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Research Review of the Knowledge Graph and its Application in Power System Dispatching and Operation

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With the construction of a new power system and the proposal of a double carbon goal, power system operation data are growing explosively, and the optimization of power system dispatching operation is becoming more and more complex. Relying on traditional pure manual dispatching is difficult to meet the dispatching needs. The emerging knowledge graph technology in the field of the artificial intelligence technology is one of the effective methods to solve this problem. Because the topological structure of the power system itself is consistent with the relational structure of graph theory, through the establishment of a relevant knowledge graph, the real operating state of the power system can be restored to the maximum extent by effectively preserving the correlation implicit in the data. Meanwhile, expressing the hidden knowledge in the power system dispatching operation in the form of a knowledge graph has become the focus of research at home and abroad. This study summarizes the development of the knowledge graph technology from the aspects of knowledge extraction, knowledge representation learning, knowledge mining, knowledge reasoning, knowledge fusion, and the application of knowledge graph and introduces the application and prospect of knowledge graph in the power system dispatching operation from the aspects of the auxiliary optimization decision, vertical risk control, operation mode analysis, optimization model improvement experience, and super regulation parameters.

Keywords: knowledge graph, knowledge graph construction, power systems, dispatching operation, application framework

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1 INTRODUCTION

The power system is an ultra-large-scale industrial system that strictly follows the laws of physics. The dispatching system plays an important role in ensuring the safe, stable, and reliable operation of the power system. Traditional power dispatching relies on power dispatchers to make manual judgments and implement dispatching operations based on the actual operation of the power system in accordance with the dispatching regulations and plans, supported by professional knowledge and artificial experience. This process is quite complicated and excessively depends on the experience of dispatchers (Zhang et al., 2021a). In recent years, with the development of the power system, the traditional dispatching methods have been unable to meet the dispatching needs. The new power system has higher requirements for the processing of power data, for the following two reasons:

1) As the environmental problems caused by carbon emissions come into focus worldwide, the development of new energy has ushered in a new wave (Seferlis et al., 2021). The continuous development of distributed power generation has made the components of the power system more and more complex, and the instability of its operation has increased significantly, resulting in a significant increase in the breadth, dimensionality, and efficiency of power data processing requirements for power dispatch operations. It is difficult to meet with traditional purely manual dispatching operations (Liu et al., 2021; Li et al., 2020);
2) With the development of marketization, it is increasingly difficult to predict users' electricity consumption behavior. Therefore, the evaluation and prediction of this behavior based on massive historical data play an important role in grid marketization transactions and real-time voltage balance. Also, it is difficult to effectively use these historical data with human resources (Guo et al., 2021a).

In order to adapt to the situation that power dispatching has higher and higher requirements for data processing, artificial intelligence represented by deep learning is gradually applied in various business fields of dispatching operation (Madan and Bollinger, 1992; Saqib et al., 2020). In recent years, the integration of the artificial intelligence technology and other disciplines has promoted the artificial intelligence technology to become the technical support for the rapid development of various industries, among which the knowledge computing engine and knowledge service technology have provided inexhaustible power (Benjamins, 2013).

As the size of the power system continues to increase, new elements in the system increase, which makes the massive and diverse structured and unstructured data in the power grid grow rapidly and presents the situation of the complex structure and a wide variety. The requirements for data analysis and understanding have far exceeded the physiological limit of human beings. Therefore, the dispatching operation is no longer satisfied with data mining and application. It faces the technical bottleneck of converting data into knowledge. Combined with the current development of the mobile Internet, the Internet of Things has become an inevitable trend of historical development. Previous AI techniques have focused on analyzing individuals within a single or small system. However, in the era of the Internet of Things, the analysis of the relationship between individuals in large-scale systems has also become a part that cannot be ignored, and its data happen to be the most valuable material for analyzing the relationship. As a complex non-linear operating system, the ultra-large-scale power system has accumulated massive amounts of data in many years of operation, but it still employs the traditional management mode based on manual experience or the exploration of intelligent operation schemes based on data. The massive amount of equipment and a huge amount of data connected to the system have not yet truly realized the Internet of Things. It is one of the effective means to improve data utilization and solve current scheduling problems by constructing a relevant knowledge map of the power system and transforming the mass data accumulated in the power system into knowledge form. By abstracting and converting information and data in a given context and the application of data and information, knowledge arises (Rowley, 2007). Therefore, the knowledge graph is expected to become the core technology of the next-generation dispatching system.

Based on this, this study briefly describes the development process of the knowledge graph by combining the development of the artificial intelligence technology, the demand analysis of the power system for the artificial intelligence technology, and the introduction of the origin and basic technology of the knowledge graph. Finally, it summarizes and forecasts the application scenarios and prospects of the knowledge graph, which provides a useful reference for its further application in power system dispatching operations.

2 BASIC CONNOTATION AND APPLICATION OF THE KNOWLEDGE GRAPH

The knowledge graph is a structured semantic knowledge base representing entities and their relationships in the objective world in the form of a graph (Yan et al., 2018). In the knowledge graph, attribute features of entities are represented by attribute-value pairs, and the basic constituent unit of inter-entity relations is the triad of entity-relationship-entity (Hogan et al., 2021). Therefore, the knowledge graph can be expressed as: $G=(E,R,S)$, where $E = \{e_1,e_2,...,e_{|E|}\}$ denotes there are $|E|$ distinct entities in the entity set; $R = \{r_1,r_2,...,r_{|R|}\}$ denotes there are $|R|$ different kinds of relations in the set of relations; $S \subseteq E \times R \times E$ is a collection of triples in the knowledge base.

The knowledge graph is essentially a kind of semantic web (Li et al., 2019; Wang et al., 2018), and its development can be traced back to the mapping knowledge domain (Garfield, 1955), which is put forward in the 1950s, and the semantic network (John, 1991). With the advent of the era of big data, traditional unilateral technologies such as data processing, knowledge representation, and natural language processing can no longer meet the needs of scientific research and application. Sheth and Kellstadt. (2020) and Shi and Zheng. (2006) described the urgent need for new and effective methods of massive data processing in various fields. The knowledge graph, which integrates multiple technical genes, provides the possibility of transferring from data intelligence to knowledge intelligence. As a result, it becomes the focus of researchers' attention. As shown in **Figure 1**.

The construction of the knowledge graph framework can be roughly divided into four processes, namely, knowledge extraction, knowledge representation learning, knowledge mining, and knowledge reasoning and fusion (Wu et al., 2018). The following is a detailed introduction of key technologies for constructing a knowledge graph based on the relevant research literature.

2.1 Knowledge Extraction

Knowledge extraction plays a decisive role in the process of constructing a knowledge graph. The quality of the extracted knowledge directly affects the quality of knowledge graph construction. It is mainly divided into three steps: term extraction, relationship extraction, and concept extraction (Wu et al., 2018).

Term extraction is the first step of knowledge extraction, and there are many methods to realize it, including four-term extraction methods (Etzioni et al., 2008) based on dictionaries, rules, statistics, and machine learning. The second step is relation extraction, and the difficulty is mainly the extraction of synonymous relations (Zhou et al., 2014). The last step is concept extraction (Fu et al., 2020). Currently, the commonly used concept extraction method is based on linguistics or statistics.

2.2 Knowledge Representation Learning

Knowledge can only be processed by a computer after reasonable representation, and it can be expressed as a database that can be understood by a computer (Dettmers et al., 2017), (Viloria and Lezama, 2019). The traditional RDF triplet knowledge representation has some problems such as low computational efficiency and severe data sparsity, so the domestic and foreign scholars begin to focus more on knowledge representation learning. Zhang et al. (2020a) point out that knowledge representation learning can significantly improve computing efficiency, effectively alleviate data sparsity and realize heterogeneous information fusion, and has important applications in similarity calculation and knowledge graph completion.

Traditional knowledge representation learning models include TransE, TransR, TransD, TransG, and TransH models (Cesar et al., 2019). Subsequently, many scholars improved them and proposed more advanced models such as PTransE (Lin et al., 1506), TransR-DT, TranSparse, and ITMEA models. In addition, in order to deal with some problems of specific conditions in specific fields, some scholars have proposed some novel methods like JAPE (Hu and Li, 2017), ConvE (Dettmers et al., 2017), MGTransE (Warren et al., 2019), MKRL (Tang Xing et al., 2019), and KG2E (Lei et al., 2020). Getting to the essence, knowledge representation is dedicated to finding suitable l_h and l_r for each triple (h, r, t) to vectorize the head entity and tail entity. The relation l_r is the translation from the head entity vector l_h to the tail entity vector l_t, such that $l_h + l_r \tilde{} l_t$.

2.3 Knowledge Mining

Knowledge mining mines out new relationships and completes the information of the knowledge graph (Zhang et al., 2021b). Knowledge mining refers to employing link prediction, neural network technology, decision tree, and other methods to mine and supplement the implicit knowledge of the knowledge graph. It is the technical basis for knowledge reasoning and fusion, and indispensable technical means in the construction of large-scale knowledge graph, which mainly can be divided into three branches: clue mining, relationship reasoning, and relationship prediction (Chen et al., 2015).

Clue mining is an important means of realizing entity relationship mining through graph processing methods such as the subgraph construction and link branch search (Kumar et al., 2008). Hossain et al. (2012) and Fang et al. (2011) used the techniques of relationship classification and correlation analysis to mine the potential entity relationships of the knowledge graph. Both these methods analyze the entities of the entire knowledge base one by one, which are not suitable for large-scale knowledge graphs due to a large amount of computation and inflexibility.

Different from clue mining, relationship reasoning focuses on reasoning only about the connection relationship between two entities. At present, there are two common relational reasoning methods, which are rule-based and probabilistic graph-based. The former mostly uses machine learning-related technologies such as Horn clauses or inductive logic (FOIL) (Mitchell et al., 2009) to reason about potential relationships between entities, while the latter tends to effectively classify the entities and relationships in the knowledge base to form the Markov logic network, from which the underlying relationships between entities are inferred.

Relationship prediction is mainly to solve the problem that the relationship between entities in the knowledge base may change with the influx of new information or the development of time. Jia et al. (2013) used the unsupervised machine learning technology to predict the implied in online data for web pages and achieved good results. Relationship prediction technology is the basis for the real-time update of the knowledge graph. It is also an important means for expanding the scale of the knowledge graph and a key research direction in the future.

2.4 Knowledge Reasoning and Fusion

Knowledge reasoning and fusion is the core step in the construction of a knowledge graph. It is actually to realize the real-time update of the knowledge graph. As mentioned in the previous relationship prediction, the real-time update of the knowledge graph is mainly due to the need to continuously add new information and knowledge and the possible changes in the relationship among its internal entities when the content of the knowledge graph changes. At present, domestic and foreign scholars have not performed in-depth research on the update of knowledge graphs, and their related implementation methods mostly stay in the manual update. In other words, the few auto-update technologies available are not very practical.

In order to meet the demand for automatic updating of the knowledge graph, automatic updating usually involves applying algorithms such as machine learning to the knowledge graph and automatically seeking updating requirements and implementation methods through continuous self-training. In terms of automatic updating, the data of the NELL (Jia et al., 2014) system comes from the Internet, and it has formulated a self-correction system during the construction of the database to realize self-correction and automatic update functions. The YAGO2 (Hoffart et al., 2013) system assigns the entity a time attribute. As time changes, the corresponding state or relationship of the entity is automatically updated, according to the internal recognition function of the system.

2.5 Application of the Knowledge Graph

The research on knowledge graphs has just started, and there is still a long way to go for the research on the application of knowledge graphs in various fields. At present, the applications of knowledge graphs are roughly divided into two categories: the

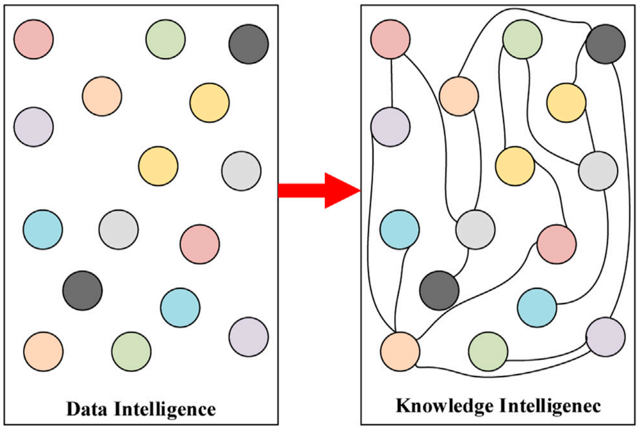

FIGURE 1 | Impact of the knowledge graph on the age of artificial intelligence.

general domain knowledge graph applications and the specific ones.

For general fields, semantic search and intelligent question answering are two common ones. Semantic search not only greatly improves the accuracy and predictability of search engines such as Google and Wiki but also injects new vitality into the analysis of abnormal crowd behaviors (Hatirnaz et al., 2020), the power field (Chen et al., 2020), and domain of World News (Kallipolitis et al., 2012).

With the rapid increase in the research interest in intelligent question-answering systems in recent years, the aforementioned systems based on the knowledge graph have been applied in many fields, such as high school education (Yang et al., 2021), medical field (Jiang et al., 2021a), speech interface (Kumar et al., 2017), and tourism (Do et al., 2021).

For specific fields, the current application of knowledge graphs in many fields is imperfect. It has only made achievements in a few fields. The more representative ones are the field of traditional Chinese medicine (Yu et al., 2017; Xiong et al., 2021), the financial field (Ma et al., 2021), and the field of computer technology (Chen, 1992).

Although the application of knowledge graphs in specific industries has just started, it can be found that the introduction of knowledge graph technology has brought great convenience and practicability to the development of various industries and also helped break through many technical problems that could not be broken before.

3 FRAMEWORK AND KEY TECHNOLOGIES OF KNOWLEDGE GRAPH APPLICATION IN POWER SYSTEM DISPATCHING OPERATION

At present, the application of artificial intelligence technology in the power system is at a relatively mature stage. A large number of new technologies are applied to multiple professional fields of dispatching operation.

In the field of load forecasting, the convolutional neural network (Yin and Xie, 2021; Sheng et al., 2021), long short-term memory network (Guo et al., 2021b; Zhang et al., 2020b), and deep recurrent neural network (Shi et al., 2018) play an important role in time series prediction. In terms of fault diagnosis, deep belief networks (Peng et al., 2018; Yu et al., 2018) and convolutional neural networks (Zera and Ayati, 2021; Do et al., 2020) are widely used in system feature extraction and classification recognition. Meanwhile, a large number of artificial intelligence technologies are applied in the optimization control of the power system, which is concentrated in the reactive voltage control (Sulaiman et al., 2015; Molzahn et al., 2017) and automatic generation control (Zhang et al., 2021c; Xi et al., 2021). Artificial intelligence technology has achieved satisfactory results in the aforementioned fields. In the field of data quality, Hu et al. (2021a) proposed a generative adversarial network based on the tri-networks form (tnGAN) to handle leak detection problems with incomplete sensor data. Hu et al. (2021d) proposes a hierarchical data recovery method based on generative adversarial networks (GANs).

In the process of development of the artificial intelligence technology, it has gradually encountered the bottleneck of data processing and management. The knowledge graph is the core of the new generation of the data system. Experts and scholars have carried out a lot of targeted research on this (**Table 1** for details):

In terms of power dispatching, Fan et al. (2020); Li. (2019); Jin. (2020); and Dou and Wang. (2020) integrated the knowledge graph into the dispatching domain, which provides a new idea for auxiliary decision-making of the dispatching system. In the study by Ji and Wang (2020), the entities and characteristics of power entity recognition are analyzed, the mechanism of entity recognition is clarified, and entity recognition techniques are analyzed in the context of the power domain. Ong and Karmakar. (2022) proposes a method of embedding energy storage into a knowledge map. Chun and Jung. (2020) proposed an energy knowledge graph (EKG) as an upper schema for the integration of knowledge resources in energy systems. Zhao and Zhao. (2020) shows that the knowledge graph can be applied to the whole power processing procedures, such as electric power-production, operation and marketing procession, and electric power equipment operation and maintenance, as well as customer service. Gao et al. (2020) targeted the distribution network topology and proposed "a picture of the power grid" to build a new generation of operation and command system platform; Jiang et al. (2021b)transformed the natural languages in different files into nodes and relationships in the knowledge base and realized an intelligent retrieval function. Chai. (2019) designed a knowledge graph framework in the power field. The framework includes basic applications such as fault handling, work order processing, and intelligent question and answering.

The mainstream research work of scholars on the knowledge graph is concentrated on the power operation maintenance and overhaul (Hu et al., 2021b). Liu. (2022) proposed a concurrent fault diagnosis method for power equipment based on graph neural networks and knowledge graphs, which can achieve the effectiveness and robustness of concurrent fault mining. Yan et al.

TABLE 1 | Research on the application of knowledge graphs in the field of power system dispatching.

Application area	References
Framework construction of the knowledge graph in the power system dispatching field	Fan et al. (2020); Chai, (2019)
Application of the knowledge graph in power operation inspection	Hu et al. (2021b)-; Liu and Ji, (2021)
Application of the knowledge graph in power marketing	Zhang, (2016); Pan and Yang. (2021)
Other	Wang and An, (2021); Wang and Zhang, (2021)

(2021) presented the graph-based knowledge acquisition method with convolutional networks for distribution network patrol robots which can analyze the defects effectively; Tang Yachen et al. (2019) proposed a graph search method for exhaustively searching for desired information to improve the efficiency of power equipment management; considering the contents and requirements of power grid dispatching business and the internal relationship of basic theoretical knowledge of power grid operation analysis, Gai et al. (2021) provided a method of constructing AC/DC power grid dispatching knowledge property graph; moreover, knowledge graphs have many research results in power equipment (Hu et al. (2021c), substations (Chen et al., 2021), and secondary equipment (Liu and Ji, 2021).

In addition, some scholars are committed to developing power marketing systems embedded in the knowledge graph. For example, Zhang. (2016) investigated how to leverage the heterogeneous information in a knowledge base to improve the quality of recommender systems. Yih. (2015)discussed three-level customer service knowledge graph construction and its knowledge reasoning mechanism; for the problem of ambiguity in Chinese expression in the customer service question and answer system, Pan and Yang. (2021) introduced the LSTM attention model to improve the answer quality of the knowledge graph.

Moreover, the knowledge graph has the following applications in power grid dispatching. Wang and An. (2021) proposed a method to identify the topology of a power network based on a knowledge graph and the graph neural network, and it can accurately identify network topology even in the presence of conflicting and missing measurement-related information. Wang and Zhang. (2021) explored and developed an intelligent robot for dispatching and controlling to ensure power supply based on multivariate information, which realizes the functions of interface integration of various service platforms, visualized monitoring of power supply information, and release and submission of power supply information.

3.1 Overall Framework

Combined with the current research technology of the knowledge graph and the requirements in the field of power system regulation and control, the basic framework of the knowledge graph applied to dispatching operation is proposed from the aspects of basic data, data processing, knowledge extraction, graph construction, and graph application, as shown in **Figure 2**.

The knowledge graph adapted to the field of large-scale power systems should have the following technical characteristics:

1) Spatiotemporal dynamic characteristics: A timestamp system should be built for the basic attributes such as entity id and name and characteristic attributes such as power and power flow in the knowledge graph according to the time-varying characteristics of the power system. Update of extreme values should be formulated, and the

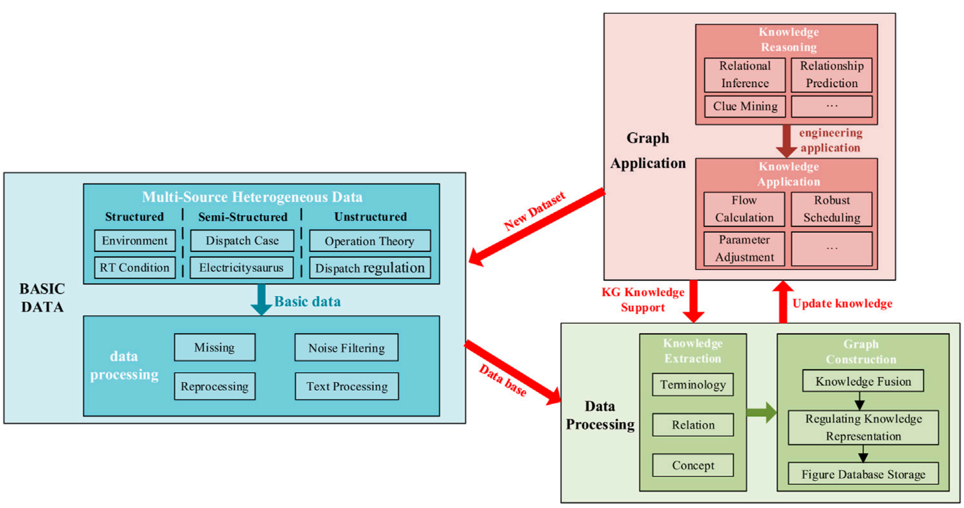

FIGURE 2 | Power system dispatching operation knowledge graph framework.

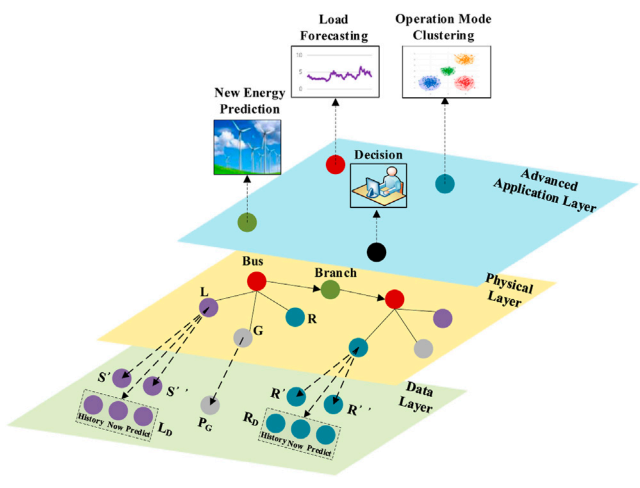

FIGURE 3 | Multi-level knowledge graph for power system dispatching operation.

dynamic information of the knowledge graph should be updated in real-time while the system is running to meet the needs of synchronous circulation of the knowledge graph and power system;

2) Multivariate data fusion: The power system dispatching field has characteristics such as huge data volume, diverse data types, and high-speed data value. In the construction process, data from multiple sources such as image recognition, semantic analysis, and equipment monitoring are integrated into the knowledge graph. A rich data foundation should be provided for realizing potential relationship mining;
3) Field business crossover: Combining the differences in business requirements such as communication, relay protection, and automation in the power system dispatching field, a business knowledge graph should be built in a refined, standardized, and differentiated manner. Cross-flow processes should be systematically built between different businesses to establish a complete domain knowledge graph for the field of dispatching.

3.2 Knowledge Graph Support Scenario for Dispatching Operation

The multi-level knowledge graph architecture suitable for power system dispatching operation business is shown in **Figure 3**. It takes the physical layer knowledge graph as the core and fits the graph theory. This layer constructs the power system graph according to the real power grid topology. The data layer corresponds to the actual operating conditions of the power grid and works with the physical layer to build a real-time updated dynamic power dispatch knowledge graph. The advanced application layer provides external technical support such as load forecasting and dispatching decisions for the dynamic knowledge graph.

3.2.1 Auxiliary Optimization Decision

With the massive new energy incorporated into the power grid, the operation mode of the power system is becoming more and more complex. Relying on the traditional dispatching means cannot meet the dispatching needs. This problem can be effectively alleviated by constructing the historical dispatching knowledge graph to assist in the optimization of decision-making. Combined with the relevant scheduling data of historical scheduling days, the historical scheduling knowledge graph is constructed based on knowledge extraction, knowledge reasoning, and other knowledge graph construction methods. In the process of formulating the scheduling plan, we combined the data of the dispatching day with the meteorological data, relevant policies, system conditions, maintenance plans, and operation constraints and made similar daily matching with the constructed knowledge base graph of the historical scheduling based on clustering so as to search for the relevant knowledge of several historical dispatching days similar to the dispatching day, such as the generation plan curve, system operation target, and maintenance knowledge. We also assisted in scheduling plans and optimizing decisions. As shown in **Figure 4**.

3.2.2 Vertical Risk Management

The construction of a new power grid has made the form of safe operation of the power grid increasingly severe. In response to the problem of "difficult to see, difficult to find, and difficult to control", it is urgently needed to be monitored in real-time, quantitatively evaluated, and intelligently controlled. At present, some scholars have conducted research on the application of knowledge graphs in power grid equipment fault or risk management. For example, by constructing a power-knowledge graph, Liang, (2022) proposed a power fault retrieval and recommendation model based on user polymorphism perception (pf2rm), which improves the effect of fault analysis, retrieval, and recommendation in the actual operation scenario of the power grid. Kieffer (2021) proposes a method to represent the grid as a knowledge graph, and it effectively solves the problem that a large number of traveling waves may be difficult to describe and evaluate when the hybrid line includes overhead and underground parts. Lan and Tang, (2010) proposed a fault diagnosis method for hydropower units based on the knowledge graph, which improves the accuracy and timeliness of the hydropower unit condition monitoring and fault diagnosis system. However, most of the current studies focus on a certain working condition or certain equipment and do not analyze it from the aspect of the whole power grid dispatching operation.

Combined with the characteristics and difficulties of current power system risk management and control, we proposed a vertical risk management and control framework for the power system based on the knowledge graph. The coupling analysis of multiple risks for complex power grids is shown in **Figure 5**, which involves semi-structured and unstructured data including textual knowledge of risk regulations and expert experience. Structured data such as operating data are

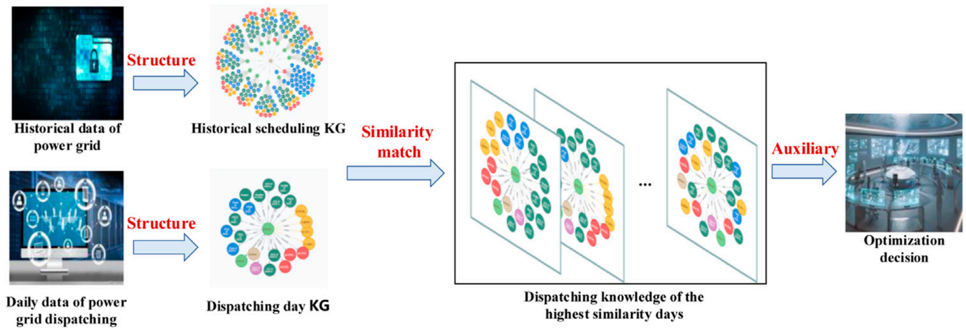

FIGURE 4 | Auxiliary optimization decision based on the knowledge graph.

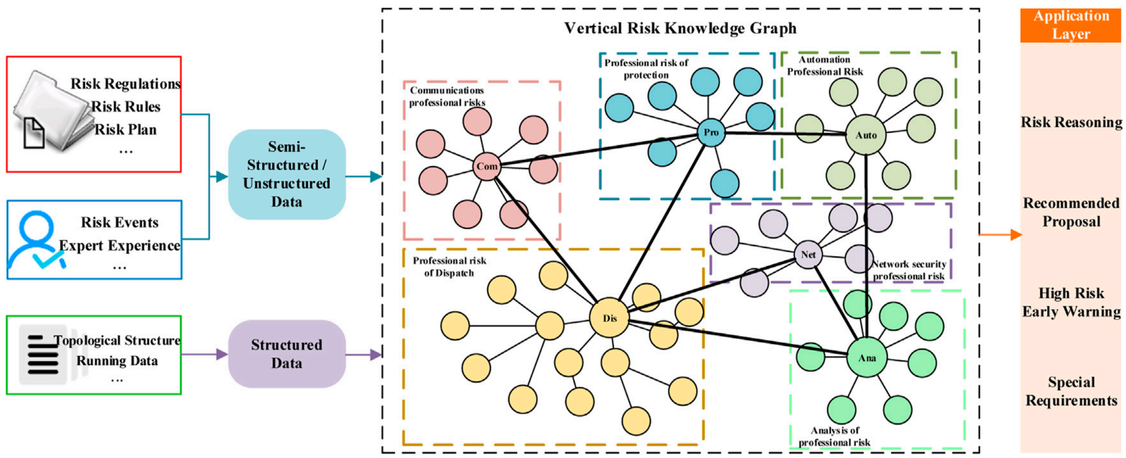

FIGURE 5 | Multiple coupling vertical risk schematic representation.

combined, and knowledge extraction and other means are used to establish a vertical risk knowledge graph.

Based on the knowledge graph in **Figure 5**, entities, attributes, relations, and other elements are updated online in real-time under actual working conditions. Combining the requirements of risk prediction and management and control plan recommendation in the dispatching business, the forward impact analysis and the reverse traceability query of the risks faced in the operation of the power grid will be helpful for the comprehensive security risk analysis and control of the complex power system.

3.2.3 Operation Mode Analysis

With the introduction of a high proportion of new energy sources and the emergence of diversified loads, the operation of the power system is gradually dominated by these new elements. In order to effectively restore the real system to more accurately evaluate the safety, stability, and reliability of the power system, the importance of studying the mechanism of power system operation modes changes has gradually become prominent. Faced with complex operation modes, as shown in **Figure 6**, the system operation mode diagram under multiple time sections is obtained through the dynamic knowledge graph. The power system operation mode includes the traditional unit output, new energy unit output, power flow, and load characteristics of transmission lines. Through the clustering algorithm and compactness index calculation, the typical operation mode of the new power system can be finely identified for the massive and changeable power system operation mode. As a result, it is possible to avoid the shortcomings in the actual operation of large-scale actual power systems in the method of selecting typical operating modes based on experience.

3.2.4 Optimization Model Improvement Experience

For dispatching optimization software, planners will have relevant optimization model improvement experience, which can significantly improve the calculation efficiency and decision-making quality of the dispatching optimization software. Using past dispatching experience as input data, a knowledge graph of procedure experience is constructed and searched for corresponding improvement experience. According to the existing dispatching optimization software, a mapping clustering model between system data such as power grid topology and load forecasting and the optimization model improvement experience is constructed through the knowledge graph of the procedure experience. As shown in **Figure 7**.

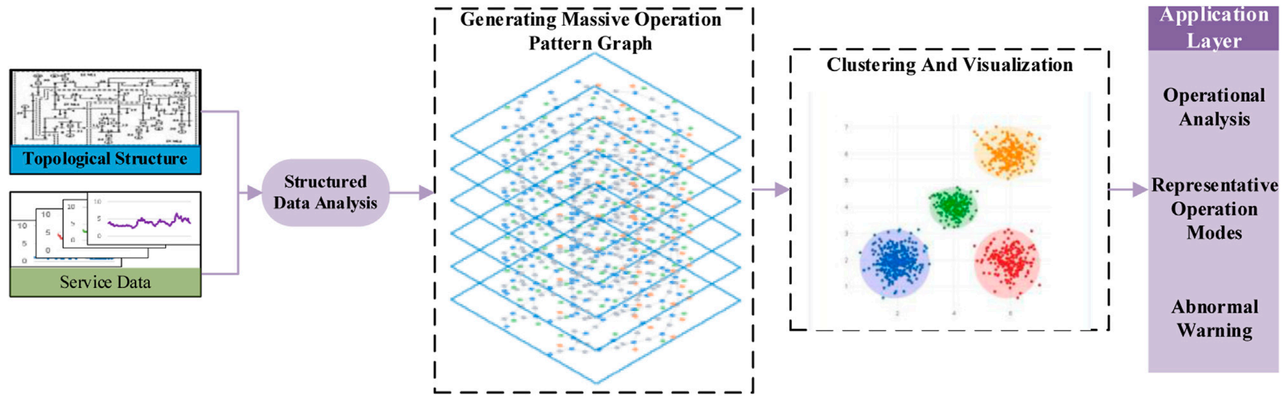

FIGURE 6 | Schematic diagram of operation mode analysis based on the knowledge graph.

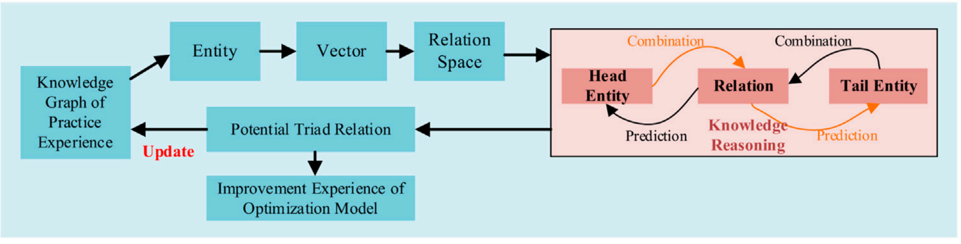

FIGURE 7 | Optimization of model improvement experience assisted by the knowledge graph.

3.2.5 Super Tuning Parameters

The operation of ultra-large-scale power systems in a highly random environment poses higher challenges to the accuracy and real-time performance of parameter adjustment. For example, the parameters of the power system stabilizer (PSS) have a key influence on the suppression of low-frequency oscillations of the power system. Traditional tuning methods adopt the root locus method, state-space model, and other methods. However, they usually do not have generalization and are easy to fall into local optimum. When the operating conditions change, they cannot realize self-update. Taking the knowledge graph as the core, heterogeneous knowledge and data are integrated into the data layer of the knowledge graph, and PSS selection and parameters are added to the advanced application layer of the knowledge graph so as to explore the deep relationship between operation status and operation parameters. Realizing super tuning with super-large-scale parameter real-time self-tuning as the core is also an important development direction of the knowledge graph.

3.3 Technical Difficulties

The knowledge graph is another technological sublimation of the application of artificial intelligence to the power system. With the gradual evolution of the knowledge graph, it has the trend to develop into the brain knowledge base of the dispatch system control center. However, there are still some problems in the process of applying knowledge graphs to actual projects:

1) Knowledge acquisition: There is a large amount of operating data in the power system, including massive empirical data and operating data. Due to the multiple heterogeneities of data, data acquisition and processing will be a huge project.
2) Knowledge representation: The power system is an extremely complex multi-layer and intersecting three-dimensional system. The data of each layer are appropriately fused into a knowledge graph including information such as source network load storage and the process of knowledge representation from data to knowledge. Here comes a very high challenge.
3) Knowledge application: The knowledge graph is essential to transform data into knowledge. Both digging out effective information accurately from the existing graph and reducing the optimization space for the optimization process of the system in specific scenarios put forward greater requirements for the flexible application of knowledge graphs.

4 CONCLUSION

As a new direction in the development of artificial intelligence, the knowledge graph combines important theoretical methods such as data storage, data processing, and heterogeneous data coexistence. It has changed the traditional artificial intelligence method of "solving problems with algorithms," provided the new idea of "getting conclusions with knowledge," and opened the path from "data" to "knowledge," which is considered to be the core field of the next generation of artificial intelligence and has received extensive attention from the academia. Therefore, further research on the knowledge graph and its application has important theoretical value and engineering significance for various industries. Through the introduction of this study, readers will have a preliminary understanding of the knowledge graph and be able to apply the knowledge graph to the fields of science and engineering.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

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REFERENCES

Benjamins, V. (2013). Information Is Not Knowledge, Knowledge Is Not Wisdom, Wisdom Is Not Truth. *Int. J. Hum-Comput Stud.* 71 (2), 166–170. doi:10.1016/j.ijhcs.2012.10.005

Cesar, S., Zhang, H., and Imran, S. (2019). Experience Based Knowledge Representation for Internet of Things and Cyber Physical Systems with Case Studies. *Futur Gener. Comp. Syst.* 92, 604. doi:10.1016/j.future.2018.01.062

Chai, B. (2019). "Research on Applications of Artificial Intelligence in Business Management of Power Grid Enterprises," in 2019 IEEE 4th Adv. Inf. Technol. Electron. Autom. Control Conf. (IAEAC), Chengdu, China, December 20–22, 2019, 683–688. doi:10.1109/iaeac47372.2019.8997608

Chen, F., Deng, P., and Wan, J. (2015). Data Mining for the Internet of Things: Literature Review and Challenges. *Int. J. Dritrib Sens. Netw.* 11 (8), 431047. doi:10.1155/2015/431047

Chen, M., Chen, D., and Jiang, Y. (2021). "Substation Operation Ticket System Based on Natural Language Analysis and Intelligent Reasoning[J]," in IOP Conference Series: Earth and Environmental Science, Guilin, China, November 13–15, 2020

Chen, T., Zhang, S., and Wang, Y. (2020). Construction Methods of Knowledge Mapping for Full Service Power Data Semantic Search System. *J. Signal Process Syst. Signal Image Video Technol.* 93 (2-3), 275–284. doi:10.1007/s11265-020-01591-6

Chen, Z. (1992). Knowledge Graphs for Information Systems. *Comput. Educ.* 18 (4), 267–272. doi:10.1016/0360-1315(92)90098-p

Chun, S., and Jung, J. (2020). Designing an Integrated Knowledge Graph for Smart Energy Services[J]. *J. Supercomput.* 76 (10), 8058–8085. doi:10.1007/s11227-018-2672-3

Dettmers, T., Minervini, P., and Stenetorp, P. (2017). "Convolutional 2D Knowledge Graph Embeddings," in 32nd AAAI Conference on Artificial Intelligence (AAAI-18), New Orleans, LA, February 2–7, 2018 (New Orleans, LA, USA.

Do, P., Phan, T., and Gupta, B. (2021). Developing a Vietnamese Tourism Question Answering System Using Knowledge Graph and Deep Learning. *ACM Trans. Asian Low-Resour Lang. Inf. Process* 20 (5), 81. doi:10.1145/3453651

Do, T., Tuyet-Doan, V., and Cho, Y. (2020). Convolutional-Neural-Network-Based Partial Discharge Diagnosis for Power Transformer Using UHF Sensor. *IEEE Access* 8, 207377–207388. doi:10.1109/access.2020.3038386

Dou, J., and Wang, Y. (2020). Research on Power Network Regulation Mechanism Based on Knowledge Mapping. *IOP Conf. Ser. Mater. Sci. Eng.* 740, 0121368. doi:10.1088/1757-899x/740/1/012136

Etzioni, O., Banko, M., and Soderland, s. (2008). Open Information Extraction from the Web[J]. *Commun. Acm* 51 (12), 68–74. doi:10.1145/1409360.1409378

Fan, S., Liu, X., and Chen, Y. (2020). How to Construct a Power Knowledge Graph with Dispatching Data? *Sci. Progrm* 2020, 8842463. doi:10.1155/2020/8842463

Fang, L., Sarma, A., and Yu, C. (2011). REX: Explaining Relationships between Entity Pairs. *Proc. VLDB Endow.* 5 (3), 241–252. doi:10.14778/2078331.2078339

Fu, S., Chen, D., and He, H. (2020). Clinical Concept Extraction: A Methodology Review. *J. Biomed. Inf.* 109, 103526. doi:10.1016/j.jbi.2020.103526

Gai, X., Ruan, M., and Zhang, H. (2021). Construction Technology of Knowledge Graph and its Application in Power Grid[J]. *E3S Web Conf.* 250, 01039. doi:10.1051/e3sconf/202125601039

Gao, Z., Luo, Y., and Tong, L. (2020). Knowledge Graph-Based Method for Identifying Topological Structure of Low-Voltage Distribution Network[J]. *J. Eng.* (6), 2020. doi:10.1049/joe.2019.1319

Garfield, E. (1955). Citation Indexes for Science: a New Dimension in Documentation through Association of Ideas. *Science* 122 (3159), 108–111. doi:10.1126/science.122.3159.108

Guo, X., Gao, Y., and Li, Y. (2021). Short-term Household Load Forecasting Based on Long- and Short-Term Time-Series Network. *Energy Rep.* 7, 58–64. doi:10.1016/j.egyr.2021.02.023

Guo, Y., Chen, C., and Tong, L. (2021). Pricing Multi-Interval Dispatch under Uncertainty Part I: Dispatch-Following Incentives. *IEEE Trans. Power Syst.* 36 (5), 3865–3877. doi:10.1109/tpwrs.2021.3055730

Hatirnaz, E., Sah, M., and Direkoglu, C. (2020). A Novel Framework and Concept-Based Semantic Search Interface for Abnormal Crowd Behaviour Analysis in Surveillance Videos. *Multimed. Tools Appl.* 79 (25-26), 17579–17616. doi:10.1007/s11042-020-08659-2

Hoffart, J., Suchanek, F., and Berberich, K. (2013). YAGO2: A Spatially and Temporally Enhanced Knowledge Base from Wikipedia. *Artif. Intell.* 194, 28–61. doi:10.1016/j.artint.2012.06.001

Hogan, A., Blqmqvist, E., and Cochez, M. (2021). Knowledge Graphs. *ACM Comput. Surv.* 54 (4), 71. doi:10.1145/3447772

Hossain, M., Butler, P., and Boedihardjo, A. (2012). "Story Telling in Entity Networks to Support Intelligence Analysts," in Proc of the 18th ACM SIGKDD Int Conf on Knowledge Discovery and Data Mining (New York: ACM), 1375–1383. doi:10.1145/2339530.2339742

Hu, J., Zhang, N., and Shang, Y. (2021). "Research on Power Equipment System of Knowledge Graph under Electric Energy in Smart Grid[J]," in IOP Conference Series: Earth and Environmental Science 714, 042034. doi:10.1088/1755-1315/714/4/042034

Hu, Q., Xie, K., and Ren, L. (2021). Research on Application of Artificial Intelligence in Power Industry[J]. *Electr. Power Inf. Commun. Technol.* 19 (1), 73. doi:10.16543/j.2095-641x.electric.power.ict.2021.01.010

Hu, W., and Li, C. (2017). "Cross-Lingual Entity Alignment via Joint Attribute-Preserving Embedding," in International Semantic Web Conference (Cham: Springer), 628

Hu, X., Zhang, H., Ma, D., and Wang, R. (2021a). A tnGAN-Based Leak Detection Method for Pipeline Network Considering Incomplete Sensor Data. *IEEE Trans. Instrum. Meas.* 70, 1–10. Art no. 3510610. doi:10.1109/TIM.2020.3045843

Hu, X., Zhang, H., Ma, D., and Wang, R. (2021d). Hierarchical Pressure Data Recovery for Pipeline Network via Generative Adversarial Networks. *IEEE Trans. Automation Sci. Eng.* doi:10.1109/TASE.2021.3069003

Ji, Z., and Wang, X. (2020). Power Entity Recognition Based on Bidirectional Long Short-Term Memory and Conditional Random Fields. *Glob. Energy Interconnect.* 3 (2), 186–192. doi:10.1016/j.gloei.2020.05.010

Jia, Y., Wang, Y., and Cheng, X. (2014). "An Open Knowledge Computational Engine for Network Big Data," in Advances in Social Networks Analysis and Mining,2014 IEEE/ACM International Conference on (Washington DC: IEEE), 657

Jia, Y., Wang, Y., and Li, J. (2013). "Structural-interaction Link Prediction in Microblogs," in Proc of the 22nd Int Conf on World Wide Web Companion (New York: ACM), 19.

Jiang, W., Zhou, Y., and Chen, S. (2021). Research on the Power Grid Project Data Mining and Knowledge Graph Construction Technologies[J]. *Electr. Power Inf. Commun. Technol.* 19 (2), 15. doi:10.16543/j.2095-641x.electric.power.ict.2021.02.003

Jiang, Z., Chi, C., and Zhan, Y. (2021). Research on Medical Question Answering System Based on Knowledge Graph. *IEEE Access* 9, 21094–21101. doi:10.1109/access.2021.3055371

Jin, L. (2020). Application and Research of Knowledge Graph in Electric Power Field[J]. *Electr. Power Inf. Commun. Technol.* 18 (1), 60. doi:10.16543/j.2095-641x.electric.power.ict.2020.01.009

John, F. (1991). *Principles of Semantic Networks: Exploration in the Representation of Knowledge*. California: Morgan Kaufmann Publishers, INC. San Mateo.

Kallipolitis, L., Karpis, V., and Karali, I. (2012). Semantic Search in the World News Domain Using Automatically Extracted Metadata Files. *Knowledge-Based Syst.* 27, 38–50. doi:10.1016/j.knosys.2011.12.007

Kieffer, M. (2021). Low-complexity Graph-Based Traveling Wave Models for HVDC Grids with Hybrid Transmission Lines: Application to Fault identification[arXiv]. *J. Pap.*, 22

Kumar, A., Schmidt, C., and Koehler, J. (2017). A Knowledge Graph Based Speech Interface for Question Answering Systems. *Speech Commun.* 92, 1–12. doi:10.1016/j.specom.2017.05.001

Kumar, D., Ramakrishnan, N., and Helm, R. (2008). Algorithms for Story Telling. *IEEE Trans. Knowl. Data Eng.* 20 (6), 736–751. doi:10.1109/tkde.2008.32

Lan, F., and Tang, L. (2010). Fault Diagnosis Model for Hydropower Generating Unit Based on Directed Acyclic Graph Support Vector Machine[J]. *J. Pap.* 34 (2), 115

Lei, Z., Sun, Y., and Nanehkaran, Y. A. (2020). A Novel Data-Driven Robust Framework Based on Machine Learning and Knowledge Graph for Disease Classification. *Futur Gener. Comp. Syst.* (102), 534–548. doi:10.1016/j.future.2019.08.030

Li, P., Wu, Q., and Yang, M. (2020). Distributed Distributionally Robust Dispatch for Integrated Transmission-Distribution Systems. *IEEE Trans. Power Syst.* 36 (2), 1193. doi:10.1109/TPWRS.2020.3024673

Li, R., Dai, W., and He, S. (2019). "A Knowledge Graph Framework for Software-Defined Industrial Cyber-Physical Systems," in Proceedings of 45th Annual Conference of the IEEE Industrial Electronics Society (Lisbon, Portugal: IEEE), 2877–2882. doi:10.1109/iecon.2019.8927285

Li, X. (2019). Construction and Application of Knowledge Graph of Power Dispatching Automation System. *Electr. Power* 52, 70.

Liang, K. (2022). PF2RM: A Power Fault Retrieval and Recommendation Model Based on Knowledge Graph[J]. *Energies* 15 (5), 1810. doi:10.3390/en15051810

Lin, Y., Liu, Z., and Luan, H. *Modeling Relation Paths for Representation Learning of Knowledge Bases*. arVix:1506.

Liu, J., Liu, Y., and Liang, H. (2021). Collaborative Optimization of Dynamic Grid Dispatch with Wind Power. *Int. J. Electr. Power Energy Syst.* (133), 107196. doi:10.1016/j.ijepes.2021.107196

Liu, L. Q. (2022). A Concurrent Fault Diagnosis Method of Transformer Based on Graph Convolutional Network and Knowledge Graph[J]. *Front. Energy Res.* 10. doi:10.3389/fenrg.2022.837553

Liu, P., and Ji, Z. (2021). Research and Implementation of Intelligent Diagnosis and Recognition of Secondary Equipment Defects Based on Knowledge Graph[J]. *Electr. Power Inf. Commun. Technol.* 19 (5), 31. doi:10.16543/j.2095-641x.electric.power.ict.2021.05.005

Ma, C., Sun, H., and Wang, S. (2021). Bond Default Prediction Based on Deep Learning and Knowledge Graph Technology. *IEEE Access* 9, 12750. doi:10.1109/ACCESS.2021.3052054

Madan, S., and Bollinger, K. (1992). Applications of Artificial Intelligence in Power Systems. *Electr. Power Syst. Res.* 41 (2), 117.

Mitchell, T., Betteridge, J., and Carlson, A. (2009). "Populating These Mantic Web by Macro-Reading Internet Text," in Proc of the 8th Int Semantic Web Conf (Berlin: Springer), 998–1002. doi:10.1007/978-3-642-04930-9_66

Molzahn, D., Dorfler, F., and Sandberg, H. (2017). A Survey of Distributed Optimization and Control Algorithms for Electric Power Systems. *IEEE Trans. Smart Grid* 8 (6), 2941–2962. doi:10.1109/tsg.2017.2720471

Ong, L., and Karmakar, G. (2022). Embedding Energy Storage Systems into a Dynamic Knowledge Graph[J]. *Industrial Eng. Chem. Res.* doi:10.1021/Acs.Iecr.1c03838

Pan, H., and Yang, X. (2021). Intelligent Recommendation Method Integrating Knowledge Graph and Bayesian Network[J]. *Soft Comput.*, 1. doi:10.1007/s00500-021-05735-z

Peng, B., Xia, H., and Liu, Y. (2018). Research on Intelligent Fault Diagnosis Method for Nuclear Power Plant Based on Correlation Analysis and Deep Belief Network. *Prog. Nucl. Energy* 108, 419–427. doi:10.1016/j.pnucene.2018.06.003

Rowley, J. (2007). The Wisdom Hierarchy: Representations of the DIKW Hierarchy. *J. Inf. Sci.* 33 (2), 163–180. doi:10.1177/0165551506070706

Saqib, S., Choi, B., and Kazmi, S. (2020). State-of-the-Art Artificial Intelligence Techniques for Distributed Smart Grids: A Review. *Electronics* 9 (6), 1030. doi:10.3390/electronics9061030

Seferlis, P., Varbanov, P., and Papadopoulos, A. (2021). Sustainable Design, Integration, and Operation for Energy High-Performance Process Systems. *Energy* (1), 120158. doi:10.1016/j.energy.2021.120158

Sheng, Z., Wang, H., and Chen, G. (2021). Convolutional Residual Network to Short-Term Load Forecasting. *Appl. Intell.* 51 (4), 2485–2499. doi:10.1007/s10489-020-01932-9

Sheth, J., and Kellstadt, C. (2020). Next Frontiers of Research in Data Driven Marketing: Will Techniques Keep up with Data Tsunami? *J. Bus. Res.* 125, 780. doi:10.1016/j.jbusres.2020.04.050

Shi, H., Xu, M., and Li, R. (2018). Deep Learning for Household Load Forecasting-A Novel Pooling Deep RNN. *IEEE Trans. Smart Grid* 9 (5), 5271–5280. doi:10.1109/tsg.2017.2686012

Shi, Z., and Zheng, N. (2006). Progress and Challenge of Artificial Intelligence. *J. Comput. Sci. Technol.* 21 (005), 810–822. doi:10.1007/s11390-006-0810-5

Sulaiman, M., Mustaffa, Z., and Mohamed, M. (2015). Using the Gray Wolf Optimizer for Solving Optimal Reactive Power Dispatch Problem. *Appl. Soft Comput.* 32, 286–292. doi:10.1016/j.asoc.2015.03.041

Tang, X., Chen, L., and Cui, J. (2019). Knowledge Representation Learning with Entity Descriptions, Hierarchical Types, and Textual Relations. *Inf. Process Manage* 56, 809–822. doi:10.1016/j.ipm.2019.01.005

Tang, Y., Liu, T., and Liu, G. (2019). "Enhancement of Power Equipment Management Using Knowledge Graph[C]," in *IEEE PES ISGT Asia 2019 Chengdu China:IEEE* (Asia (ISGT Asia): 2019 IEEE Innovative Smart Grid Technologies).

Viloria, A., and Lezama, O. (2019). An Intelligent Approach for the Design and Development of a Personalized System of Knowledge Representation. *Procedia Comput. Sci.* 151, 1225–1230. doi:10.1016/j.procs.2019.04.176

Wang, C. G., and An, J. (2021). Power System Network Topology Identification Based on Knowledge Graph and Graph Neural Network[J]. *Front. Energy Res.* 8. doi:10.3389/fenrg.2020.613331

Wang, K., and Zhang, R. (2021). Research on Intelligent Technology of Dispatching and Control to Ensure Power Supply Based on Multivariate Information. *J. Phys. Conf. Ser.* 1846 (9pp), 012023. doi:10.1088/1742-6596/1846/1/012023

Wang, X., Ma, C., and Liu, P. (2018). "A Potential Solution for Intelligent Energy Management - Knowledge Graph," in Proceedings of 2018 IEEE International Conference on Energy Internet (ICEI) (Beijing, China: IEEE), 281–286. doi:10.1109/icei.2018.00058

Warren, P., Mulholland, P., and Collins, T. (2019). Improving Comprehension of Knowledge Representation Languages: A Case Study with Description Logics. *Int. J. Hum-Comput Stud.* 122, 145–167. doi:10.1016/j.ijhcs.2018.08.009

Wu, T., Qi, G., and Li, C. (2018). A Survey of Techniques for Constructing Chinese Knowledge Graphs and Their Applications. *Sustainability* 10 (9), 3245. doi:10.3390/su10093245

Xi, L., Wu, J., and Xu, Y. (2021). Automatic Generation Control Based on Multiple Neural Networks with Actor-Critic Strategy. *IEEE Trans. Neural Netw. Learn Syst.* 32 (6), 2483–2493. doi:10.1109/tnnls.2020.3006080

Xiong, W., Cao, J., and Zhou, X. (2021). Design and Evaluation of a Prescription Drug Monitoring Program for Chinese Patent Medicine Based on Knowledge Graph. *Evid. -based Complement. Altern. Med.* 2021, 9970063. doi:10.1155/2021/9970063

Yan, D., Cao, H., Wang, T., Chen, R., and Xue, S. (2021). Graph-Based Knowledge Acquisition with Convolutional Networks for Distribution Network Patrol Robots. *IEEE Trans. Artif. Intell.* 2 (5), 384–393. doi:10.1109/TAI.2021.3087116

Yan, J., Wang, C., and Cheng, W. (2018). A Retrospective of Knowledge Graphs. *Front. Comput. Sci.* 12 (1), 55–74. doi:10.1007/s11704-016-5228-9

Yang, Z., Wang, Y., and Gan, J. (2021). Design and Research of Intelligent Question-Answering(Q&A) System Based on High School Course

Knowledge Graph. *Mob. Netw. Appl.* 26 (5), 1884–1890. doi:10.1007/s11036-020-01726-w

Yih, W. T. (2015). "Semantic Parsing via Staged Query Graph Generation: Question Answering with Knowledge Base," in Proceedings of the Joint Conference of the 53rd Annual Meeting of the ACL and the 7th International Joint Conference on Natural Language Processing of the AFNLP, Beijing, PR China, July 26–31, 2015, 1321–13311. doi:10.3115/v1/p15-1128

Yin, L., and Xie, J. (2021). Multi-temporal-spatial-scale Temporal Convolution Network for Short-Term Load Forecasting of Power Systems. *Appl. Energy* 283, 116328. doi:10.1016/j.apenergy.2020.116328

Yu, D., Chen, Z., and Xiahou, K. (2018). A Radically Data-Driven Method for Fault Detection and Diagnosis in Wind Turbines. *Int. J. Electr. Power Energy Syst.* 99, 577–584. doi:10.1016/j.ijepes.2018.01.009

Yu, T., Li, J., and Yu, Q. (2017). Knowledge Graph for TCM Health Preservation: Design, Construction, and Applications. *Artif. Intell. Med.* 77 (Mar.), 48–52. doi:10.1016/j.artmed.2017.04.001

Zera, S., and Ayati, M. (2021). Simultaneous Fault Diagnosis of Wind Turbine Using Multichannel Convolutional Neural Networks. *ISA Trans.* 108, 230. doi:10.1016/j.isatra.2020.08.021

Zhang, F. (2016). Collaborative Knowledge Base Embedding for Recommender Systems," in Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data, San Francisco, CA, August 13–17, 2016, 353–362. doi:10.1145/2939672.2939673

Zhang, M., Wu, Q., and Wen, J. (2021). Optimal Operation of Integrated Electricity and Heat System: A Review of Modeling and Solution Methods. *Renew. Sust. Energy Rev.* 135, 110098. doi:10.1016/j.rser.2020.110098

Zhang, R., Chen, X., and Luo, J. (2021). Knowledge Mining of Low Specific Speed Centrifugal Pump Impeller Based on Proper Orthogonal Decomposition Method. *J. Therm. Sci.* 30 (3), 840–848. doi:10.1007/s11630-020-1356-5

Zhang, W., Qin, J., and Mei, F. (2020). Short-term Power Load Forecasting Using Integrated Methods Based on Long Short-Term Memory. *Sci. China-Technol Sci.* 63 (4), 614–624. doi:10.1007/s11431-019-9547-4

Zhang, X., Tan, t., and Zhou, B. (2021). Adaptive Distributed Auction-Based Algorithm for Optimal Mileage Based AGC Dispatch with High Participation of Renewable Energy. *Int. J. Electr. Power Energy Syst.* 124, 106371. doi:10.1016/j.ijepes.2020.106371

Zhang, Z., Cao, L., and Chen, X. (2020). Representation Learning of Knowledge Graphs with Entity Attributes. *IEEE Access* 8, 7435–7441. doi:10.1109/access.2020.2963990

Zhao, X., and Zhao, Y. (2020). Application of Neural Network Based Knowledge Graph in Vertical Industry[J]. *J. Phys. Conf. Ser.* 1584 (5), 012018. doi:10.1088/1742-6596/1584/1/012018

Zhou, D., Zhong, D., and He, Y. (2014). Biomedical Relation Extraction: From Binary to Complex. *Comput. Math. Method Med.* 2014 (1), 298473. doi:10.1155/2014/298473

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