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EDITED BY
Yang Gao,
Shanghai Jiao Tong University, China

REVIEWED BY
Zhiyi Chen,
RMIT University, Australia
Jiaqi Ruan,
Hong Kong Polytechnic University, Hong Kong SAR, China
Jian Zhao,
Shanghai University of Electric Power, China

*CORRESPONDENCE
Xinrui Wang,
15835689822@163.com

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Fast power flow calculation for distribution networks based on graph models and hierarchical forward-backward sweep parallel algorithm

Xinrui Wang*, Wengang Chen, Ruimin Tian, Yuze Ji and Jianfei Zhu

State Grid Jincheng Electric Power Supply Company, Jincheng, China

Introduction: In response to the issues of complexity and low efficiency in line loss calculations for actual distribution networks, this paper proposes a fast power flow calculation method for distribution networks based on Neo4j graph models and a hierarchical forward-backward sweep parallel algorithm.

Methods: Firstly, Neo4j is used to describe the distribution network structure as a simple graph model composed of nodes and edges. Secondly, a hierarchical forward-backward sweep method is adopted to perform power flow calculations on the graph model network. Finally, during the computation of distribution network subgraphs, the method is combined with the Bulk Synchronous Parallel (BSP) computing model to quickly complete the line loss analysis.

Results and Discussion: Results from the IEEE 33-node test system demonstrate that the proposed method can calculate network losses quickly and accurately, with a computation time of only 0.175s, which is lower than the MySQL and Neo4j graph methods that do not consider hierarchical parallel computing.

KEYWORDS

graph model, line loss calculation, hierarchical forward-backward sweep, bulk synchronous parallel computing model, distribution network

1 Introduction

As distribution network monitoring systems become increasingly intelligent and the frequency of load data collection increases, more frequent line loss calculations can accurately capture the daily fluctuations in line losses, especially for distribution networks with high level of renewable penetrations (Ruan et al., 2024a; Wu et al., 2024a; Ruan et al., 2024b). However, this also places higher demands on calculation speed (Wang et al., 2019; Yang et al., 2022; Bennani et al., 2023). Rapid line loss calculations can help identify defective components in the system and rectify locations that violate line loss patterns. Therefore, researches on line loss calculation have practical significance for safe, stable and economic operation of distribution networks (Castaño et al., 2013; Kocar et al., 2016).

Currently, the main methods for calculating line losses in distribution networks at different voltage levels include the equivalent resistance method (Khazaee et al., 2017), artificial intelligence algorithms (Zhang, 2019; Ren et al., 2020; Guo et al., 2021; Liu et al.,

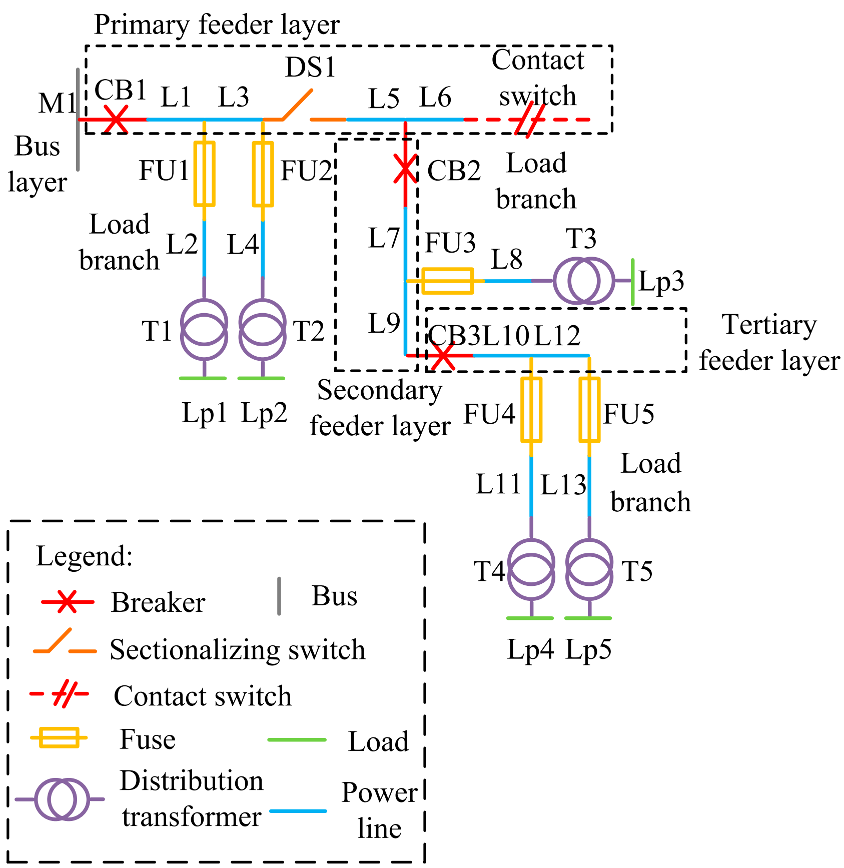

FIGURE 1
Schematic diagram of multi-layer distribution network structure.

2023; Ruan et al., 2024c), and the forward-backward sweep method (Meena et al., 2018; Yan et al., 2019; Huang et al., 2022). The equivalent resistance method has lower accuracy when calculating distribution network line losses. Artificial intelligence algorithms lack unified calculation rules, and their results often have a degree of randomness and blindness. The forward-backward sweep method has advantages such as good stability and fast calculation speed. However, when the structure of the distribution network changes, it requires re-transforming the network structure into a matrix and renumbering the network using path search algorithms, resulting in a significant workload. To address uncertainty factors, many scholars have proposed probabilistic power flow calculations (Kazemdehdashti et al., 2018; Zuluaga and Alvarez, 2018). Reference (Zuluaga and Alvarez, 2018) uses Monte Carlo simulation to analyze systems with distributed power sources, which requires large amounts of data and has relatively low computational efficiency.

Distributed computing approaches are gaining popularity in power system analysis (Wu et al., 2024b; Ruan et al., 2024d). These approaches can be divided into two categories: parallel computing (Ahmadi et al., 2021; Rodriguez et al., 2021) and graph computing (Hu et al., 2017; Ruan et al., 2023). Compared to GPU parallel methods, Neo4j-based graph parallel computing does not require complex memory management or expensive graphics processors (Pan and Jing, 2018; Zhou et al., 2021). To further improve calculation speed and accuracy, and enhance adaptability to changes in distribution network structure, this paper proposes a hierarchical parallel calculation method for distribution network line losses based on the Neo4j graph model. The method's efficiency is verified by performing power flow calculations on the IEEE 33-node test system and comparing it with two serial calculation methods based on MySQL and Neo4j, demonstrating the speed of the Neo4j-based hierarchical parallel computing method in solving distribution network line loss problems.

2 Graph model construction based on Neo4j

The distribution network can be sequentially divided into three layers based on its power supply paths and connection relationships: bus, feeder, and load branch (Nour et al., 2023). Figure 1 shows a schematic diagram of a multi-layer distribution network structure with a voltage level of 10 kV from a domestic source. Neo4j can describe the distribution network relationship model as a directed graph model in the form of $G(V, E)$, where V and E represent the set of nodes and the set of edges, respectively, as shown in Figure 2.

In graph databases, the connections between entity objects are just as important as the entities themselves, and they are stored as part of the data. This storage mechanism allows graph databases to

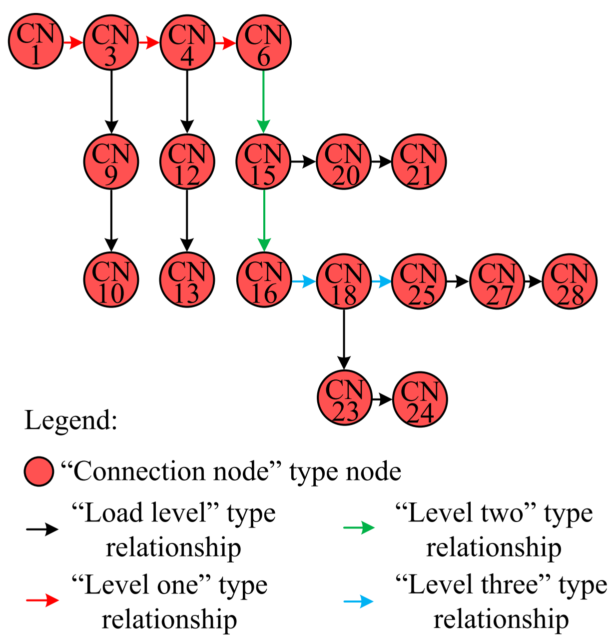

FIGURE 2
Distribution network graph model based on Neo4j.

quickly respond to complex queries about relationships between large-scale network entities, as the relationships between entities are pre-stored in the database. At the same time, graph databases can intuitively visualize entities and the relationships between them, making them the best method for storing, querying, and analyzing highly interconnected data. Consequently, when the distribution network structure changes, the Neo4j graph model can be employed to swiftly characterize the varying levels of feeder layers corresponding to different network structures, as well as the interconnections between equipment in various load branches.

3 Hierarchical forward-backward sweep power flow calculation

3.1 Layering of distribution networks

In distribution networks, the feeder layers and load branch layers are divided by lines containing circuit breaker equipment and lines containing fuse equipment. Specifically, the relationship type between electrical nodes in the first-level feeder layer is "Level One," the relationship type between electrical nodes in the second-level feeder layer is "Level Two." The connection relationship type of electrical nodes in each load branch is "Load Level," and they are correspondingly connected to the electrical nodes in various levels of feeder layers.

3.2 Equivalent loss model for load layer and feeder layer

Taking the load branch (CN25-CN27-CN28) in the load branch layer of the distribution network graph model shown in Figure 2 as an example for power flow analysis, referring to Figure 1, we can see that CN25-CN27 are connected through line L13, with line impedance parameters: $Z_{L13} = R_{L13+}jX_{L13}$; CN27-CN28 are connected through transformer T5, with transformer ratio, equivalent impedance parameters and fixed losses: k, $Z_{T5} = R_{T5}+jX_{T5}$, S_{T5}; Load Lp5 is connected after CN28, with parameters: $S_{28} = P_5+jQ_5$. Based on this, an equivalent loss model for this layer's branch is established, as shown in Figure 3A. The specific power flow analysis process is as follows.

3.2.1 Forward sweep process

The forward sweep process is shown in Equations 1-4.

$$\Delta S_{27} = \frac{P_5^2 + Q_5^2}{U_N^2}\left(R_{T5} + jX_{T5}\right) \tag{1}$$

$$S_{27} = S_{28} + \Delta S_{27} + S_{T5} = P_{27} + jQ_{27} \tag{2}$$

$$\Delta S_{25} = \frac{P_{27}^2 + Q_{27}^2}{U_N^2}\left(R_{L13} + jX_{L13}\right) \tag{3}$$

$$S_{25} = S_{27} + \Delta S_{25} = P_{25} + jQ_{25} \tag{4}$$

where ΔS_{27} represents the variable losses of transformer T5; U_N is the rated voltage of the line; S_{25} and S_{27} are the complex powers at nodes 25 and 27 respectively; ΔS_{25} is the impedance loss of line L13.

3.2.2 Backward sweep process

The backward sweep process is shown in Equations 5-9.

$$\Delta U_{25} = \left(P_{25}R_{L13} + Q_{25}X_{L13}\right)/U_{25}^{new} \tag{5}$$

$$U_{27}^{new} = U_{25}^{new} - \Delta U_{25} \tag{6}$$

$$\Delta U_{27} = \left(P_{27}R_{T5} + Q_{27}X_{T5}\right)/U_{27}^{new} \tag{7}$$

$$U_{28}^{\prime new} = U_{27}^{new} - \Delta U_{27} \tag{8}$$

$$U_{28}^{new} = U_{28}^{\prime new}/k \tag{9}$$

where U_{25}^{new}, U_{27}^{new}, and U_{28}^{new} are the updated voltages of nodes 25, 27, and 28 in the tertiary feeder layer after the forward-backward sweep; ΔU_{25} is the impedance voltage drop of line L13; ΔU_{27} is the impedance voltage drop of transformer T5. Similarly, taking the feeder (CN16-CN18-CN25) in the tertiary feeder layer as an example for power flow analysis, since its forward-backward sweep mathematical principle is similar, it will not be repeated here. Only the equivalent loss model of this layer is shown, as illustrated in Figure 3B.

3.3 Hierarchical distribution network power flow calculation process

The flowchart of the hierarchical forward-backward sweep power flow algorithm based on the distribution network graph model is shown in Figure 4. The specific calculation steps are as follows.

Step 1: For each load branch structure in the distribution network, perform forward calculations based on

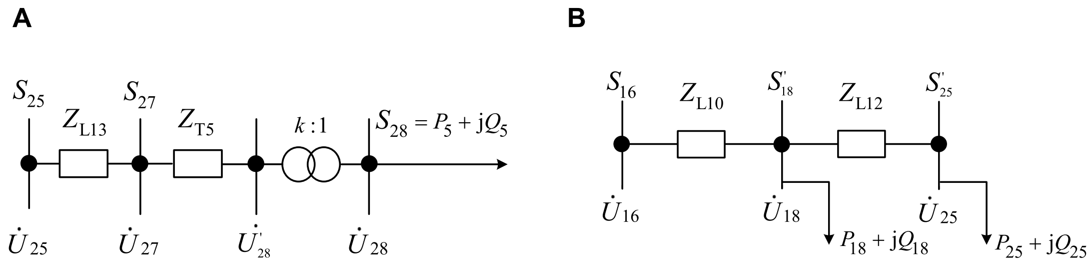

FIGURE 3
Hierarchical equivalent loss model. **(A)** Equivalent loss model of the CN25-CN27-CN28 load branch. **(B)** Equivalent loss model of the CN16-CN18-CN25 tertiary feeder.

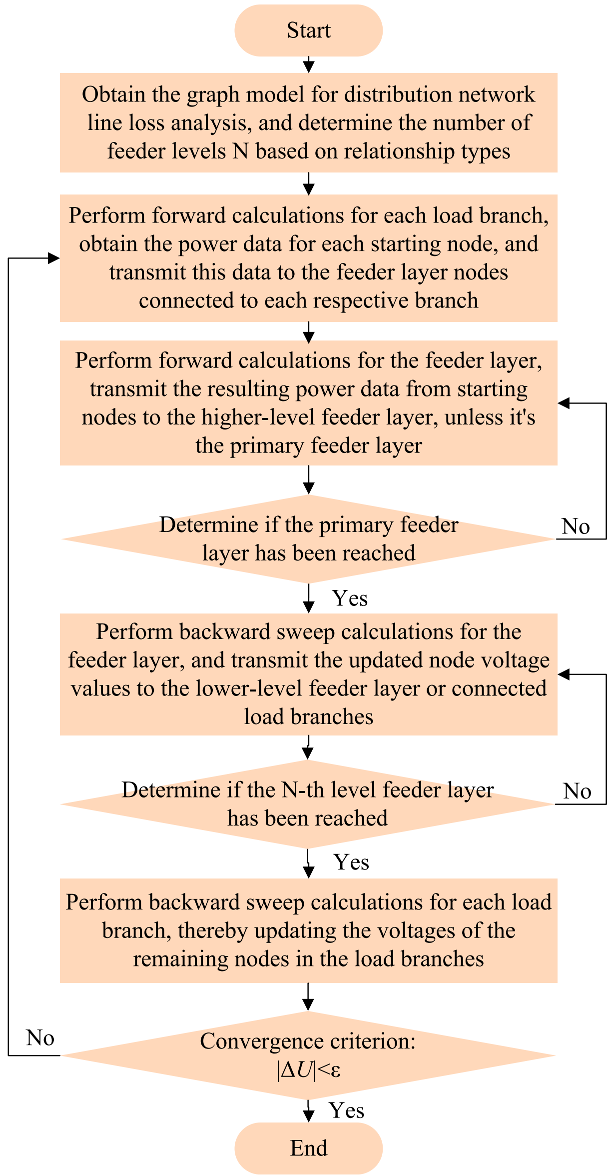

FIGURE 4
Hierarchical forward-backward sweep power flow calculation process based on distribution network graph model.

the equivalent loss model of the load branch as shown in Figure 3A. Obtain the power values at the nodes connected to the start of each load branch, and transfer these power values to the corresponding nodes in the feeder layer connected to the load branches.

Step 2: Starting from the N-th level feeder layer, perform forward calculations based on the equivalent loss model of the feeder layer as shown in Figure 3B. Obtain the power value at the node connected to the start of this feeder layer, and transfer this value to the corresponding node in the (N-1)-th level feeder layer connected to this feeder layer. Continue this process until reaching the first-level feeder layer, thus completing the entire forward calculation.

Step 3: Begin the backward sweep calculation from the first-level feeder layer. After obtaining updated voltage values for each node, transfer these to the lower-level feeder layers or connected load branches. Continue this process until the backward calculation reaches the N-th level feeder layer and the load branches connected to the N-th level feeder layer.

Step 4: For all load branches with updated voltage values at their starting nodes, perform backward calculations using the equivalent loss model of the load branch. Based on the calculation results, check the convergence condition. If satisfied, stop the calculation; otherwise, return to Step 1 for another iteration.

Finally, upon completing the iterations, the line losses for each load branch and each feeder layer can be obtained. Assuming there are n lines in the load branch layer and m lines in the feeder layer, their losses are expressed as Equation 10 and Equation 11, respectively:

$$\Delta S_F = \sum_{i=1}^{n} \Delta S_{Li} + \Delta S_T \tag{10}$$

$$\Delta S_K = \sum_{i=1}^{m} \Delta S_{Li} \tag{11}$$

where ΔS_{Li} represents the losses of the i-th conductor; ΔS_T represents the transformer losses.

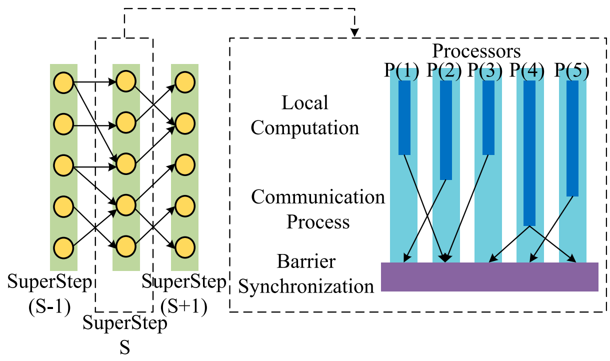

FIGURE 5
BSP computation model.

4 Distribution network line loss calculation based on BSP

4.1 BSP computation model

The BSP computation model is the core technology for parallel computation in graph databases. It implements an iterative process using multiple global SuperSteps, as shown in Figure 5. From Figure 5, we can see that a SuperStep in the BSP computation model mainly consists of 3 steps. The specific synchronous parallel steps are as follows:

Step 1: Local Computation. Multiple processors perform parallel computations of user-defined local functions. Each participating processor has assigned tasks, and these are mutually independent.

Step 2: Communication Process. Information exchange takes place between processors, transmitting calculation results to the corresponding processors.

Step 3: Barrier Synchronization. When a processor encounters a "barrier" (or fence), it needs to wait for all remaining processors to complete their respective computational tasks and finish information transfer, ending this SuperStep.

4.2 Parallelization of hierarchical forward-backward sweep power flow calculation

In the distribution network graph model G (V, E) for line loss analysis, if there exists S_i (V_i, E_i), where $V_i \in V$ and $E_i \in E$, then the

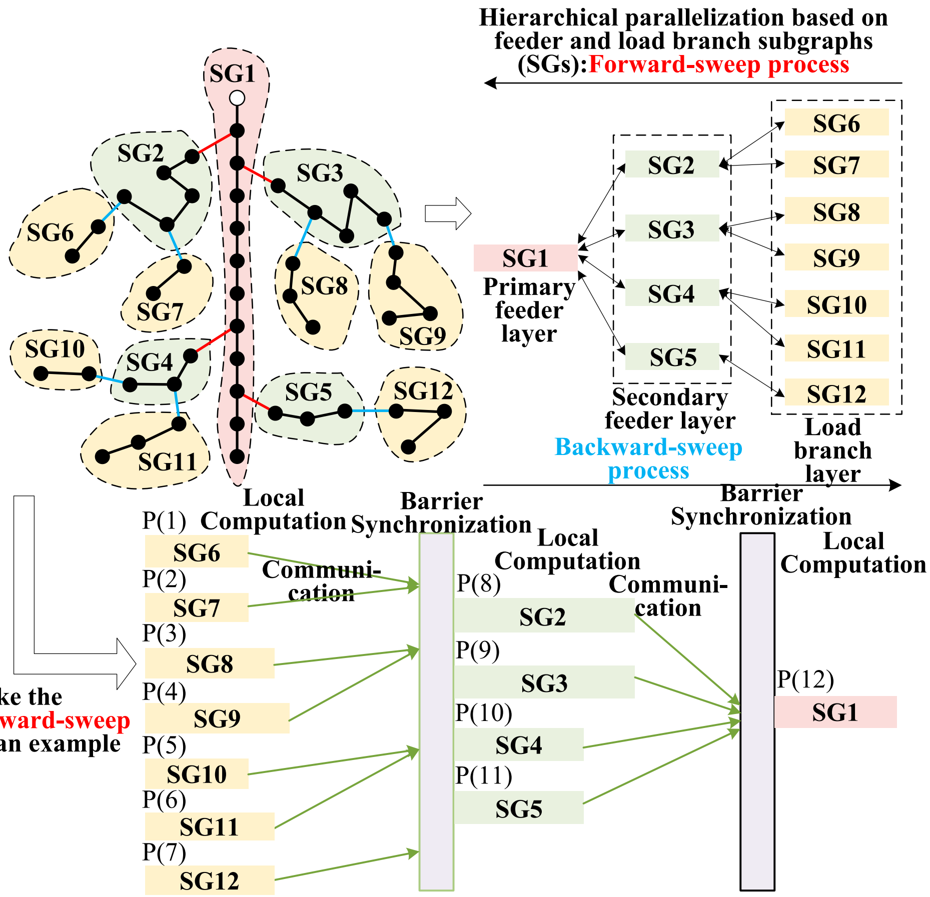

FIGURE 6
Hierarchical BSP model based on subgraphs.

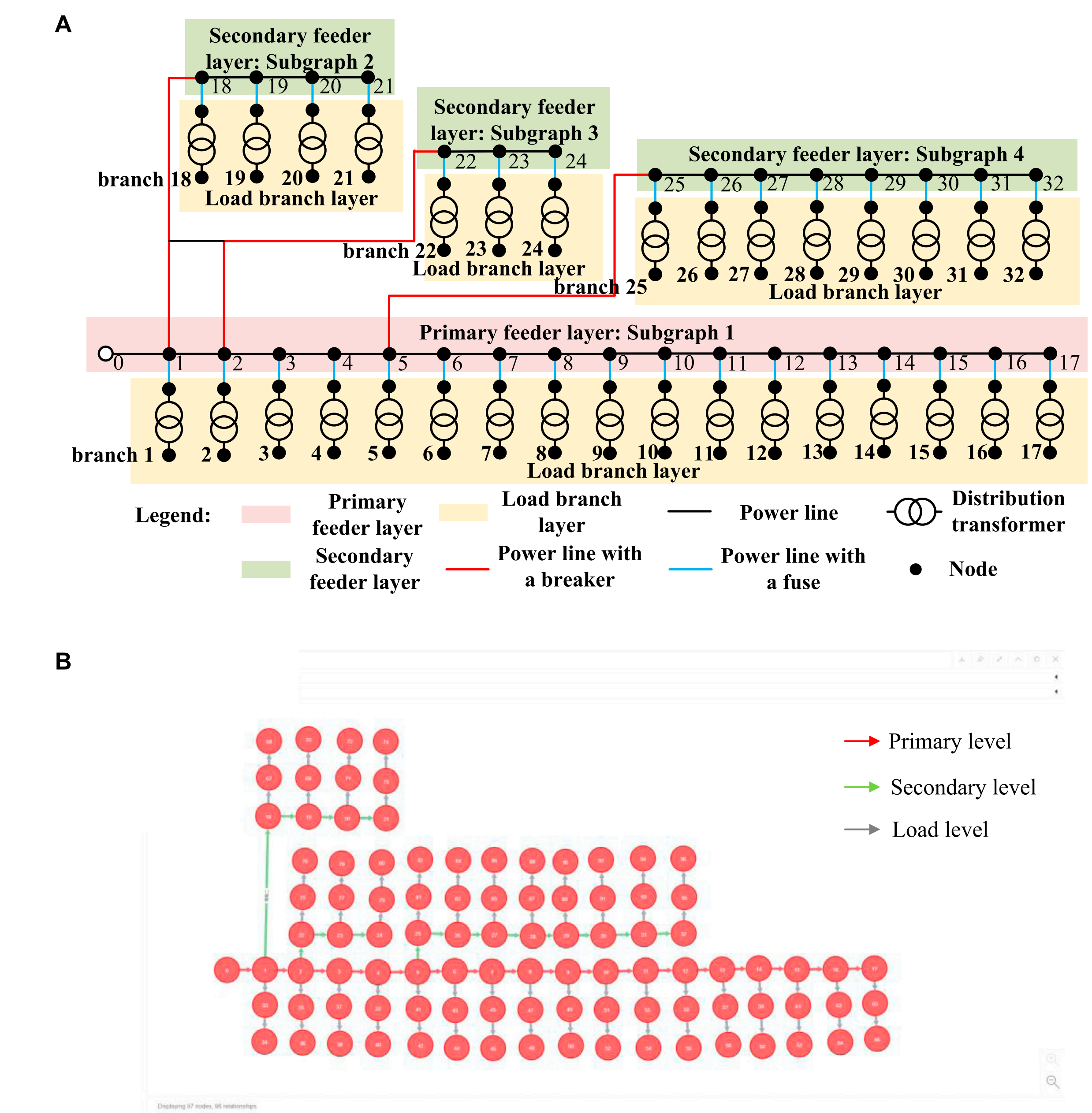

FIGURE 7
IEEE 33-node distribution network structure and its graph model. **(A)** Network structure. **(B)** Graph model for the line loss analysis.

graph S_i is called a subgraph of graph G. Based on the division of load branch layers and feeder layers, combined with Neo4j's path query statements, it is possible to query load branch subgraphs and feeder subgraphs. Using each subgraph as a unit, the layered forward-backward substitution power flow algorithm can be parallelized.

From Figure 6, we can see that, taking the forward process as an example, the hierarchical forward parallel calculation of the distribution network mainly includes 3 SuperSteps. The specific descriptions of SuperSteps 1–3 are as follows:

SuperStep 1: Seven load branch subgraphs (subgraphs 6–12) in the load branch layer complete parallel forward calculations, and transmit the calculation results to the secondary feeder subgraphs. When all communications are completed, SuperStep 1 ends and SuperStep 2 begins.

SuperStep 2: Four feeder subgraphs (subgraphs 2–5) in the secondary feeder layer perform parallel forward calculations, then transmit the updated power data to the primary feeder subgraph. When the scale of certain subgraphs is too small, the calculations for these small-scale subgraphs will be handled by the same processor, in order to improve overall computational efficiency. When all communications are completed, SuperStep 2 ends and SuperStep 3 begins.

SuperStep 3: One feeder subgraph (subgraph 1) in the primary feeder layer performs forward calculation, then updates the voltage of each node through backward calculation, and

TABLE 1 IEEE 33-node distribution network system power flow calculation results.

Layer	Active power loss/kW	Reactive power loss/kvar	Active power loss proportion/%
Primary feeder layer: subgraph 1	209.86	79.09	65.46
Secondary feeder layer: subgraph 2	0.88	0.83	0.28
Secondary feeder layer: subgraph 3	7.67	5.78	2.39
Secondary feeder layer: subgraph 4	24.50	18.79	7.64
Load branch layer	77.67	139.62	24.23
Entire system	320.58	244.11	100

transmits it to the secondary feeder subgraphs, initiating the backward process.

5 Case study

To verify the effectiveness of the method proposed in this paper for calculating line losses, the IEEE 33-node distribution network system shown in Figure 7A is selected for analysis, considering the addition of corresponding load branches and fully accounting for transformer losses. For example, 32 load branches are added to the node system, increasing the number of nodes from 33 to 97. Node 0 in the system represents the balance node, with an initial voltage of 10.5 kV, a base power of 1 MVA, and a total load of 3715 kW + 2300 kVar. Furthermore, it is assumed that all transformers are model S13-M-400/10, with a capacity of 0.4 MVA, a voltage ratio of 10 kV/0.4 kV, an equivalent impedance of 1.325 + j10 Ω, and a no-load loss of 0.95 kW.

According to hierarchical theory, the distribution network can be divided into feeder layers and load branch layers. The feeder layer is divided into two levels: the primary feeder layer (including subgraph 1) and the secondary feeder layer (including subgraphs 2–4). The load branch layer contains 32 load branch subgraphs (subgraphs 1–32), connected to their respective feeders, to be used for subsequent calculation tests.

The line loss analysis graph model corresponding to the IEEE 33-node distribution network system is shown in Figure 7B. The graph model consists of 97 nodes and 96 edges. The active and reactive power of each load is stored in the nodes, the impedance of each transformer and line is stored in the edges, and the node relationships at different layers are distinguished by the characteristics of the edges.

The line loss calculation results for subgraphs 1-4 of each feeder layer level and the 32 subgraphs of the load branch layer, obtained through the hierarchical forward-backward sweep parallel algorithm based on the graph model proposed in this paper, are shown in Table 1.

From Table 1, it can be seen that the total active and reactive power losses of the IEEE 33-node distribution network system are 320.58 kW and 244.11 kvar, respectively. Using a hierarchical approach, the active power losses and their proportions for each level of feeder layer subgraphs can be obtained. Among them, the active power loss of the primary feeder layer subgraph 1 is 209.86 kW, accounting for the highest proportion of 65.46%; while in the secondary feeder layer, compared with other subgraphs, subgraph 4 has an active power loss of 24.50 kW, accounting for the highest proportion of 7.64%. From this, the distribution network operator can identify the corresponding loss reduction areas in the distribution network and carry out targeted loss reduction modifications.

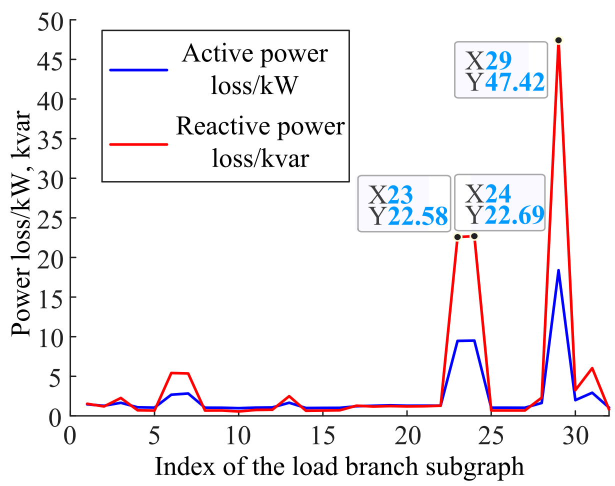

FIGURE 8
Active and reactive power loss of each subgraph in the load branch layer.

For the load branch layer, which contains 32 subgraphs, the active and reactive power loss values corresponding to each subgraph are shown in Figure 8. From Figure 8, analyzing the fluctuations of active and reactive power losses corresponding to the numbers of each load branch subgraph, it can be seen that load branch subgraphs 23, 24, and 29 have relatively large active and reactive power loss values. Therefore, measures can be taken to rectify the transformers and conductors on these numbered load branches in the load branch layer, thereby reducing the system's line losses.

To verify the advantages of the proposed method in terms of computational efficiency, Table 2 compares the line loss calculation time consumption of the method in this paper (hierarchical parallel computation based on Neo4j) with two serial computation methods based on MySQL and Neo4j.

From Table 2, it can be seen that when storing the same distribution network structure data, the serial computation based on Neo4j consumes less time than MySQL using the same method. The method in this paper has the highest performance, with a

TABLE 2 Comparison on the computational time consumption of different methods.

Computational methods	MySQL (serial computation)	Neo4j (serial computation)	Proposed method (hierarchical parallel computation)
Time consumption/s	2.551	1.842	0.175

calculation time consumption of only 0.175 s, enabling rapid completion of system line loss calculations.

6 Conclusion

This paper proposes a fast power flow calculation method for distribution networks based on the Neo4j graph model and a hierarchical forward-backward sweep parallel algorithm. It performs hierarchical forward-backward sweeps by feeder layer and load branch layer, calculating the line losses of each subgraph separately. The calculation is accurate and can clearly identify the subgraph areas that need loss reduction for the distribution network operator to take targeted measures. Under the same structure of the IEEE 33-node distribution network system with 32 additional load branches, through comparative studies of different calculation methods, it is concluded that the method proposed in this paper consumes the least computation time and has the highest analysis efficiency.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

XW: Conceptualization, Formal Analysis, Investigation, Methodology, Writing–original draft, Writing–review and editing. WC: Data curation, Methodology, Writing–original draft, Writing–review and editing. RT: Validation, Writing–review and editing, Visualization. YJ: Data curation, Formal Analysis, Writing–review and editing. JZ: Data curation, Methodology, Writing–review and editing.

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Conflict of interest

Authors XW, WC, RT, YJ, and JZ were employed by State Grid Jincheng Electric Power Supply Company.

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Publisher’s note

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