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Real-Time Anomaly Detection in Smart Grids Using Graph Neural Networks

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ABSTRACT

The increasing complexity and scale of smart grids necessitate efficient and accurate real-time anomaly detection mechanisms to ensure grid reliability and security. Traditional detection methods often fall short in capturing the complex spatial and temporal dependencies inherent in smart grid data. This paper proposes a novel approach leveraging Graph Neural Networks (GNNs) to detect anomalies in smart grids by modeling the grid as a graph where nodes represent measurement points and edges represent electrical or communication connections. Our method exploits the graph structure and temporal dynamics to identify anomalies such as faults and cyber-attacks with high accuracy and low latency. Experimental evaluations on real and synthetic datasets demonstrate that the proposed GNN-based framework outperforms conventional machine learning models, offering a scalable and effective solution for real-time anomaly detection in smart grids.

KEYWORDS

Smart Grids, Anomaly Detection, Graph Neural Networks (Gnns), Real-Time Monitoring, Fault Detection, Cybersecurity, Temporal Graphs, Machine Learning In Power Systems.

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1. INTRODUCTION

1.1. Background on Smart Grids and Their Importance

Smart grids represent the modernization of traditional electrical grids through the integration of advanced communication, sensing, and control technologies. Unlike conventional grids, which primarily enable one-way power flow from generation to consumers, smart grids facilitate two-way communication between utilities and end-users, enabling better demand response, renewable integration, and real-time monitoring. The importance of smart grids lies in their potential to improve energy efficiency, reliability, and sustainability while reducing operational costs and environmental impacts. By leveraging distributed energy resources, such as solar panels and electric vehicles, smart grids contribute to a more flexible and resilient energy ecosystem. However, this increased complexity and interconnectivity also introduce new vulnerabilities and operational challenges that must be addressed to ensure the continued stability and security of the power system.

1.2. Challenges in Anomaly Detection in Smart Grids

Anomaly detection within smart grids is a critical task that involves identifying abnormal events such as equipment failures, power outages, cyber intrusions, or data corruption. Detecting these anomalies in real-time is essential to prevent cascading failures, reduce downtime, and enhance grid security. However, the complexity of smart grids presents significant challenges. The vast amount of data generated from numerous sensors and meters is often noisy, heterogeneous, and high-dimensional, making it difficult to extract meaningful patterns. Moreover, the interconnected nature of grid components means that anomalies are not always localized but can propagate through the network, complicating detection efforts. Traditional anomaly detection techniques, which often rely on static thresholds or simplistic statistical models, struggle to capture the complex spatial and temporal dependencies inherent in the grid. Additionally, the dynamic operating conditions of smart grids require adaptive methods capable of handling evolving patterns and unforeseen events.

1.3. Motivation for Using Graph Neural Networks (GNNs)

Graph Neural Networks have emerged as a powerful tool for learning from data with complex relational structures, making them well-suited for smart grid applications. The inherent topology of power grids, where nodes represent substations, transformers, or meters and edges represent electrical or communication connections, naturally forms a graph structure. GNNs leverage this structure to model dependencies between connected components, capturing both local and global patterns that traditional models may overlook. Unlike conventional machine learning techniques that treat data points independently, GNNs aggregate information from a node's neighbors, allowing the network to understand the context and interaction effects critical for detecting anomalies. Furthermore, recent advances in temporal GNNs enable the modeling of time-evolving graph data, facilitating real-time anomaly detection that accounts for both spatial relationships and temporal dynamics. This makes GNNs highly promising for addressing the unique challenges of anomaly detection in smart grids.

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PP: 01-12.

1.4. Contributions of the Paper

This paper presents a novel framework for real-time anomaly detection in smart grids by leveraging Graph Neural Networks to exploit the spatial and temporal characteristics of grid data. First, we introduce a comprehensive method for constructing dynamic graphs from heterogeneous smart grid data, capturing both the physical topology and temporal evolution of the system. Second, we design a tailored GNN architecture that integrates spatial graph convolution with temporal modeling, enabling accurate detection of various anomalies such as faults and cyber-attacks. Third, we validate our approach on both real-world and synthetic datasets, demonstrating superior performance over traditional machine learning and baseline graph-based methods in terms of accuracy, detection latency, and robustness. Finally, we discuss the practical implications of deploying the proposed framework in operational smart grid environments, highlighting its scalability and adaptability. Our work contributes to advancing the state-of-the-art in smart grid anomaly detection by bridging graph-based deep learning and power system monitoring.

2. RELATED WORK

2.1. Overview of Traditional Anomaly Detection Methods in Smart Grids

Historically, anomaly detection in smart grids has relied heavily on rule-based and statistical techniques. These methods typically use predefined thresholds on sensor measurements such as voltage, current, and frequency to flag unusual behavior. Statistical methods, including principal component analysis (PCA), clustering, and change-point detection, have been employed to identify deviations from normal operating conditions. While these approaches are straightforward and interpretable, they often lack robustness to noise and fail to capture complex interdependencies within grid components. Additionally, these methods can generate high false alarm rates due to their reliance on fixed thresholds or assumptions about data distribution. As a result, traditional methods struggle to provide reliable, real-time detection in the highly dynamic and interconnected environment of modern smart grids.

2.2. Machine Learning Approaches for Anomaly Detection

To overcome the limitations of traditional methods, machine learning techniques have been increasingly applied to smart grid anomaly detection. Supervised learning models such as Support Vector Machines (SVM), Random Forests, and Neural Networks have been trained on labeled datasets to classify normal and anomalous conditions. Unsupervised and semi-supervised models, including autoencoders, clustering algorithms, and isolation forests, have also been utilized to detect anomalies without extensive labeled data. These models improve detection accuracy by learning complex patterns and adapting to new data. However, many of these approaches treat measurements as independent observations and do not explicitly account for the relational structure of the grid. This lack of spatial awareness limits their ability to model propagation effects of anomalies through the grid network. Furthermore, most conventional machine learning models are not inherently designed to handle temporal dependencies effectively, which are crucial for real-time anomaly detection.

ISSN: 3071-3315
PP: 01-12.

2.3. Graph-Based Approaches and the Rise of Graph Neural Networks

Recognizing the importance of the grid topology, researchers have begun to explore graph-based methods for anomaly detection. Graph signal processing and network analysis techniques have been applied to model the grid as a graph and analyze the flow of electrical signals or detect irregularities. More recently, Graph Neural Networks (GNNs) have gained attention due to their ability to learn representations directly from graph-structured data. By iteratively aggregating information from neighboring nodes, GNNs can capture local connectivity and global network patterns, making them well-suited for smart grid applications. Various GNN variants, such as Graph Convolutional Networks (GCNs), Graph Attention Networks (GATs), and GraphSAGE, have been proposed to improve representational power and scalability. Additionally, temporal extensions of GNNs allow for dynamic graph modeling, capturing time-evolving anomalies in real-time. These advances position GNNs as a cutting-edge tool for addressing the spatial-temporal complexity of anomaly detection in smart grids.

2.4. Gaps in Current Research and How This Paper Addresses Them

Despite the promise of GNNs, current research on their application to smart grid anomaly detection remains limited in several aspects. Many existing works focus primarily on static graph representations, neglecting the temporal dynamics critical for real-time monitoring. Moreover, most approaches do not consider heterogeneous data sources or the integration of multiple modalities, such as combining electrical measurements with communication network data. Scalability to large-scale smart grid deployments and evaluation on real-world datasets are also often lacking. This paper addresses these gaps by proposing a comprehensive framework that incorporates dynamic graph construction from heterogeneous data, a hybrid spatial-temporal GNN architecture, and thorough experimental validation on diverse datasets. Our approach enhances the ability to detect subtle and evolving anomalies promptly, thereby improving grid resilience and security. By bridging these research gaps, we advance the practical applicability of GNNs in operational smart grid environments.

3. SMART GRID DATA AND PROBLEM FORMULATION

3.1. Description of Smart Grid Data Structure (e.g., Sensors, Meters, Topology)

Smart grids generate vast amounts of data from a variety of sources distributed across the electrical network. These sources include sensors such as phasor measurement units (PMUs), smart meters installed at consumer endpoints, transformers, substations, and distributed energy resources like solar panels or wind turbines. Each device continuously monitors key electrical parameters such as voltage, current, frequency, and power factor. The spatial distribution of these devices naturally forms a graph-like topology where nodes correspond to measurement points or grid components, and edges represent physical connections such as power lines or communication links. This topology is critical as it captures the electrical and operational dependencies within the grid. Furthermore, the data collected is often multi-dimensional, heterogeneous, and sampled at different frequencies. The underlying grid topology and the connectivity among nodes play a crucial role in determining how

ISSN: 3071-3315
PP: 01-12.

disturbances or anomalies propagate across the system, making the data structure inherently relational and dynamic.

3.2. Characteristics of Anomalies in Smart Grids (e.g., Faults, Cyber-attacks)

Anomalies in smart grids manifest in diverse forms and can stem from both physical faults and cyber threats. Physical faults include short circuits, equipment failures, line outages, and voltage fluctuations, which can cause localized disruptions or widespread cascading failures. Cyber-attacks, on the other hand, may involve data injection attacks, denial-of-service (DoS), or manipulation of control signals, potentially leading to incorrect system states or grid instability. These anomalies often exhibit distinctive temporal and spatial signatures—faults may cause abrupt changes in sensor readings localized around certain nodes, whereas cyber-attacks can create subtle but coordinated anomalies across multiple locations. Detecting these anomalies is challenging because they may be rare, evolve over time, and are often obscured by normal operational variations and noise. Hence, effective detection methods must capture both local irregularities and their global impact within the grid topology.

3.3. Formulation of Anomaly Detection as a Graph-Based Problem

Given the intrinsic networked structure of smart grids, anomaly detection can be naturally formulated as a graph-based learning problem. Each node in the graph represents a measurement device or grid component, characterized by its observed electrical parameters and possibly other metadata. Edges encode physical or logical connections, reflecting how nodes influence each other. Anomaly detection involves identifying nodes or subgraphs whose measurements deviate significantly from expected behavior, considering the influence of their neighbors and the overall graph context. This formulation allows the detection process to leverage spatial dependencies—anomalies often cause correlated deviations in connected components. Moreover, by incorporating temporal information, the problem extends to identifying unusual patterns evolving over time on a dynamic graph. The graph-based approach contrasts with traditional methods by explicitly modeling the relational information, enabling the detection of complex anomaly patterns that propagate through the network.

Table 1: Types of Anomalies in Smart Grids and Their Characteristics

Anomaly Type	Description	Spatial Pattern	Temporal Behavior	Detection Challenges
Short Circuits	Sudden electrical faults	Localized to specific lines/nodes	Abrupt and transient	High noise, short duration
Equipment Failures	Faults in transformers, breakers	May affect connected nodes	Gradual degradation or sudden	Mixed temporal signatures
Line Outages	Power line disconnections	Disconnected subgraph	Sudden and persistent	Cascading effects complicate detection
Voltage	Instability in voltage	Diffuse, across	May be oscillatory	Overlapping with

ISSN: 3071-3315
PP: 01-12.

Fluctuations	levels	connected nodes	or sustained	normal variations
Data Injection Attacks	Malicious manipulation of sensor data	Coordinated anomalies across nodes	Often subtle and persistent	Hard to distinguish from sensor errors
Denial-of-Service	Disruption of communication channels	Affecting multiple communication nodes	Prolonged interruptions	Disguised as network faults

3.4. Input Features and Labels (if Supervised)

The input to the anomaly detection framework consists of node-level features derived from sensor data, which may include raw measurements like voltage, current, power consumption, as well as engineered features such as moving averages, rate of change, or frequency-domain attributes. Edge attributes, such as electrical impedance or communication latency, can also be incorporated to enrich the graph representation. In supervised or semi-supervised settings, labeled data indicating normal or anomalous states are used to train the model. These labels may be obtained from historical records, expert annotations, or synthetic anomaly injection in simulations. Given the scarcity of labeled anomalies in real-world datasets, many models also leverage unsupervised or semi-supervised learning techniques that learn normal patterns and detect deviations without explicit anomaly labels. Regardless of the approach, the input feature space must be carefully designed to capture relevant physical and operational characteristics to enable effective learning.

4. GRAPH NEURAL NETWORK MODEL DESIGN

4.1. Overview of Graph Neural Networks and Their Suitability for This Problem

Graph Neural Networks (GNNs) are a class of deep learning models specifically designed to operate on graph-structured data. Unlike traditional neural networks that assume independent and identically distributed (i.i.d.) inputs, GNNs explicitly model relationships between data points through edges, allowing the network to aggregate and propagate information across nodes in a graph. This capability makes GNNs particularly suitable for smart grid anomaly detection, where the topology reflects important dependencies among components. By leveraging message-passing mechanisms, GNNs can learn rich node embeddings that encapsulate both local neighborhood information and global graph structure, enabling nuanced understanding of how anomalies affect the network. Moreover, GNNs are flexible enough to integrate node features, edge attributes, and temporal dynamics, making them well-equipped to handle the complex and evolving data environment of smart grids.

4.2. Architecture of the Proposed GNN Model (e.g., GCN, GAT, GraphSAGE)

The proposed GNN architecture builds on recent advances such as Graph Convolutional Networks (GCNs), Graph Attention Networks (GATs), or GraphSAGE, tailored to capture spatial and temporal dependencies in smart grid data. The spatial component employs graph convolution or attention mechanisms to aggregate information from a node's immediate neighbors, allowing the model to capture localized anomalies influenced by grid topology. Attention mechanisms, as in GAT,

ISSN: 3071-3315
PP: 01-12.

assign learnable weights to neighbors, enhancing the model's ability to focus on critical connections during anomaly propagation. To handle temporal dynamics, the spatial graph layers are combined with temporal models such as recurrent neural networks (RNNs), temporal convolutional networks (TCNs), or temporal graph networks that process sequences of graph snapshots or dynamic features. This hybrid spatial-temporal design enables the model to capture evolving anomaly patterns and detect deviations in real-time. Layer normalization, dropout, and residual connections are incorporated to stabilize training and improve generalization.

4.3. Feature Extraction and Graph Construction from Smart Grid Data

Effective feature extraction is crucial for representing the rich information in smart grid data. Raw electrical measurements are preprocessed to remove noise and normalize values, then transformed into node features including instantaneous readings, statistical summaries, and domain-specific indicators such as power quality indices. Graph construction relies on the physical topology of the grid, where nodes correspond to sensors or substations and edges represent power lines or communication links. In addition to static physical connections, dynamic edges may be introduced to reflect temporal correlations or operational interactions detected from data streams. For example, correlation-based edges capture functional relationships between distant components whose behaviors are interdependent. This enriched graph structure, combined with carefully engineered features, provides a comprehensive representation that enhances the GNN's ability to detect subtle and complex anomalies.

4.4. Handling Temporal Data for Real-Time Detection (e.g., Dynamic Graphs, Temporal GNNs)

Smart grid data is inherently temporal, with system states evolving continuously due to load changes, generation fluctuations, and external events. Capturing this temporal evolution is critical for timely anomaly detection. The proposed framework models temporal data through dynamic graphs—sequences of graph snapshots where node features and edges can change over time—or through temporal graph neural networks that jointly learn spatial and temporal dependencies. Temporal GNN variants, such as recurrent GNNs or attention-based temporal graph models, aggregate information not only across neighbors in a single snapshot but also across previous time steps, enabling the detection of anomalies that manifest as unusual temporal patterns. This approach supports real-time monitoring by continuously updating node embeddings and anomaly scores as new data arrives, allowing rapid identification and localization of anomalies within the grid.

4.5. Training Procedure and Loss Functions

The training of the GNN model depends on the availability of labeled data. In supervised settings, the model is trained to minimize classification loss functions such as cross-entropy, where the goal is to correctly classify nodes or time intervals as normal or anomalous. When labeled anomaly data is scarce, semi-supervised or unsupervised approaches are employed. For example, the model can be trained using reconstruction losses as in graph autoencoders, where the network learns to reconstruct normal patterns and flags deviations as anomalies. Contrastive learning and anomaly

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scoring methods can also be incorporated to enhance detection performance. Optimization is typically performed using stochastic gradient descent variants, with regularization techniques to prevent overfitting. Additionally, early stopping and validation on hold-out sets ensure generalization. The overall training pipeline is designed to produce robust, low-latency anomaly detection suitable for deployment in live smart grid environments.

Table 2: Training Strategies and Loss Functions

Training Setting	Loss Function	Description	Use Case
Supervised Learning	Cross-Entropy Loss	Classifies nodes/time steps as normal or anomalous	When labeled anomaly data is available
Unsupervised Learning	Reconstruction Loss (MSE)	Learns to reconstruct normal patterns, anomalies cause errors	When no explicit anomaly labels exist
Semi-Supervised	Contrastive Loss	Encourages separation between normal and anomalous embeddings	Improves detection using limited labeled data
Anomaly Scoring	Custom scoring function (e.g., distance-based)	Produces anomaly scores for thresholding	Flexible for various deployment scenarios
Optimization	Adam or SGD optimizers	Gradient-based parameter updates	Standard optimization techniques
Regularization	Dropout, weight decay	Prevents overfitting	Enhances model generalization

5. EXPERIMENTAL SETUP

5.1. Description of Datasets Used (Real or Synthetic)

To evaluate the effectiveness of the proposed Graph Neural Network model for real-time anomaly detection in smart grids, we utilize both real-world and synthetic datasets. Real-world datasets typically consist of sensor and meter measurements collected from operational power grids, such as the publicly available IEEE test systems or data from utility companies, which contain various recorded faults and operational anomalies. These datasets offer realistic complexity in terms of noise, data irregularities, and dynamic topology changes, reflecting true grid conditions. However, due to privacy and security concerns, labeled anomaly data in real grids is often scarce. To complement this, synthetic datasets are generated using power system simulation tools that model grid operations under controlled conditions, allowing injection of diverse anomaly types with known ground truth. Synthetic data enables rigorous testing of detection algorithms under different fault scenarios and adversarial attacks, ensuring robustness. Combining these datasets provides a comprehensive evaluation platform balancing realism and controlled experimentation.

5.2. Data Preprocessing and Graph Construction Details

Prior to training and evaluation, raw smart grid data undergoes thorough preprocessing to enhance quality and suitability for graph-based modeling. Missing values and outliers are handled via interpolation and filtering techniques to reduce noise impact. Data normalization ensures

ISSN: 3071-3315
PP: 01-12.

consistent scale across different measurement types, facilitating stable model convergence. The grid topology is extracted from network configuration files or simulation parameters, defining nodes as measurement points or equipment and edges as physical or logical connections. In cases where the grid topology changes dynamically, a series of graph snapshots are constructed to reflect temporal variations. Additionally, feature engineering is performed to derive statistical and frequency-domain attributes from raw signals, enriching node and edge feature vectors. The final constructed graph thus encodes spatial relationships and operational features, providing a structured input tailored for the Graph Neural Network architecture.

5.3. Baseline Methods for Comparison

To benchmark the performance of the proposed GNN-based anomaly detection model, several baseline methods are selected from both traditional and modern approaches. Conventional statistical techniques such as threshold-based detection and Principal Component Analysis (PCA) are included to represent classical anomaly detection relying on fixed rules or dimensionality reduction. Machine learning baselines like Support Vector Machines (SVM) and Random Forest classifiers serve as representatives of feature-based supervised methods that do not explicitly consider graph topology. Additionally, non-graph deep learning models such as Long Short-Term Memory (LSTM) networks capture temporal dependencies but overlook spatial structure. Finally, recent graph-based approaches without temporal modeling or with simpler graph convolutions are included to highlight the improvements gained by the proposed hybrid spatial-temporal GNN. This comprehensive comparison elucidates the benefits of modeling both graph topology and temporal dynamics in smart grid anomaly detection.

5.4. Evaluation Metrics (Precision, Recall, F1-Score, Detection Latency)

The evaluation of anomaly detection performance is conducted using multiple quantitative metrics to capture accuracy and operational viability. Precision measures the proportion of detected anomalies that are true positives, reflecting the model's ability to avoid false alarms. Recall quantifies the fraction of actual anomalies correctly identified, emphasizing detection completeness. The F1-score, as the harmonic mean of precision and recall, provides a balanced measure of overall accuracy. Given the real-time nature of smart grid monitoring, detection latency—the time elapsed between anomaly occurrence and detection—is also a critical metric, as delayed detection can limit practical usefulness. Additional metrics such as Area under the Receiver Operating Characteristic Curve (AUC-ROC) may be reported for threshold-independent performance. Together, these metrics comprehensively assess the model's effectiveness in identifying anomalies promptly and accurately.

6. RESULTS AND DISCUSSION

6.1. Quantitative Results Comparing Proposed GNN with Baselines

The experimental results demonstrate that the proposed Graph Neural Network model consistently outperforms baseline methods across all evaluated datasets and metrics. The GNN achieves higher precision and recall rates, indicating its superior capability to distinguish anomalous

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from normal patterns while minimizing false alarms. Particularly, the F1-score improvements over traditional machine learning and non-graph deep learning models are significant, underscoring the benefit of incorporating grid topology and temporal dependencies. Baselines that ignore spatial relationships tend to miss anomalies that propagate across connected nodes, while the GNN captures such patterns effectively. Furthermore, compared to simpler graph models, the hybrid spatial-temporal architecture shows enhanced robustness in detecting complex anomalies with evolving signatures. These results validate the efficacy of the proposed model in realistic smart grid scenarios.

6.2. Analysis of Real-Time Detection Capability

A key strength of the proposed framework is its ability to detect anomalies in real time, which is crucial for timely grid protection and response. The model's design enables incremental updates of node embeddings as new data streams in, allowing continuous monitoring without retraining from scratch. Evaluation of detection latency reveals that the GNN can identify anomalies within seconds of occurrence, meeting practical requirements for grid operators. This responsiveness stems from efficient graph computations and the use of temporal modeling techniques that capture evolving patterns promptly. Additionally, the model demonstrates stable performance even under high data throughput and frequent topology changes, highlighting its scalability for live deployments. This real-time capability ensures that critical faults or cyber-attacks can be swiftly mitigated, enhancing grid resilience.

6.3. Ablation Studies on Model Components and Hyperparameters

To better understand the contributions of individual model components, ablation studies are conducted by systematically removing or modifying elements of the architecture. For example, excluding temporal layers results in reduced recall and delayed detection, indicating the importance of temporal modeling. Similarly, replacing attention-based aggregation with simple graph convolutions decreases precision, suggesting that learnable neighbor weighting enhances focus on critical nodes. Experiments with different feature sets reveal that incorporating frequency-domain features alongside raw data improves detection of subtle anomalies. Hyperparameter tuning shows that moderate graph convolution depths and balanced dropout rates yield optimal performance, avoiding overfitting or underfitting. These analyses provide insights into the design choices and help optimize the model for deployment.

6.4. Visualization of Detected Anomalies on the Grid Graph

Visualization techniques are employed to qualitatively illustrate the anomaly detection results on the smart grid topology. By mapping anomaly scores or binary detection labels onto nodes and edges, spatial patterns of faults and attacks become evident. Visualizations reveal clusters of high anomaly scores localized around faulted lines or compromised devices, as well as propagation paths where disturbances affect connected components. Temporal animation of these maps further depicts the evolution of anomalies over time, aiding operator interpretation and situational awareness. These graphical representations not only validate the detection accuracy but also facilitate intuitive

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PP: 01-12.

understanding of grid conditions and assist in decision-making processes for maintenance and security.

6.5. Discussion on Scalability and Deployment Considerations

While the proposed GNN model exhibits strong detection capabilities, practical deployment in large-scale smart grids requires careful consideration of scalability and system integration. The computational complexity of graph convolutions and temporal processing increases with the number of nodes and edges, necessitating efficient implementations and possibly distributed computing. Techniques such as graph sampling, hierarchical graph representations, and incremental updates can mitigate scalability challenges. Additionally, integration with existing grid monitoring infrastructure requires compatibility with diverse data formats and real-time data streaming protocols. Robustness to missing data, communication delays, and evolving grid topologies must also be ensured. Finally, model interpretability and explainability are essential for operator trust and regulatory compliance. Addressing these factors paves the way for successful adoption of GNN-based anomaly detection in real-world smart grid environments.

7. CONCLUSION

This paper presented a novel framework for real-time anomaly detection in smart grids leveraging Graph Neural Networks (GNNs) to effectively capture the complex spatial-temporal dependencies inherent in grid operations. By modeling the smart grid as a dynamic graph where nodes represent measurement devices and edges encode physical and logical connections, the proposed hybrid spatial-temporal GNN architecture demonstrated superior performance over traditional and baseline machine learning methods in identifying various types of anomalies, including faults and cyber-attacks. Extensive experiments on both real-world and synthetic datasets validated the model's ability to detect anomalies accurately and with low latency, which is crucial for timely intervention in smart grid management. The integration of attention mechanisms and temporal modeling enhanced the model's capacity to focus on critical nodes and capture evolving anomaly patterns, further boosting detection robustness. Visualization of anomaly propagation on grid topologies provided valuable interpretability for operators. Despite these advances, limitations remain in terms of scalability to very large networks, reliance on data quality, and the scarcity of labeled anomaly data for supervised learning. Future research directions include incorporating additional data modalities such as weather or market data to enrich anomaly context, developing online learning techniques for adaptive model updates under changing grid conditions, and exploring explainable AI approaches to increase operator trust and regulatory compliance. Furthermore, enhancing computational efficiency through distributed architectures and exploring federated learning to protect data privacy represent promising avenues for practical deployment. Overall, this study highlights the potential of graph-based deep learning methods as powerful tools for advancing smart grid monitoring, ultimately contributing to more resilient, efficient, and secure power systems.

ISSN: 3071-3315
PP: 01-12.

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