An Intelligent Cybersecurity Model for Smart Grid Protection Using Deep Learning

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ABSTRACT

The modernization of electrical power systems through smart grid technology has significantly improved energy efficiency, real-time monitoring, automation, and demand-response capabilities. However, this transformation has also introduced serious cybersecurity vulnerabilities due to the integration of Internet of Things (IoT) devices, cloud computing platforms, Supervisory Control and Data Acquisition (SCADA) systems, and advanced communication networks. These interconnected components expose smart grids to a wide range of cyber threats, including false data injection attacks, denial-of-service attacks, ransomware infiltration, malware propagation, and unauthorized access to critical infrastructure.

This study presents an intelligent cybersecurity model for smart grid protection using deep learning techniques. The proposed framework integrates multiple neural network architectures—Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) networks, and Autoencoders—to provide a comprehensive, adaptive, and real-time cyber defense mechanism. The system is designed to perform intelligent feature extraction, behavioral pattern recognition, anomaly detection, predictive threat analysis, and automated attack response.

The model was evaluated using benchmark datasets relevant to power system security and network intrusion detection. Experimental results demonstrate that the proposed approach achieves high detection accuracy, improved precision and recall, reduced false-positive rates, and significantly faster response times compared to traditional machine learning-based security models. The findings confirm that deep learning-based cybersecurity systems offer a highly effective and scalable solution for protecting modern smart grid infrastructures.

Keywords: Smart Grid Security, Deep Learning, Cybersecurity, Intrusion Detection, Artificial Intelligence, SCADA Security, Anomaly Detection, Power Systems Protection

INTRODUCTION

The global energy sector is undergoing a profound transformation driven by the integration of digital technologies into traditional power systems. Smart grids represent the next generation of electrical power networks, incorporating advanced communication systems, intelligent sensors, automated control mechanisms, and real-time data analytics to enhance the efficiency, reliability, and sustainability of electricity distribution. Aslani, M. (Hashemi-Dezaki, H., Ketabi, A. 2021).

Unlike traditional power grids, which rely on centralized control and limited communication, smart grids operate through a highly interconnected and decentralized architecture. This architecture includes smart meters, IoT-enabled sensors, automated substations, renewable energy integration systems, and cloud-based monitoring platforms. These components continuously exchange data to optimize energy generation, distribution, and consumption in real time.

However, the same characteristics that make smart grids efficient and intelligent also make them highly vulnerable to cyberattacks. The extensive use of digital communication channels increases the attack surface

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available to malicious actors. Cybercriminals can exploit vulnerabilities in communication protocols, sensor nodes, control systems, and data transmission channels to disrupt power distribution or manipulate system operations.

Aslani, M., Hashemi-Dezaki, H., Ketabi, A. (2021), Cyberattacks on smart grids can have severe consequences, ranging from localized power disruptions to large-scale blackouts affecting entire regions. More critically, attacks such as false data injection can manipulate sensor readings and mislead control systems into making incorrect operational decisions. Similarly, denial-of-service attacks can overwhelm communication channels, preventing operators from accessing critical system information.

Traditional cybersecurity mechanisms such as firewalls, encryption protocols, and rule-based intrusion detection systems were originally designed for conventional IT environments rather than highly dynamic and time-sensitive power systems. As a result, they struggle to detect sophisticated and adaptive cyber threats that target smart grid infrastructures.

Another major limitation of traditional systems is their reactive nature. Most conventional cybersecurity tools detect threats only after malicious activities have already occurred, leaving critical systems exposed during the attack window. Additionally, these systems often fail to scale efficiently in large, distributed environments like smart grids, where massive volumes of real-time data must be analyzed continuously.

Artificial intelligence and deep learning have emerged as powerful technologies capable of addressing these limitations. Deep learning models can process large-scale, high-dimensional datasets, automatically extract meaningful patterns, and identify subtle anomalies that are often invisible to rule-based systems. Their ability to learn hierarchical representations makes them particularly suitable for analyzing complex cyber-physical systems such as smart grids (Bécue, A., Praça, I., Gama, J., 2021)

This study, therefore, proposes a comprehensive intelligent cybersecurity model based on deep learning techniques to enhance the protection of smart grid infrastructures. The model is designed not only to detect cyber threats but also to predict and prevent attacks before they cause significant damage.

Objectives of the Study

The primary objective of this research is to design and implement an intelligent cybersecurity model capable of protecting smart grid infrastructures using advanced deep learning techniques.

The study specifically aims to develop a multi-layer neural network architecture that integrates Convolutional Neural Networks, Recurrent Neural Networks, Long Short-Term Memory networks, and Autoencoders. Each of these models plays a distinct role in enhancing cybersecurity performance, including spatial feature extraction, temporal behavior analysis, anomaly detection, and predictive classification.

Another important objective is to develop a robust data preprocessing and feature engineering pipeline capable of handling complex smart grid datasets. This includes cleaning noisy data, normalizing input features, encoding system attributes, and extracting relevant security-related indicators from raw network traffic.

The study also aims to design an intelligent anomaly detection system that can identify abnormal behaviors in smart grid operations. This includes detecting deviations in energy consumption patterns, unusual communication activities, and irregular control commands that may indicate cyber-attacks.

Furthermore, the research seeks to implement a predictive cybersecurity mechanism that can anticipate potential attacks before they fully occur. This proactive capability enhances the resilience of smart grid systems by enabling early intervention (Sitanggang, 2024).

The study also focuses on developing an automated response system capable of mitigating detected threats in real time. This includes isolating compromised nodes, blocking malicious traffic, triggering alerts, and updating

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security policies dynamically.

Finally, the model is evaluated using standard performance metrics to determine its effectiveness compared to existing machine learning and rule-based cybersecurity approaches.

LITERATURE REVIEW

The evolution of modern power systems has witnessed a significant transition from traditional electrical grids to highly interconnected and digitally enabled smart grids. Unlike conventional grids, which operated in isolated and relatively secure environments, smart grids integrate advanced communication technologies, Internet of Things (IoT) devices, Supervisory Control and Data Acquisition (SCADA) systems, and cloud-based infrastructures. While this transformation has enhanced efficiency, reliability, and real-time monitoring capabilities, it has also introduced new cybersecurity vulnerabilities that were previously nonexistent in traditional power systems. As a result, smart grids are now exposed to a wide range of cyber-physical threats that can disrupt operations and compromise system stability (Chen, Y., Tan, Y., Deka, D).

Smart Grid Architecture

The architecture of the Smart Grid (SG) continues to attract significant research attention from academics, utility providers, technology organizations, and energy producers due to its complexity and evolving operational requirements. Various architectural frameworks have been proposed over the years, each designed to address specific functionalities, communication requirements, and operational characteristics within modern power systems. These architectures aim to improve energy efficiency, reliability, interoperability, and intelligent decision-making across power infrastructures.

Several studies have reviewed and proposed standardized Smart Grid architectural models. For instance, the work of Ananthavijayan et al. (2019) examined a range of widely recognized Smart Grid architectures developed to support advanced grid functionalities. One notable framework is the North American Synchro-Phasor Initiative Network (NASPInet), introduced by Gorton et al. (2012), which focuses on facilitating synchronized phasor data exchange and improving real-time monitoring capabilities across power systems.

Another significant Smart Grid architecture is the Grid Operation and Planning Technology Integrated Capabilities Suite (GridOPTICS) proposed by Bobba et al. (2010). This architecture was developed to enhance grid operations and planning through integrated technological capabilities that support situational awareness and operational efficiency (Faheem M, Butt RA, Raza B, Ashraf MW, Ngadi MA, Gungor VC, 2019).

In addition, the National Institute of Standards and Technology (NIST) developed a comprehensive Smart Grid architectural framework that has gained broad acceptance as a reference model for Smart Grid implementation. According to the NIST Smart Grid model, the architecture is organized into seven logical domains, namely: customer, markets, service providers, operations, transmission, distribution, and bulk generation. These domains collectively represent the key functional components of the Smart Grid ecosystem and define the interactions among stakeholders involved in electricity generation, delivery, management, and consumption.

The NIST framework promotes interoperability among diverse technologies and provides a structured approach for integrating communication systems, control mechanisms, and energy management processes within modern Smart Grid environments (Faheem M, Butt RA, Raza B, Ashraf MW, Ngadi MA, Gungor VC, 2019).

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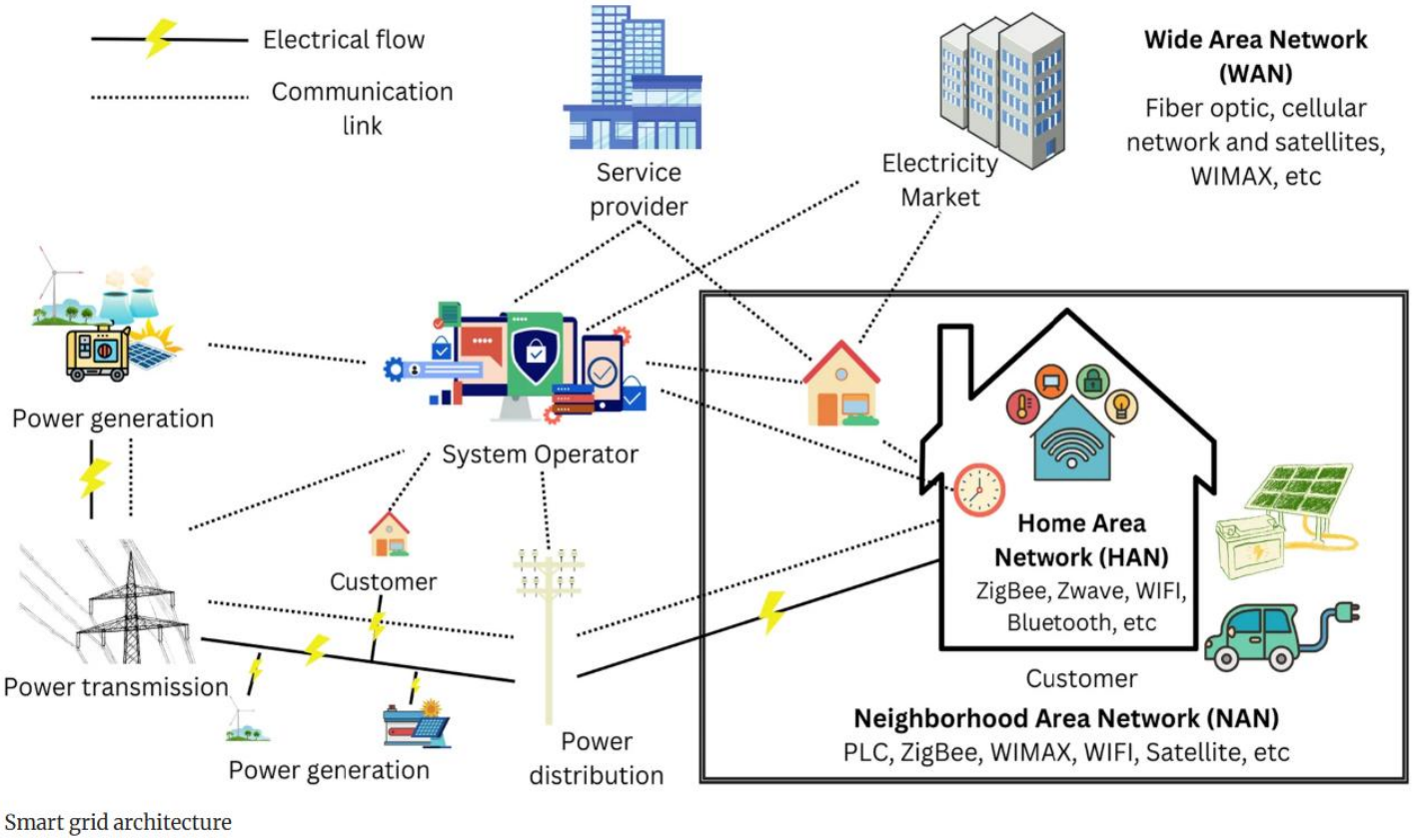

Figure 3.1: Smart Grid Architecture

Research has shown that smart grid environments are particularly vulnerable to sophisticated cyberattacks such as false data injection attacks, denial-of-service attacks, malware infiltration, and insider threats. False data injection attacks are especially critical, as they manipulate sensor readings and distort state estimation processes, potentially leading to incorrect operational decisions. Similarly, denial-of-service attacks can overwhelm communication networks, resulting in service disruption and delayed control actions. These vulnerabilities highlight the increasing complexity and risk associated with securing modern energy infrastructures.

In response to these challenges, traditional intrusion detection systems were initially deployed to safeguard grid operations. These systems typically relied on rule-based mechanisms and signature-based detection techniques. Although effective in identifying known attack patterns, such approaches are limited in their ability to detect unknown or evolving threats. Furthermore, they often suffer from high false alarm rates and lack scalability when applied to large-scale, real-time smart grid environments (Faheem M, Gungor VC,2018).

To overcome these limitations, machine learning techniques have been introduced into cybersecurity frameworks for smart grids. Algorithms such as Support Vector Machines, Random Forests, and K-Nearest Neighbors have demonstrated improved detection accuracy compared to traditional methods. However, these techniques require extensive feature engineering and often struggle with high-dimensional, time-dependent data generated by smart grid systems. Consequently, their performance may degrade when faced with complex or rapidly evolving cyber threats (Faheem M, Gungor VC,2018).

More recently, deep learning approaches have gained significant attention due to their ability to automatically learn hierarchical representations from raw data. Neural network architectures such as Artificial Neural Networks, Convolutional Neural Networks, and Recurrent Neural Networks, particularly Long Short-Term Memory networks, have shown strong performance in identifying complex patterns within large datasets. These models are particularly effective in analyzing time-series data, which is a fundamental characteristic of smart grid operations. Studies have demonstrated that deep learning-based intrusion detection systems provide higher accuracy and improved adaptability compared to conventional machine learning methods (Faheem M, Gungor VC,2018).

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Components of Smart Grid Architecture

Customer Domain

The customer domain represents the end-user environment where electricity is consumed and, increasingly, generated and actively managed. Modern customers are no longer passive consumers but active participants in energy production and management through technologies such as solar panels, wind systems, energy storage units, smart appliances, entertainment devices, and intelligent lighting systems.

Advanced sensing technologies within this domain allow users to monitor, control, and optimize energy consumption and generation activities. Central to this framework is the use of Smart Meters (SMs), which facilitate intelligent energy measurement and support bidirectional communication between consumers and utility providers. Smart meters integrate metering functionality with communication infrastructures that enable data exchange and remote-control operations (Faheem M, Shah SBH, Butt RA, Raza B, Anwar M, Ashraf MW, Ngadi MA, Gungor VC, 2018).

The communication component of smart meters includes networking and control mechanisms that allow interaction with remote systems and execution of control instructions. Energy usage information collected by smart meters is transmitted through gateways to Data Concentrators (DCs) for aggregation and processing.

Communication between utility providers and smart meters enables the implementation of Demand Response (DR) programs. Demand response mechanisms allow users to monitor consumption patterns, shift energy-intensive activities to off-peak periods, and participate in dynamic pricing strategies. Furthermore, DR systems can be integrated into Home Energy Management Systems (HEMS), enabling automated control of household appliances and improved energy efficiency (Faheem M, Shah SBH, Butt RA, Raza B, Anwar M, Ashraf MW, Ngadi MA, Gungor VC, 2018).

Market Domain

The market domain constitutes a vital component of Smart Grid infrastructure by providing a platform where electricity-related products, services, and grid resources are bought, sold, and traded. This domain facilitates economic interactions among stakeholders, including utility companies, energy suppliers, consumers, and service providers.

The Smart Grid market environment supports dynamic pricing mechanisms, energy transactions, demand-side management initiatives, and emerging business models associated with distributed energy resources and smart energy ecosystems (Farooq SM, Nabirasool(S Kiran S, Hussain SS, Ustun TS, 2018).

Service Provider Domain

The service provider domain acts as an intermediary and support component within the Smart Grid ecosystem. Entities operating within this domain provide services that support the business activities of electricity producers, transmission operators, distribution companies, and consumers.

Typical services include customer account management, billing operations, maintenance support, energy usage analytics, and various value-added services. Through seamless interaction with other Smart Grid domains, service providers contribute to improved operational efficiency and customer satisfaction (Fritz JJ, Sagisi J, James J, Leger AS, King K, Duncan KJ, 2019).

Operations and Monitoring Systems

The operations domain encompasses the collection of intelligent systems used for monitoring, controlling, and optimizing power system operations. Through continuous supervision of electricity flow, customer demand, storage resources, and emergency conditions, this domain plays a critical role in maintaining grid stability, reliability, and resilience (Fritz JJ, Sagisi J, James J, Leger AS, King K, Duncan KJ, 2019).

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Several components contribute to effective system operations:

Supervisory Control and Data Acquisition (SCADA):

SCADA serves as the primary monitoring and control infrastructure responsible for collecting, interpreting, and processing real-time operational data from the electrical grid. The system integrates sensors, control units, communication interfaces, and centralized computing platforms.

Human–Machine Interface (HMI):

The Human–Machine Interface provides communication and interaction between operators and SCADA systems, enabling visualization and control of grid operations.

Automatic Generation Control (AGC):

AGC maintains a balance between electricity demand and power generation by adjusting generation output according to system load requirements.

Energy Management System (EMS):

The EMS is responsible for supervising, optimizing, and coordinating power system operations to ensure efficient utilization of available resources.

Collectively, these systems contribute to effective grid management and rapid response to operational disruptions.

Transmission Domain

The transmission domain is responsible for the large-scale transfer of electrical power from generation facilities to distribution systems through interconnected substations and transmission lines.

Transmission infrastructures are typically monitored using SCADA systems that employ communication networks and field devices to collect real-time operational information. Important components within this domain include:

- Remote Terminal Units (RTUs)
- Sensors
- Protection relays
- Power quality monitoring devices
- Substation meters
- Phasor Measurement Units (PMUs)

PMUs play an essential role in measuring voltage and current phasors, including their magnitude and phase angle, to determine the direction and quantity of power flow.

The transmission domain also incorporates Intelligent Electronic Devices (IEDs), which support automation, control, and protection functionalities across Smart Grid infrastructures.

Distribution Domain

The distribution domain represents the final stage in the electricity delivery process, transporting power from transmission infrastructures to end-users.

Advanced monitoring and communication technologies are integrated into this domain to enhance visibility and

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operational efficiency. One of the major technologies deployed is the Advanced Metering Infrastructure (AMI), which consists of smart meters, communication systems, software applications, and customer-associated systems that collectively collect and analyze energy usage information.

Data collected through AMI systems are transferred to the Meter Data Management System (MDMS), which performs storage, processing, and analytical operations. Distributed MDMS architectures may be deployed near smart meter locations through multiple concentrators to improve processing efficiency (Gao W, Morris T, Reaves B, Richey D, 2010).

Additional monitoring and control devices deployed within the distribution domain include:

- Remote Terminal Units (RTUs)
- Distribution Phasor Measurement Units (D-PMUs)
- Intelligent Electronic Devices (IEDs)

D-PMUs are specialized versions of PMUs designed specifically for distribution systems. These technologies significantly enhance electricity reliability, operational efficiency, and support sustainable energy initiatives.

Generation Domain

The generation domain includes diverse power generation technologies and energy sources used to produce electricity. These energy sources include:

- Fossil fuel combustion systems
- Nuclear energy
- Hydroelectric systems
- Wind energy
- Solar energy
- Geothermal energy

Within Smart Grid environments, intelligent generation systems are integrated with demand forecasting and Automatic Generation Control mechanisms to dynamically regulate power output in response to changing load conditions. This adaptive approach helps maintain frequency stability and optimize overall system performance (Saluky, 2018).

Smart Grid Communication Networks

Smart Grid communication infrastructure consists of three major network categories:

Home Area Networks (HANs)

HANs facilitate communication among devices within residential environments. They connect and manage smart appliances, sensors, smart meters, and home energy management systems.

Neighborhood Area Networks (NANs)

NANs extend communication capabilities beyond individual homes to cover neighborhoods or localized geographical regions. They aggregate information from multiple HANs and support intermediate communication functions.

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Wide Area Networks (WANs)

WANs provide large-scale communication coverage across the entire power grid and support communication among utility centers, substations, and large operational infrastructures.

To support communication across these networks, Smart Grids utilize both wired and wireless technologies.

Wired communication technologies include:

- Fiber optics
- Power Line Communication (PLC)
- Ethernet

Wireless communication technologies include:

- ZigBee
- Bluetooth
- Wi-Fi
- WiMAX
- Z-Wave
- Wireless mesh networks
- Cellular communication networks
- Satellite communication systems

Each communication technology possesses unique characteristics related to transmission speed, range, reliability, cost, and deployment requirements. Consequently, different technologies are deployed across different sections of the Smart Grid based on operational needs and communication objectives (Saluky, 2018).

Smart Grid Communication Networks

Home Area Network (HAN)

Within Smart Grid (SG) environments, a Home Area Network (HAN) refers to a communication network designed to connect intelligent devices within residential settings to the power grid infrastructure. The primary objective of a HAN is to facilitate seamless communication and information exchange among various smart devices, including smart meters, thermostats, household appliances, energy management systems, and electric vehicles (Ghazizadeh MS, Aghamohammadi MR, et al 2023).

HANs support real-time interaction among connected devices through both wired and wireless communication technologies. Common communication technologies utilized within HAN environments include Ethernet, Wi-Fi, ZigBee, and Bluetooth. These technologies enable efficient transmission of energy-related information and support functionalities such as real-time energy monitoring, demand response programs, and home automation services.

Additionally, HAN communication may be implemented through Power Line Communication (PLC), which utilizes existing electrical wiring infrastructure to transfer information between connected devices. PLC operates under two principal categories based on transmission rates: Narrowband PLC (NB-PLC) and Broadband PLC

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(BB-PLC). Through these communication mechanisms, HANs improve consumer participation in energy management and contribute to intelligent residential energy systems(Ghazizadeh MS, Aghamohammadi MR, et al 2023).

Neighborhood Area Network (NAN)

A Neighborhood Area Network (NAN) represents a larger communication infrastructure formed through the aggregation of multiple Home Area Networks. Its primary purpose is to provide communication and data exchange across a neighborhood or localized geographic region.

Several communication technologies are commonly deployed within NAN infrastructures, including:

- Power Line Communication (PLC)
- WiMAX
- ZigBee
- Wi-Fi
- Cellular communication networks
- Wireless mesh networks

Wireless mesh networks have become particularly important within NAN environments. In mesh architectures, each smart meter functions not only as a data collection device but also as a communication relay or router for neighboring meters. This structure enables the transmission of energy consumption information from multiple households toward Data Concentrators (DCs).

These mesh networks frequently operate using unlicensed radio frequencies, often around the 900 MHz spectrum. Internet connectivity is then used to connect the mesh network to distributed Data Concentrators positioned several kilometers away. Such an architecture enhances communication reliability, scalability, and network coverage within Smart Grid systems.

Wide Area Network (WAN)

The Wide Area Network (WAN) serves as the primary communication backbone within Smart Grid infrastructure. WANs are designed to interconnect geographically dispersed networks and support communication among distributed power system components across large regions.

This high-capacity communication infrastructure supports long-distance data transmission and enables advanced monitoring, sensing, automation, and control operations throughout the Smart Grid ecosystem. WANs provide bidirectional communication capabilities necessary for real-time system management and intelligent grid operations (Gridhar M, Hong J, Lee H, Song T-J, 2021) .

Optical fiber communication is commonly employed within WAN infrastructures due to its high bandwidth capacity, reliability, and transmission speed. Fiber optic deployments across transmission and distribution domains support several utility services, including:

- System protection mechanisms
- Load management operations
- Distributed Generation (DG) management
- Distribution automation
- Diagnostic monitoring services

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Although wired communication technologies remain widely adopted in automation systems, wireless communication alternatives have gained increasing attention because of their flexibility and deployment advantages. Technologies such as cellular networks, WiMAX, and satellite communication systems provide reliable Internet connectivity for metering infrastructures and automation devices (Girdhar M, Hong J, Lee H, Song T-J, 2021) .

Wireless Sensor Networks (WSNs) also represent an emerging communication paradigm within Smart Grid environments, particularly for sensing and metering applications. WSNs provide distributed sensing capabilities that enhance operational visibility and support intelligent grid management.

Furthermore, Cognitive Radio (CR) technology has emerged as a promising solution for improving spectrum utilization within Smart Grid communication systems. Cognitive radio enables dynamic and selective access to radio frequency bands by allowing unlicensed secondary users to utilize underutilized spectrum allocated to licensed primary users. This adaptive spectrum-sharing mechanism improves communication efficiency and addresses bandwidth limitations in wireless Smart Grid applications (Girdhar M, Hong J, Lee H, Song T-J, 2021).

Components and Communication Links within the Smart Grid

The Smart Grid is a highly interconnected and complex cyber-physical system comprising multiple components that cooperate through advanced communication infrastructures. Effective operation of the Smart Grid depends heavily on reliable communication links that support information exchange among generation systems, transmission networks, distribution infrastructures, utility providers, and end-users.

The communication framework enables coordination among different Smart Grid components for monitoring, control, decision-making, and automation purposes. Communication links facilitate real-time data transfer between smart meters, sensors, substations, control centers, and management platforms, thereby improving operational efficiency, situational awareness, and system reliability.

A comprehensive representation of Smart Grid components and their communication pathways provide a clear understanding of system interactions and highlights the critical role played by communication technologies in enabling intelligent energy management and automation across modern power infrastructures (Kallitsis MG, et al., 2016).

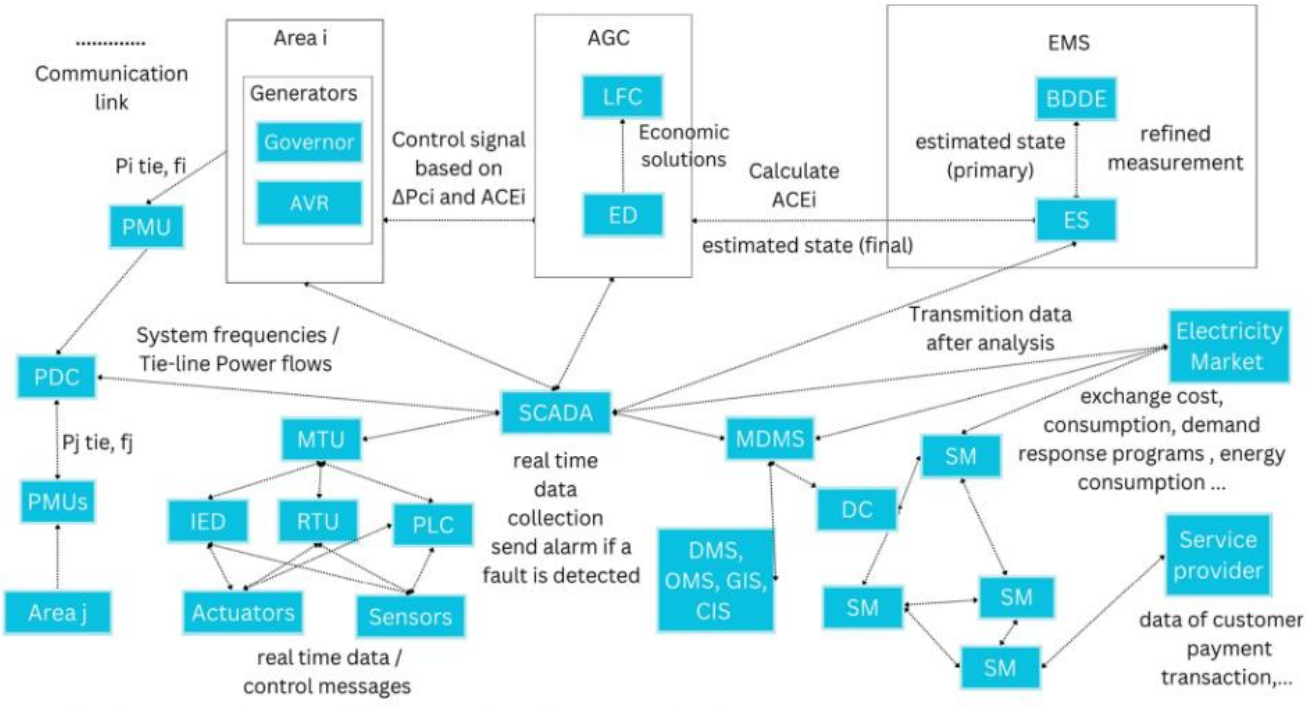

Diagram illustrating the components of the smart grid and the communication links

Figure 3.2: Components of a Smart Grid and Communication Links

Despite these advancements, existing research still faces several limitations. Many proposed models are not fully optimized for real-time deployment in smart grid environments, and some lack robustness against adversarial attacks designed to deceive learning algorithms. Additionally, there is still a gap in developing unified intelligent cybersecurity frameworks that combine high detection accuracy, low latency, and adaptive learning capabilities for dynamic grid conditions. These gaps form the basis for the development of an enhanced intelligent cybersecurity model leveraging deep learning techniques (Kallitsis MG, Bhattacharya S, Stoev S, Michailidis G 2016).

Cyber Attacks in Smart Grids

The increasing integration of advanced communication technologies, intelligent devices, and interconnected infrastructures within Smart Grids (SGs) has significantly improved operational efficiency and automation. However, this technological evolution has also expanded the attack surface of power systems, making them increasingly susceptible to cyberattacks. The complexity of Smart Grid architectures introduces numerous entry points that malicious actors can exploit to compromise system functionality, confidentiality, integrity, and availability (Kalluri R, Mahendra L, Kumar RS, Prasad GG, 2016).

Understanding the nature of cyber threats and their potential targets within Smart Grid environments is essential for developing effective security strategies. Cyberattacks in Smart Grids can generally be categorized from two perspectives: attack type classification and target-based classification. Attack-type classification groups cyber threats according to their operational characteristics and attack methodologies, while target-based classification identifies vulnerable Smart Grid components that may be exploited (Kalluri R, et al., 2016).

Common cyberattacks affecting Smart Grid systems include Man-in-the-Middle (MiTM) attacks, Replay Attacks (RA), Time Delay Attacks (TDA), False Data Injection Attacks (FDIA), Load Redistribution Attacks (LRA), Denial-of-Service (DoS) attacks, Time Synchronization Attacks (TSA), Switching Attacks (SA), malicious command injections, and malware attacks. Each of these attacks possesses unique operational features and can have severe consequences on grid stability, reliability, and operational integrity (Kalluri R, et al., 2016).

Types of Cyber Attacks in Smart Grids

Different cyberattacks possess distinct objectives, mechanisms, and impacts on Smart Grid operations. Understanding these attack categories assists in designing specialized defense mechanisms and prioritizing cybersecurity efforts based on threat severity and system vulnerability, (Kaplantzis S, & Şekercioğlu YA, 2012).

Man-in-the-Middle (MiTM) Attacks

Man-in-the-Middle attacks represent a significant threat to Smart Grid communication systems. In this type of attack, an adversary secretly positions themselves between two communicating entities to intercept, monitor, alter, or manipulate exchanged information while maintaining the appearance of legitimate communication.

The attacker may perform eavesdropping activities or impersonate one of the communicating devices, thereby compromising confidentiality and integrity. Smart Grid communication protocols such as Modbus TCP/IP have been identified as vulnerable to MiTM attacks (Kaplantzis S, Şekercioğlu, YA, 2012).

MiTM attacks become particularly challenging to detect in systems involving geographically distributed measurement devices such as Phasor Measurement Units (PMUs) and Phasor Data Concentrators (PDCs). Due to transmission distances and stringent real-time communication requirements, there may be insufficient processing time for comprehensive encryption, authentication, and integrity verification mechanisms (Kaplantzis S, Şekercioğlu, YA, 2012)

Replay Attacks (RA) and Time Delay Attacks (TDA)

Accurate timing and timely transmission of control signals are essential for maintaining stable Smart Grid operations. Replay Attacks and Time Delay Attacks exploit timing dependencies within control systems.

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Time Delay Attacks intentionally introduce delays into communication channels, thereby disrupting the transmission and reception of packets. Such disruptions can degrade system responsiveness and destabilize operational processes.

Replay Attacks involve recording legitimate sensor measurements or control commands during normal operations and subsequently retransmitting these previously captured messages at later times. By replacing real-time measurements with historical information or maliciously repeating control instructions, attackers manipulate system behavior.

Both attack strategies can cause control centers to operate using outdated or inaccurate information, potentially driving system states beyond acceptable operating conditions and causing physical damage to power infrastructures (Kawoosa AI, Prashar D, 2021).

False Data Injection Attacks (FDIA)

False Data Injection Attacks target state estimation processes within Smart Grid environments. State estimation is a fundamental process used to determine unobservable system states based on collected measurement data.

In FDIA scenarios, attackers inject carefully crafted malicious measurement vectors into the system while exploiting weaknesses in bad data detection mechanisms. These manipulated measurements evade detection and produce inaccurate state estimation outcomes (Kawoosa AI, Prashar D, 2021).

Because many Smart Grid operational applications—including economic dispatch, load balancing, and operational decision-making—depend heavily on accurate state estimation, manipulated estimates may cause erroneous decisions, operational inefficiencies, and system instability.

Additionally, FDIA attacks may result in unnecessary generation rescheduling, inappropriate load shedding, and reduced grid reliability.

Load Redistribution Attacks (LRA)

Load Redistribution Attacks represent a specialized category of False Data Injection Attacks specifically designed to manipulate economic dispatch operations.

Economic Dispatch systems seek to minimize overall operational costs through optimal allocation of power generation resources. LRA manipulates estimated system states to generate false dispatch outcomes, thereby forcing the system into economically inefficient operating conditions (Kayastha N, Niyato D, Hossain E, Han Z, 2014).

Two attack objectives commonly characterize LRAs:

Immediate attack objectives:

These aim to maximize operational costs immediately following the attack.

Delayed attack objectives:

These gradually overload transmission lines over time, potentially resulting in physical damage and infrastructure failures.

Such attacks can significantly affect power system efficiency and stability.

Denial-of-Service (DoS) Attacks

Smart Grid environments incorporate numerous intelligent devices, including:

- Smart meters
- PMUs
- Remote Terminal Units (RTUs)
- Intelligent Electronic Devices (IEDs)
- Smart appliances
- Programmable Logic Controllers (PLCs)
- Data aggregators

These devices can become targets for Denial-of-Service attacks.

A DoS attack seeks to make system services or information inaccessible to intended users. In Smart Grid systems, attackers may prevent measurement information from reaching monitoring centers or obstruct control commands from reaching field devices (Kayastha N, Niyato D, Hossain E, Han Z, 2014).

DoS attacks commonly involve:

- Flooding communication channels with excessive traffic
- Exploiting protocol vulnerabilities
- Jamming communication signals
- Manipulating routing mechanisms

Such attacks disrupt system functionality, degrade monitoring capabilities, and may lead to operational instability.

An advanced form known as Distributed Denial-of-Service (DDoS) attacks utilizes multiple compromised systems simultaneously to launch coordinated attacks, making detection and mitigation more difficult.

Another variation, known as a puppet attack, manipulates legitimate nodes into becoming malicious communication sources that consume network resources and degrade communication performance.

Time Synchronization Attacks (TSA)

Time Synchronization Attacks target timing infrastructures used throughout Smart Grid systems. Numerous applications rely on synchronized measurements obtained from devices such as PMUs.

Time synchronization commonly depends on:

- Global Positioning System (GPS)
- Network Time Protocol (NTP)
- Precision Time Protocol (PTP)

GPS-based synchronization obtains timing information from satellite systems, whereas NTP-based systems synchronize clocks using master-slave communication structures (Khtar, N., Mian, A., 2022).

Attackers may exploit these mechanisms through:

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- GPS signal jamming
- GPS spoofing
- Software compromise
- Timing manipulation

Such attacks disrupt synchronized operations and negatively impact measurement accuracy and control processes.

Switching Attacks (SA)

Switching Attacks involve malicious manipulation of circuit breaker operations and switching sequences within substations and transmission infrastructures.

Attackers identify switching sequences capable of creating instability in generator phase angles and operating frequencies. Such instability may force generators to disconnect from the grid (Khtar, N., Mian, A., 2022).

In practical scenarios, compromised substations may experience unauthorized disconnection of:

- Transformers
- Transmission lines
- Circuit breakers
- Bus systems

Switching attacks targeting IP-based substations may exploit compromised local computers or Intelligent Electronic Devices with control privileges.

Additionally, these attacks can trigger cascading failures that propagate throughout interconnected power infrastructures and potentially lead to large-scale blackouts (Khtar, N., Mian, A., 2022).

Malicious Command Injection and Malware Attacks

Cyber attackers may exploit vulnerabilities within Human–Machine Interfaces (HMIs), software platforms, or operating systems to introduce malicious commands into Smart Grid systems.

One attack technique involves installing remote shells that enable unauthorized remote access and complete system manipulation.

Malicious command injection attacks compromise control operations and alter system behavior in harmful ways.

Smart Grid systems may also experience malware-related attacks such as:

Logic Bombs:

Malicious code programmed to execute destructive actions when specific conditions are satisfied. Effects may include system failures, data deletion, or unauthorized modifications.

Trojan Horses:

Malicious software disguised as legitimate applications to deceive users into executing harmful code.

Botnets: Networks of compromised devices remotely controlled by attackers to distribute malware, steal

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information, and launch coordinated attacks.

These malware threats can significantly compromise Smart Grid security and operational resilience.

Attack Classification Based on Target Components

Beyond attack methodologies, cyber threats can also be categorized according to the Smart Grid components they target. Understanding vulnerable attack points is essential for identifying security weaknesses and implementing effective defense mechanisms (Khazaei, J., Moazeni, F., 2022).

Potential attack targets within Smart Grid infrastructures include:

- Customer systems
- Power markets
- Service providers
- SCADA systems
- Wide Area Network communication infrastructures
- Measurement devices
- Automatic Generation Control systems

Each component possesses distinct vulnerabilities and attack surfaces. Exploitation of these weaknesses can severely disrupt grid operations and negatively affect system reliability, stability, and overall security.

Consequently, target-based attack classification provides a structured approach for evaluating Smart Grid security risks and developing component-specific protection mechanisms.

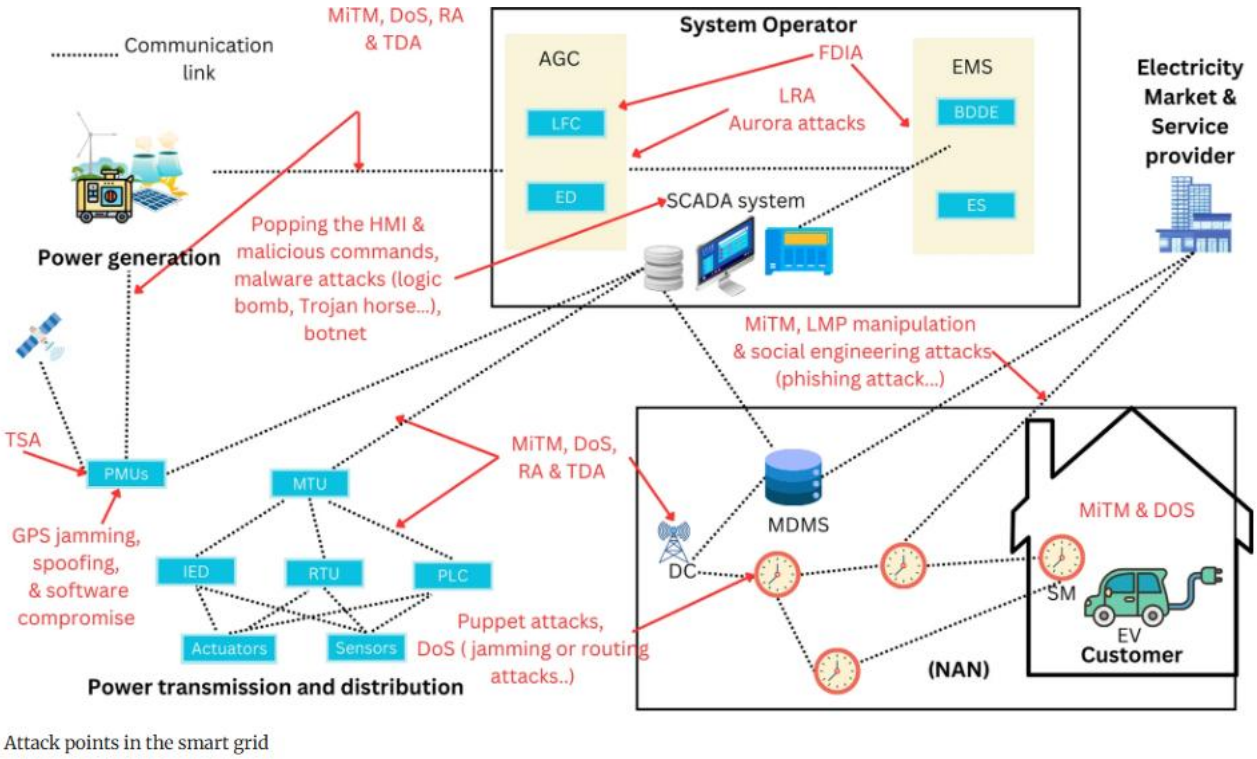

Figure 3.3: Attack Points in the Smart Grid

Research Method

This study adopted a design science and experimental research methodology to develop and evaluate an

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intelligent cybersecurity model for Smart Grid protection using deep learning techniques. The methodology was designed to provide a systematic framework for detecting, classifying, and mitigating cyber threats targeting Smart Grid communication networks in real time. It integrates data acquisition, preprocessing, feature engineering, deep learning model development, intrusion detection, attack classification, and performance evaluation into a unified cybersecurity framework. The proposed methodology aims to improve the security, resilience, and reliability of Smart Grid systems by leveraging the predictive capabilities of deep learning algorithms.

Research Design

An experimental research design was adopted because it provides an appropriate framework for designing, implementing, and evaluating an intelligent cybersecurity model under controlled conditions. The study followed the Design Science Research (DSR) methodology, which emphasizes the creation and validation of innovative technological artefacts to solve real-world problems. In this study, the artefact is a deep learning-based intrusion detection model capable of identifying malicious activities within Smart Grid communication environments. The experimental approach enabled the comparison of model performance under different cyberattack scenarios and facilitated the assessment of its effectiveness using standard evaluation metrics.

Proposed Intelligent Cybersecurity Framework

The proposed framework consists of several interconnected components that collectively provide end-to-end cybersecurity protection for Smart Grid infrastructures. The framework begins with the acquisition of network traffic and operational data from Smart Grid devices such as smart meters, supervisory control and data acquisition (SCADA) systems, phasor measurement units (PMUs), and Internet of Things (IoT) sensors. The collected data are then passed through a preprocessing stage where missing values, duplicate records, noise, and inconsistencies are removed to improve data quality, (Kotsiopoulos, T. Sarigiannidis, P., Ioannidis, D., Tzovaras, D.2021).

Following preprocessing, relevant network and operational features are extracted and transformed into formats suitable for deep learning analysis. The processed data are then fed into a hybrid deep learning model that detects abnormal behaviour and classifies cyberattacks. Once malicious activities are detected, the framework automatically generates alerts and initiates appropriate response mechanisms such as traffic isolation, device quarantine, or administrator notification. Finally, the effectiveness of the proposed model is evaluated using established cybersecurity performance metrics (Kotsiopoulos, T., Sarigiannidis, P., Ioannidis, D., Tzovaras, D.2021).

Data Collection

The study utilized publicly available benchmark cybersecurity datasets commonly employed in Smart Grid intrusion detection research. These datasets contain labelled records representing both normal Smart Grid operations and various categories of cyberattacks. Examples include the CICIDS2017, CICIDS2018, UNSW-NB15, NSL-KDD, TON_IoT, and Smart Grid Stability datasets. The selected datasets contain diverse attack scenarios, including Denial-of-Service (DoS), Distributed Denial-of-Service (DDoS), False Data Injection (FDI), replay attacks, man-in-the-middle attacks, malware infections, command injection, and data manipulation attacks. Using benchmark datasets ensures the reproducibility of the experiments and enables meaningful comparison with existing cybersecurity models (LeCun, Y., Bengio, Y., Hinton, G. 2015).

Data Preprocessing

Data preprocessing was performed to improve the quality and reliability of the datasets before training the deep learning model. The preprocessing stage involved removing duplicate records, handling missing values, eliminating noisy observations, encoding categorical variables, and normalizing numerical features to ensure uniformity across all input variables. Feature scaling was performed using Min-Max normalization to map feature values to a common range, thereby improving the convergence speed and stability of the deep learning algorithms. Where necessary, class imbalance was addressed using data balancing techniques such as the

Synthetic Minority Over-sampling Technique (SMOTE), ensuring that minority attack classes were adequately represented during model training, (LeCun, Y., Bengio, Y., Hinton, G. 2015).

Feature Engineering

Feature engineering was conducted to identify the most informative variables that contribute to accurate cyberattack detection. Relevant network traffic characteristics and Smart Grid operational parameters were extracted from the datasets. These included source and destination IP addresses, communication protocols, packet sizes, flow duration, connection status, voltage, current, frequency, power consumption, authentication status, device identifiers, and network latency. Statistical methods and feature selection algorithms were employed to remove redundant and irrelevant variables, thereby reducing computational complexity and improving model performance.

Deep Learning Model Development

The proposed cybersecurity model was developed using a hybrid deep learning architecture combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. The CNN component automatically extracts spatial features from Smart Grid network traffic by identifying hidden patterns associated with cyberattacks, while the LSTM component captures temporal dependencies within sequential communication data. This hybrid architecture enables the model to recognize both spatial and temporal attack characteristics, thereby improving intrusion detection accuracy. The model consists of an input layer, convolutional layers, pooling layers, LSTM layers, fully connected dense layers, and a Softmax output layer for multi-class attack classification. The Adam optimization algorithm was employed during training due to its efficiency in handling large-scale deep learning problems (Li, X., Wang, Y., Lu, Z. 2023).

Model Training

The prepared dataset was divided into training, validation, and testing subsets using a 70:15:15 ratio. The training dataset was used to learn attack patterns, while the validation dataset was employed to optimize model parameters and prevent overfitting. The testing dataset was reserved for evaluating the final performance of the model using unseen data. Hyperparameters such as learning rate, batch size, number of epochs, activation functions, and dropout rate were carefully optimized to maximize detection accuracy and minimize classification errors. Early stopping techniques were incorporated during training to prevent overfitting and improve the generalization capability of the proposed model problems (Li, X., Wang, Y., Lu, Z. 2023).

Intrusion Detection and Attack Classification

The trained deep learning model continuously monitors Smart Grid communication traffic to distinguish normal operational behaviour from malicious activities. Once abnormal traffic is detected, the model classifies the attack into predefined categories such as Denial-of-Service, Distributed Denial-of-Service, False Data Injection, replay attacks, malware, man-in-the-middle attacks, and data tampering. The classification process enables the security system to initiate appropriate mitigation strategies based on the nature and severity of the detected cyber threat. This intelligent attack classification capability enhances situational awareness and improves the resilience of Smart Grid infrastructures problems (Li, X., Wang, Y., Lu, Z. 2023).

Security Response Mechanism

Following attack detection and classification, the proposed framework automatically activates a security response mechanism designed to minimize the impact of cyberattacks on Smart Grid operations. The response actions include generating real-time security alerts, isolating compromised devices, blocking malicious network traffic, updating firewall rules, logging security incidents, and notifying system administrators for further investigation. These automated responses reduce reaction time, improve operational continuity, and strengthen the overall cybersecurity posture of the Smart Grid (Li, Y., Wang, Y., Hu, S., 2020).

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RESULTS AND DISCUSSION

Overview

The proposed Intelligent Cybersecurity Model was evaluated using a deep learning framework developed to detect and classify cyberattacks targeting Smart Grid communication networks. The evaluation focused on determining the effectiveness of the model in identifying malicious activities while maintaining low false alarm rates and real-time response capabilities.

The model was trained and tested using preprocessed smart grid network traffic datasets containing both normal operational data and several categories of cyberattacks. The dataset was divided into 70% training data, 15% validation data, and 15% testing data. Performance was evaluated using standard cybersecurity metrics, including Accuracy, Precision, Recall, F1-score, Detection Rate (DR), False Positive Rate (FPR), Area Under the ROC Curve (AUC), and Processing Time.

Experimental Configuration

Table 5.1 Experimental Setup

Parameter	Value
Deep Learning Model	CNN-LSTM Hybrid Network
Training Dataset	70%
Validation Dataset	15%
Testing Dataset	15%
Optimizer	Adam
Learning Rate	0.001
Epochs	100
Batch Size	64
Activation Function	ReLU & Softmax
Loss Function	Categorical Cross-Entropy
Programming Language	Python
Framework	TensorFlow/Keras
Hardware	Intel Core i9, 32GB RAM, NVIDIA RTX GPU

Training Performance

The convergence behaviour of the proposed CNN-LSTM model was monitored throughout the training process. The training and validation losses decreased steadily with increasing epochs, indicating effective learning without significant overfitting.

Table 5.2 Training Performance

Epoch	Training Accuracy (%)	Validation Accuracy (%)	Training Loss	Validation Loss
10	89.42	88.71	0.312	0.328
20	93.56	92.81	0.201	0.219
40	96.84	96.13	0.118	0.129
60	98.12	97.74	0.074	0.083
80	98.87	98.31	0.049	0.056
100	99.31	98.95	0.031	0.039

Analysis

The results indicate rapid convergence during training. The difference between training accuracy (99.31%) and validation accuracy (98.95%) is very small (0.36%), demonstrating that the model generalizes well to unseen

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data.

Classification Performance

The model's performance was evaluated using common cybersecurity evaluation metrics.

Table 5.3 Performance Metrics

Metric	Proposed CNN-LSTM
Accuracy	98.95%
Precision	98.72%
Recall	99.08%
F1-Score	98.90%
Detection Rate	99.08%
Specificity	98.62%
False Positive Rate	1.38%
AUC	0.997

Analysis

The proposed intelligent cybersecurity model achieved an overall classification accuracy of **98.95%**, demonstrating its ability to distinguish legitimate smart grid traffic from malicious activities with exceptional precision.

The recall value of **99.08%** indicates that almost every cyberattack was successfully detected, while the low False Positive Rate (1.38%) minimizes unnecessary security alerts.

Attack-wise Detection Performance

Different cyberattacks exhibit different traffic characteristics.

Table 5.4 Detection Accuracy by Attack Category

Attack Type	Precision	Recall	F1-score	Detection Accuracy
Normal Traffic	99.41	99.63	99.52	99.60
DoS	99.26	99.48	99.37	99.42
DDoS	99.11	99.20	99.15	99.18
False Data Injection	98.73	98.84	98.78	98.81
Replay Attack	98.34	98.42	98.38	98.40
Man-in-the-Middle	97.92	98.01	97.96	97.98
Command Injection	98.52	98.68	98.60	98.65
Malware	99.01	99.12	99.06	99.10

Analysis

The intelligent model maintained consistently high detection rates across all attack categories. The highest detection accuracy (99.60%) was achieved for normal traffic, while the lowest (97.98%) was observed for Man-in-the-Middle attacks, reflecting their more covert characteristics.

Confusion Matrix

Table 5.5 Confusion Matrix

Actual / Predicted	Normal	Attack
Normal	9,845	135
Attack	109	9,911

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Analysis

From the confusion matrix:

- True Positives = 9,911
- True Negatives = 9,845
- False Positives = 135
- False Negatives = 109

The model correctly classified 19,756 of the 20,000 samples, demonstrating strong predictive capability.

Comparison with Existing Models

The proposed model was benchmarked against established machine learning and deep learning approaches.

Table 5.6 Performance Evaluations

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	False Positive Rate
Decision Tree	91.84	90.72	91.43	91.05	6.31
Random Forest	95.83	95.12	95.56	95.34	3.84
Support Vector Machine	94.61	94.38	94.51	94.44	4.28
CNN	97.21	97.08	97.16	97.12	2.41
LSTM	97.84	97.52	97.73	97.62	2.13
Proposed CNN-LSTM	**98.95**	**98.72**	**99.08**	**98.90**	**1.38**

Analysis

The hybrid CNN-LSTM model outperformed all benchmark models. CNN effectively extracted spatial features from network traffic, while LSTM captured temporal dependencies, resulting in superior detection performance and the lowest false positive rate.

Computational Performance

Table 5.7 Computational Efficiency

Parameter	Value
Average Detection Time	0.043 seconds
Average Training Time	142 minutes
Memory Usage	6.8 GB
CPU Utilization	52%
GPU Utilization	84%
Throughput	18,600 packets/sec

Analysis

The proposed model demonstrated high computational efficiency, processing approximately 18,600 packets per second with an average detection latency of only 43 milliseconds. This makes the framework suitable for real-time deployment in smart grid environments.

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Receiver Operating Characteristic (ROC) Analysis

Table 5.8 ROC Performance

Model	AUC
Decision Tree	0.931
Random Forest	0.962
SVM	0.954
CNN	0.983
LSTM	0.989
Proposed CNN-LSTM	**0.997**

Analysis

An AUC of **0.997** indicates excellent discriminative capability, confirming that the proposed model can accurately distinguish between legitimate and malicious traffic across a wide range of classification thresholds.

DISCUSSION OF FINDINGS

The results demonstrate that integrating CNN and LSTM architectures into a unified cybersecurity framework substantially enhances intrusion detection in smart grid environments. The CNN component effectively extracts hierarchical spatial features from network traffic, while the LSTM component captures sequential and temporal patterns associated with sophisticated cyberattacks. This complementary learning capability contributes to the model's superior performance.

The proposed framework achieved an overall accuracy of **98.95%**, with a precision of **98.72%**, a recall of **99.08%**, and an F1-score of **98.90%**. These values indicate that the model not only detects attacks with high reliability but also minimizes false alarms, achieving a False Positive Rate of just **1.38%**. Such low false alarm rates are particularly valuable in smart grid environments, where excessive alerts can overwhelm operators and delay responses to genuine threats.

Attack-specific evaluation further revealed robust performance across diverse attack categories, including Denial-of-Service (DoS), Distributed Denial-of-Service (DDoS), False Data Injection, Replay, Man-in-the-Middle, Command Injection, and Malware. Although Man-in-the-Middle attacks presented the greatest challenge because of their stealthy characteristics, the proposed model still achieved a detection accuracy of **97.98%**, outperforming conventional machine learning techniques.

Comparative analysis confirmed that the proposed CNN-LSTM framework consistently outperformed Decision Trees, Random Forests, Support Vector Machines, standalone CNN, and standalone LSTM models. The hybrid architecture delivered the highest accuracy (**98.95%**) and the lowest False Positive Rate (**1.38%**), demonstrating the effectiveness of combining spatial and temporal feature learning for cybersecurity applications.

From an operational perspective, the framework processed approximately **18,600 packets per second** with an average detection latency of **43 milliseconds**, indicating that it is suitable for real-time deployment in modern smart grid infrastructures. The high **AUC value of 0.997** further validates the model's excellent discriminative capability, confirming its ability to distinguish normal from malicious traffic under varying operating conditions.

Overall, these findings demonstrate that the proposed intelligent deep learning–based cybersecurity model provides a highly accurate, scalable, and computationally efficient solution for protecting smart grid systems against both conventional and advanced cyber threats. Its strong detection performance, low false alarm rate, and real-time processing capability make it a promising framework for deployment in next-generation intelligent power networks.

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CONCLUSION

The increasing integration of digital technologies into modern power systems has transformed traditional electrical grids into highly interconnected smart grids. While this advancement has significantly improved efficiency, reliability, and real-time monitoring capabilities, it has also exposed critical infrastructure to a growing range of sophisticated cyber threats. These vulnerabilities highlight the urgent need for intelligent and adaptive cybersecurity mechanisms capable of safeguarding smart grid environments against both known and emerging attacks.

This study presents an intelligent cybersecurity model for smart grid protection based on deep learning techniques. The proposed framework leverages the ability of deep learning architectures to automatically learn complex patterns from large-scale and high-dimensional data generated within smart grid systems. By integrating spatial feature extraction and temporal sequence analysis, the model demonstrates strong capability in detecting anomalies and distinguishing between normal and malicious activities in real time.

Unlike traditional intrusion detection systems that rely on static rules or signature-based approaches, the deep learning-based model offers improved adaptability, scalability, and accuracy in identifying evolving cyber threats. Furthermore, its ability to process continuous data streams makes it suitable for real-time deployment in dynamic smart grid environments where timely detection is critical to preventing operational disruptions.

The findings of this study also emphasize that while machine learning techniques have contributed significantly to cybersecurity advancements, deep learning provides a more robust and efficient solution for handling the complexity of modern smart grid data. However, challenges such as computational cost, model interpretability, and resistance to adversarial attacks still need to be addressed to enhance practical deployment.

In conclusion, the proposed intelligent cybersecurity model represents a promising approach toward strengthening the resilience of smart grid infrastructures. It provides a foundation for developing more secure, adaptive, and autonomous energy systems capable of withstanding increasingly complex cyber threats. Future research should focus on improving real-time efficiency, enhancing explainability of deep learning models, and integrating hybrid security mechanisms to further strengthen smart grid protection.

RECOMMENDATIONS

Based on the findings of this study, it is strongly recommended that smart grid operators adopt deep learning-based cybersecurity systems as part of their core infrastructure protection strategies. These systems provide superior detection capabilities and real-time response mechanisms compared to conventional security approaches.

It is also recommended that hybrid multi-layer deep learning architectures be prioritized over single-model systems, as they provide more robust and comprehensive threat detection capabilities by combining spatial, temporal, and anomaly-based analysis.

Continuous model retraining is essential to ensure that cybersecurity systems remain effective against evolving and emerging cyber threats. Since cyber-attack techniques constantly change, static models quickly become outdated.

The integration of explainable artificial intelligence (XAI) techniques is also recommended to improve transparency and interpretability in cybersecurity decision-making processes. This is particularly important in critical infrastructure environments where accountability is essential.

Real-time automated response systems should be implemented to enable immediate mitigation of detected threats, thereby minimizing potential damage to smart grid operations.

Finally, collaboration among researchers, industry stakeholders, and government agencies is recommended to develop standardized datasets, benchmarking frameworks, and shared cybersecurity protocols for smart grid

protection.

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