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Review article

Artificial intelligence integrated grid systems: Technologies, potential frameworks, challenges, and research directions

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ABSTRACT

Real-time monitoring and control are crucial for ensuring the resilient, coordinated, and optimal operation of next-generation power systems, such as virtual power plants and microgrids. Artificial intelligence (AI) technologies have great potential for improving the effectiveness of monitoring, controlling, optimizing, and managing energy systems. As such, integrating AI into energy systems is seen as a promising path for developing intelligent grids, especially given the rise of distributed and renewable energy sources and the shift toward net-zero systems. This research explores the latest advancements across various areas of energy systems, revealing the current capabilities of intelligent monitoring and fault detection, control and optimization strategies, and energy management systems. The study delves into the key challenges, methods, findings, and research gaps in these areas. It further outlines a framework and the potential benefits of intelligent grid systems, offering multiple directions for future research to address these gaps. Ultimately, this comprehensive review aims to guide industry experts in the practical application of these innovations.

Contents

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1. Introduction

Intelligent systems [1] are highly sophisticated machines that are able to understand their surroundings and respond to them accordingly. A computer system that employs artificial intelligence (AI) [2] to analyze, understand, and learn from data can be referred to as an AI-based intelligent system. Likewise, an AI-based intelligent grid system refers to a computerized system that utilizes AI such as deep learning (DL) and machine learning (ML) to improve the reliability, management, distribution, and control of energy generation in the electrical grid [3]. It has emerged as a crucial instrument for assuring a clean and secure energy future as a result of the increasing demand for sustainable and dependable energy sources.

The objective of the intelligent system is to improve the reliability, efficiency, and safety of the grid significantly through monitoring, prediction, control, and adaptation. The systems can minimize energy waste and enhance the usage of renewable energy sources (RES) significantly by maximizing their integration into the grid. In addition, it can also improve grid stability by detecting and preventing potential grid failures, and reduce costs by minimizing maintenance expenses and energy losses. However, as the grid has grown increasingly complicated, malfunctions and disruptions have also become more common and challenging to control. As a result, intelligent monitoring and fault detection systems (IMFDS), control and intelligent optimization schemes (ICOS), and intelligent energy management systems (IEMS) have become potential options for enhancing the security, reliability, and sustainability of the grid system.

In recent times, several studies focus on IMFDSs to make the grid more robust and reliable [4–8]. The objective of the technology is to swiftly identify, classify, localize, and isolate faults through the integration of the internet of things (IoT), big data analysis, cloud computing, and AI models. Consequently, the system can continually monitor the functionality and health and can warn the grid operators in real time so they can take appropriate action. The potential benefits of IMFDS in smart grid (SG) and microgrid (MG) environments have been emphasized in several studies and research articles. Moreover, the MFDSs are implemented in different parts of the grid system including the low voltage grid [9], distribution grid [10], transmission line [11,12], and RES power plant [13,14]. Furthermore, the increasing number of RES and distributed energy resources (DER)s has resulted in the emergence of complicated energy systems that require adaptive control techniques to manage their variability.

The implementation of AI technology has shown promise in the development of ICOS capable of handling the complexity and uncertainties of these dynamic energy systems. The objective of the ICOS is to regulate active and reactive power, stabilize the system frequency and voltage, and control stable power flow. Several recent studies have focused on the development of AI-based ICOS for different energy grids, especially in SG and MG. Moreover, the AI-based COS has been implemented in different energy devices, such as wind turbine (WT) farms [15], photovoltaic (PV) farms [16], smart energy storage systems (ESS) [17], smart building (SB)s [18], and electric vehicle (EV)s [19–21]. In the case of grid-connected intelligent systems, flexible control of fuel cell improve the grid failure condition as alternative energy sources [22,23]. Similarly, IEMS can maximize the dependability, effectiveness, and sustainability of the electrical power grid through the integration of AI.

AI approaches are used to analyze real-time data and optimize energy production, distribution, and consumption. IEMSs estimate energy demand and supply, schedule generation and transmission activities, and balance load and generation in real time. The system can also incorporate customer preferences and demand response programs to enable more flexible and efficient energy consumption. Recently, researchers have focused on AI-based IEMS for improving the optimization process in SG, MG [24–27], and Virtual Power Plant (VPP). Moreover, IEMS has also been implemented in different systems, such as SBs, smart home (SH)s, smart industry (SI)s [28], EVs [29], and RES [30,31]. Fig. 1 illustrates the various AI-based systems discussed in this study.

Several reviews/surveys were carried out to investigate various research topics of AI-based grid systems. For instance, Zhao et al. have reviewed the study on AI-based fault detection and diagnosis methods for building energy systems (BES) from 1998 to 2018. New AI-based methodologies are needed to integrate the advantages of both data-driven and knowledge-driven methods in the future [32]. An AI framework is introduced in [33] for power system fault detection and fault diagnosis within power grids. A comprehensive assessment of various AI approaches for fault diagnosis in power grids is presented. These approaches include expert systems, artificial neural networks (ANN), Petri networks, fuzzy set theory, multi-agent systems, rough set theory, and information fusion technology. In [34], the authors provide a review of IMFDS for both stator and rotor faults. It also includes discussions on key challenges in this field and proposes potential directions for future research. Afridi et al. offer an overview of different data-related issues, such as data availability, feature engineering, interpretability, and security concerns in the existing work [35]. Moreover, the big data requirements, interpretability of AI, challenges with transfer learning, the robustness of AI, and robustness against attack are some of the significant challenges these applications face in practice. It also discussed these issues, explored the research gap, and provided potentially significant future research directions [3].

A detailed review of control applications in the power electronic interfaces of DERs for grid integration is presented in [36]. In addition, it covers different methods for grid-connected converters, explores AI-based predictive control techniques, addresses open issues, and outlines future trends. A detailed analysis is provided in [37] to study the performance of AI and conventional methods for improving power quality and investigating the impacts of PV grid-tied systems. Vrba et al. presents an examination of the utilization of agent and service-oriented technologies in intelligent energy systems, with a particular focus on ongoing research and development in the context of SGs. Moreover, significant challenges arising from the widespread integration of DER, including aggregation, generation–consumption balancing, electricity markets, and fault handling and diagnostics are addressed [38]. The authors in [39] address current concerns, methodologies, findings, and gaps while revealing the condition of IEMSs. Saadi et al. provide a comprehensive review of distinguished ICOS and a classification of the work on emerging strategies. The application of reinforcement learning (RL)-based ICOS for optimal power management in MGs and SGs, particularly energy storage is discussed [40]. Mischos et al. review

Abbreviations

AC	Alternating Current
ACO	Ant Colony Optimization
Adaboost	Adaptive Boosting
ADP	Adaptive Dynamic Programming
AI	Artificial Intelligence
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Networks
ATLA	Artificial Transgender Longicorn Algorithm
BBSA	Backtracking Search Algorithm Based
BEMS	Building Energy Management System
BESS	Building ESS
Bi-LSTM	Bidirectional-LSTM
BPNN	Back-propagation Neural Network
BPSO	Binary Practical Swarm Optimization
BT	Binary Tree
CNN	Convolutional Neural Networks
DBN	Deep Belief Networks
DC	Direct Current
DDPG	Deep Deterministic Policy Gradient
DER	Distributed Energy Resources
DHDP	Dual Heuristic Dynamic Programming
DN	Distribution Network
DNN	Deep NN
DP	Dynamic Programming
DRL	Deep RL
DT	Decision Tree
EEMD	Ensemble Empirical Mode Decomposition
EMTDC	Electromagnetic Transients Including DC
ESS	Energy Storage Systems
EV	Electric Vehicle
FFNN	Feedforward Neural Network
GA	Genetic Algorithm
GRU	Gated Recurrent Unit
HDP	Heuristic Dynamic Programming
HIL	Hardware-in-Loop
HKHSM	Hybrid Krill Herd Spider Monkey
HSO	Harmony Search Optimization
ICOS	Intelligent Control and Optimization System
IEC	International Electrotechnical Commission
IEMS	Intelligent Energy Management Systems
IF	Isolation Forest
IMFD	Intelligent Monitoring and Fault Detection
IoT	Internet of Things
KNN	K-nearest Neighbors Algorithm
LM-ANN	Levenberg–Marquardt ANN
LP	Linear Programming
LR	Linear Regression
LSTM	Long Short-Term Memory Networks
MFNN	Multilayer Feedforward Neural Network
MG	Microgrid
MILP	Mixed-Integer Linear Programming
MIMO	Multiple Input, Multiple Output
MKELM	Multi-kernel Extreme Learning Machine
ML	Machine Learning
MLP	Multilayer Perceptron
NN	Neural Networks
NPO	Nomadic People Optimizer
NRFNA	Normalized Reasoning-based Fuzzy Neural Adaptive
PCA	Principal Component Analysis
PI	Proportional Integral
PPWFNN	Petri probabilistic Wavelet Fuzzy Neural Network
PSO	Particle Swarm Optimization
PV	Photovoltaic
RBF	Radial Basis Function
RES	Renewable Energy Sources
RF	Random Forest
RL	Reinforcement Learning
RNN	Recurrent Neural Network
RTDS	Real-Time Digital Simulator
SB	Smart Building
SC	Smart City
SH	Smart Home
SI	Smart Industry
SM	Smart Grid
SVM	Support Vector Machine
SVR	Support Vector Regression
TSEB	Thermal Storage Electric Boiler
VPP	Virtual Power Plant
VSC	Voltage Source Converter
VSG	Virtual Synchronous Generators
WT	Wind Turbine

IEMSs designed for residential, commercial, and educational buildings, categorizing them into two main groups based on their provision of direct or indirect control. It also analyzes the strengths and weaknesses of these systems, explores the optimization techniques they employ, and offers insights into future improvements that can be made to enhance their effectiveness [41].

A comprehensive review of management strategies for building energy management system (BEMS), focusing on enhancing energy efficiency is presented in [42]. In addition, the classifications, functions, and effective design optimization of energy systems in diverse applications utilizing various AI methodologies are introduced in different studies. In [43], the performance of energy systems that incorporate thermal energy storage facilities is being optimized, predicted, and controlled using AI, and its subcategories are discussed. The effectiveness of these technologies is also carefully examined, showing their apparent accuracy while achieving various goals. Likewise, a review of the latest and most efficient techniques used to optimize green MGs from both an economical and reliable perspective is provided in [44].

Numerous surveys and review studies on AI-powered MFDS, COS, and EMSs in SGs, MGs, and RES have highlighted encouraging prospects for diverse AI-driven systems. However, the realm of AI-based intelligent systems remains inadequately addressed. Consequently, a comprehensive understanding of forthcoming AI-based intelligent grid systems is lacking. Hence, this study presents a thorough review to explore the potential of future intelligent grid systems. There are several motivations for systematically reviewing this study. Firstly, this study covers the comprehensive review of three important parts of the intelligent grid system i.e. IMFDS, ICOS, and IEMS. Secondly, this review provides an outlook on the future of intelligent grid system research by highlighting its key emerging areas. Thirdly, a significant

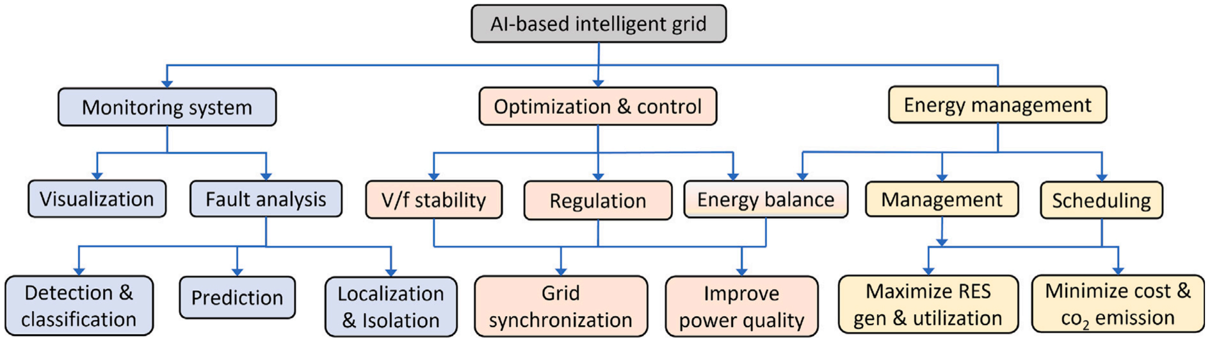

Fig. 1. Important AI-based intelligent system discussed in this work.

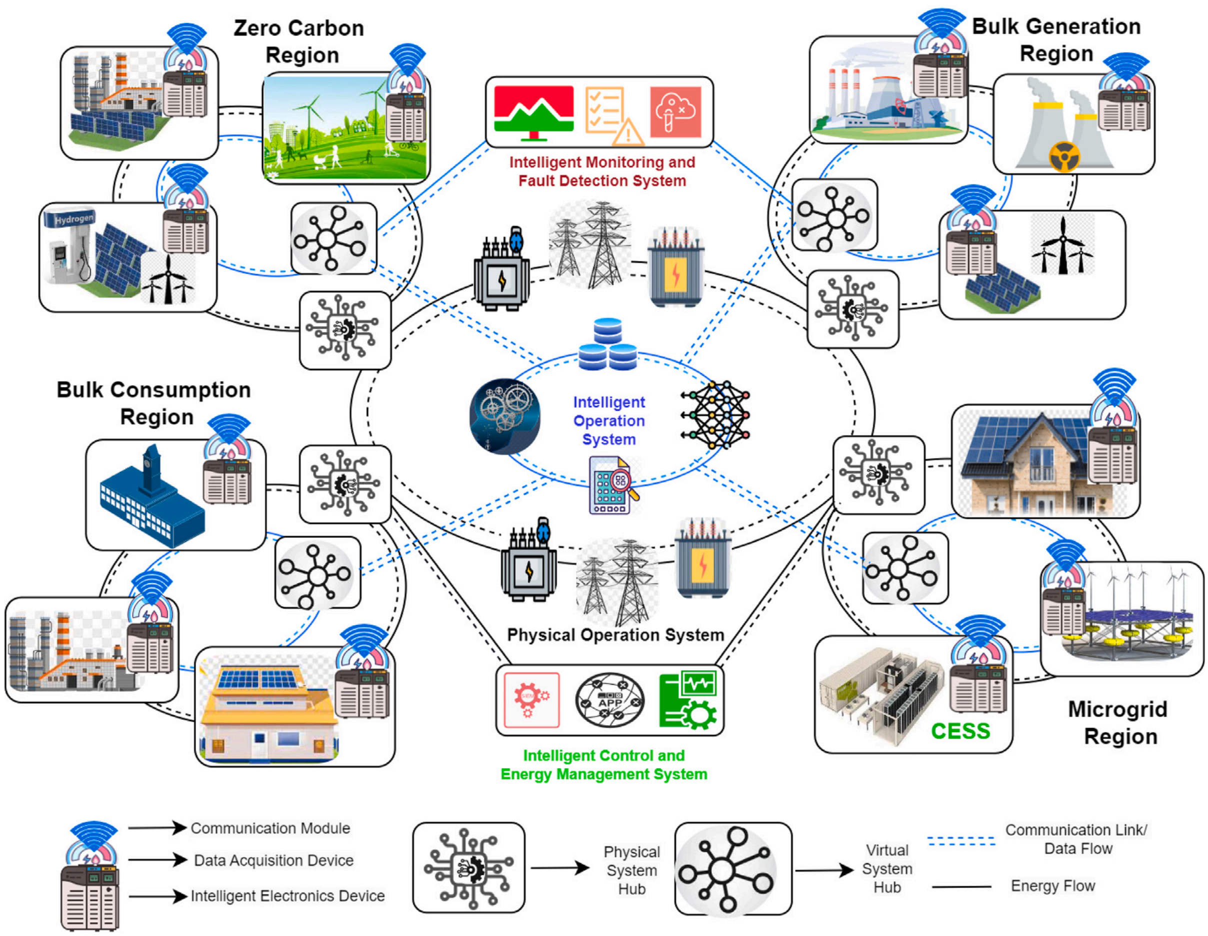

Fig. 2. Framework of AI-based intelligent grid system.

and comprehensive architecture is proposed for each part of the future grid system. Finally, due to the sudden changes and technological advancements in the energy grid, significant studies have been carried out recently. Given these significant studies, a current systematic review is required to explain the innovations of earlier contributions. This comprehensive assessment of the study is intended to help academics and industry professionals comprehend the research gaps of earlier studies. To the best of the author's knowledge, there is no comprehensive review article on AI-based intelligent grid systems.

In this study, a detailed description that covers the area of AI-integrated grid systems is presented. For better illustration, highly related surveys/reviews of AI-based intelligent systems and AI-related technologies are included in Table 1 with a brief explanation of their main contributions. This manuscript discusses the issues relating to various intelligent systems comprising AI and non-AI technologies. Different energy platforms, including SGs, MGs, RES, SB, and EV and AI technologies for example supervised learning, unsupervised learning, and RL are considered to explore the energy system. In this article, the challenges and future research directions for intelligent grid systems are included. Fig. 2 presents the architecture of an AI-based intelligent grid system, connecting regions dedicated to zero-carbon, bulk generation, bulk consumption, and microgrids. This system incorporates

Table 1
Related review/survey studies on MFDS, COS, and EMS.

Year	Author	Ref.	Journal	Main contributions			Application platform	Approach
				MFDS	EMS	COS		
2019	Zhao et al.	[32]	Renewable and Sustainable Energy Reviews	✓	×	×	BESS	AI-based data and knowledge-driven
2021	Alshorman et al.	[34]	Inter. Journal of Electrical and Computer Engineering	✓	×	×	SG	AI-based technologies
2019	Chai et al.	[33]	Chinese Control Conference	✓	×	×	Grid	AI-based technologies
2014	Pavel Vrba et al.	[38]	IEEE Transaction on Industrial Informatics	×	✓	×	DER	Service-oriented technologies
2021	Ali et al.	[39]	Journal of Cleaner Production	×	✓	×	SG & SH	AI-oriented technologies
2023	Al-Saadi et al.	[40]	Energies	×	×	✓	MG, SG, & ESS	DRL-based intelligent control strategies
2022	Afridi et al.	[35]	International Journal of Energy Research	✓	×	×	RES	AI-based technologies
2020	Shi et al.	[3]	Applied Energy	✓	×	✓	SG	AI-based technologies
2023	Mischos et al.	[41]	Artificial Intelligence Review	×	✓	✓	SB	Non AI (i.e. direct or indirect control)
2015	Kow et al.	[37]	Renewable and Sustainable Energy Reviews	×	✓	✓	PV-grid	AI & conventional technologies
2023	Olabi et al.	[43]	Thermal Science and Engineering Progress	×	✓	✓	Thermal ESS	AI-oriented technologies
2022	Kiehbadroud-inezhad et al.	[44]	Energies	×	✓	✓	MG	AI & conventional technologies
2023	Babayomi et al.	[36]	Inter. Journal of Electrical Power & Energy Systems	×	✓	✓	DER	AI-based technologies
2021	Mariano-Hernández	[42]	Journal of Building Engineering	✓	✓	✓	BESS	AI & mostly conventional technologies
This work				✓	✓	✓	Intelligent grid	Advanced AI adapted technologies

modules for monitoring, fault detection, control, and energy management, facilitating efficient data exchange and communication across energy domains. The framework emphasizes the interaction between physical and virtual hubs to support decentralized, renewable energy integration.

The main contributions of this study can be summarized as follows:

- An overview of existing and potential AI-based technologies utilized in different intelligent grid domains are summarized. Moreover, recent studies on AI and Non-AI-based intelligent energy systems are surveyed; the current trends in the field are highlighted.
- The Application of AI-integrated intelligent system scenarios in the grid, including monitoring, fault detection and diagnosis, energy management, control, and optimization systems are described.
- Important methodologies of AI-based grid systems from the existing studies are critically analyzed. Moreover, the potential framework of the IMFDS, ICOS, and IEMS are proposed and explained.
- The deployment challenges, relevant solutions, and future research direction associated with future intelligent grid systems are discussed. This can serve as a valuable resource for academics and industries seeking to develop intelligent grid systems.

The remaining sections of the study are structured as follows. The review process is explained in Section 2. In Section 3, a concise introduction to energy grid systems and the working principle of AI-based intelligent systems are given. Section 4 focuses on the application of AI in grid systems, exploring their contribution, potential, technologies, and proposed architecture. Additionally, Section 5 covers current research trends, important challenging issues, and future research directions of intelligent grid systems. Finally, Section 6 concludes the review study.

2. Review process

The approach used for this state-of-the-art AI-based system within the energy grid domains represents a systemic method. Focusing on research from the past five years, the initial stages involved an extensive search through academic databases. The process of searching for and choosing works for a review study involves several steps. First, the scopes of the intelligent grid system are defined. The article is then searched using relevant keywords such as "monitoring and fault detection", "control and optimization," and "energy management." The publications are sorted from the search list depending on the approach, such as AI-based intelligent systems or intelligent systems.

The article searches and selection process is depicted in Fig. 3. In addition, other relevant review studies were chosen to compare this work's contribution. Table 1 shows the contribution comparison. The information is gathered from scholarly resources such as journals, conferences, books, and websites. Fig. 4 depicts the percentages of information sources. Similarly, Fig. 5 illustrates the percentage distribution of the articles across various publishers. Fig. 6 also shows the percentages of yearly paper distribution.

3. System overview

3.1. Brief overview of considered energy networks for the intelligent grid systems

1. Conventional Grid: The convention grid is an interconnected network that distributes electrical power across a wide area, but faces challenges like security threats, aging infrastructure, and limited RES integration.
2. Smart Grid: The SG is a sophisticated electricity distribution system that improves efficiency, sustainability, and reliability through real-time data exchange, RES integration [45]. Although

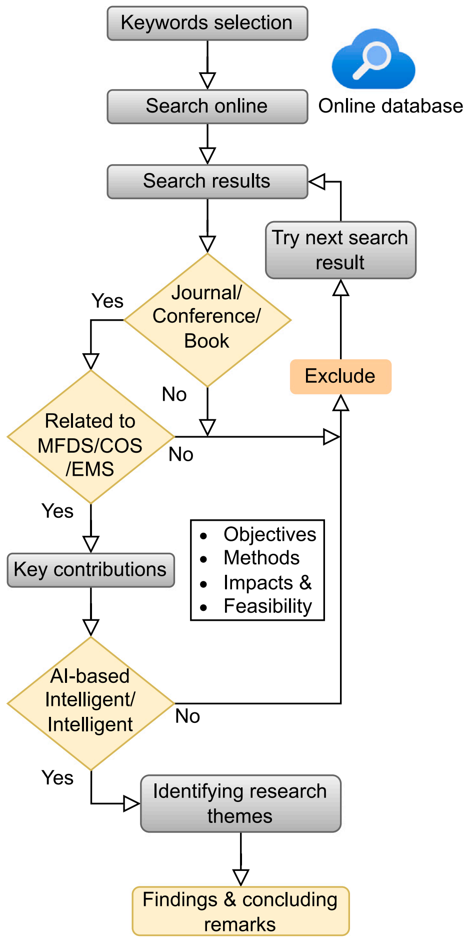

Fig. 3. Flowchart of article search and selection used in this work.

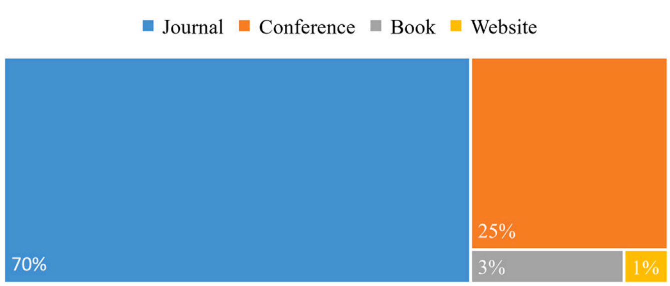

Fig. 4. Sources of articles used in this journal.

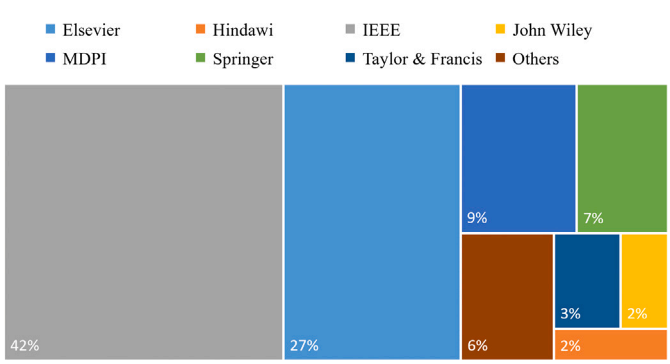

Fig. 5. Percentage of articles published by Publisher.

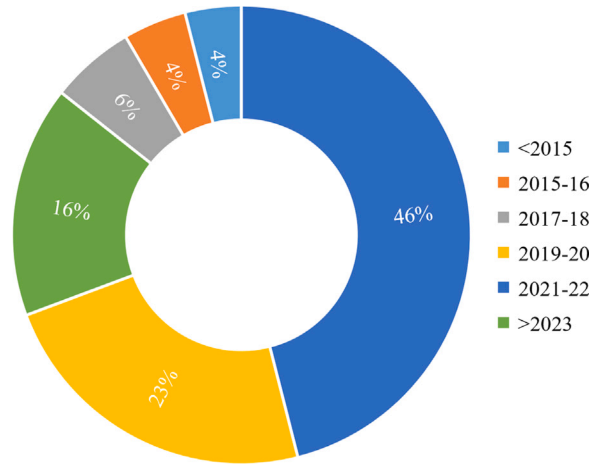

Fig. 6. Percentage of articles published in different year.

it faces difficulties like cyberattacks, the SG also offers significant advantages in terms of energy management, cost savings, and grid resilience.

3. Microgrid: A MG is an independent electrical distribution system that generates, stores, and distributes electricity within a given area using localized energy resources [46]. It provides self-sufficiency, resilience, and improves energy efficiency but has trouble meeting large-scale power demands.
4. Virtual Power Plant: A VPP is an integrated network of decentralized energy resources that operates as a unified system, enabling real-time monitoring, optimization, and trading [47]. Despite relying on a robust communication infrastructure, VPPs provide benefits such as efficient RES utilization, and grid stability.

Though every energy network has significant benefits and drawbacks, integrating AI into those networks may be more promising for the evolution of grid systems and driving the transition to a sustainable future. For instance, non AI-based systems are less reliant on data quality and have limited data analysis capabilities, which reduces their susceptibility to cyber threats. However, they face challenges such as limited efficiency and reliability, high running and maintenance costs, and low scalability for RES integration. On the other hand, AI-based systems offer improved security and reliability by automating fault detection and restoration, which reduces outage times and supports predictive maintenance. These systems also reduce operational costs by optimizing grid operations and energy distribution and enhance sustainability by providing real-time insights for decision-making. Despite these benefits, AI-based systems require substantial initial investment in terms of setup, data infrastructure, and algorithm development, and they demand high-quality data inputs and robust security measures to counteract vulnerabilities to cyber threats. Table 2 presents the main advantages and limitations of non-AI-based and AI-based intelligent grid systems. Non-AI-based systems provide simplicity, lower cybersecurity risks, and reduced maintenance needs but face challenges with efficiency and scalability. In contrast, AI-based grids improve security, operational optimization, and support for renewable energy integration, though they demand substantial setup, high-quality data, and robust cybersecurity.

3.2. How AI-based intelligent system works

The working principle of an AI-based intelligent system consists of several steps such as the integration of data acquisition, storage and management, AI analysis, and decision-making processes. The architecture of the AI-based intelligent system is illustrated in Fig. 7 [3,48–50]. In addition, the working process is described as follows:

Table 2
Key advantages and limitations of AI and Non-AI-based system.

Feature	Advantages	Limitations
Non AI-based Grid Systems	1. Less dependent on data quality 2. Required limited data analysis capabilities for operational optimization 3. Grid systems are generally less susceptible to cyber threats 4. Operate based on simple deterministic and rule-based processes 5. Require less sophisticated maintenance	1. Limited efficiency and reliability and high operational and maintenance costs 2. Low security and high risk of outages due to manual detection and restoration processes 3. Low scalability for RES integration 4. Required standard grid infrastructure setup 5. Maintenance scheduled based on fixed intervals or reactive responses to failures
AI-based Intelligent Grid Systems	1. Improved security and reliability by enabling automated fault detection and restoration, reducing outage duration, and allowing predictive maintenance 2. Reduced costs through optimizing grid operations, load management, minimizing losses, and improving energy distribution 3. Improved sustainability by providing real-time insights for decision-making and optimizing grid operations 4. Wide range of scalability for RES integration	1. Advanced substantial setup and integration efforts, including data infrastructure and algorithm development 2. Significant investment in sensors, communication networks, and control systems 3. High-quality data inputs for accurate predictions and optimal performance 4. Vulnerable to cyber threats, requiring robust security measures and constant monitoring

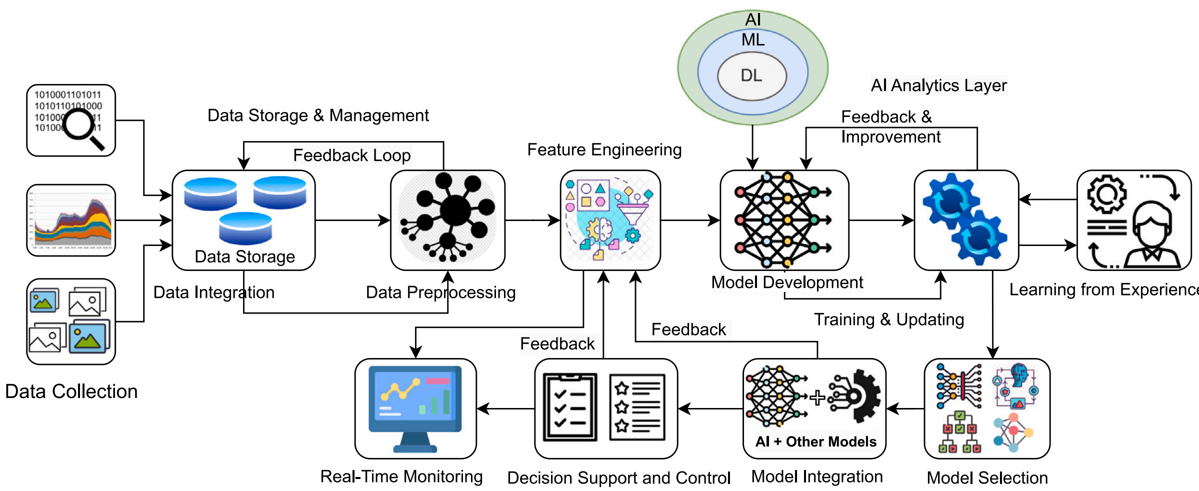

Fig. 7. AI-based intelligent architecture.

1. Data Collection:
   - Smart Meters: Collect required real-time energy data generated by smart meters.
   - Sensors and IoT Devices: Gather different real-time and historical data such as meteorological data system conditions, and equipment performance.
2. Data Storage and Management:
   - Data Storage: Store accumulated data securely and flexibly, allowing access and retrieval.
   - Data Integration: Integrate the data from single/multiple sources to create a cohesive and comprehensive dataset for the analysis.
   - Data Preprocessing: Clean, filter, standardize, and normalize the data until it ensures its reliability and compatibility for analysis.
3. AI Analytics:
   - Feature Engineering: Transform raw data into meaningful features, select relevant features, integrate existing features, creates interaction terms, scale and normalize features, and handles missing data.
   - Model Development: Creates an accurate and reliable advanced AI model to solve and identify the objectives and requirements.
   - Model Training and Updating: Incorporate the data to train, validate, and evaluate the models periodically through hyperparameter tuning, until it ensures higher accuracy, effectiveness, reliability, and adaptability.
   - Learning from Experience: Collect feedback from operational experiences, incidents, and system improvements, using it to refine AI models and enhance grid performance.
   - Model Selection: Select a suitable model such as classification, regression, clustering, dynamic programming, adaptive system, and time series analysis based on the specific requirements and objectives of the problem.
   - Model Integration: Integrate AI model with other required algorithms such as optimization, control, and management to solve complex grid problems.
4. Decision Support and Control:
   - Decision Making: Provide potential insights and recommendations to assist intelligent decision-making.
   - Control Systems Integration: Interfaces with the physical device to enable automated and adaptive systems.
5. Outcomes:
   - Monitoring & Visualization: Show real-time analysis, results, trends, patterns, errors, performance metrics, and transparency.

4. Methodology

In this work, the overall intelligent system are classified into three layers such as 1. device layer, 2. communication layer, and 3. server layer. The device layer integrates main energy generation units such as generators, alternators, DER, measurement devices, sensors, control, and protection instruments. The communication systems include wired and wireless technologies. Wired options include fiber optics and powerline communication, valued for their reliability and high data transfer capabilities, crucial for real-time grid monitoring and control. Wireless technologies involve cellular and Wi-Fi, known for their high throughput and availability; mesh networks, which enhance robustness by providing multiple data pathways; GPRS (general packet radio service) and PLCC (power line carrier communication), which integrate well with existing infrastructures; and ZigBee, GSM (global system for mobile communications), Bluetooth, and WiMax, chosen for their low power consumption, cost-effectiveness, and ease of deployment across various grid segments. Each technology is selected for its unique benefits, ensuring efficient and reliable communication throughout the grid system [51]. The network infrastructure should have sufficient capacity, low latency, and high availability to support real-time monitoring, control, and coordination of grid operations. Standardized communication protocols ensure interoperability and seamless communication between different devices and systems in the SG. Protocols like IEC 61850, DNP3, Modbus, and MQTT enable data exchange, command execution, and system integration across diverse devices and applications [52].

Moreover, there is a central data processing and analysis unit in the server that acts as the brain of the system, where AI algorithms and ML models are deployed. This processing unit is connected to multiple data sources through the communication layer, including sensors, devices, and other instruments. These sensors continuously send the required data to the processing unit for further analysis. In addition, the functions of the AI-based intelligent grid system are categorized into three: 1. IMFDS, 2. ICOS, and 3. IEMS. Figs. 9, 11, and 13 show the architecture of the proposed intelligent system. As this work primarily focuses on the impact of AI on the server layer, the architectural device and communication layers remain unchanged in the figures.

4.1. Intelligent monitoring and fault detection & diagnosis system

4.1.1. Existing work

The monitoring and identification of faults in the grid pertain to overseeing and detecting issues within the interconnected devices and equipment present in the system. For instance, an affordable monitoring device is deployed for evaluating the health of oil-immersed service transformers where key analyzed components are oil temperature, vibration, and transformer load [107]. Mudaliar et al. focus on a raspberry Pi-based IoT solution for real-time energy monitoring in the switchgear industry to effectively control and monitor energy consumption in the industry [108]. Single ML algorithms such as the support vector machine (SVM) approach are introduced to classify islanding and grid fault events in low-voltage distribution grids [95].

A combination of ML/DL and other algorithms is also used for identifying the faults in the grid. Wang et al. introduced a scheme that utilizes a pseudo-continuous quadrature wavelet transform method with a modified gabor wavelet and a compact event detection technique based on convolutional neural networks (CNN)s to detect hazardous intermittent faults in the power grid [99]. A hybrid model that combines multiclass SVM with a rule-based classifier is designed to detect changes in leakage currents in residential houses as well as energy consumption monitoring. The rule-based classifier algorithm is employed to diagnose faults related to the constructed device, such as device faults and overcurrent faults, while the MSVM approach is utilized for detecting leakage current faults [9]. Some infrastructure supports heterogeneous data collection and storage, global inter-communication,

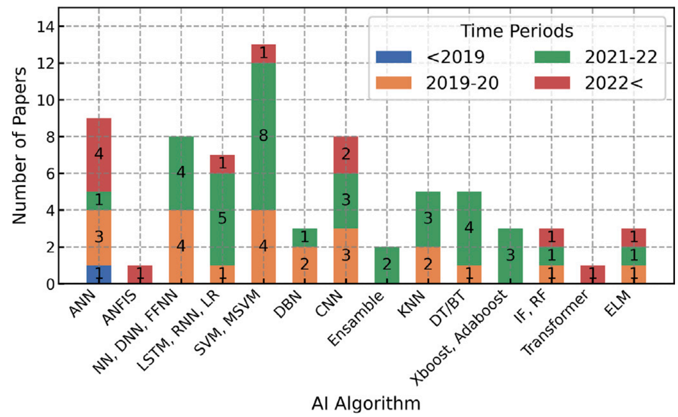

Fig. 8. Application trends of AI algorithm in monitoring and fault detection system.

real-time anomaly detection, and online dashboards with remote accessibility [103]. An embedded system is designed for remote monitoring and fault diagnosis of PV systems where ANN and ensemble learning algorithms are applied to identify faults and classify the nature of the detected faults, respectively [92].

In addition, several studies have used different algorithms for feature reduction. For example, Sharma et al. applied SVM and ANN where features are reduced in dimensionality through principal component analysis (PCA) [96]. To enhance the accuracy and reliability of the algorithm, the PCA and SVM are combined together to detect abnormal voltage regulation in an on-grid PV system [97]. Shafiullah et al. combine ML tools and signal-processing techniques where signal-processing tools are used to extract relevant features [55]. In the pre-training phase, a double particle swarm optimization (PSO) is utilized to select optimal features and hyperparameters [56]. Ardito et al. introduced a spectrogram–CNN-based representation of electrical signals to capture faulty patterns. Pre-trained models such as googleNet and squeezeNet are applied for multiple fault classification tasks [100].

In the context of electrical grids, fault diagnosis plays a crucial role in terms of economic and operational implications. While data-driven methodologies have been widely adopted in SG applications, the focus has primarily been on improving the accuracy of ML models for fault diagnosis. Mostafa et al. developed a five-step approach utilizing five distinct ML methods such as linear regression (LR), random forest (RF), decision tree (DT), CNN, and gradient-boosted DT model for predicting SG stability [109]. In [106], an ML classifier is proposed for spontaneous fault detection and classification in transmission lines. An approach called the ensemble DL approach is applied for detecting and localizing high-impedance faults in the low-voltage distribution grid [57]. By using both spatial characteristics and the frequency domain of the three-phase voltage and current time series measurements obtained from field devices, Rizeakos et al. introduced continuous wavelet transformation and CNNs model for fault location identification and classification [101]. The Hajji et al. focus on introducing the IV (current–voltage) characteristics into the dynamic model of an on-grid PV system under various operating conditions [53]. A RF-based fault detection algorithm is programmed that calculates the maximum angular difference between the positive and zero sequence components of the current at the distributed generation bus [104]. To enhance the effectiveness of corrective voltage control and improve post-fault system stability, Karim et al. proposed an offline–online data analysis approach using feature selection and ML algorithms to develop an accurate corrective voltage control framework through supervisory machine control [110].

Table 3 provides a summary of the main contribution, applied AI model, application platform, and implementation status, on IMFDS. In addition, Table 4 presents the current technologies employed for IMFDS in different articles over the year. Fig. 8 illustrates the application trends of AI algorithms in MFDS.

Table 3
Summary of current research on IMFDS.

AI Algorithm	Simulation/Implementation	Main Contributions	Mode	Platform	Ref.
ANN, RNN, Bi-LSTM	Performed in MATLAB	Identify healthy and faulty operating conditions	On	PV system	[53]
Ensemble	Implemented in MATLAB	Classify various attacks	On	Grid	[54]
FFNN	Simulated on IEEE 13 node in MATLAB/Simulink	Detect, classify, and localize faults	On	DNs	[55]
DNN, LSTM-RNN, DBN	Performed on Python version 3.9.5	Fault detection	On	Grid	[56]
DNN	Evaluated on LV distribution grid in Portugal	Detect and localize faults	On	DN	[57]
Dynamic NN	Performed on substation equipment	Fault detection	On	Substation	[58]
ANN	Performed with a real Brazilian system	Fault location	N/A	Grid	[59]
ANN	Validated on the modified IEEE 34-nodes	Fault section estimation	N/A	DNs and MG	[60]
CNN	Modeled in MATLAB/Simulink	Fault detection and classification	N/A	DC MG	[61]
LSTM	Simulated in MATLAB/Simulink	Detect, classify, and localize faults	N/A	MG	[62]
SVM	Simulated in MATLAB/Simulink	Detect short-circuit and grounding fault	N/A	DC MG	[63]
NN	Cloud–edge integration	Fault diagnosis	N/A	MG	[64]
SVM	Signal processing by HT algorithm	Detect faults from non-fault disturbances	Off	AC MGs	[65]
Regression	Simulated on an IEEE 15 bus DS	Detect, localize, and isolate the faults	Both	AC MG	[66]
KNN, SVM, DT	Evaluated on an IEEE 33 bus in Matlab/Simulink	Detect and classify the faults	On	DN	[67]
KNN	Integration of discrete WT and Ensemble kNN	Detect external and internal fault	On	Hybrid MG	[68]
CNN	Assessed on an IEEE 13 bus system	Detect disturbance and protective solutions	Both	MG	[69]
LSTM	Assessed on an IEEE 34-node system	Identify islanding events	Off	MG	[70]
KNN	Verified using PSCAD simulation	Detect, isolate, and restoration	Off	DC MG	[71]
DBN	Developed on a RTDS integrated with Matlab	Protection and fault detection	Both	MG	[72]
Ensemble	Validated in IEC test MG	Fault detection and classification	N/A	MG	[73]
DNN	Simulated in MATLAB/Simulink	Fault detection and classification	N/A	MG	[74]
SVM, DT, BT	Validated with OPAL-RT simulator	Detect, isolate, and locate faults	N/A	DG, MG	[75]
AdaBoost & LR	Evaluated on a IEC system	Fault detection and classification	Both	MG	[76]
SVM, LR	Simulated via a Matlab/Simulink model	Fault detection	On	DC MG	[77]
XGBoost	Verified on an IEEE 13 bus MG model	Fault detection and classification	N/A	MG	[78]
SVM	Validated in an IEC-based and IEEE 34-bus	Detection, location, and fault type	Off	MG	[79]
CNN	Simulated on a standard MG system	Detect, classify, and locate the faults	N/A	MG	[80]
DBN	Validated on a 25kV IEC standard MG	Fault detection and classification scheme	Both	MG	[81]
ANN	Validated in PSCAD/EMTDC and MATLAB	Fault detection scheme	N/A	DC MGs	[82]
MKELM	Tested on the IEC with MATLAB/Simulink	Fault classification and location identification	N/A	MG	[83]
RNN, RBF	Modeled in DIgSILENT Power Factory	Fault type, fault phase, and fault location	Off	MG	[84]
ANN	N/A	Fault detection and localization scheme	Off	DC MG	[85]
N/A	Simulated in MATLAB/Simulink	Fault detection and diagnosis	N/A	MG	[86]
ANFIS	Simulated in MATLAB/Simulink	Detect and identify the faults	N/A	MG	[87]
RF, SVM, KNN	Validated on the modified IEEE 13-nodes	Fault detection	Both	MG	[88]
DNN	Evaluated on an IEEE 34-bus in MATLAB/Simulink	Fault detection	On	MG	[89]

Table 4
AI techniques for IMFDS.

AI Algorithm	Publication Year			
	<2019	2019–20	2021–22	2022<
ANN	[59]	[82,85,90]	[91]	[53,60,92,93]
ANFIS	N/A	N/A	N/A	[87]
NN, DNN, FFNN	N/A	[57,74,89,94]	[55,56,58,64]	N/A
LSTM, RNN, LR	N/A	[84]	[56,62,70,76,77]	[53]
SVM, MSVM	N/A	[79,88,95,96]	[9,63,65,67,75–77,97]	[98]
DBN	N/A	[72,81]	[56]	N/A
CNN	N/A	[80,96,99]	[61,69,100]	[101,102]
Ensamble	N/A	N/A	[54,73]	N/A
KNN	N/A	[71,88]	[67,68,91]	N/A
DT/BT	N/A	N/A	[10,67,75,76,91]	N/A
XGboost, Adaboost	N/A	N/A	[10,76,78]	N/A
IF, RF	N/A	[88]	[103]	[104]
Transformer	N/A	N/A	N/A	[102]
ELM	N/A	[83]	[105]	[106]

4.1.2. Research gap

The main research gap between existing MFDS and AI-based IMFDS lies in the level of intelligent support and automation, model improvement schemes and adaptability, and predictive capabilities. Most of the studies have been only focused on AI-based monitoring, fault detection, and diagnosis in the offline process. Consequently, the system has some shortcomings in intelligent support and model improvement schemes for fault detection and diagnosis processes. The system is unable to provide supervised and self-healing predictive maintenance support that is learned from the previous experiences of the model. Moreover, the system should address the issues related to algorithm bias, interpretability, and explainability that help to build trust in AI-based systems and ensure their responsible and ethical use.

4.1.3. Exploration of prospective architecture

The methodologies utilized for IMFDS in the current research are diverse and leverage various AI algorithms to enhance fault detection, classification, and localization within grid systems. Studies implementing ensemble methods for improving fault classification accuracy by combining multiple models, thus enhancing system robustness. DNNs are applied to detect and localize faults by learning complex patterns in large datasets, often evaluated in real-world grid settings or through simulations. SVMs are noted for their ability to differentiate between faults and non-fault disturbances, typically processed in MATLAB/Simulink. LSTM networks excel in managing dynamic systems like grids by recognizing long-term dependencies, suitable for classifying and localizing faults over time. CNNs are used for their spatial data processing capabilities, ideal for multivariate time series data from distributed grid sensors. KNN analyze the similarity between operational and historical fault data, often integrated with other techniques to detect internal and external faults. Additionally, hybrid models combine various AI techniques to harness multiple strengths, improving fault detection accuracy and adaptability to evolving grid conditions.

The proposed intelligent monitoring and fault diagnosis system offers a promising resolution to address the current limitations. The

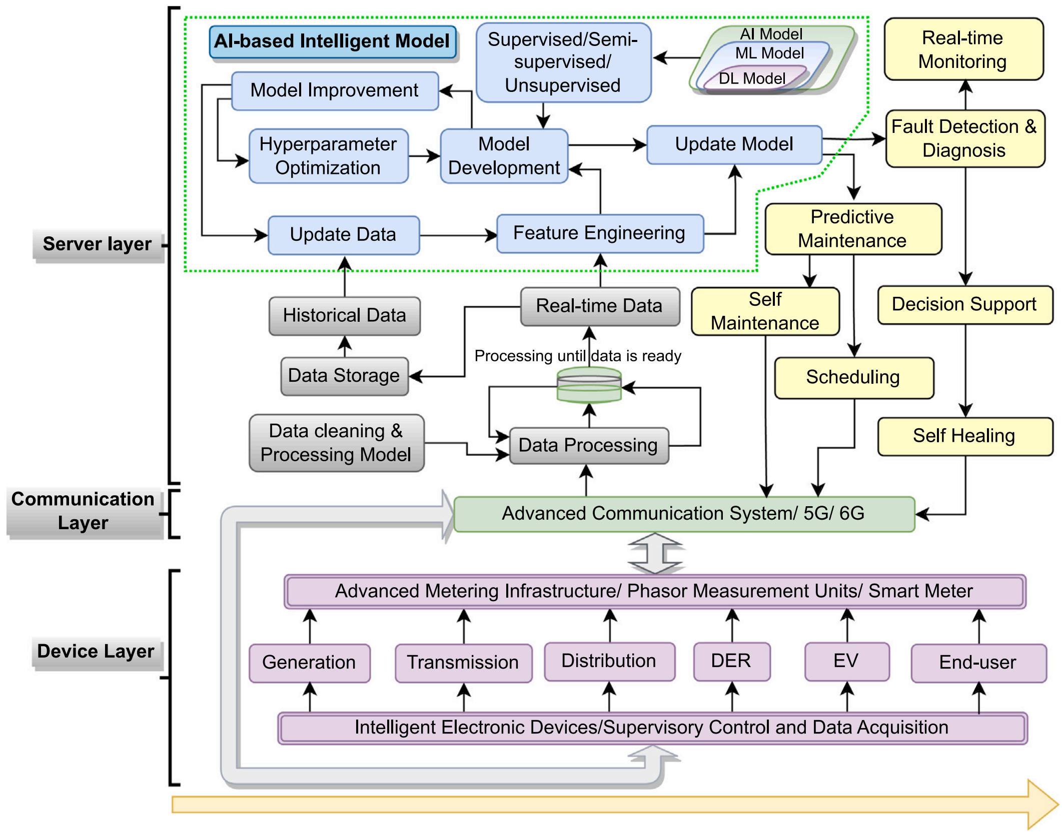

Fig. 9. AI-based intelligent monitoring and fault diagnosis system.

comprehensive architecture of the AI-based intelligent monitoring and fault diagnosis system is depicted in Fig. 9. The implementation of an AI-based monitoring system in the energy grid involves collecting real-time data from smart meters and sensors, transmitting it to a central control system, and storing it in a database. AI algorithms, such as ML, are then used to analyze the data, select features and detect anomalies or patterns [55,96]. The AI algorithms and ML models employed in the server are trained using historical data and patterns, allowing them to learn the normal behavior of the system [97].

The models can detect anomalies or deviations from the expected patterns in real-time, highlighting potential faults or performance degradation. Once a fault is detected, the system generates alerts or notifications, which are represented by the output arrows in the figure. These alerts can be sent to the operators or maintenance personnel through various communication channels, such as emails, SMS, or dedicated monitoring consoles. In addition to real-time monitoring, the system also employs advanced diagnostic capabilities. When a fault is detected, the system utilizes the collected data and historical knowledge to identify the root cause of the issue. It can analyze patterns, correlations, and dependencies within the data to pinpoint the exact source of the fault. The figure also illustrates a feedback loop between the diagnostic results and the system itself. This loop allows the system to continuously improve its fault detection and diagnosis capabilities based on the outcomes of previous incidents. By learning from past experiences, AI models ensure the effectiveness and adaptability of the system.

4.1.4. Benefits and future trends

Existing MFDS typically rely on predefined rules and thresholds to detect abnormalities and trigger alerts. These systems often require manual configuration and maintenance, to adapt and improve detection capability. On the other hand, AI-based intelligent systems can effectively learn from historical data, improve the model after every operation, adapt to evolving conditions, and provide predictive insights. Moreover, AI-based IMFDS leverage advanced ML and AI techniques to automate the monitoring process and improve fault detection accuracy. These systems can analyze large amounts of real-time data, learn patterns and trends, and dynamically adjust their detection algorithms to changing conditions. There is a need for research on integrating AI-based IMFDS with other emerging technologies such as the IoT, edge computing, and cloud platforms. This integration can enable real-time data collection from various sources, distributed processing, and seamless integration with other maintenance and asset management systems.

4.2. Intelligent control & optimization system

In the context of energy systems, the ICOS refers to a sophisticated solution that is utilized to enhance the efficiency and effectiveness of grid operations. The system can enable intelligent decision-making for load balancing, demand response, and grid optimization.

4.2.1. Existing work

In recent years, AI-based ICOS in energy systems have gained significant attention due to their potential in optimizing grid operation and control. For instance, Singh et al. applied an ANN-based control system in a DC MG to regulate the DC bus voltage and optimal utilization of ESS through OPAL-RT real-time simulator [141]. In a parallel distributed generation system, the conventional droop control strategy faces challenges in accurately regulating the inverter's reactive power output due to uncertainties in line impedance and fluctuations in load. As a result, the MG system experiences voltage deviations. ANN with droop control is proposed for regulating the voltage stability of an islanded DC MG during different transient scenarios where the ANN

Table 5
Summary of current research on ICOS.

AI Algorithm	Approach	Main Contributions	Mode	Platform	Reference
ANN	GA-optimized ANN-based controller	V/f regulation	Off	MGs	[111]
MLP	Adaptive NN	V/f stabilization	On	MG	[112]
NN	Neuro-fuzzy direct power control	Regulate active and reactive power	On	DC & AC Grid	[113]
PPWFNN	Fuzzy NN controller	Voltage stability	Off	MG	[114]
N/A	ADP approach	Frequency stability	N/A	MG	[115]
N/A	Meta-heuristic with statistical techniques	Stability of a DC/DC boost converter	N/A	DC MGs	[116]
HKHSM	MPPT and NRHSM fuzzy neural technique	Mitigate harmonics and voltage fluctuation	On	PV-SG	[117]
LSTM	Compared to SVM and ANN	Maintain stable power flow	N/A	DNs	[118]
ATLA	NPO and ATLA based approach	Regulate power flow	On	SG	[119]
LSTM	ANF control algorithm	Improve power quality and system performance	N/A	SG	[120]
ANN	ANN-BBSA and ANN-Binary PSO algorithm	Optimize the scheduling of DG	N/A	VPP	[121]
N/A	N/A	Manage and distribute energy resources	On	SG	[122]
LSTM	AI-Empowered Recommender System	Predict generation and minimize error	On	SG	[123]
N/A	Smart control approach	Fault localization, monitoring, and control	N/A	CG	[124]
ANFIS, MFNN	ANFIS and MFNN	Maximizing the PV generation	On	PV-SG	[125]
N/A	IoT-based system	Monitor consumption and enhance efficiency	N/A	SG	[126]
ANN	ADP and LM algorithm	Voltage stability	Off	DC MG	[127]
ANN	HDP approach	V/f regulation	Off	VSC	[128]
ANN	DHDP approach	Optimal control	On	Grid	[129]
RL	DDPG and a controller for MIMO case	Frequency regulation	On	MGs	[130]
RL	DDPG algorithm	Optimal control	On	VSG	[131]
ANN	Secondary control	V/f regulation	Off	VSG	[132]
ANN	DDHP controllers	Frequency regulation	Off	AC MGs	[133]
BPNN	Bellman principle and DP	Current sharing, voltage regulation	Off	DC MG	[134]
RL	Multi-agent	V/f regulation	On	MG	[135]
DRL	Local agent	Voltage restoration	Off	DC MG	[136]
RL	MLP	Frequency and voltage stabilization	Off	Multi MG	[137]
FFNN	Droop control	Power-sharing droop control	Off	MG	[138]
RL	HDP approach	Optimize voltage and frequency regulation	On	VSG	[139]
LM-ANN	ANN controller to regulates VSC	Regulates VSC	On	PV-MG	[140]
ANN	PSO based Intelligent decision support	Frequency control	On	BESS	[17]

Table 6
AI techniques for ICOS.

AI Algorithm	Publication Year			
	<2016	2016–18	2019–21	2021<
ANN	[143]	[17,111,127,132]	[19,121,128,129,133,140]	[141,144]
ANFIS	N/A	[110]	[142]	[125]
NN, FFNN	N/A	[112,138]	N/A	[113]
LSTM	N/A	[145]	N/A	[118,120,123]
SVM	N/A	[145]	N/A	N/A
RL, DRL	N/A	[136]	[130,131,135, 137,139]	N/A
BPNN	N/A	N/A	[134]	N/A
PPWFNN, HKHSM	N/A	N/A	[117]	[114]

controller is assessed using switching models of power DC converters [127]. Feedforward neural network (FFNN)-based droop control approach not only resolves the power-sharing issue but also ensures simultaneous control of MG voltage and frequency within specified limits [114,138]. Combination of adaptive compensation and neural networks (NN)–fuzzy control to achieve effective distribution of reactive power, control strategy, and stability analysis [142]. Simulations and experiments validate the robustness and stability of the adaptive compensation control strategy within the droop control framework.

Different intelligent algorithms such as genetic algorithm (GA) with ANN and PSO with ANN have been used to improve grid operations, planning, and stability control [19,111]. Furthermore, an ADP architecture and algorithm are developed to maintain the current sharing and voltage regulation without relying on an accurate model of the DC MG [134]. Mu et al. have also proposed adaptive dynamic programming (ADP) to adjust the power outputs of the micro-turbine and ESS to mitigate frequency fluctuations [115]. The adaptive RL controller [135] has a supervisory nature and can enhance the performance of various controllers by introducing an offset signal to their output control signal. A distributed RL strategy involves several steps such as equal proportional current sharing and cooperative voltage restoration, optimal pinning consensus value, and the synchronization-seeking process of the pinning reward to achieve an optimal solution [136]. In the case of secondary control, [132] explores an ML-based cascaded approach to address voltage stability in isolated MGs. Jafari et al. applied multilayer perception (MLP) by considering dynamics uncertainties, faults, and disturbances to develop an intelligent secondary controller in an MG [112]. Because of the high penetration of RES, the heterogeneity and uncertainty associated with RES can lead to frequency instability in MGs. In addition, virtual inertia devices alone cannot ensure satisfactory frequency stability. To address this issue, Skiparev et al. developed a RL-based method for virtual inertia control of islanded MGs and compared its performance with H-infinity and optimally tuned proportional integral (PI) controllers [130]. Conventional PI controllers can be replaced by NN-based heuristic dynamic programming (HDP) [128] and dual heuristic dynamic programming (DHDP) [129] approach in case of optimizing the virtual inertia-based control of grid-connected three-phase inverters. Furthermore, an online trained probabilistic wavelet fuzzy neural network (PPWFNN)-based controller is introduced as a replacement for the traditional PI controller in a battery ESS [114]. Venkatesan el al. showed that ANN controller offer advantages over conventional PI and PID controllers, especially when the MG structure changes or new RESs are added [140]. Moreover, Abdul Baseer et al. applied normalized reasoning-based fuzzy neural adaptive (NRFNA) control technique for a double-stage grid coupled solar PV system [117]. Similarly, a fuzzy NN intelligent controller model is developed for fault detection and control of a hybrid PV/WT-based SG system [146].

The data-driven DHDP model [133] can address accurate active power sharing and rapid frequency restoration without relying on precise model parameters. The control problems for virtual synchronous generators such as maintaining frequency deviation within limits, preserving well-damped oscillations, and achieving a gradual frequency

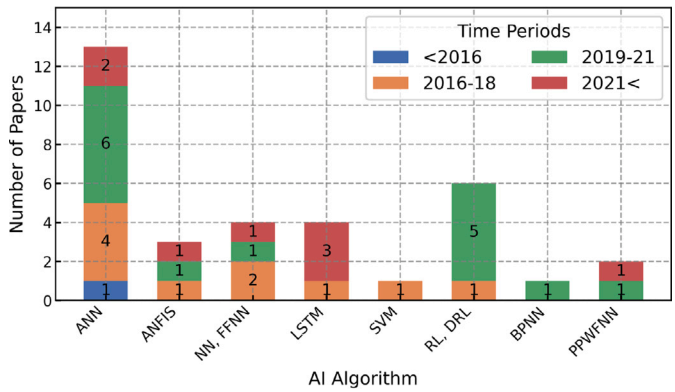

Fig. 10. Application trends of AI algorithm in optimization and control system.

drop during transients are mitigated by DRL [131]. In [137], a RL-based controller is trained on multiple switching transient scenarios, to modify generator controls during significant frequency deviations. To enhance the stability of a DC/DC boost converter, the population-based meta-heuristic algorithm is integrated with statistical techniques to effectively evaluate the behavior of the controller. The HDP-based technique is proposed to optimize voltage and frequency regulation in grid-connected virtual synchronous generators [139]. However, the combination of NN and local optimization can achieve faster scheduling of electric energy flows in SGs to balance consumption and production than meta-heuristic algorithms [147]. Furthermore, a resilient hierarchical control method is applied to control MGs intelligently where the primary control level focuses on adjusting MG voltage and frequency; the secondary control level ensures that MG voltage and frequency return to their nominal values; and the tertiary control level introduces an optimized evaluation of the weighted parameters for the multi-stage H controller through the harmony search optimization (HSO) algorithm [148]. The research has been proposed DL based intelligent controller model that incorporates four different compensators (UPFC, DPFC, USSC, and UPQC) to enhance the power quality of the system.

Table 5 summarizes the main contribution, applied technologies, implementing approach, and application platform on ICOS. Moreover, Table 6 shows the modern technology applied in different articles for ICOS. The yearly application trends of AI algorithms in ICOS are shown in Fig. 10.

4.2.2. Research gap

From the explanation, the different solutions for the existing problems such as voltage stability, frequency stability, large transient issues, different converter controlling, primary, secondary, and tertiary control, droop control, and improvement of PI controller are presented in detail. Nevertheless, the main research gap lies in the development and implementation of advanced AI techniques for efficient grid control and optimization. While existing grid systems have made progress in integrating advanced technologies for monitoring, communication, and automation, the full potential of AI-based ICOS is yet to be realized.

4.2.3. Exploration of prospective architecture

Several methodologies are used for ICOS across various energy systems to enhance performance, stability, and efficiency. For instance, GA-ANNs are utilized for precise V/f regulation, improving voltage and frequency stability in microgrids. ANNs adapt their parameters based on real-time data to stabilize voltage and frequency. Neuro-fuzzy and direct power control systems combine neural networks with fuzzy logic to manage power effectively, optimizing active and reactive power in AC grids. Fuzzy NN controllers apply fuzzy logic within neural frameworks to enhance voltage stability, especially in off-grid microgrids. Meta-heuristic algorithms with statistical techniques are used to stabilize the performance of DC/DC boost converters, crucial in DC microgrid applications. IoT-based systems integrate real-time data acquisition and control, enhancing efficiency and monitoring. Multi-agent and RL approaches provide decentralized decision-making for optimal control and frequency regulation across various grid setups. Hybrid methods, like combining ANNs with PSO, are employed for frequency control and optimizing decisions in BESS, ensuring the grid operates optimally under various conditions.

This ICOS leverages real-time data from sensors, smart meters, and other grid devices to analyze and stabilize generation, voltage/frequency regulation, and reliable distribution processes. Fig. 11 shows the proposed intelligent optimization and control architecture for future intelligent grid systems. In the server layer, the data processing unit can effectively analyze large volumes of data generated by SG sensors, devices, and consumer behavior. The sophisticated AI algorithms are developed in the AI-based intelligent unit. These algorithms are able to extract valuable insights, calculate constraints of load, DER, and grid, identify patterns, and make accurate predictions of generation and consumption. It can effectively coordinate and optimize energy consumption patterns, taking into account consumer preferences, demand response programs, and the integration of DER. Reliability and stability models can contribute to facilitating the integration of RESs. Finally, the ICOS unit processes all constraints and data to optimal control and operation, enhances grid reliability, and supports decision-making processes. The feedback process enables the system more intelligent and robust for further operation. Moreover, the intelligent real-time control systems will enable dynamic grid optimization and adapt to changing grid conditions, such as fluctuating energy demand, varying renewable energy generation, and potential grid disturbances.

4.2.4. Benefits and future trends

The ICOS facilitates automated control and coordination of grid assets to manage the grid in a more efficient, reliable, and sustainable manner, leading to improved grid stability, reduced energy costs, and enhanced customer satisfaction. Hence, future work can involve extending the application of the efficient AI-based droop control [138], DHDP-based robust voltage control [133], intelligent secondary controller [112] to a network of MGs or community-based MG with a larger number of DG units. The RL-based controller can be modified and developed for energy transmission and demand-side management problems,[130], virtual synchronous generators, [131] and conservation voltage reduction controller penetration [137]. However, further research is needed to explore more complex scenarios and conduct detailed analyses such as AI-based techniques for grid resilience and cybersecurity to ensure the security and resilience of the control system against cyber threats and physical attacks.

4.3. Intelligent energy management system

In the context of energy systems, the IEMS can revolutionize the way electricity is distributed, consumed, and generated. By harnessing advanced technologies and AI, ML, DL, and DRL algorithms, it can optimize the entire energy ecosystem, making it more efficient, reliable, and sustainable.

4.3.1. Existing work

With growing energy demands, optimal energy management among utility grid, micro-grid, DER, and other resources are crucial to minimizing the generation cost, and grid stability and reliability. To address those issues, researchers propose several energy-efficient intelligent grid architectures and management systems in different energy systems. This approach involves collecting real-time data from various sources, analyzing it with sophisticated algorithms, and using AI and optimization techniques to make intelligent decisions. Regarding this, Panda et al. proposed overall AI-based intelligent management architecture for future SG research [49]. However, most of the studies have been

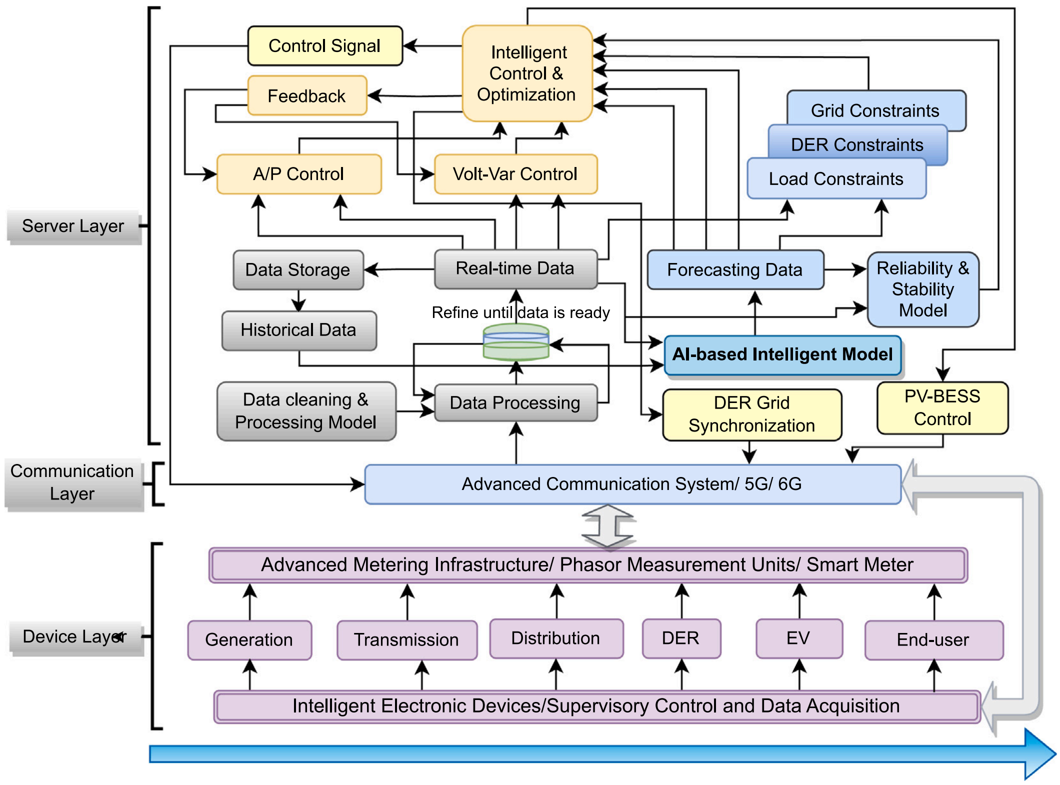

Fig. 11. AI-based intelligent optimization and control system.

Table 7
Summary of current research on IEMS.

AI Algorithm	Approach	Main Contributions	Mode	Platform	Ref.
ANN	ANN-BBSA, ANN-BPSO based approach	Energy management	N/A	VPP	[121]
FFNN	Intelligent decision-making system	Energy management	On	SG	[149]
RNN	Intelligent mechanisms	Energy management	On	SGart MG	[150]
N/A	Fuzzy logic controller based hybrid system	Energy management	N/A	SG	[146]
DRL	N/A	Grid stability and reliability	On	SG	[151]
N/A	Decisive Algorithm	Optimizing generation and balancing	N/A	PV MGs	[152]
LSTM	ANF control algorithm	Improve power quality and performance	N/A	SG	[120]
N/A	Multi-agent approach	Control energy consumption	On	SB	[153]
LSTM	Incorporating AI and IoT	Improve power quality and consumption	On	SG	[154]
LSTM	MILP	Optimal decision-making in MG	On	MG	[155]
CNN	N/A	Efficiently manage energy	On	SI	[156]
Transformer	Comprising ST and TT	Optimal energy management	N/A	SC	[157]
LSTM, GRU	Edge intelligence	Optimize energy management	N/A	SGs, SB, SC	[158]
N/A	PSO based intelligent decision support	Enhance the efficiency and performance	N/A	SG	[159]
RL	Multi-objective techniques	Controlling the operation of a multi-MG	On	Multi-MG	[160]
N/A	Fuzzy logic method	Minimizing energy consumption and cost	On	SB	[161]
N/A	Fuzzy logic and GA-PSO approach	Optimize schedule and system efficiency	On	SG	[162]
N/A	Hybridized intelligent	Optimize energy utilization	N/A	SB	[163]
N/A	Open-loop control and quadratic programming	Energy management	On	Community MG	[164]
	Fuzzy inference system	Maintains energy balance	On	PV-MG	[165]
N/A	N/A	Efficiently manage and distribute resources	On	SG	[122]
N/A	PI and Fuzzy logic method	Minimize payback time and improve reliability	On	Zero-SB	[166]
DL	DL and ADP approach	Management of DG	On	MG	[167]
DL	Comprising ST and TT	Smart Energy Management		SC	[168]
DL	Optimized DL models	Energy management	N/A	SG	[169]
DRL	Local agent	Load sharing	Off	DC MG	[136]

focused on designing and developing an individual part of the energy grid system. For instance, ML integrated data-driven scheme is designed to derive optimized local controls of the active distribution grid based on historical data processed through a coordinated optimization power flow [170,171].

The grid-connected renewable energy farms pose several challenges due to unpredictability and fluctuating behaviors. Novakovic et al. proposed NN based controller that optimizes the utilization of the distributed storage to support ancillary grid functions such as frequency regulation at the wind farm level [143]. The NN also utilized to determine the optimal power distribution over a one-week time horizon for the wind, solar, battery, and electric car systems. The objective is to minimize the reliance on the utility grid while maximizing the utilization of RES [181].

Integration of DL with an optimization algorithm provides a more efficient and robust solution for optimal scheduling of the connected resources in the grid. Regarding this, the ANN-based backtracking search algorithm (BBSA) and ANN-binary particle swarm optimiza-

Table 8
AI techniques for IEMS.

AI Algorithm	Publication Year			
	<2016	2016–18	2019–21	2021<
ANN	[143]	[17,127]	[121,140]	[141]
CNN	N/A	N/A	N/A	[109,156]
NN, FFNN	[127,147,172,173]	[149]	N/A	[174]
LSTM, GRU	N/A	N/A	[155,175]	[120,154,158]
SVM, SVR, LR	N/A	[171]	[170,176]	N/A
RL, DRL	N/A	[136,177]	[178]	[151,160,179]
RNN	[180–182]	[183]	[150]	N/A
Transformer	N/A	N/A	N/A	[157]
DL	N/A	[167]	[168,169]	N/A

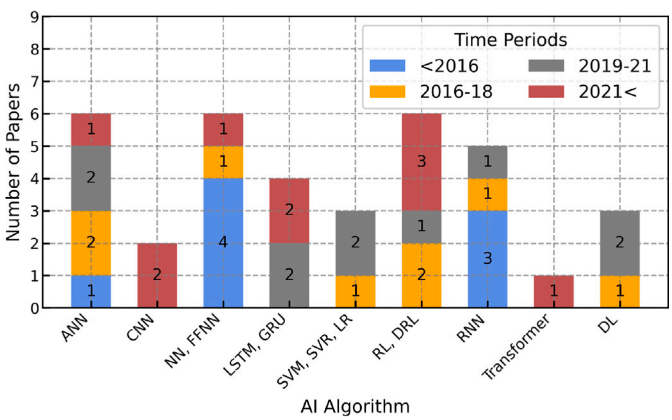

Fig. 12. Application trends of AI algorithm in the energy management system.

tion (BPSO) algorithm are applied for scheduling in VPP [121]. The NN and local optimization algorithms are combined to achieve faster calculation times compared to the GA approach [147]. Duan et al. proposed a DRL-based online optimal scheduling method among hybrid ESSs, PV systems, and diesel generators in AC-DC MGs [178]. Some RL approaches utilize a diffusion strategy to coordinate actions among multiple agents in the MG, avoiding the curse of dimensionality and ensuring convergence [177]. The multi-agents approach enables collaboration among different generation units within the MG to optimize economic exchanges with the main grid [172]. Moreover, Wu et al. proposed a DL-ADP-based framework which incorporates closed-loop feedback guides flexible load consumers to change their energy consumption habits and allows MG operators to achieve intra-day scheduling [167].

Researchers focus on the comprehensive control strategy based on NN for BESS, considering factors such as state of charge and terminal voltage [182]. In addition, they also focus on the hybrid approach for optimized scheduling in a smart MG [150], home MG [184], community ESS [179,185,186], where energy consumption and generation for the following day are predicted by different DL algorithm. For instance, Dobbe et al. proposed ML based framework for distribution system operators to efficiently plan and operate DER contributions, leading to effective distributed energy services in distribution networks [176].

Table 7 provides a brief overview of the relevant studies on IEMS including main contribution, applied technologies, application process, and application platform. Table 8 also illustrates the contemporary technology used in different research for IEMS. Fig. 12 depicts the yearly trend of AI algorithm applications in IEMS.

4.3.2. Research gap

Many challenges, including energy management, optimal energy flow, optimal operation and scheduling, and supply and demand balance, are addressed by recent research. However, most of the studies skip the development and improvement of the AI-based-IEMS architecture that promotes the integration of RES and supports the decarbonization goals. For instance, the dynamic tariff model or weather model has been overlooked and utilized AI and optimization algorithms only. Several research did not take feedback analysis or predicted constraints into account as well. Consequently, the entire potential of AI-based intelligent grids has not yet been highlighted, despite tremendous advancements in cutting-edge technologies. Moreover, the primary area for study is the real-time application of sophisticated AI methods for effective energy management.

4.3.3. Exploration of prospective architecture

In recent advancements in AI applications to energy systems, various algorithms have been developed to optimize performance, improve reliability, and enhance energy management. For example, ANNs based BSA and BN-PSO are utilized for optimal energy management systems. Intelligent decision-making systems like FRNN and RNN are widely employed for energy management and renewable energy management, respectively, illustrating their pivotal role in adaptive and real-time decision processes. Adaptive and dynamic control algorithms based on fuzzy logic enhance grid stability and optimize power distribution, ensuring efficient energy utilization across modern smart grids. LSTM integrated with ANF and MILP improve optimal energy management through IoT-enabled environments, while LSTM, GRU, CNN and transformer architectures manage and forecast energy demand on a large scale. AI also extends into system optimization and resource management with algorithms designed to manage DG systems, reflecting a shift toward decentralized energy resources. The integration of DL and DRL showcases a forward-thinking approach to achieving autonomy in energy management systems, aiming to maximize efficiency and minimize energy costs in smart grids and renewable energy based microgrids.

Following the research gap, this article proposed an IEMS architecture incorporating the AI and optimization system. Fig. 13 illustrates the future AI-based IEMS architecture. Depending on the services and applications, the most of operations will be performed on the server layer, either in the cloud or at the edge. For instance, the data processing unit at the server layer can efficiently analyze huge amounts of data produced by SG sensors, devices, and customer activity. For reliable and precise operation, the data-driven IEMS will take into account all potential constraints and dependencies. The intelligent algorithms are capable of identifying patterns, computing load, DER, and grid restraints, extracting useful insights, and creating precise generation and consumption predictions. With consideration for customer preferences, demand response initiatives, and the integration of DER, it may efficiently coordinate and optimize energy usage patterns. The intelligent management unit analyzes the weather and dynamic tariff model, which accelerates the decision-making processes through the coordination of RES, DER, and load connected in any energy network.

The system becomes more intelligent and reliable as a result of the feedback process. Moreover, the sophisticated real-time systems will enable dynamic energy management and react to shifting grid conditions, including variable energy demand, varied RES supply, and possible grid disruptions.

4.3.4. Benefits and future trends

The IEMS can ensure a highly adaptive and responsive grid system that maximizes energy utilization, minimizes waste, integrates renewable sources, and reduces costs for consumers. Hence, future research will explore the advancement of ML techniques for data-driven energy management in terms of accuracy, performance, and computational efficiency [169,170,175]. It may also involve incorporating sequential learning for real-time energy forecasting and integrating set theory concepts NN for monthly or weekly energy forecasting [156]. In addition, integration of optimization algorithm with adaptive AI model will ensure higher reliability in single or multi-MG energy

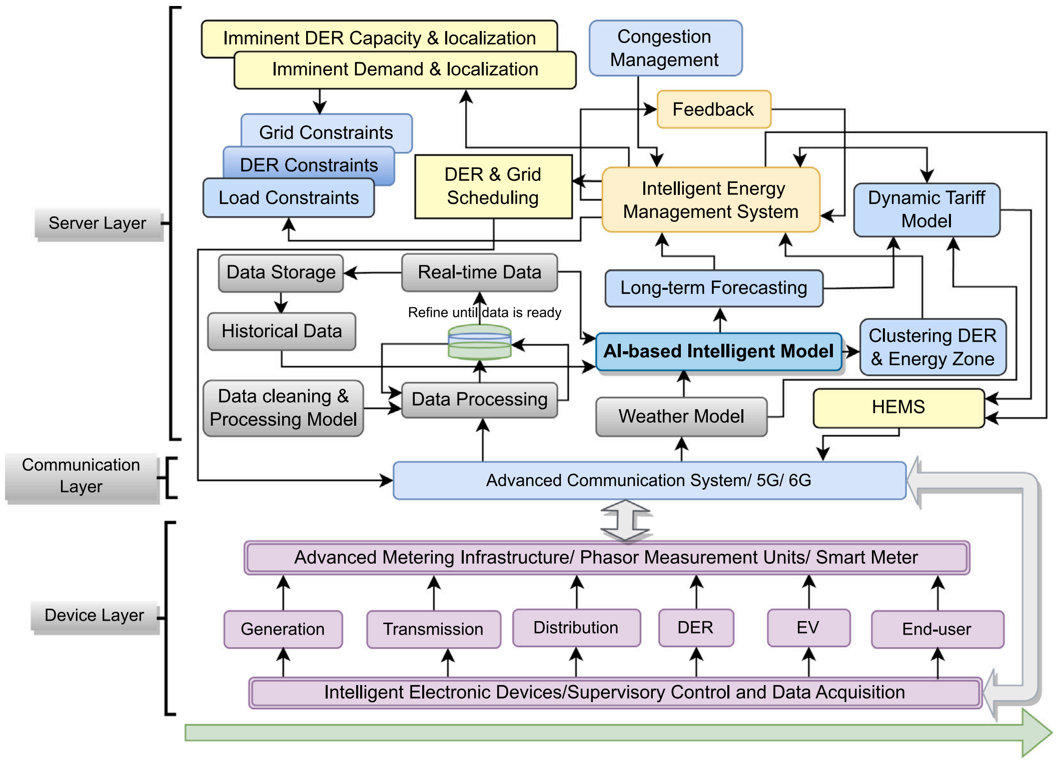

Fig. 13. AI-based intelligent management system.

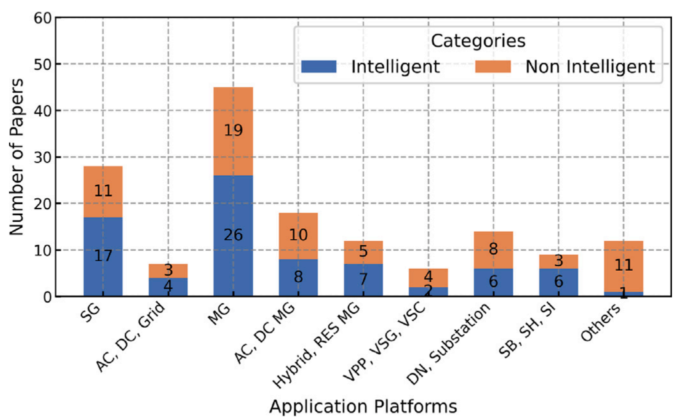

Fig. 14. AI application trend in different energy platforms.

management [178,179,187]. For enhancing training and evaluation by incorporating noisy data, voluminous data from multiple sources are managed through federated, distributed, or decentralized training. In addition, privacy and security are addressed by integrating DL models with blockchain technology [157,168].

4.4. Formulas applied in AI-based energy system

In exploring the application of AI in various energy systems, numerous studies employ specific formulas. The mathematical formulations are described in the following subsection.

4.4.1. Fault detection

In the context of fault detection within electrical systems, a variety of methods are implemented. For instance, [9] employed an SVM for real-time fault detection and classification. The data were collected and processed to produce a set of complex features. SVM utilizes a technique known as the kernel function $k(x_i, x)$. This function, $k(x_i, x)$, is equivalent to $\varphi(x_i)\cdot\varphi(x)$, and serves to project linearly non-separable patterns into a higher-dimensional feature space. As a result, the decision function can be reformulated as follows:

$$f(x) = \operatorname{sign}\left(\sum_{i=1}^{n} \alpha_i k(x_i, x) + b\right) = \operatorname{sign}\left(\sum_{i=1}^{n} \alpha_i(\varphi(x_i)\cdot\varphi(x)) + b\right). \quad (1)$$

where $x_i = [x_1, x_2, \dots, x_n]$ is an n-dimensional input vector, and b is termed as the biasing unit. Here, n represents the number of features.

4.4.2. Control and optimization

In the realm of control and optimization within energy systems, various methods are employed to regulate and optimize voltage and frequency. For example, the authors in [111] utilized the following objective function to control voltage and frequency signals to align with their rated values:

$$f_{\text{object}} = \sum_{i=1}^{K}\left[\sum_{n=1}^{N=t\cdot k_{sc}} \Delta V_i^2(n) + K_f \cdot \sum_{n=1}^{N=t\cdot k_{sc}} \Delta f^2(n)\right] \quad (2)$$

where, ΔV_i and Δf represent the voltage and frequency deviations, respectively. In addition, K denotes the number of inverter-interfaced distributed generations, and N indicates the number of samples over the simulation time t.

4.4.3. Energy management system

In the field of energy management, a variety of approaches are employed. For instance, [184] combined DL and optimization algorithms to achieve optimal energy management of BESS. In this method, forecasted outputs are used as constraints and factors in the objective function. The following equations are employed to derive the optimal solution:

$$(\hat{E}_{t+1}, \hat{E}_{t+2}, \dots, \hat{E}_{t+24}) = \text{LSTM}(E_{t-k+1}, \dots, E_{t-1}, E_t) \quad (3)$$

$$E_{\text{Dis}}^{\text{ESS}}(t) = E^{\text{AD}}(t) - \hat{E}_{\text{Avg,d}}^{FAD}(t) \cdot \frac{\hat{E}_{\text{Avg,d}}^{\text{FG}}(t)}{\hat{E}_{\text{Avg,d-da}}^{\text{FG}}(t)} \quad (4)$$

Table 9
Summary of current research trends of AI-based intelligent energy systems in different energy networks.

Network	System	Research trends	Reference
Grid	IMFD	Fault detection, location, monitoring and diagnose	[9,10,56]
	ICOS	Regulate active and reactive power	[113,124]
SG	IMFD	Fault type & zone classification	[54] [100]
	ICOS	Regulate power flow; improve power quality and system performance; voltage stability;	[119,120,122,123,126, 144]
	IEMS	Optimal energy management; scheduling of RES; energy balance;	[109,120,151,154,158, 162]
MG	IMFD	Fault detection & diagnosis, classification, localization, & isolation	[60–65,68,69,73,75,87]
	ICOS	Control, grid support, stability and regulation	[114,141,188–190]
	IEMS	Energy management; scheduling multi-MG; energy balance; energy trading; DR management;	[141,160,164,179]
RES	IMFD	Monitoring and faulty operating condition detection and diagnosis	[53,92,191]
	ICOS	Control & scheduling, grid synchronization	[125,192]
	IEMS	Energy balance, distribution management	[165,193]
Others	IMFD	Heath monitoring; fault detection, classification, & localization; voltage regulation detection; & anomaly detection;	[55,58,67,93,101,102, 106]
	ICOS	Controlling stable power flow	[118]
	IEMS	Energy management; minimizing energy consumption and payback time; improving reliability;	[156,157,174]

$$\min \sum_{t=t_{\text{start}}}^{t_{\text{end}}} \left(\text{SOC}^{\text{ESS}}(t) - \frac{E_{\text{Dis}}^{\text{ESS}}(t)}{E_{\text{C}}^{\text{ESS}}} \right) \tag{5}$$

where $\hat{E}$, E^{AD}, $\hat{E}^{FAD}$, E^{FG}, and SOC_{ESS} denote forecasted energy, active demand, forecasted active demand, forecasted generation, and state of charge, respectively.

5. Summary of current research trends, challenges, and future research opportunities

5.1. Current research trends

The current research trends in AI-based intelligent systems encompass various aspects of energy networks, including conventional grids, SG, MG, RES integration, etc. Fig. 14 shows the application of AI in different energy networks. AI techniques have been implemented in different parts of the energy system in the last few years. Those techniques are being utilized to monitor real-time system conditions, fault detection, localization, classification, and isolation to improve system robustness and security. Moreover, it is also applied to optimize energy generation, transmission, and distribution, leading to minimizing the cost as well as maximizing the RES integration. Furthermore, to facilitate seamless operation and minimize the intermittency challenges of grid stability and reliability, intelligent structures are being developed to regulate the RES generation and stabilize the voltage and frequency fluctuations.

IEMS is another area of focus, where AI algorithms are applied for forecasting the volume and patterns of energy generation and consumption for optimizing load scheduling. With intelligent schemes, energy cost optimization is also a key research area to identify and implement energy-saving measures in MG, RES, SB, and SI. For better

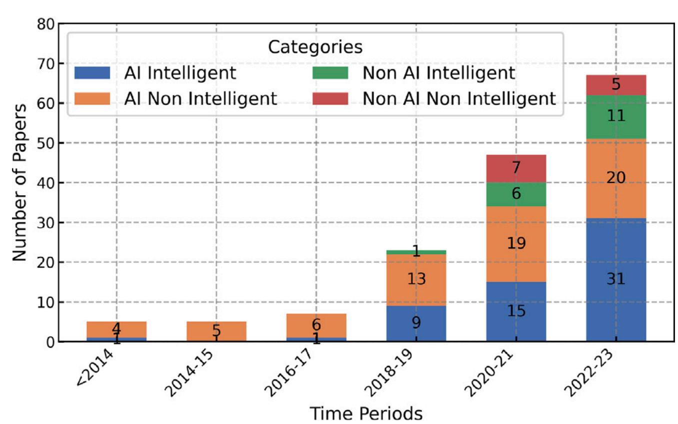

Fig. 15. Yearly research trends on different intelligent energy systems.

presentation, the summary of current research trends of AI-based intelligent systems in different energy networks is presented in Table 9. Figs. 15 and 16 present the yearly research trend on different intelligent system-based energy networks. These trends highlight the potential of AI-based intelligent systems to transform the energy sector into a more sustainable and efficient domain.

5.2. Challenges of AI-based intelligent grid systems

AI-based intelligent grid systems have the potential to revolutionize the way of energy systems. However, there are a number of challenges that need to be addressed before these systems can be widely deployed.

- Data Availability: Intelligent energy systems rely on large volumes and high resolutions of data to train and learn. Shortage

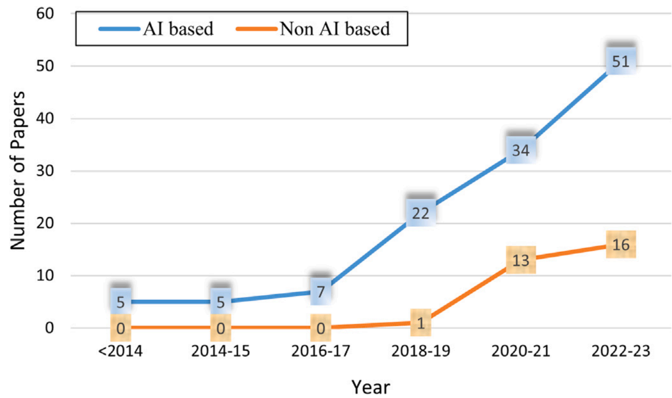

Fig. 16. Yearly research trends on AI and Non-AI based system.

of upgrade data collection/measurement systems, the secured and reliable data can be difficult to obtain. Consequently, the inaccurate decision leads negative impact on the performance of the system.
Possible solution: The application of advanced sensors is one of the potential solutions to this issue. For instance, [194,195], and [196] described some solutions regarding the development of future grid sensors.

- Cyber Security: The intelligent energy system are vulnerable to cyber attacks, including false data injection, data manipulation, malware attacks, denial of service attacks, and system manipulations. These attacks can result in power disruptions, blackouts, incorrect decisions, operational inefficiencies, financial losses, data breaches, and posing national security concerns.
Possible solutions: The system can be more secure and reliable through the implementation of advanced AI-based robust data encryption, access controls, and privacy policies [197,198] describes several processes for cyber–physical and cyber security systems in future grid systems. In addition, regular security audits and updates must be conducted to stay ahead of potential threats.
- Computational complexity: Implementation of AI, control, and optimization algorithms especially in the end devices can be very computationally expensive and complex. In addition, those devices often require specialized hardware that can be more complex to design, develop, and maintain.
Possible solutions: One of the possible solutions can be federated learning, which allows models to be trained across distributed data sources [199]. In addition, cloud, edge cloud, and edge computing can provide distributed and adaptable solutions for these issues [200,201].
- Explainability and Transparency: Intelligent systems that utilize AI algorithms such as DL, ML, and DRL are often considered "black boxes" because of their complex functionality and decision-making process. Consequently, it is difficult to trust these systems and to ensure that they are making user-friendly decisions.
Possible solution: Develop standardized trained and test protocols that enable smooth integration of trustworthy AI technologies into the system [49]. Additionally, collaboration among different sub-systems of the grid, technology companies, and policymakers for developing AI models that are interpretable and transparent in their decision-making process [50].
- Integrating AI-based systems: The current infrastructure might not be compatible with the integration of AI-based systems while retrofitting the legacy systems can be expensive and time-consuming. Moreover, implementing AI-based systems requires advanced communication protocols and data management and control systems, which can introduce the overall complexity and expenses of the process.
Possible solution: Distributed AI architectures, standardized data formats and pre-processing, effective human-AI collaboration, and advanced communication systems can be utilized to overcome these obstacles [3,202].
- RES Integration: The main challenge of RES integration in any system is its unpredictable characteristics. Variations in voltage and frequency brought on by fluctuations in RES output can influence grid stability and power quality, perhaps causing outages or equipment damage. High levels of RES integration may cause grid congestion, requiring system modifications and strengthening to handle increasing power flow.
Possible solution: Implementation of intelligent forecasting AI models able to handle the intermittent uncertainties of RES [203]. In addition, advanced and adaptive control and optimization techniques can maintain grid stability through real-time monitoring and predictive control [204].
- Ethical and social implications: Incorporating AI into the system gives rise to apprehensions, including issues related to algorithmic bias, workforce displacement, and societal inequities [205]. Addressing these concerns and advocating for responsible AI implementation becomes crucial to minimize potential risks.

Addressing these challenges are crucial to unlocking the full potential of AI-based intelligent grid systems and enabling a sustainable and efficient energy future. The comprehensive set of applications for the upcoming intelligent grid system is shown in Fig. 17.

5.3. Future research scopes

The technical challenges discussed earlier have given rise to numerous research possibilities. The following paragraphs outline several promising opportunities for future perspectives.

1. Intelligent architecture: The current infrastructure of IMFDSs, ICOSs, and IEMS partially supports the integration of emerging technologies and the increasing complexity of energy grid tasks. The infrastructure needs to be improved based on the requirements of the intelligent grid system [3,49]. The future study direction is on researching and developing a more resilient and efficient grid architecture, this initiative seeks to redesign the fundamental structure of these systems to accommodate and leverage advancements in AI and big data analytics.
2. Advanced AI algorithms: The existing IMFDs, ICOSs, and IEMS systems may lack the capability to make transparent, interpretable, and precise control decisions with maximum accuracy and computational complexity. This direction targets the need for more sophisticated AI algorithms that can adapt to and optimally manage complex, dynamic grid environments while maintaining user trust through transparency and interpretability. The exploration of advanced AI techniques such as explainable AI, self-supervised learning, multimodal learning, federated learning, DRL, and hybrid AI models aims to enhance decision-making processes in real-time applications [48,49].
3. Edge computing and IoT: The existing grid systems, including those used in IMFDSs, less effectively handle the decentralized, data-intensive operations that modern energy systems require. This approach addresses limitations related to data latency and system responsiveness, promoting a more distributed and responsive grid infrastructure. By focusing on the development of advanced IoT and energy-efficient edge devices, this research aims to bolster the grid's capacity to process data at or near the source of data generation. The research on developing advanced IoT and energy-efficient edge devices will accelerate the development of intelligent grid systems [206].
4. Blockchain-enabled system: Security, privacy, and efficiency of transactions within IMFDSs and IEMSs can be problematic due to

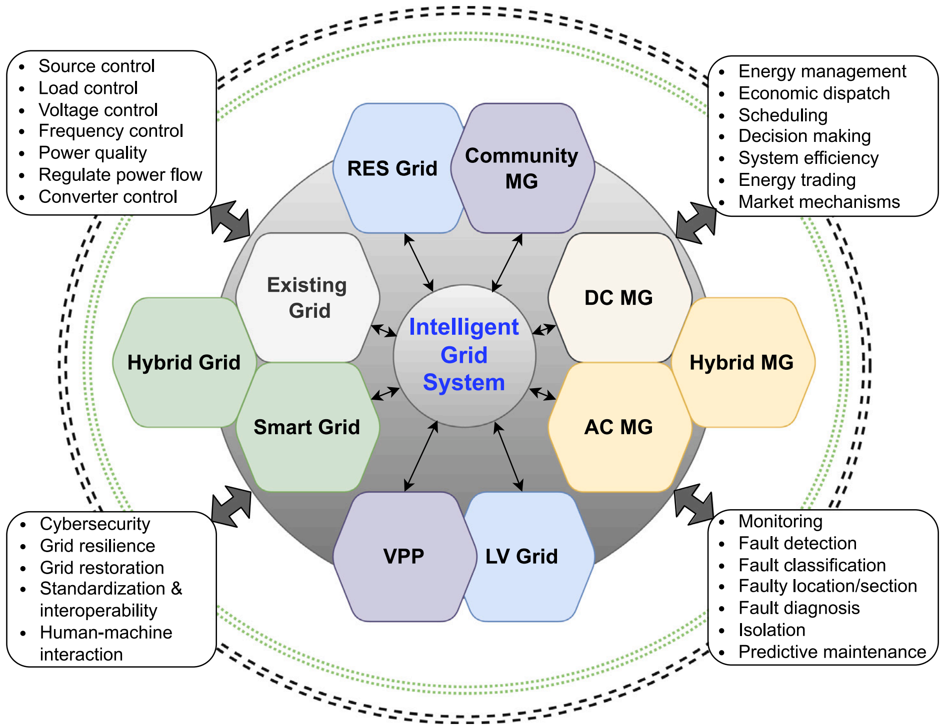

Fig. 17. Different applications of the future intelligent grid system.

centralized control systems. Integrating blockchain technology promises to enhance decentralized decision-making capabilities, improve transparency, and secure data exchanges. Research on the blockchain-based intelligent energy system will open new dimensions of intelligent grid systems [168,207,208]. This research direction seeks to fill the gaps in current systems' ability to handle transactions and interactions securely and efficiently across various grid participants.

5. Energy-aware distributed community MG architecture: The existing community MG architectures have insufficient support for zero-carbon goals or effectively manage grid congestion. The intelligent community MG can offer promising chances for the conversion of the existing grid system to the intelligent grid system. The research on developing ICOSs and IEMSs will not only support renewable integration but also enhance grid resilience and stability [185,209]. This aligns with the need for more sustainable and efficient energy distribution models that can accommodate the dynamic nature of distributed energy resources.
6. Introduction of quantum computing: Fast-responsive IMFDs, ICOSs, and IEMSs in complex grid systems pose significant computational challenges. Quantum computing could revolutionize the energy system by solving complex optimization problems far more efficiently than classical computers. Application of quantum computing on optimization and resources management, grid stability, material science and PV, and nuclear fusion research can bring unprecedented computational power and capabilities to the intelligent grid system [210]. This research could bridge the gap in computational limitations, paving the way for more advanced grid management and energy system optimization strategies.

6. Conclusion

The application of advanced AI models in various grid domains has recently been demonstrated by several studies as a part of this ongoing trend. The comprehensive implementation of those technologies in various energy domains is still in progress. This study highlights several key achievements and opportunities in the realm of AI-based intelligent grid systems. Firstly, it provides an overview of existing reviews and surveys covering AI integration in various energy domains. This analysis uncovers intriguing trends in current research and could aid in comprehending the circumstances that lead to the usage of various AI-based intelligence techniques. Secondly, the study emphasizes the transformative goal of making energy systems more reliable, sustainable, and economical through AI integration, based on an analysis of existing literature. It provides a valuable synthesis of current research and emerging trends across various energy domains, such as IMFDS, ICOS, and IEMS. The work identifies both the challenges and constraints of implementing AI technologies in grid systems and discusses future research directions, including the development of comprehensive intelligent architectures. Finally, it encourages multidisciplinary research to improve efficiency, optimize resource allocation, and facilitate the transition to a clean energy economy, highlighting the growing adoption of AI technologies in the energy and power systems domain. This synthesis of achievements and opportunities is poised to assist industry experts and foster advancements in intelligent grid systems.

The limitations of the intelligent grid system include the need for highly advanced grid infrastructure, significant investment in sensors, communication networks, and control systems, as well as high-quality data inputs and advanced algorithm development. It is also vulnerable to cyber threats, requiring robust security measures and constant monitoring. Future improvements to the system can be achieved by addressing challenges such as improving AI adaptive intelligent architecture, high-performance devices, edge computing, and IoT. Additionally, integrating Blockchain-enabled systems and introducing quantum computing could further enhance its capabilities.

In summary, this study presents different intelligent architectures and potential future research of AI-based intelligent grid systems. By overcoming the challenges, the successful implementation of AI technologies has the potential to foster the advancement of intelligent systems, which are experiencing growing adoption in the energy and power systems domain. This review will assist industry experts in applying AI to the monitoring, control, and management of energy systems. Moreover, it will enable multidisciplinary research in AI-integrated energy systems to improve efficiency, optimize resource allocation, and facilitate the transition to a clean energy economy.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT in order to improve language and readability. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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