Efficient State Estimation Through Rapid Topological Analysis Based on Spatiotemporal Graph Methodology

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ABSTRACT The seamless integration of swift and precise topological analysis with state estimation is crucial for ensuring the dependability, stability, and efficiency of the power system. In response to this need, this paper introduced a novel approach to constructing a spatiotemporal ''Power Grid One Graph'' model using a graph database, enabling rapid topological analysis and state estimation. Initially, a spatiotemporal power grid model was created by merging grid topology with dynamically updated telemetry and telesignaling data. Subsequently, utilizing the graph model and entity mapping, the spatiotemporal node-breaker graph model was obtained and the corresponding bus-branch model was generated. Based on the node-breaker graph model, topological error identification was conducted, and a fast topological analysis optimization algorithm, considering component functionality, was applied to update the bus-branch graph model, facilitating graph-based state estimation. Finally, the proposed method was validated on a real power system, and its application, along with performance enhancements of the spatiotemporal power grid model considering topological changes, was investigated. The presented method provides both theoretical and practical support for the digital transformation of the power system and the advancement of the digital twin power grid.

INDEX TERMS ''Power Grid One Graph,'' graph database, graph computing, node-breaker graph model, graph topological analysis, state estimation.

I. INTRODUCTION

THE topological analysis of the power system is crucial for ensuring its reliability, stability, and efficient operation. Through topological analysis, the relationships between various components in the grid, such as transmission lines, generators, substations, etc. can be determined to assess the system's reliability [1], [2]. Topological analysis aids in swiftly identifying areas of failure within the power system, thereby reducing outage recovery time. Real-time grid topology analysis enables load dispatch, equipment status assessment, and the implementation of control strategies [3], [4]. Furthermore, state estimation plays an irreplaceable role in the power system analysis to provide fundamental data and decision support for grid operation and planning [5], [6]. Specifically, through power system state estimation, real-time monitoring of variables such as voltage and phase angle at various components in the grid is possible. Comparing measured values with estimated values facilitates a prompt response to operational issues, shortens fault recovery time, and ensures the stable operation of the grid under normal and emergency conditions.

Traversal analysis is commonly employed for power grid topological analysis [1], [7]. The traditional traversal method, focusing on the node-breaker model [8] of the grid, typically initiates from one or multiple starting nodes, such as substations or generators. It then traverses along the

connectivity relationships in the grid, identifying all nodes and branches to establish the topological structure of the grid, namely the bus-branch model [9]. This model illustrates the interconnections among various components in the power grid, including nodes and branches, aiding in the analysis of the electrical characteristics, configuration, and operational status. Traversal analysis is often utilized for real-time monitoring of changes in the power grid's status. When the state of equipment within the grid undergoes modifications, updating the topological status can be achieved by reapplying traversal analysis. With the increasing scale of the new power system and the gradual dominance of renewable energy sources in the power generation structure, the growing randomness, fluctuations, and intermittency of power generation enhance the inadequacy of local grid regulation capabilities. This leads to more frequent topological changes, resulting in a sharp increase in the demand for computational time and resources, limiting the application of traditional methods [10]. Traversal analysis inadequately considers the uneven distribution of networks in power systems, potentially leading to errors in overall system performance. In addition, to ensure the system's stability, state estimation must be based on accurate topology analysis results and completed within a short timeframe to promptly obtain precise grid status information. Therefore, there is an urgent need for a method that ensures the accuracy of the grid topology while achieving precise and rapid topological analysis and state estimation.

To fully leverage the value of data assets, the State Grid Corporation of China has proposed and formulated a technical approach aimed at achieving multi-source data integration and sharing through ''One Data Source, Power Grid One Graph, and One Business Line [11], [12].'' This aligns with the emerging global trend of building enterprise information systems centered on data. In 2021, the State Grid Corporation introduced the digital grid technical solution in its ''14th Five-Year Plan for Digital Power Development,'' which includes the strategy of ''a data platform + Power Grid One Graph'' for data sharing [13]. Utilizing the advanced graph database, the spatiotemporal ''Power Grid One Graph'' can be constructed by integrating the power grid's topological structure, geographic information, real-time data, historical data, and equipment status information. This method vividly presents the grid's topology in graph form, allowing an intuitive understanding of the connections between elements through node and edge relationships. By merging geographic information with the power grid topology, an accurate geographical representation of the grid is achieved. The integration of continuous operational data from devices enables time-based analysis of grid demand trends, equipment health, and topology error verification, providing comprehensive decision support for grid operation, planning, and maintenance.

Noteworthy achievements have been made in studying the spatiotemporal data platform for constructing the ''Power Grid One Graph.'' In [14], the authors proposed a spatiotemporal data management system based on ''Power Grid

One Graph.'' This system leveraged the structural consistency between graph data and the actual power grid to integrate topological connections across generation, transmission, transformation, distribution, and utilization stages into a unified spatial representation. By bridging topological connections between different voltage levels, it formed the ''Power Grid Topological One Graph.'' Additionally, the plan integrated diverse data from various business departments, including operation, monitoring, maintenance, production, and marketing, into a comprehensive ''Power Grid One Graph.'' In [15], the core role of the ''Power Grid One Graph'' in constructing a spatiotemporal information management platform for building the energy internet was discussed. The technical architecture of the spatiotemporal information management system was proposed. Based on this architecture, fog nodes and edge nodes for the energy management system were developed to provide online maintenance and automatic updates for the ''One Graph'' [16]. The ''Power Grid One Graph'' serves as a comprehensive data integration platform that encompasses accurate grid topology and operational information. It facilitates the rapid and precise establishment of mathematical models for state estimation algorithms and supports queries of both real-time and historical data, thereby providing references for the computation of state estimation results. Authors in [6] introduced a state estimation method that leveraged graph computing, modeling power systems as graphs with nodes serving as both storage and logical units. The approach decomposed system-level matrices into node-based components, which optimized computational complexity and enhanced the formulation and storage of the gain matrix through graph topology analysis. In [17], based on the graph model, power system networks were partitioned into multiple areas, with reference buses selected and PMUs installed at these buses for each area. Subsequently, the network was segmented into independent regions, enabling parallel state estimation for each area, which maintained accuracy in the estimated system states. Additionally, in [18], each vertex performed local computations independently in the power system graph model, and data was efficiently compressed in sparse row format, leading to centralized computation of Weighted Least Square (WLS) state estimation through hierarchical parallel computing.

The aforementioned methods for constructing the ''Power Grid One Graph'' or graph model primarily established the power grid's topological structure by loading a static power grid model. The online calculations still relied on traditional traversal analysis, and each update of telemetry and telesignaling failed to identify whether the system model had topological or data update errors. Moreover, each update required a complete topological analysis or station-level incremental topological analysis based on the updated state data, and the state estimation gain matrix needed to be regenerated with each update. This paper proposed a method to design a spatiotemporal node-breaker graph model based on the ''Power Grid One Graph'' mechanism. Through
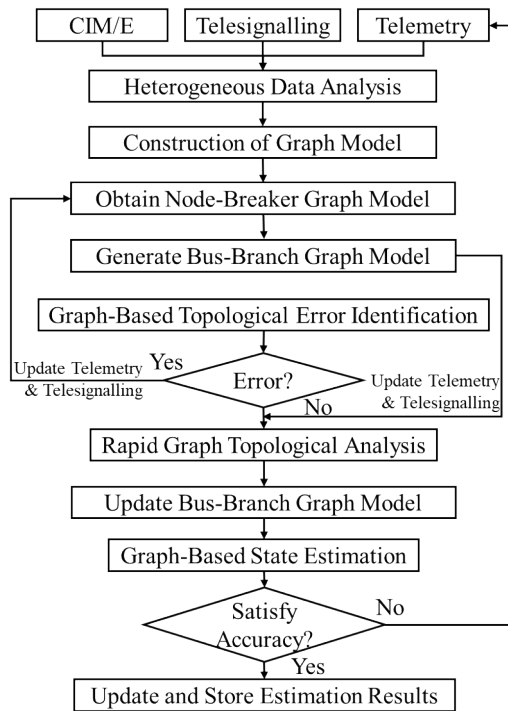
FIGURE 1. Framework of proposed methodology.

optimized rapid topological analysis, the bus-branch graph model was dynamically updated in real-time, enabling swift state estimation calculations.

Fig. 1 illustrates the overall flowchart of the proposed method in this paper. The power grid topology model used in this study was in CIM/E format [4]. CIM/E is a specification developed based on the power system common information model (CIM) and component interface specification (CIS) to address the efficiency issues associated with describing data in CIM/XML format. The model is designed for efficiently describing and exchanging large-scale power grid models. CIM/E files organize and describe relevant equipment class attributes of the physical grid model according to format specifications, including various objects such as regions, loads, bays, substations, transformers, base voltages, buses, etc. As shown in the flowchart, combined with time-series dynamically updated telesignaling and telemetry, the ontology candidate set was generated, and an ontology graph model was constructed through heterogeneous data parsing [19]. Building upon the graph model and entity mapping, the node-breaker graph model of the power grid was developed. Simultaneously, the corresponding bus-branch model was generated through graph partitioning. Topological error identification was performed using the obtained node-breaker model as a foundation. If topological errors were detected, the telemetry and telesignaling of the initial static node-breaker model were updated, and the process returned to verify the correction of the node-breaker model. If no topological errors were detected, the telemetry and telesignaling were updated in the initially generated bus-branch model.

The functionalities of relevant components were assessed, and rapid graph topological analysis was performed to update the bus-branch model. Based on the bus-branch graph model, graph-based state estimation can be performed. The results were compared with telemetry input data to obtain estimation accuracy. If there was a significant difference between the state estimation results and measurements, it indicated the presence of adverse data, necessitating telemetry verification. The main contributions of this study can be summarized as follows:

1) Distinct from static graph data modeling, this study proposed the construction of the spatiotemporal node-breaker graph model and the method for spatiotemporal data fusion;
2) Based on frequently updated telemetry (every 15 minutes), this study introduced an interactive verification for topological error identification through switch position changes and spatiotemporal numerical variations;
3) Instead of performing a complete topological analysis for each topological change cycle, this study proposed an optimized algorithm for rapid graph topological analysis considering devices' functions;
4) Based on the results of the graph topological analysis, this study determined whether it is necessary to regenerate the gain matrix within each topological change, enabling rapid graph state estimation;
5) Unlike using IEEE-provided simulated grid architectures, this study explored the application and performance enhancement of the proposed spatiotemporal "Power Grid One Graph" with rapid topological analysis and state estimation based on a real power grid.

The rest of this paper was structured as follows: Section II introduced the graph model construction of the spatiotemporal "Power Grid One Graph." Section III described the topological error identification method. Section IV introduced the optimized algorithm for rapid graph topological analysis considering component functionality. Section V demonstrated the application and verification of the proposed graph topological analysis and state estimation based on a real power system.

II. CONSTRUCTION OF SPATIOTEMPORAL NODE-BREAKER GRAPH MODEL

Utilizing a graph database to construct a power grid topology model offers significant advantages. First, various electrical devices form the power grid through physical topological connections, constituting a graph. The graph database can provide an intuitive representation of the grid's topological structure. Second, it supports real-time updates and dynamic adjustments, allowing the topology model to adapt to changes and expansions in the electrical system. Graph data modeling is fundamental for digitizing the power grid and creating the spatiotemporal "Power Grid One Graph." This modeling must adhere to the principles of comprehensiveness, uniqueness, and correlation. Comprehensiveness ensures that the graph model supports data mapping from various sources
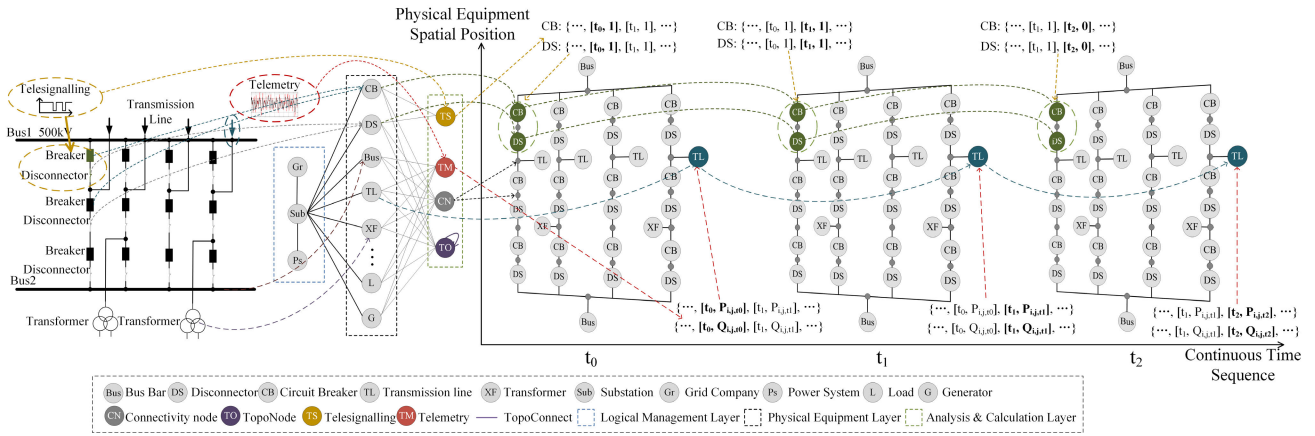
FIGURE 2. Mapping of power grid physical topology to graph model.

and meets application analysis requirements. Uniqueness involves the unified management of power grid objects based on physical ontology and logical relational ontology, ensuring unique ontology names. Correlation involves establishing topological, logical, subordinate, and managerial relationships between objects (devices) and various parameters.

A. CONSTRUCTION OF NODE-BREAKER GRAPH MODEL
As shown in Fig. 2, based on the provided physical topology of the system, the ontology candidate set was generated by parsing heterogeneous data from multiple sources, satisfying the requirements of comprehensiveness and uniqueness. Here, "ontology" can be understood as a collection of each type of device, such as mapping all Breakers in the physical grid to a unified CB node and all Transformers to the XF node, and establishing associations between various ontologies to form a logical management layer, a physical equipment layer, and an analysis and calculation layer. Time-varying telesignaling and telemetry were mapped to the corresponding devices' nodes to demonstrate the current status.

Due to the model used in this study being the CIM/E model, all physical devices were associated through connectivity nodes (CN). Therefore, in graph modeling, it was necessary to associate all physical devices with CN points. In entity mapping, all physical devices must be mutually associated based on their corresponding "head" and "tail" CNs, forming the node-breaker model, as illustrated in Fig. 2. Data was extracted from the physical device nodes in the graph model based on the unique identifier of each device type. Similarly, the associations between devices were extracted from the CNs.

The initialized node-breaker graph model served as a static model loaded at once. With real-time updates from switch status data and equipment operation measurements, the attributes of nodes and edges evolved over time, leading to real-time updates in the node-breaker graph model. The spatiotemporal changes in the graph structure can be represented through a spatiotemporal graph [20], [21]. In the

spatiotemporal graph, each node and edge possessed spatiotemporal attributes, representing both spatial correlations and temporal continuity through their attributes. The spatiotemporal node-breaker graph model maintained its graph structure unchanged during continuous time-section updates, but node attributes changed. For instance, as illustrated in Fig. 2, the connectivity status attribute of a switch node changed from a connected state (1) at time t_0 and t_1 to a disconnected state (0) at time t_2, while the active and reactive power on a transmission line varied across different time sections. The spatiotemporal graph denoted as (1):

$$G(t) = (V(t), E(t)) = (X(t), A) \tag{1}$$

where $V(t)$ was the set of nodes at time t, and $E(t)$ was the set of edges at time t. $X(t)$ represented the time-varying node features at time t and A was the static topology of the graph. $X(t)$ can be regarded as a set of time-varying attributes for $V(t)$ and $E(t)$. In the temporal graph, nodes and edges can have various attributes, such as $V(t) = v_1(t), v_2(t), \ldots, v_i(t)$, where $v_i(t)$ represents the attributes of node i at time t. Similarly, edge attributes can be expressed as $E(t) = e_1(t), e_2(t), \ldots, e_j(t)$, where $e_j(t)$ represents the attributes of edge e at time t.

The mathematical representation of the spatiotemporal graph can be further expanded to include the temporal evolution of node and edge attributes. For instance, the attributes of node $v_i(t)$ can be represented by the vector $a_i(t)$, and the attributes of edge $e_j(t)$ can be represented by the vector $b_j(t)$. Thus, the spatiotemporal graph can be expressed as (2):

$$G(t) = (V(t, a(t)), E(t, b(t))) \tag{2}$$

where $a(t) = [a_1(t), a_2(t), \ldots, a_n(t)]$ and $b(t) = [b_1(t), b_2(t), \ldots, b_m(t)]$ represented the sets of attribute vectors for all nodes and edges at time t.

Generating a spatiotemporal graph involved the mathematical description of nodes and potential evolution rules in spatial and temporal dimensions. Assuming a set of time indexes $\tau = t_1, t_2, \ldots, t_c$, where each t_c represented a time section, and in the graph $G(t)$, the node's temporal features set

was denoted as ω_t, and V_{t_k,t_l} represented the attribute change from time t_k to t_l in each node. The evolution of the spatiotemporal graph over time can be defined by functions, state transition equations, or other rule-based approaches as (3).

$$V_{t_k,t_l} \in \omega_t, f : G(t) \times \tau \rightarrow G(t') \tag{3}$$

The construction process of the spatiotemporal node-breaker graph model is a virtual replication based on the actual operational data and equivalent graph model. It aims to simulate and predict the behavior, performance, and state of the system based on synchronous real-time data. Therefore, the constructed spatiotemporal node-breaker graph model can be considered as the authentic digital twin of the power system.

B. CONSTRUCTION OF BUS-BRANCH GRAPH MODEL

The bus-branch graph model aims to describe the electrical connection characteristics of all components in the power system. Employing the concept of graph partition [22], based on the previously constructed node-breaker graph model, the computational bus model and the bus-branch graph model can be built to support two critical steps in grid topology analysis: substation bus analysis and system network analysis.

The substation bus analysis aims to partition the electrical components within the substation into sections of electrical connections, forming a computational bus for online power system analysis. It analyzes only the components within the substation, disregarding branch information carried by transformers or transmission lines. This analysis is conducted for each substation by checking the updated status of circuit breakers and disconnectors. Devices connected by circuit breakers or disconnectors in closed positions are considered electrically connected, and all electrically connected devices form a single computational bus. Therefore, substation bus analysis generates a computational bus graph model, representing the electrical connections within the substation. The system network analysis aims to transform the computational bus model developed from the node-breaker graph model into the bus-branch graph model.

As shown in Fig. 3, within the graph model, the bus-branch graph model employed custom "TopoNode" and "TopoConnect" structures to store attributes required for analysis and computation. TopoNode, i.e., topology node, contained topology analysis-related attributes, including topology ID, external ID (for calculating bus sorting), island flag, and bus name. Attributes relevant to power flow and state estimation calculations included Bus Type, Weighting for Voltage State Estimation, Voltage Level, Measurement, and Estimation Information (encompassing Voltage Amplitude, Voltage Phase Angle, Generator Active Power, Generator Reactive Power, Load Active Power, Load Reactive Power, Bus Active Injection, Bus Reactive Injection). TopoConnect was designed for all device types, storing attributes such as initial and final topology node IDs, resistance, reactance, susceptance, capacities for levels 1-3, transformer turns ratio, and line measurements and estimations.
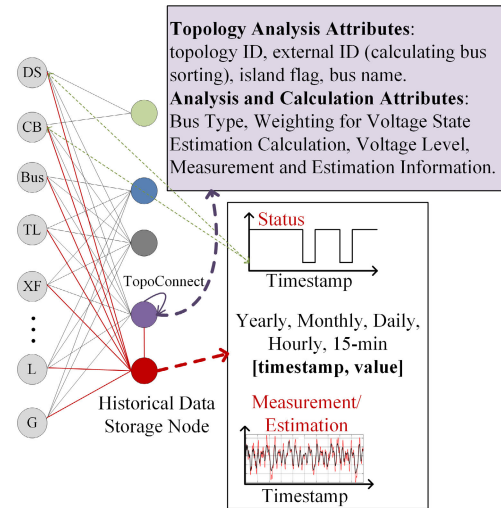

FIGURE 3. Analysis and computation storage node and spatiotemporal data storage node.
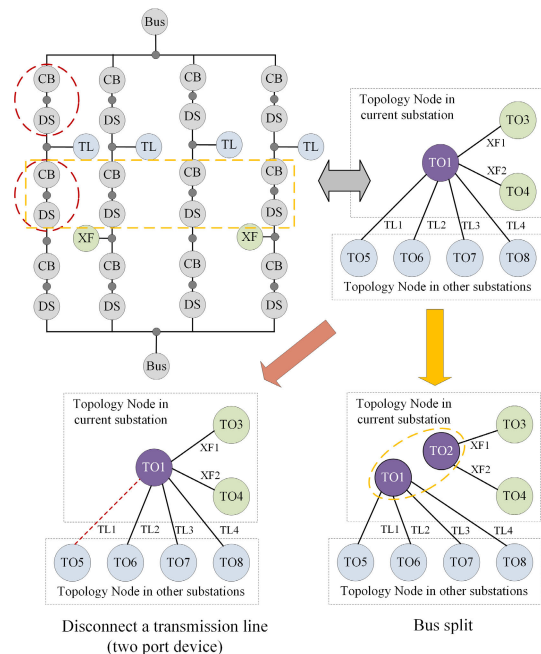

FIGURE 4. Example of conversion between node-breaker graph model and bus-branch graph model: disconnecting a transmission line and bus split.

The examples illustrated in Figs. 4 and 5 demonstrated the conversion of the bus-branch graph model based on the node-breaker graph model. Considering the example node-breaker graph model in Fig. 2, the conversion involved transforming it into one TopoNode since all devices within the substation were initially electrically connected in the static model. Each transformer was associated with a calculation bus, and each transmission line represented an entry point for the computational bus. Therefore, the TopoNode of the target substation was connected to other relevant TopoNodes. Changes in power grid topology due to the switch
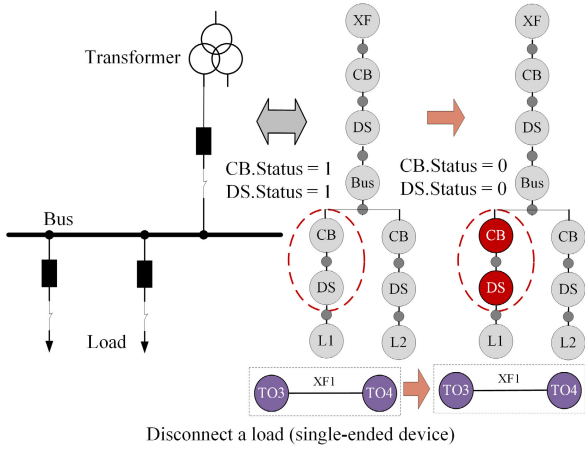
FIGURE 5. Example of conversion between node-breaker graph model and bus-branch graph model: disconnecting a load.

state changes for different device types impacted both the node-breaker graph model and the bus-branch graph model: 1) Assuming disconnection of a two-port device like a transmission line or transformer (disconnecting the switch device in the red oval in the node-breaker graph model), the number of TopoNodes in the bus-branch graph model unchanged, but the number of edges decreased. 2) Assuming a bus split (disconnecting the switch device in the yellow rectangle in the node-breaker graph model), the number of TopoNodes increased in the bus-branch model. 3) Assuming the disconnection of a single-terminal device like a load, generator, or capacitor/reactor, as shown in Fig. 5 (disconnecting the switch device in the red oval), i.e., disconnecting a load on a bus, the connection status attribute of disconnected switch devices changed, but the nodes and edges in the bus-branch model unchanged.

From the above examples, changes in switch states resulted in topological changes that only alter the state attributes of the corresponding switch devices in the node-breaker graph model, without modifying its structure. However, in the process of converting to the bus-branch graph model, these changes may affect the connectivity of edges and the number of generated TopoNodes. From the perspective of the overall "Power Grid One Graph" entity model, topological changes may impact the total number of nodes and the connectivity of edges in the model.

The bus-branch graph model, transformed from the spatiotemporal node-breaker graph model, can be considered a dynamic graph [20], [21], expressed as (4):

$$G(t) = (V(t), E(t)) = (X(t), A(t)), \qquad (4)$$

the formula indicated that both the node features $X(t)$ and model structure $A(t)$ in the dynamic graph will change with the continuous-time operation. The spatiotemporal graph can be understood as a dynamic graph with a static graph structure. From the perspective of the evolving graph, the spatial edge set was denoted as ξ_v, with each edge E_{v_i,v_j} representing the connectivity between spatial positions v_i and v_j.

In addition, the edge's temporal state set was denoted as ξ_t, with each edge E_{t_k,t_l} representing the change in edge state from time t_k to t_l. The evolution of the dynamic graph can be defined as (5) with a specified function.

$$V_{t_k,t_l} \in \upsilon_t, E_{v_i,v_j} \in \xi_v, E_{t_k,t_l} \in \xi_t, f : G(t) \times \tau \rightarrow G(t') \quad (5)$$

Unlike traditional topological analysis methods [23], [24], [25], graph-based topological analysis achieves the transformation between the two models locally and in parallel. The construction of edges between any two vertices in the computational graph was synchronized based on branch information carried by transformers or transmission lines. These edges locally represent branches between two computational buses. Thus, the computational bus graph model was mapped to the bus-branch graph model.

C. CONSTRUCTION OF SPATIOTEMPORAL DATA GRAPH MODEL

As illustrated in Fig. 3, utilizing the flexibility and scalability features of the graph model, a historical data storage node was added to facilitate the storage and querying of temporal data. Due to the associations between the newly added node and all devices, simultaneous mapping of spatial positions for each device was achieved. Based on different data sampling periods (yearly, monthly, daily, hourly, and every 15 minutes), the binary switch status of connected devices, along with temporal measurements of operational devices, were stored in this node with the form of [Timestamp, Value] arrays. Additionally, this node had associations with TopoNode, enabling the synchronized storage of temporal state estimation results for each computational bus. Thus, the construction of the spatiotemporal "Power Grid One Graph," which included the node-breaker model covering all voltage levels, the corresponding bus-branch model for analytical calculations, and the spatiotemporal data storage mechanism, had been completed.

III. TOPOLOGICAL ERROR IDENTIFICATION
A. ALGORITHM FEASIBILITY

Through topological verification within continuous time sections of various substations in a provincial power grid, it was observed that mismatches between switch status changes and corresponding spatiotemporal numerical variations occasionally occur. As the example substation illustrated in Fig. 6, a generator unit connected to the bus at the previous time step had a change in the state of its connecting switch at the current time point (the switch device in the red oval disconnected). However, the corresponding active power measurement value on the bus remained consistent from the previous time point. Therefore, it can be concluded that there was a topological error within the substation. The cause of this error might be the delay in reflecting equipment state changes in the topological model, such as switch state misoperation, communication interruption, or data transmission delay. This inconsistency might lead to a discrepancy between the topological model
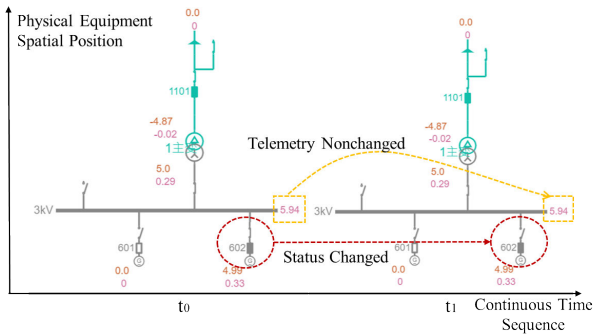
FIGURE 6. Real topological error example in a provincial power grid substation.

and the actual power grid, potentially misleading system operators into making incorrect decisions. Topological errors in the power grid have adverse effects on power system operation. Incorrect topological information can result in erroneous bus-branch graph models, affecting the accurate assessment of grid state and subsequent network analysis applications. It also complicated fault location efforts, thereby impacting judgments on system stability and reliability. In emergencies, incorrect topological information might delay fault recovery time, increasing operational risks for the power grid.

Topological connection errors may exist from the initial loading of the static power grid model. Additionally, with a fixed static grid model, incremental topological changes (telesignalling changes) can lead to this issue. Traditional methods for identifying topology errors involve obtaining and analyzing real-time information such as PMU voltages and phase angles, or leveraging load statuses provided by smart meters to aid in topology identification [26], [27], [28]. Another approach is to compare the results of power system state estimation with the topological model, analyzing the connection relationships of power grid nodes and branches to identify topological errors or inaccurate model parameters [29], [30]. However, traditional methods suffer from the drawbacks of high computational complexity and poor real-time performance when dealing with a large-scale power system.

B. GRAPH-BASED TOPOLOGY ERROR IDENTIFICATION ALGORITHM

Based on the obtained node-breaker graph model, the accuracy of the initialized static topology model was checked via graph traversal methods. Subsequently, by analyzing the state changes of switch devices in the graph model, the additions or removals of generator or load nodes in the node-breaker graph model were determined. The operational parameters of the system's current state were obtained. These values were then compared with temporal operational data and used to identify whether there was an error in the topology. Algorithm (1) illustrated the topology error identification algorithm based on the interaction verification between switching state changes and corresponding numerical changes in the spatiotemporal node-breaker graph model.

Algorithm 1 Topology Error Identification

1: **initialize** *def* node-breaker-graph $\rightarrow$ model
      def update_graph(model, telemetry, telesignalling)
2: *def* mismatch_identification(model, threshold):
  model.threshold = threshold
3: **for** ALL breakers in model.breakers:
4: **for** ALL nodes in model.nodes:
5: **if** topology_correct(model(t_i),model(t_{i+1}),model(t_{i+2})) = *True* **then**
6:   *def* identify_mismatch(model(t_j), model(t_{j+1})):
7:   **for** All breakers in model.breakers:
8:     status_changed = (breaker.telesignalling(t_j) != breaker.telesignalling(t_{j+1}))
9:     score = compare(breaker_connected_node.telemetry(t_j), breaker_connected_node.telemetry(t_{j+1}))
10:   **if** status_changed == *True* **then**
11:     **if** score < model.threshold: **then**
12:       print("Mismatch identified for node {node.id}.")
13:     **else**
14:       **if** breakers.status = 0 and score > model.threshold: **then**
15:         print("Mismatch identified for node {node.id}.")
16:       **end if**
17:     **end if**
18:   **end if**
19: **else**
20:   topology_correct(model(t_{i+1}),model(t_{i+2}),model(t_{i+3}))
21: **end if**
22: node-breaker-graph() $\rightarrow$ model
23: mismatch_detector = mismatch_identification(model,threshold)
24: **while** *update* = *True* **do**
25:   real_time_telemetry = get_telemetry()
26:   real_time_telesignalling = get_telesignalling()
27:   model.update_graph(real_time_telemetry, real_time_telesignalling)
28:   mismatch_detector.identify_mismatch(model,threshold)
29:   sleep(update_interval)
30: **end while**

Specific steps of Algorithm (1) were described as follows:

1) Initialize the static node-breaker model and update node measurements and switch states based on real-time telemetric data and device status data.
2) Define the algorithm for identifying topology errors caused by mismatched telesignalling and telemetry and set the threshold for judgment.
3) Select the node-breaker model of the initial three time sections as input, traverse all nodes and breakers, and determine if the topology model is correct.
4) If the initialized topology model is correct, traverse the breakers with status changes from the previous time t_j to the current time t_{j+1}, and compare the telemetry of nodes associated with status-changing breakers at the t_{j+1} with t_j.
5) Based on the preset threshold, determine the presence of a mismatch: if the numerical values do not correspond with the change in the breaker's status, consider it a measurement error when the switch is disconnected, and return the ID of the mismatched node.

6) If the breaker's status remains unchanged in the disconnected state, compare the telemetry of nodes associated with status-changing breakers at the current time t_{j+1} with the previous time t_j. If the numerical values do not match the current status of the breaker, consider it a change in measurement, but the switch status is unchanged, and return the mismatched node ID.

7) If the initialized topology model is incorrect, continue to traverse all nodes and switches based on continuous time sections to determine if the topology model is correct.

8) Continuous-time operation detection for any node-breaker graph model generated by a power grid topology structure: if the model is continuously updated, obtain real-time telemetric and device status data, update the node-breaker graph model, and then perform the mismatch identification algorithm.

9) Wait for the following real-time update during the numerical update interval.

Taking the topology shown in Fig. 6 as an example, the execution process of Algorithm (1) was demonstrated. Initially, the threshold was set based on the data from the terminal of the switching device. In this example, the threshold for 602 was set to 4.7405 (4.99×0.95). Assuming the topology was correct according to the node-breaker model traversed at times t_2, t_1, and t_0, two types of identifications were subsequently performed. First, the algorithm traversed and checked if any switch state changes from t_0 to t_1. It detected that 602 changed from closed to open. Then, it compared the bus telemetry values associated with 602 at t_0 and t_1 to check if $P_{Bus,t_0} - P_{Bus,t_1} \leq 4.7405$. If this condition was satisfied, the topology was deemed correct; if not, the topology was considered incorrect, and the switch device and bus ID were returned. Simultaneously, the algorithm traversed to see if the values of the buses associated with the switch had changed. Assuming in the example that at t_1 the state of 602 remained connected, but the associated bus values satisfied $P_{Bus,t_0} - P_{Bus,t_1} \leq 4.7405$, the topology was then judged to be incorrect, and the switch device and bus IDs were returned.

IV. RAPID TOPOLOGICAL ANALYSIS AND STATE ESTIMATION

A. ALGORITHM FEASIBILITY

In a substation, a single-terminal device refers to equipment that has only one connecting port with other components of the power grid, such as loads, generators, etc. For single-terminal devices, changes in their switch status only involve alterations in their own connection status and do not affect the connection status of other equipment. As illustrated in Fig. 5, in the node-breaker graph model of a substation, switch devices are typically operated independently, meaning they can be individually opened or closed without being directly influenced by the status of other devices. Consequently, when a switch changes its state, the states of other devices are independent of this change. In power systems, device statuses are

typically updated synchronously, indicating status updates occur at a specific moment rather than at different time points for different devices. This allows for the direct exclusion of devices undergoing state changes from the overall topology for a specific time point, eliminating the need for complex intra-station topological analysis.

Intra-substation topology analysis may involve numerous devices and intricate electrical relationships. However, when dealing with the state change in a single-terminal device, calculations can be simplified by only considering the components directly connected to that device without delving into the complex electrical relationships within the entire substation. From the perspective of the system's temporal evolution, real-time responsiveness to state changes is required. Based on the topological structure of a specific provincial power grid and through continuous statistical analysis of operational states, it can be observed that single-terminal devices associated with switch state changes constitute 80%-90% of all devices undergoing switching operations. To swiftly and accurately respond to changes in device states, the proposed simplified algorithm aids in enhancing the system's real-time capabilities.

B. OPTIMIZED GRAPH TOPOLOGICAL ANALYSIS ALGORITHM

The proposed optimization algorithm in this paper was based on the implemented graph topology analysis algorithm [1], [2], [3], [4], aiming to achieve a rapid transition from the node-breaker graph model to the bus-branch graph model. By considering the functionality of components, the algorithm sought to enhance the efficiency of topological analysis. In the initial phase of algorithm execution, the node-breaker graph model was updated to its real-time state based on the temporal changes in the power grid's switch statuses. The resulting bus-branch graph model underwent structural modifications due to the changes in connecting statuses of the associated devices. During the traversal of devices linked to switch state changes, the algorithm directly mapped the associated bus of single-terminal components to the TopoNode of the bus-branch graph model, thereby avoiding the complexity of traditional topological analysis for such components' state changes. Conversely, for other functional components, the algorithm employed conventional graph topology analysis methods for evaluation, conversion, and mapping. The detailed algorithm was presented in Algorithm (2):

1) Initialize the definition of the node-breaker graph model, update the switch statuses based on real-time device state data, and synchronize them with the node-breaker graph model. Initialize the definition of the intended bus-branch graph model to be generated.

2) For the node-breaker graph model of all substations, if unprocessed transmission lines exist, evaluate each unprocessed transmission line and series compensator to determine if both ends are connected.

Algorithm 2 Optimized Graph Topological Analysis

1: **initialize** *def* node-breaker-graph → model
        def update_graph(model, telesignalling)
        def update_graph → model
        def bus branch graph → TopoNodes
2: **for** ALL substations:
3: **if** *num*(unprocessed transmission Lines)
   in model.transmission_lines > 0 **then**
4:   **for** each transmission line and series compensator:
5:   **if** both sides of the device node are closed **then**
6:     **for** each substation with model:
7:     **if** *num*(unprocessed bus and
       breaker_connected_node) > 0 **then**
8:       **while** *num*(unprocessed model.bus nodes) > 0
        do
9:        identify_neighbor(unprocessed nodes)
10:        **if** type_checking(neighbor.nodes) ∈ breaker or
        disconnector **then**
11:         **if** type_checking(neighbor.nodes) ∈ single-
         terminal device **then**
12:          unique_IDs(model.bus, TopoNodes)
13:         **else**
14:          **if** status_checking(neighbor.nodes) = 1
          or type_checking(neighbor.nodes) ∈ con-
          nectivity node **then**
15:           copy model.bus.ID to neigh-
           bor.nodes.ID
16:          **end if**
17:          unique_IDs(model.bus, TopoNodes)
18:         **end if**
19:        **end if**
20:       **end while**
21:     **end if**
22:     copy generated TopoNodes's ID to transmission line
      and series compensator nodes
23:   **end if**
24: **end if**

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3) If both ends are connected, assess the associated substation in terms of unprocessed buses and connectivity nodes in the node-breaker graph model.
4) If unprocessed buses exist, identify the neighbor nodes for each unprocessed bus; if the neighbor nodes are breakers or disconnectors, determine the type of equipment associated with the far end of the neighbor nodes.
5) If the associated equipment on the far end is a single-terminal component, automatically generate a unique ID for the bus and map it to the bus-branch graph model node (TopoNode).
6) If the far-end device is not a single-terminal component, evaluate whether the connection relationship between the node and the bus is closed or if the node is a connectivity node. If so, copy the ID of the bus node to that node; if not, ignore the node. After evaluation,

automatically generate a unique ID for the bus and map it to the bus-branch graph model node.
7) Map the automatically generated unique ID of the bus in the bus-branch graph model to the corresponding transmission line and series compensator nodes.

Similarly, taking the topology shown in Fig. 6 as an example, the execution process of Algorithm (2) was demonstrated. Initially, at t_0, the bus-branch model corresponding to the node-breaker model was obtained. At t_1, when the connection state of 602 changed within the substation, the algorithm checked if the equipment associated with 602 was a single-terminal component. If it was, the initial bus-branch model remained unchanged, and there was no need to re-execute the topology analysis within the substation. However, if the equipment associated with 602 was not a single-terminal component, the topology analysis within the substation was re-executed, and a new TopoNode was generated.

The algorithm places particular emphasis on considering the functional aspects of components when maintaining a dynamic graph, ensuring that the node and edge quantities of the bus-branch graph model remain stable during component state changes. This optimization enhances the accuracy and execution efficiency of topological analysis. Through this approach, the algorithm efficiently captures temporal changes in switch statuses, adapts to the characteristics of different components in the power system, and provides accurate topological information for the operational state of the power grid.

C. STATE ESTIMATION

Graph-based state estimation represents the system's state variables and observational data as attributes of nodes and edges in the graph model. Through information propagation and state updates across nodes in the graph model, this approach efficiently handles the topology of the power grid and power flow between nodes, enabling real-time monitoring and estimation of voltage, power, and other state parameters in the system. The method employed for state estimation here is the WLS method and refers to [6] and [18]. Since capacitor reactors are treated as single-terminal components providing reactive power injection in the state estimation calculation, similar to the handling of generators and loads, they do not affect the structure of the bus-branch graph. Therefore, when a capacitor reactor undergoes a switching operation, the state estimation does not require recalculating the gain matrix, which can reduce the computation time for graph-based state estimation.

To verify the accuracy of the graph-based state estimation at each component, the study uses Equation (6) to calculate the estimation accuracy rate.

$$e_v = |\frac{(C_v(t) - T_v(t))}{T_v(t)}| \qquad (6)$$

in which, e_v represented the estimated error, which was usually set as 0.001 or less, $C_v(t)$ denoted the estimated value

of node u at time t, and $T_v(t)$ was the true value gathered from the corresponding component v at time t. Telemetry values, which rely on high-precision equipment, real-time updates, and strict standardization processes, are regarded as true values here.

To statistically evaluate the percentage of calculated results obtained by the proposed method that satisfies the threshold, the study uses Equation (7) to determine the ratio of qualified estimated measurements $R_s(t)$ for the whole system at t.

$$R_s(t) = \frac{\sum^N b(|\frac{(M_v(t) - C_v(t))}{S_v(t)}| < p)}{N} \tag{7}$$

in which, b was the bool function and N was the total number of measurements. $M_v(t)$ represented the measurement value of node v at time t, $C_v(t)$ denoted the estimated value of node v at time t, $S_v(t)$ was the reference measurement value of node v at time t, the parameter p represented the error threshold.

The ratio of qualified estimated measurements $R_s(t)$ here is a statistical result of the estimated measurements. It counts the percentage of the estimated measurements that satisfy the error threshold. The reference measurement values $S_v(t)$ are adopted here to avoid the error incurred by the small value measurements, and they represent the error tolerance of the measurements at different voltage levels. The reference measurement value was based on the typical conditions specified in the power grid design and operational standards, with different values for different voltage levels—the higher the voltage level, the larger the reference value. For instance, the reference measurement values of active power measurements for 500 kV transmission lines are 1082 MVA, 220 kV transmission lines are 305 MVA, etc. The error threshold p is constant for different types of measurements that are set by utility companies. The error threshold p in this study, for active power measurements is 2%, for reactive power measurements is 3%, and for voltage measurements is 2%.

V. APPLICATION AND VERIFICATION OF TOPOLOGY OPTIMIZATION ANALYSIS AND STATE ESTIMATION

The constructed spatiotemporal ''Power Grid One Graph,'' based on the proposed spatiotemporal node-breaker and bus-branch graph models, has been deployed in an operational power system. The presented system was based on actual data provided by the dispatch center of a provincial grid in southern China, featuring 17,927 buses and 19,487 branches. This system included 4,878 substations, 9,185 transmission lines, 11,039 two-port transformers, 6,098 three-port transformers, 703 generators, 47,723 loads, 3,255 shunt devices, and 151,994 measurement meters. Comparative studies were conducted on a CentOS 6.8 server with a 32-core CPU and 64 GB memory. The graph database utilized in this study is Tigergraph Database version 3.0. This section demonstrated the accuracy and superiority of proposed methods through a systematic presentation and comparative analysis of the validated results.

A. SYSTEM OVERVIEW AND TOPOLOGY OPTIMIZATION ANALYSIS

Fig. 7 illustrated the overview page of the constructed spatiotemporal ''Power Grid One Graph.'' On the left side of the figure was the substation power flow connection diagram for the regional power grid. Each node represented a substation within the region, with node size indicating the magnitude of power generation or load at the substation. Edges represented transmission lines connecting substations, and each edge contained the current power flow information and direction. As the system's topology and telemetry were updated, the topology, nodes' sizes and line parameters of this diagram kept refreshing. The right side of the figure displayed information about the system's operation, including system scale, topological analysis status and time, state estimation status and time, power flow calculation parameters, and information related to contingency analysis.

Fig. 8 depicted the graph model management page dedicated to the node-breaker graph model within the system. This functionality generated node-breaker graph models for the provincial power grid and its various sub-regional power grids, facilitating statistical management. Statistical information for each sub-regional power grid can be accessed through the affiliation tree or geographical map. Statistics included the classification of substations based on voltage levels, categorization of switch devices, equipment classification, and telesignaling and telemetry classification within the selected area. Various equipment quantities and coverage rates of measurements were detailed in tables. Through this page, timely updates to node-breaker graph models can be comprehensively monitored.

According to the constructed node-breaker graph model, the breakers and disconnectors in the system are divided into six subtypes accounting for their connecting devices, as shown in Fig. 9. For instance, the type ''bus_operation'''' indicated that the breaker/disconnector was connecting two busbars, ''trans_operation'''' indicated the breaker/disconnector disconnected a transformer, ''Acline_operation'''' meant the breaker/disconnector disconnected an AC transmission line, ''CP_Switching'''' meant the breaker/disconnector disconnected a capacitor/shunt reactor, ''unit_Switching'''' indicated the breaker/disconnector disconnected a unit, and ''load_Switching'''' meant the breaker/disconnector disconnected a load.

Fig. 10 demonstrated the operations of these six different types of breaker/disconnectors during a 96-time slots (24-hour) operation period. In this figure, the x-axis displayed 96-time slots, and the y-axis indicated the occurrence rate for each type of breaker/disconnector operation accounts for the total breaker/disconnect telesignalings. The capacitor/shunt reactor operations had a high occurrence rate. Among the total breaker/disconnector operations, the ''CP_Switching'''' type accounted for over 72% of all the cases.

More specifically, the six subtypes of breaker/disconnector can be combined into three types according to their function,
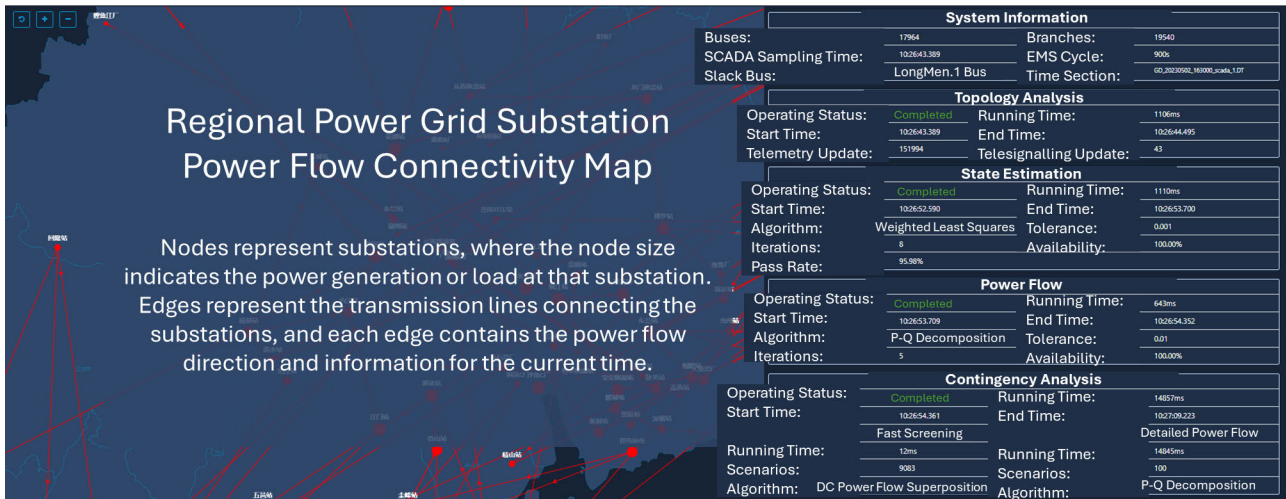
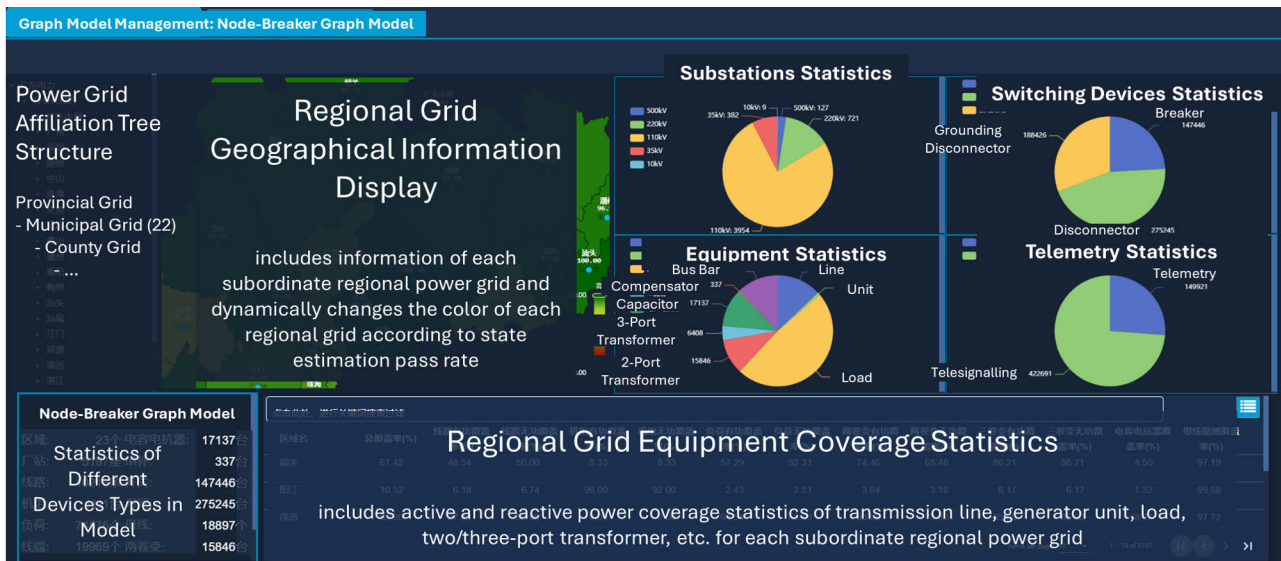**FIGURE 7.** Multi-dimensional and polymorphic "Power Grid One Graph" overview page.

FIGURE 8. Graph model management: node-breaker model.

as shown in Fig. 11. "CP_Switching," "unit_Switching," and "load_Swtching" can be combined as "one-port" connecting type as their connecting devices had one terminal. "Acline_operation" and "trans_operation" can be combined as a "two-port" connecting type as their connecting devices had two terminals. Therefore, the "one-port" type had the highest occurrence rate, and most time slots only had the "one-port" type breaker/disconnector operations. There were over 81% of the breaker/disconnector operations were "one-port" connecting type among the total operations in each time section. Since the disconnection and connection of "one-port" devices did not affect the results of topological analysis, the proposed algorithm for optimizing graph-based topological analysis can significantly enhance the efficiency of topological analysis. As shown in Fig. 7, the system adopted

the optimized graph topology analysis method proposed in this paper, with an average analysis time of approximately 1000 ms. Based on provincial grid data, the accuracy of the transmission and distribution network topology connections had improved by 5%-10%. The analysis cycle had been reduced from minutes to seconds, achieving a speedup of 5-10 times compared to traditional methods.

B. TOPOLOGICAL ERROR IDENTIFICATION

Fig. 12 displayed the analysis page for topological errors caused by discrepancies in measurement and switching status. Similar to the aforementioned page, this analysis page can monitor different ranges within the power grid. Since phenomena such as switch position changes and numerical variation only occur in the graph models of units and loads
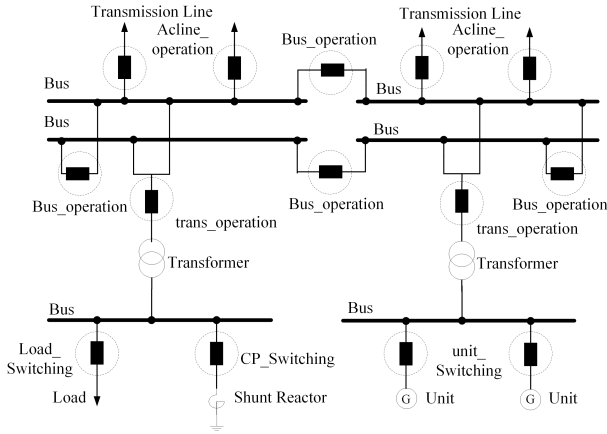
FIGURE 9. Breaker/disconnector type classification.

FIGURE 10. Occurrence rate of 6 different breaker/disconnector connection types.
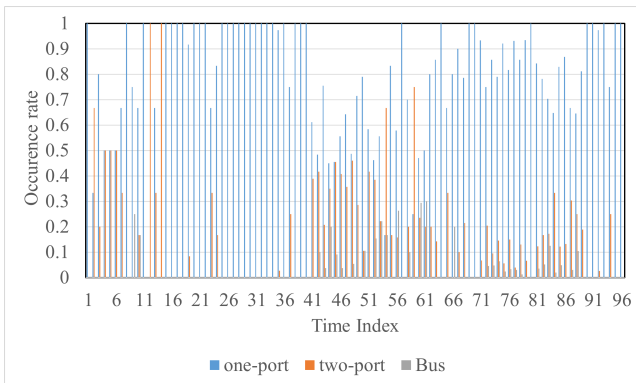

FIGURE 11. Occurrence rate of 3 different breaker/disconnector connection types.

in this system, the page categorically counted the number of topological errors for these two types of devices at the current time, based on different voltage levels. It presented a detailed table of topological error device information and error types.

Using the original data provided by the provincial power grid and selecting a specific time section for verification analysis, the original topological error probabilities for units and loads were 6.26% and 13%, respectively (as shown in Table 1). By applying the algorithm proposed in this paper

TABLE 1. Topological error in raw data.

Index	Unit	Load
Total Number of Devices	703	47723
Connecting Error	44	6204
Error Percentage	6.26%	13.0%

TABLE 2. Topological error after identification algorithm.

Index	Unit	Load
Total Number of Devices	703	47723
Connecting Error	9	1723
Error Percentage	1.28%	3.61%

for topological verification and correction, the topological error rates can be reduced to 1.28% and 3.61%, respectively (as shown in Table 2). The current correction algorithm fixed topological errors by manipulating breakers and disconnectors connected to single-terminal components that generate discrepancies between telesignaling and telemetry. If a single-terminal component had measurements but the breaker was open, the error can be corrected by merging the breaker or disconnector connected to it. However, if the error did not stem from a telesignaling error in switching this single-terminal component, but rather from a topological error on the high-voltage side of a transformer, correcting the telesignaling of the switching device alone might not be sufficient. Therefore, correcting the telesignaling status of the switching device can resolve the majority of topological errors, but it might not address complex topological errors on the high-voltage side.

C. STATE ESTIMATION

As shown in Fig. 13, the system adopted the original graph-based state estimation method, with an average computation time of approximately 1100 ms, including the time for forming the gain matrix and solving the estimation. Based on data from the provincial-level power grid, the analysis cycle for state estimation has been reduced from a minute-level to a second-level, making it already 5-10 times faster than traditional methods. As shown in Table 3, among the randomly selected 96-time slots, 34-time slots only had the "one-port" connecting type breaker/disconnector operations, which meant that during those 34-time slots, the graph state estimation algorithm did not need to update the gain matrix. The average time spent during these 34-time slots with only "one-port" connecting type breaker/ disconnect operations was 545.5 ms, around one time faster than the original graph method. The average time cost during the 96-time slots using the optimized method was 862.5 ms, which was about 150 ms more quickly than the original graph method. In the table, the average estimation accuracy rate of the original method was 96.19%, while the proposed algorithm had an average accuracy rate of 95.23%. Although there was a slight decrease, it still met the operational requirement of being above 95%.

Fig. 13 depicted the monitoring page for graph-based state estimation, displaying continuous-time measurements and estimations of historical generation and load for
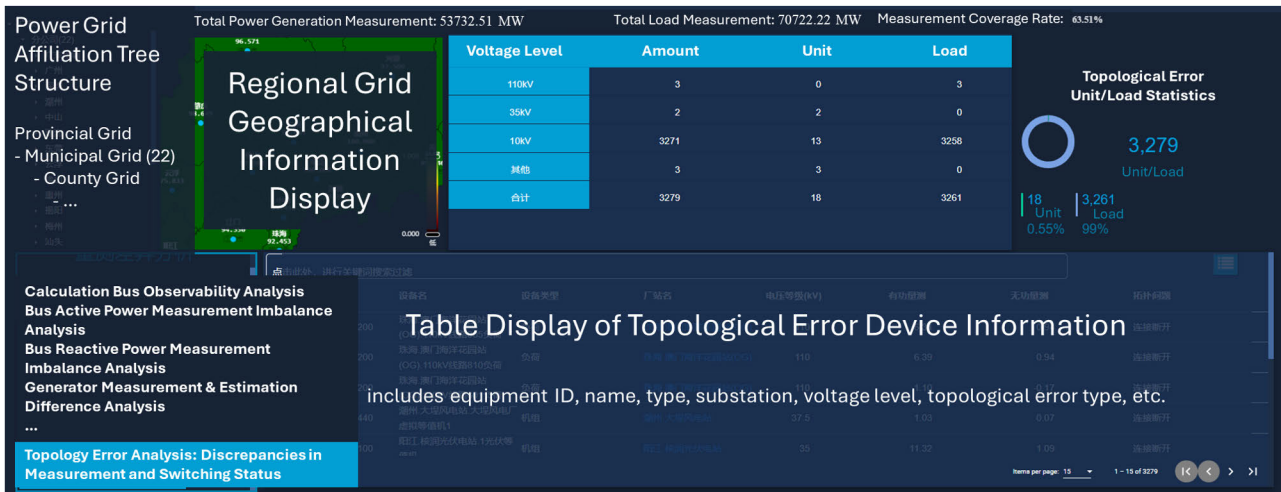
FIGURE 12. Topology error analysis: discrepancies in measurement and switching status.
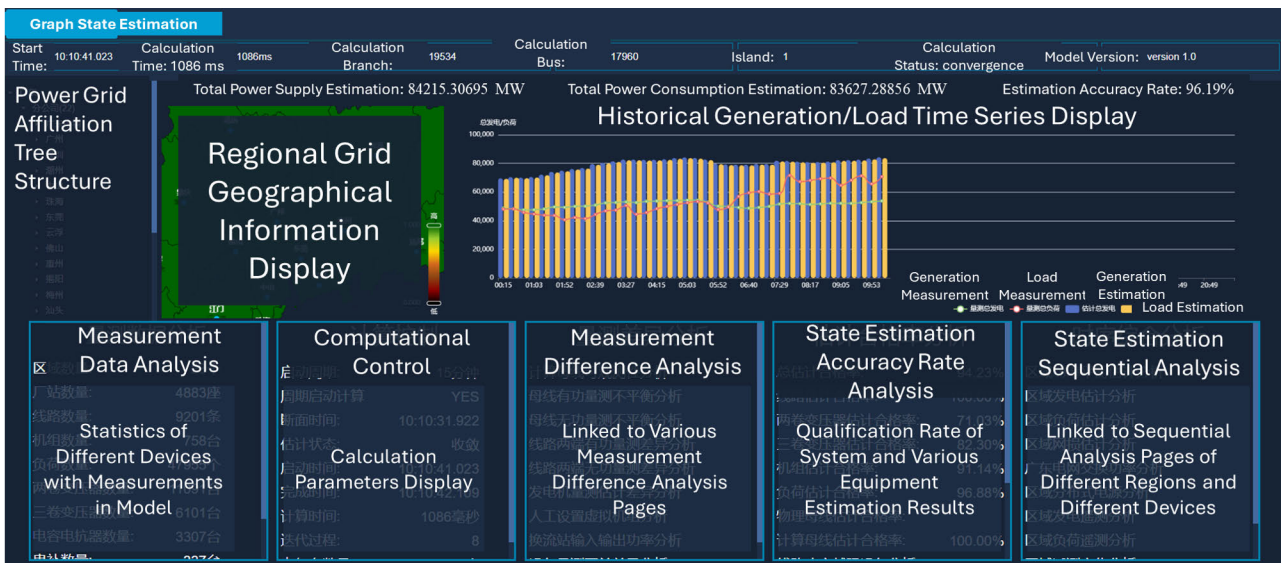

FIGURE 13. Graph state estimation monitoring interface.

TABLE 3. Computation time and estimation accuracy rate of graph-based state estimation.

Index	Original Method	Proposed Algorithm
"One-Port" Operations	1021.4 ms	545.5 ms
Average Time Cost	1034.6 ms	862.5 ms
Estimation Accuracy Rate	96.19%	95.23%

different regional power grids. Simultaneously, the page provided functionalities for analyzing measurement data, examining measurement discrepancies, and evaluating the accuracy rate of state estimation. The computational control section allowed users to configure calculation cycles, monitor calculation status, observe computation time, and record iteration counts, among other settings. This comprehensive analysis enabled a thorough examination of the actual operational state of the provincial-level power grid from both temporal and spatial perspectives.

VI. CONCLUSION AND FUTURE WORK

Leveraging advanced graph technology, this paper integrated the power grid's topological structure, geographic information, real-time data, historical data, and equipment status information into a graph database to construct a spatiotemporal grid graph. Specifically, based on the advanced grid graph model, a spatiotemporal node-breaker graph model and its corresponding bus-branch graph model were developed. Rapid state estimation calculations were achieved through optimized fast topological analysis and real-time dynamic updates to the bus-branch graph model. The proposed method presented the power grid's topological structure in a clear graphical form, accurately representing the power grid's geographical space by integrating geographical information with grid's topology. Furthermore, by integrating continuous equipment operation data, temporal aspects enable

updates to the power grid topology, verification of topological errors, real-time power grid state estimation calculations, and monitoring of power grid operational status, providing comprehensive data support for power grid operation and maintenance.

The power grid, encompassing generation, transmission, transformation, distribution, and utilization, faces challenges due to significant verticalization among various business information systems, leading to insufficient coordination and dispatching capabilities. This paper proposed a spatiotemporal grid graph to serve as a data center, resource allocation platform, and analysis system for grid dispatching operations. It aims to enhance situational awareness and static security analysis, optimize resource allocation and market coordination, ensure safe and stable operation through interaction calculations, and manage renewable energy integration. Additionally, with the adoption of carbon neutrality and zero-carbon strategies, the power system service mode is transitioning from "grid operation" to "dual-carbon strategy." The "Power Grid One Graph" can be developed to enable precise carbon emission accounting and tracking, constructing an "Electricity Carbon One Graph [31], [32]" to support the dual-carbon strategy and measure regional renewable energy development.

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