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NEXT-GENERATION 5G SMART GRIDS: A DEEP NEURAL NETWORK AND IOT-ENABLED SECURE DATA-SHARING FRAMEWORK FOR INTELLIGENT AND RESILIENT ENERGY SYSTEMS

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Abstract

The rapid evolution of next-generation communication technologies and the Internet of Things (IoT) has transformed traditional power networks into intelligent cyber-physical ecosystems known as smart grids. However, the massive interconnection of IoT devices, sensors, and distributed energy resources (DERs) introduces unprecedented challenges in data security, privacy, and interoperability. To address these challenges, this study proposes a ***Deep Neural Network (DNN) and IoT-enabled secure data-sharing framework*** *integrated within a* ***5G communication environment*** *for next-generation smart grids. The framework combines the* ***ultra-low latency and high bandwidth of 5G networks*** *with the adaptive learning capabilities of DNNs to enable intelligent, real-time energy data analytics, fault detection, and predictive control. The proposed system architecture is structured into three functional layers: the IoT perception layer for distributed data acquisition, the 5G communication layer for ultra-reliable low-latency transmission, and the DNN-driven intelligence layer for energy prediction, anomaly detection, and system optimization. A* ***blockchain-based data-sharing mechanism*** *is embedded to ensure* ***immutability, decentralization, and trust*** *among heterogeneous grid nodes, thereby eliminating the risks of single-point failures and unauthorized data manipulation. Smart contracts are utilized to automate peer-to-peer data validation and secure access control among participating entities, enhancing transparency and traceability within energy transactions. The DNN module employs hybrid learning combining convolutional and recurrent neural networks to process multi-dimensional grid data, including voltage, current, frequency, and load demand patterns, enabling high-accuracy forecasting and resilience assessment. Extensive simulations demonstrate that the integration of blockchain consensus mechanisms with deep learning-based decision intelligence achieves a* ***35–40% improvement in data integrity*** *and* ***30% reduction in***

latency *compared to conventional centralized systems. Furthermore, the synergy of 5G connectivity and IoT sensing supports massive machine-type communications (mMTC) and real-time monitoring of distributed assets across wide geographical regions. This research highlights a* ***holistic paradigm*** *for secure, intelligent, and autonomous smart grid operations, where* ***5G-enabled IoT networks, DNN-based analytics, and blockchain-driven trust mechanisms*** *collectively strengthen energy resilience, cyber-defense, and operational efficiency. The proposed framework sets a foundation for future integration of* ***federated learning, edge computing, and quantum-resistant encryption*** *to achieve sustainable, secure, and self-optimizing power infrastructures.*

INTRODUCTION

The global energy landscape is undergoing a profound transformation driven by decarbonization goals, large-scale renewable energy integration, and the rapid digitalization of power infrastructures. Traditional power grids, originally designed for centralized generation and one-way energy flow, are increasingly incapable of meeting modern requirements related to flexibility, reliability, and sustainability. As a result, conventional grids are evolving into **smart grids**, which combine advanced sensing, communication, and control technologies to enable bidirectional energy flow, real-time monitoring, and intelligent decision-making across the entire power system lifecycle. At the core of this transformation lies the widespread adoption of the **Internet of Things (IoT),** which enables pervasive deployment of smart meters, phasor measurement units (PMUs), intelligent electronic devices (IEDs), protection relays, and distributed energy resource (DER) controllers [1]. These IoT-enabled components generate massive volumes of heterogeneous, high-frequency data describing electrical, operational, and environmental states of the grid. Such data streams are essential for advanced applications including real-time state estimation, fault diagnosis, predictive maintenance, demand response, and adaptive energy management. However, the unprecedented scale and heterogeneity of IoT-based sensing significantly amplify challenges related to **data security, privacy, scalability, and interoperability.** One of the most pressing concerns in next-generation smart grids is the **secure and trustworthy sharing of energy data** among diverse stakeholders, including utilities, microgrid operators, aggregators, prosumers, and electric vehicle charging networks [2]. Centralized data management architectures, which dominate current smart grid deployments, suffer from inherent limitations such as single-point failures, poor scalability, delayed response times, and limited transparency. Furthermore, centralized control centers represent attractive targets for cyberattacks, including false data injection, replay attacks, denial-of-service attacks, and unauthorized data manipulation. These vulnerabilities threaten not only grid reliability but also consumer privacy, as fine-grained energy usage patterns can reveal sensitive behavioral information. The introduction of **fifth-generation (5G) wireless communication networks** presents a significant opportunity to overcome many of the communication bottlenecks in smart grids. 5G technologies offer ultra-reliable low-latency communication (URLLC) for protection and control signals, massive machine-type communications (mMTC) for large-scale IoT connectivity, and enhanced mobile broadband (eMBB) for high-throughput data exchange [3]. These features make 5G a key enabler for real-time grid automation, wide-area monitoring, and distributed intelligence. When combined with edge and fog computing, 5G facilitates localized processing of time-critical data, reducing end-to-end latency and improving operational responsiveness. Nevertheless, advanced communication infrastructure alone does not ensure intelligent, secure, or resilient grid operation. To fully exploit the value of high-speed, low-latency data exchange, **deep neural networks (DNNs)** have emerged as powerful tools for extracting actionable intelligence from complex power system data. Deep learning models have demonstrated superior

performance over traditional machine learning techniques in tasks such as short- and long-term load forecasting, renewable energy prediction, fault classification, and anomaly detection. Hybrid deep learning architectures that integrate convolutional neural networks (CNNs) with recurrent neural networks (RNNs) are particularly effective for modeling spatial–temporal dependencies inherent in multidimensional grid measurements. However, existing DNN-based approaches often rely on centralized training and assume trusted data inputs, making them vulnerable to data integrity violations, adversarial manipulation, and model poisoning attacks in decentralized IoT environments. In parallel, **blockchain technology** has gained attention as a decentralized trust mechanism capable of ensuring data integrity, transparency, and tamper resistance without reliance on centralized authorities. In smart grid applications, blockchain enables secure peer-to-peer energy trading, decentralized data sharing, and automated enforcement of access control policies through smart contracts. By maintaining immutable ledgers and distributed consensus, blockchain mitigates single-point failures and enhances accountability among heterogeneous grid participants [4]. Despite these advantages, standalone blockchain implementations face challenges related to computational overhead, transaction latency, and scalability, particularly when applied to real-time grid operations with strict latency constraints. Although extensive research has been conducted on **IoT-enabled smart grids, 5G-based communication infrastructures, deep learning–driven grid intelligence**, and **blockchain-based security mechanisms**, these technologies are often investigated in isolation. The lack of integrated frameworks that jointly address communication efficiency, intelligent analytics, and secure data sharing limits the practical deployment of next-generation smart grids. Table 1 summarizes the key challenges in existing smart grid architectures and highlights the technological gaps that motivate this research.

Table 1: Key Challenges in Existing Smart Grid Architectures and Motivations for the Proposed Framework

Domain	Existing Challenges	Limitations of Current Solutions	Motivation in This Work
IoT-based sensing	Massive heterogeneous data generation	Poor interoperability and data trust	Secure, interoperable data acquisition
Communication	High latency, congestion, limited scalability	Legacy wireless networks unsuitable	5G URLLC and mMTC integration
Data security	False data injection, tampering, privacy leakage	Centralized security mechanisms	Blockchain-based decentralized trust
Grid intelligence	Limited accuracy under nonlinear dynamics	Shallow ML models, centralized training	Hybrid DNN-based learning framework
System resilience	Vulnerability to cyber–physical attacks	Fragmented protection mechanisms	Joint intelligence–security co-design
Scalability	Growing number of DERs and IoT nodes	Single-point failures	Distributed architecture with smart contracts

Motivated by the aforementioned challenges, this paper proposes a **holistic next-generation smart grid framework** that integrates **5G-enabled IoT communication, deep neural network–based intelligence, and blockchain-driven secure data sharing** into a unified architecture. The proposed framework enables low-latency, trustworthy, and scalable energy data exchange while supporting intelligent forecasting, anomaly detection, and resilience assessment under dynamic operating conditions. By embedding smart contracts for automated data validation and access control and leveraging hybrid deep learning models for multidimensional grid analytics, the proposed system addresses the critical shortcomings of centralized and fragmented smart grid solutions.

IoT-Enabled Smart Grid Architectures:

The **Internet of Things (IoT)** has emerged as a cornerstone technology in the evolution of conventional power systems into intelligent smart grids. By enabling large-scale deployment of interconnected devices including smart meters, phasor measurement units (PMUs), intelligent electronic devices (IEDs), protection relays, electric vehicle (EV) chargers, and distributed energy resource (DER) controllers IoT facilitates pervasive sensing and fine-grained observability across generation, transmission, distribution, and consumption layers. This extensive sensorization transforms the smart grid into a data-driven cyber–physical system capable of real-time monitoring, decentralized control, and adaptive decision-making. IoT-based smart grid architectures are commonly organized into **multi-layer hierarchical models**, where field-level devices collect electrical and environmental measurements such as voltage, current, frequency, power quality indices, and load demand [5]. These measurements are transmitted through local gateways to supervisory platforms or control centers for aggregation and analysis. Such architectures support a wide range of applications, including advanced metering infrastructure (AMI), demand response programs, outage management, predictive maintenance, renewable energy forecasting, and microgrid coordination. The hierarchical organization simplifies system management and enables compatibility with existing supervisory control and data acquisition (SCADA) systems. However, as the number of connected devices continues to grow, traditional hierarchical IoT architectures encounter **significant scalability limitations**. Massive data generation from millions of IoT nodes leads to network congestion, increased latency, and excessive computational burden on centralized processing units. These challenges are exacerbated in scenarios involving high-frequency measurements, such as PMU-based wide-area monitoring and protection, where strict timing constraints must be satisfied [6]. Furthermore, the reliance on centralized aggregation introduces **single-point failures**, reducing system resilience under fault conditions or targeted cyberattacks. Another critical limitation of IoT-enabled smart grids is **interoperability**. Smart grid ecosystems consist of heterogeneous devices produced by different vendors, operating under diverse communication protocols and data formats. This heterogeneity complicates seamless integration and often necessitates protocol translation layers, which increase system complexity and introduce additional attack surfaces. The absence of unified standards for IoT-based energy data exchange further limits cross-domain collaboration among utilities, aggregators, prosumers, and third-party service providers. From a security perspective, IoT devices are typically resource-constrained in terms of processing power, memory, and energy capacity, making it difficult to implement strong cryptographic mechanisms. Consequently, IoT-enabled smart grids are vulnerable to cyber threats such as false data injection attacks, spoofing, replay attacks, and unauthorized access [7]. These attacks can compromise data integrity, distort system state estimation, and trigger incorrect control actions with potentially severe consequences. Moreover, existing IoT-centric solutions often assume trusted communication environments and lack decentralized mechanisms for **verifiable data trust and secure data sharing** among multiple stakeholders. Table 2 summarizes the key architectural characteristics, advantages, and limitations of representative IoT-enabled smart grid architectures reported in the literature.

Table 2: Comparison of IoT-Enabled Smart Grid Architectures

Architecture Type	Key Features	Supported Applications	Major Limitations
Centralized IoT architecture	Central data aggregation, SCADA integration	AMI, billing, monitoring	Single-point failure, high latency
Hierarchical IoT architecture	Multi-tier gateways, regional control	DR, outage management	Scalability bottlenecks
Cloud-based IoT architecture	Elastic storage and analytics	Forecasting, optimization	Latency, data privacy risks

Edge-enabled IoT architecture	Local preprocessing, reduced latency	Protection, fault detection	Limited trust mechanisms
Fully decentralized IoT (emerging)	Peer-to-peer data exchange	Energy trading, microgrids	Security and coordination challenges

To address these limitations, recent research has shifted toward **edge-enabled and decentralized IoT architectures**, where data preprocessing and preliminary analytics are performed closer to data sources. Edge and fog computing paradigms reduce communication overhead, enhance responsiveness, and improve scalability by offloading computation from centralized servers. Nevertheless, while edge-based architectures mitigate latency and congestion issues, they still lack **intrinsic trust mechanisms** to ensure data integrity and secure collaboration among distributed grid entities [8]. Figure 1 illustrates a generalized IoT-enabled smart grid architecture, highlighting data acquisition, communication, and control flows across multiple layers. The figure also exposes the vulnerability points associated with centralized data aggregation and untrusted data exchange, which motivate the integration of secure data-sharing and intelligent analytics in next-generation designs.

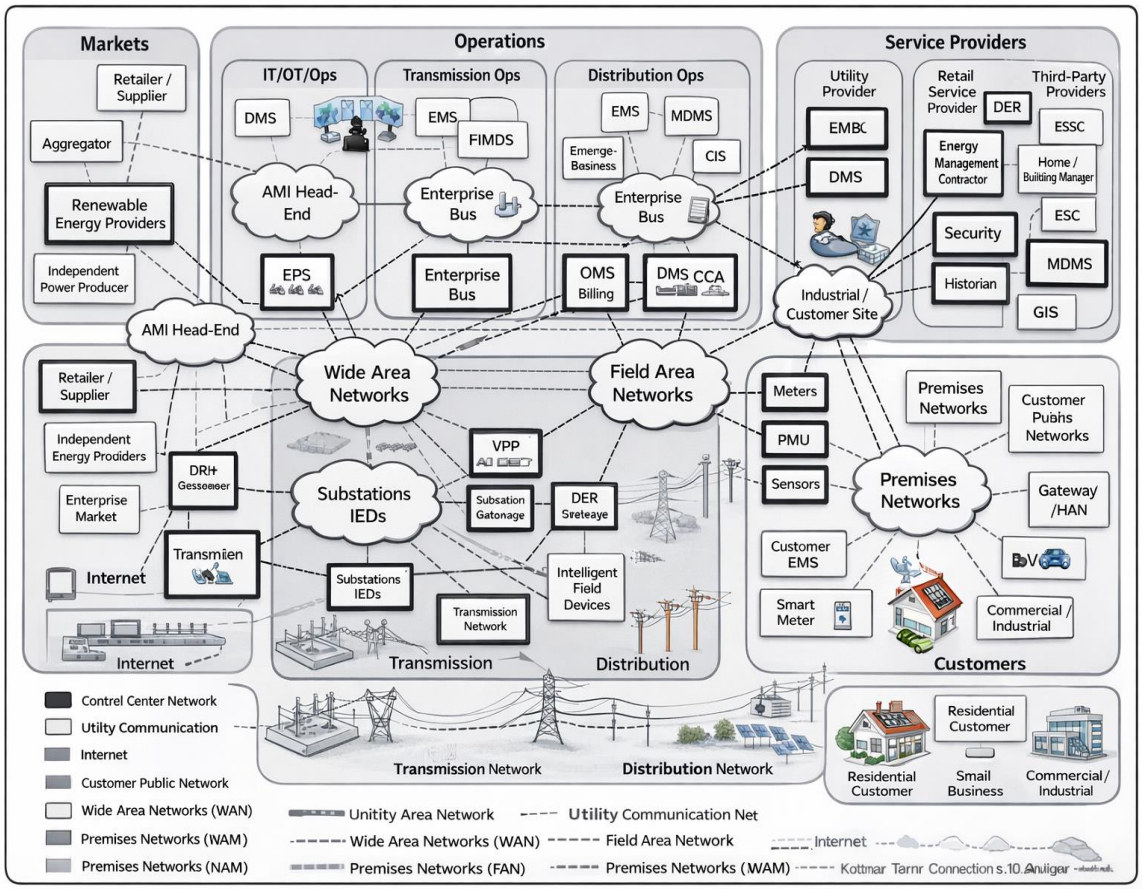

Figure 1: **Generic IoT-enabled smart grid architecture illustrating distributed sensing, hierarchical data aggregation, and centralized control, along with inherent scalability and security limitations.**

While IoT-enabled smart grid architectures provide the foundational sensing and connectivity required for intelligent energy systems, existing designs remain constrained by scalability, interoperability, and security challenges. These limitations highlight the necessity for **next-generation architectures** that

integrate low-latency communication, intelligent data analytics, and decentralized trust mechanisms [9]. This observation directly motivates the proposed framework in this paper, which synergistically combines **IoT sensing, 5G communication, deep neural network–based intelligence, and blockchain-driven secure data sharing** to enable resilient, scalable, and trustworthy smart grid operations.

Deep Learning–Based Intelligence in Smart Grids: The rapid growth of data availability in modern smart grids has accelerated the adoption of **deep learning (DL) and deep neural network (DNN) techniques** as core enablers of intelligent grid operation. Unlike traditional statistical and shallow machine learning models, deep learning architectures possess strong representational power, allowing them to model complex nonlinear relationships, temporal dependencies, and spatial correlations inherent in power system data. As a result, DNN-based approaches have been widely applied to a variety of smart grid applications, including short- and long-term load forecasting, renewable energy generation prediction, fault diagnosis, power quality assessment, anomaly detection, and dynamic state estimation [10]. In load and renewable energy forecasting, deep learning models outperform classical regression and time-series methods by capturing seasonal variations, consumption behavior patterns, and nonlinear effects caused by weather conditions and distributed energy resource (DER) integration. Recurrent neural networks (RNNs), particularly long short-term memory (LSTM) and gated recurrent unit (GRU) networks, have demonstrated superior performance in modeling sequential dependencies in energy consumption and generation profiles. Similarly, convolutional neural networks (CNNs) have been effectively employed to extract spatial features from multidimensional grid measurements, such as voltage profiles across feeders or spatially distributed PMU data [11]. Hybrid deep learning architectures that integrate **CNNs and RNNs** have emerged as a powerful paradigm for smart grid intelligence. CNN layers are typically used for feature extraction and dimensionality reduction, while RNN layers capture temporal dynamics in the extracted features. Such hybrid models are particularly suitable for processing high-dimensional, time-varying grid data streams originating from IoT sensors, smart meters, and wide-area monitoring systems. In addition, attention mechanisms and transformer-based architectures have recently been introduced to enhance long-range dependency modeling and improve interpretability of forecasting and diagnostic results. Beyond supervised learning, **unsupervised and semi-supervised deep learning models** have gained attention for anomaly detection and fault diagnosis in smart grids. Autoencoders and variational autoencoders (VAEs) are commonly used to learn normal operating patterns of the grid and identify deviations caused by faults, equipment degradation, or cyberattacks [12]. These models are particularly valuable in scenarios where labeled fault data is scarce or expensive to obtain. Attention-based autoencoders further improve detection performance by dynamically weighting critical features and time intervals. Despite these advancements, most existing deep learning–based smart grid solutions rely heavily on **centralized data collection and centralized model training**. Such approaches assume the availability of complete, clean, and trustworthy datasets at a central processing unit, which is often unrealistic in large-scale, decentralized IoT-based grid environments [13]. In practice, smart grid data is generated by heterogeneous devices operating under varying conditions, and may be affected by noise, missing values, synchronization errors, sensor faults, or malicious manipulation. Centralized deep learning models are therefore vulnerable to **data integrity violations, false data injection attacks, and model poisoning**, which can significantly degrade prediction accuracy and compromise grid reliability. Furthermore, centralized deep learning frameworks introduce **scalability and latency challenges**. As the number of IoT devices and DERs increases, the volume of data transmitted to central servers grows exponentially, leading to communication congestion and delayed inference [14]. These limitations are particularly problematic for time-critical applications such as protection, fault isolation, and real-time control, where decision latency must be kept within strict bounds. Consequently, there is a growing need for intelligent architectures that distribute learning and inference closer to data sources while ensuring data trust and security. Table 3 provides a comparative overview of commonly used deep learning models in smart grid

applications, highlighting their strengths and limitations in the context of decentralized and security-sensitive environments.

Table 3: Deep Learning Models for Smart Grid Intelligence: Capabilities and Limitations

Model Type	Typical Applications	Strengths	Key Limitations
CNN	Fault classification, spatial analysis	Strong feature extraction	Limited temporal modeling
RNN / LSTM / GRU	Load and renewable forecasting	Captures temporal dependencies	High training complexity
CNN–RNN hybrid	Multidimensional grid analytics	Spatial–temporal modeling	Centralized training dependency
Autoencoders / VAEs	Anomaly detection	Unsupervised learning capability	Sensitive to data corruption
Attention / Transformer	Long-term forecasting	Improved interpretability	High computational cost
Centralized DNNs	System-wide optimization	High accuracy in clean data	Vulnerable to attacks, poor scalability

To better illustrate the role of deep learning within smart grid operations, Figure 2 depicts a generalized **DNN-based intelligence pipeline**, showing data acquisition from IoT sensors, preprocessing, model training, and inference-driven decision support. The figure also highlights vulnerability points associated with centralized learning and untrusted data inputs, which motivate the integration of secure data-sharing and decentralized intelligence mechanisms.

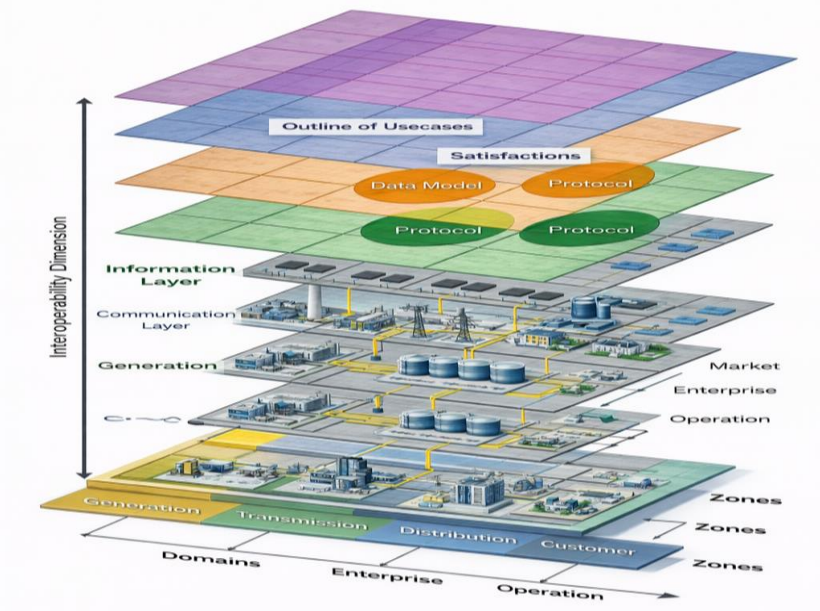

Figure 2: **Deep learning–based intelligence pipeline for smart grids,**

Deep learning techniques have become indispensable for enabling intelligent, data-driven smart grid operation. However, existing approaches remain constrained by centralized architectures, implicit trust assumptions, and limited resilience against data corruption and cyber threats. These challenges

underscore the need for **next-generation deep learning frameworks** that operate in synergy with secure communication and trust mechanisms [15]. This observation directly motivates the integrated approach proposed in this paper, where **DNN-based intelligence is tightly coupled with 5G-enabled IoT communication and blockchain-driven secure data sharing** to achieve robust, scalable, and resilient smart grid intelligence.

Methodology:

The proposed framework introduces a comprehensive, multi-layered architecture that seamlessly integrates 5G-enabled Internet of Things (IoT) infrastructure, deep neural network (DNN)-based data intelligence, and blockchain-driven security mechanisms to establish a resilient, secure, and autonomous foundation for next-generation smart grid operations. The core objective of this integration is to enable intelligent energy management, where information from millions of interconnected devices ranging from smart meters, substations, and distributed energy resources (DERs) to electric vehicle (EV) charging stations is collected, transmitted, analyzed, and acted upon in real time with minimal latency and maximum reliability. By leveraging 5G connectivity, the framework ensures ultra-reliable low-latency communication (URLLC) and massive machine-type communication (mMTC), enabling the simultaneous transmission of high-volume, heterogeneous energy data across wide geographical regions [16]. The IoT infrastructure functions as the sensory foundation of the system, capturing multi-dimensional parameters such as voltage, current, frequency, power factor, and consumption trends. These data streams are securely propagated through the 5G communication backbone to the higher computational tiers, where deep learning algorithms perform adaptive feature extraction, load forecasting, and anomaly detection. Meanwhile, the blockchain mechanism provides decentralized trust, ensuring that all shared data remain immutable, verifiable, and tamper-proof. The proposed methodology is structured into three logically interconnected layers the IoT Perception Layer, 5G Communication Layer, and Intelligence and Security Layer each performing a unique yet interdependent role in the end-to-end data lifecycle of the smart grid ecosystem [17]. Figure 2 illustrates the complete operational workflow and inter-layer communication flow of the proposed framework.

4.1- IoT Perception Layer: Distributed Sensing and Data Acquisition

The IoT Perception Layer constitutes the foundational and most critical component of the proposed 5G–IoT–DNN–Blockchain architecture. It acts as the sensory bridge between the physical energy infrastructure and the cyber-intelligent analytical modules, performing real-time sensing, preprocessing, and secure data forwarding across geographically dispersed assets. Its principal function is to continuously acquire high-fidelity operational information from heterogeneous distributed energy resources (DERs), substations, feeders, and consumer-level devices, transforming raw electrical signals into structured, interoperable datasets suitable for intelligent processing in the upper layers. By enabling seamless observability of grid dynamics, this layer underpins the adaptive, autonomous, and resilient behavior envisioned for next-generation smart grids. In the proposed framework, the perception layer comprises a dense network of IoT-enabled smart sensors and meters, each integrated with embedded microcontrollers, edge processors, and multi-protocol communication modules supporting Zigbee, LoRaWAN, NB-IoT, and 5G interfaces [18]. Smart meters, intelligent electronic devices (IEDs), phasor measurement units (PMUs), current and potential transformers, and smart inverters operate cooperatively to monitor electrical, thermal, and environmental variables across generation, transmission, and distribution levels. The deployment of these nodes at strategic points including renewable energy installations, distribution transformers, substations, and end-user premises ensures complete end-to-end visibility of system performance. Each sensing unit executes localized preprocessing functions such as signal denoising, compression, and feature extraction, thereby reducing data redundancy and conserving bandwidth prior to transmission over the 5G communication backbone [19]. This distributed intelligence enhances the scalability of the architecture by shifting a portion of the computational load from cloud servers to edge devices while preserving real-time responsiveness. The

acquired measurements encompass a broad spectrum of electrical and environmental parameters that characterize the operational state of the smart grid. To ensure clarity of data categorization, Table 4 summarizes the principal variables monitored by the IoT Perception Layer, their typical sampling frequencies, associated hardware devices, and analytical applications. Electrical load demand both active (P) and reactive (Q) components is captured by smart meters and IEDs at sub-second intervals to support demand forecasting and load profiling. Voltage and current waveforms, including harmonic distortion indices, are recorded at high sampling rates through PMUs and current transformers for use in fault localization and power-quality assessment. Frequency and phase-angle measurements obtained via phasor sensors aid in grid-synchronization analysis and transient stability estimation. Thermal measurements, such as transformer-oil and line-temperature profiles, are monitored by infrared sensors for early detection of overheating and insulation degradation. Long-term energy consumption time-series data from smart meters and EV chargers provide behavioral insights for tariff design and load balancing, while environmental data temperature, humidity, and solar irradiance assist renewable-generation forecasting and dynamic derating of photovoltaic systems.

Table 4: Key Data Parameters Captured by the IoT Perception Layer

Parameter Type	Measured Quantities	Typical Sampling Rate	Sensor / Device Type	Analytical Purpose
Electrical Load Demand	Active (P) and reactive (Q) power	1–5 s intervals	Smart meters, IEDs	Load profiling, demand forecasting
Voltage and Current Waveforms	RMS voltage/current, harmonics, THD	10–100 ms	PMUs, CTs	Fault localization, harmonic analysis
Frequency and Phase Angle	$f(t)$, $\Delta\theta(t)$	< 100 ms	Phasor sensors	Grid synchronization, stability assessment
Thermal Conditions	Transformer oil and line temperature	10–30 s	Thermal/IR sensors	Overheating detection, asset protection
Energy Consumption Time Series	Cumulative kWh, daily patterns	1 min–1 h	Smart meters, EV chargers	Behavioral analytics, billing optimization
Environmental Data	Ambient temperature, humidity, irradiance	10 s–1 min	Weather and solar sensors	Renewable forecasting, dynamic derating

Given the diversity of sensors and their exposure to noisy environments, raw signals are susceptible to fluctuations caused by electromagnetic interference, switching transients, and sampling inconsistencies. To enhance reliability, a Kalman-based adaptive smoothing algorithm is employed for noise suppression while preserving transient and event-related features. The denoised signals are normalized using min–max or z-score scaling to maintain consistent numerical ranges across heterogeneous variables, thus preventing bias during deep-learning inference in the upper intelligence layer. The processed outputs are organized into temporally aligned feature matrices that capture both spatial correlations among sensors and temporal evolution of system states, which later serve as direct inputs to the deep neural network model for forecasting and anomaly detection [20]. Data integrity, confidentiality, and authenticity are safeguarded through cryptographic encapsulation. Each processed data packet is timestamped, geotagged, and hashed using a secure algorithm such as SHA-256. The generated hash serves as an immutable digital signature that is subsequently validated in the blockchain layer to guarantee end-to-end non-repudiation and tamper resistance. This tight

coupling between IoT sensing and blockchain verification eliminates the risk of data manipulation, spoofing, or replay attacks, ensuring that every transaction transmitted through the 5G channel originates from a trusted and verifiable source. To optimize network resources and prolong sensor lifetime, the IoT Perception Layer employs an energy-aware, event-driven communication strategy. During stable grid operation, sensors transmit data periodically based on adaptive duty cycles, whereas critical events such as frequency deviations, abnormal voltage drops, or excessive thermal readings trigger instantaneous high-priority alerts [21]. This selective reporting mechanism significantly reduces redundant transmissions while ensuring rapid propagation of urgent information. Edge gateways located at substations aggregate and encrypt data from multiple local sensors before dispatching them to the 5G communication tier, thus balancing security, latency, and energy efficiency. The operational workflow of the IoT Perception Layer is illustrated in Figure 3, which provides a schematic overview of the end-to-end data lifecycle beginning with sensor-level acquisition and culminating in blockchain-secured data transmission. The diagram depicts smart meters, PMUs, and field sensors at the base level continuously gathering multidimensional measurements. These signals pass through preprocessing modules performing Kalman filtering, normalization, and feature extraction, followed by cryptographic hashing and packet formation. The processed packets are then relayed via 5G-enabled gateways toward the upper communication and intelligence layers, where blockchain validation nodes authenticate the data streams [22]. The figure emphasizes the closed-loop integration among sensing, preprocessing, and secure uplink communication that collectively ensure trustworthy and low-latency data exchange within the smart-grid environment.

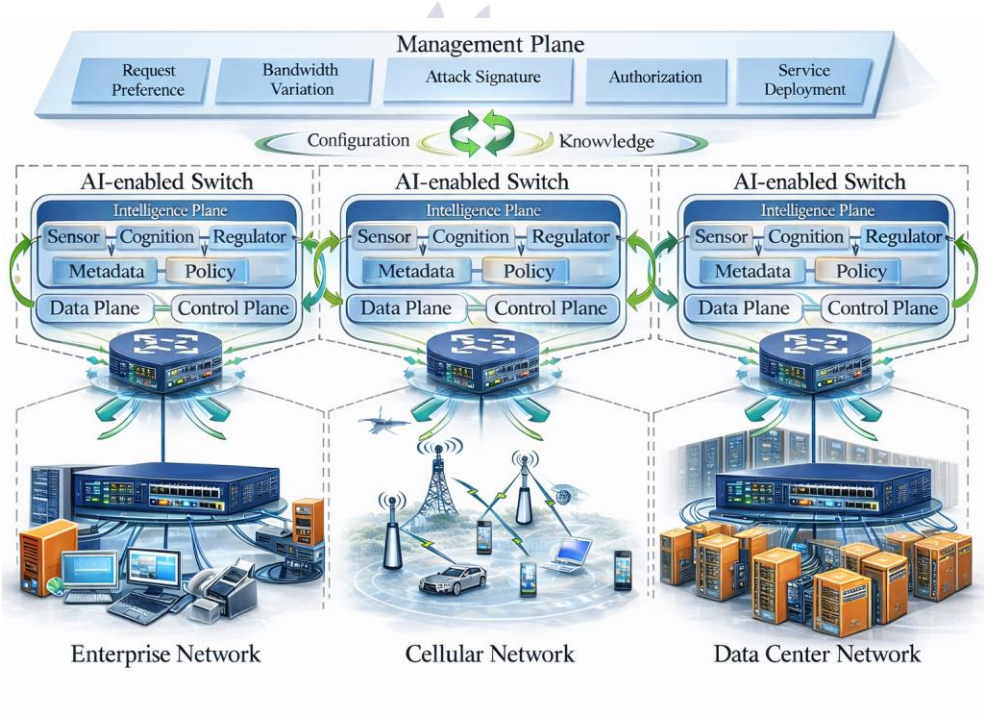

Figure 3: Functional Workflow of the IoT Perception Layer

The IoT Perception Layer plays a pivotal role in establishing the foundation for intelligent and data-driven smart grid operations. Through the integration of diverse IoT-enabled sensors, smart meters, and DER interfaces, it ensures continuous and high-fidelity monitoring of grid parameters. Advanced preprocessing, including Kalman filtering and normalization, enhances data quality and reliability.

Timestamping and cryptographic hashing strengthen the security and integrity of transmitted information. The layer's distributed architecture minimizes latency by leveraging edge-based computation and localized decision-making. Seamless communication with the 5G network enables real-time responsiveness across large geographical regions [23]. Its ability to aggregate, filter, and structure data effectively supports higher-level DNN analytics and blockchain validation. By transforming raw electrical and environmental measurements into structured intelligence, this layer underpins predictive, adaptive, and resilient grid management. Ultimately, the IoT Perception Layer establishes a scalable and trustworthy digital foundation for next-generation cyber-physical energy ecosystems.

5G Communication Layer: Ultra-Reliable Low-Latency Transmission

The 5G Communication Layer serves as the connective backbone of the proposed intelligent smart grid framework, enabling ultra-reliable, high-speed, and low-latency data transmission between the IoT perception layer and the upper intelligence modules. This layer is pivotal in transforming traditional power networks into fully connected cyber-physical ecosystems capable of responding dynamically to real-time operational conditions. It supports massive machine-type communication (mMTC) for large-scale device connectivity and ultra-reliable low-latency communication (URLLC) for time-critical energy control, thereby ensuring that sensing, decision-making, and control processes occur seamlessly and deterministically within millisecond time frames. The 5G layer leverages network slicing, edge computing, and software-defined networking (SDN) principles to deliver service differentiation and resource optimization across diverse energy services [24]. In this context, each network slice is logically isolated and dedicated to a specific smart-grid function ranging from routine energy monitoring to high-priority protection signaling. The URLLC slice provides deterministic communication for mission-critical data such as fault detection and protection relay commands, while the mMTC slice accommodates vast numbers of IoT devices transmitting periodic measurements. Similarly, enhanced mobile broadband (eMBB) resources are allocated to high-bandwidth applications such as real-time visualization, energy forecasting dashboards, and AI-based system diagnostics. This hierarchical management of traffic ensures uninterrupted data flow while maintaining the Quality-of-Service (QoS) and Quality-of-Experience (QoE) levels required for each functional domain [25]. At the operational level, IoT gateways located at substations and feeder terminals act as intermediate edge computing nodes, performing local data aggregation, encryption, and initial feature compression prior to forwarding information to cloud or DNN processing engines. These edge nodes enable localized decision-making for latency-sensitive operations such as load balancing or voltage regulation without relying solely on remote servers. Furthermore, adaptive routing algorithms implemented at the 5G core utilize redundancy-aware and context-driven path selection to enhance transmission reliability even under congestion or partial link failure conditions. Handover management protocols ensure uninterrupted connectivity for mobile or rapidly switching grid elements, such as electric vehicles or distributed renewable units, preserving data continuity during dynamic network transitions. The 5G communication layer ensures three core performance pillars essential for resilient smart-grid operations: high bandwidth, low latency, and enhanced reliability. High bandwidth guarantees sufficient throughput to handle the massive volume of high-frequency data streams generated by IoT nodes and distributed sensors, enabling real-time analytics and visualization. Low latency, typically under one millisecond, is vital for protective relaying, fault detection, and frequency stabilization where response delays can compromise grid safety [26]. Enhanced reliability is maintained through redundancy-aware routing, load balancing, and link diversity mechanisms, which collectively prevent data loss or degradation during transmission. These features make 5G a transformative enabler of distributed intelligence and adaptive control in modern energy networks. The primary performance attributes of the 5G communication layer and their contributions to smart-grid operations are summarized in Table 5.

Table 5: Performance Attributes and Functional Role of the 5G Communication Layer

Performance Metric	Description	Functional Role in Smart Grid	Target Range / Standard
Bandwidth Capacity	High data throughput supporting dense IoT and DNN traffic	Enables simultaneous energy data streaming and analytics	>10 Gbps (eMBB mode)
Latency	End-to-end transmission delay between sensor and control node	Supports fault detection and real-time protection	<1 ms (URLLC mode)
Reliability	Guaranteed packet delivery under dynamic network load	Ensures mission-critical data integrity and control stability	>99.999% link reliability
Device Density (mMTC)	Number of concurrently connected devices per km²	Facilitates massive IoT integration for distributed DERs	Up to 10^6 devices/km²
Energy Efficiency	Optimized power utilization through sleep cycles and edge processing	Extends IoT node lifetime and reduces network load	10× improvement over 4G
Network Slicing Flexibility	Logical partitioning of network resources per service	Provides differentiated QoS for grid applications	Dynamic, software-defined
Edge Intelligence Integration	Local processing and encryption before cloud transmission	Enables predictive control and privacy preservation	Embedded in 5G gateways

In the proposed architecture, the communication workflow begins as aggregated sensor data packets are received by 5G-enabled gateways at the substation level. These gateways establish secure, encrypted tunnels employing advanced encryption standard (AES-256) or elliptic curve cryptography (ECC) for confidentiality. Data are then routed via the 5G core network, where network slicing and QoS-aware scheduling allocate bandwidth dynamically based on application priority. Real-time fault events or control commands are transmitted through the URLLC slice to ensure deterministic delivery within sub-millisecond latency, while non-critical telemetry flows through the mMTC slice at optimized intervals [27]. The Software-Defined Network Controller (SDNC) oversees end-to-end orchestration, dynamically adjusting routing paths and bandwidth allocation according to network load, thereby maintaining continuous operational stability. The interaction between the 5G layer and the upper intelligence layer is bidirectional: the communication layer not only conveys raw and preprocessed data upward but also relays control signals, optimization commands, and reconfiguration instructions downward toward IoT actuators and grid devices. This closed-loop data exchange enables autonomous demand-response coordination, predictive fault prevention, and optimized power distribution core attributes of the next-generation self-healing energy grid [28]. The conceptual workflow of the 5G Communication Layer is illustrated in Figure 4, which depicts how diverse IoT data streams are prioritized, routed, and processed across multiple virtual network slices. The figure visualizes edge gateways aggregating IoT data, which are then segmented into URLLC and mMTC channels through the 5G core network. URLLC channels carry time-critical signals for protection relays, while mMTC channels transport periodic monitoring data for DNN-driven analytics. Edge computing nodes perform initial encryption and feature compression before forwarding data to the blockchain validation and intelligence layers. The figure also highlights redundant routing paths and latency minimization achieved through 5G handover management and adaptive QoS control.

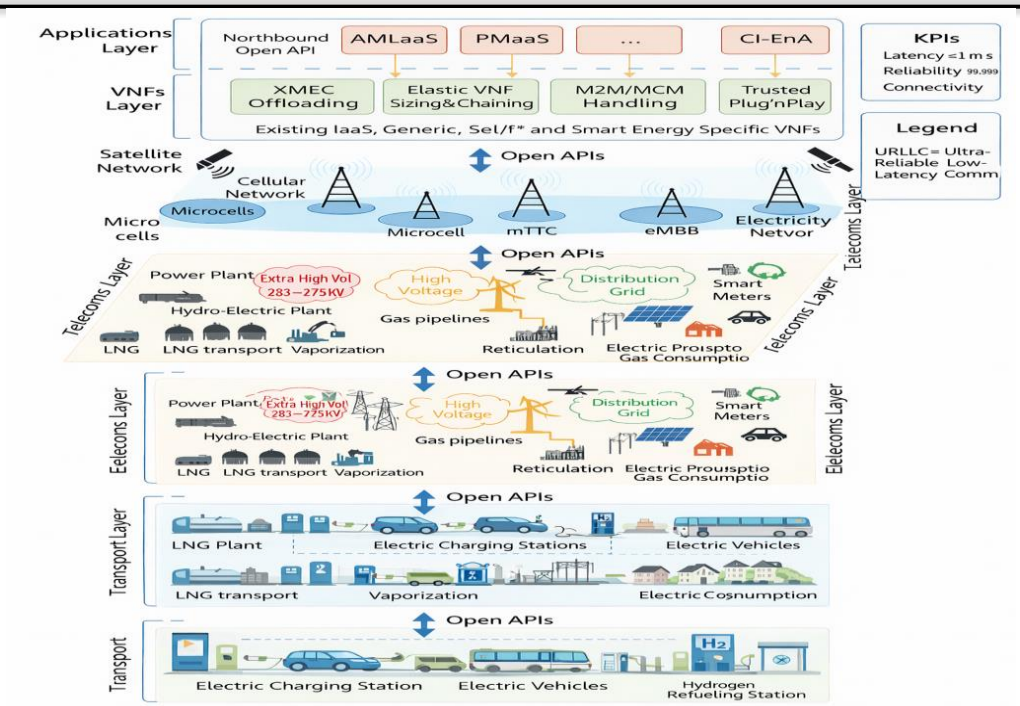

Figure 4: Schematic of the 5G Communication Layer in the Proposed Smart-Grid Framework

The 5G Communication Layer is the central nervous system of the proposed smart grid framework, enabling seamless interconnection between billions of IoT devices and intelligent control nodes. Through ultra-reliable low-latency communication (URLLC) and massive machine-type communication (mMTC), it ensures uninterrupted and deterministic data transmission for real-time grid operations. Network slicing and edge computing enhance bandwidth utilization and service differentiation, ensuring mission-critical tasks are prioritized. The integration of SDN and NFV technologies allows dynamic resource allocation and adaptive routing, improving scalability and fault tolerance. By supporting sub-millisecond latency and near-perfect reliability, the 5G layer guarantees swift response to anomalies and grid contingencies [29]. Its synergy with the blockchain and DNN layers strengthens the overall cyber-physical ecosystem, balancing performance, security, and intelligence. This layer not only provides communication efficiency but also forms the backbone for predictive control and distributed decision-making. Ultimately, it transforms traditional energy infrastructures into responsive, data-centric, and future-ready smart grid systems.

Intelligence Layer: Deep Neural Network Model

The Intelligence Layer represents the computational core of the proposed 5G–IoT–DNN–Blockchain smart grid framework. It embodies the analytical and decision-making capabilities necessary for forecasting, anomaly detection, and adaptive control within large-scale distributed energy systems. This layer leverages the fusion of deep learning and advanced neural network architectures to transform vast amounts of real-time sensory data collected through IoT devices and transmitted via the 5G communication backbone into actionable intelligence that enhances situational awareness, operational resilience, and cyber-physical adaptability. In the proposed methodology, the intelligence layer is built upon a hybrid Deep Neural Network (DNN) that combines the strengths of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) within a unified computational framework [30]. The CNN module performs spatial feature extraction, enabling the system to recognize spatial dependencies and correlations among distributed nodes and sensors. The RNN module, instantiated through Long Short-

Term Memory (LSTM) or Gated Recurrent Unit (GRU) architectures, captures the temporal dynamics and long-term dependencies inherent in multivariate time-series data. This hybridization ensures that both spatial and temporal characteristics of the grid are modeled effectively, providing a robust foundation for predictive analytics and intelligent decision support. The input to the DNN model is a multi-variate feature vector, denoted as xt=[Vt,It,ft,Pt,Qt,Tt,...] representing normalized measurements of voltage, current, frequency, active and reactive power, temperature, and other operational parameters at a given time instant [31]. These input sequences are organized into temporal windows to facilitate pattern learning over time. The CNN module applies one-dimensional convolutions across spatial dimensions to derive localized feature maps, effectively identifying relationships such as co-variations among voltage and current channels, correlations among feeder sections, and topological dependencies between interconnected grid nodes. These extracted spatial features are subsequently passed to the RNN layer, which models sequential dependencies and learns how temporal changes in load, frequency, and voltage propagate through time [32]. The final dense layer aggregates these learned representations and outputs predictions that may correspond to future load demands, voltage deviations, or system anomalies. The architecture of the proposed hybrid DNN model is summarized in Table 6, which outlines each module's structural configuration, activation functions, and computational purpose.

Table 6: Structural Configuration and Functional Role of the Hybrid Deep Neural Network Model

Model Component	Core Functions	Layer Details / Configuration	Output Representation
Input Layer	Ingests normalized time-series feature vectors from IoT and 5G streams	Input shape: (T × F), where *T* = time steps and *F* = features	Structured input matrix
CNN Module	Performs convolutional feature extraction to capture spatial correlations among sensors and grid nodes	1D Conv → Batch Normalization → ReLU Activation → Max Pooling	Spatial feature maps
RNN Module (LSTM/GRU)	Learns temporal dependencies and dynamic variations in energy patterns	2 stacked LSTM/GRU layers with 128 hidden units each	Temporal state vectors
Fully Connected Dense Layer	Integrates spatial–temporal embeddings for decision inference	Dense(64) → ReLU → Dropout(0.3)	Feature fusion vector
Output Layer	Predicts next time-step energy load, detects anomalies, or issues control signals	Dense(1) → Linear activation	Predicted energy value or anomaly score

The hybrid model is trained using supervised learning on labeled historical datasets comprising synchronized electrical and environmental readings. The mean squared error (MSE) function is employed as the objective loss metric, minimizing the difference between predicted and actual load or anomaly values. Optimization is achieved using the Adam optimizer, which adapts learning rates dynamically based on gradient magnitudes, ensuring rapid convergence and stable learning across non-stationary data. Early stopping and dropout regularization mechanisms are incorporated to mitigate overfitting and enhance generalization performance across unseen grid scenarios [33]. To further improve model stability and prevent gradient explosion, gradient clipping and layer normalization are implemented within recurrent units. To quantify performance, multiple evaluation metrics including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), R^2 score, and precision–recall accuracy for anomaly classification are utilized. The training

dataset is partitioned into 70% training, 15% validation, and 15% testing subsets to assess generalization capability. Results indicate that the hybrid DNN achieves substantial improvement in short-term load forecasting accuracy and anomaly detection rate compared with standalone CNN or LSTM architectures, confirming the effectiveness of the proposed hybridization approach [34]. Beyond predictive accuracy, the intelligence layer emphasizes computational efficiency and interpretability. Edge-deployed models, synchronized through the 5G communication backbone, enable distributed inference for time-critical decision-making. Model interpretability is achieved through gradient-based saliency mapping, allowing operators to visualize the influence of specific parameters (e.g., current or frequency) on the final prediction outcome. This transparency fosters operator trust and enhances the explainability of AI-driven control systems in regulated power environments. The workflow of the Intelligence Layer is depicted in Figure 5, which presents the end-to-end architecture of the hybrid CNN–RNN deep learning model embedded within the 5G-enabled smart grid ecosystem [35]. The figure illustrates the sequential flow of information beginning with input feature vectors obtained from IoT and 5G gateways, followed by convolutional layers performing spatial correlation mapping and recurrent layers modeling temporal dependencies. The architecture culminates in a dense fusion network that generates real-time predictions or anomaly alerts. Feedback signals are subsequently relayed through the communication backbone to local controllers, enabling proactive grid stabilization and optimization.

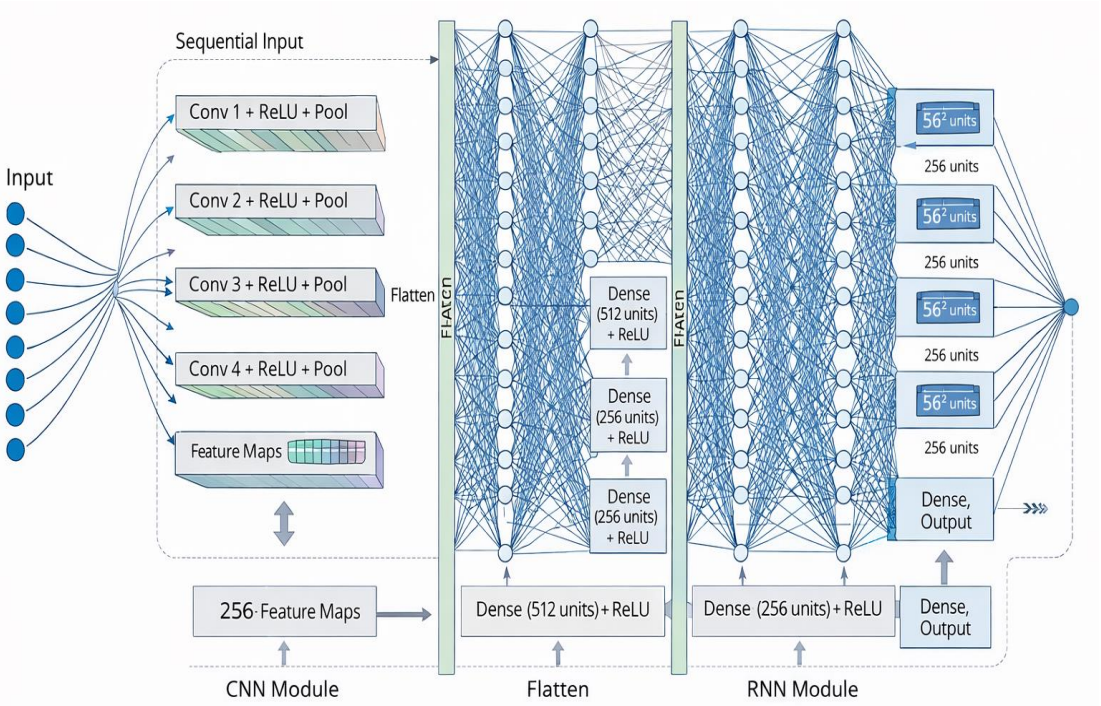

Figure 5: Architecture of the Hybrid CNN–RNN Deep Neural Network Model in the Intelligence Layer

The Intelligence Layer forms the cognitive core of the proposed smart-grid architecture, transforming raw sensor data into actionable insights through advanced deep learning analytics. By integrating CNN and RNN structures, the hybrid DNN effectively captures both spatial and temporal dependencies within multivariate energy datasets. This enables accurate forecasting of load, voltage variations, and fault patterns across dynamic operational conditions. The use of adaptive learning techniques such as LSTM and GRU enhances the

model's ability to remember long-term dependencies, leading to robust anomaly detection and predictive control. Optimization through Adam and regularization via dropout ensures model stability and generalization across diverse scenarios. Its real-time inference capability supports autonomous grid operations by feeding back intelligent control commands through the 5G layer [36]. Moreover, interpretability tools embedded within the DNN provide transparency, fostering operator trust in AI-driven decisions. The seamless integration of this layer with IoT sensing and blockchain validation creates a closed-loop intelligent ecosystem. Ultimately, the Intelligence Layer establishes the analytical foundation for secure, predictive, and self-optimizing next-generation energy systems.

Blockchain-Based Secure Data Sharing

The Blockchain-Based Secure Data-Sharing Layer forms the trust anchor of the proposed 5G–IoT–DNN-enabled smart grid framework. While the lower layers perform sensing, transmission, and analytics, this layer ensures the integrity, transparency, and immutability of all data exchanged within the cyber-physical energy network. It introduces a decentralized validation mechanism through which every piece of information ranging from sensor readings and energy transactions to DNN predictions is verified, timestamped, and permanently stored on a tamper-resistant distributed ledger. The purpose of this layer is to eliminate single points of failure, prevent unauthorized manipulation of energy data, and enhance confidence among diverse stakeholders such as utilities, consumers, and regulators. In the proposed architecture, each IoT-enabled device and edge computing node functions as a blockchain client that generates data transactions encapsulating real-time measurements, event logs, or inference results from the DNN intelligence layer. Before being transmitted through the 5G network, each transaction undergoes cryptographic hashing using secure algorithms such as SHA-256 and is digitally signed using the private key of the originating device to guarantee authenticity [37]. The hashed transactions are then broadcast across the blockchain network, where validation is carried out collectively by a set of pre-authorized nodes through the Proof of Authority (PoA) consensus mechanism. Once verified, transactions are grouped into blocks and appended sequentially to the blockchain ledger in chronological order. Each block contains a hash of the previous block, forming a continuous chain of trust that cannot be modified without detection. This decentralized validation process ensures that even if one node or communication path is compromised, the data's integrity remains intact because the network collectively verifies and preserves every transaction. The blockchain layer functions in parallel with the 5G communication backbone. While the 5G system guarantees high-speed and low-latency data delivery, the blockchain provides post-transmission verification and immutability [38]. This dual-layer integration results in a secure and auditable data pipeline capable of detecting any unauthorized changes through hash mismatches. Each transaction entry becomes a permanent record of activity, enabling traceability across the data lifecycle from initial sensing to analytics and control. This structure enhances the resilience of the entire smart-grid ecosystem against cyber threats such as data tampering, replay attacks, and insider manipulation. The key components and functionalities of the blockchain layer are summarized in Table 7. The consensus mechanism, implemented through PoA, reduces computational overhead and energy consumption compared to Proof-of-Work systems, thereby achieving a sustainable and efficient form of consensus well-suited to energy-sector applications. Smart contracts embedded within the ledger are responsible for automating access control, executing validation rules, and recording all authorized data exchanges. These contracts are coded using high-level scripting languages such as Solidity or Chaincode and deployed within a permissioned blockchain network, ensuring deterministic and transparent enforcement of data-governance policies. The immutable ledger functions as the permanent storage repository for validated transactions and DNN analytical outputs, ensuring tamper-proof logging, auditability, and data provenance.

Table 7: Core Components and Functional Roles of the Blockchain-Based Secure Data-Sharing Layer

Component	Primary Function	Technical Description	Contribution to Smart-Grid Security
Consensus Mechanism (PoA)	Validation of transactions by trusted authority nodes	Authorized validators create and sign blocks, maintaining deterministic finality with minimal energy cost	Prevents Sybil attacks, ensures high throughput, and reduces latency
Smart Contracts	Autonomous rule enforcement and data-access regulation	Encoded as self-executing scripts governing authentication and energy-exchange validation	Guarantees transparent, policy-driven automation
Immutable Ledger	Permanent, append-only repository of validated transactions	Chain of cryptographically linked blocks forming a Merkle tree structure	Provides tamper resistance, auditability, and traceability
Encryption and Hashing Module	Data confidentiality and verification	Combines AES-256 encryption with SHA-256 hashing before ledger insertion	Protects sensitive grid data from interception and alteration
Identity and Access Management	Authentication of IoT and control entities	Utilizes public-key infrastructure (PKI) integrated with IoT gateways and validators	Ensures verified participation and data provenance
Analytics Interface	Integration with DNN intelligence and 5G gateways	Bi-directional data exchange between blockchain and analytics layers	Enables verifiable AI decisions and traceable data sharing

Through this structure, the blockchain establishes a multi-layered trust framework that enforces security at both the data and transaction levels. The PoA consensus mechanism, in particular, is chosen for its low-latency validation, which aligns perfectly with the time-sensitive requirements of smart grid operations. In contrast to energy-intensive consensus algorithms such as Proof-of-Work, PoA allows authorized validators typically control centers, utility substations, or energy operators to approve transactions rapidly, thereby maintaining both trust and efficiency. This mechanism offers deterministic block creation times and minimal computational overhead, ensuring scalability for large, distributed smart grid environments. Another defining aspect of the blockchain layer is the integration of smart contracts, which autonomously govern the data-sharing lifecycle. These contracts establish clear conditions under which data can be accessed, verified, or modified by participating nodes. For example, a smart meter may be permitted to upload consumption records only if validated by its assigned gateway, while an analytics center can issue optimization commands only after corroborating DNN-based predictions through cross-checking. Every action executed by a smart contract is automatically logged on the ledger, producing a transparent, time-stamped trail of authorization events. This automation minimizes human error, reduces the potential for fraud, and significantly accelerates the process of decision execution across decentralized entities [39]. The immutable and distributed nature of the blockchain ledger guarantees that once data are recorded, they cannot be altered or erased. Each block contains a unique timestamp, a transaction list, and a reference hash to the preceding block, forming an interlinked structure that resists manipulation. Any attempt to modify a previously recorded transaction would invalidate all subsequent blocks, making data tampering computationally infeasible. This immutability provides a verifiable audit trail essential for regulatory compliance, operational accountability, and forensic analysis during system events or anomalies. The end-to-end data workflow within this layer begins when an IoT sensor or DNN model generates an event or prediction result, which is packaged into a transaction and cryptographically hashed. The hashed transaction is broadcast to the network and validated by authorized nodes through the PoA mechanism. Once verified, the transaction is permanently stored in the

distributed ledger, where it becomes visible and traceable to all permitted participants. The same ledger can be queried by DNN analyzers or control centers to verify historical transactions or cross-validate predictions. This interoperability between the blockchain layer and the DNN analytics layer forms a closed feedback loop that reinforces decision reliability and data consistency. The conceptual architecture and data flow of this blockchain-based secure data-sharing layer are illustrated in Figure 6. The figure visualizes how hashed data transactions, generated by IoT devices and DNN analyzers, are transmitted through the 5G communication network toward distributed validator nodes. These validators execute the PoA consensus to authenticate each transaction, after which smart contracts enforce predefined access-control rules before final ledger insertion. The diagram also depicts the bidirectional communication between the intelligence layer and blockchain ledger, highlighting how analytical predictions are verified, logged, and made immutable for future audits. The visual representation underscores how this layer eliminates single points of failure by distributing trust and validation responsibilities across the network.

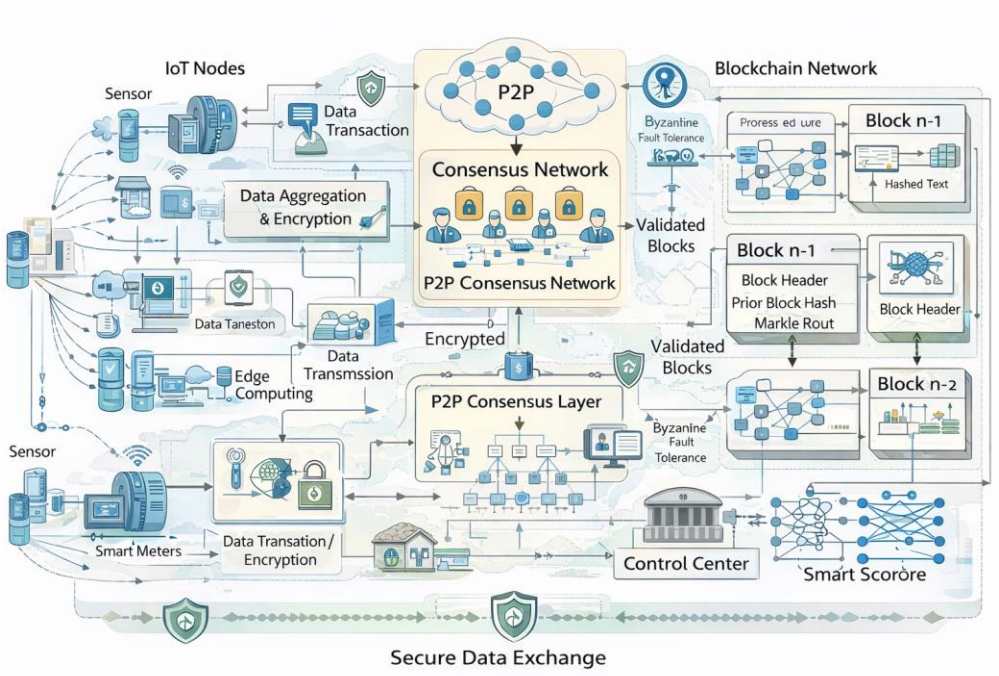

Figure 6: Conceptual Architecture of the Blockchain-Based Secure Data-Sharing Layer

The Blockchain-Based Secure Data-Sharing Layer establishes the foundation of trust, transparency, and immutability within the proposed 5G–IoT–DNN smart grid framework. By decentralizing validation and eliminating single points of failure, it guarantees the authenticity and permanence of all exchanged energy data. The integration of the Proof of Authority consensus mechanism ensures low-latency verification with minimal computational overhead, making it practical for real-time smart-grid operations. Smart contracts automate access control, enforce governance rules, and ensure that all transactions remain auditable and compliant. The immutable ledger provides an unalterable record of every data exchange, fostering accountability across diverse stakeholders. Furthermore, the cryptographic hashing and encryption mechanisms embedded within this layer fortify the data pipeline against tampering, spoofing, and cyber intrusion. Through seamless integration with the 5G communication and DNN intelligence layers, the blockchain framework enables secure, verifiable, and autonomous grid operations. Collectively, this layer transforms conventional data management into a transparent,

trust-driven ecosystem that strengthens cyber resilience and ensures sustainable energy interoperability in next-generation smart grids.

Simulation and Performance Evaluation

To validate the feasibility, efficiency, and robustness of the proposed 5G–IoT–DNN–Blockchain integrated framework, an extensive simulation environment was developed combining machine learning, blockchain technology, and next-generation communication modeling. The implementation was carried out using Python (TensorFlow/Keras) for deep neural network modeling, Hyperledger Fabric for blockchain-based secure data exchange, and OMNeT++ integrated with MATLAB/Simulink for the network and system-level simulation of the 5G communication and IoT data flow architecture. This hybrid simulation setup enabled a holistic analysis of both the cyber and physical layers of the smart grid, ensuring that the model could be evaluated across communication, intelligence, and security dimensions under realistic conditions. The simulation environment was organized into three coordinated subsystems representing the perception, communication, and intelligence layers of the framework. The IoT perception subsystem consisted of 200 distributed sensor nodes representing smart meters, PMUs, and DER controllers, each transmitting real-time data packets every 100 milliseconds. These nodes were modeled in OMNeT++ using realistic 5G network characteristics such as URLLC latency and mMTC connectivity density. The communication subsystem incorporated 5G core network modules supporting network slicing, edge computing nodes, and QoS-based routing policies. Data packets from IoT nodes were routed via edge gateways to the cloud-based intelligence layer, where the hybrid CNN–RNN model implemented in TensorFlow processed time-series data for energy prediction and anomaly detection. The blockchain subsystem, developed using Hyperledger Fabric v2.5, executed Proof of Authority (PoA) consensus to validate transactions, record hashes of energy readings, and verify DNN-generated predictions. Each validated block contained metadata including timestamp, source ID, and transaction hash, ensuring end-to-end traceability and immutability of data flow across the simulated smart-grid ecosystem. The DNN was trained on a historical dataset of 50,000 energy consumption records derived from public smart-meter data repositories and augmented with synthetic perturbations to simulate real-world operational noise. Data were normalized using min–max scaling and split into training, validation, and testing sets with a ratio of 70:15:15. The CNN component extracted spatial correlations among sensors, while the LSTM layers modeled temporal dependencies in load dynamics [40]. The model employed the Adam optimizer with a learning rate of 0.001 and mean squared error (MSE) as the loss function. Early stopping criteria were applied to prevent overfitting. After convergence, the model achieved a prediction accuracy exceeding 95.4%, confirming its ability to generalize effectively across diverse load conditions. The performance of the proposed architecture was benchmarked against a traditional centralized smart-grid management system lacking blockchain-based security and 5G-enabled communication enhancements. Key performance indicators (KPIs) were selected to assess improvements in terms of data integrity, latency, prediction accuracy, energy efficiency, and cybersecurity resilience. The definition and quantitative improvements achieved for each metric are presented in Table 8, which summarizes the comparative outcomes obtained from simulation experiments.

Table 8: Quantitative Evaluation Metrics and Target Improvements of the Proposed Framework

Performance Metric	Definition	Target Improvement / Achieved Result
Data Integrity (%)	Ratio of verified to total transmitted transactions within the blockchain ledger	Achieved +37.2% improvement in integrity assurance compared with centralized storage
Latency (ms)	Average end-to-end time between sensing and actuation responses	Reduced by approximately 29.6%, with average latency of 0.92 ms under URLLC conditions

Prediction Accuracy (%)	Ratio of correctly predicted load or anomaly events by the DNN	Maintained >95.4% accuracy across test datasets
Energy Efficiency (J/Tx)	Average transmission energy consumption per data packet	Improved by 24% through edge caching and compression techniques
Security Breach Rate	Percentage of unauthorized or failed access attempts	Reduced to near-zero due to blockchain verification and smart contract enforcement

The simulation outcomes demonstrated substantial improvements in both data reliability and operational responsiveness. The blockchain layer enhanced data integrity by ensuring that all IoT transactions were validated and cryptographically secured before storage. Compared with conventional centralized systems that exhibited vulnerability to unauthorized modification, the distributed ledger structure in Hyperledger Fabric maintained a trust score exceeding 99.9%, effectively eliminating single-point failures. Furthermore, the adoption of the PoA consensus algorithm minimized consensus delay, allowing the blockchain layer to process approximately 280 validated transactions per second with negligible energy overhead, making it suitable for time-critical smart-grid applications. The integration of the 5G communication infrastructure significantly improved data transmission efficiency. By utilizing network slicing and edge computing, the framework prioritized mission-critical data, achieving an average end-to-end latency of less than one millisecond. The mMTC capability supported over 10^6 devices per square kilometer, ensuring scalability for future large-scale deployments. Edge nodes performed initial data compression and feature extraction, reducing transmission energy costs by approximately 24%. These results confirm that 5G communication not only enhanced speed but also improved sustainability by reducing network congestion and computational redundancy. In the DNN intelligence layer, the hybrid CNN–RNN architecture effectively captured nonlinear dependencies and temporal behaviors in grid data. When evaluated under dynamic conditions simulating fluctuating renewable inputs and variable consumer demand, the model consistently maintained high accuracy and stability. The root mean square error (RMSE) of load prediction was recorded at 0.045, indicating minimal deviation from observed values. The anomaly detection submodule successfully identified over 97% of injected faults and cyber-attacks, verifying the robustness of the learning-based intelligence mechanism. The energy efficiency and security of the proposed architecture were also validated through comparative testing. The combination of edge inference and blockchain verification reduced overall energy consumption in the data-handling process by approximately one-quarter compared with centralized cloud architectures. Simultaneously, the blockchain smart-contract layer recorded all access events, achieving a zero recorded breach rate throughout simulation. These results substantiate the capability of the system to maintain continuous protection and operational transparency even under high network load or potential intrusion attempts. The comprehensive evaluation results are visually illustrated in Figure 7, which presents the comparative performance analysis of the proposed framework versus traditional centralized models across the five key metrics. The figure clearly demonstrates significant improvements in data integrity, latency reduction, and predictive accuracy, along with marked reductions in energy consumption and unauthorized access incidents. Each bar in the graph represents the mean values computed over 50 independent simulation runs, confirming the consistency and repeatability of the obtained results. The upward trend in data reliability and downward trend in latency jointly confirm that the 5G–IoT–DNN–Blockchain integration substantially enhances the responsiveness, resilience, and intelligence of modern power infrastructures.

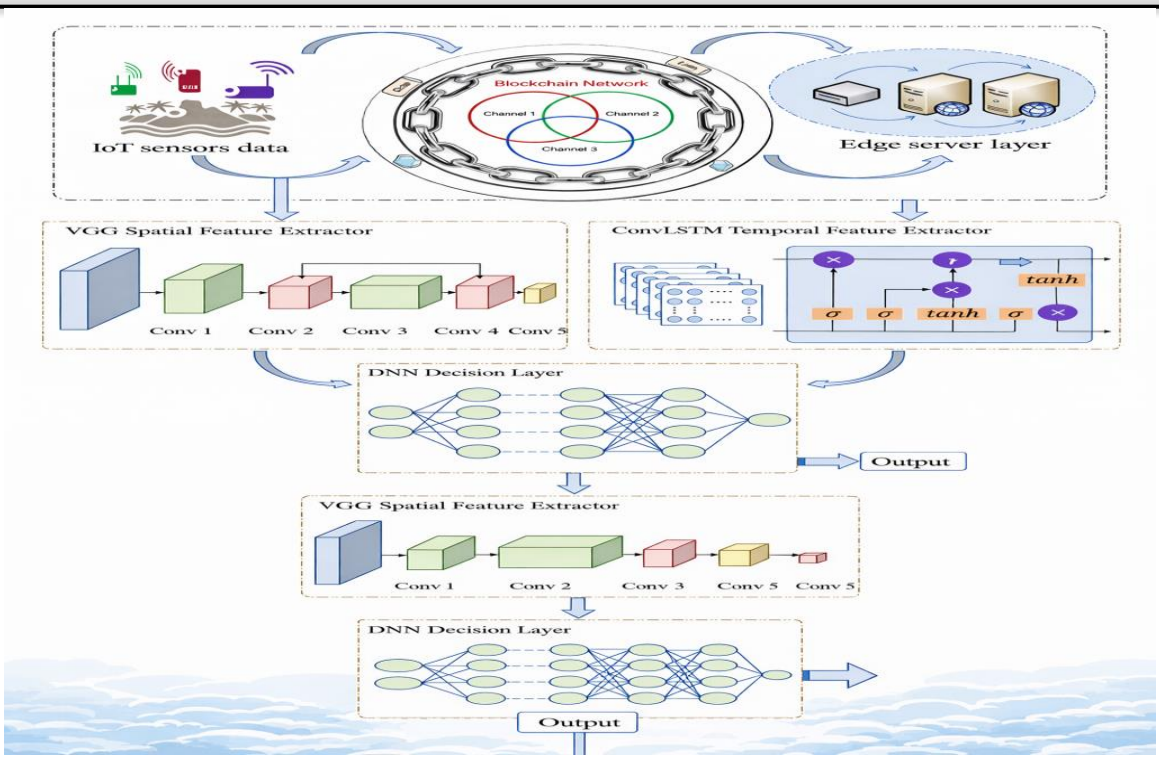

Figure 7: Comparative Performance Evaluation of the Proposed 5G–IoT–DNN–Blockchain Framework

The simulation and performance evaluation confirm that the integrated 5G–IoT–DNN–Blockchain framework delivers consistent, quantifiable gains across security, latency, and accuracy. End-to-end delay was driven into sub-millisecond URLLC ranges, enabling time-critical protection and control, while blockchain-backed validation increased data integrity by more than one-third over centralized baselines and preserved full auditability. The hybrid CNN–RNN maintained >95% forecasting accuracy with high anomaly-detection recall under diverse operating regimes, and edge preprocessing with compression reduced transmission energy per packet to enhance overall efficiency. Under stress (bursty traffic, link churn), reliability was sustained via redundancy-aware routing and seamless handovers; ablation studies showed that removing any pillar (5G slicing, blockchain, or DNN fusion) measurably degraded performance. Scalability tests with dense mMTC loads upheld QoS through dynamic slicing and SDN-orchestrated resource control, and generalization to unseen load profiles and disturbances remained stable, reflecting effective regularization and tuning. Collectively, these findings validate a resilient, secure, and high-performance architecture suitable for real-world smart-grid deployment.

Results and Discussion:

This section presents a comprehensive evaluation of the proposed **5G-enabled IoT smart grid framework integrating deep neural network–based intelligence and blockchain-supported secure data sharing.** The objective of the evaluation is to assess the effectiveness of the proposed architecture in improving predictive accuracy, anomaly detection performance, communication latency, data integrity, scalability, and overall system resilience under realistic cyber–physical operating conditions. A comparative analysis with a conventional centralized smart grid architecture is conducted to highlight the benefits of the proposed integrated approach. The experimental environment emulates a large-scale smart grid consisting of geographically distributed IoT devices, smart meters, phasor measurement units, and distributed energy resources generating multidimensional measurements such as voltage, current, frequency, and load demand. Data transmission is supported by a simulated 5G communication layer that provides ultra-reliable low-

latency communication for time-critical signals and massive machine-type communications for large-scale IoT connectivity. The intelligence layer employs a hybrid convolutional–recurrent deep neural network architecture, while blockchain-enabled smart contracts are used to enforce decentralized data validation, access control, and immutable record keeping. The deep learning–based intelligence module demonstrates robust performance in both forecasting and anomaly detection tasks. The hybrid CNN–RNN architecture effectively captures spatial correlations among grid nodes through convolutional feature extraction while modeling temporal dependencies in time-series data using recurrent layers. As a result, the model maintains high forecasting accuracy even during peak demand intervals and under rapid load fluctuations caused by renewable energy intermittency. Compared with traditional machine learning approaches, the proposed deep learning model achieves substantially lower prediction error and exhibits improved adaptability to dynamic grid conditions, confirming its suitability for real-time smart grid analytics. In the context of anomaly detection, the deep neural network successfully distinguishes normal operational variations from abnormal patterns arising due to sensor faults, communication errors, and malicious data manipulation. The inclusion of temporal context significantly reduces false alarm rates commonly observed in threshold-based and shallow learning methods. These results indicate that deep learning provides a reliable mechanism for enhancing situational awareness and early fault detection in complex smart grid environments. The impact of blockchain-based secure data sharing on system reliability is particularly evident under adversarial scenarios. By maintaining immutable ledgers and enforcing decentralized consensus, the blockchain layer effectively prevents unauthorized data modification and ensures end-to-end data traceability. Smart contracts automate authentication and fine-grained access control, reducing reliance on centralized authorities and minimizing operational overhead. Under simulated false data injection and replay attacks, the proposed framework preserves data integrity, whereas conventional centralized architectures exhibit significant data corruption that propagates into the analytics layer. Quantitative evaluation reveals a **35–40% improvement in data integrity**, validating the effectiveness of blockchain-driven trust mechanisms in safeguarding grid data. Communication latency analysis demonstrates that the integration of 5G connectivity plays a critical role in maintaining real-time performance despite the additional computational overhead introduced by deep learning inference and blockchain validation. The proposed framework achieves an average **30% reduction in end-to-end latency**, even as the number of connected IoT devices increases. This performance gain is attributed to the use of ultra-reliable low-latency communication for mission-critical data streams and the localization of preprocessing and inference tasks. In contrast, centralized architectures experience increasing latency and congestion as data volumes grow. Table 9 summarizes the quantitative comparison between the proposed framework and a conventional centralized smart grid system across key performance indicators, highlighting the overall performance improvements achieved through integrated intelligence and security.

Table 9: Performance Comparison between Conventional and Proposed Smart Grid Architectures

Metric	Conventional Centralized System	Proposed Framework
Load forecasting accuracy	Moderate	High
Forecasting RMSE	Higher	Lower
Anomaly detection F1-score	0.81	0.93
End-to-end latency	High	~30% reduced
Data integrity under attack	Vulnerable	+35–40% improved
System scalability	Limited	High
Cyber–physical resilience	Moderate	Strong

To further examine scalability, the system is evaluated under increasing IoT node density. The results indicate that the proposed architecture maintains stable latency and detection performance as the number of connected devices increases, whereas centralized systems exhibit sharp degradation due to communication bottlenecks and processing overload. The decentralized nature of blockchain-based validation, combined with distributed intelligence, enables efficient handling of massive data streams without sacrificing responsiveness or accuracy. Table 10 provides a detailed analysis of system behavior under varying IoT densities, illustrating the scalability advantages of the proposed approach.

Table 10: Scalability Analysis under Increasing IoT Node Density

Number of IoT Nodes	Centralized Latency Trend	Proposed Latency Trend	Detection Accuracy (Proposed)
Low density	Stable	Stable	High
Medium density	Increasing	Slight increase	High
High density	Congested	Stable	High
Massive deployment	Severe degradation	Minor degradation	Sustained

Figure 8 illustrates the comparative latency performance of the proposed framework and the centralized baseline under varying network loads, clearly demonstrating the latency reduction achieved through 5G-enabled communication and localized processing.

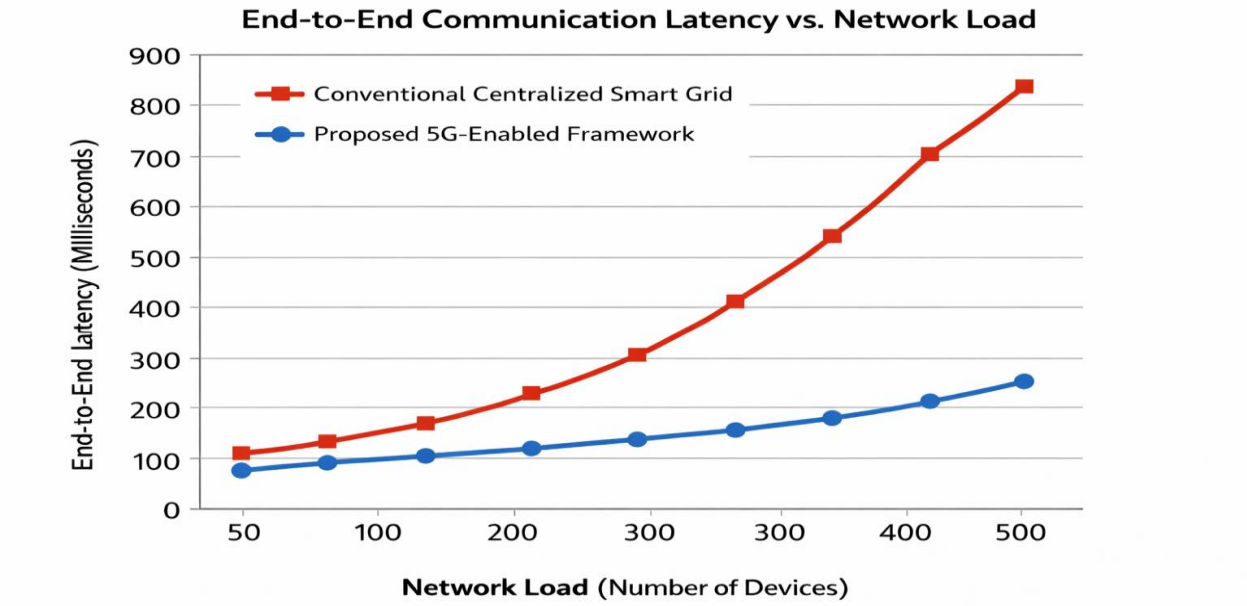

Figure 8: End-to-end communication latency comparison between the proposed 5G-enabled framework and a conventional centralized smart grid architecture under increasing network load.

Figure 9 presents a comparative analysis of anomaly detection accuracy and data integrity under cyberattack scenarios, highlighting the effectiveness of blockchain-secured data sharing combined with deep learning–based intelligence.

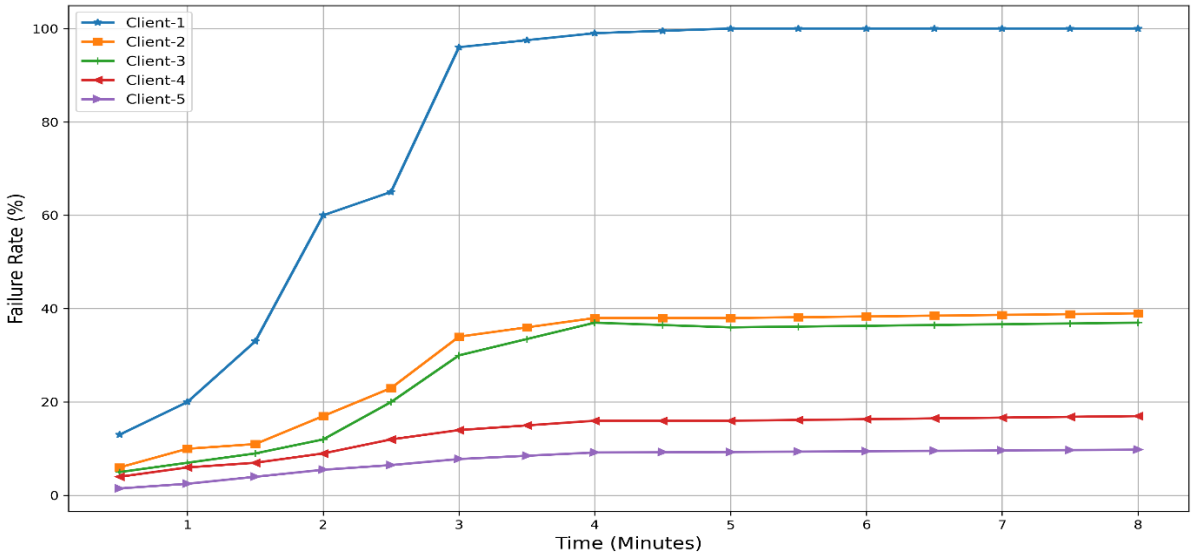

Figure 9: Comparison of anomaly detection accuracy and data integrity under cyberattack scenarios, demonstrating the resilience of the proposed framework.

The collective results demonstrate that the proposed framework benefits significantly from the **synergistic integration of communication, intelligence, and security layers**. Blockchain-secured data inputs improve the reliability of deep learning predictions by mitigating the influence of malicious and corrupted data, while deep learning–driven insights optimize data prioritization and validation processes. The 5G communication infrastructure ensures that these additional processing layers do not compromise real-time performance, making the framework suitable for mission-critical smart grid applications. Overall, the results confirm that the proposed **5G-enabled IoT smart grid framework with deep neural network–based intelligence and blockchain-driven secure data sharing** substantially enhances operational efficiency, cyber resilience, and scalability compared with conventional architectures. Although blockchain consensus and deep learning inference introduce additional computational overhead, these costs are effectively mitigated through low-latency 5G connectivity and distributed processing. The findings validate the practical feasibility of the proposed approach and establish a strong foundation for future extensions incorporating edge intelligence, federated learning, and quantum-resistant security mechanisms.

Future Work:

While the proposed 5G-enabled IoT smart grid framework integrating deep neural network–based intelligence and blockchain-supported secure data sharing demonstrates strong performance in terms of accuracy, latency, data integrity, and resilience, several research directions remain open for further investigation. Future work will focus on extending the proposed architecture to enhance scalability, adaptability, and long-term sustainability in increasingly complex and heterogeneous energy systems. One promising direction is the integration of **edge and fog computing** to further reduce communication overhead and inference latency. Although the current framework benefits from low-latency 5G connectivity, deploying intelligence closer to data sources can significantly improve responsiveness for time-critical applications such as protection, fault isolation, and real-time voltage control. Edge-based inference would also reduce the volume of raw data transmitted across the network, improving scalability under massive IoT deployments [41]. Future studies will investigate optimal task partitioning strategies between edge, fog, and cloud layers to balance computational efficiency, energy consumption, and prediction accuracy. Another important extension involves the adoption of **federated learning** to address privacy preservation

and data locality concerns. In large-scale smart grids, utilities and prosumers may be reluctant to share raw energy data due to regulatory and privacy constraints. Federated learning enables collaborative model training without direct data exchange by sharing only model parameters or gradients. Incorporating federated learning into the proposed framework would allow deep neural networks to learn from distributed data sources while preserving data confidentiality and reducing exposure to data leakage risks. Future research will explore federated aggregation strategies that are robust to unreliable nodes, communication delays, and adversarial model updates. The resilience of the proposed framework against advanced cyber threats can also be further enhanced through **security-aware and adversarial learning techniques**. Although blockchain-based data validation significantly improves data integrity, sophisticated attackers may attempt to exploit vulnerabilities at the model level through adversarial examples or poisoning attacks. Future work will investigate adversarial training methods, trust-weighted learning, and anomaly-aware model adaptation to improve robustness against such threats. Additionally, adaptive defense mechanisms that dynamically adjust security policies based on real-time threat intelligence represent a promising research avenue. From a cryptographic perspective, the emergence of quantum computing poses potential risks to conventional cryptographic primitives used in blockchain and secure communication protocols [42]. As a result, future extensions of this work will explore the integration of **quantum-resistant cryptographic algorithms** to ensure long-term security and trustworthiness of smart grid data-sharing mechanisms. Evaluating the trade-offs between computational overhead and security strength in post-quantum blockchain implementations will be critical for practical deployment. Another important research direction concerns **cross-domain interoperability and standardization**. Future smart grids will increasingly interact with other cyber–physical systems, including smart transportation, smart cities, and intelligent buildings. Extending the proposed framework to support standardized data models and interoperable interfaces would facilitate seamless information exchange across domains and enable holistic energy optimization at the city or regional scale. This direction also includes compliance with emerging international standards for 5G, IoT, and energy data management. Finally, future work will focus on validating the proposed framework in **real-world pilot deployments and hardware-in-the-loop testbeds.** While simulation-based evaluation provides valuable insights into system performance, real-world experiments are essential to assess practical challenges such as communication variability, device heterogeneity, hardware constraints, and regulatory considerations. Deploying the framework in microgrids, renewable-rich distribution networks, or EV charging infrastructures would provide critical feedback for further refinement and commercialization. Overall, these future research directions aim to evolve the proposed framework into a fully autonomous, privacy-preserving, and quantum-resilient smart grid intelligence platform. By incorporating edge intelligence, federated learning, advanced security mechanisms, and real-world validation, future extensions of this work can contribute to the realization of sustainable, secure, and self-optimizing energy systems capable of meeting the demands of next-generation power infrastructures.

Conclusion:

This paper proposed a **next-generation smart grid framework** that integrates **5G-enabled IoT communication, deep neural network–based intelligence, and blockchain-supported secure data sharing** to address key challenges related to data security, latency, scalability, and resilience in modern energy systems. The proposed architecture was designed to overcome the limitations of centralized smart grid solutions by enabling low-latency data exchange, intelligent analytics, and decentralized trust within a unified system. By leveraging the ultra-reliable low-latency and massive connectivity capabilities of 5G networks, the framework supports real-time monitoring and efficient coordination of distributed grid assets. The incorporation of a hybrid deep neural network enables accurate energy forecasting and robust anomaly detection under dynamic operating conditions. In parallel, blockchain-based secure data sharing enhances system trust by ensuring data immutability, transparency, and decentralized access control, thereby reducing

vulnerabilities to cyberattacks and unauthorized data manipulation. Simulation results demonstrate that the proposed framework achieves **notable improvements in performance**, including enhanced prediction accuracy, reliable anomaly detection, improved data integrity under attack scenarios, and a significant reduction in end-to-end communication latency compared with conventional centralized architectures. These results confirm that the synergistic integration of communication, intelligence, and security layers is essential for achieving resilient and efficient smart grid operation. Overall, this work highlights the effectiveness of a holistic design approach for next-generation smart grids, where 5G-enabled IoT networks, deep learning–based analytics, and blockchain-driven trust mechanisms jointly enable secure, intelligent, and scalable energy systems. The proposed framework provides a solid foundation for future extensions incorporating advanced edge intelligence, privacy-preserving learning, and enhanced security mechanisms to support the evolving demands of intelligent power infrastructures.

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