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Transformer Substation Network Disconnection Prediction via Semantic Reasoning with Causal Modeling

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Abstract. Reliable communication networks are indispensable for the stable operation of smart grids and substations. Currently, WAPI networks have been widely adopted in relevant scenarios. Nevertheless, WAPI networks are confronted with disconnection risks attributed to complex network topologies, dynamic traffic fluctuations, and external environmental disturbances. Most methods rely on correlation analysis and lack causal interpretability, which restricts their effectiveness in root-cause localization and preventive maintenance practices. To address the problem, we propose a disconnection prediction approach that integrates prompt-driven semantic reasoning with structured causal analysis. The approach constructs a causal event graph that models semantic, temporal, and topological dependencies across devices and alarm sequences after extracts heterogeneous information to unified event representation. Based on the established graph, an inference module combines causal path analysis, structural causal models, and counterfactual reasoning to assess the influence of events, predict emerging disconnection risks, and identify plausible root causes with coherent and interpretable justification. By tightly coupling semantic abstraction with causal reasoning, the proposed approach provides a proactive, explainable, and extensible mechanism for anticipating network disruptions and supporting informed maintenance decisions. Experiments demonstrate that the proposed approach improves prediction accuracy and interpretability, verifying its value for smart grid communication networks.

Keywords: Causal Inference, Network Disconnection Prediction, Root Cause Analysis, Incident Causality Graph, Substation, Disaster Recovery.

1. Introduction

The developing energy transition and the advancement of power system intelligence have made smart grids and substations vital infrastructures for secure and stable power system operation [23]. In these systems, communication networks enable device interaction and control signal transmission, forming the backbone of business continuity and reliability [14] . To meet the stringent security, reliability, and low-latency requirements of such environments, WAPI (Wireless Local Area Network Authentication and Privacy Infrastructure) network has been widely adopted due to its robust encryption, mutual authentication, resistance to common wireless attacks, and ability to maintain stable communication under high traffic and interference. As a result, WAPI-based devices are extensively deployed in substations, supporting secure and dependable operations. However, due to the complexity of topology, traffic fluctuations, and external disturbances, these devices often experience disconnection events, leading to service interruptions and even cascading failures [25], which undermine both operational safety and economic efficiency.

To achieve high-assurance communication networks, traditional approaches generally rely on post-event response and static redundancy design [2]. However, these approaches are increasingly inadequate under highly dynamic and uncertain operating environments. In contrast, preventive maintenance mechanisms can proactively mitigate potential risks before failures occur, thus reducing the likelihood of network disconnections [18]. Within this framework, network disconnection prediction becomes a critical component: only when potential risks are predicted and explained in advance can operators take timely countermeasures, thereby enhancing the stability and resilience of the overall network. Existing mainstream approaches for network fault detection are predominantly based on correlation modeling, such as analyzing time-series fluctuations, delay drifts, and clustering of anomalous behaviors [21]. While effective to some extent, these approaches cannot generally capture causal mechanisms among variables, making it difficult to distinguish between "fault symptoms" and "fault root causes" [20]. This limitation directly constrains both the accuracy and interpretability of disconnection prediction.

Recently, the emergence of Large Language Models (LLMs) has opened new opportunities for knowledge modeling and semantic reasoning in complex systems [19]. LLMs can extract key semantic events from unstructured sources such as logs, configuration documents, and alarm texts [29]. Moreover, when integrated with causal discovery algorithms (e.g., the Peter-Clark algorithm, also known as PC) and prompt engineering, LLMs can help construct causal dependency graphs and uncover potential fault propagation paths [7]. Leveraging these capabilities, LLMs demonstrate strong potential in enhancing the generalization, interpretability, and timeliness of disconnection risk prediction.

To address the limitations of conventional approaches, we propose a novel network disconnection prediction approach that integrates LLMs-based semantic reasoning with causal modeling for WAPI network devices in smart grid and substation environments. The approach leverages LLMs to unify heterogeneous operational data and construct causal event graphs, while incorporating causal inference techniques such as path analysis, structural causal models, and counterfactual reasoning to identify root causes and predict potential disconnection risks. By combining the semantic strengths of LLMs with the interpretability of causal modeling, the proposed approach enhances adaptability to complex and unseen fault scenarios. Experimental results confirm its effectiveness in improving the accuracy and timeliness of disconnection prediction. Overall, we introduce a LLMs–causal modeling approach for proactive disconnection prediction, offering a practical paradigm for preventive maintenance in mission-critical communication systems of smart grids and substations. This study differs from existing correlation-based approaches by combining the semantic reasoning of LLMs with causal inference, enabling both accurate prediction and interpretable root-cause analysis. The proposed approach unifies heterogeneous data into causal structures and supports proactive disconnection prevention through scalable causal reasoning. The main contributions of our approach are summarized as follows:

(1) We present a unified event representation scheme that transforms heterogeneous network data into structured semantic events, providing a standardized basis for causal inference and prediction.

(2) We propose an LLMs-driven causal graph construction mechanism that leverages prompt engineering to extract causal dependencies among events, combining semantic reasoning with temporal and topological constraints to enhance accuracy and interpretability.
(3) We design a pluggable inference module that integrates causal path analysis, structural causal models, and counterfactual reasoning, enabling the identification of root causes and the prediction of high-confidence disconnection.
(4) We conduct experiments under representative smart grid network scenarios that demonstrate improved prediction accuracy, causal explainability, and response timeliness.

In the subsequent sections, section 2 reviews the relevant prior work, section 3 presents the methodology proposed in this study, section 4 details the experimental setup and configurations, section 5 provides a comprehensive analysis of the experimental results to demonstrate the effectiveness of the proposed approach, and section 6 concludes the study.

2. Related Work

2.1. Network Fault Diagnosis and Prediction

With the continuous growth of network scale and increasing diversity of services, traditional rule- or threshold-based network fault diagnosis struggles to handle the dynamic and complex modern networks effectively. Consequently, machine learning and deep learning have been widely applied to network disconnection prediction and root-cause diagnosis in recent years. They take advantage of network flow, delay, packet loss, and bandwidth utilization to identify potential anomalies or failures [17]. However, traditional machine learning models face challenges in high-dimensional, dynamic, and structured networks, including strong label dependence, insensitivity to topology changes, and limited ability to capture multi-failure dependencies, which restrict their practical effectiveness.

Deep learning approaches offer automatic feature extraction and complex pattern modeling. Recently, various neural networks have been applied to network disconnection prediction tasks. For instance, Alkaberi et al. used CNNs with MLPs to predict software faults [1]; Gupta et al. applied DNNs with hyper-parameter tuning to assess the impact of software faults [10]; and Cheng et al. introduced Attention-LSTM for time series prediction of intermittent faults [6]. While these approaches improve prediction accuracy, they largely remain black-box models, lacking interpretability and clear root-cause identification, and have limited ability to locate critical network links.

Recently, causal reasoning has been increasingly incorporated into network fault diagnosis to enhance interpretability and reasoning. Causal approaches model dependencies between variables and identify true trigger sources and propagation paths. For example, Ghosh et al. [9] proposed a cascading disconnection prediction approach using causal graphs for early warning in power transmission networks. Li et al. [12] designed a root-cause analysis approach for online service systems using causal Bayesian networks, which significantly improved response accuracy and speed.

These studies indicate that, although machine learning and deep learning show initial success in network fault diagnosis, they still struggle with modeling causal structures, handling multi-hop dependencies, and providing interpretable insights for practical operations.

2.2. Causal Analysis

Causal analysis provides an effective means to compensate for these deficiencies and has gradually become a significant research direction in the field of intelligent operation and maintenance. With the rapid development of general artificial intelligence tools, such as large models, causal analysis approaches are also gradually integrating with multimodal intelligence components, including natural language understanding and knowledge extraction. This integration provides a new technological path to realize network disconnection prediction systems with strong interpretability and generalization capabilities.

Causal analysis algorithms are classified into three categories: constraint-based, scoring-based, and non-Gaussian assumption-based. The PC algorithm is a typical constraint-based causal discovery approach, in which dependencies between variables are inferred through conditional independence tests. The approach consists of two stages: first, constructing an undirected causal skeleton graph, then determining the direction of some edges based on a series of rules, and finally forming a partially directed acyclic graph, which is suitable for data with both discrete and continuous variables [22][15].

In contrast, the GES algorithm (Greedy Equivalence Search) is a scoring-based search approach that does not require independence tests. It performs greedy optimization using scoring functions (e.g., Bayesian Information Criterion, also known as BIC) by performing structural modification operations (e.g., adding edges, deleting edges, reversing edges) in the equivalence class space to find the optimal Bayesian network structure. The approach is efficient but prone to fall into local optimality [11][16].

LiNGAM algorithm (Linear Non-Gaussian Acyclic Model) is a linear causal discovery approach based on structural equation modeling, which takes advantage of the non-Gaussian characteristics of the variables and recovers the directed acyclic structure among the variables by Independent Component Analysis (ICA), which breaks through the limitation that the direction of causality is not identifiable under the Gaussian assumption [24][4]. These approaches have been widely applied in the fields of biomedicine, social sciences, and economic modeling, providing important tools for understanding causal mechanisms in complex systems.

2.3. Large Language Models

In recent years, a large number of unstructured logs and heterogeneous alarms, such as syslog, SNMP Trap, NetFlow, etc., have been generated in network operation and maintenance scenarios, which are semantically diverse and confusing, and are often difficult to be uniformly abstracted and fused by traditional rules or keyword matching approaches. LLMs such as GPT, LLaMA, and Claude have powerful contextual understanding and linguistic reasoning capabilities [3], which can automatically map these unstructured texts into unified fault event labels, thus improving the quality of event normalization and cross-source fusion capabilities [5].

Through Chain-of-Thought (CoT) and Prompt Chaining techniques, LLMs can analyze temporal and semantic logical relationships in event sequences to help identify potential causal trigger paths. It has been demonstrated that the in-context learning approach using GPT-4 can significantly enhance the accuracy and readability of automated root cause analysis, eliminating the need for fine-tuning, in the context of fault analysis in cloud platforms [28]. In addition, studies have also designed reliability assessment mechanisms, such as the PACE LM framework [27], to calibrate the confidence level of LLMs through the cue-enhancement and retrieval-enhancement (RAG) strategy, which effectively reduces the risk of generating “hallucinatory” information and improves the usability and security in real system scenarios.

LLMs have significant advantages in log abstraction, causal reasoning, disconnected prediction, and natural language interpretation, making them an important technical component of network fault diagnosis and prediction systems.

In addition to the above applications, recent research has explored the integration of LLMs with causal graph construction and preventive maintenance frameworks. By combining LLMs-based semantic reasoning with structural causal models, these approaches enable proactive disconnection prediction, root-cause identification, and explainable fault propagation analysis. Such integration not only enhances the interpretability of automated diagnostics but also provides practical guidance for network operators in large-scale and complex infrastructures, highlighting the potential of LLMs as a core component in intelligent network operation and maintenance systems.

3. Methodology

This section proposes a disconnection prediction approach for network devices that integrates a large model and a causal reasoning approach, aiming to solve the problems of strong dependence on structural assumptions, weak scalability, and limited predictive foresight in traditional causal modeling. With LLMs as the core, the proposed approach automatically generates causal event maps based on multi-source alarm data and structural information. It combines with a downstream pluggable root cause analysis module to realize real-time localization and prediction of disconnected faults.

3.1. Overview

As shown in Fig. 1, our proposed disconnected prediction approach comprises three core stages: data preprocessing and unified representation, large model-driven causal mapping construction, and a pluggable root cause localization and disconnection prediction mechanism. The goal of this process is to fully utilize the advantages of LLMs in processing unstructured data and reasoning about contextual relationships, while retaining the explanatory power and decision support capabilities of causal modeling in complex systems.

In the data preprocessing stage, we unify the abstraction and standardization of heterogeneous information, including network device logs, status monitoring indicators, and topology. By uniformly modeling information such as Syslog, SNMP alarms, and link state changes in the network, we establish a structured event flow that provides a consistent basis for subsequent causal modeling.

Subsequently, we design a prompt-based event recognition and causality extraction mechanism that leverages the semantic understanding and generation capabilities of LLMs. The large language model can generate a directed causal graph reflecting the dependencies between alarm events by receiving historical event context, a priori network structure, and system configuration information.

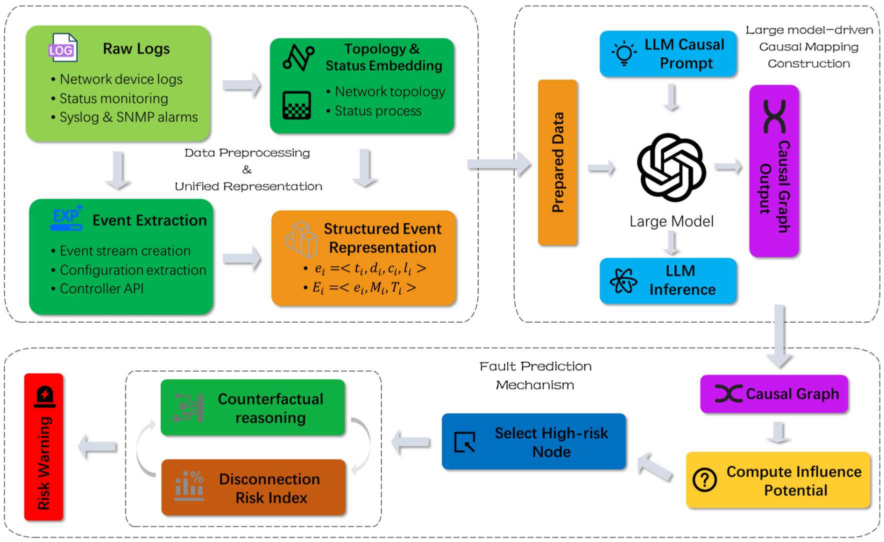

Fig. 1. The overview of our approach. The disconnected prediction approach proposed comprises three core stages: data preprocessing and unified representation, large model-driven causal mapping construction, and a pluggable root cause localization and disconnection prediction mechanism.

Finally, based on the completion of causal graph construction, we introduce a set of plugin causal inference modules, including multiple algorithms such as path analysis, structural causal modeling (also known as SCM), and counterfactual inference, among others, for identifying potential disconnection triggers and enabling high-confidence risk warnings in future windows. This multi-strategy fusion design ensures the approach's stability and migratability in different types of network environments.

Our approach constructs a network disconnection prediction framework that offers high generalization, interpretability, and predictive ability through the deep integration of large models and causal modeling. The following section introduces the design and implementation details of key modules, including causal event graph construction and the root cause inference mechanism.

3.2. LLMs-based causal event graph construction

In network operation, maintenance, and fault analysis, the first step requires accurately constructing a causal map between device anomalies. The traditional approach relies on statistical tests (e.g., conditional independence tests) and structural learning algorithms (PC, GES). These models typically require variables to satisfy specific distributional assumptions and are poorly suited for network environments with complex structures and sparse data. To this end, we propose an automatic causal event graph construction approach centered on the LLMs, which replaces the heavy dependency test and graph structure generation process in traditional algorithms.

Structured Event Representation. In the actual network operation and maintenance environment, fault data exists in various forms, including Syslog logs, SNMP Traps, NetFlow messages, and link state monitoring. These data sources have obvious heterogeneity. These data sources are obviously heterogeneous, comprising both structured metric information and a large amount of unstructured textual content, such as alarm descriptions and log records. To ensure the accuracy of subsequent causal inference and generation structure, we will construct a unified, structured event representation mechanism to support the approach's subsequent steps effectively.

We adopt a standardization approach based on event quaternions to uniformly abstract network operation and maintenance data from different sources into structured alarm event units. Each base alarm event is represented in the following form:

$$e_i =< t_i, d_i, c_i, l_i >, \tag{1}$$

where t_i denotes the timestamp of the event, which is used to indicate the timing information of the event, d_i denotes the device number or unique identifier number that the event belongs to, i.e., device ID; c_i denotes the type of the event or the alarm category, including "link interruption", "route drift", etc.; denotes the severity level of the event, which is graded from 1 to 5, with higher levels indicating more seriousness. c_i denotes the type of event or alarm category, including "link interruption", "route drift", etc.; l_i denotes the severity level of the event, which is divided into 1 to 5 levels, with the higher level denoting the more serious.

As an example, a real-world scenario in which device R1 detects a severe link anomaly at 13:12 can be represented as:

$$e =< 2024 - 07 - 15\ 13 : 12 : 15,\ R1, linkinterruption, 5 > . \tag{2}$$

To enhance the contextual connectivity of the event, we expansively introduce two additional fields M_i and T_i, the former denoting a snapshot of the device state at the time of this base event, such as the device's bandwidth usage and CPU utilization at the time of the event, etc., and the latter denoting the network topology neighbors at the time of the event, which form an expanded event with the base event, which can be represented as follows:

$$E_i =< e_i, M_i, T_i > . \tag{3}$$

Such an event representation preserves the important contextual features of network anomalies on the one hand, and facilitates inter-event comparisons, ordering, and relationship modeling on the other. The structured representation greatly reduces the ambiguity of language model inputs and provides a standard, unified semantic foundation for subsequent causal cue design, graph structure generation, and path inference.

Causal Edge Generation. Based on structured event representation, we further utilize LLMs to reason about potential causal relationships between events and construct a directed causal event graph accordingly. The core of the process lies in the use of prompt

The following are network events during a certain period of time, the event format is: $E_i =< e_i, M_i, T_i >, e_i =< t_i, d_i, c_i, l_i >$,

{Event Symbol Explanation},

determine which events may lead to other events:

[Event 1]:<<2024-07-15 13:02:10, R1,Link Outage,5>,{CPU:0.8,Interface Utilization:0.87,Packet Loss:0.02},[R2,R3]>>

[Event 2]:<<2024-07-15 13:03:19, R2,Route Drift,3>,{CPU:0.4,Interface Utilization:0.82,Packet Loss:0.0},[R1,R4]>

...

Please output the possible causal relationships between events in the format [event i] -> [event j].

Fig. 2. Prompt template used to convert structured event sequences into natural-language queries that guide the LLMs in inferring causal relationships between events.

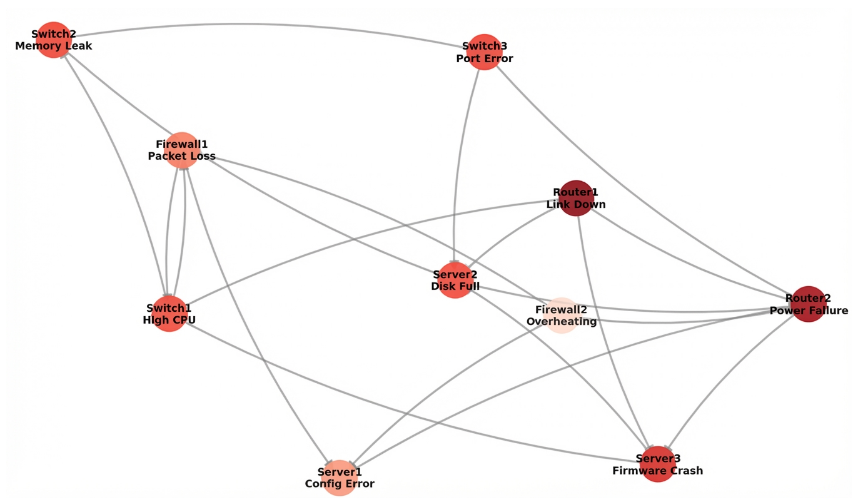

Fig. 3. Illustration of the resulting structural causal graph constructed from validated event dependencies.

engineering to guide the LLMs to identify causal dependencies between events, thus replacing traditional structural learning algorithms such as the PC approach. By combining temporal, semantic, and structural information, the generated causal graph can be more closely related to the fault propagation paths in real networks.

First, we transform the event sequences collected within the time window into a unified natural language input template, which is then fed to the LLMs for causal edge inference. Each event in the template is presented in either the base event format or the extended event format, as described in the previous section, ensuring that the model has sufficient contextual information. A sample prompt template is shown in Fig.2.

After receiving the cue, LLMs will output a set of candidate causal edges $E_{causal} = \{(e_i \rightarrow e_j)\}$ based on the context. To enhance the credibility of the edges and mitigate the noise in the graph structure, we have developed a three-stage causal edge scoring and screening mechanism.

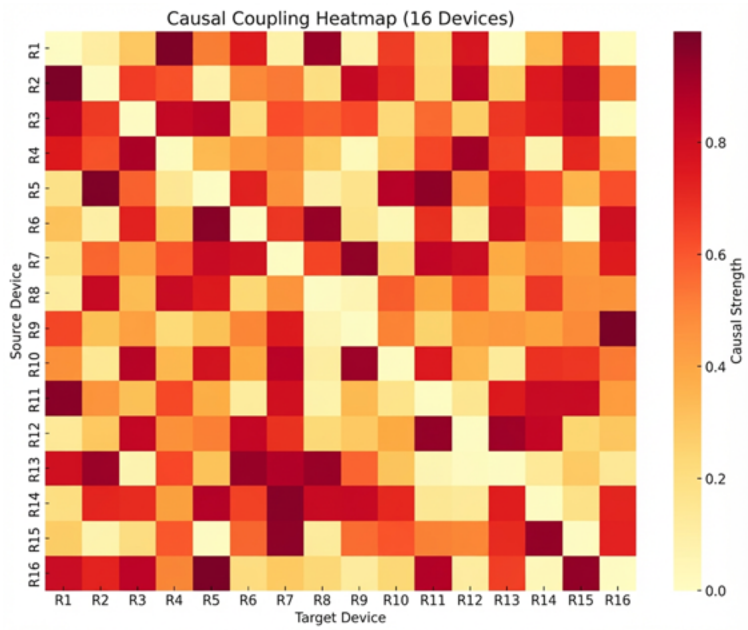

Fig. 4. Coupled heat map visualizing the pairwise causal influence scores between events in the final graph.

First, for each candidate edge, we define the following causal confidence scoring function:

$$\text{score}(e_i \rightarrow e_j) = \alpha \cdot \text{sim}(c_i, c_j) \quad + \beta \cdot e^{-\lambda(t_j - t_i)} \quad + \gamma \cdot \text{adj}(d_i, d_j), \tag{4}$$

where sim (c_i, c_j)denotes the cosine similarity of two events in the semantic space, which the LLMs calculate after generating the event embedding; $e^{-\lambda(t_j - t_i)}$ is the temporal decay factor, which ensures that the causal direction adheres to the principle of temporal sequentiality; adj (d_i, d_j), on the other hand, indicates the proximity of two event-generating devices on the network topology. The weights of the three terms α, β, γ can be adjusted according to the actual application to strengthen the model perception.

Second, for causal edges with scores higher than the threshold τ, we further guide the LLMs to generate explanatory text, which is used to verify whether the model outputs have logical rationality, e.g., ask the model, "Why does event e_i cause event e_j?", and if the model cannot reasonably explain a causal relationship, e.g., the reason is ambiguous or semantic conflict, the edge will be eliminated. This step enhances the interpretability of the causal graph and reduces the inference error caused by "language illusion".

Finally, to avoid structural conflicts, we perform consistency checking in conjunction with network device topology graphs to remove unreasonable edges. This procedure consists of two constraints: loop exclusion and topology direction constraints.

Loop exclusion means that if adding the edge $(e_j \rightarrow e_i)$ would form a closed loop, it is removed to maintain the topologically orderable nature of the graph.

The topological direction constraint requires that if events e_i and e_j originate from devices d_i and d_j, respectively, then a causal edge is retained only when the inter-device hop count $dist_T(d_i, d_j) \leq 2$ and the topological direction between them is either downstream or at the sibling level. The process can be formally expressed as follows:

$$(e_i \to e_j) \in E_{\text{causal}} \Leftrightarrow \begin{cases} \text{acyclic after addition} \\ d_T(d_i, d_j) \leq 2 \\ \delta_T(d_i, d_j) \in \{\downarrow, =\} \end{cases} \tag{5}$$

Graph Construction Mechanisms. After completing causal edge extraction and multi-stage filtering, the remaining high-confidence edges are aggregated to form the final directed causal graph $G_{causal} = (V, E_{causal})$, where the node set V corresponds to all structured events and the edge set E_{causal} represents validated causal dependencies. Unlike a conventional correlation graph, the resulting structure preserves both temporal directionality and physical topology constraints, ensuring that the generated causal pathways are consistent with real-world fault propagation characteristics in substations and intelligent grid networks.

Fig. 3 shows the directed structural causal event graph of an example by the proposed construction pipeline, where nodes represent semantically encoded events and arrows denote validated causal relations. Fig. 4 provides the corresponding heat map, in which darker cells indicate more substantial causal influence from event e_i to event e_j.

Temporal Enhancement of Causal Graphs. We introduce a sliding time window mechanism to serialize the construction process of the causal event graph for modeling purposes. Given a time span T, we construct the set of events ε_i within the current window at each time step t and generate the corresponding causal graph $G_t = (V_t, E_t)$ on its basis. As the window slides, the model will obtain a series of causal event graph sequences $G_{t-k}, \ldots, G_t$, forming a type of time-evolutionary map that provides the basis for subsequent trend modeling and forecasting.

And then, considering that the causal strength of different edges may change over time, we introduce a time-sensitive dynamic weight function w_t for each causal edge $e_i \to e_j$, which is defined as follows:

$$w_t\left(e_i \to e_j\right) = \eta \cdot s_0 + (1 - \eta) \cdot \text{EMA}_t\left(s_t\right), \tag{6}$$

where s_0 denotes the initial causal confidence score, s_t denotes the frequency of triggering of this edge within the current window (i.e., the number of times that event e_i occurs that causes e_j within the window), EMA_t is an exponential moving average function reflecting the recent trend of dependence, and $\eta \in [0, 1]$ controls the proportion of fusion between the prior and the current dynamics.

3.3. Downstream Causal Reasoning and Disconnected Prediction Mechanisms

After completing the causal graph construction and temporal enhancement based on large models, the system has obtained a sequence of directed causal graphs covering major

Algorithm 1: Causal Graph-Based Disconnection Prediction

```
Input: G_t = (V_t, E_t), w_t, θ, k
Output: Alert node list alerts
Function ComputeInfluencePotential(G_t, w_t)
    Ψ ← {}
    foreach node e_i ∈ V_t do
        P ← FindAllPaths(G_t, e_i) path_energies ← []
        foreach path p ∈ P do
            prod ← 1.0 foreach edge (e_j → e_k) ∈ p do
                prod ← prod × w_t(e_j → e_k)
            path_energies ← path_energies ∪ {prod}
        Ψ[e_i] ← ∑ path_energies
    return Ψ
Ψ ← ComputeInfluencePotential(G_t, w_t)
sorted_nodes ← SortDescending(V_t, Ψ)
high_risk ← sorted_nodes[1 : ⌈k · |V_t|⌉]
alerts ← []
foreach node e_i ∈ high_risk do
    G_t^{¬e_i} ← RemoveNode(G_t, e_i)
    R_orig ← FindReachableNodes(G_t, e_i)
    broken ← 0
    foreach node e_j ∈ R_orig do
        if not IsReachable(G_t^{¬e_i}, e_i, e_j) then
            broken ← broken + 1
    DLI(e_i) ← broken/|V_t|
    if DLI(e_i) > θ then
        alert ← { node : e_i,
                  DLI : DLI(e_i),
                  broken_nodes : broken,
                  Ψ : Ψ[e_i] }
        alerts ← alerts ∪ {alert}
return alerts
```

network alarm events, device states, and structural paths. To transform this causal structure into a usable prediction capability, we design a downstream disconnection prediction mechanism, the core of which consists of root cause identification, risk scoring, and disconnection warning.

The primary goal of disconnection prediction is to identify the "source events" in the system, i.e., the root cause nodes of the current historical events that are most likely to trigger a wide range of impacts. Based on the constructed causal graph $G_t = (V_t, E_t)$, we use a weighted directed path analysis strategy to calculate the causal impact potential of each node:

$$\Psi\left(e_i\right) = \sum_{p \subset \mathcal{P}(e_i)} \prod_{(e_j \to e_k) \subset p} w_t\left(e_j \to e_k\right) \tag{7}$$

where $\mathcal{P}(e_i)$ denotes the set of all causal paths reachable from node e_i; $w_t(e_j \to e_k)$ is the causal weight of the edge on the current time window t; a larger value of $\Psi(e_i)$ indicates that the e_i event has a more substantial system-level influence and is prioritized as a candidate for a disconnected risk source.

After identifying the high-risk event nodes in the current window, the system enters the prediction mode to determine whether they will cause the downstream links or devices to be disconnected. At this stage, we introduce the idea of counterfactual reasoning. It estimates the question of "whether the occurrence/non-occurrence of node e_i will cause the disconnection of e_j" through the local perturbation simulation mechanism of the causal graph.

First, select the high-risk node e_i from the current graph G_t; second, construct its "counterfactual version" $G_t^{\neg e_i}$, i.e., set the node e_i did not occur, and recalculate its impact paths; if some nodes e_j are reachable by e_i in G_t but the paths break in $G_t^{\neg e_i}$, it means that $e_i \to e_j$constitutes a potential disconnected propagation.

We define the "Disconnection Risk Index" DLI (e_i) accordingly:

$$\mathrm{DLI}(e_i) = \frac{\left|\{\, e_j \in V_t :\ e_i \rightsquigarrow_{G_t} e_j \wedge e_i \not\rightsquigarrow_{G_t^{\neg e_i}} e_j \,\}\right|}{|V_t|} \tag{8}$$

This indicator reflects the potential systemic threat level of event e_i. Once DLI(e_i) exceeds the threshold θ, the system will trigger a risk warning. The flowchart of the approach is shown in Algorithm 1.

4. Experiments Settings

4.1. Data and Preprocessing

The data used in this experiment were collected from network operation and maintenance logs obtained from a large data center and several intelligent substations within a regional power grid. These datasets comprehensively reflect the operating characteristics of both IT infrastructure and industrial communication environments. The data consist of three main parts. The first part includes device-level status information such as CPU utilization, memory usage, interface error rate, BGP neighbor status, and link Up/Down events. The second part contains multi-source alarm events generated by protocols including Syslog, SNMP Trap, NetFlow, and BFD. The third part involves structured information derived from LLDP, configuration extraction, and controller APIs, including network topology and protocol relationship counts, physical topology, and protocol dependency graphs. An example has been shown in Table 1.

All data were uniformly processed and transformed into structured event representations in the form of ternary tuples $< e_i, M_i, T_i >$, and sliding event sequences were constructed within five-minute time windows for causal inference modeling based on the large language model.

4.2. Experimental Platform and Parameters

The hardware environment of the platform used in this experiment is a NVIDIA RTX A6000 GPU, the software environment is Python 3.10, and the primary LLMs tool is

Table 1. Example of network operation and maintenance data used in .

(A) Device Status Information						
Timestamp	Device	CPU(%)	Mem(%)	Interface	Error Rate	Link
10:23:01	RT-01	38	62	ge-0/0/1	0.2‰	Up
10:23:01	SW-22	12	48	eth1/3	1.5‰	Down
(B) Multi-source Alarm Events						
Timestamp	Device	Type	Severity	Description		
10:25:12	RT-01	Syslog	Warning	CRC errors on ge-0/0/1		
10:25:14	SW-22	SNMP Trap	Major	Link eth1/3 down		
(C) Topology and Protocol Dependencies						
Local Device	Local Port	Remote Device	Remote Port	Protocol Dependency		
RT-01	ge-0/0/1	SW-22	eth1/3	BGP $\rightarrow$ {BFD, OSPF}		

OpenAI GPT-4 API for causal extraction and interpretation verification, and the other tools are NetworkX for performing graph structure construction, and Neo4j for graph storage and interactive query.

The dataset size of this experiment comprises 10,000 windows, approximately 1,400 link failure events, and 15 abstract alarm types. LLMs' prompt templates are constructed based on alarm content, time, and neighbor structure, and batch reasoning and caching mechanisms are used to improve efficiency.

4.3. Metrics

To evaluate the model performance, we design the following key metrics:

(1) **Root Cause Accuracy:** whether the earliest cause event inferred by LLMs covers the actual faulty equipment or not;
(2) **Lead Time:** the average time for the first warning to be issued before the actual occurrence of a fault event;
(3) **Edge Precision:** the proportion of the edges predicted by LLMs for which there is a real causal relationship;
(4) **Edge Recall:** the proportion of real causal relationships correctly identified by LLMs;
(5) **Causal Explainability:** the proportion of edges that are validated by natural language feedback;
(6) **False Positive Rate:** the proportion of non-root-cause devices that are misidentified as risk sources.

5. Results and Analysis

This section aims to validate the effectiveness and practicality of the proposed network device disconnection prediction approach that integrates LLMs and causal reasoning in real scenarios. We simulate typical device failure scenarios by constructing multi-source

Table 2. Experimental results demonstrating how sample size influences the accuracy, interpretability, and computational cost of the proposed causal graph generation approach, with estimated standard deviations.

Sample	Edges Extracted	Precision	Recall	Explainability	Processing Time (s)
500	84 ± 4	0.74 ± 0.03	0.69 ± 0.03	0.72 ± 0.03	3.4 ± 0.2
1,000	110 ± 4	0.81 ± 0.02	0.74 ± 0.02	0.76 ± 0.02	5.8 ± 0.3
5,000	138 ± 3	0.86 ± 0.02	0.82 ± 0.02	0.84 ± 0.02	13.5 ± 0.5
10,000	142 ± 3	0.88 ± 0.01	0.85 ± 0.01	0.87 ± 0.01	22.9 ± 0.7
50,000	146 ± 2	0.90 ± 0.01	0.87 ± 0.01	0.91 ± 0.01	88.4 ± 2.0
100,000	148 ± 1	0.91 ± 0.01	0.88 ± 0.01	0.92 ± 0.01	174.1 ± 3.0

Table 3. Comparison of root-cause localization performance across baseline approaches and the proposed LLMs-based approach, including estimated standard deviations for accuracy, prediction lead time, and false positive rate.

Approaches	Root Cause Accuracy ↑	Prediction Lead Time (min) ↑	False Positive Rate ↓
NetRCA	$75.0\% \pm 1.5\%$	3.0 ± 0.3	0.150 ± 0.010
REASON	$81.5\% \pm 1.2\%$	5.0 ± 0.4	0.120 ± 0.008
RUN	$83.0\% \pm 1.0\%$	5.5 ± 0.3	0.110 ± 0.007
Attention-LSTM	$89.5\% \pm 0.8\%$	-	-
Ours	$\mathbf{90.2\% \pm 0.7\%}$	$\mathbf{7.1 \pm 0.4}$	$\mathbf{0.074 \pm 0.005}$

alarm flow datasets in real network environments. We systematically evaluate the quality of causal graph construction, root cause localization accuracy, alerting capability, and module effectiveness.

5.1. Quality Assessment of Causal Graphs Evaluation

We input samples of different sizes into the LLMs to evaluate their performance in automatically generating causal edges.

The results in Table 2 show that larger sample sizes substantially enhance the model's ability to extract causal edges: the number of identified relations increases from 84 to 148. It begins to stabilize once the sample size exceeds 50,000. Precision and recall also improve steadily (from 0.74/0.69 to 0.91/0.88), indicating clear gains in both accuracy and coverage. Complementing these numerical results, Fig. 5 visualizes the same trends and highlights the smooth, monotonic improvement of all metrics as data scale grows. The curves gradually flatten at larger sample sizes, illustrating the diminishing incremental benefits and the model's convergence behavior.

Meanwhile, the causal interpretation rate also increases from 0.72 to 0.92, indicating that the causal edges generated by LLMs are increasingly rational and semantically consistent, providing strong support for interpretability in practical applications. Although the processing time increases significantly with the sample size, it is within the acceptable range, indicating that the approach has good scalability while maintaining the quality of graph building and is suitable for large-scale network disconnection prediction scenarios.

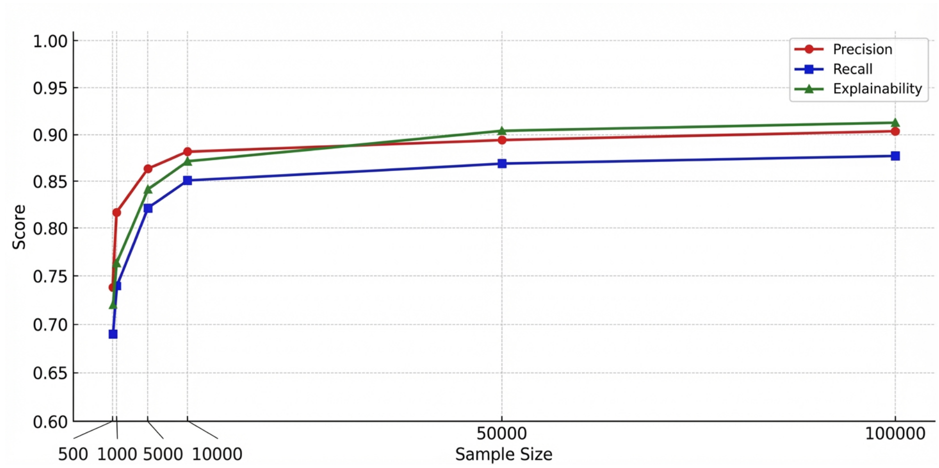

Fig. 5. Causal Graph Construction Performance Evaluation

The comparison in Fig. 6 verifies that the larger the sample size, the more stable and complete the causal structure becomes, which helps to improve the accuracy of root cause localization and the explanation of disconnected propagation paths.

5.2. Root Cause Localization Performance Evaluation

To comprehensively evaluate the performance of the proposed approach in root cause localization and disconnection risk prediction, we select four representative studies as baseline approaches, including traditional feature-based ensemble models, graph neural networks, neural Granger causal discovery, and generative adversarial frameworks:

(1) **NetRCA[26]**: A root cause localization approach that integrates multi-type feature engineering, data augmentation, and ensemble learning (including XGBoost, rule-based learning, and graph algorithms). It is primarily designed for network failure scenarios with limited samples.
(2) **REASON[20]**: A hierarchical graph neural network that constructs cross-layer causal structures and combines random walk with extreme value theory for root cause identification. It is particularly suited for analyzing multi-level fault propagation.
(3) **RUN[13]**: A approach based on neural Granger causal discovery and contrastive learning, further enhanced with PageRank to localize root causes of microservice failures. Experiments on both synthetic and real microservice datasets demonstrate superior performance over traditional approaches.
(4) **FaultGuard[8]**: A generative adversarial framework tailored for smart grids, which exhibits high robustness and ensures accurate disconnection prediction and detection even under adversarial attacks.

As shown in Table 3, the proposed approach achieves the best performance across all three key evaluation metrics. First, in terms of **root cause localization accuracy**, our approach attains 90.2%, outperforming RUN (83.0%) and REASON (81.5%), and

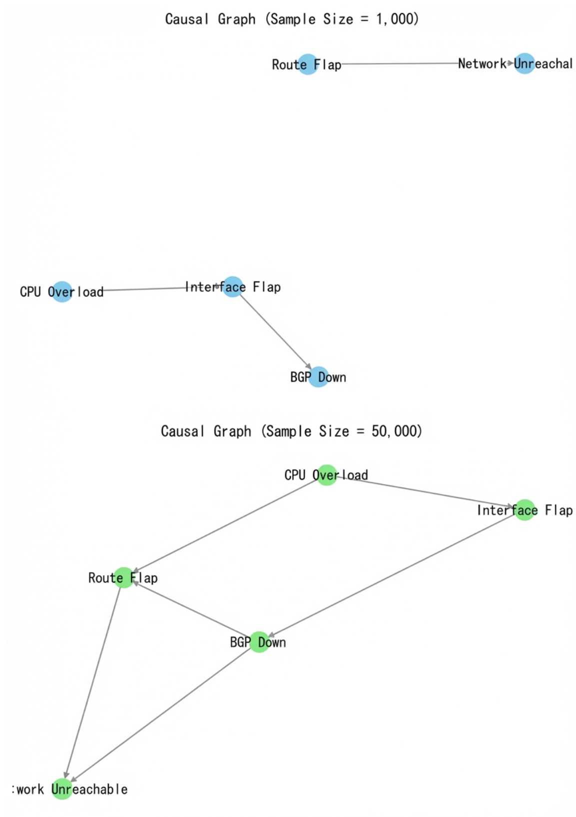

Fig. 6. Effect of sample size on the stability and completeness of the causal structure, which improves root cause localization and the explanation of disconnected propagation paths.

slightly surpassing FaultGuard (89.5%). This demonstrates the superior capability of our approach in handling complex network failure scenarios. Second, regarding **prediction timeliness**, the approach issues warnings approximately 7.1 minutes before disconnection events occur, significantly ahead of REASON and RUN (5.0–5.5 minutes), thereby providing a longer response window for preventive maintenance. Third, in terms of **false alarm control**, our approach achieves a false positive rate of only 7.4%, substantially lower than REASON (12%), RUN (11%), and NetRCA (15%). This highlights the advantage of the causal reasoning module in mitigating "language hallucinations" and reducing noise-induced misjudgments.

Overall, these results clearly demonstrate the benefits of deeply integrating LLMs with causal modeling: the proposed approach achieves significant breakthroughs in root cause localization accuracy, responsiveness, and predictive reliability, suggesting its potential to serve as a new paradigm for preventive maintenance in smart grids and critical communication systems.

Table 4. Comprehensive ablation study showing the impact of individual components and their combinations on model performance. SCC, NLE, and PO denote Structural Consistency Check, Natural Language Explanation, and Prompt Optimization, respectively. RCA, PLT, and FPR represent Root Cause Accuracy, Prediction Lead Time, and False Positive Rate, with estimated standard deviations.

Configuration	SCC	NLE	PO	RCA ↑	PLT (min) ↑	FPR ↓
Full Model	Y	Y	Y	**90.2% ± 0.7%**	**7.1 ± 0.4**	**0.074 ± 0.005**
w/o Consistency	N	Y	Y	80.1% ± 1.2%	6.6 ± 0.4	0.120 ± 0.010
w/o Explanation	Y	N	Y	83.4% ± 1.0%	6.9 ± 0.3	0.103 ± 0.008
w/o Prompt Optimization	Y	Y	N	78.0% ± 1.5%	5.3 ± 0.5	0.131 ± 0.012
w/o SCC + NLE	N	N	Y	75.8% ± 1.3%	6.2 ± 0.4	0.135 ± 0.012
w/o SCC + PO	N	Y	N	72.5% ± 1.5%	5.8 ± 0.5	0.142 ± 0.013
w/o NLE + PO	Y	N	N	77.1% ± 1.4%	5.9 ± 0.4	0.128 ± 0.011
w/o SCC + NLE + PO	N	N	N	68.0% ± 1.8%	5.0 ± 0.5	0.155 ± 0.015

These results demonstrate that the introduction of LLMs into network disconnection prediction and root cause localization tasks can significantly enhance the interpretability and foresight of the models, providing a more practical technical path for risk prevention and control in highly available network systems.

5.3. Disconnection Propagation Path Analysis

To further validate the explanatory ability and causal path modeling effect of the large model in the disconnection prediction task, we selected two typical types of network failure events from the experimental set, demonstrated the causal propagation paths automatically constructed by the model, and analyzed them in combination with the network operation data and topology.

In a particular core switching cluster, the physical layer fluctuations occur continuously on the device interfaces, and the model automatically generates the following causal chain:

```
[Interface Flap] → [OSPF Adjacency Lost] → [Route
        Withdrawal] → [Service Unreachable]
```

The explanatory text in the path states:

```
"OSPF adjacency outages are usually caused by physical link
          instability or interface restarts."
    "Route convergence failures cause service paths to
    disappear, triggering service unreachable alarms."
```

In the edge access device. The system monitors a continuous spike in resource utilization. Eventually, the user application experiences frequent timeouts. The causal path generated by LLMs is as follows:

```
[CPU Overload] → [Routing Loop Detected] → [Packet Loss] →
                  [Application Timeout]
```

The path reveals the complete mechanism that begins with the underlying device state anomaly and gradually leads to the control plane, forwarding path, and ultimately affects the application layer. The explanatory text in the path states:

```
"High CPU load may lead to delays in processing control
packets, which generates routing convergence jitter"
"Routing loops trigger forwarding congestion and packet
loss, which ultimately affects upper-layer application
response times."
```

Similar resource bottleneck paths are frequently identified in multiple experimental samples, demonstrating the stability and generality of the LLMs approach to capture the propagation of the state protocol-data-service chain.

5.4. Ablation Experiments

To further assess the role of each module in the overall approach, we designed three sets of ablation experiments, excluding key components such as large model cue optimization, structural consistency checking, and natural language causal validation, and observing their impact on root cause prediction ability.

The results presented in Table 4 provide clear evidence of each component's contribution. Removing the Structural Consistency Check (SCC) results in a substantial increase in the false positive rate, underscoring its crucial role in maintaining prediction reliability. Excluding the Natural Language Explanation (NLE) module reduces Root Cause Accuracy (RCA). It slightly shortens the Prediction Lead Time (PLT), demonstrating that semantic validation enhances both interpretability and early-warning capability. Omitting Prompt Optimization (PO) causes the largest drop in RCA, reflecting the importance of carefully designed prompts for stable LLMs' reasoning.

Furthermore, the joint ablation experiments, where two or all three components are removed simultaneously, show a compounded deterioration in performance: RCA declines sharply, PLT decreases, and FPR rises markedly. This highlights the synergistic effect among the modules, where each component not only contributes individually but also reinforces the others to improve overall model robustness and reliability.

Overall, these ablation studies confirm that each sub-module in the proposed approach is indispensable. The SCC ensures low false positives, the NLE provides causal interpretability, and PO stabilizes LLMs' outputs, together achieving enhanced accuracy, interpretability, and robustness of the disconnection prediction system.

6. Conclusion

In this paper, we propose a network device disconnection prediction approach that integrates large language models (LLMs) with causal analysis. The approach leverages structured event abstraction, combines network topology and operational state information, employs LLMs for causality extraction, and is enhanced with consistency checking and causal path interpretation, enabling accurate root-cause identification, interpretable reasoning, and early warning capabilities.

Empirical evaluation of real data center operation and maintenance logs reveals that the proposed approach outperforms traditional rule-based and statistical approaches in terms of causal graph construction quality, root-cause localization accuracy, prediction reliability, and false alarm reduction. These results demonstrate the practical utility of the framework for proactive network management and preventive maintenance in mission-critical infrastructures.

Future work will focus on adaptive prompt engineering, more efficient incremental causal graph construction, improving LLMs' generalization across diverse network environments, and enhancing model security and robustness. With ongoing technological advancements, integrating LLMs-based causal reasoning is expected to become a foundational capability for intelligent, resilient, and automated network operation and maintenance.

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