Analysis of Intelligent Power Grid Based on Internet of Things

Zongheng Yang[1]

[1]DEPU Foreign Language School, Chongqing, 401300, China
`yangziyinhg0324@gmail.com`

Abstract. The rapid development of the Internet of Things (IoT) has driven innovation in the power sector, and traditional power grids face challenges like energy waste and low reliability. This paper explores IoT-based intelligent power grids, analyzing their theoretical basis, including global power grid development differences and IoT's concept, evolution, and core characteristics, and key applications: intelligent operation via AI for load forecasting, fault diagnosis, etc., with cases like ENEL's Long Short-Term Memory (LSTM) system, adjustable regulation, and measurable monitoring. It also addresses challenges such as protocol fragmentation. In conclusion, IoT-integrated smart grids are crucial for modern energy systems. They are the fundamental for a sustainable, efficient, and resilient global energy future. Against the backdrop of global energy transition—with rising renewable energy penetration—traditional grids' limitations (poor real-time monitoring, supply-demand imbalance, high maintenance costs) become prominent. IoT, with comprehensive perception, reliable transmission, and intelligent processing, connects equipment into a unified network, enabling full-life-cycle energy management. Typical cases verify IoT's role in improving efficiency and reducing emissions, while noting that resolving protocol fragmentation and regional differences is key to advancing its large-scale application, supporting global carbon neutrality goals.

Keywords: IoT, Smart Grid, Intelligent Operation, Adjustable Regulation

1 Introduction

The dramatic development has bought series innovations to different regions and the energy sector also included. The power grid has become helpless in many challenges such as inefficient energy level, incomplete operation system and so on. In face of these issues, IoT based on smart grid emerges to innovate in ways such as using a range of devices, sensors, communication methods. These measures greatly improve the security and electric transforming efficiency, and have significance contribution to sustainable energy infrastructures.

© The Author(s) 2026
S. Zhang (ed.), *Proceedings of the 2025 International Conference on Electronics, Electrical and Grid Technology (ICEEGT 2025)*, Advances in Engineering Research 292,
https://doi.org/10.2991/978-94-6463-986-5_92

In this context, Gungor's research provide important references for people to understand the communication structure and technical standards involved in IoT-enabled smart grids [1]. And real-time data exchange is crucial for the fault detection and load balancing. If we want to satisfy the requirements of latency and reliability, then we need to use proper structure.

This paper focuses on different regions of an IoT-enabled smart grid including theory， practice and operation, and discuss related challenges about agreement division and smart grids extensibility. Apart from these, it also highlights how IoT integration is helpful towards automation, sustainable and modern energy system.

2 Theoretical basis analysis

2.1 The IoT-based power grid

The applying of IoT-enabled smart grids is important to solve the problems about energy production and transmission, such as energy consumption, expensive operation costs and instability factors. Using these appliances make smart grids can gain related electrical system information from a large amount of data. The data can be used to predict issues may appear, and identify system faults. Additionally, these system operations make users participate with energy saving on a large scale, through methods like smart measurements. The power grid is the entire electrical production and consumption system, which is the infrastructures of modern energy system. Basically speaking, it is the crucial fundamental basics of electric transmission, and is a complex chemical system [2]. Its main task is to transfer electricity from different types of primary energy sources, and ensure the security, reliability, efficiency of the whole electric system at the same time. The IoT-based power grid is shown in Fig.1.

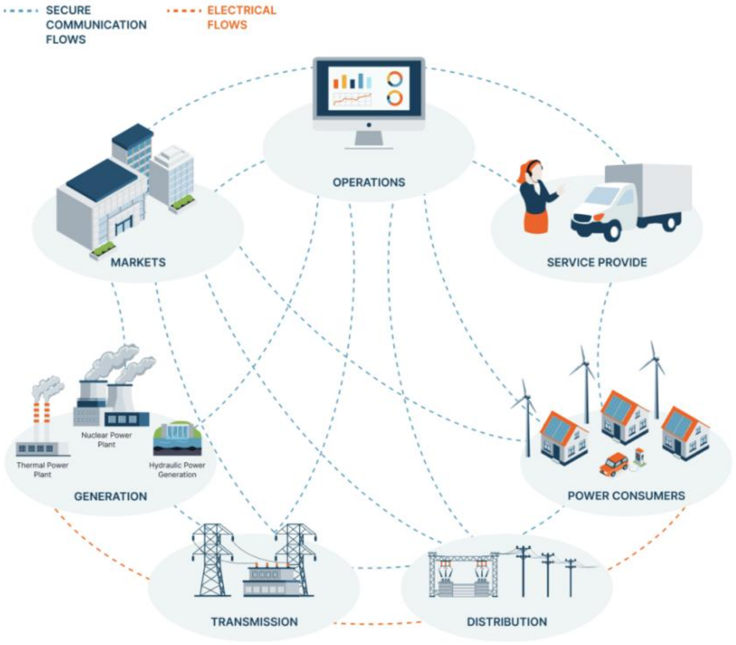

Fig. 1. IoT-based power grid [2]

The development of global power grids has obviously regional differentiation characteristics. Different countries and regions vary in terms of power grid technical levels, architectural features, and challenges faced. An in-depth analysis of the current status of power grids in major countries and regions helps to grasp the overall situation and future direction of global power grid development.

Global Power Grid Development Status. China possesses the world's largest power grid, boasting ample reserve capacity, cutting-edge UHV technology, and a high degree of intelligence. However, it confronts challenges such as increased scheduling complexity due to the high integration of new energy sources and reduced resilience of AC-DC hybrid grids. The United States exhibits a high level of marketization and robust technological innovation capabilities. Nonetheless, it grapples with aging infrastructure, difficulties in obtaining expansion approvals, constraints of the private investment-driven model, and delays in connecting new energy sources to the grid. Europe boasts a high level of cross-border interconnectivity and a leading share of renewable energy [3]. Yet, it experiences inadequate grid investment, complex coordination across borders, and heightened effects of extreme weather conditions.

Architecture of Power Grid IoT. A modern power grid IoT typically comprises three layers: the perception layer, the network layer, and the application layer. The perception layer consists of various sensors and intelligent terminals deployed on power equipment, such as temperature sensors, current transformers, and fault indicators, which are responsible for collecting grid operation data. The network layer realizes data transmission through wired or wireless communication technologies, including power optical fiber private networks, 5G, and power line carriers. The application layer processes and analyzes massive amounts of data based on cloud computing, big data, and artificial intelligence technologies, supporting advanced applications such as intelligent scheduling, prediction and early warning, and equipment health management. In the perception layer, electrical quantity measurement technology is relatively mature, but there are still technical bottlenecks in online monitoring of mechanical status and chemical status (such as insulation aging). In the network layer, the backbone communication network coverage is relatively complete, but the "last mile" problem of edge node access has not been fully resolved, especially in remote areas. In the application layer, basic applications such as Supervisory Control and Data Acquisition (SCADA) and Energy Management Systems (EMS) have been popularized, but advanced applications based on artificial intelligence, such as predictive maintenance and autonomous decision-making, are still in the promotion stage [4].

With the continuous maturity of technologies and the expansion of application scenarios, the power grid IoT is evolving from a single device connection to comprehensive system intelligence, and its core goal is shifting from improving operational efficiency to supporting energy transformation and the construction of new power systems. In this process, technological innovation, standard unification, business models, and network security will become key factors affecting the development of the power grid IoT.

2.2 The Internet of Things

Concept and Evolution of IoT. The IoT refers to a large-scale network system that connects various objects in the physical world with the Internet through information sensing devices and network protocols to realize intelligent identification, positioning, tracking, monitoring, and management. The concept can be traced back to the coffee pot monitoring project at the University of Cambridge in 1991, while the term "Internet of Things" was formally proposed by Kevin Ashton from MIT in 1999. The essence of IoT is the deep integration of the physical world and the digital world, and its core value lies in realizing information interaction and intelligent decision-making between objects through data collection, transmission, and analysis.

The standardization of IoT communication protocols is crucial to ensuring device interoperability. Currently, mainstream protocols include IPv6 (to solve the problem of insufficient address resources), MQTT (lightweight publish/subscribe protocol), and CoAP (Constrained Application Protocol), etc. However, the problem of protocol fragmentation still exists, with multiple standards such as Zigbee, LoRa, and NB-IoT coexisting, which increases the complexity of system integration [5]. The industry is addressing this issue by developing intelligent gateways that support multi-protocol conversion; for example, industrial IoT gateways can realize data intercommunication between devices with different protocols.

From the perspective of technological development, IoT has gone through three stages of evolution: the concept germination period (1991-2005), marked by the application of RFID technology; the technological breakthrough period (2008-2015), during which the popularization of 4G promoted the development of applications such as the Internet of Vehicles; and the large-scale commercialization period (2016-present), where the integration of 5G, AI, and other technologies has spawned new application scenarios such as smart cities and industrial Internet. Currently, IoT is accelerating its development towards the "Internet of Everything (IoE)", with connected objects expanding from traditional electronic devices to almost all physical entities. The only suspense is which other objects will be connected in the future and how fast new technologies will be popularized.

Core Characteristics of IoT. The core characteristics of IoT can be summarized as comprehensive perception, reliable transmission, and intelligent processing. Comprehensive perception refers to the use of various sensors to obtain real-time information about objects and the environment; reliable transmission ensures that information is accurately delivered through wired or wireless networks; intelligent processing involves analyzing and mining data to realize intelligent identification, positioning, tracking, monitoring, and management. These three aspects complement each other and jointly form the technical foundation of IoT.

3 Intelligent power grid based on the Internet of Things

3.1 Intelligent Operation

AI technology in smart grids refers to a technical system that realizes load forecasting, fault diagnosis, and dynamic scheduling through algorithms such as machine learning and deep learning, with its core being data-driven optimization of grid energy efficiency.

ENEL's Deep Learning Load Forecasting System in Italy ENEL has deployed 32,000 Landis+Gyr E350 smart meters to collect 12-dimensional data such as voltage, current, and power factor, and built a LSTM load forecasting model [6]. The model inputs 72-hour historical load data and meteorological information (temperature, humidity) and outputs the load curve for the next 24 hours, with weights updated every 6 hours through an online learning mechanism. Experimental data show that the prediction error of the system is still less than 4.1% under extreme weather conditions, such as typhoons. Optimization effects: 1. The number of start-ups and shutdowns of coal-fired units has been reduced by 37%. 2. The annual carbon dioxide emission reduction has reached 80,000 tons.

PJM Grid's Reinforcement Learning Scheduling System in the United States. The PJM grid adopts the Deep Deterministic Policy Gradient (DDPG) algorithm to build a dynamic scheduling model, abstracting the power grid as a Markov Decision Process (MDP). The state space includes 23 parameters, such as node voltage, line load rate, new energy output. The reward function is designed as: R = 0.7 × absorption rate + 0.2 × network loss reduction - 0.1 × regulation cost.

Unit combination schemes are generated every 5 minutes and delivered to the GE gas turbine control system through the OPC UA protocol. Optimization effect: The wind curtailment rate has dropped from 9.2% to 2.3% [7].

CNN Fault Diagnosis System of China Southern Power Grid China Southern Power Grid has deployed high-frequency recorders (with a sampling rate of 10kHz) in 500kV substations and adopted a 3-layer Convolutional Neural Network (CNN) to extract fault features (such as transient zero-sequence current amplitude and phase mutation). The diagnosis process includes: 1. The first convolutional layer (with a kernel size of 5x5) identifies partial discharge pulses. 2. The maximum pooling layer compresses the data dimension. 3. The fully connected layer output's fault type concepts (softmax activation). The diagnosis result triggers protection actions through IEC 61850 GOOSE messages, and the entire process takes less than 2 seconds [8].

The successful applications above fundamentally rely on the powerful capability of machine learning algorithms in processing high-dimensional grid data and identifying complex patterns. The integration of AI and machine learning is pivotal for transitioning from traditional static grid management to a dynamic, self-optimizing smart grid. These technologies enable the system to learn from historical and real-time data, thereby improving the accuracy of forecasting models, accelerating fault detection, and optimizing decision-making processes. The adaptability of machine learning models is particularly crucial for managing the uncertainty and variability introduced by large-scale renewable energy integration, ensuring grid stability and efficiency [9].

3.2 Adjustable Regulation

The reliability of smart grids is achieved through a collaborative three - tier control system consisting of "cloud - edge - end". Each tier relies on differentiated technical strategies to provide a solid guarantee for the real - time performance and reliability of regulation. At the device layer (end - side), which serves as the "nerve endings" of power grid regulation, intelligent terminals with edge computing capabilities are deployed. Typical examples include Feeder Terminal Units (FTUs) and intelligent circuit breakers. They adopt an improved adaptive PID control algorithm, enabling millisecond - level rapid responses. Taking voltage control as an example, once a voltage deviation exceeding ±5% is detected, the preset VQC (Voltage and Reactive Power Control) logic will be quickly activated to automatically adjust the on - load tap - changer and switch the capacitor banks. The whole response time will only take about 200ms.This layer uses the IEC 61850-9-2 sampled value transmission method. GOOSE messages enable different devices to connect with each other in a peer-to-peer way. This technical measure guarantees the transmission delay time of important control command information. A speed no greater than 10ms is required to form the first line of protection for swift, steady movement. The function of the power grid.

The functions move to the regional layer (edge-side). Act as an organizer for an optimal regulation within the local power grid. Capable of realizing minute-level optimized regulation based on Model Predictive Control. The control center acquires the PMU measurement data from different points. Runs node every 5 minutes and sets up a prediction model consisting of 128 states. This model takes minimizing network loss as the objective function and fully considers 87 inequality constraints such as voltage constraints and line thermal stability， using the interior point method to solve the optimal power flow. According to the actual operation data of a provincial power grid， this strategy has achieved the remarkable results brought down the average network loss rate by 2.3 percentage points. Raising the qualification rate of the voltage to 99.92% [10]. In addition, for distribution networks with a distributed generation penetration rate exceeding 30%, this tier introduces cooperative game theory to establish a dynamic aggregation model of virtual power plants and conducts benefit distribution through the Shapley value, effectively encouraging all parties to actively participate in demand response and further improving the operational efficiency of the regional power grid.

Looking at the system layer (cloud - side), as the "smart brain" of the entire power grid regulation, it relies on the powerful big data analysis and supercomputing capabilities of the cloud platform and adopts Deep Reinforcement Learning (DRL) to achieve hour - level forward - looking scheduling. This tier constructs a state space containing 156 - dimensional features such as weather forecasts and load characteristics, designs a composite reward function (with 70% considering economy, 20% focusing on safety, and 10% emphasizing environmental protection), and trains the scheduling strategy through the Proximal Policy Optimization (PPO) algorithm. The application practice of a regional power grid shows that this scheme has achieved excellent results, increasing the new energy absorption rate by 8.7% and reducing the peak shaving cost by 12 million yuan per year [11]. It is worth mentioning that these three tiers of architecture are not isolated from each other. Instead, they are closely interconnected through high - speed communication networks and realize virtual - real mapping using digital twin technology. This ensures that the regulation strategies can be coordinated and unified on different time scales, jointly promoting the efficient, stable, and reliable operation of the smart grid.

3.3 Measurable Monitoring

The measurable system of smart grids is realized by constructing a global perception network and a multi-source data fusion platform, with its core technical architecture comprising three key layers. At the perception layer, a heterogeneous sensor network is employed to achieve full-state monitoring of power equipment. For transmission lines, a set of micro-meteorological sensors (with a wind speed accuracy of ±0.5m/s) and distributed optical fiber temperature measurement systems (with a spatial resolution of 1m and a temperature accuracy of ±1℃) are deployed every 200 meters. In substations, SF6 gas component monitors (with a detection limit of 0.1μL/L) and ultrasonic partial discharge sensors (with a frequency band of 20-200kHz) are configured. Distribution terminals are integrated with high-precision merging units (with a sampling rate of 4000Hz and an amplitude error of ≤0.2%). The application in a UHV project shows that this scheme increases the coverage rate of equipment state monitoring from 78% to 99.6%, and the integrity rate of sampled data reaches 99.92% [12].

At the communication layer, a hybrid transmission network of "5G + optical communication + PLC" is built. Critical measurement data are transmitted through 5G uRLLC slices (with an end-to-end delay of 8ms and a reliability of 99.999%), while non-real-time data adopt HPLC broadband carriers (with a transmission rate of 2Mbps). The time-sensitive network (TSN) technology is innovatively applied, and microsecond-level time synchronization across devices is achieved through the IEEE 802.1AS-2020 protocol, ensuring that the angle error of PMU phasor measurement is less than 0.01°. Measured data indicate that this architecture reduces the data transmission packet loss rate of the Wide-Area Measurement System (WAMS) to below 0.001% [13].

At the platform layer, a measurement data center is constructed based on digital twin technology. The Flink stream process framework is used to satisfy real-time processing of millions of measurements points per second, and an improvement of Kalman filtering algorithm is applied for data cleaning. A deep learning-based anomaly detection model (noise Q=0.01, observation noise R=0.1), which is LSTM-AE structure with 128 hidden layer nodes, is developed to accurately identify data anomalies of more than 0.5%. An application case in a provincial power grid shows that this platform shortens the state estimation convergence time by 62% and increases the availability rate of measurement data to 99.89% [14].

4 Conclusion

All summed up, bring IoT into smart grid is the an important turning point in modern energy system and conquer existing questions， which includes poor energy distribution，unstable stability, security performance and so on. This proves that he is really important and helpful to us. IoT-enabled smart grid is layer-structure which made up of perception layer, network layer, and application layer. The network layer and application layer together build a strong structure. Through different kinds of sensor technology, perception layer can collect different variety of data. Network layer ensures high efficiency transmission of data in mixed internet. Application layer uses this technology to explain data physically. Through the great cooperation between these three layers help enhancing the real-time detection ability and increase operation efficiency, then promote automation and intelligent process in smart grid side.

Although the development of power grid face obviously differences among different global regions across the world, such as China focus on power integration of new energy resources, American concern itself coordination questions, but IoT-enabled smart grid still show its role as a stable model. What's more, IoT-enabled smart grid will be helpful for them to solve these obstacles depend on global main trends.

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