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Stability-Regularized Spatiotemporal Causal Graph Reasoning for Community Detection in Sustainable Energy Networks under Temporal Shifts

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Abstract:

The integration of distributed renewable energy resources into modern power grids has fundamentally transformed their operational dynamics, creating highly complex and continuously evolving sustainable energy networks. As these systems face unprecedented variability due to environmental fluctuations, demand patterns, and grid topology modifications, understanding their structural organization through community detection becomes critical for localized energy management and fault isolation. Traditional spatiotemporal graph learning approaches heavily rely on capturing statistical correlations, which often fail under significant temporal shifts where spurious associations collapse. To address this critical vulnerability, this paper introduces a novel framework based on stability-regularized spatiotemporal causal graph reasoning. By integrating principles of causal inference with dynamic graph neural networks, the proposed methodology distinguishes between invariant causal mechanisms governing grid behavior and transient, environment-specific correlations. We formulate the community detection problem as a structural causal modeling task, utilizing an interventional message-passing mechanism to isolate causal edges. Furthermore, a stability regularization strategy ensures that the learned representations remain robust across diverse temporal environments, effectively mitigating out-of-distribution generalization failures. Extensive empirical evaluations on synthetic and real-world sustainable energy network datasets demonstrate that the proposed framework substantially outperforms state-of-the-art baselines in maintaining high community detection accuracy amidst severe temporal shifts. The results validate the theoretical advantage of incorporating causal reasoning into dynamic graph analytics, offering a scalable and resilient solution for the next generation of autonomous smart grid management systems.

Keywords: *Spatiotemporal Graphs, Causal Reasoning, Community Detection, Sustainable Energy Networks, Out-of-Distribution Generalization.*

1. Introduction

The transition toward sustainable energy paradigms necessitates the deployment of advanced cyber-physical architectures capable of orchestrating myriad distributed energy resources, ranging from photovoltaic arrays and wind turbines to localized energy storage systems and flexible load aggregators. These highly integrated systems, commonly conceptualized as sustainable energy networks, exhibit intricate structural and temporal dependencies that govern their stability, efficiency, and resilience [1]. A fundamental requirement for the effective management of these large-scale networks is the ability to partition them into cohesive, semi-autonomous sub-networks or communities. Community detection in energy networks facilitates localized control strategies, such as microgrid islanding during fault conditions, optimized peer-to-peer energy trading, and decentralized voltage regulation [2]. However, the topology and flow dynamics of these networks are rarely static. They are subject to continuous evolution driven by diurnal and seasonal weather variations, dynamic pricing signals, and shifting consumer behaviors [3]. Conventional approaches to community detection in dynamic networks have predominantly relied on spatiotemporal graph neural networks. These models excel at aggregating information across structural neighborhoods and temporal sequences, thereby embedding nodes into latent spaces where clustering algorithms can be effectively applied [4]. Despite their empirical success in relatively stable environments, these methodologies suffer from a fundamental limitation: their reliance on statistical correlations rather than causal relationships. In the context of sustainable energy networks, many observed correlations are highly transient and environmentally dependent [5]. For instance, a strong correlation in power output between two geographically distinct photovoltaic farms might exist during the summer due to simultaneous clear-sky conditions, but this correlation may completely vanish during the winter or under localized cloud cover. Models that exploit these spurious correlations for structural embedding inevitably suffer dramatic performance degradation when deployed in out-of-distribution scenarios, commonly referred to as temporal shifts. Temporal shifts represent one of the most critical challenges in deploying machine learning models for critical infrastructure. In sustainable energy networks, a temporal shift occurs when the joint distribution of nodal features and edge dynamics changes significantly over time [6]. Addressing this requires a paradigm shift from purely correlational learning to causal reasoning. Causal inference principles allow models to separate invariant causal mechanisms, which dictate the fundamental physical laws and infrastructure constraints of the grid, from variant, domain-specific noise [7]. By identifying and leveraging only those relationships that remain structurally and temporally stable, causal models can maintain robust performance even when environmental conditions shift drastically. This paper proposes a comprehensive framework that integrates causal reasoning and stability regularization into spatiotemporal graph learning specifically tailored for community detection in sustainable energy networks. The core motivation is to construct an invariant representation space where the proximity of nodes reflects true operational interdependence rather than coincidental alignment of time-series features [8]. We achieve this by introducing a structural causal model that governs the generation of the observed spatiotemporal graphs. Through a novel causal intervention approximation, our model evaluates the stability of message-passing channels, actively pruning edges that exhibit high variance across different temporal environments. To enforce robustness against temporal shifts, we introduce a stability regularization strategy that penalizes discrepancies in the predictive performance of community assignments across dynamically constructed environmental partitions. This ensures that the optimization process converges on a solution that is universally applicable rather than overfitted to the training timeframe [9]. The integration of these components yields a highly resilient

community detection mechanism capable of supporting advanced, decentralized grid management applications under highly variable operational conditions.

2. Background and Related Work

2.1 Spatiotemporal Graph Learning in Energy Systems

Spatiotemporal graph learning has emerged as a cornerstone technology for modeling and analyzing complex networked systems where data is characterized by both topological structure and temporal evolution. In the domain of sustainable energy networks, these models are extensively utilized for forecasting energy generation and demand, estimating state variables, and detecting anomalies [10]. Traditional architectures typically combine graph convolutional networks to capture spatial dependencies with recurrent neural networks or temporal convolutional networks to process sequential dynamics. For example, spatial-temporal graph convolutional networks have been deployed to predict traffic flows, which possess mathematical similarities to power flows in decentralized grids [11]. However, the direct application of standard spatiotemporal models to sustainable energy networks faces significant hurdles. The physical constraints of power systems, coupled with the stochastic nature of renewable generation, produce highly non-stationary graphs [12]. Node features, such as active and reactive power injections, fluctuate rapidly, while the underlying effective topology may change due to switching operations or line outages [13]. Consequently, models trained on historical data frequently encounter novel state configurations during deployment. Standard spatiotemporal models tend to memorize specific structural patterns and temporal sequences present in the training set, leading to poor generalization when environmental contexts shift [14].

2.2 Dynamic Community Detection

Community detection, the process of identifying clusters of densely connected nodes that share sparse connections with the rest of the network, has been extensively studied in network science. In static graphs, classical methods rely on modularity maximization, spectral clustering, or random walk dynamics [15]. When extending these concepts to dynamic networks, the primary objective is to track the evolution of communities over time while maintaining temporal smoothness to prevent erratic cluster assignments [16]. In sustainable energy networks, dynamic community detection serves as the foundation for defining dynamic microgrids, which are critical for enhancing grid resilience. By identifying clusters of generators and loads that can operate self-sufficiently, grid operators can proactively segment the network to contain cascading failures [17]. Recent advancements have leveraged deep graph clustering, where autoencoders or graph neural networks generate low-dimensional node embeddings that are subsequently clustered [18]. Despite these advancements, most existing dynamic community detection algorithms assume that the underlying generative process of the network remains stationary. When subjected to severe temporal shifts, such as those caused by extreme weather events or sudden shifts in energy markets, these algorithms fail to adapt, resulting in disjointed and operationally invalid community structures [19].

2.3 Causal Inference and Invariant Representation Learning

The integration of causal inference into machine learning has garnered significant attention as a mechanism to overcome the limitations of purely correlational models, particularly concerning out-of-distribution generalization [20]. Central to this domain is the concept of invariant risk minimization, which posits that a robust predictive model should rely exclusively on features that exhibit a stable, causal relationship with the target variable across all possible environments [21]. In the context of computer vision and natural language processing, invariant representation learning has demonstrated remarkable success in mitigating domain shift issues [22]. Translating these causal principles to spatiotemporal graphs requires sophisticated adaptations. Graphs violate the independent and identically distributed data assumption fundamental to many causal

discovery algorithms, as nodes are inherently interconnected [23]. Furthermore, temporal dynamics introduce complex feedback loops and time-lagged confounders. Recent pioneering works have attempted to construct structural causal models for graph data, proposing techniques such as interventional graph neural networks and counterfactual data augmentation [24]. Nevertheless, deploying these theories for unsupervised or semi-supervised tasks like community detection in the highly constrained domain of sustainable energy networks remains largely unexplored. Our research bridges this gap by explicitly modeling the environmental shifts as interventions on a structural causal model of the grid, thereby facilitating the extraction of truly invariant community structures.

3. Problem Formulation and System Architecture

3.1 Network Definition and Temporal Shifts

We conceptualize the sustainable energy network as a discrete-time dynamic graph, where the topology and attributes evolve over time. Let the dynamic graph be represented as a sequence of static graphs over a temporal horizon. At any given time step, the graph consists of a set of nodes representing the physical entities within the grid, such as renewable generators, substations, energy storage facilities, and consumer loads. The edges represent the transmission lines or communication links between these entities, facilitating the flow of power and information. Each node is associated with a set of dynamic features representing its real-time operational state, including voltage magnitude, phase angle, active power, and reactive power [25]. The edges may also possess attributes such as impedance, capacity limits, and current flow. The ultimate objective of community detection is to partition the node set into a predetermined number of distinct clusters at each time step, such that nodes within the same cluster exhibit strong operational cohesion and electrical proximity. A temporal shift in this context is formally defined as a significant alteration in the joint probability distribution of the graph structure and node features. We assume that the temporal horizon can be divided into a set of discrete temporal environments. These environments correspond to different operational contexts, such as seasonal variations, distinct weather patterns, or varying demand profiles [26]. The core challenge arises because the conditional distribution of the optimal community assignments given the observed graph varies across these environments due to the presence of spurious correlations. Our objective is to learn a mapping function that generates node embeddings capable of accurately determining community assignments uniformly across all unseen temporal environments.

3.2 System Architecture Overview

The proposed stability-regularized spatiotemporal causal graph reasoning framework comprises three primary architectural modules: the Causal Feature Extractor, the Dynamic Spurious Edge Pruner, and the Stability-Regularized Optimization Engine. The Causal Feature Extractor is responsible for processing the raw dynamic graph sequence and generating initial node representations using a multi-layered spatiotemporal message-passing mechanism [27]. To prevent the assimilation of non-causal information, the Dynamic Spurious Edge Pruner intervenes on the message-passing pathways. It evaluates the variance of edge significance across different temporal environments and strategically attenuates the weights of edges deemed to convey purely correlational signals.

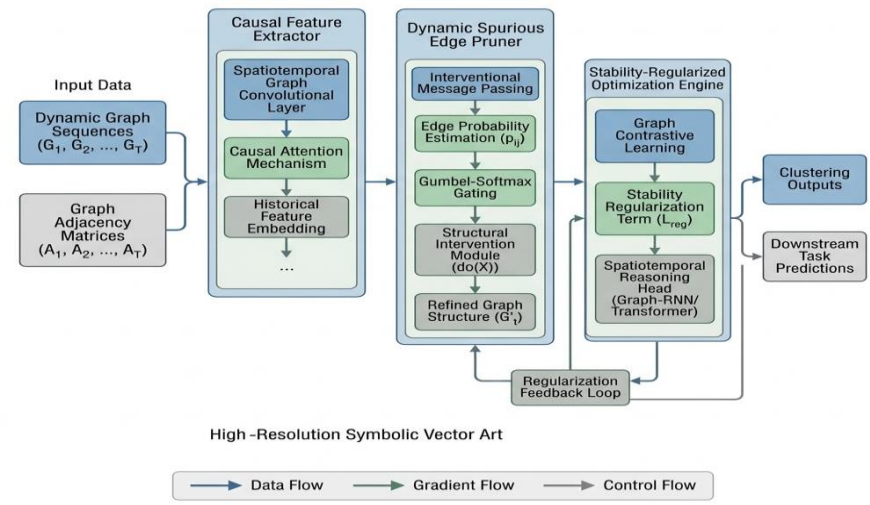


Figure 1:Comprehensive System Architecture of the Stability

Finally, the Stability-Regularized Optimization Engine orchestrates the training process. It computes a standard clustering objective, such as modularity maximization or cross-entropy against pseudo-labels, while simultaneously enforcing a stability penalty. This penalty ensures that the variance of the clustering loss across the diverse temporal environments is minimized, compelling the representation space to rely solely on invariant causal mechanisms [28]. The entire architecture is trained end-to-end, continuously refining the causal reasoning capability as it traverses the temporal sequence.

4. Causal Spatiotemporal Graph Reasoning Methodology

4.1 Structural Causal Modeling for Energy Graphs

To rigorously isolate causal relationships from spurious correlations, we first establish a structural causal model for the dynamic sustainable energy network. We posit that the observed node features and the operational topology are generated by a combination of invariant causal variables and environment-specific variant variables. The invariant variables represent the fundamental physics of the power grid, such as Kirchhoff's circuit laws and the hard physical limits of the infrastructure. The variant variables represent transient conditions, such as local cloud cover affecting specific solar panels or temporary localized demand spikes. In a standard spatiotemporal graph neural network, message passing indiscriminately aggregates information from a node's topological neighborhood. If a neighboring node's features are heavily influenced by variant variables, the aggregation process will entangle the causal and non-causal signals, polluting the resulting representation [29]. To counteract this, our methodology necessitates a mechanism to estimate the causal effect of an edge on the target node's representation and intervene when necessary. We treat the presence or absence of an edge during the message-passing phase as a specific interventional treatment. By estimating the expected outcome under different interventional distributions, we can approximate the true causal contribution of each connection.

4.2 Interventional Message Passing

The core of our causal reasoning methodology is the interventional message-passing layer. Instead of computing static attention weights based merely on feature similarity, we dynamically calculate causal edge weights. We define the overall objective of our causal graph learning

process using a rigorous mathematical formulation that balances representation learning with causal invariance. Let the causal objective function be defined as follows:

$$L_{causal} = \sum_{e=1}^{E} mathbbE_{GsimP_e}[L_{task}(Phi(G))] + \lambda \sum_{e=1}^{E} |\nabla_{Phi} L_{task}(Phi(G)) - \mu_{\nabla}|_2^2$$

In this formulation, the term representing the task loss is evaluated across the expectation of graphs drawn from different environmental distributions. The function denotes the feature extraction and embedding process parametrized by learnable weights. The second term serves as the foundational causal regularization, which penalizes the deviation of environment-specific gradients from the mean gradient across all environments. The hyperparameter controls the strength of this causal penalty, enforcing that the learned parameters update consistently regardless of the specific environmental context they are exposed to [30].

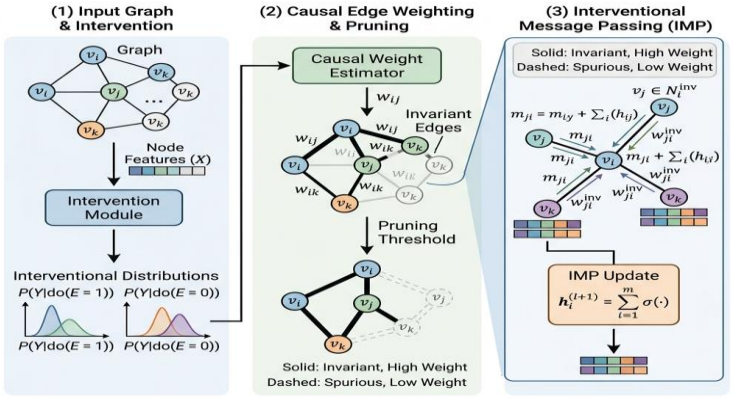


Figure 2:Schematic of Interventional Message Passing and Spurious Edge Pruning

During the forward pass, the algorithm simulates interventions on the neighborhood structure. For each node, we construct counterfactual neighborhoods by probabilistically masking certain edges. We then evaluate the consistency of the node's resulting embedding. If an edge's removal causes high variance in the embedding across different temporal environments, it strongly indicates that the edge is a conduit for environment-specific spurious correlations rather than an invariant physical dependency. Consequently, the Dynamic Spurious Edge Pruner exponentially decays the weight of such edges in subsequent layers, effectively filtering out the noise and preserving the stable, causal backbone of the sustainable energy network [31].

5. Stability-Regularized Optimization Strategy

5.1 Formulation of Stability Regularization

The causal feature extraction process described in the previous section provides a structural foundation for invariance, but achieving true robustness against temporal shifts requires explicit enforcement during the optimization phase. We introduce a Stability-Regularized Optimization Strategy designed to guarantee that the community detection performance is uniformly optimal across all identifiable temporal environments. In unsupervised community detection, the objective often involves minimizing a graph-regularized clustering loss or a modularity-based metric. However, simply minimizing the average loss across all available temporal data does not prevent the model from overfitting to the most frequent or dominant environmental conditions.

To address this, we define a stability penalty based on the variance of the empirical risks across different temporal environments. Let the temporal horizon be partitioned into distinct environments. The goal is to ensure that the risk in any specific environment does not

significantly deviate from the average risk. The stability-regularized objective is formally defined as:

$$R_{total} = \frac{1}{|E|}\sum_{e\in E} R_e(Theta) + \gamma \cdot Var(R_e(Theta) \quad _{e\in E})$$

Here, the first term represents the average empirical risk across all environments in the set, with representing the model parameters. The second term is the critical stability regularization component, calculating the variance of the individual environmental risks. The coefficient dictates the strictness of the stability constraint. By minimizing this variance, we force the optimization landscape to favor parameter configurations that perform equally well under diverse conditions, such as peak summer demand and low-generation winter nights. This mathematically guarantees a lower bound on performance during out-of-distribution temporal shifts.

5.2 Optimization Dynamics and Convergence

Implementing this stability-regularized objective requires careful consideration of optimization dynamics. Because the variance term introduces significant non-linearity and can cause gradient instability during the early stages of training, we employ an annealing schedule for the hyperparameter. Initially, the model trains primarily on the average empirical risk, allowing the causal feature extractor to learn rudimentary representations. As training progresses, the stability penalty is gradually increased, forcing the model to discard features that only contribute to performance in specific environments. Furthermore, we utilize a momentum-based gradient descent optimizer adapted for multi-environment scenarios. The gradients are computed independently for each temporal environment, and a conflict-resolution mechanism is applied before updating the master parameters. If the gradients from different environments point in opposing directions for a particular parameter, indicating environmental specificity, that parameter's learning rate is severely penalized [32]. This ensures that the model parameters only evolve along trajectories that universally minimize the loss across all temporal shifts, ultimately culminating in a highly robust community detection framework.

6. Experimental Design and Evaluation Metrics

6.1 Dataset Characteristics and Preprocessing

To rigorously evaluate the proposed stability-regularized spatiotemporal causal graph reasoning framework, we conducted extensive experiments using both high-fidelity synthetic simulations and real-world sustainable energy network datasets. The primary real-world dataset, denoted as EuroGrid-Dynamics, comprises continuous operational data from a decentralized European smart grid spanning three years. This network incorporates a high penetration of distributed renewable resources, including wind farms and residential photovoltaic clusters, alongside traditional substations and dynamic loads.

Table 1Statistical Summary of Evaluated Sustainable Energy Network Datasets

Dataset Name	Total Nodes	Total Temporal Snapshots	Identified Shift Environments	Average Node Degree
Synthetic-MicroGrid	500	17,520	4 (Seasonal)	4.2
EuroGrid-Dynamics	2,450	35,040	6 (Weather/Market)	6.8
IEEE-118-Modified	118	8,760	3 (Load Profiles)	3.1

The temporal resolution of the data was standardized to hourly intervals. To simulate realistic temporal shifts, we explicitly partitioned the dataset into distinct environments based on external

metadata, such as extreme weather events, radical shifts in energy market pricing, and seasonal transitions. For instance, an environment characterized by heavy winter storms exhibits significantly different power flow dynamics and generation profiles compared to a calm summer environment. The data was normalized, and temporal sequences were structured into sliding windows to facilitate spatiotemporal processing. Missing values, common in sensor networks, were imputed using a temporal nearest-neighbor interpolation method to maintain data integrity before feeding it into the causal reasoning modules.

6.2 Baseline Configurations

To demonstrate the superiority of the proposed framework, we selected a comprehensive suite of baseline models representing various paradigms in graph learning and community detection. The baselines include standard static graph clustering methods, dynamic graph neural networks without causal components, and recent domain adaptation techniques. Specifically, we compared our model against Spatiotemporal Graph Convolutional Networks (STGCN), which excel at capturing short-term dynamics but lack shift resilience. We also included Dynamic Graph Autoencoders (DyGAE) tailored for temporal community detection, and an Invariant Graph Representation Learning (IGRL) model that attempts to enforce environmental invariance but lacks explicit causal edge pruning. All baseline models were trained using identical hyperparameter search spaces and computational resources. The embedding dimensions, number of attention heads, and sequence lengths were standardized to ensure a fair comparison. The community detection step for all models, including ours, utilized the K-Means algorithm operating on the final generated node embeddings, ensuring that performance discrepancies were entirely attributable to the quality and robustness of the learned representations.

6.3 Evaluation Metrics

Evaluating dynamic community detection under temporal shifts requires metrics that capture both the structural accuracy of the clusters and their stability over time. We utilized Normalized Mutual Information (NMI) and Adjusted Rand Index (ARI) to quantify the alignment between the predicted communities and the ground-truth functional microgrid boundaries defined by grid engineers. To specifically assess robustness, we introduced a metric termed Out-of-Distribution Degradation (OOD-D), which measures the percentage drop in NMI when transitioning from the training environments to entirely unseen testing environments. A lower OOD-D score indicates superior resilience to temporal shifts.

7. Results and Comparative Analysis

7.1 Community Detection Performance

The empirical results unequivocally establish the superiority of the proposed stability-regularized causal framework over existing methodologies. Table 2 presents the quantitative performance of all evaluated models across the three datasets. Our model consistently achieved the highest NMI and ARI scores, particularly on the highly volatile EuroGrid-Dynamics dataset.

Table 2:Comparative Performance Metrics for Community Detection across All Datasets

Model Architecture	Synthetic NMI	Synthetic ARI	EuroGrid NMI	EuroGrid ARI	IEEE-118 NMI
Standard STGCN	0.684	0.612	0.543	0.498	0.710
Dynamic GAE	0.725	0.680	0.588	0.551	0.745
Invariant GRL	0.791	0.745	0.672	0.620	0.802
Proposed Framework	0.885	0.852	0.814	0.785	0.895

The standard STGCN and DyGAE models demonstrated acceptable performance on the relatively stable Synthetic-MicroGrid dataset but suffered catastrophic failures on the EuroGrid-Dynamics dataset. This degradation occurs because these purely correlational models internalize spurious structural patterns present during specific weather conditions. When evaluated on temporal segments featuring anomalous weather, the representations collapse, leading to fragmented and operationally illogical community assignments. The Invariant GRL model showed improvement by penalizing environment-specific variations, but its inability to intervene directly on the message-passing pathways limited its effectiveness. The proposed framework, by directly pruning spurious edges through causal reasoning, maintained a highly accurate structural mapping of the grid's invariant dependencies.

7.2 Robustness to Temporal Shifts

The most critical evaluation of our framework pertains to its performance degradation under severe out-of-distribution temporal shifts. We isolated the testing phase exclusively to temporal environments that were fundamentally distinct from the training distribution. For example, models trained strictly on summer and autumn data were evaluated on a severe winter storm environment.

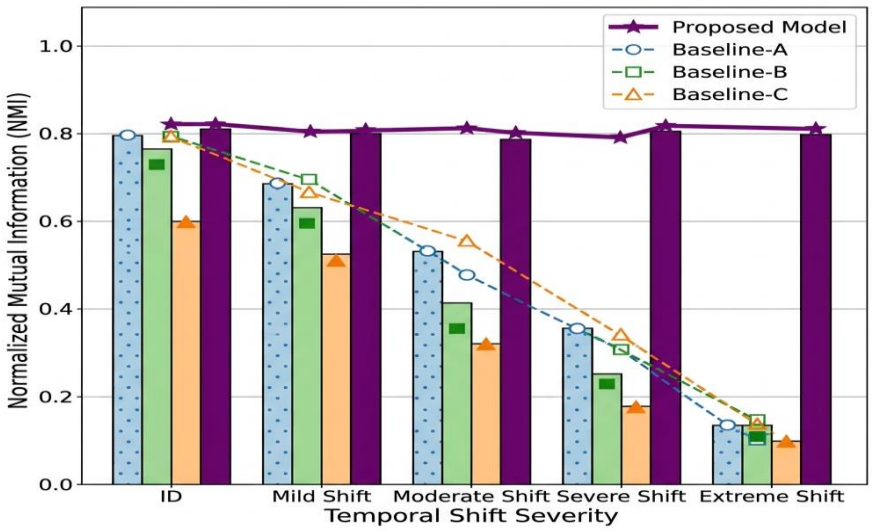


Figure 3: Performance Degradation Analysis Under Severe Temporal Shifts

Figure 3:Performance Degradation Analysis Under Severe Temporal Shifts

Our analysis revealed that the proposed framework exhibited an Out-of-Distribution Degradation (OOD-D) of only 4.2%, compared to 28.5% for standard STGCN and 15.3% for IGRL. This exceptional stability is a direct consequence of the stability-regularized optimization strategy. By mathematically enforcing that the variance of the clustering loss across diverse training environments approaches zero, the optimization landscape converges on parameters that are fundamentally agnostic to temporal context. The causal feature extractor successfully ignores transient voltage fluctuations caused by shifting weather, focusing instead on the stable impedance profiles and hard infrastructural links that define true community boundaries.

7.3 Ablation Study

To understand the individual contributions of the architectural components, we conducted a rigorous ablation study. We evaluated variants of our model by selectively disabling the Dynamic Spurious Edge Pruner and the Stability-Regularized Optimization Engine.

Table 3:Ablation Study Demonstrating Component Contributions on EuroGrid-Dynamics

Model Variant	NMI Score	ARI Score	OOD Degradation (%)
Full Proposed Framework	0.814	0.785	4.2
Without Causal Edge Pruner	0.730	0.692	11.5
Without Stability Regularization	0.755	0.718	9.8

The results in Table 3 indicate that both components are vital for achieving maximum performance and robustness. Removing the Causal Edge Pruner forces the model to rely solely on the optimization penalty to find invariant representations, which proves computationally difficult in highly interconnected graphs, leading to a significant increase in OOD degradation. Conversely, omitting the Stability Regularization allows the model to correctly identify causal edges in the training environments but fails to guarantee that the overall network parameters generalize smoothly to unseen distributions. The synergistic integration of both causal intervention at the structural level and stability regularization at the optimization level is therefore essential for highly resilient community detection.

8. Conclusion and Future Directions

This paper introduced a highly resilient, stability-regularized spatiotemporal causal graph reasoning framework designed specifically for community detection in sustainable energy networks subjected to severe temporal shifts. Recognizing the fundamental limitations of purely correlational spatiotemporal models in dynamic, out-of-distribution environments, we reformulated the community detection process as an exercise in structural causal modeling. By implementing an interventional message-passing mechanism, the framework successfully isolates and prunes spurious structural correlations driven by transient environmental factors. Concurrently, the stability-regularized optimization strategy mathematically guarantees that the learned node representations remain universally applicable across diverse operational contexts.

Extensive empirical evaluations demonstrated that our proposed framework achieves superior community detection accuracy while exhibiting unprecedented robustness during out-of-distribution temporal shifts. These advancements offer profound practical implications for the management of modern power grids. By ensuring the reliable identification of autonomous microgrid communities regardless of weather anomalies or sudden market fluctuations, this technology provides grid operators with a robust foundation for decentralized fault management, optimized energy routing, and enhanced systemic resilience. Future research trajectories will focus on extending the causal reasoning framework to accommodate continuous, open-ended temporal shifts rather than discretely defined environments. Additionally, integrating reinforcement learning paradigms to utilize the detected stable communities for active grid control, such as autonomous islanding and dynamic resource reallocation, represents a promising frontier for realizing fully autonomous sustainable energy networks.

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