Eng Int Syst (2023) 4: 265–275

Engineering
Intelligent Systems

Application of Data Center Knowledge Graph Based on Power System Fusion Algorithm Design

Chengyue Yang[1]*, Xin Ji[2], Xiaolong Zhao[3], Linxiao Dong[4] and Yuliang Zhao[5]

Big Data Center of State Grid Corporation of China, BeiJing, China, 100052

With the emergence of the Internet and the developments of science and technology, people have entered the information era where they encounter and need to analyze a significant quantity of information every day. Hence, as required by the times, the data center knowledge graph emerges, which can help people to automatically acquire knowledge from massive amounts of data. However, the research on the application of the data center knowledge graph has been confined mainly to the education domain, which has not been not conducive to the development of broader and more comprehensive applications of data center knowledge graphs. In order to help solve these problems, this article conducts a scientific and comprehensive research and analysis on the application of knowledge maps in data centers. The research results show that the robustness of HoPKG model is 3.92% higher than RippleNet model on F1. Compared with traditional algorithms, Hermite fusion algorithm based on HoPKG model has a lower error value, which is of great significance for innovation in data center knowledge map applications.

Keywords: Data Center Knowledge Graph; Power System Fusion Algorithms; HoPKG Model; Hermite Algorithm; Back Propagation Neural Network Algorithm

1. INTRODUCTION

In 2012, in order to allow users to acquire knowledge more quickly and conveniently, Google released a knowledge graph integrated with Google search. Since then, knowledge blueprint technology has developed rapidly and has been broadly applied in various fields such as abstracts analysis, able retrieval and recommendation, and customized human-computer interaction. With the development of a knowledge blueprint, it was more than a simple semantic network; it was an complex arrangement comprised of entities, attributes, concepts, and various rich semantic relationships. Compared with the traditional semantic network, knowledge blueprint has the characteristics of huge scale, rich semantic information, and a user-friendly structure. In order to promote the development of data center knowledge graph, in this paper, we research and analyze the application of data center knowledge graph in terms of the power system fusion algorithm.

In this paper, the research on the application of data center knowledge graph comprises an analysis of the power system fusion algorithm, an examination of the composition and development of data center knowledge graph from a novel perspective, and an exploration of more branches. In terms of power system fusion algorithms, we compare and analyze data center knowledge graphs using various algorithms from the performance and propagation perspectives. The innovations reported in this paper are: (1) the data center knowledge graph was compared and analyzed based on different models; (2) the Hermite fusion algorithm based on the HoPKG model was used to research and analyze the application of a knowledge graph in the data center. We comprehensively and accurately verified the timeliness of the algorithm in processing big data after parallelization.

*Corresponding Author: [1]Email: chengyue-yang@sgcc.com.cn [2]Email: xin-ji@sgcc.com.cn, [3]Email: xiaolong-zhao@sgcc.com.cn, [4]Email: linxiao-dong@sgcc.com.cn, [5]Email: zhaoyuliang@sgcc.com.cn

2. LITERATURE REVIEW

With the ongoing social and technological improvements and developments, individuals are paying more attention to the information center knowledge blueprint, which is currently being used in several different areas. For some time, numerous researchers have conducted in-depth investigations on the application of knowledge blueprints in information centers. Li J addressed this problem by discussing how to convert formal specifications into knowledge graphs, which provided developers and computers with understandable and well-organized specification details [1]. Kang Y proposed a new method called "Policy Knowledge Graph for Coordination between Government Departments" [2]. Fan T used software such as data mining, information processing, and knowledge graphs to generate sepsis-related research content, analyzed historical evolution, and predicted development trends. A total of 8189 papers related to sepsis have been published [3]. Wu Y proposed knowledge graph reasoning based on a tensor decomposition path [4]. Du YJ proposed and constructed a prototype of a channel assurance knowledge blueprint, which is a knowledge management and sharing tool based on knowledge mapping technology. It aims to help enterprises or organizations better manage and utilize their own knowledge assets, and support knowledge sharing, collaboration, and innovation. [5]. The research discussed and analyzed the application of data center knowledge graph in several fields, and continuously improved the application of data center knowledge graph. Therefore, it is necessary to use more technological and comprehensive algorithms to research and analyse the application of knowledge graphs in data centers.

In view of the problem, this paper will study the application of data center knowledge graph in terms of the power system fusion algorithm, which has already been widely used in other fields. The increase in the penetration rate of solar power generation has led to the need for additional flexibility in the operation of the power system. Cui M proposed a market-based flexible ramp service to solve this problem [6]. Zhao J B developed a robust iterative extended Kalman filter based on generalized maximum likelihood method for estimating the state dynamics of power systems under disturbance [7]. The reliability of a power system can be affected by various network attacks. Zhang Y considered four attack scenarios for network components in SCADA system networks that may trigger circuit breakers for physical components. Zhang built two Bayesian attack graph models to illustrate the attack process and determined the probability of a successful network attack [8]. Mathaios provided axiological insights into animation clay and altitude and introduced a probabilistic multi-time and multi-region animation appraisal adjustment based on optimal ability and consecutive Monte Carlo simulations [9]. Nosair H proposed the abstraction of an adaptability envelope to call the adaptability basal dynamics of the ability arrangement and its assets in operation [10]. The research showed the application of power system fusion algorithms in many fields, although most of them were used for computer and model analysis. There is a lack of research on and analysis of data center knowledge graph. Therefore, in this paper, we analyze the application of data center knowledge graph based on the power system fusion algorithm design, provide a theoretical direction for its subsequent development, and lay a foundation for future practical applications.

3. APPLICATION OF DATA CENTER KNOWLEDGE GRAPH BASED ON POWER SYSTEM FUSION ALGORITHM DESIGN

3.1 Data Center Knowledge Graph Application

In the era of big data, traditional knowledge engineering has been unable to meet the needs of open applications in large-scale situations, and the rapid growth of data volume and the substantial increase in computing power have made it possible to automatically acquire knowledge from massive data. Therefore, the knowledge graph concept has emerged. As the cornerstone of cognitive intelligence, knowledge graphs help machine language translation, enhance machine learning capabilities, and enable the interpretability of artificial intelligence. In addition, knowledge blueprints have been widely applied to abstract analysis, intelligent search and recommendation, accustomed human-computer alternation and accommodation support, etc., and has become a focus of attention in the artificial intelligence (AI) field.

A knowledge graph, as a large-scale heterogeneous semantic network, offers rich semantics, high quality, and a user-friendly structure. Many researches examine knowledge graphs and investigate their interpretable suggestions based on knowledge graphs. Figure 1 depicts an example of a knowledge graph.

Knowledge graph construction technology is a complex technical system, which requires knowledge extraction, knowledge fusion, knowledge processing and other technologies to support it, as shown in Figure 2 [11]. Heterogeneous data begins with the formation of a knowledge graph, and involves many key technologies, including knowledge collection, processing, and structured representation. Knowledge extraction is the process of extracting valuable knowledge from a variety of heterogeneous information sources. Knowledge fusion uses related technologies to solve the problem of knowledge ambiguity, and to form a standard knowledge base through the fusion of multiple knowledge bases. Knowledge processing is the process of inferring and representing knowledge, which determines the final quality of the knowledge graph.

(1) Knowledge extraction

Knowledge extraction involves the use of appropriate algorithms to extract knowledge from semi-structured and unstructured data, which is the first link in knowledge graph construction. It involves the following:

Entity extraction: Entity extraction, also known as named entity recognition, is a very critical part of knowledge extraction. It implements related technologies to extract

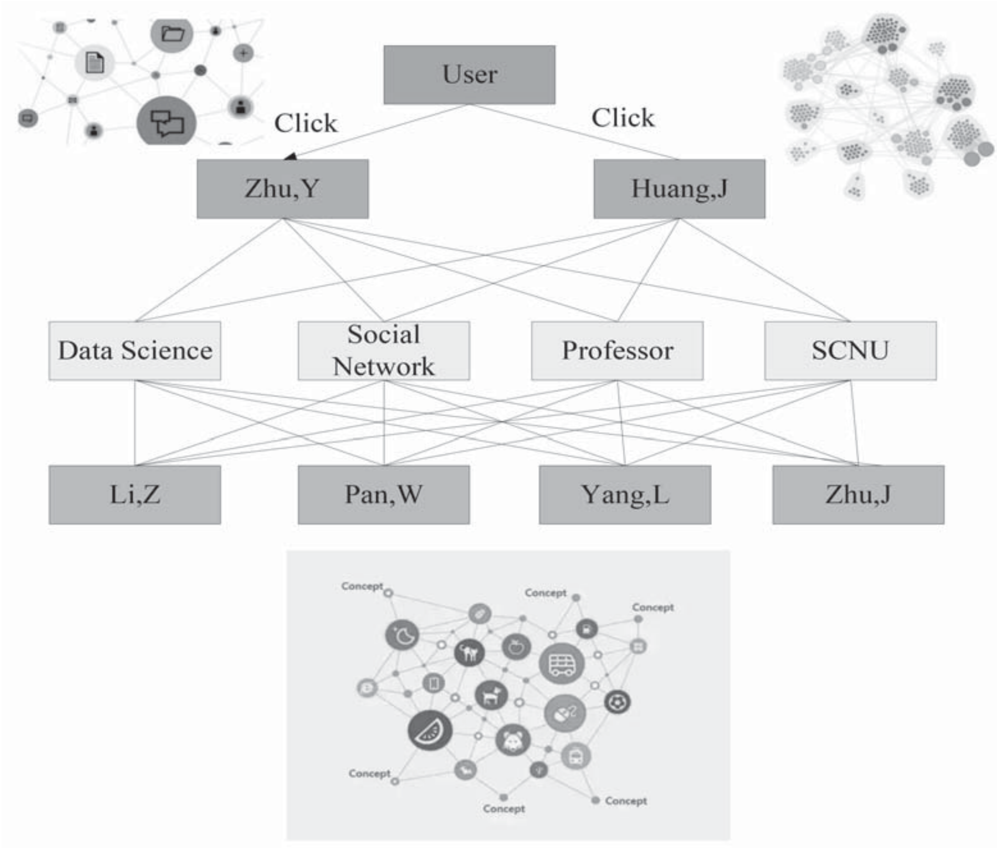

Figure 1 Knowledge graph.

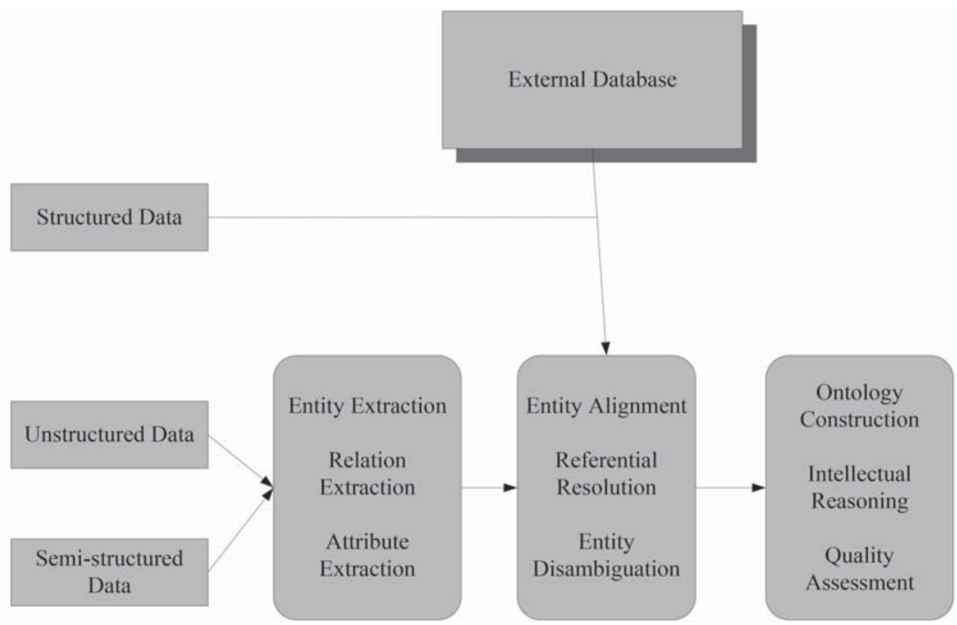

Figure 2 Knowledge graph construction flow chart.

proper nouns and phrases in the current field from the text, and then classify them [12]. The early entity extraction method extracted entities from a single field. However, with the continuous development and progress of technology, the Internet-oriented entity extraction technology has gradually been developed. There are various extraction methods: rule-based methods, statistical model-based methods and open -fields methods.

Relation extraction: Relation extraction extracts semantic-rich relationships between target entities from source data by using suitable algorithms [13]. After relationship extraction, the extracted entities can be connected through this relationship, so that the entities are closely connected. In earlier studies, relation extraction mainly relied on hand-designed grammars and rules, with which the relations between entities in texts can be accurately extracted. Although this method is

Table 1 Graph database vs RDF.

	Graph Database	RDF
Storage Method	Node storage, High query efficiency	Triple storage
Advantage	Easy to manage Easy to model	Easy to transferEasy to update
Shortcoming	Insertion is slow	Inefficient query

highly accurate, it has not been used on a large scale because it requires a large number of professionals to construct the rules and is difficult to extend to other fields.

Attribute extraction: Attribute extraction involves obtaining various attribute information of entities from heterogeneous information sources, and improving the description of entities according to these attribute information [14]. Attributes of entities contain a variety of information. Essentially, entities and attribute values are connected by relationships, so this can be viewed as a special relation extraction task.

(2) Knowledge fusion

Knowledge fusion fuses multiple information sources into a knowledge graph by identifying the equivalent entities, relationships and attributes of the knowledge graph of multiple information sources. In general, knowledge fusion has three parts: entity alignment, entity disambiguation and referential resolution.

Entity alignment: Entity alignment is the technology used to distinguish whether entities in two or more heterogeneous information sources represent the same object simultaneously. The development of entity alignment technology plays a key role in the construction of knowledge graph and knowledge reasoning [15].

Entity disambiguation: Entity disambiguation refers to the technology of resolving ambiguity caused by the existence of more than one entity with different semantics within an entity. For example, the term "Xiaomi" might represent a company, a person, a food, or a pet. Then, it is necessary to use entity disambiguation technology to know exactly what the term "Xiaomi" refers to. Most of the entity disambiguation methods use a clustering model to determine whether multiple entities all point to the same entity name. Through clustering, all entities pointing to the same entity name are clustered together to form an entity target set. However, the real meaning of the entity cannot be clearly known in this way, and the entity-to-entity name matching needs to be performed by calculating the similarity between the entity name and each entity in the entity target set. Two types of similarity calculation methods can be applied to entity disambiguation: the methods based on context content and the methods based on external knowledge bases. The similarity calculation methods based on contextual content d the real semantics of an entity according to the contextual information in the text. Common methods include bag-of-words model, semantic matching model, etc. Similarity calculation methods based on external knowledge bases use external knowledge bases (such as Wikipedia, Wordnet, Freebase and Baidu Baike, etc.) to determine the similarity between entities in the knowledge base, and then realize entity disambiguation [16].

Referential resolution: Referential resolution is the technique of resolving the occurrence of multiple referents to the same entity but representing only the same meaning [17].

(3) Knowledge storage

With the increasing scale of knowledge graphs, the traditional knowledge storage method using files as databases can no longer meet the needs of user query, retrieval and application. In addition, traditional relational databases cannot store graph data that have complex structures and rich relationships. Therefore, the following two graph data storage schemes are derived.

Storage based on graph database: A graph database is a non-relational database based on nodes and edges while retaining the original structure of graph data [18]. Compared with relational databases, it can effectively solve the problem of low query efficiency in graph data storage with massive scale and complex relationships. Graph databases usually store data in the form of graphs and retain attribute information of nodes. Currently, the widely-used graph databases are: Neo4j, Titan, Allegrograph, OrientDB, etc.

Storage based on Resource Description Framework (RDF): RDF is a data model used to describe entities or resources. It is represented in the form of triples (Subject-Predication-Object, SPO), and a collection comprising multiple triples can be regarded as a knowledge graph [19]. In the knowledge graph, an SPO triplet represents a piece of knowledge. RDF is stored by nodes and edges, where nodes usually represent entities and attributes, and edges usually represent relationships. The comparison between graph database-based storage and RDF-based storage is shown in Table 1. The storage method based on graph database has certain advantages in terms of query, management, and modeling, but also has the disadvantage of slow insertion speed. RDF-based storage has advantages in transmission and update, but has poor query efficiency.

(4) Knowledge graph embedding technology

Knowledge graph embedding is a method used to project entities and relationships into vector space to achieve vectorized representation, so as to perform efficient computation between entities and relationships. Common knowledge graph embedding techniques can be divided into two types according to the difference in the realization of knowledge representation: translation distance model and semantic matching model [20].

The translation distance model projects entities and relations into vector space by setting the corresponding scoring function, and calculates the distance of entities in the vector space. The score is calculated with the scoring function Formula (1).

$$\mathrm{f}(a, b, c) = \|a + b + c\|_2^2 \tag{1}$$

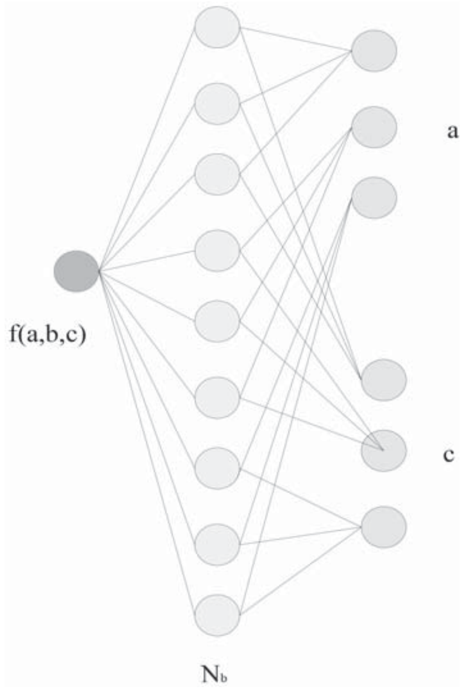

Figure 3 Semantic-matching model.

The TransH model replaces the original relationship vector by introducing a hyperplane; the hyperplane vector can be used to represent different objects when the same node has different relationships.

$$a_s = a - w_b^C a w_b \tag{2}$$

$$c_s = c - w_b^C c w_b \tag{3}$$

The difference between the TransR model and the TransH model is that the TransR model establishes a mapping matrix.

$$f(a,b,c) = \|N, a + b - N, c\|_2^2 \tag{4}$$

KG2E model:

$$a \sim M(\mu_a, N_a) \tag{5}$$

$$b \sim M(\mu_b, N_b) \tag{6}$$

$$c \sim M(\mu_c, N_c) \tag{7}$$

The KG2E model uses a concept similar to the translation distance model to represent the score, and its score function is calculated with Formula (8) and Formula (9), respectively.

$$f(a,b,c) = -\int M_x(\mu_a - \mu_c,\ N_a + N_c)\, In\frac{M_x(\mu_a - \mu_c, N_a + N_c)}{M_x(\mu_b, N_b)}dx \tag{8}$$

$$f(a,b,c) = \int M_x(\mu_a - \mu_c,\ N_a + N_c) \cdot M_x(\mu_b, M_b)dx \tag{9}$$

Semantic-matching model: The semantic matching model obtains the knowledge representation by computing the similarity score between the latent semantic information of entities in the knowledge graph and their relational representations in the vector space. The score function calculated with Formula (10) is shown in Figure 3.

$$f(a,b,c) = a^C N_b c =_{i=0}^{d-1}\ _{j=0}^{d-1}[N_b]_{ij}[a]_j[c]_j \tag{10}$$

Structural equation model: The input layer projects entities and relations into the vector space, and encodes the relations and head entities, relations and tail entities separately in the hidden layer, and finally calculates the score through the score function.

$$f(a,b,c) = (N_1^1 a + N_2^1 b + h_1)^c (N_2^1 a + N_2^2 b + h_2) \tag{11}$$

$$f(a,b,c) = [(N_1^1 a \circ N_1^2 b) + h_2]^c [(N_2^1 a \circ N_2^2 b) + h_2] \tag{12}$$

The entity representation of the multilayer perceptron model is:

$$f(a,b,c) = W^c\ \tan a(N_1 a + N_2 b + N_3 c) \tag{13}$$

3.2 Power System Fusion Algorithm

In recent years, with the rapid development of the smart grid, higher demand standards have been established for the construction, operation and maintenance of power systems. The short-term goal of modern power system technology development is to establish a real-time monitoring system that includes multiple links in the power system to solve the problems of single data acquisition channels, narrow application of monitoring data, and incomplete analysis as in the past.

At present, big data in a power system can be classified as shown in Figure 4.

Electric power big data can be divided into structured and unstructured data according to the type of internal structure of

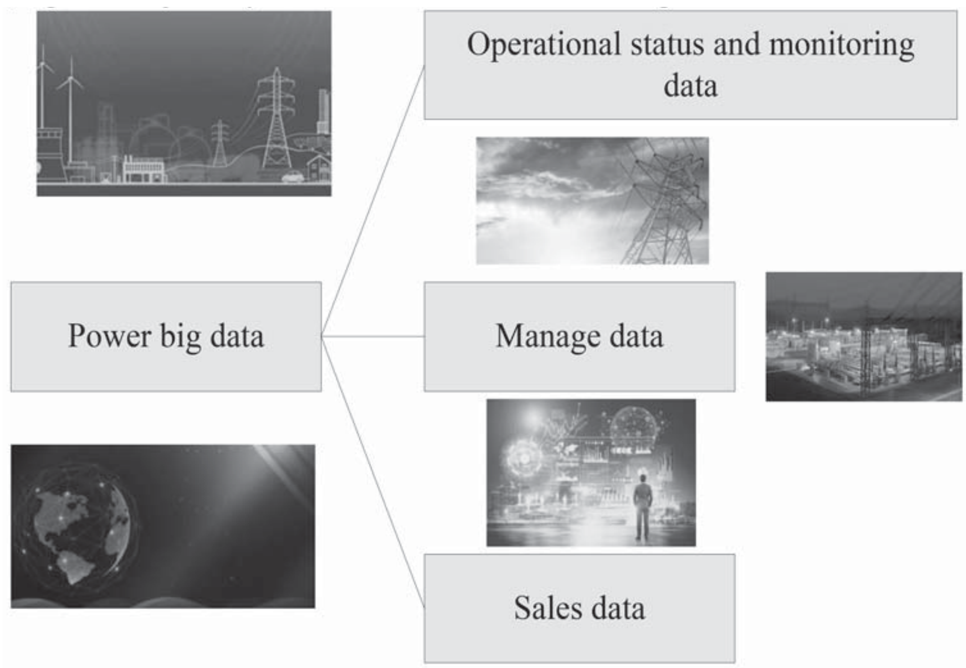

Figure 4 Electric power big data classification.

Table 2 Comparison of big data with traditional data.

	Traditional Data	Big Data
Data Volume	GB → TB	TB → PB
Speed	Stable data growth	Explosive growth of data
Diversity	Structured data	Structured, semi-institutional and unstructured data
Value	Statistics and reports	Condition monitoring and prediction

the system. The amount of unstructured data being generated is growing very rapidly due to more sophisticated means of system monitoring. Unlike structured data, unstructured data generated by video and image processing is generally difficult to store in databases.

Given the current rate at which the amount of unstructured data is increasing, generated by the production, operation, management and other application processes of power systems, in the near future, it will exceed the amount of structured data being produced. Different device types mean that the data collected by the system is diverse in terms of structure, and therefore cannot be effectively correlated. Such system data does not give an accurate description of the system state characteristics. Therefore, the understanding of the distribution of heterogeneous data in the system is also the basis of data processing. The data in the smart grid business can be classified according to three aspects: the power generation side, the power transmission and transformation side, and the power consumption side:

Power generation side: With the development of informatization construction of large-scale power plants, process data with rich information is generated, and these process data are used to monitor equipment operation status and fault warning.

Power transmission and transformation side: Thousands of monitoring points such as phasor measurement devices are continuously collecting data, continuously generating a large amount of unstructured data in forms such as image and video information.

Electricity side: With the popularization of a large number of intelligent monitoring devices at the electricity end, the daily data collection scale has reached tens of thousands of times that of the previous ones.

Through the understanding of the current distribution and types of power-related big data, the data of modern power systems are greatly different from traditional data, as shown in Table 2.

The processing technology for the big data in a power system is shown in Figure 5.

Traditional information fusion processing algorithm: The traditional data fusion algorithm uses the Back Propagation (BP) network. The BP network model has three layers: input layer, hidden layer and output layer.

In the network topology diagram, the input is:

$$X = (x_1, x_2, \ldots, x_m)^T \tag{14}$$

The output is:

$$Y = (y_1, y_2, \ldots, y_n)^T \tag{15}$$

The activation function is:

$$f(x) = \frac{1}{1 + e^{-x}} \tag{16}$$

In the i neuron of the h layer, the input value is:

$$X_i^h = \sum_{j=1}^{m+1} W_{ij} X_j^{h-1} \tag{17}$$

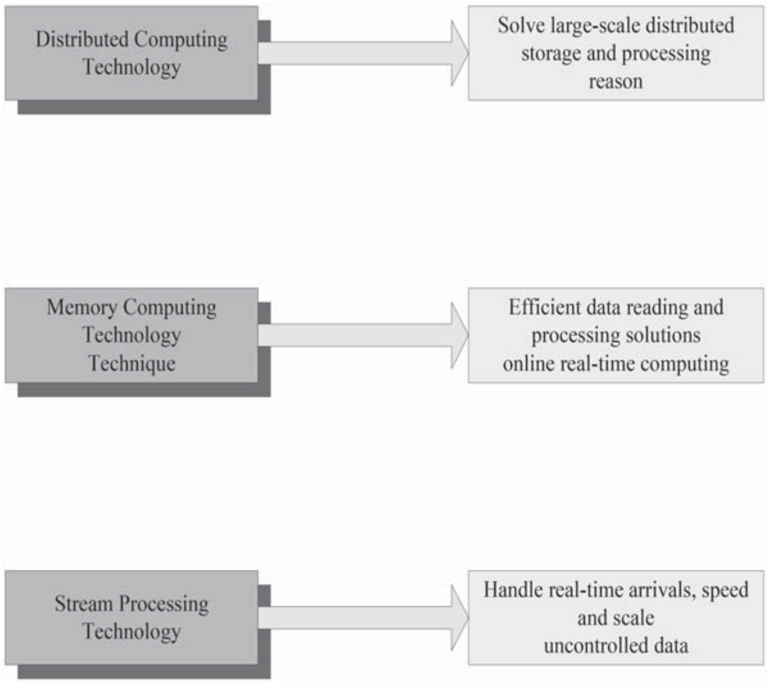

Figure 5 Big data processing technology of a power system.

The output of this neuron is:

$$Y_i^{'h} = f(x_i^h) \tag{18}$$

The error is:

$$e_i^h = Y_i^{'h}(1 - Y_i^{'h}) \sum W_{ij} e_j^{h-1} \tag{19}$$

The mean square error of the entire BP network is:

$$E = \frac{\sum\sum(Y_p - Y_p')_2}{2R} \tag{20}$$

The weight-adjustment formula is:

$$W_{ij}(a+1) = W_{ij}(a) - \eta e_i^h Y' h_j \tag{21}$$

4. EXPERIMENT OF DATA CENTER KNOWLEDGE GRAPH APPLICATION DESIGNED BY POWER SYSTEM FUSION ALGORITHM

4.1 Data Center Knowledge Graph Application

The experimental results are as follows after comparing the data center knowledge maps of several algorithms:

(1) Overall performance assessment

Table 3 and Figures 6 and 7 give the overall performance results. When compared to all other techniques, the HoPKG model has certain benefits in terms of AUC and F1. HoPKG improves from 4.92 percent to 25.85 percent in F1 and from 3.45 percent to 22.54 percent in AUC when compared to RKGE, CKE, MCRec, and PER. HoPKG outperforms CKE, PER, MCRec, and RKGE, because other approaches fail to use higher-order semantic information in knowledge graphs.

Table 3 Comparison of overall performance.

Model	AUC	F_1
PER	0.6525	0.5965
MCRec	0.7524	0.6524
CKE	0.7525	0.6852
RKGE	0.7645	0.7252
RippleNet	0.7854	0.7258
HoPKG-GraphSage	0.7856	0.7256
HoPKG-BiPart	0.7965	0.7525

As shown in Figures 6 and 7, HoPKG also performs the best in agreement of Rec@K and Pre@K compared with other methods. The reason why PER and MCRec do not perform as well as other methods is that the meta-paths need to be constructed manually, which will lead to some uncertainties. Therefore, when the dataset is sparse, the performance is average. In addition, different aggregation methods produce different results. The bifold accession adjustment BiPart has a definite advantage over GraphSage in terms of both AUC and F1. This is because the HoPKG model is a combination of entity representations aggregated in two different ways, which can propagate entity information more efficiently.

(2) Propagation level impact evaluation

Generally, when the knowledge blueprint is propagated, each time the propagation level rises, the number of nodes introduced will rise sharply, and the encryption workload will also increase. Through the suggestion experiment, it was found that with the entry of l, when $l = 3$, the evaluation indicators AUC and F1 also increased, and there was a downward trend again. The results are shown in Figures 8 (a) and 8 (b). The advantage of this aspect is that as the level of progress increases, more abundant entity information

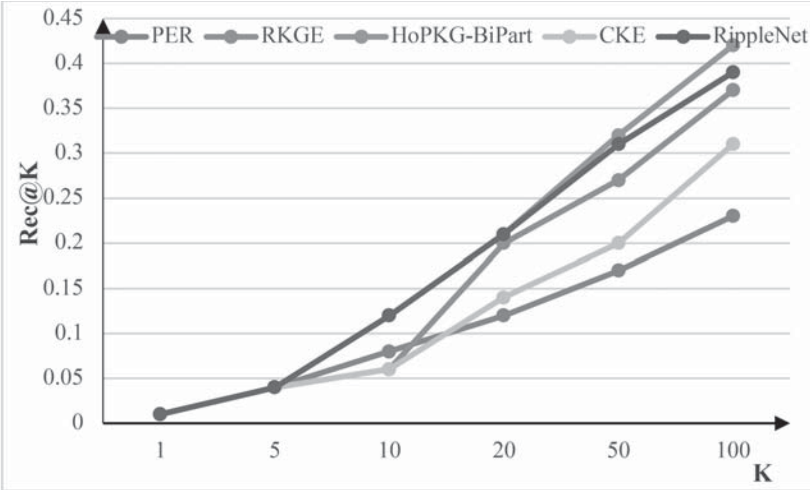

Figure 6 Performance comparison of different models (Rec@K).

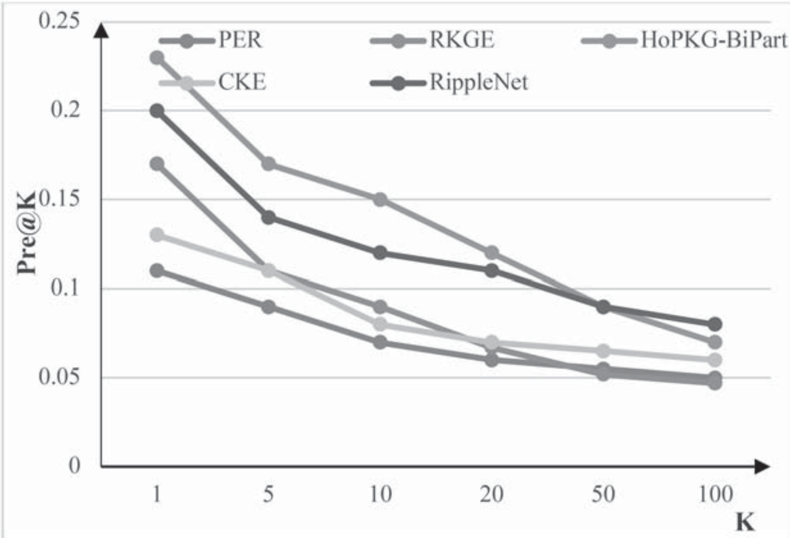

Figure 7 Comparison of performance of different models (Pre@K).

is introduced, and too many unrelated entities are introduced. At the same time, massive encryption will explode predictions will gradually decrease. In terms of time complexity, with the increase of l, the time complexity increases slowly at the beginning, and increases sharply when $l = 4$. This is because as the propagation depth increases, the number of nodes participating in the computation increases sharply. This leads to a further increase in the amount of computation, as shown in Figure 8(c). In view of the above, $l = 3$ is the optimal propagation level by considering the performance and time complexity.

4.2 Application of Power System Fusion Algorithm to Knowledge Graph

As can be seen from Figure 9, whether it is the standard error or the mean absolute percentage error, the Hermite fusion algorithm based on HoPKG has a lower error value than the traditional algorithm, and the fluctuation of the mean absolute percentage error is smaller. This indicates that the prediction model of the "HoPKG-Hermite" algorithm is closer to the true value.

In order to comprehensively and accurately verify the timeliness of the proposed algorithm when processing big data after parallelization, the data set is expanded and experiments are carried out on different data set capacities. In this paper, the speedup ratio was used to measure the performance and efficiency of the HoPKG model. In the experiment, the expanded four sets of data 5G, 15G, 45G, and 135G were used for four separate tasks to record the time using the traditional single-processing system and the processing time in the HoPKG system in this paper. Finally, the difference between the parallel system proposed in this paper and the traditional single-processing system for processing big data is compared by calculating the speedup ratio. The comparison of the acceleration ratio of each group of data is shown in Figure 10.

The simulation results of the acceleration ratio showed that under the same set of data samples, the greater the number of cluster points, the greater the value of the acceleration ratio. It can be seen that the calculation speed of the algorithm based

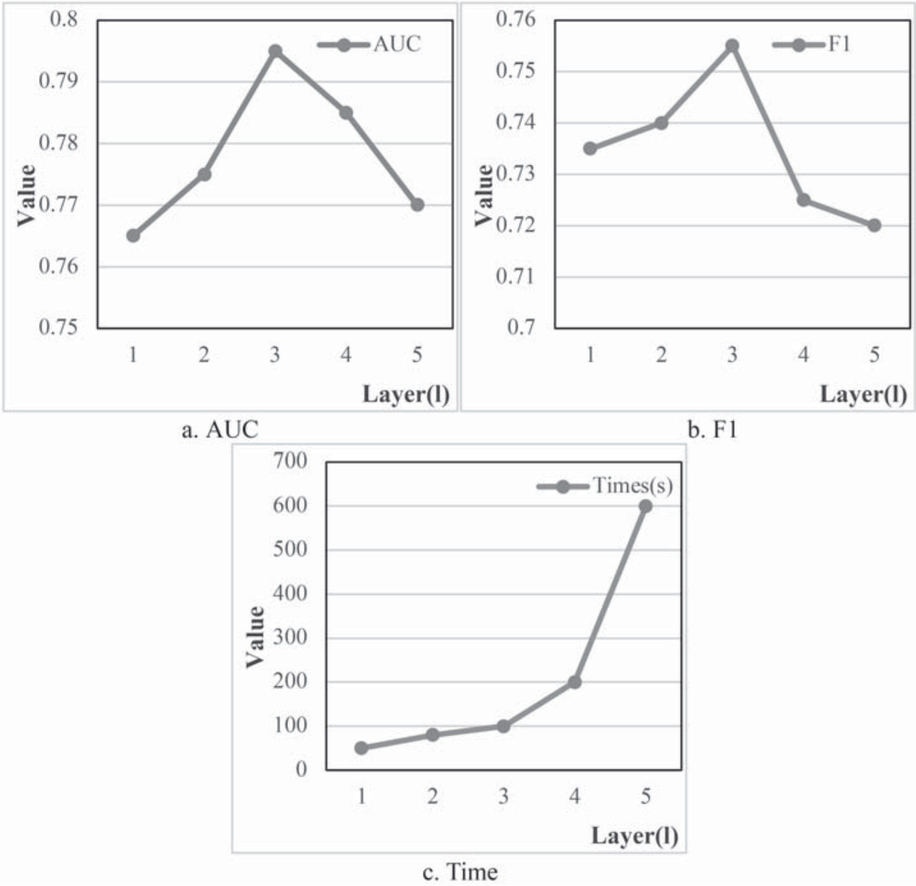

Figure 8 Effect of propagation hierarchy on performance.

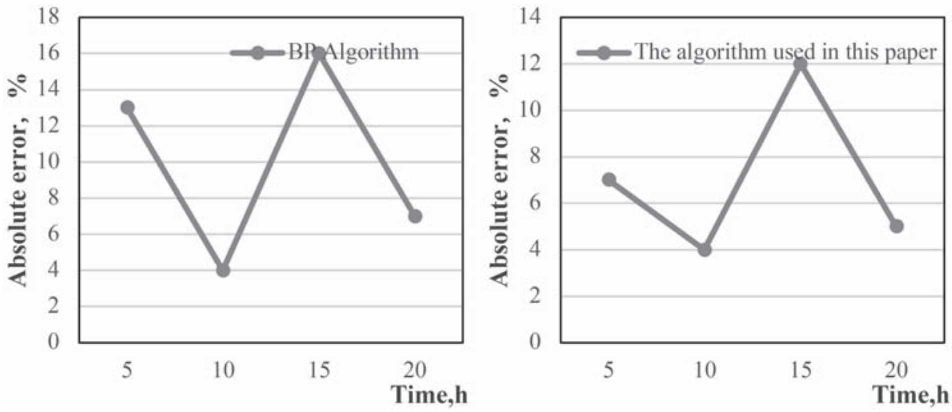

Figure 9 Error comparison of different algorithms.

on the HoPKG model increased gradually with the increase of parallel computing nodes. For the same number of nodes, the larger the sample size of the experimental data, the higher the value of the speedup ratio. The relationship between the speedup ratio and the cluster points becomes more and more linear with the increase of the data volume. Obviously, the HoPKG structure was more suitable for the calculation of massive data. The experimental data was divided into 5G, 15G, 45G, and 135G. There were four sets of data in total, and the experiments were conducted on each of these. The processing time was used as the measurement standard. The time required by the two algorithms for each data set is shown in Table 4.

As the amount of data increases, the processing time of the proposed algorithm tends to increase linearly, which is more suitable than the traditional algorithm for the processing of big data.

5. CONCLUSION

This paper studied the application of data center knowledge graph based on power system fusion algorithm design, which can provide a better foundation and method for the improvement and development of a data center knowledge

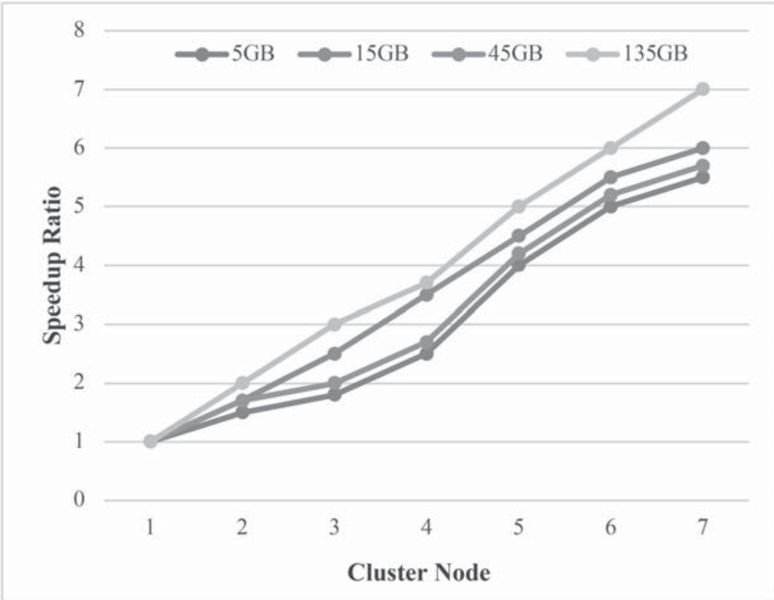

Figure 10 Speedup experiments on different data samples.

Table 4 Time usage for different data groups.

Data volume (GB)/Algorithm	Traditional Algorithm	Algorithm(s) in this paper
5	320.52	250.25
15	400.25	350.48
45	752.15	352.12
135	1600.52	495.25

graph. To date, the application of a data center knowledge graph has been limited to the field of education, and its understanding has not been sufficient and comprehensive. In this paper, we studied the application of knowledge graphs in data centers from the perspective of power system fusion algorithm design. Through scientific and systematic analysis methods, the application of data center knowledge graphs can be continuously developed so that the public can have a better understanding of data center knowledge graphs and achieve better development and progress.

REFERENCES

1. J. Li, S. Liu, A. Liu, R. Huang. Knowledge Graph Construction for SOFL Formal Specifications. *International Journal of Software Engineering and Knowledge Engineering, 32*(04) (2022), 605–644.
2. Y. Kang, R. Ou, Y. Zhang, H. Li, S. Tian. PG-CODE: Latent Dirichlet Allocation Embedded Policy Knowledge Graph for Government Department Coordination. *Tsinghua Science and Technology, 27*(4) (2022), 680–691.
3. T. Fan, S. Song, H. Li, Y. Bai, B. Cheng. Knowledge graph characteristics of sepsis research based on scientometric study. *Zhonghua Wei Zhong Bing Ji Jiu Yi Xue, 33*(4) (2021), 433–437.
4. Y. Wu, D. Zhu, X. Liao, D. Zhang, K. Lin. Knowledge Graph Reasoning Based on Paths of Tensor Factorization. *Moshi Shibie yu Rengong Zhineng/Pattern Recognition and Artificial Intelligence, 30*(5) (2017), 473–480.
5. Y. J. Du, C. X. Li, Q. Hu, XL. Li, XL. Chen Ranking webpages using a path trust knowledge graph. *Neurocomputing, 269*(Dec. 20) (2017), 58–72.
6. M. Cui, J. Zhang. Estimating ramping requirements with solar-friendly flexible ramping product in multi-timescale power system operations. *Applied Energy, 225*(SEP.1) (2018), 27–41.
7. J. B. Zhao, M. Netto, L. Mili. A Robust Iterated Extended Kalman Filter for Power System Dynamic State Estimation. *IEEE Transactions on Power Systems, 32*(4) (2017), 3205–3216.
8. Y. Zhang, L. Wang, Y. Xiang, Ten C.W. Power System Reliability Evaluation With SCADA Cybersecurity Considerations. *IEEE Transactions on Smart Grid, 6*(4) (2017), 1707–1721.
9. Mathaios, Panteli, Cassandra, Pickering, Sean, Wilkinson, Richard, Dawson, Pierluigi, Mancarella. Power System Resilience to Extreme Weather: Fragility Modeling, Probabilistic Impact Assessment, and Adaptation Measures. *IEEE Transactions on Power Systems, 32*(5) (2017), 3747–3757.
10. H. Nosair, F. Bouffard, Flexibility Envelopes for Power System Operational Planning. *IEEE Transactions on Sustainable Energy, 6*(3) (2017), 800–809.
11. S. Benati, J. Puerto, AM Rodríguez-Chía. Clustering data that are graph connected. *European Journal of Operational Research, 261*(1) (2017), 43–53.
12. Y. Wu, T. Mu, J. Y. Goulermas. Translating on Pairwise Entity Space for Knowledge Graph Embedding. *Neurocomputing, 260*(Oct.18) (2017), 411–419.
13. C. Zhang, Z. Miao, H. Xiao, H. Zheng, J. Yanget. Knowledge graph embedding for hyper-relational data. *Tsinghua Science & Technology, 22*(2) (2017), 185–197.
14. C. Wang, X. Ma, J. Chen, J. Chen. Information extraction and knowledge graph construction from geoscience literature. *Computers & Geosciences, 112*(Mar.) (2018), 112–120.
15. K. Natthawut, I. Ryutaro. An Automatic Knowledge Graph Creation Framework from Natural Language Text. *IEEE Transactions on Information & Systems, 101*(1) (2018), 90–98.

16. G. Sun, S. Chen, Z. Wei. Multi-period integrated natural gas and electric power system probabilistic optimal power flow incorporating power-to-gas units. *Journal of Modern Power Systems & Clean Energy, 5*(3) (2017), 412–423.
17. G. Yang, A. Zhang, S. Li, W. Yang, H. Ling. Multi-objective evolutionary algorithm based on decision space partition and its application in hybrid power system optimisation. *Applied Intelligence, 46*(4) (2017), 827–844.
18. G. Fei, X. Zheng, S. Bozhko, C. Hill, G. Asher. Modal Analysis of a PMSG-Based DC Electrical Power System in the More Electric Aircraft Using Eigenvalues Sensitivity. *IEEE Transactions on Transportation Electrification, 1(*1) (2017), 65–76.
19. Y. Hao, X. Yuan, J. Hu. Modeling of Grid-Connected VSCs for Power System Small-Signal Stability Analysis in DC-Link Voltage Control Timescale. *IEEE Transactions on Power Systems, 32*(5) (2017), 3981–3991.
20. S. S. Reddy, Optimal scheduling of thermal-wind-solar power system with storage. *Renewable Energy, 101*(FEB.) (2017), 1357–1368.