grid construction, multidisciplinary cross integration and other fields, and emphasizes the importance of knowledge graph for promoting the intelligent development of power system.

Keywords: knowledge graph; power system; overhead line, grid operation and maintenance

1. INTRODUCTION

With the rapid development of the global economy and increasing energy consumption, the complexity of power systems is becoming increasingly apparent. The power network involves multiple links, including generation, transmission, distribution, and consumption, but also relates to environmental protection, energy security and economic efficiency and other factors. This diversity makes the power system show highly complex characteristics, which places stricter requirements on its management and control technologies. In the process of coping with the challenges of demand fluctuations, equipment failures and climate change, power systems urgently need to introduce intelligent technologies to achieve more efficient, stable and sustainable operation.

In this context, the rise of knowledge graph provides new opportunities for power system intelligence. Knowledge graph integrates a large amount of heterogeneous data in a structured way, which can effectively represent complex relationships and knowledge and provide support for intelligent decision-making. Especially in the era of big data, the amount of data involved in the power system is exploding, and the use of knowledge graph can help the system to solve the problems of information silos, data redundancy and knowledge acquisition.

The application of knowledge graph in power system is of great significance. Firstly, it can realize the comprehensive modeling of each component of the power system, improve the visualization and understanding of the system, and thus provide more intuitive decision-making basis for the operation and maintenance personnel. Secondly, by constructing knowledge graphs for equipment monitoring, fault diagnosis and load forecasting scenarios, it can improve the accuracy of power system fault identification and accelerate the speed of emergency response. In addition, the reasoning ability of knowledge graph can support intelligent trading in the power market, realize optimal allocation of resources, and improve economic efficiency.

n summary, as the complexity of power systems increases and the demand for intelligence rises, knowledge graph, as an emerging knowledge representation, shows a wide range of application prospects in power systems. In this review, we will discuss in detail the basic concepts of knowledge graph, analyze the current status and challenges of its application in power system, and look forward to the possible future development direction. By summarizing the existing research results and practical experience, it provides reference and reference for promoting the intelligent construction of power system.

2. AN OVERVIEW OF THE KNOWLEDGE GRAPH

The concept of the Knowledge Graph was formally proposed by Google in 2012, aiming to create a more intelligent search engine. It began to gain popularity in academia and industry after 2013. At present, with the continuous development of intelligent information service applications, the Knowledge Graph has been widely used in various fields.

The Knowledge Graph is a structured semantic knowledge base that represents entities and their interrelationships in the objective world in the form of graphs. Through effective processing, treatment, and integration of data from intricate documents, it is transformed into a simple and clear ternary structure of ‘entity, relationship, entity.’ Finally, it aggregates a large amount of knowledge, thus enabling rapid knowledge response and reasoning.

2.1 the basic components of a knowledge graph

The basic components of a knowledge graph are entities and edges. The nodes of the graph represent entities, the edges represent relationships between entities, and the associated attributes are used to characterize the entities. A visual representation of the power system knowledge graph is shown in Figure 1.

From a logical structure perspective, the knowledge graph of the power system can be divided into a data layer and a schema layer [1]. The data layer stores facts and instances, where the entities are generally more specific, actual items in the power system, such as people, grid equipment, organizations, locations, dates and times, and specific operations within the grid. The schema layer stores concepts, rules, axioms, and constraints. Entities in the schema layer are generally abstract concepts refined in the power system, also known as ontologies [2]. Knowledge is stored in the form of refined entity triplets or attribute-value pairs at these two levels.

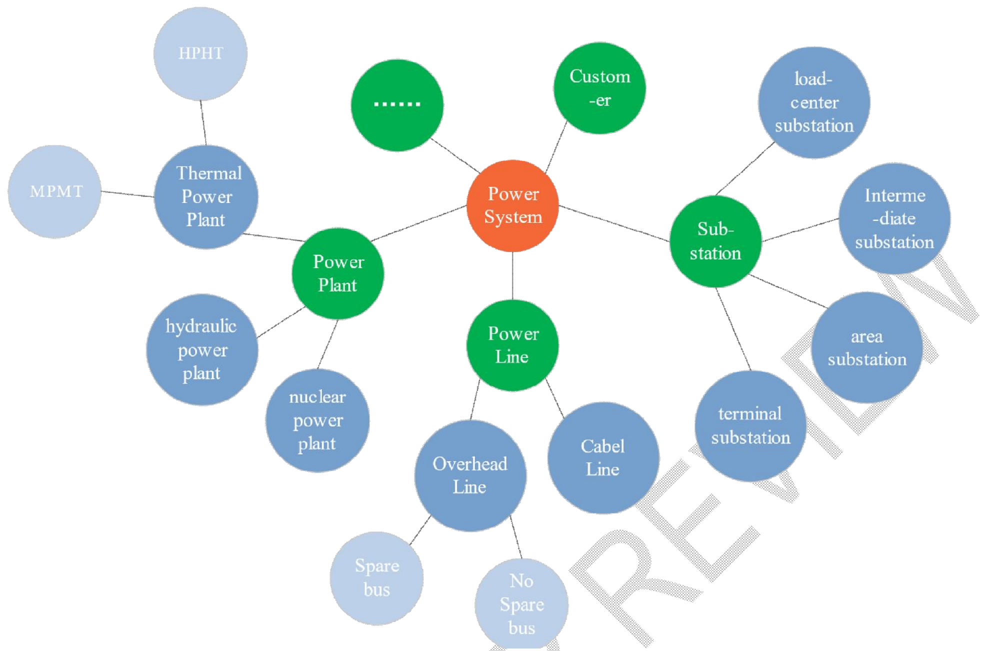

Fig 1 Sample ofknowledge graph of power system

The knowledge graph visually represents the relationships among information in the real world using a graph model. Since the introduction of the concept, the construction and application of knowledge graphs have rapidly developed, leading to the emergence of numerous open knowledge graphs, including WordNet[3], Dbpedia[4], NELL[5], YAGO[6], and Freebase[7]. Knowledge graphs reveal patterns of knowledge development and are applied in practical tasks, playing an increasingly important role in various fields, including semantic parsing[8], entity disambiguation[9], information extraction[10], and question answering[11].

2.2Methods of constructing knowledge graphs

The construction of a knowledge graph is a systematic project involving several key steps, aimed at extracting, integrating, and organizing knowledge from heterogeneous data sources to facilitate subsequent information retrieval and reasoning. Generally, there are two approaches to constructing a knowledge graph: top-down and bottom-up. The top-down approach involves extracting ontology and pattern information from high-quality data using structured data sources, such as encyclopedic websites, and adding this information to the knowledge base. The bottom-up approach involves extracting resource patterns from publicly available data using specific technological means, selecting new patterns with higher confidence, and adding them to the knowledge base after manual review. Figure 2 shows the basic technical architecture of knowledge construction.

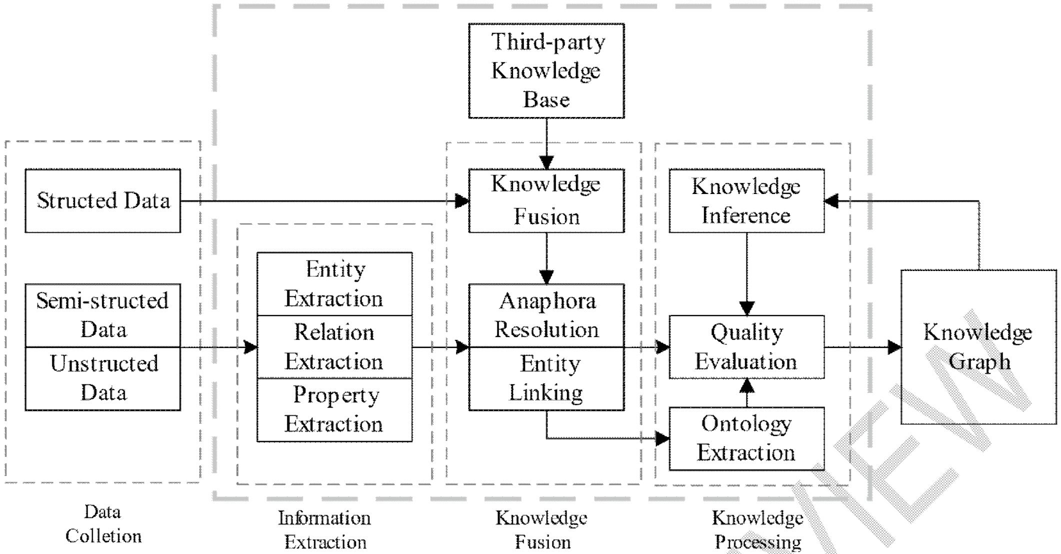

Fig2 Technical architecture of knowledge graph

2.2.1 data acquisition and pre-processing

Data collection is the first step in constructing a knowledge graph, which involves obtaining information from various data sources. These data sources may include databases, documents, web pages, and information presented in various forms. These data can be categorized into structured data, semi-structured data, and unstructured data. The common storage formats include SQL databases and NoSQL databases for subsequent processing.

table1 Data Type

Data type	Definition	Characteristics
Structured Data	Data arranged in a format that is easy for machines to read and search, with a well-defined data model and structure	Easy to seared and query; Fixed pattern; Can be easily analyzed.
Semi-structured Data	Not conforming to a strict data model, but containing tags or other markup to separate semantic elements and describe the data	Contains labels or tags; Does not follow a strict data model; Usually require specificparsers to parse andunderstand the data.
Unstructured Data	Data that does not have a predefined data model or is not suitable for storage in traditional relational databases, and data that is not organized in a fixed form, making difficult to automate analysis and processing.	No fixed format; Difficult to machine read andanalyze; High storage andmanagement costs.
Structured Data	Data arranged in a format that is easy for machines to read and search, with a well-defined data model and structure	Easy to seared and query; Fixed pattern; Can be easily analyzed;

After data collection, data pre-processing is crucial for ensuring data quality. The primary objective of data cleansing is to remove noisy data, duplicate records, and inconsistent data to ensure the accuracy and reliability of the dataset. Specific measures include noise removal, format standardization, handling of missing values, and more. In addition, for unstructured data, it is necessary to perform processes such as tokenization, removal of stop words, and stemming to prepare for subsequent analysis.

2.2.2knowledge integration and reasoning

The goal of knowledge fusion is to integrate identical or similar entities from different sources, eliminate redundancy, and construct a unified knowledge representation. This process involves data alignment, entity disambiguation, and knowledge updating and completion. For example, during entity disambiguation, contextual analysis can be employed to determine the precise reference of different entities that share the same name.

Knowledge reasoning involves inferring new knowledge by utilizing the structure and relationships within the knowledge graph. Reasoning can be achieved through logical reasoning technologies (such as OWL, RDF, and other rule engines) and graph-based reasoning methods (such as shortest path analysis and adjacency reasoning). In recent years, graph neural networks and other deep learning methods have garnered increasing attention, as they can extract potential relationships from complex graph structures and enable efficient inference.

3. KNOWLEDGE GRAPHS IN POWER SYSTEMS

Based on application fields, knowledge graphs can be divided into two categories: general knowledge graphs and domain knowledge graphs [12]. The knowledge stored in general knowledge graphs encompasses comprehensive and common-sense knowledge that is not limited to specific application fields [13-14]. A typical application scenario is the intelligent search engine on the Internet. This type of graph has high requirements for knowledge breadth but relatively low requirements for knowledge accuracy. The domain knowledge graph is oriented towards specific industry fields and is also known as the industry knowledge graph [15]. The knowledge stored in this graph is mainly professional domain knowledge.

The power system, as a complex and knowledge-intensive asset for electricity production and consumption, facilitates the conversion, interconnection, transmission, and interaction of various energy sources. It involves a systematic knowledge framework that encompasses multiple areas, including generation, transmission, transformation, distribution, and consumption. The power system knowledge graph is a technical form of knowledge graph technology applied in the power system domain, belonging to the category of domain knowledge graphs. Typical application scenarios include knowledge management, auxiliary analysis, and decision support [16].

The power system knowledge graph can be classified in various ways: based on the type of entities, it can be divided into text knowledge graphs, image knowledge graphs, and multimodal knowledge graphs [17]; based on the storage scale, it can be divided into single-sample-based knowledge graphs and sample set-based knowledge graphs [18]; and based on the storage and expression modes of entity data, it can be classified as resource description framework (RDF) database knowledge graphs and graph database knowledge graphs [19].

In the Internet industry, knowledge graphs have become mature technologies after several years of development, including intelligent semantic search, mobile personal assistants, and in-depth Q&A systems. The core technology supporting these applications is knowledge graph technology. In the electric power sector, the application of knowledge graphs is still in its early stages. Simultaneously, the power system has a wide variety of data sources, which are highly structured; however, the correlation among the data is relatively low. Therefore, using a knowledge graph to conduct inductive analysis of different data within the power system is a promising choice [20]. This review categorizes the applications of knowledge graphs in power systems into three main aspects: grid data management and intelligent search, operation maintenance and fault handling, and power system operation management and decision-making.

3.1Data management, intelligent search and Q&A

The normal operation of the power system relies on data transmission and mutual cooperation among various business systems, which have been built in different years and on different platforms. Furthermore, the databases, operational platforms, and specific data structures they use may differ, leading to a large amount of heterogeneous structured and unstructured data in the automation system. Such data includes the topology of the power grid in various formats, operational data, power equipment information, geographic data, meteorological data, audio and video, as well as a substantial amount of text data in different formats. To enable communication and interaction among these heterogeneous data sources and facilitate information integration, the power system must implement numerous data conversion interfaces and intermediate links between different platforms. These data platforms are relatively independent of one another, resulting in a lack of connectivity between the data, which hinders rapid, cross-platform data retrieval and integrated management. Heterogeneous data management and integration have become bottlenecks that restrict the improvement of the power grid's automation level.

Taking fault handling in power networks as an example, the scheduling work after a fault occurs mainly relies on the subjective decisions of operators. They must analyze the status and parameter changes of the grid in real time, identify the causes of the fault, and develop corresponding fault-handling measures [21]. This approach requires operators to repeatedly consult and memorize a large volume of fault-handling information, often found in non- or semi-structured text formats, such as system stability requirements, post-fault operating modes, and key points for fault resolution. Although traditional text retrieval methods that use keyword matching can provide paragraph location functionality, the search results are often fragmented and poorly organized, leading to incomplete retrieval and irrelevant answers. This can lead to oversights, thereby reducing the efficiency of emergency fault handling [22]. Therefore, there is an urgent need for methods in power systems to refine unstructured data into a systematic knowledge framework, assisting operators in quickly analyzing incident causes, comprehensively grasping key information for fault handling, and making informed decisions to enhance the grid's emergency response capability.

The power system knowledge graph leverages the advantages of ontology and semantic web technologies in heterogeneous data integration and management. In the knowledge graph, entities can consist of data with different structures, and these entities are interconnected through relationships to form a mesh structure. By utilizing the power system knowledge graph, heterogeneous data within the power system can be effectively organized, stored, and queried, allowing for the construction of a knowledge base for grid operations that can be shared across various business systems. Typical business scenarios for the power system knowledge graph in heterogeneous data management include energy data management within the energy internet and power equipment information management which contains heterogeneous information of many equipment, so as to establish a unified data center for the whole business in power system.

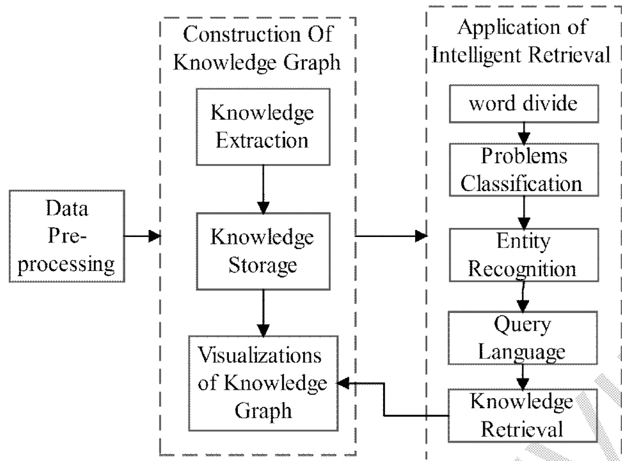

Fig3 Intelligent searching application architecture based on knowledge graph of electrical equipment

The data center will organize the heterogeneous data collected and scattered across various professional databases to achieve unified knowledge management, data correlation reasoning, and data retrieval services across disciplines. The unified data center can enable 'one entry, whole system use' of data in the power system, ensuring the authenticity, integrity, and consistency of data, while reducing the human resource costs required for cross-disciplinary data retrieval and communication. Building on the data center, we can further develop an intelligent retrieval and Q&A system based on the power system knowledge graph, as shown in Figure 3

Peng Chen et al.[23] explored the development of a knowledge graph-based question-and-answer system for power equipment defects. The system utilizes natural language processing technology to automatically answer questions regarding power equipment defects by understanding and analyzing user inquiries. This paper presents the implementation method and technical approach of the system, verifying its effectiveness through experiments. The results demonstrate that the system can accurately recognize user intent and provide corresponding answers. This research is highly significant for improving the fault diagnosis efficiency of electrical equipment and reducing maintenance costs.

Hu Zhiqiang et al. [24] proposed a question-answering system for the wind power assembly process, which integrates multimodal knowledge graphs and large language models. As shown in Figure 4, the system first employs keyword matching, using tags in the sequence and graph pattern layers as category keywords to obtain more detailed parsing results. At the same time, to avoid errors or omissions of entities, the Sentence BERT model is also utilized to determine the nodes corresponding to the header text entities. This paper introduces a novel approach for applying multimodal knowledge graphs in power systems.

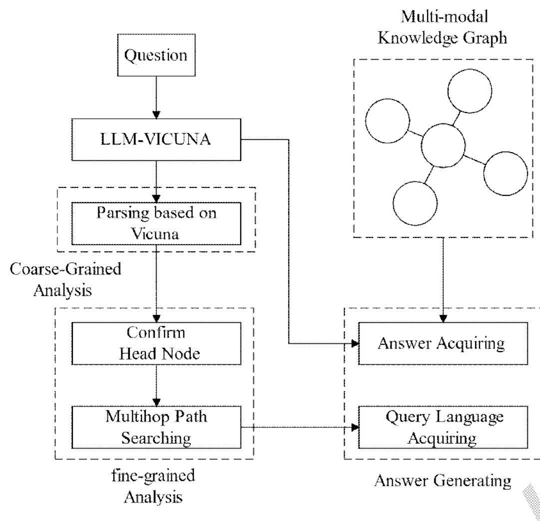

Fig4 Technical route of wind power system assembling Q&A system

3.2Operation and maintenance of equipment

The assessment of the status of power equipment—such as generators, transformers, and relay protection devices—includes tasks like wind turbine status prediction, transformer residual life estimation, and transmission line condition monitoring, which are of significant theoretical importance for ensuring the safe and stable operation of power systems [25]. At the same time, resource scheduling and optimization in the power system are core activities to ensure the reliability, economy, and efficiency of power supply. It involves the collective allocation and management of various resources in the power system to meet established power demand and policy objectives.

The power distribution network, as a complex system with vast amounts of data [26], has reliability that directly affects electricity users. Therefore, during scheduling, the emergency response capability and efficiency in handling faults within the distribution network are particularly important for its operation [27]. Traditional manual inspection and diagnostic work methods are increasingly inadequate due to high labor costs, a singular diagnostic approach, and decentralized data management, failing to meet the real-time and efficient diagnostic requirements for power equipment. As a result, substation inspection faces significant challenges, and the trend toward using intelligent devices to replace manual inspections has become inevitable. When power equipment in a substation fails during operation, it can lead to widespread and large-scale power outages, resulting in significant losses to the national economy and industrial production. Therefore, ensuring the safety of the power supply has become crucial for safeguarding national strategic energy security, particularly by enhancing the intelligence of the power system to ensure stable operation.

Currently, researchers have proposed various systems to analyze grid faults, such as fault recording systems and power quality monitoring systems. These systems handle large-scale data by recording, calculating, and analyzing to fulfill the functions of different fault analysis systems. However, they overlook a substantial amount of implicit electrical text corpus, leading to poor interpretability. Intelligent inspection is a crucial service method for ensuring the safe, stable, and economical operation of the grid and power equipment. Combining knowledge graph technology with visual inspection algorithms offers a new and efficient decision-making approach in the field of intelligent inspection [28]. Knowledge graphs can effectively transform the complex, multi-structured data involved in fault handling in distribution networks into actionable knowledge, enabling efficient text data mining while enhancing interpretability, thereby better supporting decision-making related to fault types.

Zhao Zhenbing et al. [29] proposed a method for recognizing missing pin bolts in transmission lines based on graph knowledge reasoning. The method first learns category representations of various types of bolts with discriminative features through the knowledge expression module and then further explores the correlations between bolt types in the dataset to extract label co-occurrence information. Finally, the category representation is used as the input feature to characterize the label co-occurrence information with correlation probability matrices from static and dynamic diagrams. Knowledge propagation and enhancement of the diagram knowledge are completed through the knowledge inference module to achieve recognition of missing pin bolts. The experimental results demonstrate that this method is more effective than others in recognizing missing pin bolts and improves recognition accuracy.

Zheng Jieyun et al. [30] proposed an intelligent planning method for distribution networks based on knowledge graphs and graph convolutional neural networks, aiming to improve the efficiency and reliability of equipment selection, connection configuration, and grid layout. This method utilizes knowledge graph (KG), graph neural network (GNN), and convolutional neural network (CNN) technologies to establish the KG for the power network and employs GNN to analyze the structural data of the power network to capture relationships and impacts between equipment. Finally, CNN is employed to enhance the physical layout of the power grid, determining the optimal location and connection mode for equipment to improve performance and reliability. Experimental results indicate that this method can more effectively address the complex topological structure of the power grid and is better suited for processing and optimizing its physical layout.

Xiaolu Li et al. [31] utilized knowledge graph technology to develop a solution for wind turbine operation and maintenance data and proposed a method for constructing a knowledge graph specifically for wind power operation and maintenance. The method encompasses entity extraction, fault type identification, relationship extraction, and knowledge processing. By effectively managing and processing wind power O&M data, the method improves the efficiency of fault diagnosis and auxiliary operations, reduces the downtime of O&M units, and ensures power generation. Additionally, the method is characterized by its ability to meet the dynamic updating requirements of time-varying data, making it adaptable to ever-changing business needs. The experimental results demonstrate that the method can effectively identify different fault types of wind turbines and extract key entity and attribute information, providing robust support for the operation of wind turbines.

Ma Fuqi et al. proposed a three-in-one reasoning method that integrates rule, logic, and path reasoning, combined with the specificity of knowledge related to electric power production safety, as shown in Fig. 2. This method dynamically adjusts the candidate domains through reasoning and comparative analysis, achieving inter-class and intra-class categorization and target localization.

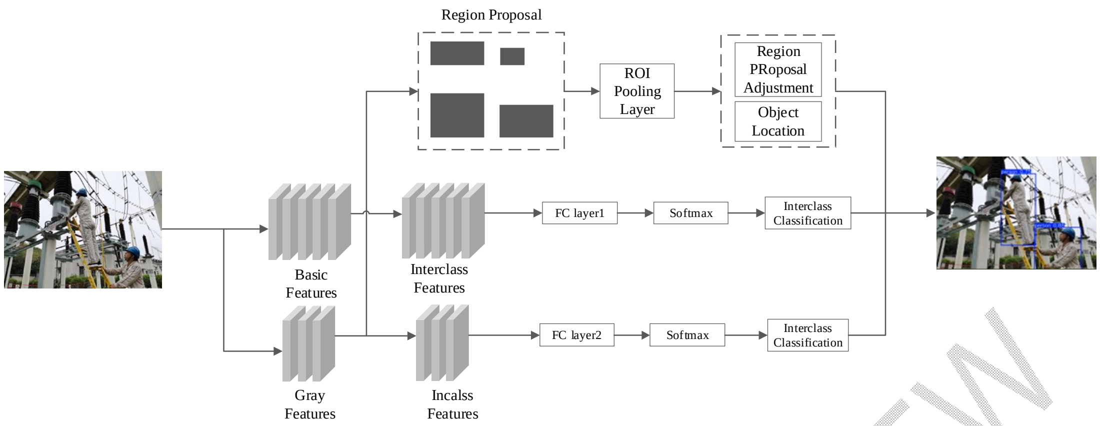

Fig5 Target detection framework for high discrimination characterization of similar power production safety objects

3.2Operation and maintenance of equipment

With the rapid development of information technology, power electronics and communication technology, the traditional power grid is being transformed into a smart grid. The basic requirement of a smart grid is to enable the operation center to collect electricity data through user-equipped smart meters, thereby obtaining real-time electricity data from all users within its jurisdiction. This capability allows for dynamic electricity dispatching and pricing operations[33]. and intelligent operation and maintenance and decision-making, as an important part of the smart grid, is increasingly becoming a key means to ensure the efficient, reliable and sustainable operation of the power system. Power system scheduling decision-making is essentially a multi-dimensional data processing and reasoning process, the data to be processed not only contains the actual state of the current grid and the specific information of the accident, but also contains the scheduling specifications, fault handling plans, the existing accident handling process and experience.

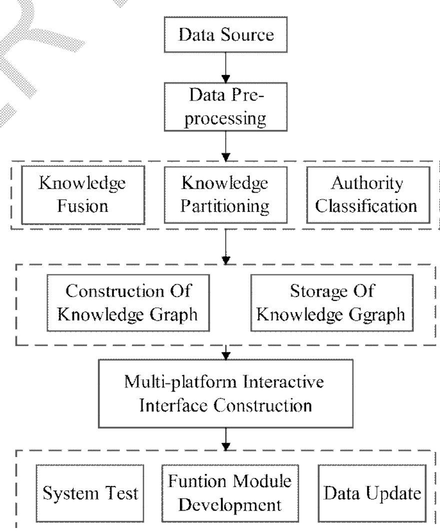

Fig 6 Application architecture of power system aided intelligent decision-making

Scheduling decision-making is the process by which the dispatcher, based on multi-dimensional data, combines their work experience and professional knowledge to reason about the causes of accidents and disposal methods, formulating decisions to isolate faults, reduce outage losses, and restore the electric power system to its normal operational state. Existing scheduling automation systems cannot comprehend the deeper meanings of this multi-dimensional information and cannot utilize this data for accident disposal reasoning and decision-making. As a result, current grid scheduling still relies on the dispatcher's manual decision-making. Moreover, the dispatcher's ability to handle large volumes of information is limited by human reaction speed and cognitive capacity, making it difficult to accurately identify faults in a timely manner amidst the massive fault information and make informed decisions. Additionally, the experience of dispatching experts is often difficult to pass on and accumulate. The power system knowledge graph can facilitate auxiliary decision-making in power system dispatching.

Currently, typical scenarios for the power system knowledge graph in assisting decision-making include grid scheduling control and the intelligent management of power communication networks. In intelligent power grid scheduling, Fu Xin et al. [34] designed a monitoring and analysis system for power grid operations based on knowledge graph technology, which consists of three layers: a perception layer, a cognitive layer, and an application layer. The perception layer utilizes artificial intelligence technology to intelligently transform the information collected from terminal equipment. The cognitive layer employs search engines, knowledge graphs, and deep learning technologies to transform massive data, business designs, and citations into multi-dimensional and systematic knowledge resources, providing capacity support for the application layer's functions. The application layer offers proactive services based on the knowledge graph of the grid, including intelligent search, intelligent push notifications, and intelligent decision-making, aimed at promoting the continuous improvement of the power grid's lean management level.

Additionally, in the context of auxiliary decision-making for power grid faults, existing fault scheduling requires control personnel to maintain a comprehensive awareness of the grid's status and data [35]. By using fault information as a focal point, they must coordinate various departments to develop quick and accurate responses and work deployments based on scheduling regulations, safety protocols, fault response plans, historical fault records, and operational experience, ensuring that the distribution network can safely and stably return to economic operation in a short time. This approach relies heavily on experience and manual analysis, highlighting the connection between knowledge and experience [36].

The personnel's understanding of fault handling knowledge, their experience in processing faults, their ability to reference information, and their logical judgment skills often determine the effectiveness of fault resolution [35]. Enhancing decision-making capabilities in fault management can standardize operational practices, reduce errors and safety incidents, optimize response strategies, and improve overall work efficiency. Meanwhile, the knowledge graph can extract, express, learn, organize, and store the multidimensional data required for accident handling. When an accident occurs, the knowledge graph can be queried and reasoned based on the characteristics of the incident, providing relevant knowledge and decision-making schemes as auxiliary references for the dispatcher. Some non-critical aspects of accident handling, such as initial fault reports, protection information summaries, log records, and information notifications, can be efficiently managed by directly accessing relevant modules from the knowledge graph, thereby minimizing interruptions to the dispatcher during the incident response.

Wang Jundong et al. [37] developed an auxiliary dispatching decision system based on the knowledge graph for distribution network fault dispatching. In this study, the entity component of the graph is constructed based on dispatching rules and safety regulations. TF-IDF and Text Rank algorithms are employed to extract electrical power terms, supplemented by screening methods combined with data sources. Using the experience of regulators as a data foundation, we thoroughly investigated the actual work of fault scheduling and established logical relationships combining time, scenarios, and specific tasks. This method considers real-world scenarios of regulatory and operational tasks, making it both scientific and practical. It can enhance the dispatcher's fault management capabilities and the safety operation level of the distribution network, providing a new approach for establishing an auxiliary decision-making system for power grid faults.

Additionally, electricity prices exhibit non-stationary and non-constant characteristics in energy markets, leading to significant anomalies. These factors increase uncertainty and complexity in the electricity market, resulting in challenges in short-term price forecasting. Short-term price forecasts in modern smart grids can help power companies develop more effective strategies to meet the diverse electricity demands of various consumers [38]. In this context, Hu Yanmei et al. [39] proposed a multi-kernel extreme learning machine (MKELM) for short-term electricity price forecasting and classification based on predefined price thresholds. This method offers significant advantages over traditional extreme learning machines (ELMs) that use random weights between the input and hidden layers. Additionally, the study employed the water cycle algorithm (WCA) to optimize the MKELM method, resulting in the WCA-MKELM approach, which aims to enhance the accuracy of short-term price forecasting and classification.

The reasoning process of the knowledge graph, based on logical symbols, can be explained to users, and understanding this decision-making process can enhance trust in the results, thereby increasing the utility of assisted decision-making. Based on the outcomes of each decision-making practice, the knowledge graph can be continuously updated and improved, providing comprehensive, multi-level, and dynamic support for decision-making.

4. TRENDS IN DEVELOPMENT

With the rapid development of the electric power sector, digital transformation has emerged as one of the primary directions for industry development. The knowledge related to power systems is vast and complex. As a powerful tool for knowledge expression, organization, and connection, the knowledge graph can intuitively and structurally describe various complex concepts in the field. In the context of the digital transformation of the power grid, it will be widely used. A comprehensive overview of the application of knowledge graphs in power systems suggests that future development trends can be summarized as follows:

1. Power System Operations and Maintenance. The knowledge graph has significant potential in the field of power grid operations and maintenance. Operation and maintenance of the power network is an extremely complex task due to the intricate nature of the power system, which impacts the entire network. Therefore, every decision in power grid operations and maintenance must be thoroughly considered. By integrating knowledge graphs, these complexities can be better managed.

2. Construction of Smart Grids. Smart grids are built on integrated, high-speed, two-way communication networks, utilizing advanced sensing and measurement technologies, sophisticated equipment technologies, advanced control methods, and decision support systems to ensure the reliability, security, economy, efficiency, environmental friendliness, and safe operation of the power grid. In the construction of smart grids, knowledge graphs play a crucial role. Compared to other methods, knowledge graphs have unique

advantages in data integration and knowledge modeling, as well as in intelligent scheduling and optimization of power grids.

3. Multidisciplinary Integration. The safe, reliable, and high-quality operation of the power grid is significantly influenced by environmental factors, such as weather conditions and ambient temperature. Therefore, in the operation and maintenance of power grids, it is essential to consider the impact of these conditions. Knowledge graphs can be integrated with meteorological data to inform grid scheduling decision-making. Additionally, economic factors must also be considered in grid operations, which can be integrated with interdisciplinary knowledge graphs.

5. CONCLUSION

This paper primarily discusses the application of knowledge graphs in power systems. Firstly, it presents the background of the field, followed by an introduction to the concept and construction steps of knowledge graphs. It then discusses the current development status of this field from three perspectives: data management, intelligent search and in-depth Q&A, equipment operation and maintenance, and power system operation management and decision-making, and finally looks forward to the development prospects.
In recent years, the rapid development of artificial intelligence has significantly enhanced its application in power systems, contributing to the intelligent development of the power grid and improving productivity. Security, stability, high quality, and economic efficiency are fundamental requirements for power system operation. Knowledge graphs have significant potential for managing complex data and knowledge associations, which are crucial for addressing the complexities of power systems. Their large-scale application is a general trend. This paper summarizes the development of the field regarding knowledge graph applications, providing valuable insights for researchers and power grid professionals.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during writing or editing of this manuscript.

REFERENCES

1. GAO Haixiang, MIAO Lu, LIU Jianing, LIN Xiangning, DONG Kai, HE Xiangzhen. Review on Knowledge Graph and Its Application in Power Systems[J]. GUANGDONG ELECTRIC POWER. 2020,33(09):66-76. DOI:10.3969/j.issn.1007-290X.2020.009.009 https://www.DOI.org/10.3969/j.issn.1007-290X.2020.009.009
2. HUANG Bo,WUShen'ao, WANG Wenguang,YANGYong,LIUJin,ZHANG Zhenhua, et al. KG-LLM-MCom:A Survey on Integration of Knowledge Graph and Large Language Model[J]. J. Wuhan Univ.(Nat. Sci. Ed.). 2024,70(04):397-412. DOI:10.14188/j.1671-8836.2024.0040. http://xblx.whu.edu.cn/en/article/DOI/10.14188/j.1671-8836.2024.0040/
3. George A.WordNet:A lexical database for English[J]. Communications of the ACM,1995,38(11):39 41. https://dl.acm.org/DOI/10.1145/219717.219748
4. Lehmann J,Isele R,Jakob M,et al. DBpedia—A large scale,multilingual knowledge base extracted from wikipedia[J]. Semantic Web, 2015,6(2):167 195. https://www.semanticscholar.org/paper/DBpedia-A-large-scale%2C-multilingual-knowledge-base-Lehmann-Isele/d2946a868682e4141beabc288d79253ae254c6e1
5. Carlson A,BetteridgeJ,KisielB,etal.Toward an architecture for never-ending language

learning. Proc of the 24th AAAI Conf on Artificial Intelligence[C].Menlo Park, CA:AAAI,2010:1306 1313.
https://dl.acm.org/DOI/10.5555/2898607.2898816

6. Fabian M,GjergjiK,GerhardW.Yago:A core of semantic knowledge[C]//Proc of the 16th Int Conf on World Wide Web.New York:ACM,2007:697 706.
https://DOI.org/10.1145/1242572.1242667
7. Bollacker K D,EvansC,ParitoshP,etal.Freebase:A collaboratively created graph database for structuring human knowledge[C]//Proc of the 2008ACM SIGMOD Int Conf on Management of Data.New York:ACM,2008:1247 1250.
https://DOI.org/10.1145/1376616.1376746
8. BerantJ,ChouA,FrostigR,etal.Semantic parsing on Freebase from question-answer Pairs[C]//Proc of the 2013 Conf on Empirical Methods in Natural Language Processing. Stroudsburg,PA:ACL,2013:1533 1544.
https://aclanthology.org/D13-1160/
9. Alhelbawy A, Gaizauskas R. Graph ranking for collective named entity disambiguation[C]. Proc of the 52nd Annual Meeting of the ACL. Stroudsburg, PA:ACL, 2014:75 80.
https://aclanthology.org/P14-2013/
10. Hoffmann R, Zhang C, Xiao Ling, et al. Knowledge-based weak supervision for information extraction of overlapping relations[C]. Proc of the 49th Annual Meeting of the ACL: Human Language Technologies ACL. Stroudsburg, PA: ACL, 2011:541 550.
https://aclanthology.org/P11-1055/
11. Bordes A, Weston J, UsunierN.Open question answering with weakly supervised embedding models[C], Proc of the 2014Machine Learning and Knowledge Discovery in Databases-European Conf. Berlin:Springer, 2014:165 180.
https://DOI.org/10.48550/arXiv.1404.4326
12. Liu Qiao, Li Yang, Duan Hong, Liu Yao, and Qin Zhiguang. Knowledge Graph Construction Techniques[J]. Journal of Computer Research and Development. 53(3):582-600,2016. DOI:10.7544/issn1000-1239.2016.20148228.
https://d.wanfangdata.com.cn/periodical/jsjyjyfz201603008
13. Yang YJ, Xu B, Hu JW, Tong MH, Zhang P, Zheng L. Accurate and efficient method for constructing domain knowledge graph[J]. Ruan Jian Xue Bao/Journal of Software, 2018,29(10):2931-2947. DOI: 10.13328/j.cnki.jos.005552.
https://jos.org.cn/jos/article/abstract/5552?st=search
14. Guodong Z, Jian S, Jie Z, et al. Exploring Various Knowledge in Relation Extraction.[C]// ACL 2005, Meeting of the Association for Computational Linguistics, Proceedings of the Conference, 25-30 June 2005, University of Michigan, Usa. DBLP, 2005:419--444.
https://aclanthology.org/P05-1053/
15. Su Mu, Xiao Ren-Bin. A Dynamic Knowledge Extraction Method Based on Sentence-Clustering Recognition.[J] CHINESE J.COMPUTERS, 2001,(05):487-495.
https://api.semanticscholar.org/CorpusID:63438805
16. QI Ning. Deep Learning Based Chinese Entity Relaton Extraction Research[J]. Changjiang Information & Communications, 2024,37(01):64-66. DOI:10.20153/j.issn.2096-9759.2024.01.018.
https://d.wanfangdata.com.cn/periodical/ChlQZXJpb2RpY2FsQ0hJTmV3UzIwMjQwNzA0Eg9oYnlkanMyMDI0MDEwMTgaCHBwanI3dXc2
17. Ou Yanpeng. A Survey on Research Technologies of Knowledge Graphs[J]. Electronics World, 2018,(13):54+56.DOI:10.19353/j.cnki.dzsj.2018.13.021.
https://DOI.org/10.48550/arXiv.2002.00388
18. ZHU Muyijie,BaoBingkun,Xu Changsheng. Research progress on development and construction of knowledge graph[J].Journal of Nanjing University of Information Science & Technology. 2017,9(06):575-582. DOI:10.13878/j.cnki.jnuist.2017.06.002.

http://nxdxb.cnjournals.org/njqxxyxb/article/abstract/20170602

19. Wang Renwu, Yuan yi, Yuan Xuping. Study on the Construction of Chinese Knowledge Graph Based on Deep Learning and Graph Database[J].Library & Information. 2016,(01):110-117. DOI:10.11968/tsyqb.1003-6938.2016017. https://xueshu.baidu.com/usercenter/paper/show?paperid=e1eda6a49365ef15aaa4562ada354002&site=xueshu_se
20. LI Shiming. Research of power system knowledge atlas[J]. Applied Science and Technology. 2023,50(04):79-83.DOI:10.11991/yykj.202202004. https://d.wanfangdata.com.cn/periodical/ChlQZXJpb2RpY2FsQ0hJTmV3UzIwMjQwNzA0Eg15eWtqMjAyMzA0MDEzGghkenJwMmVhdg%3D%3D
21. DONG Xiangyu, JI Kun, ZHU Jun, YANG Bo. A retrofitted ant colony algorithm for inspection robot path planning in UHV substations[J]. Power System Protection and Control, 2021,49(18):154-160. DOI:10.19783/j.cnki.pspc.201581. https://www.dlbh.net/dlbh/ch/reader/view_abstract.aspx?file_no=20211818&st=alljournals
22. GUO Rong, YANG Qun, LIU Shaohan, LI Wei, YUAN Xin, HUANG Xianghong. Construction and Application of Power Grid Fault Handing Knowledge Graph[J], Power System Technology. 2021,45(06):2092-2100. DOI:10.13335/j.1000-3673.pst.2021.0065. https://www.semanticscholar.org/paper/Construction-and-Application-of-Power-Grid-Fault-Li-Tian/e372aacc2aae8b8cf6b3a1ef3ba189918aadd371
23. CHEN P, TAI B, SHI Y, et al. Research on power equipment defect question answering system based on knowledge graph[J]. Journal of Guangxi Normal University(Natural Science Edition), 2024, 42(6) :1-14. DOI:10.16088/j.issn.1001-6600.2024021901. https://kns.cnki.net/kcms2/article/abstract?v=tH39KOVtnoEYmqmS96muuDqM9gQ52VEga6ul6Xb3Z_PyMa4AcYDNsYV0NWS99N3e_hJFKHXgXUTH2WOxCL63gJx7k17Rh_jtExv4C7GROF1UCctOQXy5VrLvkkJdL9T9qH8r3M5QWmnGdmR4yVO-VTFFrUWZYDNSqyrlNKLOTGqGKjCKIn5IVSvlhXwQH9sV&uniplatform=NZKPT&language=CHS
24. HU Zhiqiang,PANXinyu,WENSijie,LIXinyu,BAOJinsong. Assembly process question answering system of wind turbines combining multi-modal knowledge graphs with LLMs[J]. JOURNAL OF MACHINE DESIGN. 2023,40(S2):20-26.DOI:10.13841/j.cnki.jxsj.2023.s2.006. https://kns.cnki.net/kcms2/article/abstract?v=tH39KOVtnoFtMm3CedS7BGpoaiKeUEWg_d_zNOdVODYtCY4emqCaihwiSq019urP7h3u1YKgMaNuY383-gP_eg06uU26EbElH7cWdXKBx-tprJPMXy_jsba8xjGCo9XAkXdqiCfPUpImPenuk_RaJXpO8zMyk29UraQgvBlcIeD5AWCSukBDqwdWUIC1rQ5M&uniplatform=NZKPT&language=CHS
25. JIA Xuefeng, LI Cunbin. Real-time Electricity Price Forecasting of Electricity Market Using DeepESN Considering Short-term Load Impact[J]. Electric Economic.2021,49(01):64-70. https://d.wanfangdata.com.cn/periodical/ChlQZXJpb2RpY2FsQ0hJTmV3UzIwMjQwNzA0Eg94YmRsanMyMDIxMDEwMTAaCDJ0YXFkYzk4
26. Hu Xuyang, Wang Zhizheng, Sun Yuanyuan, XuBo, and Lin Hongfei.Knowledge Graph Representation Method Combined with Semantic Parsing[J]. Journal of Computer Research and Development. 2022,59(12):2878-2888. DOI:10.7544 /issn1000-1239.20210849. https://crad.ict.ac.cn/article/DOI/10.7544/issn1000-1239.20210849
27. ZHANG J X,ZHANG X S,WU C X,et al. Survey of knowledge graph construction techniques[J] .Computer Engineering, 2022,48(3):23-37. https://www.ecice06.com/EN/10.19678/j.issn.1000-3428.0061803
28. XIAO Falong, WU Yuezhong, SHEN Xuehao, HE Zhenkai, QIN Ye. Intelligent Fault Diagnosis of Substation Equipment on the Basis of Deep Learning and Knowledge

Graph[J]. Electric Power Construction, 2022,43(03):66-74. DOI: 10.12204/j.issn.1000-7229.2022.03.008.
https://www.cepc.com.cn/CN/10.12204/j.issn.1000-7229.2022.03.008

29. ZHAO Zhenbing,WANGRui,ZHAOWenqing,ZHANGKe,ZHAIYongjie. Pin-missing bolts recognition method for transmission lines based on graph knowledge reasoning[J]. CAAI transactions on intelligent systems, 2023, 18(2): 372–380. DOI: 10.11992/tis.202205004.
https://tis.hrbeu.edu.cn/oa/DArticle.aspx?type=view&id=202205004
30. ZHENG Jieyun, ZHANGZhanghuang, XUAN Juqin, WEI Xin , XUE Jingwei. Intelligent planning method of distribution network based on knowledge graph and graph convolutional neural network[J]. Computer Engineering, 1-15[2024-10-30], DOI:10.19678/j.issn.1000-3428.0069531.
https://www.ecice06.com/EN/10.19678/j.issn.1000-3428.0069531
31. LI Xiaolu, WANG Ke, ZHAO Bing, LIAO Wenyu. Knowledge Graph Construction Method for Wind Turbine Operation and Maintenance Data[J]. Journal of Chinese Society of Power Engineering ,2024,44(06):886-894. DOI: 10.19805/j.cnki.jcspe.2024.230235.
https://jcspe.speri.com.cn/EN/10.19805/j.cnki.jcspe.2024.230235
32. MA Fuqi, WANG Bo, DONG Xuzhu, YAO Liangzhong, WANG Hongxia. Safety Image Interpretation of Power Industry: Basic Concepts and Technical Framework[J]. Proceedings of the CSEE. 2022,42(02):458-475. DOI:10.13334/j.0258-8013.pcsee.210315.
https://www.researchgate.net/publication/359425947_Safety_Image_Interpretation_of_Power_Industry_Basic_Concepts_and_Technical_Framework
33. LIU Li, YAN Xiaomei, LI Gang. Knowledge Graph in Distribution Network Fault Handing: Advances, Challenges and Prospects[J]. Electric Power Information and Communication Technology, 2023,21(07):19-26. DOI:10.16543/j.2095-641x.electric.power.ict.2023.07.03.
https://d.wanfangdata.com.cn/periodical/ChlQZXJpb2RpY2FsQ0hJTmV3UzIwMjQwNzA0Eg5kbHh4aDIwMjMwNzAwMxoIeTE4emM4dWc%3D
34. FU Xin,GUOYang,NIELing,etal.Design of power grid operation monitoring and analysis system based on knowledge graphtechnology[J].Distribution & Utilization,2021,38(7):45-50.DOI:10.19421/j.cnki.1006-6357.2021.07.008.
https://d.wanfangdata.com.cn/periodical/gyd202107007
35. XU Hongqiang. Architecture of Dispatching and Control Cloud and Its Application Prospect[J]. Power System Technology, 2017,41(10):3104-3111.DOI:10.13335/j.1000-3673.pst.2017.1521.
https://www.researchgate.net/publication/321697471_Architecture_of_Dispatching_and_Control_Cloud_and_Its_Application_Prospect
36. LI Gang,ZHANG Bo,ZHAO Wenqing,et al. Data science issues in state evaluation of power equipment:challenges and prospects[J]. Automation of Electric Power Systems,2018,42(21):10-20.
https://www.researchgate.net/publication/330039141_Data_Science_Issues_in_State_Evaluation_of_Power_Equipment_Challenges_and_Prospects
37. WANG Jundong, YANG Jun, PEI Yangzhou, ZHAN Xiangpeng, ZHOU Ting, XIE Peiyuan. Distribution Network Fault Assistant Decision-making Based on Knowledge Graph[J]. Power System Technology, 2021,45(06):2101-2112. DOI:10.13335/j.1000-3673.pst.2020.1677.
https://www.researchgate.net/publication/353840802_Distribution_Network_Fault_Assistant_Decision-making_Based_on_Knowledge_Graph
38. Hu Yanmei, Wang Pin, Ding Yixin. Short-term Electricity Price Prediction and Classification in Smart Grids Based on MKELM[J]. High Voltage Engineering, 2023,49(S1):47-52.DOI:10.13336/j.1003-6520.hve.20230225.

https://kns.cnki.net/kcms2/article/abstract?v=tH39KOVtnoEcy1t2Ji46fEV-blpkTkAV5DbQf6iHCeqU2gJz91jxNAqtgsCApGY-TG_tGB_zFaP7xkxFEkxqtfTmYRzOvJjjeAINwOlY1fqz5htA2P1bNYyc1LVPoHsdHFmuZ6YS9Ds9Wxs0Ymns9GdDdv9hqWN71IV5UKO9GtzbgMiEgLDvpg1QEYK-PgGH&uniplatform=NZKPT&language=CHS