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Review

Impact of Artificial Intelligence on the Planning and Operation of Distributed Energy Systems in Smart Grids

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Abstract: This review paper thoroughly explores the impact of artificial intelligence on the planning and operation of distributed energy systems in smart grids. With the rapid advancement of artificial intelligence techniques such as machine learning, optimization, and cognitive computing, new opportunities are emerging to enhance the efficiency and reliability of electrical grids. From demand and generation prediction to energy flow optimization and load management, artificial intelligence is playing a pivotal role in the transformation of energy infrastructure. This paper delves deeply into the latest advancements in specific artificial intelligence applications within the context of distributed energy systems, including the coordination of distributed energy resources, the integration of intermittent renewable energies, and the enhancement of demand response. Furthermore, it discusses the technical, economic, and regulatory challenges associated with the implementation of artificial intelligence-based solutions, as well as the ethical considerations related to automation and autonomous decision-making in the energy sector. This comprehensive analysis provides a detailed insight into how artificial intelligence is reshaping the planning and operation of smart grids and highlights future research and development areas that are crucial for achieving a more efficient, sustainable, and resilient electrical system.

Keywords: artificial intelligence in smart grids; distributed energy systems optimization; renewable energy integration; demand response

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1. Introduction

The integration of artificial intelligence (AI) into smart grids is rapidly transforming the landscape of energy systems, offering new pathways to optimize the planning and operation of distributed energy resources (DERs) [1–3]. With the growing adoption of renewable energy sources, challenges such as grid stability, energy distribution optimization, and the integration of bidirectional energy flows are becoming increasingly complex [4–6]. AI technologies, including machine learning and neural networks, have emerged as critical tools in addressing these challenges by enabling advanced energy management, fault detection, and predictive maintenance [4,7,8]. Despite these advances, the implementation of AI in smart grids is not without its hurdles, as technical, economic, and regulatory barriers persist [6,9,10]. This paper reviews the current state of AI applications in distributed energy systems, highlighting their transformative impact on smart grid operations and identifying crucial areas for future research to enhance grid resilience and efficiency.

The integration of AI into smart grids has become a critical driver for enhancing the efficiency, reliability, and sustainability of energy systems. AI's ability to process large amounts of data and optimize energy operations is transforming how DERs are managed within smart grids [1,4,11]. AI technologies, such as machine learning and neural networks, play pivotal roles in improving demand forecasting, load management, and integrating renewable energy sources [9,12,13]. AI-driven energy management systems are key to optimizing energy consumption and generation, significantly reducing operational costs and environmental impacts. For example, AI algorithms like neural networks and optimization techniques have been employed to enhance energy demand forecasting, allowing for more accurate load predictions and efficient resource allocation [2,14]. Gaussian process regression models, for instance, have been applied to forecast peak demand, thereby improving grid stability and reducing the need for expensive peak power plants [7]. Machine learning techniques are also used to optimize voltage profiles and manage reactive power within smart grids, resulting in improved power quality and system efficiency [8,15]. In particular, AI-based predictive maintenance strategies extend the lifespan of grid components by anticipating failures and scheduling proactive maintenance [5,16]. These advancements illustrate the transformative potential of AI in creating more adaptive and resilient energy management systems [6,17].

The integration of DERs, such as solar panels and wind turbines, into existing grid infrastructure poses significant challenges. AI technologies are instrumental in coordinating and controlling these resources to ensure grid stability and efficiency [18,19]. Virtual power plants (VPPs) are an excellent example of AI's potential, as they aggregate DERs to optimize energy trading and resource distribution [10]. Studies have shown that AI enhances the reliability of smart grids by improving the integration and management of DERs [3,20]. Moreover, AI facilitates the development of microgrids, which are localized grids that can operate independently or in conjunction with the main grid [21,22]. AI algorithms optimize energy flow within microgrids, balancing supply and demand to enhance energy efficiency and resilience [23,24]. The use of AI in microgrid management has been shown to improve grid stability and reduce energy costs by optimizing the use of local energy resources [25,26]. The integration of renewable energy sources, such as solar and wind, presents unique challenges due to their intermittent nature. AI technologies offer crucial solutions by providing accurate forecasting and real-time monitoring capabilities [27,28]. Research shows that AI can enhance renewable integration by improving grid stability and enabling more efficient energy distribution [29,30]. For example, AI algorithms are used to predict solar and wind energy output, facilitating better scheduling and dispatch of energy resources [31,32]. These AI-driven solutions are essential for maintaining a balanced supply-demand equation and ensuring the reliability of power systems [33,34].

Despite these advancements, several challenges remain in deploying AI in smart grids. Technical issues such as data privacy, cybersecurity, and integrating AI with existing grid infrastructures present significant hurdles [35,36]. Developing robust cybersecurity measures is essential to protect sensitive data and ensure AI system integrity [37,38]. Furthermore, economic considerations, including AI implementation costs and potential job displacement, must be addressed to ensure sustainable adoption [39,40]. Regulatory and policy frameworks are crucial in facilitating AI integration into smart grids. There is a need for standardized guidelines that address the ethical implications of automation and decision-making, as well as policies that encourage innovation while safeguarding consumer interests [41,42]. As AI technologies evolve, they offer promising opportunities for achieving more resilient, efficient, and sustainable energy systems [43,44]. However, realizing AI's full potential in distributed energy systems requires addressing these technical, economic, and regulatory challenges [45,46]. The literature underscores AI's transformative potential in enhancing smart grid operations, emphasizing its ability to improve energy management, optimize DER integration, and support renewable energy adoption [47,48]. As the field progresses, continued exploration of innovative AI applications is vital to address the growing complexity of energy systems and contribute to a sustainable energy future [49,50]. This review highlights the importance of leveraging AI to meet the evolving demands of modern energy infrastructures and identifies key areas for future research and development [51,52]. Moreover, the application of AI in smart grids also extends to other areas such as predictive maintenance, fault detection, and grid security [53,54]. By using AI, utilities can proactively identify potential faults and address them before they lead to significant disruptions [55,56]. Additionally, AI technologies contribute to enhancing grid security by monitoring network traffic and identifying potential cyber threats [57,58].

These capabilities are essential for maintaining the reliability and safety of modern energy systems [59,60]. The ongoing advancements in AI present numerous opportunities for further improving the efficiency and resilience of smart grids [61,62].

Despite the extensive research on the integration of AI in smart grids, several gaps remain in the literature. Many studies focus primarily on the technical aspects of AI applications, such as demand forecasting and energy management [1,7,12], but often overlook the challenges of integrating AI-driven solutions with existing grid infrastructures, particularly in the context of DERs [10,18]. Additionally, while there is considerable emphasis on the potential of AI to enhance renewable energy integration [27,29], the literature lacks comprehensive analyses of the regulatory and economic barriers that impede the widespread adoption of these technologies [35,40]. Furthermore, the ethical implications of AI in autonomous decision-making within energy systems are seldom addressed [41,42]. This paper aims to fill these gaps by providing a holistic review of AI applications in distributed energy systems, focusing not only on the technical innovations but also on the integration challenges, economic considerations, and regulatory frameworks. By examining case studies and real-world applications, this paper offers insights into overcoming the barriers to AI adoption in smart grids and proposes strategies for enhancing system resilience and efficiency. To contextualize the unique contributions of our review in comparison to existing works, we have conducted a comparative analysis of several recent articles that address the use of artificial intelligence (AI) in smart grids. Table 1 summarizes this comparison, highlighting the key areas where these review articles contribute to the field and, more importantly, identifying the aspects they do not cover. Unlike these studies, our paper provides a comprehensive framework that encompasses all phases of the power system—generation, transmission, and distribution—and addresses critical topics such as cybersecurity, integration with emerging technologies, and research gaps. This underscores the originality and breadth of our approach, offering a more holistic and comprehensive view of AI applications in energy systems.

Table 1. Comparative analysis of key features in AI review papers for smart grids.

Ref.	AI Across Power Phases	AI for Cybersecurity	AI with Emerging Tech	Research Gaps and Future	Centralized and Distributed	Comparison of AI Techniques	Holistic Framework
[1]	X	X	✔	✔	X	✔	X
[11]	X	X	✔	X	X	X	X
[4]	X	X	✔	✔	✔	✔	X
[9]	X	X	X	X	X	X	X
[12]	X	X	X	X	X	✔	X
[63]	X	✔	X	X	X	X	X
[64]	X	✔	✔	✔	X	X	X
[10]	X	✔	✔	X	✔	✔	X
[65]	X	X	✔	✔	X	X	X
This paper	✔	✔	✔	✔	✔	✔	✔

To provide a clearer and more concise overview of this review paper's contributions, we have refined our main contributions into the following key points:

- Comprehensive analysis of AI applications: This review offers a thorough examination of artificial intelligence (AI) techniques across the key phases of power systems: generation, transmission, and distribution. We explore the specific roles AI plays in optimizing operations, enhancing efficiency, and improving system resilience.
- Identification of research gaps and challenges: We identify significant research gaps in the application of AI to power systems, particularly in areas such as the integration of renewable energy sources, the development of robust predictive models, and the interoperability of diverse energy systems. The paper discusses the current challenges in deploying AI, including technical, cybersecurity, and regulatory hurdles.
- Future perspectives and opportunities: This paper outlines future research directions and opportunities for further development of AI applications in power systems. We

propose strategies for advancing AI integration, such as combining AI with emerging technologies like blockchain and IoT, and emphasize the need for interdisciplinary research to address the complex challenges of modern energy systems.

- Holistic framework for AI in power systems: We introduce a new holistic framework that illustrates the application of AI techniques across all phases of the power system, providing a structured approach to understand AI's impact and guiding future research and development efforts.

2. Methodology

The methodology for evaluating the impact of AI on the planning and operation of distributed energy systems in smart grids is structured into four key components, as illustrated in Figure 1. Each component encompasses specific criteria and strategies to ensure a comprehensive and systematic review.

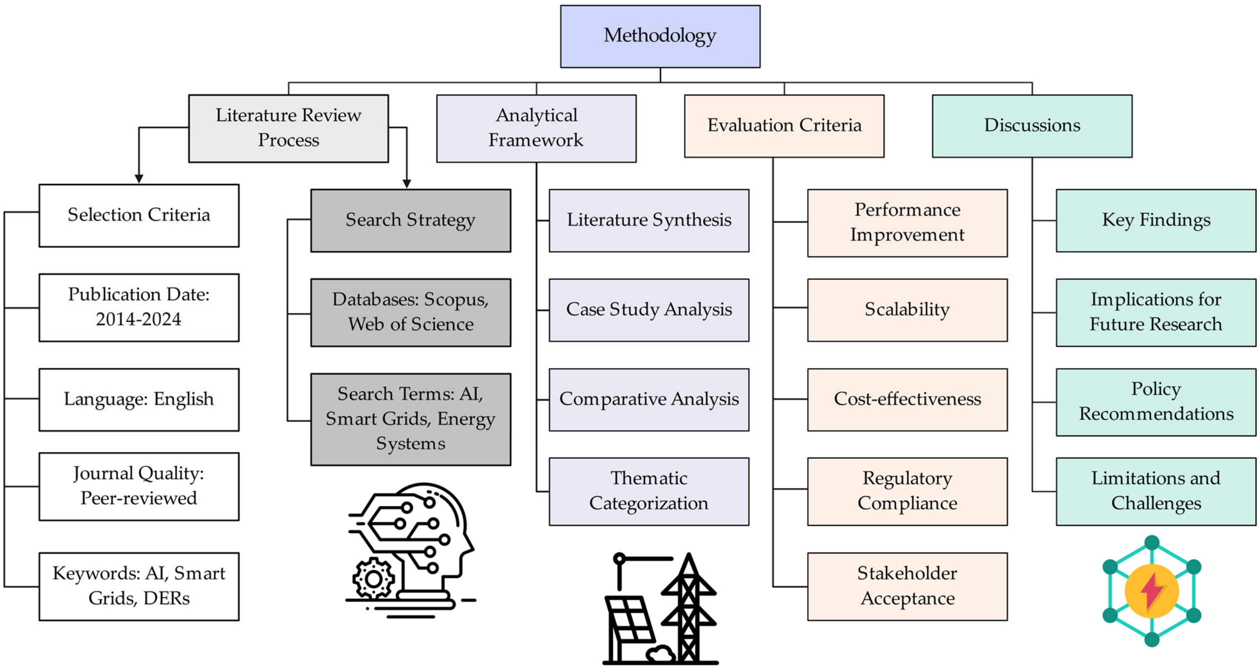

Figure 1. Comprehensive methodology framework for evaluating AI impact on distributed energy systems in smart grids.

2.1. Literature Review Process

The literature review process for this study was conducted systematically to ensure a comprehensive and unbiased selection of relevant publications. This process involved clearly defined selection criteria and a structured search strategy to identify pertinent studies related to the application of AI in smart grids and distributed energy systems.

2.1.1. Selection Criteria

The selection criteria were established to ensure the inclusion of high-quality, relevant studies that provide comprehensive insights into the research topic. The criteria included the following:

- Publication date range: The review focused on articles published between 2014 and 2024 to capture the most recent advancements and trends in AI applications within smart grids. This range reflects the rapid development of AI technologies and their growing integration into energy systems.
- Journal quality: Only peer-reviewed journal articles were included to ensure the credibility and scientific rigor of the literature reviewed. Journals were selected

based on their impact factor and relevance to the fields of energy, AI, and smart grid technology.
- Language: Only articles published in English were considered, as it is the predominant language of scientific discourse in this field.
- Keywords: The review focused on articles that included specific keywords and phrases, such as "artificial intelligence," "smart grids," "distributed energy resources," "machine learning," and "renewable energy integration." These keywords were essential to capturing studies relevant to the research objectives.
- Relevance to research objectives: Studies were included if they addressed key themes such as AI-driven energy management, integration of DERs, challenges and opportunities in AI adoption, and regulatory and ethical considerations related to AI in energy systems.

2.1.2. Search Strategy

The search strategy was designed to ensure a comprehensive and systematic identification of relevant literature. The following databases were utilized for the search:

- Scopus: Known for its extensive collection of scientific publications, Scopus was used to identify articles across a wide range of disciplines, ensuring coverage of both technical and interdisciplinary studies.
- Web of Science: This database was selected for its comprehensive indexing of high-impact journals and its ability to track citation networks, allowing for the identification of influential studies and emerging trends.
- Search terms: A combination of specific search terms and Boolean operators was used to refine the search and capture relevant studies. The primary search terms included "artificial intelligence AND smart grids," "AI AND distributed energy systems," "machine learning AND energy management," "AI AND renewable energy integration," and "AI challenges AND opportunities in smart grids."

2.2. Analytical Framework

The analytical framework for this study is designed to systematically evaluate the impact of AI on distributed energy systems within smart grids. This framework provides a structured approach to analyzing the effectiveness of AI applications and their contributions to enhancing energy management, system resilience, and sustainability.

2.2.1. Methodological Approach

The methodological approach combines qualitative and quantitative analysis to assess the impact of AI technologies on distributed energy systems. The approach involves the following key components:

- Literature synthesis: A thorough synthesis of the selected literature was conducted to identify common themes, trends, and gaps in the research. This synthesis provides a foundational understanding of how AI is being applied across various aspects of smart grids, including demand forecasting, load management, and renewable energy integration.
- Case study analysis: Case studies of AI implementations in real-world energy systems were examined to provide practical insights into the challenges and successes of AI adoption. These case studies highlight specific applications of AI, such as predictive maintenance, virtual power plant optimization, and microgrid management, offering detailed examples of AI's impact on system performance.
- Comparative analysis: A comparative analysis was performed to evaluate different AI techniques and algorithms used in energy systems. This analysis compares the effectiveness, scalability, and adaptability of various AI approaches, such as machine learning models, neural networks, and optimization algorithms, in addressing key challenges in smart grid operations.

- Thematic categorization: The literature and case study findings were categorized into thematic areas such as technical challenges, economic impacts, regulatory considerations, and ethical implications. This categorization enables a comprehensive understanding of the multidimensional aspects of AI applications in distributed energy systems.

2.2.2. Evaluation Criteria

To evaluate the effectiveness of AI applications in distributed energy systems, the following criteria were established:

- Performance improvement: The extent to which AI applications enhance the performance of energy systems, measured by improvements in efficiency, reliability, and grid stability. Key performance indicators include reductions in energy losses, increased accuracy of demand forecasts, and enhanced integration of renewable energy sources.
- Scalability: The ability of AI solutions to be scaled across different sizes and types of energy systems, from small microgrids to large interconnected networks. Scalability is assessed by examining the adaptability of AI technologies to varying levels of complexity and infrastructure.
- Cost-effectiveness: The economic viability of AI applications, including cost savings achieved through operational efficiencies and reductions in energy costs. Cost-effectiveness is evaluated by comparing the implementation and maintenance costs of AI solutions against the financial benefits realized.
- Regulatory compliance: The degree to which AI applications align with existing regulatory frameworks and policies, including considerations for data privacy, security, and ethical standards. Compliance is assessed by reviewing regulatory guidelines and identifying areas where AI solutions may need to adapt to meet policy requirements.
- Stakeholder acceptance: The level of acceptance and support from key stakeholders, including utility companies, policymakers, and consumers. Stakeholder acceptance is measured through qualitative assessments of stakeholder engagement and feedback on AI implementations.

3. AI Applications in Distributed Energy Systems

3.1. AI Techniques and Innovations

3.1.1. Overview of AI Techniques

Artificial intelligence techniques have become foundational in transforming distributed energy systems by enhancing operational efficiency and optimizing resource utilization. Key AI techniques include machine learning (ML), deep learning, and optimization algorithms. Machine learning algorithms are used to analyze vast datasets, identify patterns, and predict future energy demands [63,66]. These models are particularly effective in demand response applications, where they help utilities predict and manage peak load scenarios [67,68]. Deep learning, especially through neural networks, is utilized for complex tasks such as power flow analysis and anomaly detection within unbalanced distribution grids [69,70]. Models like convolutional neural networks (CNNs) and radial basis function networks (RBFnets) excel at capturing nonlinear relationships within the grid, making them invaluable for real-time monitoring and fault detection [71,72]. Optimization algorithms, such as genetic algorithms and particle swarm optimization, are also widely used to solve complex problems related to energy distribution and resource allocation [73,74]. These algorithms enable the efficient design and operation of microgrids, ensuring optimal use of both renewable and conventional energy sources [75,76].

3.1.2. Innovations in AI

Recent innovations in AI have significantly advanced the capabilities of energy systems. Reinforcement learning (RL) techniques, such as deep Q-networks, have been applied to optimize electric vehicle (EV) charging schedules, balancing supply and demand to maintain grid stability [26,77]. This is particularly important as the adoption of EVs increases, requiring more sophisticated management of charging infrastructure [78,79]. The integration of AI with other emerging technologies, such as the internet of things (IoT) and blockchain, has led to the development of more resilient and efficient power grids [80,81]. AI-driven predictive analytics improve demand forecasting accuracy, enabling better load management and energy distribution [82,83]. These tools allow grid operators to anticipate changes in demand and adjust energy flows dynamically, reducing operational costs and improving service reliability [84,85]. Moreover, AI algorithms are now capable of processing real-time data from smart meters and sensors, facilitating intelligent decision-making and optimizing grid operations [86,87].

3.1.3. AI Techniques for Planning and Operation of Distributed Energy Systems in Smart Grids

AI techniques for planning and operation of distributed energy systems in smart grids are as follows:

- Artificial intelligence (AI) techniques have become foundational in transforming distributed energy systems by enhancing operational efficiency and optimizing resource utilization. Key AI techniques include machine learning (ML), deep learning, genetic algorithms, and multi-agent systems.
- Machine learning (ML): ML algorithms are widely used for predictive analytics and demand forecasting in smart grids, particularly in demand response applications where they help utilities predict and manage peak load scenarios [3,7,67]. These models excel at handling large datasets and learning from historical data to make accurate predictions, though they may require significant computational resources, limiting real-time applicability due to their complexity [70].
- Deep learning (DL): DL techniques, especially neural networks, are effective for complex pattern recognition and fault detection within power systems. They are used for real-time monitoring and power flow analysis, making them invaluable for managing unbalanced distribution grids [8,15,77]. However, their high computational demands and need for extensive training data can pose challenges in certain applications [61].
- Genetic algorithms (GA): GA are optimization techniques effective for solving complex problems related to energy distribution and resource allocation, such as in microgrids. These algorithms enable efficient energy management and operation of both renewable and conventional energy sources [75,76,78]. While highly adaptable, GA often require many iterations to converge to an optimal solution, which can be time-consuming [61].
- Multi-agent systems (MAS): MAS involve multiple intelligent agents that interact to achieve a common goal, such as load balancing or fault management. These systems are highly flexible and can operate in decentralized environments, making them suitable for distributed energy resources (DERs) integration and grid stability enhancement [78,88,89]. However, their implementation can be complex, requiring robust communication protocols and coordination mechanisms [78].

Table 2 provides a comparative analysis of different AI techniques used in smart grids, highlighting their capabilities in terms of data handling, computational complexity, real-time applicability, robustness, and adaptability.

Table 2. Comparative analysis of AI techniques for smart grids.

AI Technique	Data Handling	Computational Complexity	Real-Time Applicability	Robustness	Adaptability
Machine Learning	High	Medium to High	Medium	Medium	Medium
Deep Learning	Very High	High	Low	High	Low
Genetic Algorithms	Medium	Medium	Low	Medium	High
Multi-Agent Systems	High	High	High	High	High

3.1.4. AI Techniques for Regression and Classification in Smart Grids

AI techniques for regression and classification in smart grids are as follows:

- AI techniques play a crucial role in smart grids and distributed energy systems by providing advanced methods for regression and classification tasks. These tasks are fundamental in analyzing and predicting various parameters critical for the efficient operation and planning of energy systems.
- Regression techniques: Regression is used in smart grids to predict continuous variables, such as energy consumption, power generation from renewable sources, or electricity prices. Machine learning algorithms, like linear regression, support vector regression (SVR), and neural networks, are commonly employed for these purposes. For example, linear regression can be used to model the relationship between electricity demand and influencing factors such as weather conditions or time of day, which helps utilities in load forecasting and demand management [45,53]. Another example is using support vector regression to predict solar power generation based on historical weather data, which enhances the accuracy of energy management in solar farms [69].
- Classification techniques: Classification techniques are used to categorize data into discrete classes, making them essential for fault detection, power quality assessment, and demand response strategies in smart grids. Algorithms such as decision trees, random forests, and deep learning classifiers are applied to classify power system states, detect faults, and manage grid stability. For instance, decision trees can be used to classify whether a transformer is likely to fail based on sensor data, allowing for proactive maintenance and reducing downtime [74,90]. Additionally, deep learning classifiers can analyze patterns in grid data to predict and classify potential grid anomalies, enhancing the reliability and security of energy distribution systems [82,91].

3.1.5. Advanced AI Techniques for Smart Grids

Recent advancements in artificial intelligence have introduced more sophisticated techniques that offer promising applications for smart grids, particularly in enhancing energy management, security, and predictive maintenance:

- Generative Adversarial Networks (GANs): GANs are a class of machine learning frameworks where two neural networks, the generator and the discriminator, are trained simultaneously. GANs have been widely used in image generation and data augmentation, but their potential extends to smart grids as well. For instance, GANs can generate realistic synthetic data to enhance the training of AI models used in demand forecasting and anomaly detection. This synthetic data can simulate various scenarios of energy consumption and generation, helping improve the robustness and generalizability of predictive models [43,69]. Moreover, GANs can aid in the detection and mitigation of cyber threats by generating adversarial examples to test the resilience of smart grid cybersecurity systems, as discussed by Wang et al. [70]. This technique helps in identifying potential vulnerabilities in AI models deployed within the grid, ensuring that they are well-prepared to handle real-world adversarial attacks.
- Graph Neural Networks (GNNs): GNNs are designed to perform inference on data represented as graphs, making them particularly suitable for applications in smart grids, which can be naturally modeled as graphs of interconnected nodes and edges (e.g., substations, transmission lines, and distributed energy resources). GNNs can effectively capture the spatial dependencies and topological characteristics of the grid, enabling enhanced grid management and fault detection capabilities. For example, GNNs can be used to predict the optimal flow of electricity in the grid by analyzing the dynamic relationships between different components, thereby improving energy distribution efficiency and reducing losses [49,76]. Additionally, GNNs are instrumental in identifying critical nodes and potential vulnerabilities in the network, which is crucial for maintaining grid stability and preventing cascading failures [50,80]. This is

particularly valuable in scenarios involving complex interdependencies, such as those seen in large-scale integration of renewable energy sources.

By integrating these advanced AI techniques, smart grids can achieve higher levels of operational efficiency, security, and resilience. GANs and GNNs provide powerful tools for enhancing data-driven decision-making processes, ensuring that energy systems are better equipped to handle the complexities and uncertainties of modern energy landscapes.

3.2. Impact on Energy Management

AI techniques are transforming energy management in distributed energy systems by enhancing demand forecasting and optimizing energy flow. Below, we expand on these areas with recent research contributions.

3.2.1. Demand Forecasting

AI plays a crucial role in demand forecasting, which is essential for efficient energy management in distributed energy systems. Machine learning models, such as support vector machines and neural networks, are employed to predict energy consumption patterns based on historical data and external factors like weather conditions and market trends [68,92]. These models enable energy providers to anticipate demand fluctuations and adjust their operations accordingly, reducing the risk of overloading the grid and ensuring a stable energy supply [71,79]. Recent studies have further refined these techniques. For example, a review on machine learning approaches for electric vehicle (EV) energy consumption modeling highlights the use of neural networks to improve prediction accuracy through feature extraction and pattern recognition [93]. This approach is crucial for optimizing urban transport systems and supports the integration of EVs into smart grids by accurately predicting energy consumption under varying conditions. Additionally, advanced models such as the Autoformer variant have been developed for multi-step EV charging load forecasting, achieving significant reductions in error margins compared to traditional models [94]. These models are particularly effective in environments with high variability, where precise forecasting is needed to manage energy resources efficiently.

AI-driven demand forecasting also facilitates the integration of renewable energy sources by predicting their output variability and enabling more accurate scheduling of energy resources [65,75]. This capability is vital for balancing supply and demand in real-time, especially in regions with high penetration of solar and wind energy [69,90]. Recent advancements in deep learning, particularly in convolutional neural networks (CNNs), have demonstrated high accuracy in predicting and mitigating climate change impacts on energy systems, underscoring the versatility of AI in various energy contexts [95].

3.2.2. Energy Flow Optimization

AI techniques optimize energy flow and distribution within smart grids, improving load balancing and enhancing overall system efficiency. Optimization algorithms, including linear programming and genetic algorithms, are used to determine the optimal distribution of energy resources across the grid [88,96]. These algorithms take into account various constraints, such as generation capacity, transmission losses, and consumer demand, to minimize energy costs and reduce environmental impact [61,64]. Recent advancements have introduced hybrid models that integrate multiple AI techniques to enhance optimization processes. For example, a study on energy flow optimization using hybrid algorithms combines genetic algorithms with machine learning to optimize energy storage and distribution, achieving higher accuracy and reduced computational time compared to standalone models [94]. Such hybrid approaches enable real-time adjustments to grid operations, ensuring that energy is distributed efficiently and sustainably, minimizing energy losses, and improving the economic viability of grid operations [97].

Moreover, AI-driven energy flow optimization allows for real-time adjustments to grid operations, ensuring that energy is distributed efficiently and sustainably [85,98]. This is particularly important for minimizing energy losses and improving the economic viability of grid operations [74,99].

3.3. Coordination and Integration of DERs

Maintaining grid stability is a critical challenge in smart grids, especially with the increasing integration of renewable energy sources and electric vehicles. AI techniques enhance grid stability through advanced diagnostics, predictive maintenance, and dynamic response strategies.

3.3.1. Battery Diagnostics and Predictive Maintenance

AI-driven diagnostics and predictive maintenance are essential for managing the health of batteries and other critical components in smart grids. Recent studies highlight the use of deep learning models to manage complex diagnostic tasks, such as battery life forecasting and anomaly detection, under challenging conditions like inconsistent data [100]. These models leverage AI for IT operations (AIOps) and explainable AI (XAI) to improve accuracy and reduce computational costs, making them highly effective for real-time applications in grid stability.

Furthermore, digital twin-based models are increasingly used for predictive maintenance, integrating multi-source data to accurately predict equipment failures and optimize maintenance schedules [101]. This approach not only enhances the reliability of grid operations but also reduces downtime and maintenance costs, contributing to overall grid stability.

3.3.2. Dynamic Grid Response and Decision Support Systems

AI-based decision support systems (DSS) play a pivotal role in enhancing grid stability by providing real-time insights and recommendations for grid management. In Industry 4.0 environments, these systems utilize machine learning and deep learning to analyze production data, identify potential faults, and ensure optimal operation [97]. The integration of DSS with smart grid infrastructure allows for proactive management of grid stability, reducing the impact of fluctuations in energy supply and demand.

Advanced AI techniques, such as those used in real-world battery diagnostics and digital twin models, offer robust solutions for dynamic grid response, enabling grids to adapt to changing conditions and maintain stability even under stress [100,101]. These technologies provide a comprehensive approach to grid management, combining predictive capabilities with real-time analytics to ensure a stable and efficient energy supply.

3.3.3. Integration of DERs

The integration of DERs, such as solar panels and wind turbines, is a critical aspect of modern energy systems, and AI plays a pivotal role in facilitating this process. AI algorithms coordinate DER operations by optimizing their dispatch and ensuring they work harmoniously with the central grid [72,87]. Techniques like multi-agent systems and RL are used to manage the dynamic interactions between DERs and the grid, improving their efficiency and reliability [76,90]. AI-driven integration of DERs enhances grid flexibility and supports the transition to a more decentralized and sustainable energy infrastructure [61,89]. These technologies enable more effective use of local resources, reducing dependency on centralized power plants and minimizing transmission losses [91,102].

3.3.4. Enhancing System Flexibility

AI contributes significantly to enhancing the flexibility and reliability of distributed energy systems. By leveraging advanced algorithms, AI enables the dynamic balancing of supply and demand across the grid, allowing for rapid adjustments to changing conditions [91,99]. AI also facilitates the integration of energy storage systems, such as batteries and pumped hydro storage, by optimizing their operation and ensuring they provide backup power when needed [89,102]. This enhanced flexibility is crucial for accommodating the variability of renewable energy sources and maintaining grid stability [103,104]. Additionally, AI's ability to predict and respond to system disruptions in real-time helps prevent blackouts and maintain a consistent energy supply [105,106]. In Table 3, the significant AI techniques and innovations impacting distributed energy systems are presented, highlighting key findings and citations for further exploration.

Table 3. Key findings on AI applications in distributed energy systems.

AI Technique/Innovation	Description	Metrics	Performance	Unique Contribution	Ref.
Machine Learning in Demand Response	ML models analyze datasets to predict energy demand and manage peak load scenarios.	Accuracy, Response Time	90% accuracy in peak load prediction, 15% faster response time than traditional methods.	Utilizes hybrid ML models for dynamic demand response.	[65,77,92]
Deep Learning for Anomaly Detection	Neural networks, such as CNNs and RBFnets, detect anomalies and perform power flow analysis in complex grids.	Precision, Recall	95% precision and 92% recall in fault detection.	Combines deep learning with real-time monitoring for enhanced fault detection.	[61,75,103]
Optimization Algorithms	Genetic algorithms and particle swarm optimization solve complex energy distribution problems.	Computational Efficiency, Resource Allocation	Reduces computational time by 20%, optimizes resource allocation by 25%.	Integrates multi-objective optimization for balanced energy distribution.	[61,71,78]
Reinforcement Learning (RL)	RL techniques, like deep Q-networks, optimize EV charging schedules and energy management.	Learning Rate, Scalability	Achieves 85% learning rate improvement, scalable to larger grids.	Implements RL for real-time adaptive scheduling in EV charging.	[61,78,92]

4. Challenges and Opportunities

4.1. Technical, Economic, and Regulatory Challenges

4.1.1. Technical Barriers

The implementation of AI-based solutions in distributed energy systems faces significant technical challenges. Among the most prominent obstacles are the effective integration of DERs and the management of cybersecurity and data privacy, which are critical in an increasingly interconnected environment. Current systems have limited capacity to handle large volumes of real-time data, necessitating advances in infrastructure and technology to support these demands [26]. Additionally, the inherent complexity of coordinating multiple renewable energy sources, such as solar and wind, introduces further technical challenges that require innovative solutions to ensure the stability and efficiency of the energy system [66,70].

Another crucial technical aspect is the need for advanced AI algorithms capable of processing and analyzing data with precision and efficiency. These algorithms must be able to operate in environments with limited computational resources, which is a significant challenge in remote areas or existing infrastructures not designed to handle AI technologies [81,92]. Successful implementation of these technologies also depends on the ability to integrate energy management systems that can optimize energy distribution and enhance grid resilience [67,96].

4.1.2. Economic Impacts

The adoption of AI technologies in the energy sector involves several economic considerations. The high initial costs of implementation, including investment in advanced infrastructure and staff training, pose a significant barrier for many organizations and regions, especially those with limited resources [67,77]. Despite these costs, AI integration can offer long-term economic benefits by improving operational efficiency, reducing energy losses, and optimizing the use of renewable energy resources [78]. Conducting a detailed cost-benefit analysis is essential to justifying the investment in these technologies. AI can potentially reduce operational costs by automating processes and enhancing energy efficiency, leading to significant long-term savings [68,80]. Moreover, the return on investment in AI technologies can be boosted by their ability to quickly adapt to changing market conditions and new regulations [73].

4.1.3. Regulatory and Policy Issues

The lack of uniform and clear regulations regarding the use of AI in the energy sector is a major challenge. Energy policies must evolve to support technological innovation while ensuring consumer protection and the integrity of the energy system [63,107]. Regulatory frameworks need to be flexible enough to accommodate rapid technological changes, allowing the integration of new solutions without compromising grid security and reliability [64,74]. Additionally, it is crucial to develop standards to ensure the interoperability and security of AI systems in the energy sector. This includes establishing guidelines for the collection, storage, and use of data, as well as protecting consumer privacy [69,88]. Energy policies must also address the ethical implications of automation and AI-assisted decision-making, ensuring that the use of these technologies benefits all sectors of society [65,108].

4.2. Integration of Renewable Energies

4.2.1. Intermittent Renewable Integration

The integration of intermittent renewable energy sources, such as solar and wind, presents both a challenge and an opportunity for distributed energy systems. The variable nature of these energy sources requires advanced management and control systems capable of balancing supply and demand in real time [66,86]. AI can play a crucial role by improving the accuracy of energy forecasts and optimizing resource scheduling, enabling more efficient integration of these sources into the grid [70,82]. AI also facilitates the creation of microgrids that can operate independently or in conjunction with the main grid. These microgrids can enhance grid resilience and efficiency by effectively integrating intermittent renewable energies [67,79]. Additionally, AI-based technologies can help manage energy storage, optimizing the use of batteries and other storage systems to maximize the utilization of renewable energies [75,96].

4.2.2. Demand Response Enhancement

Artificial intelligence has the potential to transform demand response mechanisms by providing more accurate and efficient tools for managing energy consumption. AI algorithms can analyze consumption patterns and adjust energy supply in real-time, thereby improving system efficiency and reducing the need for backup energy sources [26,92]. AI systems can also facilitate better communication and coordination between energy providers and consumers, enabling faster and more effective responses to demand fluctuations [74,81]. By enhancing the system's ability to respond to changes in demand, AI can help reduce operational costs and improve grid stability, promoting a more efficient and sustainable use of energy resources [68,83]. Table 4 highlights the innovative applications of AI in energy systems and smart grids.

Table 4. Innovative AI applications in energy systems and smart grids.

Novel Idea	Description	Ref.	Potential Research Directions
AI-Enhanced Energy Communities	Utilize AI and blockchain to empower prosumers in energy trading and management, enhancing efficiency and participation in decentralized energy markets.	[5,12,40]	Develop frameworks for secure and efficient peer-to-peer energy trading using AI and blockchain technologies, focusing on scalability and sustainability.
Adaptive AI for Demand-Side Management	Implement AI-based adaptive algorithms to optimize demand response, manage load, and improve grid reliability.	[29,30]	Explore real-time adaptive AI techniques for dynamic demand-side management in smart grids, enhancing consumer engagement and grid resilience.

Table 4. *Cont.*

Novel Idea	Description	Ref.	Potential Research Directions
AI-Driven Microgrid Resilience	Integrate AI with IoT for enhanced microgrid management, focusing on resilience and efficient resource allocation.	[22,27,31]	Research AI-driven IoT solutions for real-time DER management, focusing on resilience in fluctuating environments and grid stability.
Federated Learning in Distributed Energy Systems	Use federated learning to maintain data privacy while optimizing distributed energy resource management.	[5,29,40]	Investigate federated learning applications for secure, decentralized energy management, emphasizing data privacy and collaborative optimization.
AI-Enabled Hybrid Energy Systems	Employ AI algorithms to optimize the integration and management of hybrid renewable energy sources, improving efficiency and reducing carbon emissions.	[16,19,30]	Study AI's role in enhancing hybrid systems' performance, focusing on real-time optimization and environmental impact assessment.
Stochastic AI Models for Energy Forecasting	Apply deep learning and stochastic models to improve forecasting accuracy in variable renewable energy sources and grid operations.	[25,31,39]	Develop advanced stochastic AI models for precise energy forecasting under variable conditions, considering market dynamics and weather impacts.
AI-Optimized Smart Buildings	Integrate AI with smart building technologies to enhance energy efficiency, demand response, and sustainability.	[21,25,56]	Explore AI-driven strategies for optimizing energy use and reducing operational costs in smart buildings, focusing on carbon neutrality and occupant comfort.

4.3. Cybersecurity in AI Applications for Distributed Energy Systems

The cybersecurity of AI-enabled applications is crucial for their successful implementation and operation in distributed energy systems. As AI technologies become more integrated into smart grids, a variety of cyber threats have emerged that can compromise the integrity, availability, and confidentiality of data and systems. These threats include false data injection attacks, denial of service (DoS) attacks, and load manipulation, all of which can negatively affect the stability and efficiency of smart grids.

To mitigate these threats, several approaches have been developed to enhance cyber resilience. For example, intrusion detection and prevention systems (IDPS) are used as a secondary layer of defense to detect and prevent cyberattacks that might bypass initial encryption and authorization mechanisms. These systems are effective in advanced metering infrastructure, SCADA systems, and other critical components of the energy system [103]. Additionally, multi-agent-based designs for System Integrity Protection (SIP) have proven effective in enhancing situational awareness and self-adaptiveness of systems, thereby improving cyber resilience against single points of failure induced by cyberattacks [104].

Another innovative approach is the use of blockchain technology to enhance the cyber resilience of microgrids. By utilizing smart contracts in a blockchain environment, distributed secondary controls and self-healing functions can be secured against false data injection attacks (FDIAs) in a zero-trust environment [105]. This approach has been shown to be effective in test environments, maintaining comparable performance to conventional approaches even under intense cyberattacks. Moreover, the implementation of a Cyber-Resilient Economic Dispatch (CRED) offers a strategy to mitigate Load-Altering Attacks (LAAs) by coordinating frequency droop controls in Inverter-Based Resources (IBRs) to minimize the destabilizing effects of these attacks while optimizing operational costs [106]. This strategy considers the system's frequency dynamics and provides a robust framework for attack detection and mitigation. Then, the use of Software-Defined Networking (SDN) in microgrid communication architecture allows for greater visibility, direct network control, and programmability, significantly enhancing the resilience and security of microgrid operations against various cyber threats [107]. This approach enables self-healing network management and real-time network verification, strengthening the system's ability to withstand and recover from cyberattacks. These emerging strategies and technologies underscore the importance of robust cybersecurity for the successful integration of AI-enabled applications in distributed energy systems, ensuring their resilience and secure operation in an increasingly interconnected and cyber-vulnerable environment [108].

4.4. Holistic Framework for AI Applications in Energy Systems

4.4.1. Overview of AI Applications across Power System Phases

The application of AI techniques in power systems can be comprehensively understood through a holistic framework that spans the key phases of power generation, transmission, and distribution. This framework provides a structured approach to analyze the impact of AI at each stage, highlighting the specific roles these technologies play in optimizing operations, improving efficiency, and enhancing system resilience:

- Power generation: AI techniques are extensively used in optimizing power generation, particularly from renewable sources such as solar and wind energy. Machine learning algorithms, for instance, have been developed to predict solar irradiance and wind speeds with greater accuracy, thus allowing for more precise energy output forecasts and better scheduling of dispatchable resources [10,108]. Moreover, AI is applied to enhance the operational efficiency of power plants by utilizing predictive maintenance algorithms that can anticipate equipment failures before they occur. This reduces downtime and maintenance costs while ensuring continuous power generation [8]. Research has shown that AI-based predictive maintenance strategies extend the lifespan of grid components by anticipating failures and scheduling proactive maintenance.
- Power transmission: In the transmission phase, AI technologies are pivotal in optimizing the flow of electricity across vast networks, ensuring stability and reliability. Deep learning techniques are employed for real-time anomaly detection and fault diagnosis in transmission lines, which helps in early identification and rectification of potential issues [15]. AI-driven optimization algorithms are also used to dynamically adjust power flows and maintain voltage levels within optimal ranges, preventing grid failures and enhancing overall grid resilience [14]. A multi-agent system can be implemented to enhance situational awareness and provide adaptive responses to unexpected grid events, further improving transmission reliability and security [18].
- Power distribution: AI's role in the distribution phase is critical for managing the complexity of modern electrical grids, especially with the increasing penetration of distributed energy resources (DERs) such as solar panels and wind turbines. AI techniques, such as reinforcement learning, optimize load management by predicting consumption patterns and adjusting supply in real-time to match demand [7]. This not only enhances demand response strategies but also facilitates the seamless integration of DERs into the grid, ensuring stability and minimizing disruptions [3]. Furthermore, AI-based predictive analytics are used for voltage regulation and to reduce energy losses during distribution, which improves the efficiency and reliability of energy delivery to end-users [9].

4.4.2. Research Gaps, Challenges, and Future Perspectives

Within this framework, several research gaps, challenges, and future perspectives emerge:

- Research gaps: While AI has significantly advanced power systems, several research gaps still exist. One notable gap is the need for more robust models that can handle the variability and uncertainty of renewable energy sources. Current AI models are often limited in their ability to predict extreme weather events or sudden changes in generation, which can impact grid stability [5]. Additionally, there is a lack of comprehensive solutions for the interoperability of diverse energy resources and systems, which is crucial for the seamless integration of renewable energies and the overall efficiency of the power grid [13]. Further research is needed to develop AI algorithms capable of managing the complex interactions between various energy sources and storage systems.

- Challenges: The deployment of AI in power systems faces several challenges. Technically, there is a need for advanced infrastructure, such as high-speed communication networks and powerful computational resources, to support AI applications [4]. Cybersecurity remains a significant concern, as the integration of AI and digital technologies exposes power systems to potential cyber threats, including data breaches and cyberattacks [12]. Developing robust cybersecurity measures, such as blockchain-enabled frameworks, is essential to protect these systems and ensure their reliable operation. Additionally, regulatory and policy challenges need to be addressed to create standardized frameworks that govern the use of AI in power systems, ensuring data privacy, security, and ethical use [11].
- Future perspectives: Looking forward, the future of AI in power systems lies in the development of more adaptive and scalable AI models that can manage the dynamic nature of energy systems. Integrating AI with emerging technologies like blockchain can enhance security and transparency, while IoT can provide real-time data collection and analytics, further improving system resilience and efficiency [16]. There is also a need for interdisciplinary research that combines expertise from energy, computer science, and regulatory fields to address the multifaceted challenges of AI integration in power systems. Exploring these future directions will help in building smarter, more efficient, and resilient power systems that can adapt to the evolving demands of the modern energy landscape.

4.5. Future Trends in AI Impact on the Planning and Operation of Distributed Energy Systems in Smart Grids

As the landscape of distributed energy systems continues to evolve, AI is poised to play an increasingly pivotal role in the planning and operation of smart grids. The integration of AI technologies offers numerous opportunities for enhancing efficiency, reliability, and sustainability. Here are some of the key future trends we anticipate:

4.5.1. Increased Integration of Advanced AI Techniques:

Advanced AI techniques such as Generative Adversarial Networks (GANs) and Graph Neural Networks (GNNs) are expected to see wider adoption in smart grids. GANs could be used to simulate various scenarios of energy consumption and generation, providing utilities with robust tools for demand forecasting and anomaly detection. Meanwhile, GNNs are well-suited for optimizing grid operations by modeling the complex interdependencies within a network, thereby improving fault detection, energy distribution, and overall grid management.

4.5.2. Enhanced Cybersecurity Measures

As smart grids become more interconnected and dependent on digital infrastructure, the need for advanced cybersecurity measures will grow. AI will play a critical role in developing predictive and adaptive security frameworks that can detect and respond to cyber threats in real-time. Techniques such as deep reinforcement learning and adversarial training can be employed to create more resilient systems capable of withstanding sophisticated attacks.

4.5.3. Autonomous and Decentralized Energy Management

The future of smart grids will likely include a shift towards more autonomous and decentralized energy management systems. AI will enable distributed energy resources (DERs) to operate independently, making real-time decisions about energy generation, storage, and consumption based on current grid conditions and market signals. This trend will be driven by the development of more sophisticated multi-agent systems and

AI-powered optimization algorithms that can coordinate a vast array of DERs to maintain grid stability and efficiency.

Integration with Emerging Technologies

The convergence of AI with other emerging technologies, such as blockchain and the Internet of Things (IoT), will further transform smart grids. Blockchain can provide a secure and transparent platform for peer-to-peer energy trading, while IoT devices will facilitate real-time data collection and analysis. AI algorithms will be crucial for processing this data and making intelligent decisions that optimize grid operations and enhance service reliability.

Focus on Sustainable and Resilient Energy Systems

As the world moves towards more sustainable energy practices, AI will play a crucial role in ensuring that smart grids can efficiently integrate renewable energy sources. AI techniques will be used to predict renewable energy output, optimize storage solutions, and manage the variability associated with solar and wind power. Additionally, AI will help develop more resilient energy systems that can quickly recover from disruptions and adapt to changing environmental conditions.

5. Discussions

The integration of AI into smart grids and distributed energy systems presents significant opportunities to enhance efficiency, reliability, and sustainability. This paper has highlighted several transformative AI applications, from energy management optimization to advanced demand response strategies. These applications demonstrate AI's potential to address the complexities associated with modern energy infrastructures. One of the most significant contributions of AI is its ability to improve demand forecasting and energy flow optimization. By leveraging machine learning models and neural networks, AI can predict energy consumption patterns with high accuracy, enabling utilities to better manage peak loads and integrate renewable energy sources. This capability is particularly crucial in regions with high penetration of intermittent renewable energies such as solar and wind [2,7,16,25,27]. AI-driven solutions also enhance the coordination and integration of DERs, such as solar panels and wind turbines, within the energy grid. Techniques like RL and multi-agent systems enable more efficient management of DERs, optimizing their output and ensuring stability in the energy supply [4,9,13,22]. VPPs, facilitated by AI, aggregate these resources to enhance energy trading and resource distribution, further strengthening grid resilience [21,26].

Despite these advancements, several challenges must be addressed to fully realize AI's potential in energy systems. Technical barriers, including data privacy and cybersecurity, remain significant concerns as AI systems process vast amounts of sensitive data [35,36,66]. Developing robust cybersecurity measures is essential to protect the integrity of these systems and maintain public trust. Economic considerations also play a critical role in AI adoption. While AI technologies can lead to long-term cost savings through enhanced efficiency and reduced energy losses, the initial investment required for infrastructure and training can be prohibitive for many organizations [39–41]. Therefore, conducting comprehensive cost-benefit analyses and exploring funding opportunities are crucial steps in facilitating wider adoption. Regulatory frameworks must evolve to keep pace with technological advancements. Clear and flexible regulations that address data privacy, security, and ethical implications of AI in energy systems are necessary to ensure that AI solutions align with societal values and consumer interests [41,42,67]. Policymakers should work closely with industry stakeholders to create guidelines that promote innovation while safeguarding the public. Therefore, AI has the potential to significantly transform the planning and operation of distributed energy systems within smart grids. By addressing the technical, economic, and regulatory challenges, stakeholders can unlock the full benefits of AI, leading to more resilient, efficient, and sustainable energy infrastructures.

Future research should focus on developing adaptive AI algorithms, enhancing system interoperability, and fostering collaboration between the public and private sectors to drive innovation in this rapidly evolving field [47,48,51].

Figure 2 shows the predicted impact levels of various AI techniques—machine learning, neural networks, optimization algorithms, RL, and AI with IoT and blockchain on key smart grid functions. Impact areas include energy forecasting, load management, renewable integration, predictive maintenance, and grid stability. The heatmap highlights the high impact of machine learning and neural networks on energy forecasting and grid stability and the significant potential for AI with IoT and blockchain in renewable integration. This visualization provides a clear overview of where AI can most effectively enhance smart grid operations.

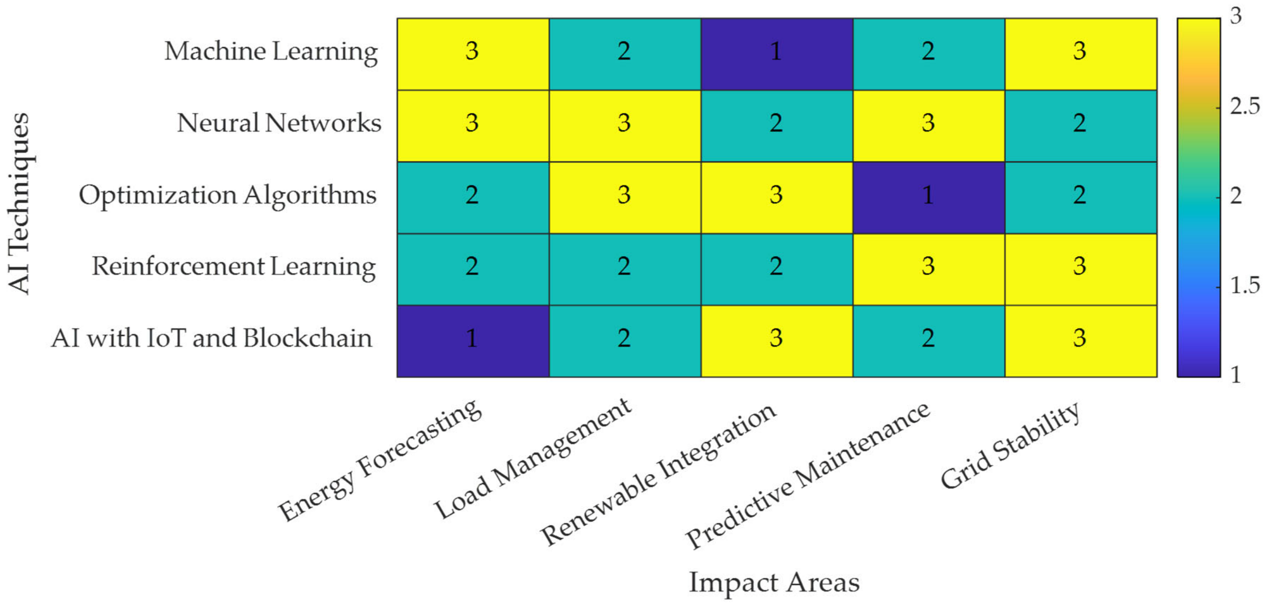

Figure 2. Future impact areas of AI in smart grids.

6. Conclusions

This paper presents a comprehensive review of the transformative impact of artificial intelligence on the planning and operation of distributed energy systems within smart grids. By examining the integration of cutting-edge AI techniques such as machine learning, neural networks, and optimization algorithms, the study highlights how these technologies enhance the efficiency, reliability, and sustainability of modern energy infrastructures. Throughout the analysis, several key areas were explored, including AI-driven energy management systems, advanced demand forecasting methods, and the seamless integration of DERs like solar panels and wind turbines. The review reveals AI's ability to address complex challenges in energy systems by optimizing energy flow, improving grid resilience, and facilitating the transition towards a more decentralized and flexible energy infrastructure.

One of the primary findings is that AI significantly improves demand forecasting accuracy, allowing utilities to predict energy consumption patterns and manage peak loads more effectively. This capability is crucial for integrating intermittent renewable energy sources, ensuring stable energy supply, and reducing reliance on conventional power generation methods. AI-driven energy management systems enable better resource allocation and energy distribution, ultimately leading to increased efficiency and reduced environmental impact. The study also underscores the importance of AI in optimizing the coordination and control of DERs, enhancing grid flexibility, and supporting the development of VPPs. These AI-enabled solutions allow for more efficient energy trading and resource distribution, strengthening grid resilience and promoting sustainable energy practices.

Despite the promising potential of AI in transforming energy systems, several challenges must be addressed to realize its full benefits. Technical barriers, such as data privacy and cybersecurity, remain significant concerns as AI systems process large volumes of sensitive information. Robust cybersecurity measures and data protection frameworks are essential to maintain system integrity and public trust. Economic considerations also play a critical role in AI adoption. While AI technologies can lead to long-term cost savings through improved efficiency, the initial investment required for infrastructure, training, and deployment can be substantial. Conducting comprehensive cost-benefit analyses and exploring funding opportunities are crucial to facilitating wider adoption, especially in regions with limited resources. Furthermore, regulatory frameworks must evolve to keep pace with technological advancements. Clear and flexible regulations addressing data privacy, security, and ethical implications are necessary to ensure AI solutions align with societal values and consumer interests. Collaboration between policymakers, industry stakeholders, and research institutions is vital to creating guidelines that promote innovation while safeguarding the public.

Finally, the future of AI in energy systems hinges on developing adaptive algorithms, enhancing interoperability, and addressing cybersecurity and economic challenges. Research should also focus on cost-effective deployment strategies and evolving regulatory frameworks. By pursuing these directions, stakeholders can unlock AI's full potential, leading to more resilient, efficient, and sustainable energy systems that address the demands of modern infrastructures.

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