A Synopsis Report

On

SMART GRID PROTECTION FROM CYBER THREATS USING MACHINE LEARNING ALGORITHMS

A Project Report Submitted
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1. Introduction

With the increasing integration of advanced communication infrastructure, real-time monitoring, and automation, modern electrical networks have evolved into **Cyber-Physical Smart Grids (CPSG)**. While this digital transformation enhances flexibility and efficiency, it simultaneously exposes power systems to a broad range of **cyberattacks**, especially at critical control and measurement points such as AGC loops, substations, PLCs, and SCADA systems.

Cyberattacks such as **False Data Injection (FDI)**, **Denial of Service (DoS)**, **Replay Attacks**, and **Coordinated Multiclass Attacks** aim to mislead the control center or degrade stability. Traditional rule-based protection schemes are inadequate against these intelligent, dynamic threats.

To address these challenges, this project proposes a **Machine Learning–based Intrusion Detection and Protection Framework** for smart grids. A **MATLAB Simulink-based 9-Bus Power System** is integrated with **AI/ML algorithms** such as Spatio-Temporal Graph Neural Networks (ST-GNN), Deep Learning classifiers, and multiclass detection models. The model identifies cyber anomalies in real time and initiates protection actions (e.g., breaker tripping) through a simulated **Modbus–SCADA communication layer**.

Objectives

1. To design a MATLAB Simulink-based **9-Bus Cyber-Physical Smart Grid Testbed** for generating voltage-current time-series data.
2. To simulate **cyberattacks** including FDI, DoS, and Replay through MATLAB Function-based attack injection.
3. To perform **multi-class attack detection** using advanced Machine Learning algorithms.
4. To develop a **graph-based feature extraction model** for capturing spatial and temporal dependencies of power system measurements.
5. To integrate a **SCADA–Modbus layer** for real-time model communication and automatic protection control.
6. To implement a **virtual protection mechanism** (breaker operation) triggered by machine learning–based anomaly alerts.
7. To evaluate model performance using accuracy, confusion matrix, and response time.

2. Literature Review

2.1 Cyber-Physical Fusion for GNN-Based Attack Detection

The paper *"Cyber-Physical Fusion for GNN-Based Attack Detection in Smart Power Grids"* presents a hybrid GNN-based approach to model both electrical topology and cyber dependencies. It highlights the importance of **graph representation learning** for attack detection and shows that GNNs outperform traditional ML models in detecting complex cyber-physical intrusions. This study supports our choice of using **graph-based machine learning** for anomaly detection in smart grids.

2.2 Cyber-Physical Power System: Modeling and Cyber Security Applications

The paper provides a detailed review on modeling and simulation techniques for CPSG systems. It emphasizes the need for integrated testbeds that combine **power system simulation, cyber network emulation, and control logic**. The authors highlight vulnerabilities in SCADA, PLCs, and communication channels. This paper validates our approach of creating a **Simulink–SCADA integrated testbed** for cyberattack experimentation.

2.3 Deep Learning-Based Multiclass Attacks Detection in AGC Systems

The paper proposes a deep learning model for detecting multiple attack types in Automatic Generation Control (AGC). It introduces the idea of **multiclass classification**, where attacks like FDI, DoS, load alteration, and ramp attacks are detected simultaneously using deep neural networks.
This supports our implementation of **multiclass ML models** to detect multiple types of cyberattacks in real time.

3. System Design and Methodology

The proposed system consists of three integrated layers:

3.1 Smart Grid Simulation Layer (MATLAB Simulink)

A **3-Bus transmission system** with generators, transmission lines, loads, and measurement blocks is implemented in MATLAB Simulink.
Key features include:

- Three-phase Voltage and Current measurement using Vabc/Iabc blocks
- powergui for discrete simulation

- MATLAB Function blocks for cyberattack injection
- Controlled Breaker for protection actions
- Workspace logging of real-time data

Simulated cyberattacks:

- **False Data Injection (FDI)** → modifies measurements using biased offsets
- **DoS** → sensor data blocking or freezing
- **Replay Attack** → substitutes live data with stored historical values

3.2 Machine Learning Detection Layer (Python)

The dataset exported from MATLAB is preprocessed using:

- Sliding window segmentation
- Normalization
- Graph-based feature grouping

Machine Learning models used:

1. **Spatio-Temporal Graph Neural Network (ST-GNN)**
2. **Deep Learning Multiclass Classifier**
3. **Graph Attention Network (GAT)** for topology learning

These models classify grid conditions as:

- Normal
- FDI Attack
- DoS Attack
- Replay Attack

3.3 SCADA–Modbus Communication Layer

A virtual communication channel is implemented to simulate real SCADA behavior.

- AI model writes attack detection signals through **MATLAB Engine API** or virtual **Modbus registers**
- Simulink reads “AI_Alert” and “attack_type”

- If attack detected → breaker is tripped (protection action)
- Protection logs are stored in workspace

3.4 Working Principle

The working principle of the proposed Smart Grid Cyberattack Detection and Protection System is based on the integrated functioning of a Power System Simulation Layer (MATLAB Simulink), a Machine Learning Attack Detection Layer (Python), and a SCADA–Modbus Protection Layer. The interaction between these layers enables real-time anomaly detection and automated protection response against cyberattacks.

The working principle can be understood in the following detailed stages:

<u>Stage 1: Smart Grid Simulation and Data Generation (Simulink Layer)</u>

1. A 3-Bus power system is designed in MATLAB Simulink, consisting of:
    - Three-phase transmission lines
    - Loads
    - Generators
    - Circuit breakers
    - Measurement units (Vabc and Iabc)
2. The Simulink model continuously generates three-phase voltage and current data for each bus.
3. This output represents the physical layer of the cyber-physical smart grid.
4. These signals are captured using "To Workspace" blocks and stored as:
    - Bus1_Vabc, Bus2_Vabc, Bus3_Vabc
    - Bus1_Iabc, Bus2_Iabc, Bus3_Iabc
5. This data is exported into CSV/NumPy format to be processed by Python.

<u>Stage 2: Cyberattack Injection Mechanism (MATLAB Function Block)</u>

Cyberattacks are simulated inside Simulink using "MATLAB Function" blocks that modify measurement signals.

Types of attacks simulated:

1. False Data Injection (FDI)

- A biased offset is added to the Vabc or Iabc signals.
- Example:
  Vabc_modified = Vabc_original + offset

2. Denial of Service (DoS)

- Measurement data is frozen, blocked, or replaced by zeros.
- Example:
  Iabc_modified = [0 0 0]

3. Replay Attack

- Old stored data is played back instead of live measurements.

Attack variables such as:

- attack_on
- attack_type
- fdi_offset
- replay_buffer
- attack_target_bus

are controlled from Python or MATLAB workspace.

These attacks represent the cyber layer of the smart grid.

<u>Stage 3: Data Preprocessing (Python Layer)</u>

Once the data is exported from Simulink:

1. The dataset is normalized for ML compatibility.
2. A sliding window technique creates sequences of 10 time steps at a time.
3. Each window is flattened into a feature vector.
4. These windows capture temporal trends in bus voltages and currents.
5. The dataset is labeled for:
   - Normal
   - FDI

  - DoS
  - Replay attacks

This prepares the data for training the AI/ML models.

<u>Stage 4: Machine Learning Detection (ST-GNN Model)</u>

The core of the detection system is a Spatio-Temporal Graph Neural Network (ST-GNN).

How ST-GNN works:

1. Spatial Modeling (Graph Neural Network – GAT layer)
   - Each bus is considered a node in a graph.
   - Transmission lines are the edges.
   - The GAT layer learns interactions and dependencies between buses.
2. Temporal Modeling (1D Convolution Layer / Temporal Blocks)
   - Voltage-current data across time steps is used.
   - The CNN layer extracts temporal features to detect trends and anomalies.
3. Classification
   - The output layer predicts:
     - 0 → Normal
     - 1 → FDI
     - 2 → DoS
     - 3 → Replay

The ML model continuously evaluates incoming data from the MATLAB simulation.

<u>Stage 5: SCADA–Modbus Virtual Communication Layer</u>

Once the AI model detects an attack, it must notify the power system.

Process:

1. When predicted_label != 0, the AI activates: AI_Alert = 1
2. Python sets this flag in MATLAB using:
   - MATLAB Engine API, or

    - Virtual Modbus holding registers

3. Simulink continuously reads:
    - AI_Alert
    - attack_type

This layer simulates real SCADA communication between control center and substations.

Stage 6: Protection Mechanism (Breaker Operation)

When Simulink receives AI_Alert = 1:

1. The breaker connected to the targeted bus or line is triggered.
2. The breaker:
    - Isolates the compromised bus
    - Disconnects the load
    - Prevents further propagation of the cyberattack

Example:

If an FDI attack is detected at Bus-1:

- Breaker between Bus1 & Bus2 opens
- Bus1 is isolated
- Load or generator is disconnected

This prevents false measurements from destabilizing the grid.

Simulink logs the protection event:

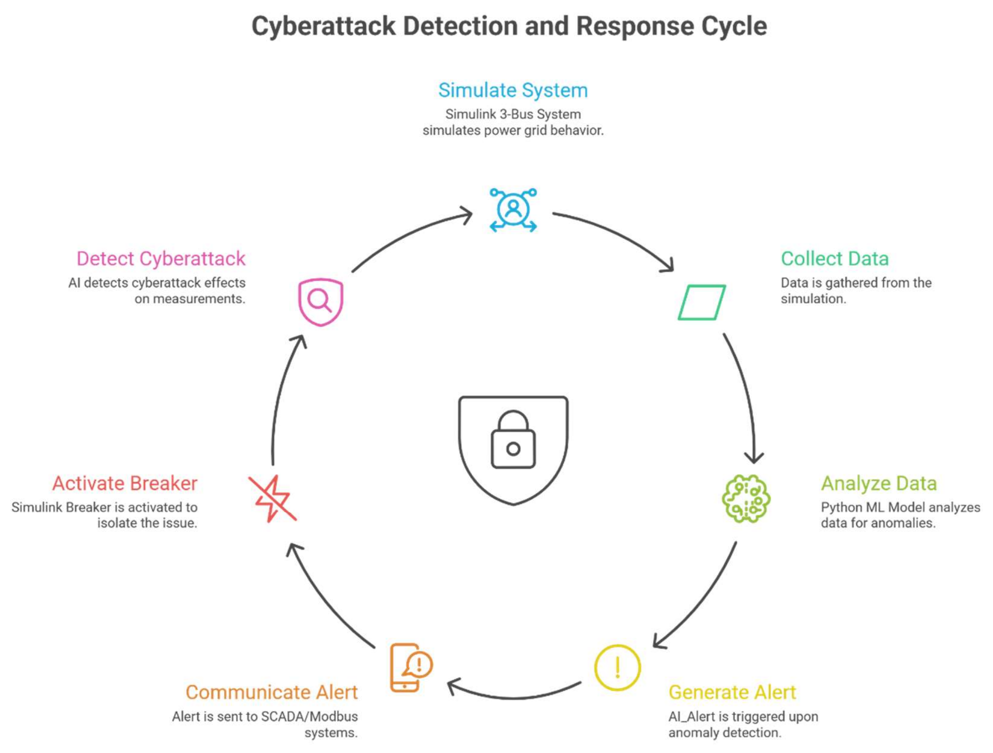
- Protection_Action = [time, bus_id, action_type]

The system includes real-time visualization via Python:

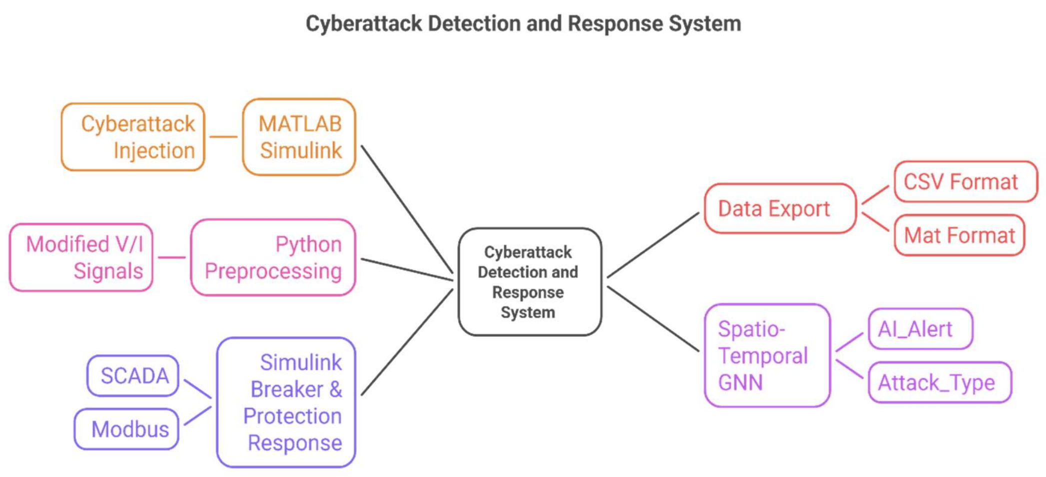
1. Live SCADA Dashboard
    - Animated voltage/current waveforms
    - Shows attack-induced disturbances
2. AI Decision Console
    - Prints prediction results in real time

3. Simulink Scopes
    - Shows physical response (breaker trip, waveform changes)

This demonstrates the complete cyber–physical interaction of the system.


Cyberattack Detection and Response Cycle
Simulate System
Simulink 3-Bus System simulates power grid behavior.
Collect Data
Data is gathered from the simulation.
Analyze Data
Python ML Model analyzes data for anomalies.
Generate Alert
AI_Alert is triggered upon anomaly detection.
Communicate Alert
Alert is sent to SCADA/Modbus systems.
Activate Breaker
Simulink Breaker is activated to isolate the issue.
Detect Cyberattack
AI detects cyberattack effects on measurements.

3.5 Block Diagram



4. Hardware / Software Used

Software

- MATLAB 2021+ (Simulink, powergui, Simscape)
- Python (VS Code)
- NumPy, Pandas, PyTorch, PyTorch Geometric
- MATLAB Engine API for Python
- Modbus-TCP (virtual)
- Matplotlib, Seaborn
- Anaconda Environment

Hardware

No physical hardware—fully software-based simulation.

5. Progress Made

1. 3-Bus Simulink smart grid model designed successfully.
2. V-I measurement and workspace data logging implemented.
3. Cyberattack injection (FDI, DoS, Replay) tested and validated.
4. Data preprocessing and sliding window segmentation completed.
5. ST-GNN model trained on synthetic and real Simulink data.
6. Integration of Python AI alerts with Simulink protection logic completed.
7. Real-time dashboard (SCADA-style visualization) implemented in Python.
8. Initial results show successful detection of attacks with high accuracy.

6. Outcomes

- Accurate multiclass detection of cyberattacks in smart grids.
- Development of an integrated cyber-physical testbed for research.
- Implementation of AI-based real-time protection (breaker trip).
- High classification performance validated with confusion matrix.
- Demonstrated end-to-end smart grid cybersecurity workflow.

7. References (IEEE Standard Format)

1. W. Xue, J. Zhao, and Z. Chakraborty, “Cyber-Physical Fusion for GNN-Based Attack Detection in Smart Power Grids,” *IEEE Transactions on Smart Grid*, 2022. DOI: 10.1109/OAJPE.2025.3594625

2. S. Ahmed, A. Hooshyar, and V. Dinavahi, “Cyber-Physical Power System (CPPS): A Review on Modeling, Simulation, and Analysis With Cyber Security Applications,” *IEEE Access*, vol. 9, pp. 126192–126218, 2021. DOI: 10.1109/ACCESS.2020.3016826

3. J. Gupta, M. Abdelmalek, and S. Singh, “Deep Learning-Based Multiclass Attacks Detection and Classification in Automatic Generation Control,” *Electric Power Components and Systems*, vol. 51, no. 4, pp. 368–381, 2023. DOI: 10.1109/TII.2025.3575806