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Construction and optimization technology of power grid dispatching knowledge graph based on multi-modal data fusion

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Abstract

The data in the field of power grid dispatching has multi-modal characteristics such as text, images, and time series. How to deeply integrate these heterogeneous data is a key challenge in building an intelligent knowledge graph. The research aims to construct and optimize a power grid dispatching knowledge graph based on multi-modal data fusion. To this end, a unified framework integrating text, images, and time series data is proposed. This framework first uses joint extraction technology to extract entity relationships from text; subsequently, an improved RESCAL model (fusing L2 regularization and data augmentation) is introduced for knowledge embedding to enhance generalization ability; for the multi-modal association problem, a cross-modal transformation network (CMTN) is designed to map different modal data to a shared semantic space to achieve precise retrieval. At the system level, the perceptual hashing algorithm is integrated for fast similarity matching, and a distributed storage architecture is adopted to ensure the efficient processing and dynamic update of massive multi-modal data. Experimental results show that the joint extraction technique achieves high accuracy and recall in entity recognition and relationship extraction tasks, with F1-scores of 0.82 and 0.86 on the PowerGraph and OmniCorpus datasets, respectively. The CMTN exhibits superior performance in cross-modal retrieval, with mean inter-modal similarities of 0.72 and 0.75 and Top-1 alignment accuracies of 0.85 and 0.88 on the two datasets. The constructed knowledge graph effectively supports intelligent power grid dispatching by accurately representing and managing complex multi-modal data. The research provides an effective solution for enhancing the representation, association, and update capabilities of grid dispatching knowledge through multi-modal data fusion technology. At the same time, it can focus on the lightweighting and real-time optimization of the model to promote the integration of this technology into online intelligent dispatching systems.

Keywords: Multi-modal data fusion; Power grid dispatching; Knowledge graph; Distributed storage; Knowledge mapping

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1. Introduction

As the power system grows more intricate, the intelligence of Power Grid (PG) scheduling has become a key requirement for the functioning of modern power systems. PG dispatching involves multiple types of data, including structured and unstructured data, with a wide range of sources and diverse forms, covering various modalities such as text, images, time series, etc. [1-2]. In recent times, Knowledge Graph (KG) has garnered extensive focus within the domain of PG dispatch as an effective tool for knowledge representation and management. It can transform complex PG data into structured knowledge networks, providing support for intelligent PG regulation. Text mining technology can extract valuable entity, relationship, and event information from massive text data, providing rich semantic content for the construction of

KGs. It is one of the key technologies for efficiently constructing PG dispatch KGs. However, the data in the field of PG dispatching is not only diverse, but also has the characteristic of dynamic updates. At present, the construction of PG dispatching knowledge map mainly depends on the processing of single modal data, such as text-based relationship extraction or image-based feature extraction [3-4]. However, these methods are difficult to fully utilize the complementary information of multi-modal data.

Currently, scholars have conducted research on the construction of a KG for PG dispatching. Xiao N et al. proposed a method for constructing and implementing a KG based PG fault handling KG to address the low efficiency of information management in PG fault handling. This method condenses a large amount of unstructured text content related to PG faults into a structured knowledge network that can be expressed, operated, and inferred. The outcomes showed that this approach could validly improve the emergency response capability and intelligent scheduling level of the PG [5]. Ji Z et al. proposed a joint entity relationship extraction method for PG scheduling fault handling based on pre trained models to address the problems of diverse fault modes and difficult control caused by the expansion of PG scale. This method utilizes multi-source heterogeneous data from PG dispatching to construct a KG for PG dispatching fault handling, and designs and develops a fault handling auxiliary decision-making system based on the KG. The outcomes demonstrated that the system could validly improve the capability to deal with PG accidents and the level of intelligence in accident management and control [6]. Liu Z et al. proposed a substation fault event inference method based on KG technology to address the increasingly complex situation of safe operation of the PG. By using the entity diagram, concept diagram, business logic diagram, and historical case diagram of PG equipment, combined with the key information flow after fault signal analysis, and utilizing the logic, rules, and empirical knowledge of PG operation and control, auxiliary decision-making for fault handling operation modes can be achieved. The results indicated that it implemented the functions of substation PG fault analysis and handling, and improved the intelligent level of fault management [7].

The above research has achieved good results in constructing a KG for PG dispatching, but there are difficulties in cross-modal semantic alignment and low efficiency in large-scale data processing. Based on this, a PG dispatch KG is constructed by combining multi-modal data, aiming to improve the efficiency and accuracy of KG construction through improved KG embedding technology and cross-modal retrieval technology. The innovation of the research lies in proposing an approach for constructing a PG dispatch KG based on multi-modal data fusion, and combining distributed storage and processing frameworks to achieve efficient expansion and dynamic updating of the KG.

2. Methods and materials

2.1 KG embedding technology based on improved RESCAL model

In PG dispatching, building an efficient & accurate KG is key to intelligent regulation, with KG embedding and cross-modal retrieval as key building links [8-9]. The study adopts joint extraction technology, and first uses a pre-trained BERT model to encode the input PG dispatch text. The input sentence is defined as S, and the relevant embedded mathematical expression is shown in formula (1).

$$H = BERT(s) = [h_1, h_2, h_3, \cdots h_n] \tag{1}$$

In formula (1), H represents the context embedding matrix of the sentence. For the recognition of entity relationships, the study uses conditional random fields to label the relevant types and boundaries. The study defines the relationship classification task as a fine-grained classification problem to solve relationship extraction. It uses a scoring function to evaluate the relationship types between entities [10-11]. The relevant mathematical expression is shown in formula (2).

$$score(h_i, h_j, r_k) = V^{(r)} \cdot f(U^{(r)} h_i + W^{(r)} h_j + b^{(r)}) \tag{2}$$

In formula (2), h_i and h_j are the embedding representations of the entity head and tail, r_k represents the relationship type, and f represents the activation function. For the loss function (LF) of the joint extraction model, it needs to integrate the losses of entity recognition and relationship extraction, and the relevant mathematical expression is shown in formula (3).

$$Loss = L_s + \alpha L_R \tag{3}$$

In formula (3), L_s and L_R are the losses of entity recognition and relationship extraction, and α is the balance parameter. After implementing entity relationship extraction, the RESCAL model is introduced into the bilinear model to embed representations of entities and relationships. The schematic diagram of its related entity relationship matrix is shown in Figure 1.

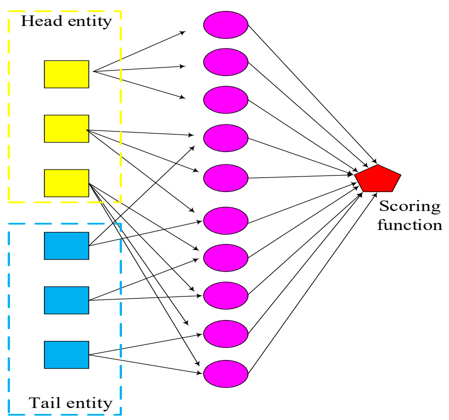


Figure 1. RESCAL model relational matrix operation diagram

In Figure 1, the RESCAL model represents each entity as a k-dimensional vector, while each relationship r is represented as a $k \times k$ matrix R. Therefore, for a triplet (h,r,t), the mathematical expression of its scoring function is shown in formula (4).

$$score(h,r,t) = h^T Rt \tag{4}$$

In formula (4), h and t represent the embedding vectors of the head entity and tail entity, respectively. Considering the complex nature of PG dispatch data, the research introduces L2 regularization and data augmentation methods to optimize it and avoid overfitting. The relevant diagrams of normal fitting and overfitting are shown in Figure 2.

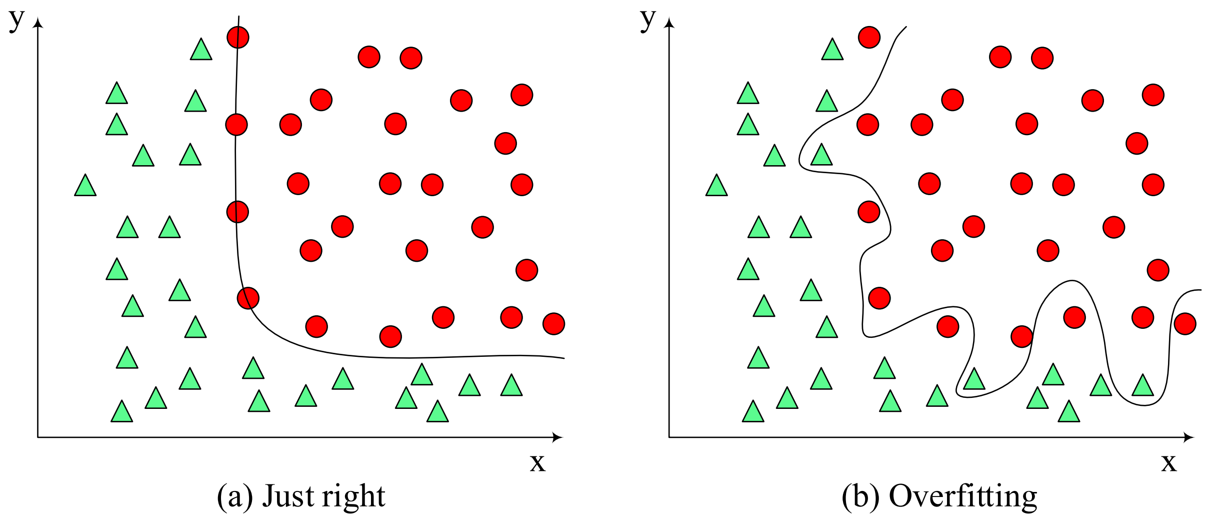


Figure 2. Diagram of normal fitting and overfitting phenomena

Figure 2 illustrates the differences between normal fitting and overfitting phenomena. L2 regularization is one of the most commonly used regularization methods, which constrains the complexity of the model by adding the sum of squares of parameters to the LF. For RESCAL models, L2 regularization can effectively limit the size of entity embedding vectors and relationship matrices, preventing parameters from being too large [12-13]. The mathematical expression of the regularization term is shown in formula (5).

$$L_{reg} = \lambda(\sum_{e\in\varepsilon} \| e \|_2^2 + \sum_{r\in R} \| R_r \|_2^2) \tag{5}$$

In formula (5), ε is the entity set, e is the entity embedding vector, R_r is the relationship matrix, and λ is the regularization coefficient. In the KG of PG dispatching, data augmentation can be achieved through generating negative samples, data perturbations, and other methods [14-15]. Firstly, for a triplet of positive sample (h,r,t), an entity $h^{\sim}$ is randomly selected to replace the head entity and generate negative sample $(h^{\sim},r,t)$. Then an entity $t^{\sim}$ is randomly selected to replace the tail entity and generate negative sample $(h,r,t^{\sim})$. At the same time, to distinguish between positive and negative samples, the LF is optimized, and the mathematical expression of the LF is shown in formula (6).

$$\begin{aligned} L_{reg} = & \sum_{(h,r,t)} (score(h,r,t) - y_{hrt})^2 + \\ & \lambda(\sum_{e\in\varepsilon} \| e \|_2^2 + \sum_{r\in R} \| R_r \|_2^2) + \gamma \sum_{(h^{\sim},r,t)\in T_{neg}} \max(0, 1 + score(h^{\sim},r,t) - score(h,r,t)) \end{aligned} \tag{6}$$

In formula (6), T_{neg} represents the negative sample set, and $score(h,r,t)$ and $score(h^{\sim},r,t)$ represent the scores of positive and negative samples, respectively.

2.2 Cross-modal retrieval technology based on cross-modal transformation network

To cope with the complexity and heterogeneity of multi-modal data within the domain of PG scheduling, a Cross-modal Transformation Network (CMTN) is studied to achieve cross-modal retrieval [16-17]. Firstly, the network extracts features from different modalities. For image modalities, the VGG network is used for feature extraction. BERT is used for extracting text modalities. The core of the CMTN lies in the cross-modal attention module. Specifically, for two modalities, cross-modal attention can be implemented through formula (7).

$$y_a = soft\max(\frac{Q_a K_b^T}{\sqrt{d_k}})V_b \tag{7}$$

In formula (7), a and b respectively represent two modalities. Q_a represents the query matrix of modality a, and K_b and V_b represent the key and value matrices of modality b, respectively. To further enhance the interaction between modalities, a multi-layer cross-modal Transformer architecture is adopted for the CMTN. In terms of the selection of LFs, the comparative LF finds extensive application in twin networks and cross-modal retrieval tasks. The relevant mathematical expression of the comparative loss is shown in formula (8).

$$L_d = \frac{1}{2N}\sum_{n=1}^{N} y \cdot d^2 + (1-y)\cdot \max(m-d,0)^2 \tag{8}$$

In formula (8), y represents the label of the sample pair, $y=1$ and $y=0$ represent positive and negative sample pairs respectively, d represents Euclidean distance, and m represents hyperparameters. Finally, to improve the convergence speed and training efficiency of the model, the Adam optimizer is introduced to speed up the convergence of the model.

2.3 Construction of KG for PG dispatching

The study further integrates multi-modal PG data and constructs a PG dispatch KG. This KG mainly consists of three modules, namely the sub graph module of PG dispatch text knowledge, the module of building PG dispatch image knowledge base, and the module of cross-modal entity linking. For the text knowledge sub-graph module of PG dispatch, the BERT model is employed for text encoding and relationship extraction, while the improved RESCAL model is used for embedding the KG. By combining entities and their corresponding relationships, a textual knowledge sub-graph of PG scheduling can be obtained. Regarding the construction module of the PG dispatch image knowledge base, this study introduces the Perceptual Hash Algorithm (pHash) to finalize the establishment of the PG dispatch KG. This algorithm can quickly identify and correlate similar PG data [18]. The process based on pHash is shown in Figure 3.

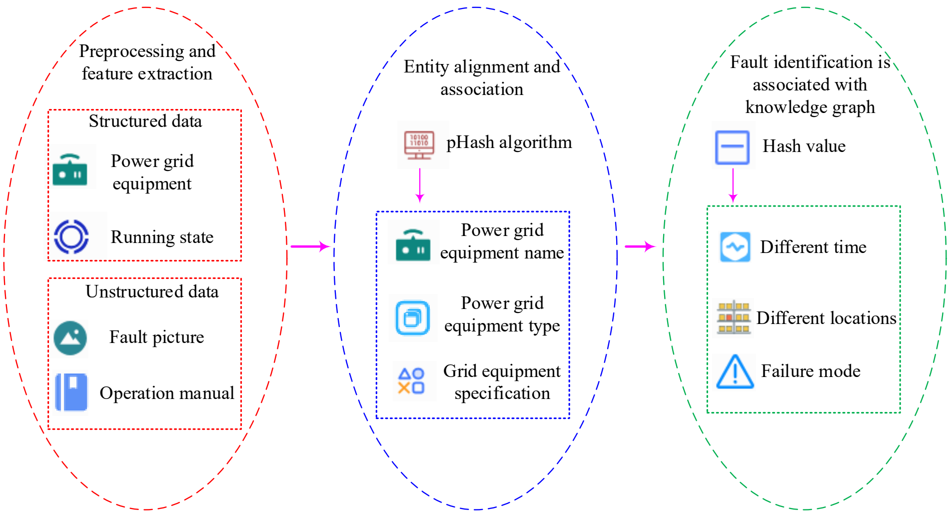


Figure 3. Flow chart of pHash

In Figure 3, the pHash can quickly identify similar data by extracting features from these data and generating hash values. For image data, the pHash can generate corresponding hash values to achieve fast retrieval and association of similar images. For text data, the corresponding content is transformed into feature vectors and then hashed using the pHash for text similarity detection. After data processing and feature extraction are completed, the pHash can align and associate entities. By comparing the hash values of entities in different data sources, it is possible to quickly identify identical or similar entities, thereby achieving the fusion of KGs. Finally, considering the strong diversity of PG data, similarity detection of hash values can be used to associate similar fault patterns and form a fault knowledge base. Due to the dynamic and large-scale nature of PG operation data, the research will adopt distributed hash calculation and storage methods to improve the pHash. Firstly, the PG data is divided into multiple subsets, and each subset is assigned a computing node. Secondly, on each computing node, the hash value for the allocated subset of data is independently calculated to compute the local hash. Finally, the hash values generated by all nodes are aggregated into the master node to construct a global hash table.

During the development of the KG for PG dispatching, distributed storage is a key technology for dealing with massive data and dynamic update requirements. Its basic process is shown in Figure 4.

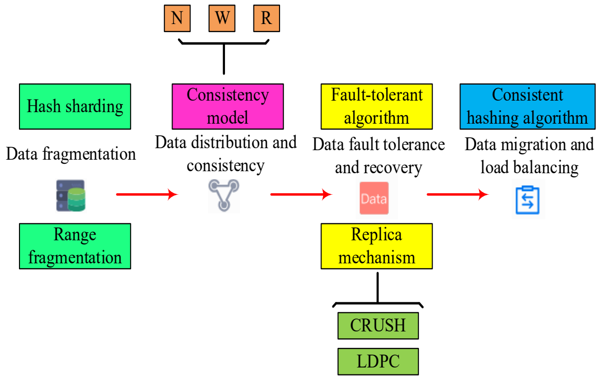


Figure 4. Basic flow of distributed storage

In Figure 4, distributed storage first involves data sharding, and common sharding methods include hash sharding and range sharding. The study uses hash functions to map data keys to storage nodes, and the relevant mathematical expression is shown in formula (9).

$$node\_id = h(key) \quad \text{mod} \quad n \tag{9}$$

In formula (9), $h(key)$ represents the hash function, n represents the storage node, and $node\_id$ represents the mapping to the storage node ID. In data distribution and consistency, the consistency model mainly balances consistency and availability by adjusting the number of replicas, write nodes, and read nodes. The relevant mathematical expression is shown in formula (10).

$$\begin{cases} W + R \succ N \\ W + R \le N \end{cases} \tag{10}$$

In formula (10), W, R, and N respectively represent the quantity of replicas, the quantity of write nodes, and the quantity of read nodes. When $W + R \succ N$, it was strong consistency, while the opposite was weak consistency. In terms of data fault tolerance and recovery, the replica mechanism mainly stores multiple replicas of grid data on multiple nodes to prevent single point failures. Finally, in data migration and load balancing, data can be evenly distributed across storage nodes through consistent hashing algorithms. The cross-modal entity linking module is a crucial component in the development of PG dispatch KG, which achieves semantic alignment and ambiguity resolution between modalities by processing multi-modal data. In the KG of PG dispatching, the cross-modal entity linking module mainly realizes the association between images and text, the association between time series and text, as well as fault diagnosis and knowledge retrieval. The research adopts a dual encoder architecture to implement cross-modal entity linking modules. Firstly, feature extraction involves extracting feature vectors for both the image and text separately. Next, feature mapping is performed to align image features with text features. Next, the similarity between the aligned feature vectors is calculated. Finally, based on similarity, the image entities are linked to the text entities in the PG KG.

3. Results

3.1 Performance evaluation of KG embedding technology

The experimental environment for the study was as follows: AMD Ryzen 9 9950X3D CPU, NVIDIA RTX 3060 graphics card, 16GB of memory, and Windows 11 Professional operating system. The PowerGraph dataset and OmniCorpus dataset were selected for the dataset. The PowerGraph dataset contains various task data for power system analysis. OmniCorpus is a large-scale multi-modal dataset that contains billions of images and text interlaced data. The study first compared the accuracy of entity recognition and relationship extraction, while introducing feature level fusion multi-modal technology, Transformer multi-modal model, and traditional pipeline method for comparison. Therefore, the performance comparison based on the four technologies is shown in Figure 5.

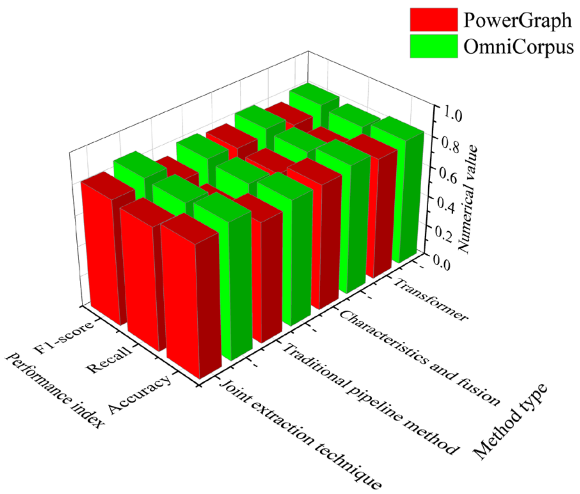


Figure 5. Performance comparison of the four technologies

Figure 5 indicates the performance comparison of four KG embedding techniques. On the PowerGraph dataset, the F1-score of the joint extraction technique was 0.82, which was higher than traditional pipeline methods (0.74), feature level fusion multi-modal techniques (0.78), and Transformer multi-modal models (0.76). On the OmniCorpus dataset, the F1-score of the joint extraction technique was 0.86, higher than traditional pipeline methods (0.80), feature level fusion multi-modal techniques (0.82), and Transformer multi-modal models (0.81). The results indicated that the joint extraction technique could achieve a more balanced balance between accuracy and recall in entity recognition and relationship extraction tasks of PG dispatch text data. The study further validated the advantages of the improved RESCAL model through ablation experiments, as presented in Table 1.

Table 1. Ablation results

Data set name	Model configuration	Accuracy	Loss	Balanced accuracy
PowerGraph	RESCAL	0.75	0.3	0.68
	RESCAL+L2 regularization	0.8	0.25	0.74
	RESCAL+Data enhancement	0.82	0.24	0.76
	RESCAL + L2 regularization + data enhancement	0.85	0.22	0.8
OmniCorpus	RESCAL	0.78	0.28	0.72
	RESCAL+L2 regularization	0.83	0.23	0.77
	RESCAL+Data enhancement	0.84	0.22	0.79
	RESCAL + L2 regularization + data enhancement	0.87	0.2	0.83

In Table 1, the improved model accuracy on the PowerGraph dataset increased from 0.75 to 0.85, the balanced accuracy increased from 0.68 to 0.80, and the loss value decreased from 0.30 to 0.22; The improved model accuracy on the OmniCorpus dataset increased from 0.78 to 0.87, the balanced accuracy increased from 0.72 to 0.83, and the loss value decreased from 0.28 to 0.20. The outcomes indicated that the use of L2 regularization and data augmentation significantly improved the generalization ability of the RESCAL model.

3.2 Performance evaluation of cross-modal retrieval technology

After verifying the excellent performance of the KG technology, the study further compared the performance of CMTN in aligning PG data of different modalities into a shared semantic space. The result is shown in Figure 6.

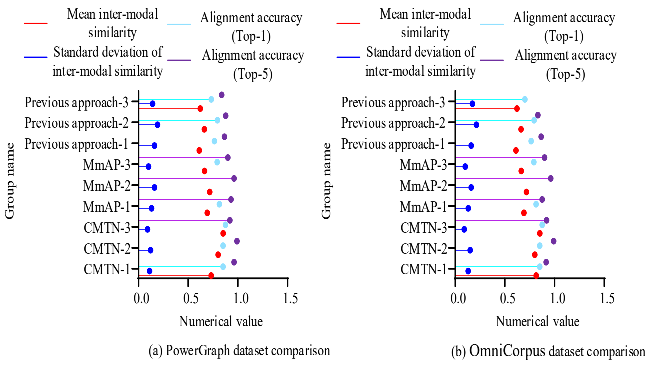
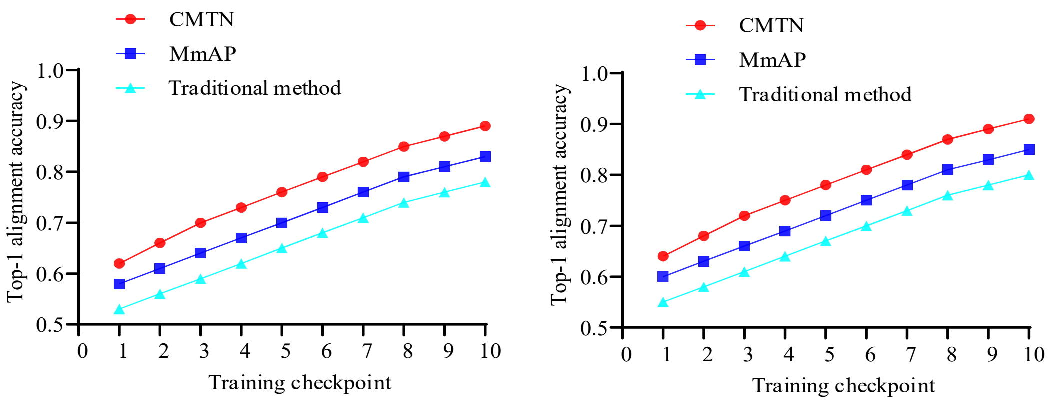


Figure 6. Shared semantic spatial representation contrast

In Figure 6, the results showed that CMTN exhibited the highest mean inter modal similarity on both datasets, indicat-ing its ability to more effectively map different modal data to a shared semantic space. Meanwhile, the alignment accuracy of this model was significantly higher than other methods, es-pecially in Top-1 accuracy, with values of 0.85 and 0.88, re-spectively. In summary, CMTN could more effectively achieve semantic alignment of different modal data, and at the same time, it could more accurately complete cross-modal retrieval tasks, reducing the possibility of mismatches. The study further compared the Top-1 accuracy of various meth-ods under different training checkpoints, and the results are shown in Figure 7.



(a) PowerGraph dataset comparison

(b) OmniCorpus dataset comparison

Figure 7. Top-1 Comparison of alignment accuracy over training time

In Figure 7, CMTN showed high Top-1 alignment accuracy in the early stages of training (checkpoint 1), with values of 0.62 and 0.64, respectively. Meanwhile, in the later stages of training, the gap with other methods gradually increased, with corresponding accuracies of 0.89 and 0.91 for checkpoint 10. The results showed that the performance improvement of CMTN was relatively stable, and it exhibited good stability and convergence during the training process.

3.3 Analysis of the effect of building a KG for PG dispatching

After comparing the performance of CMTN in aligning PG data of different modalities into a shared semantic space, the study finally verified the effectiveness of constructing a PG dispatch KG. The study first characterized the frequency of significant entries in the KG of PG dispatching, as presented in Figure 8.

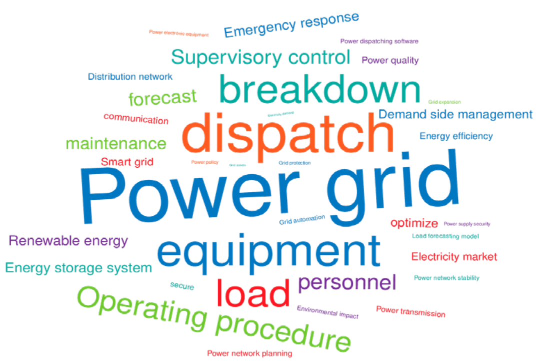


Figure 8. Grid dispatching knowledge map entry numerical map

Figure 8 indicates a comparison of significant entries in the KG of PG dispatching, where larger fonts indicated higher frequency of occurrence. The results indicated that the term "PG" had the highest frequency of occurrence as the core concept, at 12521 times. Secondly, there were 8536 occurrences of scheduling and 7121 occurrences of equipment, indicating the importance of grid scheduling activities and equipment management in grid operation. In addition, the entries also included some related to human resources and the environment, such as personnel, environmental impact, etc. Finally, the validity of multi-modal data fusion in PG dispatch KG was compared and studied, and the outcomes are in Table 2.

In Table 2, on the text knowledge sub-graph module, RESCAL outperformed traditional feature concatenation and GNN methods in accuracy, recall, and F1-score, while having a shorter processing time of only 230.4ms, demonstrating its advantages in text data processing. On the image knowledge base module, the pHash outperformed traditional feature stitching and GNN methods in accuracy, recall, and F1-score. The processing time was also shorter, with a value of 240.1ms. The dual encoder architecture of the modal entity linking module outperformed the other two methods in all performance metrics. Especially in processing time, it was significantly shorter than traditional feature concatenation and GNN methods. This demonstrated the excellent ability of the dual encoder architecture in fusing multi-modal data.

Table 2. Numerical table of multi-modal data fusion effect

Module name	Method name	Accuracy (%)	Recall (%)	F1-score(%)	Processing time(ms)
Text knowledge subgraph module	RESCAL	88.5	86.3	87.4	230.4
	Traditional feature splicing	82.1	79.8	80.9	300.2
	GNN	85.4	84.2	84.8	280.7

Image knowledge base module	pHash	89.7	87.6	88.6	240.1
	Traditional feature splicing	85.3	83.2	84.2	280.1
	GNN	88.1	86.4	87.2	260.4
Link modules across-modal entities	Dual encoder architecture	92.4	91.1	91.7	220.6
	Traditional feature splicing	86.5	84.3	85.4	290.8
	GNN	89.2	87.6	88.4	270.3

4. Discussion

To address the issue of diversified and dynamically updated data forms within the domain of PG dispatching, this study used joint extraction technology to achieve entity recognition and relationship extraction of PG dispatching text data. An improved RESCAL model was introduced for KG embedding, and CMTN was used for semantic alignment and cross-modal retrieval of multi-modal data. Finally, a PG dispatching KG was constructed by combining pHash and distributed storage technology. In the research results, the joint extraction technique achieved an F1-score of 0.82 on the PowerGraph dataset and 0.86 on the OmniCorpus dataset, both higher than other traditional methods. This indicated that it could achieve a more balanced balance between accuracy and recall in PG dispatch text data processing, and had better overall performance. This aligns with the research outcomes of Liu P et al., who proposed a method for constructing an aviation assembly KG based on a joint knowledge extraction model, and the results showed the advantages of the joint knowledge extraction model in the field of aviation assembly [19]. In cross-modal retrieval technology, CMTN exhibited the highest mean similarity between modalities on both datasets (PowerGraph was 0.72, OmniCorpus was 0.75), with Top-1 alignment accuracies of 0.85 and 0.88, respectively, indicating that it could more effectively achieve semantic alignment of different modal data and reduce the possibility of mismatches. In terms of the construction effect of the PG dispatch KG, RESCAL had an accuracy of 88.5% in the text knowledge sub-graph module, pHash had an accuracy of 89.7% in the image knowledge base module, and the dual encoder architecture had an accuracy of 92.4% in the cross-modal entity linking module, all of which had relatively short processing times, demonstrating the efficiency and superiority of each module in multi-modal data fusion. This aligns with the outcomes of Shang Y et al., except that they used the pHash to screen representative images of entities in the multi-modal KG, in order to improve the quality and consistency of image information in the multi-modal KG [20].

In conclusion, the knowledge graph constructed by the research institute has superior performance and performs well in multi-modal data fusion.

5. Conclusions

The research on the construction of PG scheduling KG through joint extraction technology, improved RESCAL model, cross-modal retrieval technology and multi-modal data fusion has significant advantages in terms of accuracy, recall rate, similarity between modalities and processing efficiency. The research verified that multimodal data fusion was the key path for building a more comprehensive, intelligent and adaptive knowledge system for power grid dispatching. It not only improved the accuracy of knowledge extraction in a single modality, but also discovered deeper integrated knowledge through cross-modal correlation. However, there are still certain deficiencies in the research. Although CMTN performs well in cross-modal retrieval, when dealing with large-scale real-time data, the computational efficiency and resource consumption of this model still need to be optimized. The future work will initially focus on the research of system lightweighting and edge deployment to reduce computational costs. On this basis, the research plan will collaborate with a domestic regional power grid dispatching center to conduct pilot application research. The specific case study will be centered around the scenario of "grid stability assistance decision-making under high proportion of new energy", integrating the knowledge graph system into the actual dispatching data platform to verify its fault diagnosis speed, scheduling plan recommendation accuracy, and system throughput capacity in a real dynamic environment.

Conflict of Interest

The authors declare no conflict of interest.

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Author Contributions

Conceptualization: Wei Li and Chao Hu; methodology: Siqi Shen; software: Chao Hu; validation: Wei Li: Chao Hu and Zhangguo Chen; formal analysis: Wei Li; investigation: Zhangguo Chen; resources: Siqi Shen; data curation: Zhangguo Chen; writing—original draft preparation: Chao Hu; writing—review and editing: Wei Li; visualization: Zhangguo Chen; supervision: Wei Li; project administration: Wei Li; funding acquisition: Chao Hu. All authors have read and agreed to the published version of the manuscript.

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