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A Comprehensive Review of Artificial Intelligence Applications in Power System

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مراجعة شاملة لتطبيقات الذكاء الاصطناعي في أنظمة الطاقة

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Abstract:
The growing complexity and demands of modern electrical power systems necessitate the integration of intelligent technologies to ensure efficiency, resilience, and sustainability. This review comprehensively examines the multifaceted applications of Artificial Intelligence (AI) in power system infrastructure, encompassing optimization, fault detection, cyber-security, and renewable energy integration. By categorizing AI techniques, ranging from heuristic algorithms and machine learning to deep learning and federated learning, the paper highlights their role in solving key challenges in conventional and smart grid systems. Specific attention is given to AI's contributions in economic load dispatch, predictive maintenance, intelligent monitoring, and cyber-attack mitigation. Moreover, the study discusses the integration of AI in renewable energy management, including solar and hydropower systems, alongside challenges such as data privacy, software vulnerabilities, and interoperability limitations. The article identifies AI not only as a tool for automation and control but also as a transformative enabler for adaptive, decentralized, and secure energy systems. Through its systematic analysis, the study underscores the critical role of AI in shaping the future of power infrastructure in the context of global energy transitions and smart grid evolution.

Keywords: Power System, Artificial Intelligence, Cyber-attacks.

الملخص
تفرض التعقيدات المتزايدة والمتطلبات المتنامية لأنظمة القدرة الكهربائية الحديثة ضرورة دمج التقنيات الذكية لضمان الكفاءة والمرونة والاستدامة. تستعرض هذه الدراسة بشكل شامل التطبيقات المتعددة الأبعاد للذكاء الاصطناعي في بنية أنظمة الطاقة، بما يشمل مجالات التحسين، واكتشاف الأعطال، والأمن السيبراني، ودمج مصادر الطاقة المتجددة. ومن خلال تصنيف تقنيات الذكاء الاصطناعي - ابتداءً من الخوارزميات التوجيهية والتعلم الآلي، وصولًا إلى التعلم العميق والتعلم الاتحادي - تبرز الورقة دور هذه التقنيات في معالجة التحديات الرئيسية في كل من الشبكات التقليدية والشبكات الذكية. تشهد أنظمة الطاقة الكهروضوئية (PV)اعتمادًا متزايدًا في الآونة الأخيرة، مما يجعل من الضروري رفع كفاءة توليد الطاقة من خلال الكشف المبكر عن الأعطال وتحديدها داخل أنظمة الطاقة الكهروضوئية (PVS) ، إلى جانب ضمان الحماية السيبرانية. تولي الدراسة اهتمامًا خاصًا بمساهمات الذكاء الاصطناعي في التوزيع الاقتصادي للأحمال، والصيانة التنبؤية، والرصد الذكي، والتخفيف من تأثير الهجمات السيبرانية. كما تناقش الدراسة كذلك دمج الذكاء الاصطناعي في إدارة الطاقة المتجددة، بما يشمل الأنظمة الشمسية

والكهرومائية، إلى جانب التحديات المرتبطة بخصوصية البيانات، وثغرات البرمجيات، ومحدودية التوافق بين الأنظمة. وتخلص الدراسة إلى أن الذكاء الاصطناعي لا يمثل مجرد أداة للتشغيل الآلي والتحكم، بل يُعد محفزًا تحويليًا نحو أنظمة طاقة أكثر تكيفًا، ولامركزية، وأمانًا. ومن خلال تحليل منهجي، تؤكد الدراسة على الدور الحاسم للذكاء الاصطناعي في تشكيل مستقبل البنية التحتية للطاقة في ظل التحولات العالمية نحو الطاقة المستدامة وتطور الشبكات الذكية.

الكلمات المفتاحية: أنظمة القدرة، الذكاء الاصطناعي، الهجمات السيبرانية.

Introduction

Optimization is an integral aspect of daily life, guiding the effective and efficient utilization of available resources. To address contemporary challenges across various domains, mathematicians and scientists have translated this concept into Artificial intelligence systems are developed using Artificial Intelligence (AI) has emerged as a key enabler in numerous industries, supporting critical operations such as enhancing organizational efficiency and securing infrastructure, including solar power plant defense systems [1-3]. Given their technological configuration, solar power plants are often situated in zones requiring heightened security oversight. Artificial intelligence holds significant potential for improving defect detection in renewable energy systems, particularly in solar power plants and wind turbines [4-8].

The emergence of information and communication technology (ICT) has significantly simplified human life and transformed various practical domains [9-11]. A prevailing trend in recent years is the enhancement of these technologies through intelligence inspired by natural processes and environmental interactions. Within this context, artificial intelligence (AI) and machine learning (ML) have become pivotal in scientific and engineering disciplines, Machine learning algorithms have demonstrated the capability to meet the operational control requirements of modern power systems [12-15].

The electricity system has evolved into an intelligent framework, known as the Smart Grid (SG), primarily aimed at efficient load management hydropower contributes significantly to the national energy mix. However, many existing hydropower plants are underperforming, highlighting the need for improved operational strategies. Efficient management of these facilities is essential to meet growing energy demands while minimizing environmental impact. Nonetheless, challenges such as climate variability, complex operational conditions, and evolving energy requirements call for the adoption of innovative, intelligent solutions to optimize hydropower generation [16-19].

As articulated in [20], the realization of an intelligent smart grid hinges upon the integration of artificial intelligence (AI) to supplant conventional manual operations, thereby enhancing overall efficiency, reliability, and cost-effectiveness throughout the entire energy supply chain, from generation to end-use. The effective deployment of AI-driven solutions necessitates the acquisition and assimilation of diverse and voluminous datasets to facilitate informed and adaptive decision-making processes. AI applications in smart grids function through the processing of extensive data inputs, leveraging advanced computational capabilities and robust communication infrastructures.

In [21], the study explores the efficacy of the Extra Trees algorithm within a robust two-phase framework for fault detection and diagnosis in grid-connected photovoltaic systems. The proposed methodology comprises an initial binary fault detection phase, followed by a multi-class fault diagnosis phase, achieving impressive classification accuracies of 99.5% and 98.7%, respectively. The research highlights the critical role of oversampling techniques in enhancing model performance, particularly in the context of class-imbalanced datasets. Furthermore, the integration of explainable artificial intelligence (XAI) methodologies augments the interpretability of the model by elucidating the relative importance and hierarchical influence of input features.

In [22], the authors identified eight principal challenges that distributed energy resources (DERs) impose on power grid operations and reviewed contemporary academic advancements concerning the deployment of artificial intelligence (AI) in modern power systems. While AI techniques demonstrate significant promise in enhancing power system stability and protection, the transition from theoretical research to commercial deployment remains unrealized. In this context, our study critically examines the key limitations and barriers impeding the practical implementation of AI in power system protection and stability. These include the reliance on synthetic datasets, the scarcity of high-fidelity real-world measurement data, issues surrounding protection selectivity, and the inherent opacity associated with black-box AI models.

This article provides a comprehensive overview of artificial intelligence (AI) applications in power system infrastructure, highlighting how AI techniques enhance grid efficiency, reliability, and resilience. It examines key areas such as load forecasting, fault detection, renewable integration, and predictive maintenance, while addressing current challenges including data limitations, model interpretability, and integration issues. The study emphasizes the potential of emerging approaches like explainable AI and physics-informed learning, offering valuable insights to guide future research and practical implementation in modern power systems.

Artificial Intelligence Applications in Power Systems

The global energy sector is undergoing a paradigm shift driven by the growing penetration of renewable energy sources, increased electrification, and the integration of smart grid technologies [23-26]. In this context, Artificial Intelligence (AI) has emerged as a powerful enabler in modernizing power systems. AI offers sophisticated tools for data-driven decision-making, optimization, and automation, thereby addressing many of the complex challenges associated with power system planning, operation, and control [27-30]. Through machine learning, deep learning, neural networks, and expert systems, AI facilitates enhanced efficiency, resilience, and sustainability across various layers of the electricity value chain.

- Load Forecasting

One of the earliest and most widely adopted AI applications in power systems is load forecasting. AI models, particularly artificial neural networks (ANNs), support vector machines (SVMs), and deep learning architectures, are capable of predicting short-term, medium-term, and long-term power demand with high accuracy [31-35]. These predictions incorporate multiple variables such as historical consumption data, weather conditions, time of day, and economic indicators, enabling utility companies to optimize resource allocation and reduce operational costs.

- Renewable Energy Forecasting and Integration

The intermittency and unpredictability of renewable energy sources such as solar and wind pose significant operational challenges [36-40]. AI techniques, especially recurrent neural networks (RNNs) and convolutional neural networks (CNNs), are extensively used to forecast solar irradiance and wind speed. These forecasts help in dynamic scheduling, grid balancing, and minimizing the curtailment of renewable energy, thereby supporting a smoother transition to low-carbon power systems [41-44].

- Fault Detection and Diagnosis

AI enhances the reliability of power systems through automated fault detection, classification, and diagnosis. Machine learning algorithms analyze real-time data from sensors and protection devices to identify anomalies, locate faults, and recommend corrective actions. This application is vital for reducing outage durations and improving system stability. Techniques such as decision trees, fuzzy logic, and ensemble methods are commonly employed in these diagnostic systems [45-49].

- Predictive Maintenance and Asset Management

AI-driven predictive maintenance utilizes sensor data and historical failure records to forecast equipment degradation and schedule maintenance activities proactively [50-53]. By applying pattern recognition, anomaly detection, and time-series analysis, utilities can optimize the performance of transformers, circuit breakers, cables, and other critical infrastructure, reducing downtime and extending asset life.

- Grid Optimization and Control

Real-time grid optimization requires intelligent coordination among distributed energy resources (DERs), demand response mechanisms, and energy storage systems. AI algorithms facilitate optimal power flow (OPF), voltage stability control, and reactive power management through reinforcement learning and optimization techniques [54-59]. These capabilities are essential for smart grid operation and achieving high levels of automation [60-63].

- Energy Management Systems (EMS)

AI is at the core of next-generation energy management systems, enabling real-time monitoring, data analytics, and adaptive control strategies. EMS powered by AI ensures optimal energy dispatch, minimizes energy wastage, and manages energy trading in deregulated electricity markets. Additionally, AI enhances decision-making in microgrids and hybrid energy systems where conventional algorithms fall short [64-68].

- Cybersecurity in Power Systems

As power systems become increasingly digitized, they are also more vulnerable to cyber-attacks as shown in Figure 1. AI can bolster cybersecurity by detecting anomalies in network traffic, identifying malicious behavior, and implementing intrusion detection systems (IDS). These intelligent systems learn from previous attacks and adapt to new threats in real time, ensuring secure grid operations [69,70].

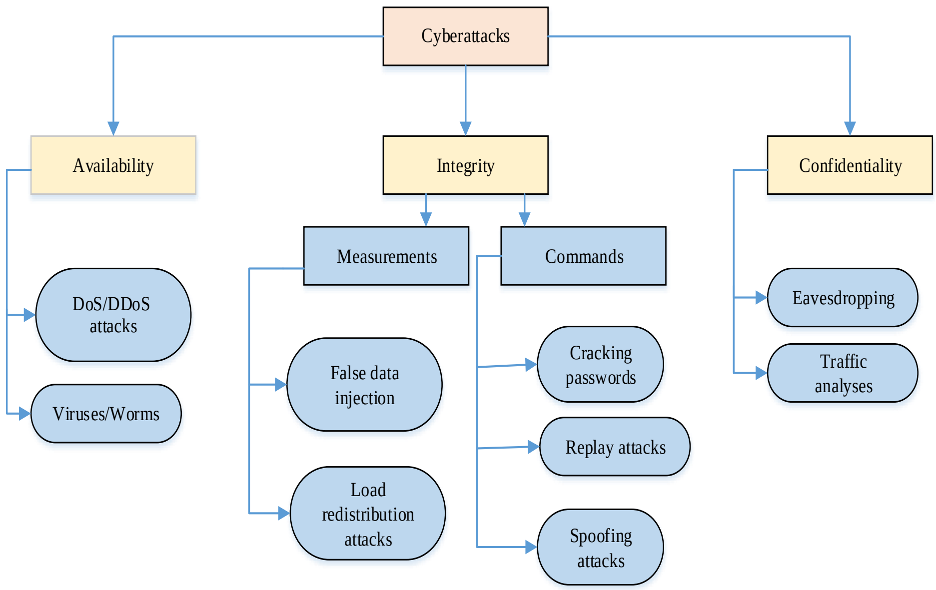

Figure 1: Cyber-attacks on electrical power grid.

- Electric Vehicle (EV) Integration

The rapid deployment of electric vehicles necessitates smart charging infrastructure. AI algorithms optimize vehicle-to-grid (V2G) interactions, charging schedules, and load balancing to mitigate stress on the power grid [71-74]. AI also supports mobility-as-a-service (MaaS) platforms that coordinate energy demand from fleets of EVs based on real-time grid conditions.

Artificial Intelligence is revolutionizing the way power systems are designed, operated, and maintained. From predictive maintenance and fault diagnosis to renewable energy integration and cybersecurity, AI provides the intelligence necessary to handle increasing system complexity and the demands of sustainability. While challenges related to data quality, transparency, and infrastructure readiness remain, the opportunities for AI to enhance the resilience, flexibility, and efficiency of modern power systems are substantial. Continued research and investment in AI-driven technologies will be pivotal in shaping the future of smart, sustainable, and intelligent power grids.

Role of AI in Electrical Power Systems

Numerous AI techniques are applicable for data collection and analysis in power systems; the selection of these methods depends on specific requirements and the complexity of the system under consideration as presented in Figure 2. Data acquisition in electrical power systems encompasses the collection, processing, and analysis of information gathered from a range of sensors, meters, and other devices [75-77]. The implementation of intelligent data acquisition techniques contributes significantly to improving data quality. Given the pivotal role of power systems in supporting national economic stability and public welfare, their development must prioritize objectives such as safety, reliability, and environmental sustainability.

- **Machine Learning**

Machine learning (ML) is a fundamental approach to achieving AI as illustrated in Figure 3. It is defined as a field of study that enables computers to learn from data without being explicitly programmed. As a subset of AI, machine learning emphasizes the development of systems that can automatically improve their performance through experience [78,79]. By employing advanced algorithms, machines are capable of analyzing large datasets, identifying underlying patterns, and making predictions, without the need for manually coded instructions. Moreover, machine learning systems can enhance their performance over time by learning from errors, thereby improving their ability to recognize complex patterns.

Machine learning is the process of supplying a system with data, referred to as training or learning data, and utilizing this data to automatically infer the system's parameters (i.e., variable values). Machine learning techniques are generally categorized into three primary types: supervised learning, unsupervised learning, and reinforcement learning. Commonly used machine learning algorithms include neural networks, logistic regression, Support Vector Machines (SVM), decision trees, and random forests, among others.

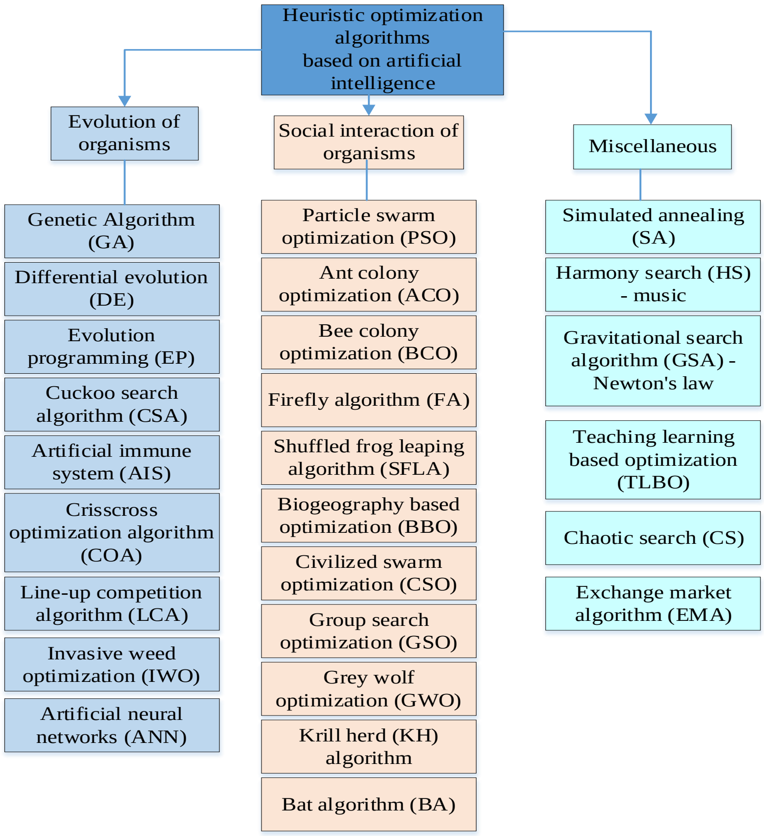

Figure 2: Categorization of AI techniques.

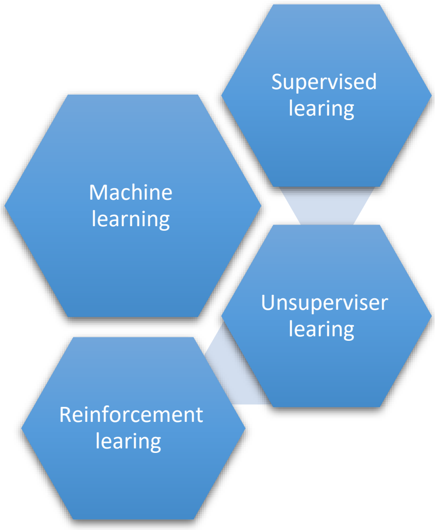

Figure 3: The components of machine learning.

- **Supervised learning:** consists of two main phases: learning phase and the inference phase. Unsupervised learning primarily involves the task of grouping or clustering similar data instances from large datasets. This approach is widely utilized in various applications, including anomaly detection, peacekeeping operations, and recommendation systems.
- **Reinforcement Learning:** Reinforcement Learning (RL) is a branch of machine learning that focuses on decision-making strategies based on interactions with an environment, with the goal of maximizing cumulative rewards. The foundational concept of RL is rooted in behaviorist psychology, which posits that organisms adapt their behavior through repeated exposure to environmental stimuli, such as rewards or punishments, eventually developing habitual responses that aim to optimize outcomes.
- **Deep learning**: is particularly well-suited for processing large-scale datasets, whereas traditional machine learning methods tend to be more effective when data availability is limited. By enabling

a wide range of machine learning applications, deep learning has significantly expanded the capabilities of artificial intelligence. It underpins numerous advanced technologies, including autonomous vehicles and predictive healthcare systems.

The primary distinction between deep learning (DL) and reinforcement learning (RL) lies in their training paradigms and application domains. Deep learning typically relies on labeled datasets for supervised learning, whereas reinforcement learning operates in environments where feedback is provided through rewards rather than explicit labels. While deep learning is predominantly applied to perceptual tasks such as image and speech recognition, reinforcement learning is more focused on sequential decision-making problems.

Challenges

- Data Quality and Availability

AI models require vast amounts of high-quality, labeled data for training and validation. However, in many power systems, especially in developing regions, data may be incomplete, inconsistent, or outdated. The lack of real-time, granular, and standardized datasets limits the effectiveness of machine learning algorithms, particularly for predictive maintenance, fault detection, and load forecasting.

- Cybersecurity and Privacy Risks

The integration of AI into power systems increases vulnerability to cyber threats. Intelligent algorithms connected to SCADA systems or grid components may be exploited by malicious actors to disrupt operations or access sensitive data. Ensuring secure AI deployment and compliance with data privacy regulations remains a significant challenge.

- System Complexity and Explainability

Power systems are inherently complex, and the use of black-box AI models (e.g., deep learning) can make decision-making processes opaque. The lack of interpretability and explainability in many AI tools undermines trust among operators and regulators, making their adoption in mission-critical applications challenging.

- Integration with Legacy Systems

Many power infrastructures rely on legacy equipment that was not designed for AI-based interaction. Seamless integration of AI with these systems requires substantial upgrades, increased interoperability, and standardized communication protocols, factors that may incur high costs and technical hurdles.

- Regulatory and Ethical Considerations

The absence of established regulatory frameworks and ethical guidelines for AI applications in power systems can slow down innovation and deployment. Concerns regarding accountability in automated decision-making and biases in algorithmic outputs need to be systematically addressed.

Opportunities

- Enhanced Grid Reliability and Resilience

AI enables real-time monitoring and predictive analytics, allowing grid operators to anticipate failures, optimize load dispatch, and swiftly respond to disturbances. This enhances grid resilience against outages and improves the stability of supply, especially under high penetration of renewables.

- Integration of Renewable Energy Sources

AI algorithms are critical in managing the variability and intermittency of solar and wind power. Techniques such as deep learning and reinforcement learning can forecast generation, optimize storage utilization, and dynamically adjust demand-response schemes, thus facilitating a cleaner and more flexible power system.

- Smart Load Forecasting and Demand Response

Machine learning models can provide highly accurate short- and long-term load forecasting by analyzing weather data, historical demand patterns, and consumer behavior. This enables proactive grid management, cost reduction, and improved energy efficiency.

- Asset Management and Predictive Maintenance

AI-driven diagnostics tools can assess the health of assets such as transformers, cables, and circuit breakers using sensor data. Predictive maintenance strategies, supported by anomaly detection and pattern recognition algorithms, reduce downtime and extend equipment lifespan.

- Decentralized and Autonomous Operation

The emergence of distributed energy resources (DERs) and microgrids necessitates decentralized control systems. AI agents can facilitate autonomous coordination, peer-to-peer energy trading, and local optimization, promoting energy democratization and resilience.

Conclusion

Artificial Intelligence (AI) has emerged as an indispensable component in the advancement and modernization of power system infrastructure. This comprehensive review illustrates that AI technologies, spanning machine learning, deep learning, heuristic optimization, and federated learning, offer transformative potential across various operational domains of electrical power systems. From enhancing economic load dispatch and improving fault diagnostics to optimizing renewable energy resources and defending against sophisticated cyber-attacks, AI significantly boosts the reliability, security, and sustainability of both traditional and smart grid systems. The integration of AI in power systems brings forth numerous benefits, including adaptive learning capabilities, decentralized decision-making, real-time responsiveness, and intelligent automation. Specifically, the deployment of AI-driven models in grid coordination, predictive maintenance, and cyber-attack detection contributes to enhanced operational stability and resilience, particularly in the face of increasing penetration of renewable energy sources such as solar and wind. The article also highlights AI's capability to facilitate advanced energy management systems, enabling real-time monitoring, forecasting, and resource optimization under dynamic conditions. Despite these advancements, the study acknowledges several persistent challenges that could hinder the full-scale adoption of AI in power systems. These include concerns over data privacy and cybersecurity, interoperability with legacy systems, the opacity of AI decision-making processes, and the demand for extensive computational resources and labeled data. Furthermore, the potential risks associated with AI's "black-box" nature necessitate the development of explainable AI (XAI) frameworks to ensure transparency and trustworthiness in critical power infrastructure applications.

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