A Graph Neural Network Multi-Task Learning-Based Approach for Detection and Localization of Cyberattacks in Smart Grids

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Introduction

- Smart grids rely on measurement data to ensure proper supply and demand management and system stability.
- The cyber-physical nature of smart power grids makes them vulnerable to false data injection attacks (FDIAs) where malicious entities manipulate power system measurement data.
- Such attacks can bypass traditional bad data detectors, which lead to making wrong decisions and may result in system instability.
- Existing FDIA detectors perform one of two tasks, detection or localization and offer limited detection performance.

Contributions

We propose a multi-task learning graph neural network (GNN) detector that offers the following:

- It performs two tasks: graph classification to determine the system status (under attack/normal operation) and node classification to localize the attack (the attacked node). This is performed efficiently using a three-stage GNN with joint, task-specific, and fusing layers.
- It captures the complex patterns of measurement data and spatial aspects of power grids using convolutional Chebyshev graph layers. It is examined against FDIAs on IEEE 14, 39, and 118-bus systems.
- It makes decisions based on features learned from both tasks and offers enhanced system status identification and attack localization with detection rates (DRs) of 98.5-100% and 99-100%, respectively.

System Modeling

Power System Modeling

- Modeled using an undirected graph where buses and power lines are represented by nodes and edges, respectively.
- **Spatial aspects:** we adopt IEEE 14, 39, and 118-bus systems.
- **Temporal aspects:** electric power injections and flows.
- Power flow analysis using Newton's method is carried out to determine the real and reactive power flows in the system.

Benign Samples

- Measurement data during normal operation.
- Include 96 daily power dynamics timestamps over six months.

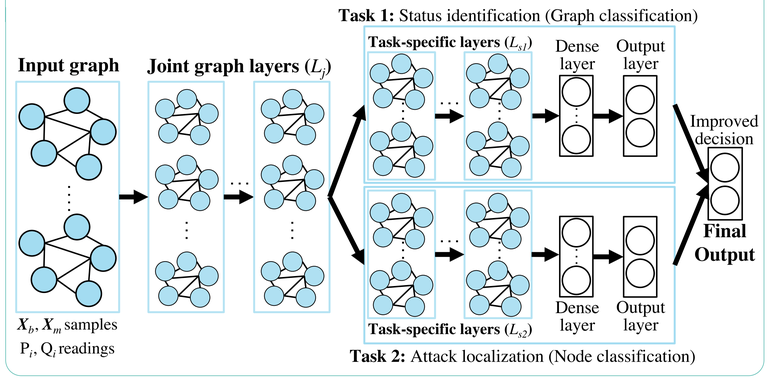
Attack Data

- We adopt three FDIA functions that are used to mimic the power system's operation under attack.
- **Direct attack:** randomly applies bounded perturbations into samples.
- **Replay attack:** uses a false repetition of a reading from a previous timestamp to replace the reading of a current timestamp.
- **General attack: g**enerates malicious samples using a range of true measurement values.
- We use an equal number of benign and malicious samples.

Model Architecture

We propose a multi-task learning-based approach that performs system status identification and attack localization simultaneously using a GNN with stacked convolutional Chebyshev graph layers. The model is divided into three stages:

- The first stage presents the joint graph layers that are used to extract preliminary features from the data that are needed for both tasks.
- The second stage consists of task-specific graph layers that are designated to capture relevant features for a specific task.
- The third stage is the final decision of the two tasks based on previously learned features, which boosts the performance.
- We adopt such a structure to calculate the initial weights and parameters (shared parameters) once, which are then transmitted to the next stage for further processing.



Experimental Results

- We examine task-specific benchmark detectors that perform tasks separately including auto regressive integrated moving average (ARIMA), support vector machine (SVM), multi-layer perceptron (MLP), recurrent neural network (RNN), convolutional neural network (CNN), autoencoder (AE), convolutional graph neural network (CGNN), and graph AE (GAE).

Task 1 (system status identification)

- The proposed multi-task GNN detector offers superior DR by 23.2 - 30.1%, 15 - 21.2%, and 9.4 - 11.5% compared to shallow, deep, and graph-based benchmarks, respectively.

Task 2 (attack localization)

- The proposed multi-task GNN detector offers superior DR by 20.2 - 26.6%, 9.6 - 17.3%, and 4.1 - 5.8% compared to shallow, deep, and graph-based benchmarks, respectively.

Conclusions

- Smart power grids are subject to cyber false data injection attacks (FDIAs) where detection and localization of attacks are critical.
- The proposed detector performs both tasks with improved detection performance compared to task-specific detectors.
- The proposed there-stage structure helped in boosting the detection performance since the final decision is based on the outputs of the two tasks (graph and node classification).

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