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Article

Power Supply Reliability Analysis of Distribution Network Based on Knowledge Graph

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Abstract: The reliability of the power supply is intrinsically linked to the robustness of the distribution network. Constructing a distribution network model is highly challenging due to its complex structure, the large number of equipment and users, and the randomness of load variations and equipment failures. Knowledge graphs, a structured data representation describing entities and their relationships, can address challenges by modelling various devices, users and real-time operation data as entities in a graphical manner. As a result, the constructed large network graphs are not only easy to interpret, but also efficient in data management and reliability analysis. The results are promising and validate our hypothesis.

Keywords: knowledge graph; the reliability of power supply; distribution network

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1. Introduction

The distribution network includes substations, feeders, branch lines and other multi-level connections, involving various types of electrical equipment and serving a wide range of user groups. Load demand fluctuates with time and weather, and equipment may have unpredictable failures. With the continuous expansion of distribution network scale, these factors make it increasingly difficult to build a distribution network model. Currently, only a limited number of literature studies focus on reliability prediction for power grids, primarily emphasizing prediction algorithms [1] that analyze historical fault statistics of local small power stations. However, these studies do not model the complexity of the entire power grid.

A knowledge graph is a technique for representing knowledge in a graphical manner [2], and has recently found widespread application across various fields [3–6]. Constructing knowledge graphs and performing hierarchical analysis over their relational structures play a critical role. Therefore, it is especially suitable for the modeling and management of complex networks. Nowadays, various mature application software tools are coming out, such as FineReport, FineVis, Graphviz, Gephi, Cytoscape, D3.js, Neo4j and Palladio. This paper aims to explore the application of knowledge graphs in modeling real power grid for reliability analysis.

To present the distribution network structure in a graphical way in knowledge graph, we need to abstract devices, users and operational data into entities nodes for easy management and querying. By defining connections between entities, such as physical connections between devices or logical control relationships, the constructed knowledge graph can be integrated into a database system to support efficient data retrieval and management. Data processing and calculation by the knowledge graph help evaluate power grid reliability and optimization strategy, enhance fault detection and recovery speed, and improve load forecasting and scheduling efficiency.

Currently, the application of knowledge graphs within the power grid has not been thoroughly exploited, mainly confined to edge functions associated with the power grid [7]. Zhou et al. [8] designed a failure model of power communication equipment according to its failure data. It combines BERT and BILSTM-CRF models for knowledge extraction, accurately constructs an equipment fault knowledge map, form a visual model for fault analysis, and effectively improves the speed of fault diagnosis and the work efficiency of maintenance personnel. Fei et al. [9] designed a framework for the construction of power domain knowledge graphs, and analyzed its key technologies for comprehensive control and accurate analysis of the safe operation of power grid, as well as the role of intelligent reasoning and decision-making based on knowledge graphs. Qin et al. [10] proposed a knowledge graph construction method for heterogeneous data sources. Based on the multi-source data collected from marketing management system (MBS), production management system (PMS) and geographic information system (GIS) using big data technology, semantic representation is used to extract the attributes and relationships of knowledge entities from the structure. The knowledge fusion technology and case fusion algorithm based on biological fusion are proposed to construct knowledge graph and the ontology model of multi-source data is developed. Tang et al. [11] combined existing multi-source heterogeneous data of power equipment to construct a knowledge map for power asset management. Chun et al. [12] proposed an energy knowledge graph to provide semantic integration of various energy services. Due to the inability of traditional power information acquisition system knowledge bases to obtain effective decision-making capabilities, Yun F., et al. [13] designed a solution using knowledge graphs for the operation and maintenance of telecommunications information acquisition. Feng et al. [14] studied the transformer temperature model based on ontology and agent for thermal analysis. Liao et al. [15] combined association rules with ontology to analyze substation alarm information and converted structured and unstructured data into extensible Markup language (XML) data, allowing logical reasoning and numerical calculation. In terms of power system asset management, Yan et al. [16] introduced a kernel-based consensus clustering algorithm embedded in domain ontology to improve the document repository of power substation. Based on ontology and semantic framework, Wang et al. [17] compiled the ontology dictionary of power equipment to extract the defect components and attributes of power equipment.

The complexity of power supply computation is highly challenging due to the intricate structure and large number of devices in a large-scale distribution network [18–20]. To address this, we propose an algorithm based on knowledge graphs, bidirectional search method and distributed parallel computing framework of Apache Spark, namely, the distributed power supply reliability algorithm based on knowledge graphs.

This paper mainly expounds from the following aspects: Section 2 constructs knowledge map in the field of distribution network. Section 3 presents the method of calculating the reliability index of power supply. Section 4 considers the actual distribution network structure of a region in Shanghai taken as an example to verify the proposed algorithm. Section 5 concludes the paper.

2. Construction of Knowledge Map Based on Distribution Network

2.1. Knowledge Graph Principle

A knowledge graph is typically defined as a graph-structured knowledge base in which real-world entities and abstract concepts are represented as nodes, and their semantic relationships are represented as labeled edges. Entities, which appear in the form of nodes, are the fundamental elements of knowledge graphs. Each entity has a unique identifier and rich attributes, such as entity type, name, description, image, etc. Attributes are used to describe the characteristics of an entity, such as a person's age, gender, height, weight, etc. Attributes appear as key-value pairs with each attribute having an attribute name and an attribute value, as shown in Figure 1. Relationships are connections between entities and used to describe associations or interactions between entities, represented as edges. Each edge has a starting point, an ending point and a label. The label describes the type of relationship between the starting point and the ending point, such as "parent-child relationship", "classmate relationship" and so on. In many formulations, these elements are organized according to an explicit schema or ontology that specifies permissible classes and relations, enabling both humans and machines to interpret and reason over the represented knowledge in a consistent manner.

To store and manage a large amount of entity, attribute and relational data, traditional relational databases are insufficient for efficiently storing and querying knowledge graphs. As a result, graph databases have become one of the main choices for storing and querying knowledge graphs. Common graph databases include Neo4j and Allegro Graph, with Neo4j being the most widely used.

The basic features of the Neo4j graph data structure include three basic elements: node, relationship and attribute. The relationship connects the start node and end node, and the attributes of the node and relationship are a set composed of Key-Value data. In Neo4j, for the most part, relationships do not require attributes. Therefore, it can be seen that Neo4j stores attribute diagrams, nodes represent entities, attributes of nodes represent entity content, and relationships between entities are represented by relationships between nodes, such as friends and dependencies.

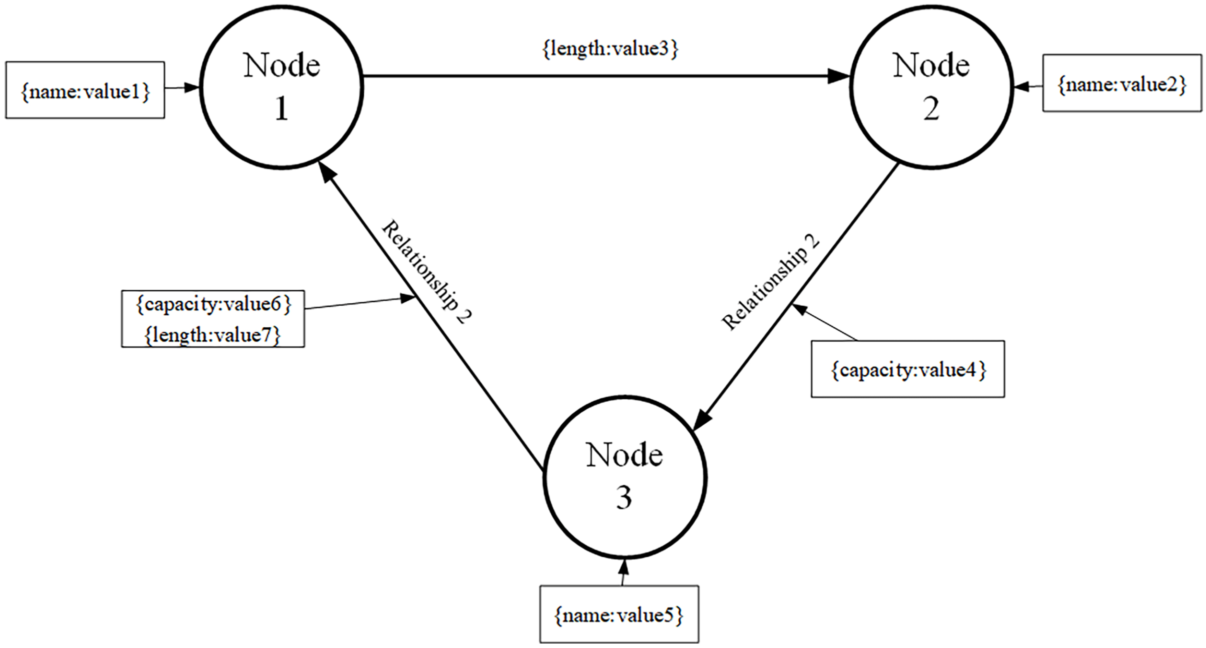

Figure 1. Basic elements of the knowledge graph.

2.2. Knowledge Graph Construction of Distribution Network Based on Neo4j

The knowledge graph structure based on the distribution network, in the power sector encompasses a wide range of information about power equipment, such as contact switches, feeders, transformers, operating loads, current transformers, bus-bar switches, tap boxes, voltage transformers, etc., as well as the relationships between these power equipment components. The data of distribution network topology structure comes from the database of each information system in the power network. The topology structure of the distribution network is standardized. There is a connection relationship between power devices, and the connection direction of the graph is determined based on the current flow direction. Power devices retain their own attributes according to the data characteristics and structural characteristics in the distribution network topology, as shown in Figure 2.

(1) Ontology model construction: Identify each table in the database, as well as each field and record in the table, and define the ontology model field.
(2) Entity model construction: Define entities. For example, in the knowledge map of distribution network, entities such as feeders, substations and circuit breakers should be defined.
(3) Relationship model building: Determine the relationship between each entity. For instance, in the distribution network knowledge map, establish a relationship between devices.
(4) Triplet data construction: The format needed to convert extracted data into a knowledge graph, for example, RDF (Resource Description Framework) format, which is triplet data format.
(5) Creation of nodes and relationships: Import the transformed data into the knowledge graph database to form the required knowledge graph structure.

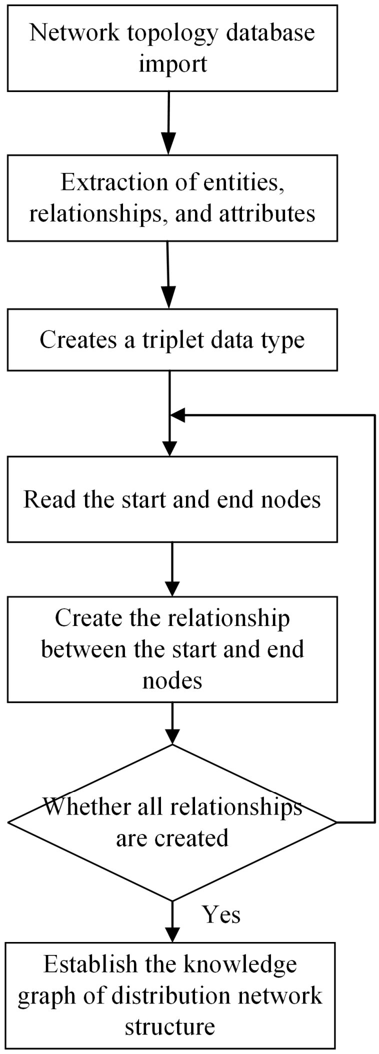

Figure 2. Knowledge map construction of the distribution network.

3. Reliability Algorithm of Distributed Power Supply Based on Knowledge Graph

3.1. Bidirectional Search Algorithm Based on Knowledge Graph

The bidirectional search algorithm is used to calculate the reliability of power supply. The longest path between the power source point and the load is obtained by searching the whole grid from the power source point. The distance between these two points affects the continuous power supply to the related load nodes during a line failure. Next, starting from each load point, proceed to search upward and backward step by step until the parent node is identified.

We can see that the shortest path from the load point to the power point needs to be determined regardless of whether the distribution network structure includes a backup power supply. An algorithm to query the shortest path, contained in a knowledge graph, is the bidirectional depth-first traversal algorithm. The advantage of this algorithm is that the knowledge graph traverses entities characterized by global uniqueness and path uniqueness. Global uniqueness means that each entity is accessed only once, thus reducing redundant access. Path uniqueness means that all paths from the starting entity to the specified entity are accessed only once. Even if there are multiple paths, the path segments are not accessed repeatedly, which ensures the accuracy of finding the shortest path.

Here are details for Bidirectional depth-first traversal algorithm. The entity set in the knowledge graph is $F=\{f_1,f_2,...,f_n\}$, and the traversal starting point set $F_S=\{f_i,f_j,...,f_k\}$ and ending point $F_p=\{f_m\}$ are selected, where $F_S,F_p\in F$. Combined with attribute values and connection relations in each entity, the traversal operation is carried out from the starting point of traversal to form the entity path set $\{ES_i,ES_j,...,ES_k\}$. When $ES_i\cap ES_j\neq\varnothing$, it indicates that the two entity sets overlap and the traversal operation continues after fusion. When the traversal reaches the termination point F_p, the traversal ends, and the minimum path set is $F_L=\{ES_1,ES_2,...,ES_{\text{n}}\}$. The starting point of bidirectional traversal can be two or more.

Compared with the traditional traversal method, this method breaks through the traditional idea by allowing multiple starting points to be used for traversal, instead of just one starting point. When the size of the network structure is fixed, traversal processes starting from different starting points will always meet and collide. In this case, the traversal direction can be unified through node fusion. Because of the unique entity globally and entity path of the knowledge graph, the traversal direction after fusion will not pass through the entity that has been visited.

Therefore, the bidirectional depth-first traversal method in the knowledge graph is applied to the bidirectional search algorithm to calculate the reliability of power supply. The minimal path set of all the loads to the power supply can be rapidly obtained by making all the loads in the feeder traverse simultaneously, which significantly improves the efficiency of calculating the reliability of power supply in the distribution network.

3.2. Bidirectional Search Algorithm Based on Apache Spark and Knowledge Graph

Apache Spark is a high-performance, versatile, distributed computing engine for efficient data processing, machine learning, and image processing on large-scale data sets. Apache Spark can be integrated with Neo4j graph database to realize efficient processing and analysis of large-scale graph data. Additionally, it can make use of the advantages of distributed computing and memory computing to quickly process large-scale graph data, while Neo4j provides an efficient graph database to store and query graph data. The combination of these two techniques offers the following advantages: 1. Efficient distributed computing; 2. Rich graph data processing capability; 3. Scalability 4. Flexibility 5. High reliability.

The main process of the workflow is as follows:

Step 1: Data preprocessing. The data is thoroughly cleaned and extracted from the original dataset, resulting in a curated set of relevant information. The topology structure information of the distribution network and the reliability parameters of each power supply device are used for calculation, including the failure rate and repair rate of the device. Additionally, the data is stored in the form of triples.

Step2: Construction of knowledge map distribution network. The construction of distribution network knowledge map was completed in the form of triplets by integrating the above construction methods and Neo4j graph database platform.

Step 3: Calculation of the reliability index for each 10 kV feeder. For this task, we use Golang programming language to write the Spark application program according to the completed knowledge graph structure and combined with the knowledge graph search algorithm as outlined in Section 2.1. The Spark SQL module is selected to read the data in the knowledge graph and is converted into Spark RDD format. The forward search method, provided functions by the Spark application based on the bidirectional search algorithm, is used to obtain the minimum line set and the influential line set, among which the minimum line set can be obtained by the bidirectional depth-first traversal algorithm of Neo4j. Furthermore, if the line contains standby power, the reversible line set can be obtained by the reverse search method. Finally, the reliability index of the feeder is calculated.

Step 4: Calculation of the reliability index of each substation and the whole region. We summarize the reliability parameters of the load points calculated by the corresponding feeders in each substation and put them into the calculation formula of the reliability index to obtain the reliability index of the corresponding substation. The reliability index of the region is calculated by aggregating the reliability parameters of all load points in the region.

To fully leverage the advantages of Spark distributed computing, we use the distributed computing engine provided by Spark Core to distribute computing tasks across multiple nodes in the Spark cluster. This enables parallel computing, significantly improving computing efficiency. Figure 3 illustrates the overall computing process. The parallel calculation operation (go(func1)) is performed on all feeders in the original data. The Spark engine is used to partition all feeders, and each partition is a computing unit. Parameters of func1 are the original data of different feeders. Following this, Step 1 and Step 2 operations are performed on feeders in each partition, resulting in feeder knowledge graph. In addition, partition is created for each load in each feeder by go(func2), allowing for parallel computation for individual loads. Subsequently, Step 3 is performed to obtain the reliability parameters of the load point. By incorporating these load point parameters into a formula, the reliability index of the feeder can be calculated. Finally, the reliability indicators of the load points in each substation and the whole region are collected into the Spark engine to calculate the reliability indicators of each substation and the whole region.

Overall, by leveraging the Apache Spark framework, knowledge graph technology, and the Golang language, we can achieve distributed and parallel computation of the power supply reliability index for large-scale power grids in a region. These strategies utilize Spark's distributed computing capabilities to efficiently process large-scale power system model data, while enabling flexible data storage and management through knowledge graphs. Meanwhile, Golang language is efficient and easy to use, enabling the Spark task code to be concise and clear, and improve code maintainability and extensibility.

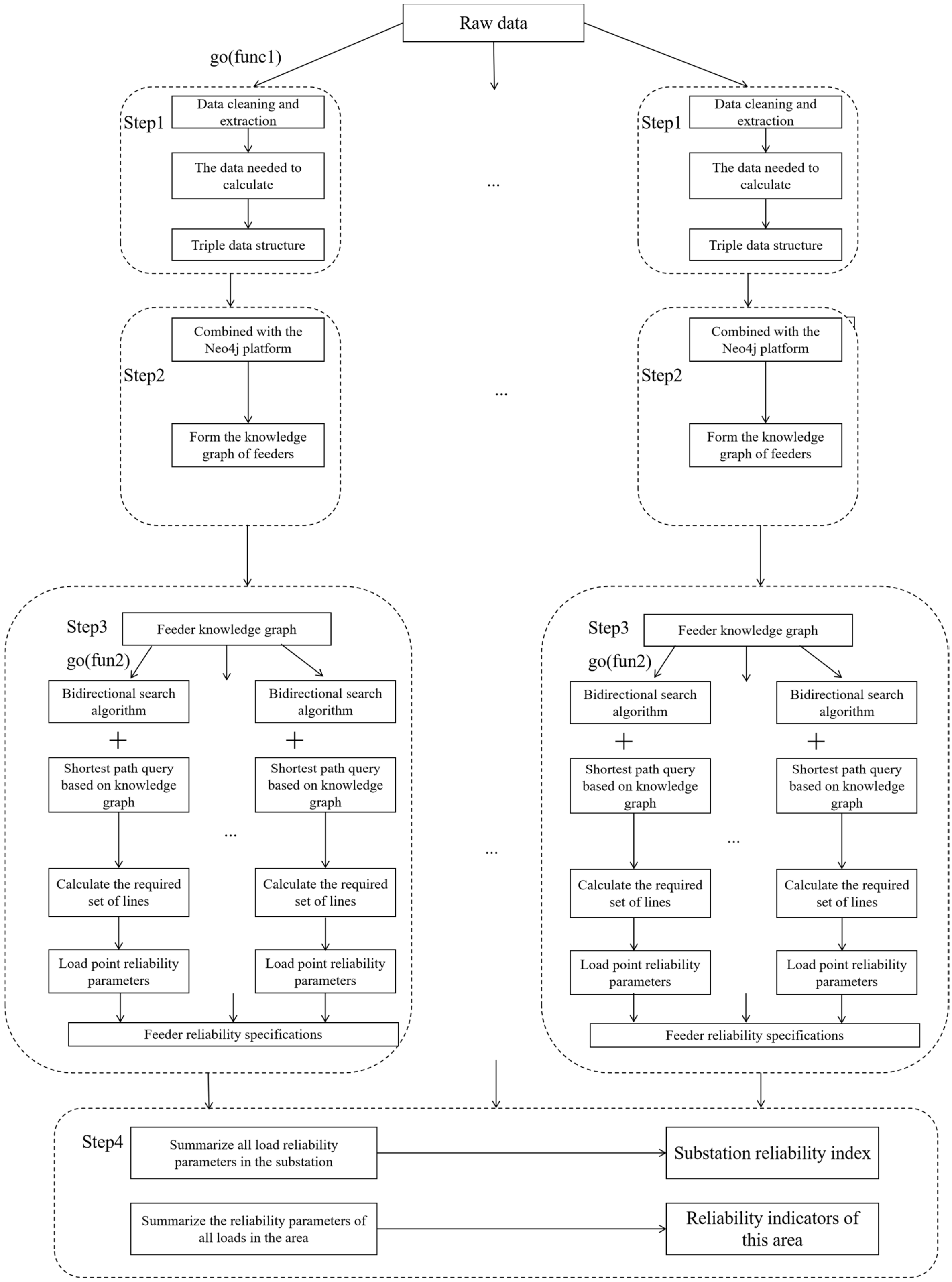

Figure 3. Calculation process of the distributed power supply reliability algorithm based on knowledge graph.

4. Case Study

4.1. The Construction Process of Distribution Network Knowledge Graph

The distribution network, provided by Shanghai Electric Power Company, is structured data. Our paper narrates the construction process of distribution network knowledge map in detail from ontology model construction, entity model construction, relationship model construction, triplet data construction, and distribution network node and relationship creation. The knowledge map construction process for the distribution network domain is shown in Figure 4.

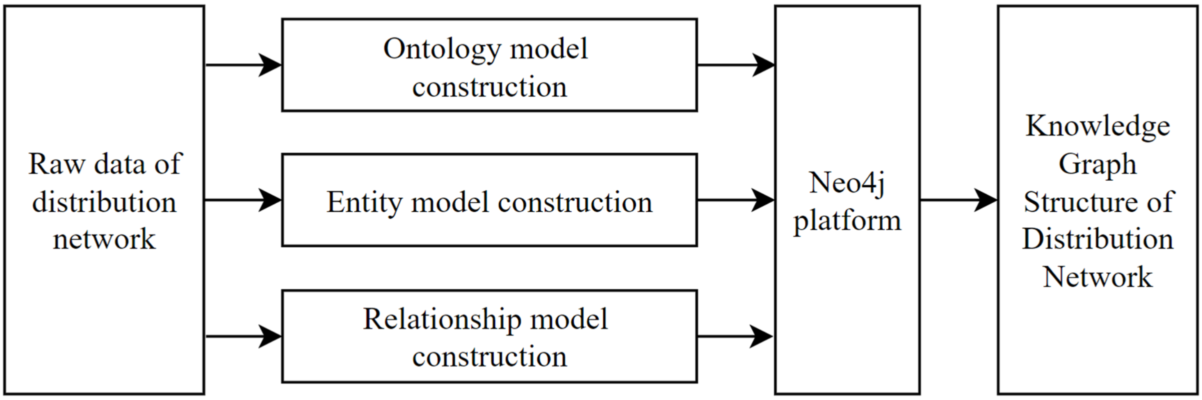

Figure 4. Constructed Knowledge Graph of the distribution network.

4.1.1. Ontology Model Construction

An ontology model serves an abstract rule specification for a class of power equipment concepts, providing foundation for entity construction. In the context of distribution network topology, an ontology model is constructed by referencing the data structure of each device in the CIM (Computer-Integrated Manufacturing) model. There are several key steps for the construction of the ontology model. Firstly, based on the relationship between the model packages in the CIM, it is determined that the ontology model constructed in this article includes substations, transformers, feeders etc. Secondly, data type fields are extracted from the relational database and compared with the device attributes in the CIM model package to form the ontology model of various devices. Lastly, the ontology model relationships of different power equipment can be obtained based on the attribute relationships in the CIM model package. The resulting ontology model includes a comprehensive representation of power equipment concepts, as illustrated in Table 1.

Table 1. Ontology model relationship table.

Ontology	Relationship	Ontology	Directivity
feeder	connect	bus	directed
feeder	connect	Contact switch	undirected
feeder	connect	breaker	directed
feeder	connect	Segmented switch	directed
transformer	connect	breaker	directed
transformer substation	connect	feeder	directed

Relationships are divided into two types: directed and undirected. The direction of the relationship determines whether it is a directed or undirected relationship. From Table 1 it can be seen that “transformer” and “feeder” are the main entities, and “connection” is the relationship between these two entities. As a step-down device for power transmission, transformers usually flow from “transformer” to “feeder”, so the relationship “connection” of the main entity is directional. The direction of the connection between the “Contact switch” and the “feeder” is uncertain, and its current direction varies depending on actual operating conditions, therefore it is undirected.

4.1.2. Entity Model Construction

For the construction of the distribution network entity model, knowledge extraction is performed through direct mapping from the distribution network database. This involves converting the data structure and attributes in the relational database into the structural form of triple groups. It follows the mapping rules. Each row of data in the relational database represents each device’s information, which contains information about the basic attributes of the device and the connection relationship with other devices. Each column of data in the relational database represents the description of different attribute values for similar entities. Through the overview of the distribution network ontology model in the previous section, the generated triplet data can be interconnected to construct all device entities in the distribution network. For example: feeder (length, name, start ID, end ID, etc.), switch (name, start ID, end ID, switch type, etc.), transformer (connection point ID, name, capacity, etc.).

After analyzing the actual data provided by the power grid company, some physical models required for constructing the distribution network are shown in Table 2. From the table, it can be seen that transformers have four attributes: name, type, model, and capacity. In contrast, the feeder has five attributes: namely start ID, end

ID, name, length, and model. Having established the entity models in each ontology, the next step is to construct the relationship model.

Table 2. Entity model set for power equipment.

Ontology	Entity	Properties	Attribute Value Collection
transformer	transformer 1	name, kind, model, capacity	AnLin, specific power transformer, SCB10-800, 100
feeder	feeder 1	start ID, end ID, name, length, model	15, 16, 912936787, 264.15, DL-ZRYJV-400
transformer substation	transformer substation 1	name, kind	Maidong Station, 110 kV
breaker	breaker 1	start ID, end ID, name, model	45, 46, 21 JinXiu Switch, T_SB_ZNYC_DLQ
bus	bus 1	start ID, end ID, name, model	21, 22, 912936785, DX_ZWCLJX_LGJ-400
contact switch	contact switch 1	start ID, end ID, name, model	70, 71, 10 kV interconnection switch, T_SB_ZNYC_DLQ
segmented switch	segmented switch 1	start ID, end ID, name, model	75, 76, 10 kV interconnection switch, T_SB_ZNYC_DLQ

4.1.3. Relationship Model Construction

The key to a knowledge graph is that different nodes are not independent, but rather form a whole due to their relationship attributes. Therefore, the construction of a relational model is the core of constructing a knowledge graph for distribution networks. Relationships have two meanings in the knowledge graph, one is the relationship between entities and the other is relationship between entities and their own attributes. In the field of distribution networks, the relationship between entities is a connection relationship, such as “feeder 1 connection feeder 2” and “switch 1 connection feeder 3”.

The relationship between an entity and its own attributes needs to be defined according to the device attribute values extracted from the relational database. The name of each column field in the database is the relationship value. For example, when the field name in a physical feeder is “model”, it indicates that the relationship between the feeder and the field value is the actual feeder model of the physical feeder, such as “feeder 1 model DX_ZWLJX_LGJ-400”. In Table 3, provided by the power grid company, we can see the partial relationship models required for constructing the distribution network in actual data.

Table 3. Relational model table of power equipment.

Ontology	Relationship	Ontology
feeder 1	connect	bus 1
feeder 2	connect	contact switch 1
feeder 3	connect	breaker 1
feeder 4	connect	segmented switch 1
transformer 1	connect	breaker 2
transformer substation 1	connect	feeder 5

4.1.4. Construction of Triple Data

After the ontology model, entity model, and relationship model of the distribution network have been constructed, entities and attributes can be combined through relationships to form a triplet data structure. According to the actual data provided by the power grid company, Tables 4 and 5 present some examples of triplet data required for constructing the distribution network.

Table 4. Entity and entity triple data.

Entity	Relationship	Entity
160014714	connect	Shu 35 MinZhi 101
Shu 35 MinZhi 101	connect	160005911
160005911	connect	912173930
912173930	connect	911062093
911062093	connect	140051757
140051757	connect	160119713

Table 5. Triple data for entities and attributes.

Entity	Relationship	Attribute
160005911	Start ID	15
160005911	End ID	16
160005911	Name	160005911
160005911	Length	92.64
160005911	Model	DL-ZRYJV-400

Table 4 shows an example in triplet data of distribution network, from which it can be seen that the "160014714" entity is connected to the "Book 35 MinZhi 101" entity. Similarly, Table 5 offers another illustration of how attribute values are represented for specific entities. From this, the starting ID attribute value of entity "160005911" is 15, and the ending ID attribute value is 16.

4.1.5. Completion of Knowledge Graph Construction for Distribution Network

Import the obtained triplet data into the Neo4j platform and construct a knowledge graph structure for the distribution network, as shown in Figure 5. It displays the constructed knowledge graph, which shows the nodes names representing entities, their connection relationships, and the overall network structure.

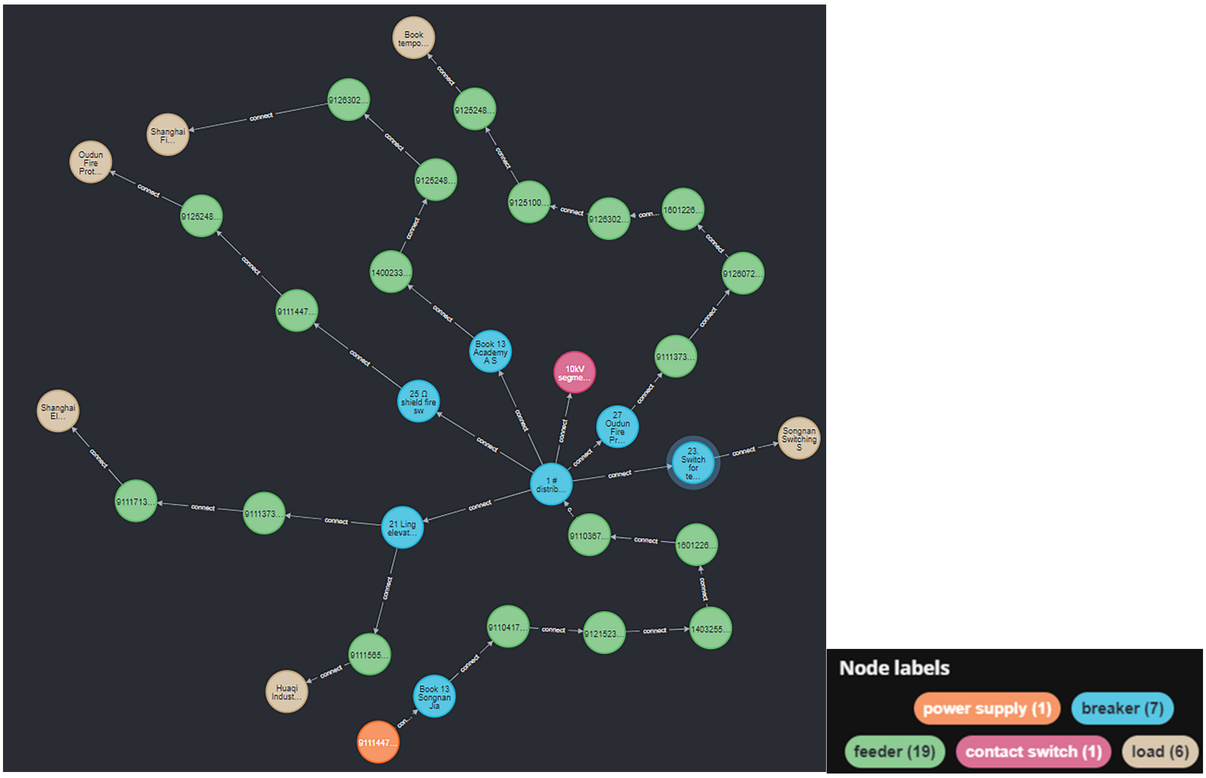

Figure 5. Knowledge graph structure of the distribution network for a certain feeder.

4.2. Power Supply Reliability Calculation Based on a Regional Distribution Network

To validate the distributed power supply reliability algorithm based on the knowledge graph proposed in the previous section, we apply it to the distribution network of a town in Shanghai. According to statistics, there are only two substations in the region, including one 110 kV substation and one 35 kV substation. A knowledge graph was constructed for these two substations, incorporating relevant information such as feeder connections, substation names, and capacity details. Figure 6 presents some of the key insights derived from this analysis. Notably, it reveals that the Construction Station has eight 10 kV feeders, while the Forest Station boasts seven 10 kV feeders.

The power supply reliability indicators for the region, each substation, and each 10 kV feeder, are obtained by applying the regional knowledge graph to the proposed algorithm. Table 6 presents the calculation results for a detailed analysis of comprehensive indicators, where SAIFI represents System Average Interruption Frequency Index, SAIDI represents System Average Interruption Duration Index, CAIDI represents Customer Average Interruption Duration Index, ASAI represents Average Service Availability Index, EENS represents Expect of Energy Not Supplied.

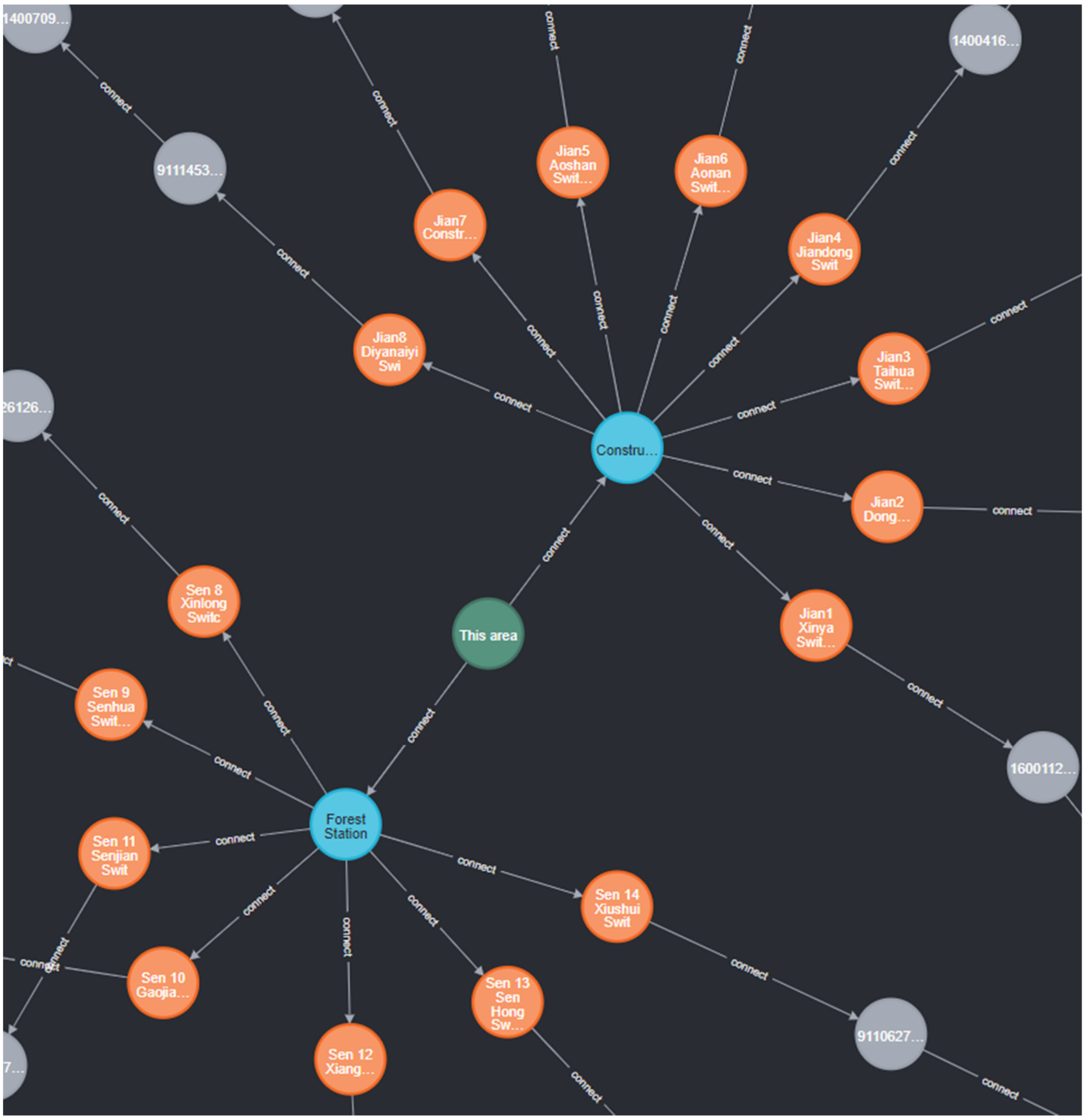

Figure 6. Knowledge graph structure of some distribution networks in the region.

Table 6. Calculation results of power supply reliability in the region.

Name	SAIFI	SAIDI	CAIDI	ASAI	EENS
This area	0.79124	2.873	3.6214	99.9662	166,155.2
Construction Station	0.77385	2.801	3.6196	99.9680	75,394.5
Forest Station	0.85387	3.0933	3.6227	99.9646	90,760.7
Jian 1 Xinya Switch	0.20085	0.7411	3.6903	99.9915	2845.83
Jian 2 Dongping Switch	0.092731	0.34269	3.6955	99.9961	188.3
Jian 3 Taihua Switch	0.27904	1.0327	3.7011	99.9882	495.71
Jian 4 Jiandong Switch	0.53866	1.9924	3.6989	99.97725	4795.8427
Jian 5 Aoshan Switch	0.55219	2.0444	3.7023	99.9766	6035.6529
Jian 6 Aonan Switch	0.62163	2.2968	3.6948	99.9738	10,806.433
Jian 7 Construction Switch	0.97443	3.6024	3.6969	99.9589	20,969.6738
Jian 8 Diyanaiyi Switch	1.014	3.7423	3.6905	99.9573	24,111.3337
Sen 8 Xinlong Switch	1.1594	4.2794	3.691	99.9511	31,942.2114
Sen 9 Senhua Switch	0.9394	3.4709	3.6948	99.9604	19,134.553
Sen 10 Gaojiazhuang Switch	0.55244	2.0419	3.6962	99.9767	3490.9521
Sen 11 Senjian Switch	0.4654	1.7103	3.6748	99.9805	11,665.0996
Sen 12 Xiangming B switch	0.46637	1.7207	3.6896	99.9804	11,358.3219
Sen 13 Sen Hong Switch	0.49593	1.8337	3.6974	99.9791	7886.639
Sen 14 Xiushui Switch	0.3864	1.4861	2.9864	99.9887	4284.917

From Table 6, it can be seen that the power supply reliability indicators of each substation and 10 kV feeder in the region are feasible, providing strong evidence of the feasibility of the distributed power supply reliability algorithm based on knowledge graph.

We compare our method with traditional methods by studying 10 kV feeder lines of different scales in the Lingang area. The results in Table 7 revels that the time required to calculate the power supply reliability using the traditional adjacency matrix and BFS increases exponentially with the expansion of the distribution network scale. In Contrast, the distributed power supply reliability algorithm based on knowledge graph proposed in this article can effectively solve this problem. Firstly, the number of nodes is greatly reduced through simplification. Secondly, the minimum path from the power point to the load can be quickly found by combining with the path search algorithm in Neo4j. Moreover, combined with the Apache Spark distributed computing framework, parallel computing can be performed on all load points. Therefore, the effectiveness of our approach lies in successfully solving the difficulties of simplifying complex networks in computer programming implementation and is suitable for the reliability analysis of power supply in large-scale complex regional distribution networks.

Table 7. Comparison of power supply reliability calculation time of power grid of different scales.

Number of Nodes/Piece	Traditional Methods for Calculating Power Supply Reliability Time/s	Calculating Power Supply Reliability Time Using Knowledge Graph/s
78	8.167	4.162
166	16.562	5.412
253	28.384	6.057
356	53.846	6.739
461	86.716	7.515
549	134.816	8.436

5. Conclusions

With the development of intelligent distribution networks, knowledge graphs have various application prospects in the field of power distribution network. They can effectively simplify the management of complex power grids and improve their operation efficiency.

The main contributions and conclusions of this paper are as follows:

(1) A novel knowledge graph construction method is proposed in the field of distribution networks. By combining the topological structure attributes and characteristics of the distribution network, a triplet data format is constructed, which is then imported into the Neo4j graph database to complete the construction of the distribution network knowledge graph.

(2) A method for calculating the reliability of power supply in distribution networks is proposed. The bidirectional depth first search algorithm in the knowledge graph is introduced, which can quickly obtain the minimum path set from each load point to the power point. Additionally, based on the distributed operation characteristics of regional distribution networks, combined with the Apache Spark distributed computing framework, parallel calculations are performed on the feeders for each substation, resulting in faster computational efficiency.

Future research directions will focus on incorporating additional factors such as load to be transferred, the margin of standby power supply, distributed generation into the existing framework to improve the rationality of power supply reliability analysis of the distribution network.

Author Contributions

Conceptualization, W.C., Y.Z. and W.S.; method-ology, W.C., H.R.K. and Y.Z.; software, W.S. and W.C.; validation, W.C. and W.S.; formal analysis, W.C.; investigation, H.Z.; resources, W.S.; data curation, W.S.; writing—original draft preparation, Y.Z., H.R.K. and W.C.; writing—review and editing, W.S. and H.R.K.; visualization, H.R.K.; supervision, H.Z.; project administration, W.C.; funding acquisition, H.Z. and W.C. All authors have read and agreed to the published version of the manuscript.

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Informed Consent Statement

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Data Availability Statement

The authors do not have permission to share data.

Conflicts of Interest

The authors declare no conflicts of interest.

Use of AI and AI-Assisted Technologies

No AI tools were utilized for this paper.

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