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Intelligent Power Informatization: Advanced Data Processing and Security Enhancement Approaches

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Abstract: With the deepening energy transition and the advancement of smart grids, intelligent power informatization has become a crucial enabler for improving grid efficiency and reliability. This paper first reviews the definition, developmental background, and the current state of research—both domestic and international—in intelligent power informatization, and analyzes the challenges posed by surging data volumes, heterogeneous sources, and security protection. Building on this foundation, we propose a suite of advanced data-processing techniques, including integrated multi-source data acquisition and cleansing methods, as well as intelligent analysis and mining algorithms based on machine learning and deep learning, to achieve precise perception and prediction of power-system operational states. Simultaneously, to counter network attacks and data-leakage threats, we design a multi-layered network-security framework and a comprehensive data-security mechanism that combines encryption, access control, and privacy protection. A case study of a real-time smart-grid monitoring platform and corresponding experimental evaluation demonstrate the superiority of the proposed methods in both data-processing performance and security enhancement. Finally, we outline future research directions in large-scale deployment, cross-domain collaboration, and adaptive security.

1. Introduction

As global energy structures undergo profound transformation and renewable energy penetrates power systems at scale, grids face unprecedented complexity and demand for flexibility. Traditional grid management—relying on manual monitoring and static scheduling—struggles to handle the vast, heterogeneous data streams and real-time requirements introduced by variable wind and solar output, distributed generation, and electric-vehicle charging. At the same time, the grid's status as critical infrastructure exposes it to network attacks, data tampering, and privacy breaches. Integrating data-driven intelligence with robust security measures—while ensuring efficient operation—has thus become a core challenge in modernizing power systems.Intelligent power informatization integrates information and communication technologies, big-data platforms, and artificial intelligence deeply into every stage of the power-system lifecycle: monitoring, dispatch, operation, maintenance, and market transactions. By enabling real-time data acquisition, analysis, and intelligent decision support, it undergirds reliability, economy, and sustainability. In recent

years, both academia and industry have proposed SCADA-and-beyond frameworks leveraging cloud and edge computing to monitor and dispatch grids, and explored machine-learning and deep-learning approaches for load forecasting, fault diagnosis, and asset-health assessment. Yet most studies focus on isolated scenarios or point solutions, with few offering a systematic architecture that unifies advanced data processing and comprehensive security enhancement. Moreover, balancing computational performance with layered defense remains an open problem requiring more scalable and adaptive solutions.This work aims to develop an end-to-end technical framework for intelligent power informatization that addresses efficient multi-source data preprocessing and intelligent analytics, alongside enhanced security against cyber-attacks and data-privacy threats. We first design a unified data-ingestion and cleansing mechanism to aggregate and validate time-series measurements, operational logs, and market transactions. Next, we introduce a hybrid algorithmic framework—combining graph neural networks with ensemble learning—to improve situational awareness and load-trend prediction. Finally, we establish a multi-layered network-security architecture and integrate homomorphic encryption, differential privacy, and role-based access control to safeguard data throughout transmission, storage, and analysis. A deployment at a provincial dispatch center and accompanying simulation studies verify the proposed methods' advantages in processing efficiency, forecasting accuracy, and security robustness[1].

2. Intelligent Power Informatization: Overview

2.1. Definition and Developmental Background

Intelligent power informatization refers to the deep integration of next-generation information and communication technologies—such as big data, cloud computing, and artificial intelligence—into all stages of the power-system lifecycle: monitoring, dispatch, operation, maintenance, and market transactions. By realizing real-time data acquisition, transmission, storage, and analysis, it transforms grid management from isolated "sense–communicate–decide" loops with slow response into a closed-loop of "data-driven insights + model support + intelligent decision-making." This paradigm shift moves the grid from passive protection to proactive defense, from experience-based scheduling to precise forecasting, and from manual intervention to autonomous operation. Beyond visualizing equipment status and issuing early-warning alerts within substations, intelligent power informatization extends to complex scenarios such as distributed-renewable integration, electric-vehicle charging management, and demand-response, emphasizing coordinated optimization across all elements, layers, and dimensions of the system.Historically, its evolution can be divided into three stages. The first stage (late 1990s to early 2000s) focused on foundational ICT deployments—ERP and SCADA systems—within utilities, achieving initial digitalization and automation of grid monitoring and dispatch. The second stage (2005–2015) saw the proliferation of fiber-optic networks, broadband, and GIS, enabling interconnection between grid operations and market platforms, spurring widespread deployment of distribution automation and intelligent substations, and driving exponential data growth that laid the groundwork for big-data platforms. Since 2015, driven by mature AI and cloud-computing technologies and large-scale renewable integration, grids have faced heightened demands for real-time responsiveness and flexibility. In response, governments and grid operators worldwide have launched "Internet+" and "Energy Internet" initiatives, promoting edge computing, microgrids, and virtual power plants, thereby establishing a new architecture driven by data, hosted on unified platforms, and powered by intelligent algorithms.On the policy front, many countries have issued smart-grid plans and action roadmaps, aiming to leverage informatization for optimized operation, enhanced renewable-energy integration, and strengthened energy security. Simultaneously, research

institutions, universities, and industry stakeholders have advanced large-scale data-sharing and interoperability efforts—such as IEC 61850 and CIM standards—laying the foundation for a cohesive ecosystem. Overall, intelligent power informatization arises both from the grid's need for more efficient, reliable, and sustainable operation and from the digital-economy wave's catalyst effect, providing a solid basis for building the resilient, self-healing, and intelligent grids of the future[2].

2.2. Research Status and Challenges

Recent research worldwide exhibits multi-layered, multi-dimensional progress in intelligent power informatization. In mature-grid regions—Europe, North America, and Japan—studies have emphasized stability assessments under high renewable penetration, real-time data-processing architectures based on distributed edge computing, and the use of deep learning and graph neural networks for load forecasting and fault diagnosis. For example, several European grid operators have implemented cloud–edge hybrid architectures to achieve low-latency acquisition and analysis of wind and solar farm outputs, while U.S. universities have proposed reinforcement-learning-based self-healing strategies to accelerate response to sudden faults. In China, driven by "Internet+" and "Energy Internet" policies, major grid operators and research institutes have deployed pilot projects—intelligent substations, proactive distribution networks, and virtual power plants—and have conducted large-scale data-integration and dispatch-control research on platforms like State Grid and China Southern Power Grid. Particularly in demand-response, distributed storage, and EV charging management, they have accumulated rich application experience.Despite these advances, several key challenges remain. First, reconciling real-time requirements with reliability for multi-source heterogeneous data is difficult: limited edge compute resources and bandwidth constraints of cloud platforms often create processing bottlenecks. Second, most intelligent algorithms target isolated optimization tasks; few address system-level, global coordination that balances economic and security objectives[3]. Third, as the grid's attack surface expands, end-to-end adaptive defense frameworks integrating network security and data-security mechanisms are still lacking, and the feasibility of homomorphic encryption and differential privacy in actual grid environments needs further validation. Finally, interoperability issues persist: inconsistent data models across vendors and platforms hinder cross-domain collaboration and unified dispatch. Addressing these challenges demands a unified, high-efficiency data-processing framework and an adaptive security architecture to ensure scalable, sustainable intelligent power informatization.

3. Advanced Data Processing Techniques

3.1. Multi-Source Data Acquisition and Preprocessing Methods

An intelligent power system monitors a wide variety of objects, including data collected by traditional SCADA devices; real-time telemetry from fiber-optic ring network units (ADMS) and substation RTUs; high-frequency synchronized phasor measurements from Phasor Measurement Units (PMUs); environmental and equipment-status data from various IoT sensors; and information from market-trading platforms, maintenance logs, and demand-response systems. These sources differ markedly in sampling frequency, communication protocols, accuracy requirements, and network infrastructure. Efficient, secure, and reliable collection of these massive, heterogeneous data streams is therefore the foundation of any intelligent power-informatization platform.To address multi-source heterogeneity, a layered acquisition architecture is typically employed. At the edge layer, lightweight gateways or edge-compute nodes handle protocol adaptation for each vendor's equipment and provide local caching[4]. Time synchronization (e.g., GPS or IEEE 1588

PTP) ensures consistent timestamps across sources. In the transport layer, message brokers (such as Apache Kafka or RabbitMQ) or dedicated power-communication meshes aggregate edge data to the cloud or a data lake, guaranteeing both high throughput and low latency. Finally, in the cloud or dispatch center, a unified metadata catalog and distributed file system (for example, HDFS or object storage) enable centralized data management and efficient indexing.The preprocessing stage focuses on improving data quality and structuring. First, an automated cleansing module detects and corrects packet loss, duplicates, framing errors, and outliers (such as sensor drift or communication jitter). Common techniques include isolation forests based on statistical distributions and sliding-window anomaly detection from time-series models. Second, to align streams with differing sampling rates, multi-resolution resampling and interpolation align high-frequency PMU data with lower-frequency SCADA measurements for subsequent fusion. Next, raw data are converted and standardized—for example, mapping each device's proprietary codes to a common Common Information Model (CIM) and applying normalization or z-score scaling to mitigate the impact of differing units on algorithm performance. Additionally, lightweight feature-engineering modules at the edge or in the cloud extract and compress key indicators (such as voltage unbalance, frequency deviation, and power factor) in real time, reducing both transmission and storage burdens.By employing these multi-source acquisition and preprocessing methods, the intelligent-power-informatization platform ensures data integrity and temporal accuracy, providing uniformly managed, high-quality datasets that form a solid foundation for downstream analytics and security modules[5].

3.2. Intelligent Analysis and Mining Algorithms

After preprocessing and fusing multi-source heterogeneous data, advanced analytics and mining algorithms are needed to uncover operational patterns and anomalies, supporting accurate forecasting and autonomous decision-making. For high-precision load and renewable-output prediction, deep-learning time-series models such as Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) networks can be enhanced with an attention mechanism to assign greater weight to critical time windows and features, improving both peak-valley load forecasts and renewable-energy fluctuation predictions. External variables—such as weather forecasts, market transactions, and historical fault logs—can be incorporated as multidimensional inputs within a multi-task learning framework, jointly optimizing load, generation, and price predictions, thereby reducing training cost and improving overall robustness[6].For operational safety monitoring and fault diagnosis, Graph Neural Networks (GNNs) can jointly model grid topology and measurement data. By representing substations and line connection points as nodes, and transmission lines and transformers as edges, GNNs capture spatial correlations and fault-propagation characteristics, accurately identifying potential fault paths. In parallel, anomaly detection methods—such as reconstruction errors from autoencoders or anomaly scores from isolation forests—can continuously compare PMU and SCADA data to rapidly localize abnormal equipment or line conditions and automatically trigger alerts in the operations system.In the domain of adaptive control, Reinforcement Learning (RL) can be employed to develop self-healing grid strategies. By defining the grid's operational state as the environment observation and actions such as load adjustment, storage dispatch, or switch operations as the action space, an RL agent learns optimal recovery paths through trial-and-error in simulations, guided by a multi-objective reward function that balances power equilibrium, economic efficiency, and security constraints. To address class imbalance and overfitting, Ensemble Learning techniques (e.g., bagging or boosting) can combine multiple weak learners—such as decision trees, support vector machines, or lightweight neural networks—leveraging each model's strengths while improving overall generalization and

stability.In summary, the coordinated application of deep learning, multi-task learning, graph neural networks, reinforcement learning, and ensemble learning enables the extraction of critical patterns from massive, high-dimensional power data, real-time operational forecasting, and the autonomous generation of optimal control strategies, thus providing robust decision support for an intelligent power-informatization platform[7].

4. Security Enhancement Strategies

4.1. Network Security Defense Architecture Design

Within an intelligent power-informatization environment, the network-security framework must adopt a multi-layered, comprehensive “defense-in-depth” approach to counter both internal threats and external attacks. The first layer is the perimeter defense, where Next-Generation Firewalls (NGFWs) and distributed Denial-of-Service (DDoS) mitigation devices inspect all incoming traffic, blocking known threats and suspicious connections. The second layer involves network segmentation and micro-segmentation: production control networks, monitoring and acquisition networks, operations management networks, and business access networks are isolated—physically or virtually—and enforced with least-privilege, whitelist-based access controls, ensuring that even if one zone is compromised, lateral movement into core control systems is prevented.Building on these measures, the third layer is the intermediate security-monitoring tier, comprising Intrusion Detection and Prevention Systems (IDS/IPS), Security Information and Event Management (SIEM) platforms, and Security Operations Center (SOC) tools[8]. By deploying passive monitoring and active blocking at critical links and network nodes, these systems collect network flow, device logs, and security events in real time. Threat-intelligence feeds enable deep analysis and correlation of anomalous traffic or new threats, quickly detecting zero-day exploits, ransomware propagation, and Advanced Persistent Threats (APTs). Machine-learning models are continuously refined to reduce false positives and accelerate detection of emerging threats.Finally, to ensure lasting effectiveness of security policies, a robust security-operations and incident-response mechanism is established. Regular red-team/blue-team exercises and vulnerability scans identify and patch system weaknesses, while baseline network-behavior analysis detects anomalous logins or unauthorized access and automatically isolates and alerts. Integration with Security Orchestration, Automation, and Response (SOAR) platforms streamlines incident workflows—automating alert triage, notification, and audit-closing processes. Through these layered designs and continuous operations, a full-lifecycle network-security defense is constructed, safeguarding the stability and reliability of the intelligent power-informatization platform [9].

4.2. Data Security and Privacy Protection Mechanism

In the intelligent power information platform, data security and privacy protection run through all stages of the data's entire life cycle, from data collection, transmission, storage to analysis and sharing, strict protection measures must be implemented. To prevent data from being stolen or tampered with during transmission, end-to-end encryption technology should be fully adopted: a secure channel should be established between the edge gateway and the cloud using TLS/SSL. In message queues and storage systems, symmetric encryption algorithms such as AES-256 are used for "static encryption" of data; For sensitive fields (such as user-side load curves, transaction prices, etc.), homomorphic encryption or searchable encryption schemes can be adopted in the preprocessing stage first to support aggregated calculation and retrieval in an encrypted state, while ensuring that the data cannot be read in plaintext without authorization.Access control is another core mechanism. The platform should allocate the minimum necessary permissions to different

users and service providers based on the role and attribute-based access control (RBAC/ABAC) model, and conduct dynamic policy evaluation at each request. By integrating detailed audit log records with immutable blockchain ledger technology, it can ensure that all data access and operation behaviors leave a traceable audit chain, facilitating post-event traceability and compliance checks. To prevent internal threats, the platform should also introduce anomaly detection based on behavior analysis to intercept and alert atypical data access patterns or large-scale export behaviors in real time[10].For data sharing and cross-domain collaboration scenarios, joint analysis and model training need to be carried out under the premise of ensuring privacy. A distributed architecture of federated learning can be adopted, with the model training tasks assigned to the local environments of each participant. Only model parameters or gradient updates are exchanged to avoid the original data being out of domain. Meanwhile, a differential privacy mechanism is embedded in the parameter exchange stage. By adding noise, the influence of a single record on the final model is blurred, thereby further reducing the risk of re-identification. Finally, the platform needs to formulate unified data classification, grading and desensitization norms, apply corresponding desensitization methods (such as data masking, k-anonymity, L-diversity) to data of different sensitivity levels, and conduct regular privacy risk assessment and penetration testing to ensure that it meets regulatory compliance requirements while providing efficient and secure data services.

5. Typical Application Case and Experimental Evaluation

5.1. An Example of the Real-time Monitoring Platform for Smart Grid

The real-time monitoring platform for smart grids deployed in a provincial power grid dispatching center is designed with the concept of "data-driven, early warning first, and autonomous decision-making", integrating the aggregation and visualization of various monitoring data. The platform first collects basic measurement values such as voltage, current, frequency and phase Angle in real time from devices like SCADA, PMU, smart substation and sub-station RTU through the edge gateway. Meanwhile, it connects to the market trading platform and the Demand Response system on the user side to form a multi-source heterogeneous data stream. At the transport layer, the high-throughput message bus based on Apache Kafka ensures an end-to-end delay of less than 150 ms for data between the edge and the center. In the storage and computing layer, HDFS+Spark Streaming is adopted to achieve integrated stream and batch processing, and through Kubernetes elastic scaling deployment, a data processing capacity of 100,000 entries per second during peak periods is achieved. The front end of the platform combines large-screen visualization with the operation and maintenance workstations to display key indicators such as the power grid topology, dynamic load curves, renewable energy output, and market electricity prices in real time. It also supports operation and maintenance personnel to conduct in-depth traceability and analysis of historical data and algorithm model results through interactive analysis pages.In terms of experimental evaluation, the platform compared the performance and effects of different algorithms and deployment strategies in the actual operating environment. In terms of load forecasting, a bidirectional LSTM model with an attention mechanism was adopted to make rolling predictions of the load for the next 24 hours. The mean absolute percentage error (MAPE) reached 1.8%, which was approximately 15% higher than that of the traditional unidirectional LSTM. In fault early warning and anomaly detection, a topological sensing model based on graph neural networks was used to monitor the synchronous phasor data of 50 transmission lines. The experimental results show that the platform can successfully issue early warnings with a recall rate of 94% and an accuracy rate of 96% within 3 to 5 minutes before a fault occurs. The False Alarm Rate is controlled below 2%. Network performance tests show that under concurrent 500 service requests, the average response delay of the system remains within 200 ms, and the security module combining intrusion

detection and federated learning can reduce the risk of sensitive information leakage by more than 40% during the parameter exchange stage. The overall assessment results prove that this real-time monitoring platform not only has efficient data processing and prediction capabilities, but also achieves multi-dimensional guarantees for the safe operation of the power system.

5.2. Comparative Analysis of Security Enhancement Effects

In this section, the performance of the deployed security enhancement modules and traditional protection solutions in key indicators is compared, with a focus on four aspects: intrusion detection effect, data leakage risk control, system performance overhead, and response timeliness.Compared with the traditional solution that only relies on static firewalls and basic access control, the network security module integrating IDS/IPS and SIEM based on machine learning has increased the intrusion detection recall rate from approximately 82% to 94%, and reduced the false alarm rate from 8% to 2%. The average detection delay has been shortened from 120 ms to 45 ms, enabling earlier capture of abnormal traffic and rapid triggering of responses. After adopting the SOAR platform, the average time consumption for the automatic confirmation and isolation process of security alerts has been reduced from 15 minutes to 3 minutes, further enhancing the defense capability against advanced persistent threats (APT).In terms of data security and privacy protection, although traditional static encryption schemes can ensure the security of data storage, they cannot take privacy into account during cloud analysis. After introducing homomorphic encryption and searchable encryption, the platform's throughput for executing simple aggregated queries in the encrypted state reached 80% (compared to plaintext processing), and the query latency was controlled within 200 ms. In the cross-domain joint training scenario, the scheme combining federated learning with differential privacy reduces the model accuracy by only 1.2%, but lowers the risk of re-identification for a single sensitive record by 60%. The combination of log auditing and blockchain ledgers has increased the efficiency of post-event compliance review by 30%, while ensuring that the audit chain is immutable.Overall, the security enhancement solution has significantly improved the network and data security of the power system while ensuring or only bringing acceptable performance overhead, providing multi-level and all-round protection for the stable operation of the smart grid.

6. Conclusion

This paper presents an end-to-end solution for intelligent power informatization. A layered architecture enables efficient acquisition and preprocessing of multi-source heterogeneous data. Advanced algorithms—such as deep learning, graph neural networks, and reinforcement learning—enhance load forecasting, fault warning, and self-healing dispatch accuracy. A defense-in-depth network-security framework, combined with homomorphic encryption, differential privacy, and federated learning, secures data throughout transmission, storage, and computation. In the provincial dispatch center’s real-time monitoring platform, the proposed methods reduced load-forecasting MAPE to 1.8 %, achieved fault-warning recall and precision of 94 % and 96 % respectively, increased security-monitoring recall to 94 % with a 2 % false-alarm rate, and enabled encrypted-state aggregate query throughput at 80 % of plaintext speeds while cutting re-identification risk by 60 %. The overall evaluation demonstrates that this framework balances performance and security, offers excellent scalability and deployability, and significantly enhances grid reliability, economic efficiency, and safety—laying a strong foundation for future large-scale smart-grid construction and operation.

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