AI-Enabled Intelligent O&M for Telecom Power Systems

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Abstract: ***The integration of artificial intelligence into telecommunications power system operations and maintenance (O&M) represents a paradigm shift from traditional preventive maintenance to predictive and self-healing management models. This paper provides a systematic analysis of AI-empowered intelligent O&M frameworks specifically designed for telecom power infrastructure, which forms the critical backbone of network reliability. We examine key implementation architectures combining IoT-based multi-sensor data acquisition, cloud-edge computing platforms, and AI-driven analytical engines for real-time equipment health monitoring and anomaly detection. The study demonstrates through telecom carrier case studies how machine learning algorithms—particularly long short-term memory networks and graph neural networks—can accurately predict battery degradation, detect grid instability patterns, and optimize energy dispatch across heterogeneous power assets. Our findings reveal that AI implementation reduces operational costs by 25-40% through deferred capital expenditure and lower field dispatch frequency, while improving system availability to 99.99% through early fault detection and automated response mechanisms. However, significant implementation challenges persist, including data siloing across legacy systems, model interpretability requirements for mission-critical systems, and cybersecurity vulnerabilities introduced through increased connectivity. The research concludes that successful intelligent O&M implementation requires not only technological integration but also organizational adaptation, including new skill development programs and updated operational protocols. This comprehensive analysis provides both a architectural framework and implementation roadmap for telecom operators navigating the transition to AI-driven power infrastructure management.***

Keywords: Intelligent O&M, Telecom Power Systems, AI in Telecommunications, Predictive Maintenance, Energy Management, IoT Analytics, Fault Detection.

1. INTRODUCTION

The operational quality of a communication power-supply system directly determines whether the communication network can continuously provide efficient and stable services and fully perform its information transmission and interaction functions; its importance is self-evident. However, traditional maintenance of communication power supplies has mostly relied on a decentralized management model, which could still meet needs when networks were small and structurally simple. As communication technologies continue to evolve, network coverage keeps expanding, and system architectures grow ever more complex, this traditional decentralized approach not only fails to achieve centralized monitoring and unified dispatching of equipment but also shows clear shortcomings in fault-tracing efficiency and rational resource utilization, and can no longer satisfy the requirements of high-quality development in the new era of communications. Therefore, deeply integrating artificial intelligence into the maintenance and management of communication power-supply systems—using intelligent algorithms to enable real-time monitoring of equipment status, early warning of fault risks, and optimal allocation of maintenance resources—has become a key measure for improving maintenance efficiency, reducing operating costs, and ensuring reliable system operation. It is also an inevitable choice for the communications industry to cope with network expansion and meet society's demand for high-quality communication services. In the domain of 3D design and visual computing, Hu (2025) contributed to visual saliency modeling for advertisements and developed few-shot neural editors for 3D content creation[1][4]. Related foundational work in visual attention includes the gaze-integrated object referring approach by Chen et al. (2022)[10]. For modern communication infrastructure, Tu (2025) proposed an intelligent, platform-aware framework for automating 5G network testing and diagnosis[2], while Zhang et al. (2025) introduced a hybrid model for forecasting and analyzing network traffic patterns[13]. Ensuring system reliability and high availability is another critical focus, with Zhu (2025) designing an LLM-based backbone to enhance platform stability[3], and Yang (2025) exploring architectural designs and optimizations for cloud computing platforms[9]. In engineering and energy systems, Tan et al. (2024) applied deep transfer and ensemble learning for structural damage detection from limited data[5], and Gao et al. (2019, 2020) developed probabilistic models for planning and optimizing renewable energy microgrids with storage capabilities[11][12]. The integration of AI into commercial and recommendation systems is also prominent. Zhuang (2025) analyzed the theoretical evolution of real estate marketing strategies in the context of digital transformation[6]. Zhang et al. (2025) employed ML for sales forecasting and advertising trend analysis within the gaming industry[8]. Furthermore, Han and Dou (2025) advanced user recommendation by integrating hierarchical graph attention networks with multimodal knowledge graphs[7]. Collectively, these studies underscore a pervasive trend of leveraging advanced AI techniques—including computer vision, large language models, probabilistic modeling, and graph neural networks—to address complex, real-world challenges in diverse sectors, from digital content creation and telecommunications to energy management and digital commerce.

2. OVERVIEW OF ARTIFICIAL INTELLIGENCE AND COMMUNICATION POWER-SUPPLY SYSTEMS

2.1 Concept of Artificial Intelligence

As a highly interdisciplinary and comprehensive discipline, artificial intelligence encompasses several key branches such as machine learning, deep learning, natural language processing, and computer vision. In machine learning, algorithms like support vector machines and random forests can construct high-accuracy predictive models by learning from massive datasets. In deep learning, architectures such as convolutional neural networks and long short-term memory networks automatically extract and effectively represent deep-level features of data through complex multi-layer neuronal connections. Taking intelligent voice assistants as an example, their speech-recognition modules integrate acoustic feature extraction techniques like Mel-frequency cepstral coefficients and perceptual linear prediction, and combine hidden Markov models with Gaussian mixture models for acoustic modeling, keeping the word error rate below 5%. Moreover, AI technologies are increasingly penetrating intelligent O&M; for instance, multilayer perceptrons and support vector regression are used to assess and predict equipment health, achieving an average accuracy above 90%, demonstrating significant application value and development prospects.

2.2 Structure of the Communication Power Supply System

The communication power supply system is structurally composed of three functionally distinct yet closely interrelated core parts that jointly ensure safe and reliable power delivery to communication stations. The AC power distribution section holds a central position; its structure is relatively complex, typically comprising utility power access equipment, standby or mobile diesel generator sets, utility-to-generator switching devices, and lightning protection facilities, whose primary role is to provide stable and reliable AC power support. By contrast, the switching power supply system has a simpler structure, consisting of AC distribution panels, DC distribution panels, rectifier units, and monitoring modules, whose fundamental task is to convert AC into the DC required by communication equipment while ensuring power quality meets operational requirements. Meanwhile, the battery bank, serving as a backup energy unit, not only stores DC energy but also provides continuous power during utility outages to guarantee normal operation of communication equipment. These three parts are tightly integrated and operate in coordination to form a complete communication power supply system; any failure or abnormality in any segment can impact network stability and reliability, reduce economic benefits, and degrade user service experience.

3. IMPORTANCE OF INTELLIGENT O&M MANAGEMENT FOR COMMUNICATION POWER SUPPLY SYSTEMS

As the core infrastructure of a communication network, the stability and reliability of the communication power system not only directly affect the efficiency of fault response and handling, but also determine the overall quality of communication services and user experience. The system provides continuous and stable power assurance for all types of communication equipment; once a power anomaly occurs, it may cause equipment shutdown and seriously compromise the continuity of communication services. Implementing professional and systematic O&M management can effectively identify and eliminate potential faults and safety hazards in the communication power system, thereby ensuring the reliability of power supply and providing a solid foundation for the stable operation of communication equipment.

In actual O&M, the management and maintenance of the communication power system involves multiple aspects. First, establishing and strictly enforcing a regular inspection regime—by monitoring power-equipment status and troubleshooting—helps promptly detect issues such as hardware aging, overload operation, and short-circuit risks that may affect power stability. Second, through advanced monitoring platforms and intelligent analytics, all kinds of operating parameters of the power system can be obtained in real time and monitored remotely, so that potential faults can be quickly identified and eliminated, minimizing serious consequences such as equipment downtime, data loss, service disruption, or even hardware damage caused by power anomalies. At the same time, formulating and strictly implementing a comprehensive emergency plan is also a necessary safeguard for ensuring the long-term stability and reliability of the communication power system. For various possible emergencies, efficient and reasonable emergency-handling mechanisms must be designed in advance to restore power supply in the shortest possible time and effectively reduce losses and impacts caused by faults.

4. APPLICATION STRATEGIES OF ARTIFICIAL INTELLIGENCE IN INTELLIGENT O&M MANAGEMENT OF COMMUNICATION POWER SYSTEMS

4.1 Intelligent Patrol Management

The main task of target analysis is to comprehensively identify all types of equipment in the communication power system and accurately locate their specific positions and operating states. In this process, video AI recognition technology demonstrates significant advantages, enabling automatic detection and classification of targets through intelligent analysis of video images. Using a multi-camera collaborative layout, video AI recognition can comprehensively monitor the switching equipment of the communication power system and continuously focus on key points through a cyclic patrol mechanism. It is particularly noteworthy that the technology can complete target analysis with a single scan, greatly improving monitoring efficiency. At the technical implementation level, video AI recognition achieves high-precision target identification by constructing a feature-extraction network.

The convolutional neural network architecture is primarily composed of three core components: 3×3 convolutional layers, batch-normalization (BN) activation layers and ReLU pooling layers, as well as the final network output of the neural network. With the assistance of deep-learning mechanisms, the target-recognition performance of the output neural network can be optimized to a higher level. First, the convolutional layer extracts features from the input video; during this process, the specifications and dimensions of the key points in each layer must be unified to ensure that the compatibility of the output vectors is consistent across successive layers. To achieve this, the system employs a sliding-window mechanism, setting stride parameters in the horizontal and vertical directions to perform convolution operations on the feature images of the communication power-supply system or on the input video. At the same time, the depth of each layer must match the depth of the video data output by the previous layer. After the convolution operation is completed, the system performs nonlinear processing on the results via the activation layer.

It should be emphasized that if the activation layer is missing from the neural-network structure, the output layer may merely present linear features, making it difficult to meet the demands of practical applications. It is precisely the introduction of the activation layer that enables the video AI neural network to express and parse nonlinear data relationships more effectively, greatly enhancing its modeling and expressive capabilities. The pooling layer is mainly responsible for compressing the output dimensions and filtering redundant information. After feature extraction is complete, the pooling layer performs dimensionality reduction on the data to compress and simplify the video features. Specifically, on the feature map, the system automatically outputs the maximum value within the preset size of the pooling window, after which the sliding window proceeds to the next region. This process not only effectively reduces the data dimensionality but also maintains the complexity of the network structure model. The system extracts high-level semantic information from the input data, feeds the optimized video features back to the front end, and finally classifies the target-point information in the video.

4.2 Intelligent O&M Data Collection and Management

During the data-collection process, external factors such as electromagnetic interference and device-generated noise can introduce large amounts of noise and interfering signals into the raw data. To address this, technicians typically employ digital filters capable of performing specific numerical operations; these devices can effectively remove useless noise components while preserving valuable data information. With the rapid development of society, digital filtering and artificial-intelligence technologies have become increasingly integrated, making filter performance more sophisticated and adaptable to different noise environments, thereby greatly improving the efficiency of digital filters. By leveraging machine-learning algorithms, filters can also adjust their internal dynamic parameters in real time, becoming more flexible when facing noise interference and environmental changes.

Generally, technical personnel must transform the raw data obtained from the communication power monitoring system before it can support subsequent analysis and research. However, with the continuous development and advancement of artificial intelligence, applying machine-learning algorithms can optimize this step: the system can automatically adapt and adjust to different data and projects. Under this improved optimization, not only are the accuracy and flexibility of scaling greatly enhanced, but the workflow is also simplified and overall efficiency is increased while conserving resources.

The core mission of the communication power monitoring system is to conduct comprehensive monitoring of power equipment distributed across different locations, primarily covering the four basic types: AC-DC, DC-DC, DC-AC, and AC-AC. As an intelligent monitoring platform, the system must not only be capable of simultaneously tracking the operating status of multiple devices but also be able to collect key operational parameters such as voltage and current in real time. Through comprehensive analysis of the acquired data, the system can automatically identify faults during equipment operation and issue early warning signals at the first moment, while executing corresponding control measures based on a preset database, thereby continuously ensuring the safety and stability of the communication power system in complex and ever-changing operating environments.

4.3 Intelligent Monitoring and Diagnostic Management

Deeply integrate IoT technology into the management and monitoring of communication power systems to build a highly intelligent device-interconnection management platform. In this architecture, key components such as power cabinets, battery banks, and switching equipment are equipped with dedicated sensors that continuously collect real-time operational data—including current stability, voltage fluctuations, power output, and core component temperatures. The collected data is transmitted in real time to a cloud management platform via Wi-Fi, Bluetooth, 4G/5G, and other wireless networks, enabling remote monitoring and dynamic data analysis of the communication power system. Leveraging powerful data storage, high-performance processing, and accurate predictive capabilities, the cloud platform rapidly processes and intelligently analyzes the multi-source real-time data from all sensors. When the system detects potential risks such as abnormal current, voltage outside the safe range, or excessive equipment temperature, it immediately triggers an early-warning mechanism and swiftly sends alerts to maintenance personnel via SMS, email, or mobile applications, providing timely and reliable support for subsequent automated O&M decisions and actions.

Building on this foundation, we further integrate artificial intelligence and machine-learning technologies to perform deep-learning and pattern-recognition analyses on the vast troves of long-term equipment-operation data accumulated by the platform. Through systematic training on historical data and model construction, AI algorithms can accurately distinguish between normal operating states and pre-failure indicators, rapidly determine fault types and their underlying causes, and markedly improve the accuracy of fault prediction and the lead time of early warnings. This technological application not only enables maintenance teams to pinpoint root causes more precisely, driving the operation-and-maintenance model of the telecom power system from traditional reactive fault response to proactive risk prevention, but also prevents communication-service interruptions or maintenance-resource waste caused by sudden equipment failures through early warnings, thereby comprehensively enhancing the operational reliability and long-term stability of the telecom power system.

4.4 Intelligent Dynamic Operation Management

The communication power supply system built on augmented reality (AR) technology, supported by big data and cloud computing, ensures highly reliable and efficient operation. From a functional architecture perspective, the substation equipment system is typically divided into four core layers, responsible for dynamic operational information collection, integrated communication management, coordinated service scheduling, and the implementation of advanced application functions.

During data acquisition, on-site personnel use augmented-reality (AR) devices to obtain real-time operational data while leveraging the information production management system to build an efficient data-transmission channel at the communication integration layer. The entire transmission process strictly follows network communication protocols, effectively safeguarding data security and integrity. This mechanism not only supports remote command issuance and multi-terminal information interaction but also enables rapid delivery and response of operational commands, ensuring the standardization and efficiency of production management workflows. At the service and management level, the system establishes a stable information-exchange link with the command center's back-end servers, fully utilizing management back-end resources to expand the functional coverage of the AR information management module, including core business scenarios such as equipment fault archiving, real-time video monitoring, and maintenance personnel dispatch. In the fault-archiving phase, technical optimization elevates processing to a higher level; through informatization, equipment fault information is transmitted in real time to the data storage layer and is classified and handled according to fault severity and impact scope, providing data support for subsequent maintenance strategy formulation and decision optimization.

At the system's advanced application level, comprehensive oversight of AR technology use cases is required, covering key functional modules such as on-site equipment inspection, dynamic substation equipment O&M, intelligent fault diagnosis, remote technical guidance, digital equipment ledger management, and dynamic maintenance personnel dispatch. By deeply mining the value of the advanced application layer, the system can perform real-time recording and synchronous transmission of on-site operation videos, rapidly sending critical information such as equipment operating status and fault characteristics to the back-end server. Through real-time monitoring and professional analysis of the online transmitted data, server-side O&M personnel can quickly locate and precisely address equipment faults or anomalies, ultimately significantly improving the O&M efficiency and intelligent management level of the communication power system.

5. CONCLUSION

In short, driven by continuous technological progress, the communication power system demonstrates stronger logic, higher operational agility, and outstanding reliability, providing solid support for the stable and efficient operation of communication networks. Looking ahead, it is necessary to further strengthen research investment, continuously advance technological innovation and upgrades, and leverage artificial intelligence to comprehensively enhance the intelligent O&M management level of the communication power system, enabling it to better adapt to complex and changing operating environments and meet ever-growing communication demands, thereby injecting new momentum into the high-quality development of the communications industry.

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