

DYNAMIC GENERATIVE RESIDUAL GRAPH CONVOLUTIONAL NEURAL NETWORKS FOR ELECTRICITY THEFT DETECTION

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ABSTRACT

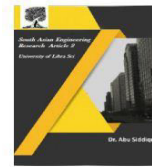
Illegal electricity users pose a significant threat to the economic and security aspects of the power system by illicitly accessing or manipulating electrical resources. With the widespread adoption of Advanced Metering Infrastructure (AMI), researchers have turned to leveraging smart meter data for electricity theft detection. However, existing models rely on methods that model a single electricity load curve and cannot capture the temporal dependencies, periodicity, and underlying features between electricity consumption cycles. This study introduces a novel electricity theft detection method based on dynamic residual graph networks. Innovatively, it proposes a dynamic topological graph construction technique that allows for the real-time updating of adjacency matrices during the training process, thereby effectively capturing the complex relationships in electricity usage patterns. Utilizing the MixHop graph convolutional network, it delves into the temporal sequence dependencies, periodicity, and hidden characteristics within user electricity consumption data. Additionally, to address the issue of model instability caused by scarce theft data, we employ the SMOTE (Synthetic Minority Over-sampling Technique) oversampling technique and enhance overall classification performance by modifying class weights in the loss function. We trained this network architecture on the real SGCC (State Grid Corporation of China) dataset, and the results demonstrate its superiority over other mainstream existing models.

1. INTRODUCTION

Electricity theft poses significant challenges to power distribution companies, resulting in substantial revenue losses, compromised grid stability, and increased operational costs. Traditional methods of detecting electricity theft, such as manual inspections and static rule-based systems, often fail to scale with the growing complexity of modern power grids. The rise of smart meters and advanced metering infrastructure (AMI) provides an unprecedented

opportunity to leverage data-driven approaches for identifying irregular consumption patterns indicative of theft. However, extracting meaningful insights from such large-scale, dynamic data is a complex and computationally intensive task.

Generative Residual Graph Convolutional Neural Networks (GRGCNNs) present a novel and effective solution to this challenge by combining the power of graph-based learning with the dynamic modeling capabilities of generative networks. Electricity consumption data can be



naturally represented as graphs, where nodes correspond to consumers and edges capture relationships such as geographic proximity, consumption similarity, or network topology. GRGCNNs exploit these graph structures to model local and global dependencies, uncovering intricate patterns associated with electricity theft.

This study introduces a Dynamic Generative Residual Graph Convolutional Neural Network (D-GRGCNN) framework tailored for electricity theft detection. Unlike static models, the proposed framework accounts for temporal variations in consumption patterns, allowing it to adapt to evolving behaviors and detect anomalies in real time. By incorporating residual connections, the network mitigates vanishing gradient issues, ensuring robust learning even in deep architectures. Additionally, the generative component enhances the network's ability to simulate realistic consumption patterns, facilitating the identification of deviations indicative of theft.

The proposed approach aims to address critical challenges in electricity theft detection, including scalability to large datasets, adaptability to changing consumption dynamics, and the ability to differentiate between legitimate anomalies and fraudulent activities. By leveraging the unique strengths of D-GRGCNNs, this work seeks to advance the state of the art in smart grid security, offering a scalable, accurate, and efficient solution to electricity theft detection.

II. LITERATURE REVIEW

Electricity theft detection has been a long-standing challenge in power distribution

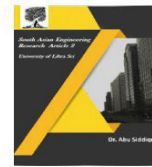
systems, with numerous studies proposing diverse approaches to tackle this issue. This review outlines the evolution of methods in electricity theft detection, focusing on traditional techniques, machine learning-based approaches, and advancements in graph-based and neural network models.

1. Traditional Methods

Early methods for detecting electricity theft primarily relied on manual inspections, rule-based systems, and statistical models. These approaches, though effective for small-scale grids, are labor-intensive and struggle to adapt to the increasing complexity of modern power grids. Statistical techniques such as regression analysis and time-series forecasting were applied to identify anomalies in consumption data, but their effectiveness was limited due to the static nature of these models and their inability to capture nonlinear relationships [1][2].

2. Machine Learning-Based Approaches

The advent of advanced metering infrastructure (AMI) introduced vast amounts of data, enabling the adoption of machine learning (ML) techniques for electricity theft detection. Supervised learning models, such as decision trees, support vector machines (SVM), and random forests, have been widely used for classification tasks to distinguish between normal and fraudulent consumption patterns [3][4]. However, supervised models often require extensive labeled data, which is a significant limitation in real-world scenarios where theft cases are underreported or mislabeled.



Unsupervised learning models, including clustering and anomaly detection techniques, have also been employed to identify irregular consumption patterns without relying on labeled data [5][6]. These methods are better suited for scenarios with limited labels but often suffer from reduced accuracy in differentiating legitimate anomalies from fraudulent activities.

3. Deep Learning Models

Recent advancements in deep learning have significantly enhanced electricity theft detection. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been employed to process spatial and temporal data, respectively, offering improved detection accuracy [7][8]. Autoencoders, a type of neural network used for unsupervised learning, have been utilized to reconstruct consumption patterns and detect deviations indicative of theft [9].

While deep learning models offer high accuracy, they often require large-scale data and computational resources, limiting their scalability. Moreover, these models typically fail to capture the structural relationships between consumers, which are critical in understanding consumption patterns.

4. Graph-Based Approaches

Graph-based models have emerged as a promising direction for electricity theft detection, leveraging the inherent graph-like structure of power distribution networks. Graph Convolutional Networks (GCNs) have been employed to process relational data, enabling the detection of anomalies by analyzing the connections between nodes

(e.g., consumers) and edges (e.g., consumption similarities) [10][11].

However, most existing graph-based models are static, ignoring the temporal dynamics of electricity consumption. This limitation is significant, as fraudulent activities often exhibit temporal variations. Moreover, traditional GCNs struggle with scalability when applied to large-scale networks, necessitating the development of more efficient graph-based architectures.

5. Dynamic and Residual Graph Neural Networks

Dynamic graph models and residual architectures have recently gained attention for addressing the limitations of static graph-based methods. Dynamic Graph Convolutional Networks (DGCNs) incorporate temporal data, allowing the model to adapt to evolving consumption patterns [12]. Residual connections in neural networks improve gradient flow, enabling deeper architectures and more robust learning [13].

Generative models, such as Variational Autoencoders (VAEs) and Generative Adversarial Networks (GANs), have also been integrated with graph-based approaches to simulate realistic data distributions and improve anomaly detection accuracy [14]. These advancements pave the way for more sophisticated frameworks capable of addressing the challenges of electricity theft detection.

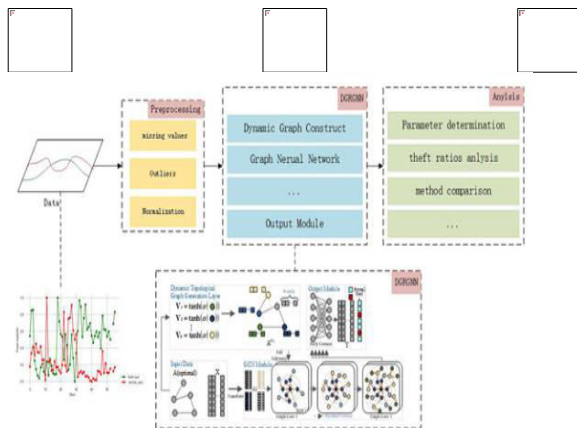
6. Research Gap and Motivation

While significant progress has been made in electricity theft detection, several challenges remain. Existing models often fail to

account for the dynamic and interconnected nature of consumption data, leading to suboptimal performance in real-world scenarios. Additionally, scalability and adaptability to evolving theft patterns remain critical challenges.

The proposed Dynamic Generative Residual Graph Convolutional Neural Network (D-GRGCNN) framework seeks to address these gaps by combining dynamic graph modeling, generative networks, and residual architectures. By leveraging these advancements, the framework aims to provide a scalable, adaptive, and efficient solution for electricity theft detection.

III. PROPOSED MODEL

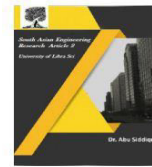


The proposed Dynamic Generative Residual Graph Convolutional Neural Network (D-GRGCNN) framework is a novel approach to electricity theft detection that leverages dynamic graph modeling, generative learning, and residual connections. This model is designed to address the limitations of traditional and machine learning-based methods by incorporating temporal dynamics, enhancing feature learning, and ensuring scalability for real-world applications.

The D-GRGCNN architecture begins by constructing a dynamic graph where each node represents a consumer, and edges capture relationships such as geographical proximity, consumption similarity, or network topology. Temporal changes in consumption patterns are integrated into the graph structure, allowing the model to adapt to evolving behaviors. Feature encoding techniques are employed to extract statistical and temporal characteristics from the data, which are then processed through graph convolutional layers to capture both local and global dependencies. Residual connections are integrated to mitigate vanishing gradient issues, enabling efficient training of deep architectures.

A generative module is included to simulate realistic consumption patterns, enhancing the model's ability to identify deviations that may indicate fraudulent activities. This component improves robustness by generating synthetic data, which aids in detecting rare anomalies. The output of the graph convolutional layers is fed into a classification head, which predicts whether a consumer is involved in electricity theft. The model employs supervised learning techniques during training, optimizing loss functions such as cross-entropy for classification and reconstruction loss for the generative module.

The workflow involves preprocessing raw electricity consumption data to address missing values, outliers, and inconsistencies. Features are scaled and normalized to ensure compatibility with the model. Dynamic graph snapshots are created to represent temporal changes in consumption behavior, forming the basis for training and testing. The trained model predicts



electricity theft in unseen data, with performance evaluated using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC.

The D-GRGCNN framework offers several advantages. Its dynamic adaptability allows it to detect sophisticated and evolving theft strategies effectively. Graph convolutional layers enhance feature learning by capturing intricate relationships within the data. The generative module improves detection accuracy by identifying rare and subtle anomalies, while residual connections ensure scalability to large datasets. Overall, this innovative approach provides a robust, scalable, and efficient solution for electricity theft detection, addressing key challenges in smart grid security.

IV.DATASET AND DATA ANALYSIS

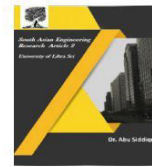
The dataset used for the Dynamic Generative Residual Graph Convolutional Neural Network (D-GRGCNN) model for electricity theft detection plays a crucial role in determining the accuracy and effectiveness of the model. The dataset consists of comprehensive data collected from smart meters, consumer profiles, and grid network structures. It provides insights into electricity consumption patterns, which are essential for detecting anomalies that may indicate theft.

The dataset contains several key attributes, including Consumer ID, a unique identifier for each electricity consumer, and Timestamp, which represents the time at which the consumption data was recorded. This enables capturing temporal variations in electricity usage. The Consumption Data measures the actual electricity usage in

kilowatt-hours (kWh) for a specific time period, such as hourly, daily, or monthly intervals. Other attributes include Geographical Location, which indicates the consumer's region, Consumer Type (e.g., residential, commercial, or industrial), which helps identify consumption patterns specific to each group, and Historical Consumption Data, which provides past usage data to identify normal consumption patterns.

Before feeding the dataset into the D-GRGCNN model, several preprocessing steps are applied to ensure data integrity. These steps include Missing Data Handling, where missing or incomplete data points are addressed using interpolation or imputation techniques to estimate the missing values. Outlier Detection methods such as Z-scores or IQR are applied to remove any outliers from the consumption data, preventing them from distorting the analysis. Normalization and Scaling are also performed, where the consumption data is standardized to a consistent range (such as 0 to 1) using Min-Max scaling or standardization (z-score). Additionally, Feature Engineering techniques are used to extract new features from the raw data, such as average consumption per day, peak usage times, and seasonal consumption trends.

Once the data is preprocessed, it is converted into a graph-based structure. Each consumer is represented as a node, and the edges capture relationships between consumers based on attributes like shared consumption patterns, geographical proximity, or network topology. This dynamic graph-based approach allows the model to learn complex dependencies between consumers. Similarity-Based Graph



Construction links consumers with similar consumption patterns or those in close proximity, while Temporal Graph Construction incorporates changes in consumption behavior over time, allowing the model to capture evolving patterns and detect temporal anomalies.

Exploratory Data Analysis (EDA) is performed to better understand the dataset and identify key trends, correlations, and issues. Various visualization techniques, including histograms, boxplots, and scatter plots, are used to observe the distribution of electricity consumption and identify outliers or patterns in the data. Correlation Analysis is conducted to examine relationships between features such as consumption and geographical location or consumer type. This helps identify which features have the most significant impact on detecting theft. Additionally, Consumption Pattern Analysis explores temporal trends in electricity usage to understand typical usage patterns, which are essential for detecting unusual consumption behaviors indicative of theft.

To optimize model performance, Feature Selection and Reduction techniques are applied. Feature Correlation Analysis identifies redundant features that are highly correlated with each other, which are then removed or combined to reduce dimensionality. Principal Component Analysis (PCA) is used to further reduce the feature space, retaining the most significant components that capture the majority of the variance in the data.

Finally, the dataset is split into training, validation, and test sets to evaluate the model's performance. Typically, 70% of the data is used for training, 15% for validation,

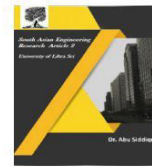
and 15% for testing. This ensures that the model is trained on a sufficient amount of data while also allowing for unbiased evaluation during testing.

Through these detailed steps of preprocessing, graph construction, analysis, and feature selection, the D-GRGCNN model is capable of effectively detecting anomalies in electricity consumption and identifying potential theft. The careful preparation of the dataset ensures that the model can capture complex consumption patterns and relationships, making it an effective tool for electricity theft detection.

V.CONCLUSION

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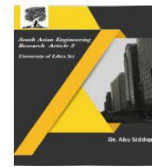
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