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REGULAR PAPER

Sustainable energy management in the AI era: a comprehensive analysis of ML and DL approaches

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Abstract

This study comprehensively analyzes the application of innovative deep learning (DL) and machine learning (ML) techniques in smart energy management systems (EMSs), with an emphasis on load forecasting, demand response, and the development of smart energy sectors. The application of various ML and DL models were examined in over 200 studies from 2014 to 2024 in an electrical network's EMS to highlight the key benefits and advances made by each technology for the sustainable management systems in energy sector. The findings emphasize DL and ML models' enhanced precision and predictive capabilities in load forecasting, their efficacy in enabling efficient demand response mechanisms, and their significance in supporting the development of smart energy sectors. Furthermore, recommendations are made based on the survey results to assist in incorporating these techniques into EMS frameworks, such as investment in data infrastructure, model training and validation, and collaboration between researchers, industry experts, and policymakers. The study also discusses the limitations identified in the literature, such as limited real-world implementations, challenges regarding quality and data availability, and the need for enhanced ML and DL model interpretability. Addressing these limitations can assist in increasing the application and efficacy of ML and DL techniques in EMSs, enabling a more efficient and sustainable energy landscape. Finally, this study facilitates researchers' exploration of ML and DL in energy management, highlighting relevant limitations, strengths, and alternative approaches associated with sustainable energy management. It also indicates potential future research directions for further investigation.

Keywords Machine learning algorithms · Sustainable energy · Prediction model · Energy management

Abbreviations

ANFIS	Adaptive neuro-fuzzy inference system
ANNs	Artificial Neural Networks
AR	Autoregressive

Extended author information available on the last page of the article

ARMA	Autoregressive moving average
CFS	Correlation-based feature selection
CGP	Cartesian genetic programming
CRBM	Conditional restricted boltzmann machines
CRO	Coral reefs optimization
EEMD	Ensemble empirical mode decomposition
ELM	Extreme learning machine
EMD	Empirical mode decomposition
FFNN	Feed forward neural network
FIS	Fuzzy inference system
GA	Genetic algorithm
GARCH	Generalized autoregressive conditional heteroskedasticity
GPR	Gaussian processes regression
IoT	Internet of things
LM	Levenberg–Marquardt
MLP	Multilayer perceptron
MR	Multi-resolution
NDP	Neuro-dynamic programming
NN	Neural networks
PSO	Particle swarm optimization
RMSE	Root mean squared error
SVM	Support vector machine
SVR	Support vector regression

1 Introduction

Climate change has emerged as a significant global challenge, necessitating the transition to renewable energy sources to mitigate its adverse effects. As renewable energy production increases, effective resource management becomes increasingly crucial [1]. Energy management system (EMS) automation and optimization are crucial for maximizing efficiency and sustainability. Machine learning (ML) and deep learning (DL) methods have emerged as viable approaches for addressing the complexities of sustainable management systems. These systems may automate decision-making processes, enhance energy utilization, and contribute to a greener and more robust energy infrastructure by utilizing ML and DL techniques [2, 3]. Because ML and DL are prominent fields of artificial intelligence (AI) research, they encompass an extensive array of applications ranging from autonomous vehicles to customer service conversational bots [4, 5]. These methods are also beneficial for optimizing EMSs. ML can enable computers to learn from data and render predictions based on acquired patterns, enabling accurate demand forecasting for energy systems over varied durations [6, 7]. ML employs various methods that allow computers to make decisions with the minimal human intervention [8–10]. Researchers have applied these techniques in different fields of EMSs, including load forecasting, electric vehicle charging, demand response, and building energy management [11–13]. This study serves as a comprehensive guide for researchers looking to select the most suitable Machine Learning (ML) or Deep Learning (DL) algorithms for their specific research challenges. By detailing the key characteristics and applications of various ML and DL algorithms within Energy Management Systems (EMSs), our analysis provides valuable insights into how these technologies can be leveraged to advance the field. The exploration of these algorithms underscores their potential to revolutionize EMS by enhancing efficiency and predictive capabilities.

The adoption of Machine Learning (ML) and Deep Learning (DL) for enhancing Energy Management Systems (EMSs) marks a recent yet swiftly expanding trend. ML, a branch of Artificial Intelligence (AI), allows computers to extract insights from large volumes of data autonomously, bypassing the need for direct programmingTop of Form [14, 15]. Algorithms, which are just step-by-step instructions for a computer to follow, are employed to accomplish this. However, DL is a subset of ML that utilizes neural networks to process data and make decisions [16, 17]. For example, the adaptive model managed to learn from the historical data set and estimate future demand using this data. The predictive model predicted demand with high accuracy; however, it required more computing power than the other two models [18],. This aspect indicated that it required to be trained with more data than the other two models could handle to achieve high accuracy. Finally, the unsupervised model managed to identify groupings of comparable types of demand without any external user input. These groups proved the capability of forecasting future demand based on past performance [19]. Moreover, the landscape of Machine Learning (ML) and Deep Learning (DL) in Energy Management Systems (EMSs) has witnessed remarkable advancements, underscoring the importance of this research. Initially, ML algorithms like Support Vector Machine (SVM) broke new ground in load forecasting, enabling unprecedented accuracy in predicting electricity demand. Similarly, the Random Forest technique revolutionized demand response, optimizing energy consumption by adapting to real-time data and grid conditions. As the field evolved, DL methodologies, particularly Convolutional Neural Networks (CNNs), transformed fault detection within photovoltaic (PV) systems through superior image recognition capabilities, significantly boosting system reliability and performance [20]. Moreover, the advent of Long Short-Term Memory (LSTM) networks, a specialized form of Recurrent Neural Networks (RNNs), enhanced time series analysis for load forecasting, offering precise energy demand predictions based on historical data patterns. This decade-long journey highlights a dynamic evolution in the applications of ML and DL, shaping a more efficient, reliable, and predictive energy management landscape [21].

Figure 1 depicts some of the general and detailed information.

ML algorithms such as support vector machine (SVM) have been employed in the EMSs for load forecasting to predict electricity demand accurately. Another ML technique, Random Forest, has been utilized for demand response, enabling efficient energy consumption by dynamically adjusting energy usage based on real-time data and grid conditions. These applications demonstrate ML's potential for more effective energy management. Furthermore, DL techniques like convolution neural networks (CNNs) have been extensively used in image recognition and fault detection within photovoltaic (PV) systems. CNN models are adept at analyzing PV system

Fig. 1 AI vs machine learning vs deep learning comparison model

images to detect defects, anomalies, or malfunctions, thus enhancing system reliability and performance. Long short-term memory (LSTM), a type of recurrent neural network (RNN), has been applied in time series analysis for load forecasting, enabling accurate predictions based on historical data patterns and facilitating effective energy planning.

AI technologies have also recently discovered application in renewable energy, with companies such as Google utilizing them in wind farms to improve data prediction [22] and others using them to improve solar panel efficiency [23]. Numerous AI and ML methods for predicting wind and PV power output, predictive maintenance systems for wind turbines, and search for novel solar panel materials are currently available [24, 25]. The potential of ML applications in developing renewable energy is nearly limitless [26]. ML solutions enable maximizing the efficiency of plant operations by anticipating meteorological variables such as PV panel exposure to sunlight, wind direction and intensity in generating wind energy, and rainfall for hydroelectric generators [27]. In addition, ML and forecasting can aid in managing the energy supply for city residents by improving their distribution system [28]. According to the International Energy Agency, AI will be crucial in the energy sector in the future; drastically transforming electricity generation systems has made them more integrated, dependable, and efficient [29]. Several studies on ML applications in solar systems have been presented recently. This study addresses recent advancements and improvements in ML for solar and renewable technologies, providing academics and practitioners with an in-depth evaluation of existing advanced methodologies [30, 31]. Papers published in international journals between 2014 and 2024 were considered. This study extensively used Google scholar, ScienceDirect, Web of Science, SpringerLink, Nature, Scopus, and IEEE Xplore.

This study presents a novel approach by conducting a comprehensive examination of the latest machine learning (ML) and deep learning (DL) applications in multiple domains of smart energy management systems (EMSs), going beyond the scope of a single domain analysis. It offers a detailed evaluation of ML and

DL methods' effectiveness across various EMS-related areas, such as load forecasting, demand response, and smart energy sector development, based on an extensive review of over 200 studies from 2014 to 2024. The study not only showcases the improved accuracy and predictive capabilities of these technologies but also addresses their pros and cons, offering insights for future research and practical implementation challenges. It underscores the importance of investment in data infrastructure and collaboration among stakeholders to enhance the applicability and impact of ML and DL in creating a more sustainable energy landscape, while also discussing potential limitations and future research directions.

The study highlights and discusses the following key aspects:

1. Novelty of the publication: This study gathers and examines the most recent and practical applications of ML and DL methods across numerous domains related to multiple EMSs; rather than focusing on just one domain.
2. Comprehensive analysis: This study provides a detailed analysis of each domain, demonstrating the successful utilization of ML and DL methods in various applications. These methods address challenges and solve problems in different domains, particularly EMSs.
3. Evaluation of pros and cons: This study assesses the advantages and disadvantages of each solution discussed. It highlights the benefits and limitations of employing ML and DL methods in the domains under consideration. Furthermore, the study offers suggestions for further investigation and research.

The rest of the study is structured as follows: Sect. 2 is a rational introduction to ML techniques or, more broadly, data-driven techniques. Section 3 compiles all recently published papers on the subjects related to ML techniques used in energy management covered in this study. Section 4 explores the applications of ML in sustainable energy systems. Section 5 reports on recent research on algorithms (fault diagnostic) in PV, Sect. 5 addresses the strengths, limitations, and alternatives; furthermore, Sect. 5 focuses on the future directions. Section 6 includes the conclusion of this study.

2 Sustainable management systems: ML and DL methods

EMSs are becoming increasingly automated, intelligent, and powerful. This aspect implies that they can manage our power more efficiently and with the less human intervention [32–34]. ML has been used for decades in the energy sector but only recently has it become popularized by companies such as Tesla Motors, Google, Microsoft, Amazon.com, Apple, Facebook, and Twitter, which all rely significantly on ML algorithms for their business models' success [35]. Users benefit from AI every day and sometimes without even realizing it: from Alexa (a ubiquitous implementation of an area of ML defined as natural language processing (NLP)); to Netflix's classification method, which recommends data for users to view next based on related users' interests; to the automated driving that is equipped across many new updated vehicles [36].

EMSs are becoming more intelligent as modern technology advances [37]. Traditional EMSs have several limitations, such as low precision and slow response time. New methods, including AI, ML, and DL, can be employed in EMS to solve these limitations. This study initially discusses the fundamentals of AI, ML, and DL [38]. Then it discusses how they are used in EMS. Predicting variations in the availability of renewable energy sources is essential to improve efficiency in their utilization. ML is a vital tool in predicting these variations [39]. ML can also be used for demand forecasting. Demand forecasting will aid in system planning. Load forecasting also aids in load balancing. Figure 2 depicts various ML models with their types: -

Bayesian classification systems, regression approaches, decision trees, and neural networks are examples of DL classification. The above approaches are also used to analyze building operating system data and forecast short, intermediate, and long, term power consumption in various building environments [40]. DL methods [41], ANNs [42], SVMs [43], and decision-tree-oriented groups [44] are some of the controlled learning approaches used to incorporate the intricate interactions between dependent and independent variables accurately. Multiple regression analysis and SVM algorithms can have higher accuracy with shorter computation time for houses with complicated and uncertain occupant plans and energy consumption histories [45].

Previously, EMSs, smart cities, and big data were typically published independently, with advanced analytics in microgrids/buildings being unusual. Zhou et al. reviewed advanced analytics power generation, focusing on structure and industrially applicable resource management techniques [46]. SVMs have also been employed in electricity supply error detection [47].

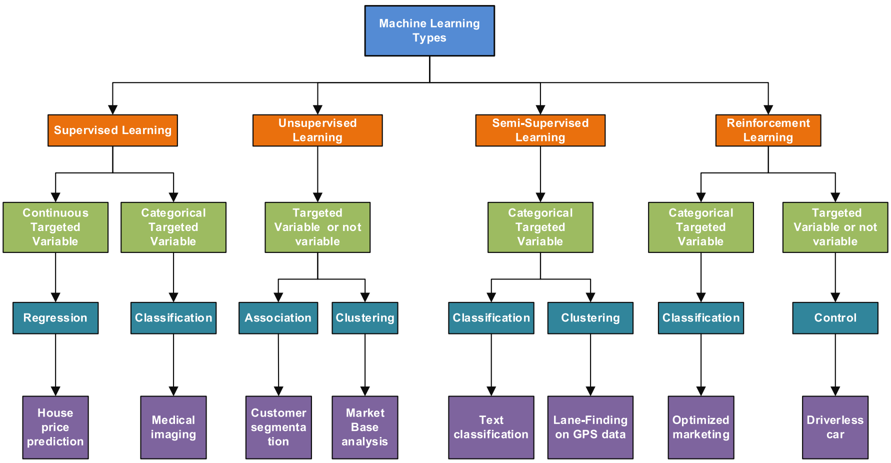

Fig. 2 A comprehensive framework of machine learning techniques and their applications

This research also examined supervised learning ML approaches for wind energy generations. Supervised classification investigates data models and relationships independently. Mahsal et al. [48] and Fan et al. [49] evaluated uncontrolled big data analysis for building energy consumption big data. It focused on unsupervised activity mining forecasts for the Internet of Things. The current research primarily focuses on unsupervised activity mining and linear programming, which might not fully capture the complexity of energy consumption patterns. It could benefit from incorporating supervised learning and hybrid ML models for more accurate predictions and a deeper understanding of energy behaviors.

In [50] and [51] propose ML strategies for developing customized behavior models based on the factor data. Linear programming can be utilized to address an information retrieval issue. However, this research could focus on integrating deep learning (DL) techniques for increased model sophistication and precision, while employing natural language processing (NLP) that could refine data interpretation and retrieval. Additionally, enhancing the scalability and adaptability of these models to accommodate various datasets represents a crucial area for further exploration.

Validation and training are two crucial stages to understanding ML. Validation is the process of determining the model's accuracy or how well it performs. It can advance the model into the validation phase because it will waste considerable time and money if inaccurate. Training is the process of fine-tuning the model to make it as accurate as possible. This aspect can be accomplished through various techniques, such as modifying the algorithm, adding more data, or experimenting with different architectures. While training and validation are vital, they serve distinct purposes: training is intended to improve the model's performance by enhancing its accuracy (i.e., reducing false positives). It also assists in ensuring that the data does not overfit, which implies that it does not perform as well on new or unseen data sets (i.e., increase generalization). Validation evaluates how well-trained models perform with real-world data sets that were not previously utilized by earlier versions of the same models (i.e., measure generalizability). Figure 3 depicts the validation and training processes:

ML approaches are further classified as supervised, unsupervised, semi-supervised, or DL on the format of the training "signal" and "feedback" provided to a learning management system DL. The more advanced analytics and related methods for building automation have been based on (supervised or unsupervised) ML/DL algorithms, which perform in a situational manner for EMSs and thus do not encourage cross-stakeholder DL, Intelligence model reusability and high-speed cross-domain software transformation.

Artificial Intelligence (AI) represents a cutting-edge domain within computer engineering, focused on creating intelligent programs that transform traditional Energy Management Systems (EMSs) into smart, autonomous systems [52]. Within this realm, Machine Learning (ML) and Deep Learning (DL) stand out as pivotal AI methodologies. ML, as a branch of AI, enables systems and programs to self-learn from data without needing explicit instructions, offering a data-centric approach that empowers smart grids to make informed, effective decisions [53]. ANN is a computer science application that assists in various energy applications. DL, also known as a deep neural network (DNN), is a unique type of neural network that varies from

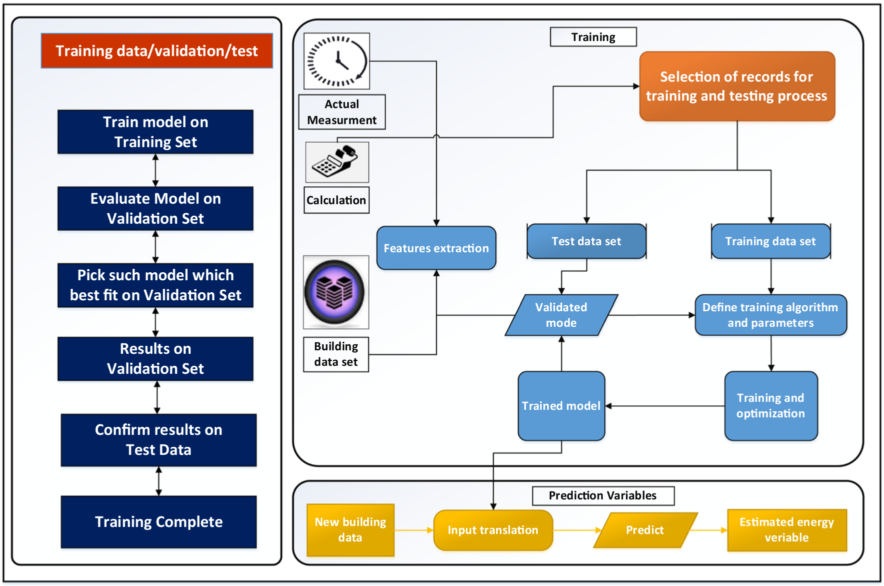

Fig. 3 Machine learning training and validation processes

traditional ANNs (sometimes defined as DNNs or shallow neural network (SNNs)) as it has various layers, complicated connection designs, and various transmission operations to improve the power quality of PV or wind systems.

However, while these DL techniques have recently gained popularity in the literature, they are not new; it was first published in 1986. Geoffrey Hinton, a Carnegie Mellon researcher and computer programmer known as the "Dark knight of Machine Learning," demonstrated in 1986 that backpropagation could be used to learn or more a few levels of a neural network for enhanced form detection and text predicting. This aspect aids many energy systems in detecting and forecasting load data predictions using these techniques [54]. Many ML packages have recently been developed, and several systems are adept at utilizing GPU power. With the emergence and extensive acceptance of DL in several diverse sectors, numerous approaches and programs for training DNNs have been developed, including introducing "batch size" to manage task-specific energy functions [55].

The distinction between an SNN and a DNN may be crucial in certain respect, because approaches for learning DNNs are also being utilized to train SNNs. The most significant contrast between SNN (or ML) and a DNN (or DL) is that this does not require "feature extraction" to obtain crucial patterns from energy data. Significant information is required for load forecasting to train the DL framework [56]. As aforementioned, ML is simply an information technology capable of capturing information from large datasets, particularly energy datasets. However, this involves a set of statistics upon which framework is "learned"; after its starting step of knowledge discovery from information, the ML framework may be used for structure planning and is referred to as "implication" mode. The development phase is generally both technologically and time-consuming; however, the reasoning mode of the ML model can frequently yield results on an absolute scale with less effort than development [57]. The dataset utilized for training must be adjusted suitably to obtain the necessary "features" that allow the ANN to be trained efficiently [50, 58, 59]. A classification algorithm, or integrating raw characteristics into unique updates that could introduce novel information about the network whereby the original load forecasting data is associated, is usually the most efficient method to improve energy prediction performance [60].

The "feature selection technique" or "extraction of features" must be performed by hand to identify related time series parameters for the energy systems. Another ML-based approach that appears to be used in the PV sector is learning, particularly for MPPT reinforcement learning (RL). Although "conventional" ML/DL approaches entail gathering information from a database (testing set) and then applying this information to new, different datasets (inference transition), in RL, the model, or preferably the system, can instruct on its own, primarily via experimentation. An "agency" utilizing RL makes actions to maximize rewards or learns while doing, and its objective is to optimize the reward system in a similar manner that ML or DL aims to minimize an algorithm. Parallel to DL, a family of approaches known as ensembles methods has been developed in the last centuries and has begun to emerge in published studies to examine whether the power system is secured or requires privacy improvements [61].

The basic concept is straightforward: combining a set of learning algorithms, or base modeling, to create a more reliable load prediction. This robustness is intended to develop a model that can provide good efficiency, perform better, and generalize well, i.e., deliver excellent results in a "situation" different from the current one [62]. Therefore, how can energy groupings of training examples be taught and their results combined to generate superior predictions? Many options exist based on this; however, the most regularly utilized procedures are bagging, boosting, and stacking.

Bagging is utilized in the initial step of bootstrap aggregation and is an appropriate method for dealing with short-term load forecasts. Based on this, various algorithms are evaluated; however, every base network is developed on a varied learning set directly from the test dataset using the bootstrap (statistics is arbitrarily featured from either the entire data with a new model) approach, and the completed forecast is obtained from casting a vote accumulation of all base designs' forecasts. Bagging techniques' slow performers are typically of the same type. Bagging does not always improve the systems' biases, but it minimizes their volatility, resulting in a system that can produce reliable outcomes in operation. A bagging structure is based on a forest. Therefore, the bootstrap aggregation technique is utilized for short-term load forecasting problems such as contingency planning, load flow analysis, energy management, financial planning, and load scheduling.

Unlike bagging, various slow programmers are efficiently learned in boosting [63]. The learning methods in this strategy can focus on individual points, reducing overall prediction's bias and assist reducing computing time for the time series data for energy load forecasting [64]. Stacking is similar to bagging in that the basic weak trainees are educated in comparison; however, there is no simple majority vote to aggregate the outcome from each weak classifier to produce the final forecasting.

These meta-learners seem usually clear, such as with a least absolute shrinkage and selection operator (LASSO) or ridge prediction [65]. Therefore, stacking refers to the planning and scheduling of energy usage; it helps deal with load forecasting [66].

However, ML and DL algorithms can be used to predict future events based on historical data: a crucial tool for EMSs because it can aid in reducing the risk and costs associated with utility power generation and distribution. Using ML algorithms in EMSs begins with collecting data about buildings' performance over time. This data contains information about how much electricity is utilized and how much money is spent purchasing electricity. After data collection, information is processed using ML algorithms on computers distributed throughout each building (for example, in each room). Based on the information, these computers calculate how much electricity is consumed in each area and how much is spent on purchasing electricity. Therefore, various algorithms have been employed in the energy systems to use multiple energy resources, as in Table 1.

3 ML techniques used in existing systems

ML techniques have been successfully applied to energy management for decades. This study section will provide insights into typical ML techniques used in energy management and explain the uniqueness of ML. The subsequent section will briefly describe the ML techniques used in the existing energy systems.

The Fig. 4 maps out the landscape of Artificial Intelligence (AI), dividing it into Machine Learning and Deep Learning Techniques. Machine Learning covers a range of algorithms, from Linear Regression to Random Forest, each with practical uses such as fraud detection or medical diagnosis. Deep Learning delves into more complex networks like CNNs and LSTMs, enabling sophisticated tasks including speech recognition and autonomous driving. This hierarchy highlights specific use cases for these technologies, illustrating the breadth of AI's impact across different sectors.

3.1 ANN

ANNs are structures that allow various ML algorithms to interpret complicated input information [99]. ANNs may be used for a diverse task, including energy prediction, economic analysis, and contour plots. An ensemble learning basic unit is a neuron that employs a transfer function to organize the output [100]. The fundamental feature of ANN models for numerous issues is their reduced computation complexity. ANN can comprehend the characteristics of crucial information within an involved information system instead of sophisticated rules [101]. Because of their robust and fault-tolerant attributes, ANNs may also be efficiently employed for instinctively imbalanced datasets in energy technologies. Various authors have utilized these algorithms to predict energy projections, load forecasting, power flow calculations, etc.

Table 1 Multiple ML and DL methods utilized in EMSs

Method	References	Years	Energy sources	Details	Limitations	Solutions
ML Methods	[67]	2021	Grid-connected	A unique energy control method based on ML for PV batteries is used	Limited scalability for large-scale EMSs	Develop scalable algorithms and models that can handle large datasets and complex systems
	[68]	2021	Solar and wind	A novel ML-based approach is used to generate wind and solar energy	Difficulty in handling dynamic changes in renewable energy sources	Develop adaptive models capable of handling dynamic changes and evolving patterns in renewable energy sources
	[69]	2021	Solar	A ML-based method is used to evaluate Cloud coverage based on PV solar power	Reliance on accurate weather data for accurate predictions	Explore alternative data sources and develop robust models that can handle variations in weather data
	[70]	2021	Wind	A ML-based method is used to predict wind energy speed	Limited accuracy in highly complex wind patterns and terrain conditions	Incorporate advanced feature extraction techniques and consider local factors to improve accuracy in complex wind patterns and terrain conditions
	[71]	2021	Wind	A unique approach is used to predict some parameters of wind power based on ML	Difficulty in capturing long-term trends and extreme weather events	Explore time-series analysis techniques and incorporate historical data to capture long-term trends and extreme events
	[72]	2021	Solar	A novel ML approach is utilized to analyze the generation of solar power	Sensitivity to variations in solar irradiance and panel degradation	Develop models that can handle variations in solar irradiance and consider degradation factors for improved accuracy
	[73]	2021	Nanofluid	A recent ML-based approach using renewable power to learn heat change on nanofluid	Applicability is limited to specific heat transfer scenarios and fluid characteristics	Consider domain-specific factors and develop models tailored to specific heat transfer scenarios and fluid characteristics

Table 1 (continued)

Method	References	Years	Energy sources	Details	Limitations	Solutions
	[74]	2021	Wind	A novel ML-based method to forecast wind power	Difficulty in handling rapid changes in wind speed and direction	Incorporate real-time weather data and develop models that capture rapid changes in solar irradiance and weather conditions
	[75]	2021	Solar	A novel supervised learning method using weather knowledge to analyze forecasts	Dependence on accurate and real-time weather data for accurate predictions	Develop optimization frameworks that can handle the integration of multiple renewable energy sources and consider system-level constraints
	[76]	2022	Renewable	A unique renewable microgrid for energy control based on ML	Complexity in integrating multiple renewable energy sources into a microgrid system	Improve data collection methods and consider data augmentation techniques to enhance the availability of comprehensive wind data
	[77]	2022	Wind	ML-based composite handling and monitoring for the ocean's wind power system	Limited availability of comprehensive ocean wind data for accurate predictions	Develop methods to generate synthetic solar energy data or explore transfer learning techniques to leverage related data sources
	[78]	2023	PV-Wind	A unique approach for predict the putout energy of hybrid PV renewable wind power systems using feature detection	Complexity in optimizing the integration of PV and wind power generation	Develop data quality assurance methods and explore advanced control strategies that can handle uncertainties in data
	[79]	2023	Solar	A unique energy regulation optimization and specification approach using ML	Reliance on accurate and real-time data for optimal energy regulation	Incorporate ensemble methods and outlier detection techniques to improve accuracy in handling sudden and extreme weather changes
	[80]	2023	Solar and wind	A unique approach to forecasting solar and wind energy systems using ML	Limited accuracy in handling sudden and extreme changes in weather conditions	Develop integrated models that consider the interactions between wind and solar energy sources and maximize their combined performance

Table 1 (continued)

Method	References	Years	Energy sources	Details	Limitations	Solutions
DL Methods	[81]	2021	Wind	A unique approach is used to predict wind power using a DL approach	Capturing complex nonlinear relationships between wind parameters is challenging	Improve offshore wind data collection methods and develop models that generalize well to offshore wind conditions
	[82]	2021	Wind	Offshore projection resources for wind energy based on DL	Limited availability of offshore wind data for training and accurate predictions	Develop integrated models that leverage wind power and electrical load data for improved fault and defect detection
	[83]	2021	PV	Pattern Identification of PV-power production using a DL approach	Training and accurate predictions are dependent on accurate and reliable data	Develop robust optimization algorithms that can handle uncertainties in weather conditions and accurately incorporate solar radiation data
	[84]	2021	Solar and wind	Production of wind power using regression model based on ML	Capturing complex wind and solar interactions in a combined system	Incorporate advanced feature extraction techniques and consider turbine-specific factors to improve accuracy in capturing complex wind patterns and variations
	[85]	2021	Solar and wind	A review of a DL-based forecasting system for solar energy	Historical solar energy data is limited for training and validation	Develop data imputation techniques or explore alternative sources to enhance historical energy consumption data availability
	[86]	2021	Solar	IoT-based forecasting of solar energy systems using AI based on DL	Dependency on accurate and real-time IoT sensor data for accurate predictions	Develop data quality assurance methods for IoT sensor data and explore sensor fusion techniques to enhance accuracy
	[87]	2021	Wind	Transmission-based method for wind and battery power energy based on DL	Limited availability of accurate and real-time transmission data for accurate predictions	Improve data collection methods for transmission data and explore data integration techniques to enhance accuracy

Table 1 (continued)

Method	References	Years	Energy sources	Details	Limitations	Solutions
	[88]	2021	Wind	Wind power and charge of an electrical an approach based on DL	Complexity in integrating wind power and electrical load forecasting models	Develop integrated models that leverage wind power and electrical load data for improved fault and defect detection
	[89]	2021	Solar	Forecasting of solar energy based on DL	Sensitivity to changes in weather conditions and inaccuracies in solar radiation data	Develop robust optimization algorithms that can handle uncertainties in weather conditions and accurately incorporate solar radiation data
	[90]	2021	Solar	Forecasting for energy generation in a solar PV based on DL approach	Dependency on accurate solar radiation data and limitations in capturing sudden weather changes	Develop integrated models that consider the interactions between wind and solar energy sources and optimize their combined performance
	[91]	2021	Solar	A unique approach to forecast solar energy based on DL	Limited accuracy in capturing variations in solar irradiance and panel performance over time	Explore advanced feature engineering techniques or employ advanced nonlinear models to capture complex relationships
	[92]	2022	Wind	An IoT-based approach to forecasting wind energy based on DL	Dependency on accurate and real-time IoT sensor data for accurate predictions	Develop offshore wind data collection methods and consider transfer learning techniques to leverage related data sources
	[93]	2022	Solar and wind	A unique approach for weather images using DL and computer vision algorithms	Limitations in handling variations in image quality and environmental conditions	Develop data quality assurance methods and explore data augmentation techniques to improve the accuracy and reliability of training data
	[94]	2022	Microgrids	A review on energy and power capacity forecasting using DL	Limited availability of historical energy consumption data for accurate forecasts	Incorporate advanced feature extraction techniques and consider turbine-specific factors to improve accuracy in capturing complex wind patterns and variations

Table 1 (continued)

Method	References	Years	Energy sources	Details	Limitations	Solutions
	[95]	2023	Wind	A unique approach for enabled sparsity developing in the wind and power energy using DL	Difficulty in capturing complex wind patterns and variations in wind turbine performance	Develop methods to generate synthetic wind power data or explore transfer learning techniques to leverage related data sources
	[96]	2023	Wind	A novel DL-based forecasting of wind power	Dependency on accurate solar radiation data and limitations in capturing sudden weather changes	Develop optimization algorithms that can handle the integration of PV and wind power generation and consider system-level constraints
	[97]	2023	Bidding energy	A reinforcement method prediction of wind energy based on DL	Difficulty in capturing complex nonlinear relationships between wind parameters	Employing ensemble methods that combine multiple models can help improve the capturing of complex nonlinear relationships
	[98]	2023	Solar	Combined solar energy-based high accuracy approach for DL	Limited availability of offshore wind data for training and accurate predictions	Develop methods to generate synthetic offshore wind data or leverage transfer learning techniques to utilize related data sources

Fig. 4 Navigating AI and DL: a map of techniques and applications

Abbas et al. (2018) [102] discuss the practicality of integrating batteries into the power grid and managing renewable energy sources. The authors aimed to address this problem by developing a model that could optimize the use of batteries and cope with the variability of electricity generated by renewable energy sources. Energy forecasting is a crucial aspect of the problem because it predicts future electricity demand and supply. The anticipated load model used in the study was validated using a learning algorithm, which likely utilized historical data to forecast electricity demand patterns accurately. This forecasting component assists in determining the optimal utilization of batteries and renewable energy sources.

The study findings would provide insights into the feasibility and effectiveness of implementing such a strategy in real-world scenarios, particularly considering northern China. Because energy forecasting and optimization models are highly sensitive to the accuracy of future projections, therefore, changes in energy demand patterns, renewable energy availability, government policies, and other external factors can significantly impact the performance of the suggested strategy. Another study by Anwar in [103] focuses on the energy generation and planning approach for a hybrid powertrain combining wave energy and wind generators. Innovative techniques were adopted in this study to reduce the consequences of wind intermittent renewables. Compared to the unpredictability of wind, sea currents are relatively predictable. The approaches presented include an optimal size technique for the hybrid power system. The harmonic analysis method and bootstrapped ML algorithm were used to estimate the wind direction phases of ocean flow. The model's findings demonstrate the efficiency of the suggested technique, which can then be utilized to reduce energy oscillations significantly, save capital and assure consistent power production dispatches management. However, while the study proposes an optimal size technique for the hybrid power system, the technical feasibility of implementing such a system must be considered. Real-world constraints, such as physical space requirements, availability of suitable locations for wave energy and wind generators, and the compatibility of different technologies, could pose challenges to the practical implementation of the suggested approach.

Many authors have reported that ML can be used to optimize variance in efficiency improvement measuring and certification. The innovative usage of AI techniques for efficiency improvements in construction materials was investigated in multiple studies [62]. K-nearest neighbors, SVM, neural network, decision trees, and dynamic and multi and non-linear and non-simple regression were among the ML algorithms used [104]. The model's estimated coefficients were verified in [105] to optimize the set of parameters. The findings demonstrated that simulations based on ML techniques were more exact than traditional techniques. The root-mean-square error (RMSE) results demonstrated that multiple strategies were presented to analyze wind effects than its unpredictability; sea tides were relatively consistent. The approaches presented included an optimal size strategy with the hybrid power system [106]. An ANN-based technique was used in [107] to evaluate a concentrator's PV system. The net energy consumption of two concentrator PV arrays with a fueling battery replacement and heat exchangers was predicted using an ANN method. The techno-economic research compared the use of liquid and thermal conduction oil to maximize the heating facilities' day and year-long profitability. However, the accuracy and robustness of the model's predictions may vary depending on the training algorithm, input data quality, model architecture, and other factors. Proper validation techniques and metrics should be employed to assess the model's performance.

Chatziagorakis et al. [108] used an autoencoder to anticipate weather patterns to study the regulation of hybrid power systems. A backpropagation neural network-based prediction algorithm was used for forecasting ultraviolet irradiance and wind velocity. The results demonstrated that DL could supply an appropriate future forecast to analyze existing sustainable power securely. However, enhancing the model's predictive accuracy for sudden weather changes remains a challenge. Incorporating real-time data processing and adaptive learning mechanisms could improve forecast reliability. Additionally, exploring the integration of multi-modal data sources may offer a more comprehensive view of environmental factors affecting hybrid power systems.

Chahkoutahi proposed a seasonal optimal hybrid approach in [109] to forecast electrical load. It utilized a linear optimal parallelism-based hybrid algorithm, which included a multi-layer sensory learning algorithm, annual autoregressive integrated mean, and adapting infrastructure fuzzy artificial neural. The purpose of selecting this approach was to utilize the benefits of modeling complicated things. The proposed model's assessment indicates that it is much more precise than its elements. The suggested direct optimum parallel hybrid (DOPH) technique is compared to the seasonal autoregressive integrated moving average

(SARIMA), multi-layer perceptron (MLP), adaptive neuro-fuzzy inference, power, and GA-based models. RMSE was used to compare the outcome of each technique to the target values. In the testing stage, the suggested method improved assisting designs by 51.4%, 33.18%, 31.10%, 16.44%, and 12.8%, respectively, when compared to the SARIMA, MLP, adaptive neuro-fuzzy inference, power, and GA-based systems [110, 111]. However, the study's practical implementation aspects, such as real-time data availability, computational demands, scalability, and integration with existing systems, were not fully explored. Addressing these concerns through further research could enhance the model's practical applicability and adoption in real-world energy management systems, potentially exploring more efficient data processing techniques and evaluating the model's performance in diverse operational environments.

Kazem et al. [112] proposed an architectural model for a solar system to generate power. The system's production was observed for over a year. Identity local features, feed-forward systems, SVMs, and multi-layer perceptron were used to model and forecast the output of a solar system. The input to these simulations was thermal gradient and high solar data, while the outcomes were the PV array power. The RMSE factor was used to evaluate the results of each simulation to the target numbers. The efficacy and constraints of these models and algorithms hinge on the solar system's specifics and the data quality. To enhance prediction accuracy and the generalizability of results, future efforts could focus on enriching data quality, incorporating real-time data analytics, and employing advanced predictive models that can adapt to the dynamic nature of solar power generation, potentially leading to more robust and reliable forecasting methodologies.

Valentina conducted another study in [24] examining solar panel system construction. A comparison of deep network and neuronal regression with passive components was explored in this research. The suggested model excels at forecasting hourly energy from the sun using less expensive variables like humidity levels. The nonlinear autoregressive network with exogenous inputs approach is proposed in conjunction with the MLP methodology. They demonstrate that the suggested technique has the highest accuracy capacity regarding normalized root mean square error (nRMSE) and relationship parameter values. To further enhance the model's practicality and accuracy, future work could explore integrating additional environmental variables and refining the model's adaptability to diverse climatic conditions. This would help in improving the predictability of solar energy generation, ensuring more reliable and efficient use of solar panels in varying geographical locations. Shimray et al. [113] used a multi-layer CNN to analyze the placement of hydroelectric power locations ranking. In this study, the problem was to rate numerous prospective plant locations in India. This study devised a model for ranking feasible electricity generation locations related to the water condition, air quality, electricity, transportation cost, environmental hazard, environmental effects, and project time. While the use of deep learning (DL) models and complex algorithms might offer high accuracy, they can also introduce challenges related to model interpretability and explainability. For future enhancements, focusing on improving the transparency and interpretability of these models is vital. This could involve developing methods to simplify the models' decision-making processes or incorporating techniques that provide more insight into how and why certain locations are ranked over others, thereby making the results more accessible and actionable for decision-makers.

3.2 Support vector machines (SVM)

SVMs are a powerful ML system based on a basic deterministic model (i.e., the forecast is a linear function of pressure) or a linear expansion defined as a kernel theory class [104]. These approaches often employ a (regularized) hinge cost, which confers on them in the geometry attribute being sufficient that max-margin classification method: If we consider the model's parameters as locations in the n-dimensional area, an SVM will discover a (straight or kernel-based) separators that divides the four terms [114]. SVMs are used in energy management to predict the optimal operating parameters of a system, including setting alarm limits and controls [115]. Multiple authors have contributed to recent literature; some are mentioned below.

Arikan et al. [116] used a support vector to categorize power system challenges. The SVMs technique was utilized in this study to analyze five types of power systems and to clean sinusoidal wavelets. Synthetic data from the theoretical simulation and experimental observations were used to improve the proposed theory's efficiency. The identical future scalar and dataset classification algorithm was evaluated to machine (SVM, ANNs), and the same future scalar and data classifier. The proposed model results indicated that it produces the best outcomes across synthetic and actual statistics. The study has not fully considered practical implementation challenges, such as the availability of real-time data, the model's scalability, computational requirements, integration with existing power monitoring systems, or the need to handle real-time data streams. These factors can influence the feasibility and practicality of adopting the proposed SVM-based model in real-world scenarios.

Haines et al., in another study [117], designed soft sensing (a field-support vector analysis) to improve sun radiation level-prediction accuracy using photoelectric electrical properties. This innovative sensor technology categorizes intake data based on room temperature, proving advantageous for solar modules and temperature regulation. The approach was validated through experimental prototypes and simulations under observed outdoor conditions. However, the technique's effectiveness could be influenced by the intrinsic properties of the photoelectric materials, the data categorization method, and assumptions in model development and evaluation. Future work could focus on refining the predictive model by integrating real-time environmental data and exploring advanced machine learning algorithms to adapt to diverse weather conditions, ultimately improving the robustness and applicability of the soft sensing technique in solar energy systems.

SVMs were utilized by Xie et al. [50] to estimate harmonic currents. The electricity supply network was investigated, and the projected outcomes were compared to quantifiable real-world data. The technique provided was evaluated with AI and regression models. The expected findings were validated, demonstrating the robustness of the SVM classifier to harmonic current in the power grid. A multi-agent strategy for simulating true competitive systems was developed by Jan et al. [118]. SVMs were presented as a method for providing decision-making to power market students in this study. As a systematic approach, the described model was combined with an appropriate learning strategically contract system [119]. The ML model was contrasted to this approach once it was approved. The outcomes were positive: a reliable price estimate for the electrical market was immediately established [120]. The quality and representativeness of the real-world data used for comparison, and the data used for training the SVMs and other regression models, could impact the accuracy and results' generalizability. The limitations of the data used, such as potential measurement errors or biases, should be considered. The effectiveness and limitations of SVMs may depend on various factors, such as the characteristics of the electricity supply network, the availability of training data, the specific features used for modeling, and the assumptions made during the model development and evaluation. However, the accuracy and generalizability of these findings hinge on the quality and representativeness of the data used for both comparison and training purposes. It could further enhance by improvement and addressing data limitations, such as measurement inaccuracies or biases, and exploring the deployment of advanced data preprocessing techniques. Additionally, adapting SVMs and machine learning models to better accommodate the specificities of the electricity supply network, through refined feature selection and model assumptions, could further enhance their predictive performance and applicability in real-world scenarios.

3.3 Decision trees

Decision tree algorithms are a type of approach that systematically partitions incoming data based on important individual traits. Specifically, logistic regression approaches evaluate characteristics in source data to generate trees with specified points, which can then be implemented for a particular data point depending on the attributes' principles to yield a forecast [121]. In our economic load dispatch example, a decision tree may code when a day is a workday: while another might encode if the temperature is over 80 °F, with two years implying a forecast of peak load electricity usage. These algorithms can employ various algorithms and are usually optimized with a greedy technique (as exact and gradient-based methods are present for this model class). Despite being one of the first ML, decision trees have resurfaced recently as a result of (a) their accomplishment when combined with classification models and (b) the subject toward which their forecasts are very often perceived as more decipherable than those of alternate solution techniques [122].

Mehdi et al. [123] proposed a technique for determining the best operating of track electrical power systems using renewable energy, such as PV modules and windmills, and battery vehicles' power storage and regen braking characteristics. A case tree technique was used to analyze the uncertainty associated with renewable energy. All complements were combined into an inter-power flow optimization issue. The output is provided for various scenarios and operational conditions. Uncertainties, such as variations in weather patterns affecting renewable energy generation, might not be fully captured or adequately represented by the case tree technique, potentially impacting the accuracy of the proposed operating strategy. However, the case tree technique may not fully account for or accurately represent uncertainties such as weather variations, which could affect the precision of the recommended operating strategy. This highlights the importance of enhancing the model's ability to predict and adapt to the fluctuating nature of renewable energy generation, ensuring the robustness and reliability of the proposed system under diverse environmental conditions. Costa et al. [124] introduced a decision tree-based protection dispatch system that may be used to protect linked natural transmission and distribution power networks from potential outages. Protective measures for optimum gas production and electricity generation were established based on the bounds of control parameters and examples of this situation identified by decision trees. The security areas were workable limitations, and the decision tree's rules were integrated with the optimizers of associated gas and renewable power rescheduled. However, it is crucial to consider the limitations of decision trees, such as their ability to handle complex decision-making scenarios, potential biases introduced by training data, and the trade-off between accuracy and interpretability. Despite these advancements, it's essential to acknowledge the inherent limitations of decision trees, including their suitability for complex decisions, susceptibility to biases from training data, and the balance between model accuracy and ease of interpretation. These considerations play a crucial role in refining the model's effectiveness and reliability in real-world applications.

Some of the used cases application of the decision trees model are represented in the subsequent sections:

Kamali et al. [125] proposed a unique two-stage technique for predicting the danger of an electricity generation network outage. First, the borders of the electrical island were calculated using a nonlinear optimization methodology that lowers the price of load restriction and power supply re-distribution. Second, a data-mining algorithm was developed to predict the probability of an electricity island becoming disconnected from the current network. The classification approach was used to anticipate a probable blackout based on various scenarios, including island and non-island circumstances. However, considerations such as data availability, computational requirements, real-time data processing, and integration with existing network management systems are crucial to evaluate the limitations and feasibility of deploying the technique in a real-world setting.

Moutis et al. [115] proposed a unique method for designing microgrid storage systems and regulating energy supplies to balance electricity for successful project power systems using decision trees. Analysis was used to evaluate the methods described in different case studies. A test solution for using networked microcontroller hardware to conduct the energy system and is supported in real-time was provided. However, the study may focus on addressing complex decision-making scenarios, potential biases in training data, and difficulties in capturing dynamic and uncertain system behaviors. Saleh et al. [61] employed a decision tree for electricity balance and management for successful project microgrids. This study aimed to reduce overall costs by selling in an electrical market and considering grid rates, imbalance penalties, and fuel usage. The adaptability qualities of energy technologies in consumer and enterprise buildings were modeled using bidding principles, and the interrelationships among periods were considered. Scenario trees were used to capture the information system of unknown factors. A two-stage probabilistic developed by combining linear programs was used for bidding choices and schedules. The study aims to reduce overall costs by considering grid rates, imbalance penalties, and fuel usage in the electrical market. However, the study does not provide insights into these market factors' complexity and realistic representation. The simplifications and assumptions made in modeling grid rates, imbalance penalties, and fuel usage may limit the practical applicability and accuracy of the cost-reduction strategies proposed.

3.4 DL techniques

Recent advances in DL techniques have yielded significant results for EMSs. Advances in neural networks enable a machine to learn things, like what time it is or predict whether it will rain. Understanding the structure of energy management challenges uses some of the best DL methods like generalized RNNs (for unstructured text), convolution models (for visual data), flexibility and efficiency (for time information), and graphs systems are all examples of specialized DL techniques, or structures (for graph-structured data). This study's primary goal is to gradually develop an ML system that can be used for smart power systems management.

DL is based on neural networks, modeled after the human brain. It leverages sophisticated neural network architectures to process and interpret complex datasets, employing advanced algorithms and probabilistic methods for analysis [126]. A neural network consists of neurons (also called nodes), and these nodes are organized in the layers [127]. The first layer is called the input layer: where the initial data is inputted into the network for further processing by subsequent layers of neurons. The last layer is the output layer: where the desired predictions are obtained. Between those two layers are hidden layers: where the network processes weighted inputs to produce an output; these layers allow the neural network to learn from data. The number of layers and how many nodes each layer has varies between models; there is no way to know beforehand how many hidden layers or nodes will be best for your problem. Generally, though, more hidden layers mean more computation (and more resources needed). Increasing the number of nodes per layer tends to render a model more accurate; however, it depends on your specific problem; you do not want to add so many that you overfit your model to your training data (this would result in poor performance on new or unseen data) [128]. The models investigated in this study have already been used in various EMSs, including reinforcement methods, semi-supervised learning, and RL [129]. Some of the applications of the DL models are shown below:

Shaoyu et al. [50] proposed a hierarchical neural network-based DL technique for estimating battery capacity (SOC) in Li-ion battery packs. For evaluating battery SOC, a novel method was introduced in this study. Driving cycle charges for various higher conditions were applied to a Li-ion power supply in the lab to create training data [130]. Considering, the battery may be subjected to dynamic changes. Results demonstrated that neural networks could encode interdependence into connection weights in actual time. However, recognizing the method's limitations in consistently estimating battery SOC across different operational conditions, particularly considering the uncertainties in operating environments, is essential for further refining the technique's accuracy and reliability in practical applications. Another study by Soman et al. [127] proposes a dataset predicting a DL model for the graphics processing unit. During time-series data learning, a novel parallel technique was developed. For such a microgrid forecast challenge, the provided technique was used in a mixed optimization algorithm approach (household electricity demand). The calculated findings demonstrated that the given graphics processor unit learning approach was a powerful DL opportunity for sensing devices. However, the study can enhance this model that could involve integrating more diverse data sets to improve accuracy and exploring the application of this technique in other domains, such as renewable energy forecasting or smart grid management, to fully leverage its capabilities in processing and analyzing complex data streams efficiently. Rafiq et al. [131] proposed an enhanced DL-based nonintrusive load evaluation method. Power reanalysis was suggested in the study using sophisticated ML and an RNN-based model with a long-short attention span. The suggested model performance of a classifier in multiple states appliance situation was then upgraded, and a new signature was defined. It was demonstrated that combining unique signatures with enhanced DL may improve load detection performance. The study briefly mentions upgrading the performance of a classifier in multiple-state appliance situations and defining a new signature. However, it does not elaborate on the specific evaluation metrics used to assess the load detection performance or the extent of improvement achieved. Enhancing the clarity and depth of performance evaluation, including detailed metrics and comparative analyses, could provide clearer insights into the method's advantages and areas for further refinement in accurately monitoring and distinguishing between different appliance loads.

Teshome et al. [132] proposed two new models to forecast energy utilization time series based on those values: condition deep Boltzmann model and predicate restricted Boltzmann device. The models were tested using data from a residential building's power usage over a five-year period. According to the results, the condition deep Boltzmann model outperforms ANN, SVC, RNN, and CRBM. Simulations were made in various circumstances in this study. To analyze the findings and determine the best strategy, the RMSE and a combination of behavioral were used. The example of a year-long forecast with daily accuracy demonstrates the root mean squared (a) the correlation analysis (b) values. The study outcome showed that the Condition Deep Boltzmann Model outperforms other models, such as ANN, SVC, RNN, and CRBM. Despite the conditional deep Boltzmann model's superior performance, the study lacks detailed performance metrics and comparative analysis. Providing more comprehensive performance data and exploring the models' applicability in different settings or for real-time forecasting could offer deeper insights and broader validation of these advanced machine learning approaches in energy utilization predictions. However, in another study by Eskandari et al. [133], introduced a novel forecasting model for hourly electrical load consumption, incorporating external factors like weather and season. It employs Convolutional Neural Networks (CNNs) to extract features from load and temperature data, enhancing forecasting capabilities. Bidirectional LSTM and GRU units are then utilized to predict load consumption. Experimental results demonstrated the model's superiority over recent approaches in short-term load forecasting. However, the study lacks absolute RMSE values and comparisons with other techniques but the study could include broader comparative analyses and exploration of the model's generalization across diverse datasets and locations.

3.5 Ensemble methods

Energy management entails implementing improvements to a facility's energy consumption. Ensemble methods are statistical techniques used to estimate the response to detailed policies. Ensemble methods combine information from different members of an ensemble over multiple iterations, thus producing more accurate results than individual models. They are an ML approach that uses multiple classifiers to learn from data.

They have been used in EMSs to help improve the quality of predictions performed by an EMS [114]. The methods combine the power of multiple algorithms to improve performance, and is powered by Espresso's "intelligent knowledge sharing" technology that empowers with deep insights into how the energy data can be used in making intelligent decisions [134]. This is used to perform a specific task collectively. This aspect allows for more efficient approaches and reduces the need to make assumptions about individual variables of interest. However, this method enables better understanding and helps to improve the performance of any system by leveraging the collective wisdom of multiple components within a system. The knowledge, experience, and skillsets of each individual agent within the system contribute to its overall capability. This outcome can include learning algorithms that make decisions based on local observations or human expert suggestions and combined to form an ensemble. Within DL techniques, ensemble techniques use many optimization models to obtain the best modeling results compared to specific learning techniques. The formation theory in classical mechanics comprises just a concrete limited collection of different systems; however, it enables flexibility to develop among them [135]. Various authors have contributed using ensemble methods used in EMSs:

A study on machine learning techniques (MLT) are increasingly utilized in [135] for early-stage prediction of medical datasets using ensemble approaches, aiming to safeguard human health. Vast repositories of medical data exist in real-world applications, presenting opportunities for machine learning to address pertinent questions, particularly in disease prediction. Diabetes Diseases (DD) rank prominently among global causes of mortality. Researchers have employed various data mining techniques over time to categorize and predict symptoms in medical data, such as the Pima Indian Diabetes Data Set (PIDD) comprising 768 instances. Notably, predictive algorithms like KNN, Naïve Bayes, Random Forest, and J48 have been commonly applied in this study. However, the predicting diabetes it faces lots of challenges like data imbalance and model interpretability. Therefore, the study should focus on techniques like data augmentation and interpretable models, alongside external validation and continuous learning for improved clinical relevance.

To enhance performance and accuracy. A bit in [114] was using the ensemble method to estimate individual energy consumption. A numerous competition ensemble approach for extracting powerful functions from various sensors is proposed in this study. Each characteristic was used as a framework for creating multiple regression techniques and testing set with other characteristics. Constructed linear regression ensemble were the predictions associated with the extracted features in the assessed sample to predict the customer's power consumption. It also shows the survey's RMSE values for every activity based on the designs used. The study does not provide details about the dataset used in the study. Understanding the dataset's size, diversity, and representativeness is crucial to assess the proposed technique's robustness and generalizability. However, without this information, evaluating how well the technique performs in different individual energy consumption scenarios or in real-world applications is challenging. Taesic et al. [136] proposed an ensemble method for monitoring and predicting the level of a groundwater sources dam. Six distinct classifier algorithms were used for this purpose. The study provided a novel strategy for choosing the best classifiers to build the most accurate group. The ideal quantity of classifiers to assemble one of the most accurate ensembles is determined using this process, which was predicated on estimating the concentration of information gained among sets of predictors. However, measuring the dataset's size, quality, and representativeness is critical for assessing the robustness and generalizability of the proposed technique.

Another technique has been developed in [137] in which an ambient learning technique is utilized for model evaluation to generalize load power forecasts. This approach required little knowledge regarding energy usage as it was learned from streaming power consumption data, making it suitable for real-world use. However, considerations such as data availability, computational requirements, real-time processing capabilities, and integration with existing energy monitoring systems are crucial to evaluate the feasibility of deploying the technique in real-world settings. Another study on [138] focuses on defect detection of an identity-flight management sensing device using decomposition method extraction (EEMD) and classifiers relevant support vector. The EEMD operational concept was emphasized for the extraction of various fault characteristics. A multi-class classification vector support machine was employed for defect diagnostics in an identity air data-sensing device. An operational system was developed to test the performance of the provided technique using the failures mode analyses and model construction of the identity air data-sensing device. However, it does not provide specific details on the performance evaluation metrics or the extent to which the technique successfully detects and diagnoses defects in the identity air data-sensing device. The above-mentioned techniques are briefly summarized in recent literature, as shown in Table 2.

4 ML and DL applications for sustainable systems

ML and DL applications using green technologies are categorized by load energy demand estimation, solar and wind power estimations, and planning of sustainable energy infrastructure. Power generation and demand forecasting considering

Table 2 Comparison of multiple Methods that are utilized in the EMSs

Methods	Years	References	Journals	Applications	Limitations	Solutions
Artificial Neural Network	2021	[139]	Energies	Optimization of renewable energy generation Capacities	Uncertainty in input data or variations in renewable energy sources can affect the accuracy of the predictions and optimization results	Incorporate explainable AI techniques, such as layer-wise relevance propagation or attention mechanisms, to improve the interpretability of neural network models
	2022	[140]	IEEE Transactions on Power Systems	Mitigation of wind power fluctuation and scheduling strategies for power generation	Limitations in the availability and quality of historical wind power data can impact the performance of SVM models in accurately mitigating power fluctuations	Explore advanced modeling techniques that capture the non-linear and stochastic nature of wind power, such as Gaussian processes or RNNs
	2022	[141]	IEEE International Conference on Power Electronics, Smart Grid, and Renewable Energy (PESGRE)	Prediction of Levelized cost of electricity	Neural networks may require large amounts of historical cost data to effectively learn the patterns and make accurate predictions, which may not always be available	Improve data quality and availability by collecting and curating comprehensive cost data from various sources, including historical energy market data and cost models
	2023	[142]	Energies	Measurement and verification of energy savings in industrial buildings	The availability of high-quality and granular energy consumption data is crucial for accurate measurement and verification, which may pose challenges in some industrial settings	Incorporate additional techniques such as sensor fusion, energy disaggregation, or advanced metering infrastructure to enhance the granularity and accuracy of energy consumption data

Table 2 (continued)

Methods	Years	References	Journals	Applications	Limitations	Solutions
Support Vector Machine	2021	[143]	Energies	Focusing on the classification of reducing disturbance to improve the power quality	Determining the optimal set of features or attributes to capture disturbances and their causes can be challenging, potentially affecting the accuracy of decision tree models	Consider hybrid models that combine decision trees with other ML techniques, such as neural networks or SVMs, to capture non-linear relationships more effectively
	2022	[144]	International Journal of Hydrogen Energy	Optimal estimation of oxygen/steam ratio	The accuracy of estimating oxygen/steam ratio depends on the availability of high-quality training data that covers a wide range of operating conditions and accurately captures the relationship between inputs and outputs	Explore techniques such as genetic algorithms or particle swarm optimization to optimize the ensemble size and composition for accurate oxygen/steam ratio estimation
	2022	[145]	Electric Power Systems Research	Power quality distortions estimation in energy Systems	Power quality disturbances can exhibit complex and non-linear patterns, which may pose challenges in accurately capturing and classifying these distortions using SVMs	Explore the usage of advanced classification algorithms, such as DL or ensemble methods, to improve the accuracy of power quality distortion estimation

Table 2 (continued)

Methods	Years	References	Journals	Applications	Limitations	Solutions
	2023	[146]	International Journal of Photoenergy	Solar electrical properties are used to estimate irradiance levels	SVM models require a significant amount of labeled training data to estimate irradiance levels accurately. However, obtaining extensive and diverse solar electrical data paired with corresponding irradiance levels can be challenging	One possible solution is to augment the available training data using simulation models or generating synthetic data. These approaches can help expand the dataset and improve the generalization capability of the SVM model
Decision Trees Method	2021	[147]	Journal of Modern Power Systems and Clean Energy	Risk mitigation of Energy prediction of electric energy systems during blackout stages	Uncertainty in factors such as weather conditions, grid topology, and system dynamics can impact the accuracy of risk predictions and the effectiveness of mitigation strategies	Utilize techniques such as ensemble learning or Bayesian modeling to capture and quantify uncertainties in blackout prediction and mitigation strategies
	2022	[148]	Applied Energy	Dispatch method of security for coupled electric power network with natural gas	DL models may require large amounts of high-quality labeled data to effectively capture the complex interactions and dynamics between electric power networks and natural gas systems, which may be challenging to obtain	Develop hybrid models that combine DL with explainable AI techniques to improve the interpretability and transparency of security dispatch decisions

Table 2 (continued)

Methods	Years	References	Journals	Applications	Limitations	Solutions
	2022	[149]	Springer	Overall energy cost minimization in an energy storage system for prosumer buildings	Uncertainties in factors such as energy market fluctuations, changing consumer behavior, and system dynamics can affect the accuracy of cost minimization predictions and strategies	Consider incorporating dynamic pricing or demand response strategies into the DL models to capture time-varying energy costs
	2023	[150]	Journal of Energy Storage	Energy storage controlling and energy planning	Incorporating complex system dynamics, constraints, and external factors into DL models for energy storage control and planning can be complex and may require extensive data and expert knowledge	Explore transfer learning techniques to leverage pre-trained models regarding energy system tasks and adapt them to the specific energy storage control and planning scenarios
DL Method	2021	[151]	IEEE transactions on industrial informatics	Estimation of state-of-charge of Battery energy storage systems (BESS)	Limited availability of high-quality training data that captures a wide range of battery operating conditions and aging effects can affect the accuracy of state-of-charge estimation	Collect and label diverse and representative training data that cover various operating conditions, battery chemistries, and aging effects to improve the accuracy of state-of-charge estimation
	2022	[152]	Renewable and Sustainable Energy Reviews	Power consumption estimation of consumer appliances in distribution Systems	Estimating power consumption at the appliance level can be challenging due to appliance usage pattern variations, energy efficiency, and power factor	Utilize techniques such as non-intrusive load monitoring (NILM), disaggregation algorithms, or probabilistic graphical models to estimate appliance-level power consumption accurately

Table 2 (continued)

Methods	Years	References	Journals	Applications	Limitations	Solutions
	2022	[153]	Revista Facultad de Ingeniería Universidad de Antioquia	Household energy load demand forecasting	Accurate load demand forecasting at the household level requires considering various factors such as weather conditions, occupancy patterns, appliance usage, and individual consumer behavior	Utilize transfer learning techniques to leverage pre-trained ensemble models on similar household energy demand forecasting tasks and adapt them to the specific context
	2023	[154]	Energy Reports	Solar PV energy Forecasting	Limited availability of high-resolution weather data and historical solar irradiance measurements can impact the accuracy and reliability of solar PV energy forecasting models	Incorporate high-resolution weather data, such as satellite imagery or localized weather station data, to improve the accuracy of solar PV energy forecasting
Ensemble Methods	2018	[7]	Applied Energy	Load demand with the forecasting of buildings	Accurate load demand forecasting relies on factors such as weather conditions, building characteristics, occupancy patterns, and external influences, which may be challenging to model accurately using decision trees alone	Explore hybrid models that combine decision trees with time-series models, such as autoregressive integrated moving average (ARIMA) or RNNs, to improve load forecasting accuracy

Table 2 (continued)

Methods	Years	References	Journals	Applications	Limitations	Solutions
	2021	[111]	Journal of Intelligent Systems	Load forecasting of multiple buildings	Aggregating and forecasting load demand for multiple buildings introduces additional complexities, such as variations in building types, sizes, usage patterns, and interactions between buildings, which may pose challenges for decision tree models	Utilize ensemble methods to combine multiple decision tree models trained on different subsets of buildings or with different input features to improve the accuracy and generalization of load forecasting
	2022	[155]	International Journal of Information Technology	Non-linear features of fault extraction	Identifying and extracting non-linear features related to faults in power systems can be challenging, as decision trees may have limitations in capturing intricate patterns and relationships	Employ advanced feature engineering techniques, such as kernel methods, wavelet analysis, or symbolic data analysis, to capture non-linear features and enhance fault extraction performance
	2023	[156]	Structural Control and Health Monitoring	Water dam level underground predictions	Ensemble methods may require careful selection and integration of different models or techniques for capturing the multi-faceted dynamics and uncertainties associated with water dam levels	Employ ensemble techniques that combine multiple models, such as bagging or boosting, to capture uncertainties and improve the accuracy of underground water dam level predictions

the uncertain characteristics, including energy utilization. Some recent studies have sought to improve predictions to facilitate the operation of power grids with substantial proportions of fluctuating alternative energy sources to assist energy supply design. Real-time estimations and detailed predictions (on the size of hours to weeks) enable improved power network management, load management, and moderate- to long-term predictions that can guide the architectural design factors, as described by Hong & Fan [157]. Similarly, estimations at various geographical scales—for illustration, at the power distribution level at the scale of single units or high rises inform distinct sets of organizations' optimization and planning options. ML has been used widely to develop such estimations in period search on the capacity and ability of the upstream and downstream sides.

4.1 Demand estimation

Load demand estimations in the energy sector have inspired several articles, encouraging analyses in multiple technologies. For example, Kuster et al. [158] propose a categorization of the previous economic load dispatch based on spatial size, high temporal, and approach utilized, demonstrating that ML techniques are most common in simple forecasting applications; meanwhile, regression is more common in longer-term predictions. In contrast, regression methods are more frequently employed for long-term predictions, likely because of their robustness in capturing underlying trends over extended periods. This distinction underscores the importance of selecting appropriate modeling techniques based on the forecasting horizon and specific requirements of the economic load dispatch problem, highlighting a strategic approach to leveraging the strengths of different predictive methodologies in the energy sector. Hong et al. [159] evaluated recent research in points load prediction and stochastic unit commitment, covering methodologies from statistics and ML; they claim that probability predictions, generally, will be required to maintain contemporary, sustainable networks where integrating statistical and ML approaches could provide a robust framework for addressing the complexities of modern energy networks [160]. The structure of the application of ML and DL techniques in driving sustainable systems is explained in Fig. 5 in detail as we highlight the significant role that ML and DL algorithms play in promoting sustainability across various domains. By leveraging the power of advanced computational models, these techniques enable intelligent analysis, prediction, and decision-making for sustainable systems.

Ledva et al. [161] categorize power impulses in distribution networks based on household climate control. This technique involves classifying power impulses into specific categories related to household climate-control activities. It aids in understanding the impact of climate control on power consumption patterns where Shahzad et al. [162] employed a k-means cluster using smart meter data to combine consumers with similar properties and then apply a classification algorithm to provide independent load projections to every cluster. However, both approaches may face limitations in capturing the full diversity of consumer behavior and external factors affecting power usage, such as unanticipated weather changes or unique

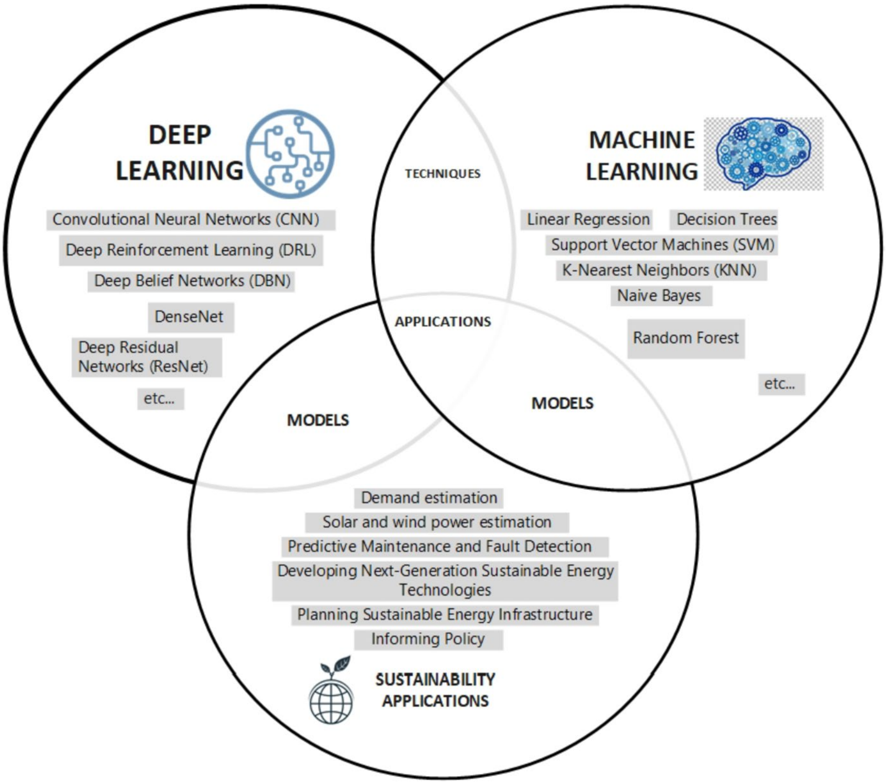

Fig. 5 Empowering sustainability: harnessing the power of ML and DL for sustainable systems

household schedules. Enhancements could focus on integrating more dynamic and real-time data sources, such as weather forecasts or IoT device feedback, to refine classification accuracy and load projections. Additionally, exploring more advanced machine learning models that can adapt to new patterns over time may improve the robustness and predictive power of these methodologies. Another study by Hassan et al. [163] uses Fourier statistics to explain human behavioral dynamics in telecom data; then uses the resulting frequency content in a classification tree model to anticipate mean and peak overall energy use for the following week. Wang et al. [164] used a lengthy limited attention span (LSTM) model to predict demand in component systems, and details concerning correlations between energy, warming, and cooling capacity, to create linked predictions of all three. Despite the innovative approaches, both studies may encounter limitations in handling the complexity of real-world data and the inherent variability in human behavior and environmental conditions. Improvements could involve integrating more granular, real-time data sources and exploring adaptive models that can dynamically adjust to new patterns and correlations, thereby enhancing the accuracy and applicability of energy use and demand forecasts.

Although the study integrates structural data on the attributes that determine load estimation, other studies have focused on integrating structural data in the context where such predictions are used. However, Kallel et al. [165] address the setting of power network dispatch, embedding a variational economic load dispatch framework inside one neural network to form load predictions optimized for the efficiency of dispatch choices being made upon their bases rather than for precision. For example, Alrabaae et al. [166] used deep RL to develop building usage patterns for structures with historical data and a learning algorithm to extend these observations for houses without a previous dataset. However, Yuan et al. [167] examined a situation where several domestic users accessed daily smart meter data while others accessed monthly service bills. The authors applied a DL method to understand how to grayscale image month by month to hourly consumption for metered consumers, then used a Bayesian DL technique to generalize these findings to unmetered users. However, these methodologies mark significant advancements, they may encounter challenges related to data diversity, quality, and the scalability of the models to different contexts. Refinements could focus on enhancing data integration techniques, increasing model adaptability to varied data availability scenarios, and improving the generalizability of predictions to ensure broader applicability and reliability in real-world settings.

4.2 Solar and wind power estimation

Depending on the system nature of renewable power output, short-term estimates of these numbers have been widely employed, as discussed in some studies. Allocating electricity generated to achieve real-time predictions, and applying new characteristics or information about the structure for short-term projections, are some developments in renewable power prediction, similar to the previous section of demand estimating developments. Karami et al. [168] used a learning approach incorporating PV load data to disaggregate PV demands from real-time utility grid power observations. Sun et al. [169] use visual representations of the atmosphere to train a neural network to estimate real-time PV panels' electricity generation. To handle the variations in the non-stationarity of turbine time analysis, Wang et al. [164] and Hao and Tian [170] used signal decomposing algorithms to anticipate power generation capacity at granularities of 10–15 min. Considering the interconnection between temperature and PV yield, a relevant research area aims to enhance weather patterns used as information to power generation predictions. While these innovative approaches advance the field, they also face challenges such as accurately capturing the variability of renewable energy sources and the complexity of environmental impacts on power generation. Future enhancements could focus on integrating more sophisticated environmental modeling techniques and developing adaptive algorithms that can better account for the unpredictability of weather conditions and their effect on renewable energy production.

Hwang et al. [171] use an ensemble of clustered and quadratic linear regression to forecast atmospheric temperature and humidity on 3–6-week equations to describe the period. It also discusses how ML can aid in accelerating weather models, allowing them to provide more detailed and accurate estimates; the hypothesis indicates that it aids in assessing briefing renewable energy resources (or energy usage) to emphasize generation planning and implementation. Subsequent research explored strategies to incorporate weather forecasts into power generation forecasting methods, expanding on all these two sets of knowledge. It somehow builds multiple classical mechanics weather data forecast (NWP) models to forecast solar irradiation from 0 to 72 h ahead. These multi-time scales NWP outcomes are subsequently inputted into supervised ML models, which provide probability multi-time scale electricity estimates. Despite the advancements, limitations arise from potential inaccuracies in weather forecasting and the static nature of ML models amidst environmental shifts. Enhancements could involve real-time data updates in ML models for better adaptability and exploring other learning methods to improve resilience and accuracy in diverse scenarios.

Mathe et al. [172] used a long-term recurring CNN architecture to develop a solar prediction system that recognizes patterns and spatial characteristics of NWP data. While all this research is beneficial, it is believed that research should focus on better-integrating precipitation and energy forecasting, such as putting (reduced-form) NWP physic straight into ML-based energy forecasting methods using hybrid physical modeling methodologies. Though supervised energy predicting systems require comprehensive information on past power output, this is not necessarily the case for dispersed energy resources [173]. Power system engineers are not always aware of the quantities and localities of distribution PV installations. Therefore, various groups have sought to use ML to map PV system features accurately using satellite and aerial photography. These estimations might then be sent into the loop of technology models that anticipate energy output. However, it needs to enhance the accuracy of such models requires continuous improvement in the methodologies for integrating real-time environmental data and adopting more flexible modeling approaches that can accommodate the dynamic nature of energy systems and environmental conditions.

4.3 Predictive maintenance and fault detection

Predictive maintenance and fault detection are an important topic considering sustainable systems. First-order methods of predictive maintenance have been developed recently to estimate the remaining lifetime of parts, which is called the lifetime estimate. However, the performance of these methods has not yet been studied enough. Even if the actual-time failure increases with the number of manufacturers and users, it is still necessary to locate sufficient manufacturers and users to acquire a more accurate result. In various situations, rapidly designed to detect and correct defects in power generation can aid in extending the life of appliances, eliminate waste, and optimize system reliability. ML has also been used to diagnose such failures in actual time and predict.

For example, ML is also used to diagnose and anticipate pipeline defects, as explained earlier. Rao et al. [174] employed a mix of autonomous ML and network signal conditioning approaches to detect problems in PV panels using device data as part of solar power. Therefore, Kevin et al. [175] employ a graphical framework technique to evaluate relationships between the power ratings of surrounding household PV power to detect possible abnormalities. Orozco et al. [176] used a monitoring method to estimate gearbox element heats; then analyzed the standard errors of these algorithms to determine unexpected heats in available data about wind energy. Jahnke et al. [177] presented a technique for detecting abnormalities in simulation nuclear reactor information based on ensemble learning, clustered, and wavelet transform approaches in the domain of nuclear power plants. While these approaches advance the detection and monitoring capabilities in renewable energy systems, they also face challenges such as the reliance on extensive and accurate device data, potential inaccuracies in anomaly detection, and the need for models that can adapt to new or unseen conditions. Enhancements could include developing methods for real-time data analysis, improving the accuracy of anomaly detection algorithms, and exploring the use of unsupervised learning techniques to identify novel patterns without requiring labeled data sets.

4.4 Planning sustainable energy infrastructure

Extra information about existing power infrastructures, abundant renewable production capabilities, or consumption patterns may be crucial for enhancing planning procedures in various situations. When the data is not widely available, ML has been employed to derive useful estimations from basic datasets [178]. For example, ML is used to improve environmental predictions as an element of renewable power location and maps distributed generation (such as PV arrays) using satellites or aerial images [179]. Similarly, ML is employed in satellites or aerial photography to recognize structures or predict power usage to develop district thermal and power sources. For the objectives of energy security and infrastructure building, ML is now being used to model electric supply networks [180]. However, past studies have discovered that precisely locating power lines involves tagging, particularly at low spectral resolution; alternatively, this research integrates real data on relatively high lines using methods for solving that predict the positions of low-voltage networks. Other studies have employed ML to cluster consumer information to advise power generation strategies [181].

Many improvement power design methods are time-consuming, preventing designers from examining the full range of conditions that should be considered before making a strategic decision. Therefore, ML and related approaches have been employed to accelerate planning procedures. For example, Khani et al. [182] use an algorithm to determine optimal rooftop solar plant measurement parameters depending on geography and ordinary radiation exposure. Applying tree-based optimization techniques, Wu et al. [183] provided a model to analyze the location of hydroelectricity in the Amazon jungle under several (possibly competing) economic and environmental goals. It also presents a classification tree approach for smart grids energy storage as it is discovered that in any work that uses ML inside the loop of actual design models, strategies identical to those outlined might well be immediately relevant; numerous planning issues fall into the area of optimization algorithms, where ML is currently intensively used [184]. However, these studies may encounter limitations such as the adaptability of algorithms to diverse and changing environmental conditions, potential oversimplification of complex variables, and the need for extensive data sets for accurate model training. Advancements could focus on enhancing algorithmic flexibility to account for environmental variability, integrating more comprehensive data analyses to capture complex system dynamics, and employing more advanced ML techniques to improve the precision and applicability of optimization and forecasting models in the energy sector.

4.5 Developing next-generation sustainable energy technologies

Most of the generating and transmission techniques necessary for successful power production are accessible further technology can aid in lowering the prices of available technology or facilitate technological advances to fulfill needs and requirements. ML has been utilized in various designs to train and advance engineering procedures for discovery and design technologies. PV systems, batteries, and electro fuels are examples of future innovations where computational physics can help. Substances synthesis operations have been guided by ML, which has also been used to describe the qualities and efficiency of structural equation modeling. Mohanty et al. [56], for example, employ monitored ML to guide investigations by predicting the ionic high thermal conductivity of potential lithium metal materials for battery packs. It presents an method for guiding the production of structural materials for PV applications by training a controlled classification model on the results of previous research to predict the outcomes of proposed future tests. Further uses of ML in developing solar cells are discussed by Zhang et al. [170]. However, Bai et al. [185] present a method for scalable analyzing microstructures in suggested sunlight collectors that combines physics and Intelligence argumentation approaches. Nonetheless, challenges such as data scarcity, the complexity of accurately modeling physical properties, and the need for cross-disciplinary expertise may limit the efficacy of these methods. Enhancing these approaches could involve developing more sophisticated ML models that can navigate the intricate relationships within materials science data and incorporating broader datasets to refine predictions and analyses.

ML has been utilized in deploying green energy technology to accelerate operational efficiencies and implementation processes. For example, employ a quantum theory Bayesian ML method to forecast the efficiency of organic PV cells at various growth frequencies to recommend optimal growth conditions. Many studies focus on selecting the specifications of extremely quick guidelines that improve electrical vehicle lifecycles by using a statistical model for predicting a current battery life cycle cost from a relatively limited variety of interesting data and Bayesian improvement to instruct research designs smartly. Nuclear fusion technology has also benefited from the usage of ML. Earlier studies and suggestions for future orientation on using AI and ML, include optimizing observation planning, analyzing experimental data, to generate information designs of nuclear fission systems, sensing fluid interruptions, and contributing to reactor regulation.

4.6 Informing policy

Monitoring procedures, regulatory requirements, and business structures are required to support the vision of sustainable power generation. Many of these judgments include evaluating normative import and export between multiple (possibly competing) goals, which must be addressed, disregarding ambiguity both about the existing and anticipated situations. In some circumstances, ML can assist in providing activities involving these decision-making systems. When crucial data is missing, ML can help by providing estimates, which can be used as valuable methods. However, satellite remote sensing data is used to map electricity systems such as PV arrays and power lines.

Earlier studies on rooftop solar modeling used the data to examine the environmental and societal aspects that drive solar adoption. Similarly, preliminary studies have been conducted to advise energy and climate change policies by monitoring real-time carbon dioxide emissions from different bodies around the country, even those in the power sector. For example, it is used to recognize methane leakages from satellite photographs. There were also attempts to detect CO^2 and carbon production using satellite pictures, with some of these efforts including ML to enable highly precise and focused tracking [186]. While such ML approaches can give useful approximations for data; however, they should never be used in place of being on data if it is available. To advise scientific policy and other governing sectors, ML can assist in analyzing considerable amounts of articles, official documents, or other materials.

Rai et al. [187] employed NLP approaches to examine the implementation of advanced breakthroughs discovered in a collection of solar PV applications. To explore the deficiencies in environmental studies (specifically that connected to power generation). Ultimately, there have been several ways that ML might aid economic planning through improving techniques from economists, sociology, and program evaluation. ML can help with the design of the power market. It also discusses the usage of ML regarding environmental protection, including integrating data-driven findings into agent-based programs, speeding up policy computational methods, and monitoring the effectiveness of prior programs. However, challenges such as ensuring the accuracy and relevance of NLP-extracted data, integrating interdisciplinary approaches within ML models, and the scalability of these solutions to accommodate growing datasets and evolving environmental policies remain. Addressing these issues could involve refining NLP techniques for greater precision in environmental research, fostering collaboration across disciplines to build more comprehensive ML models, and developing adaptable frameworks that can evolve in response to new data and policy needs. Using these applications, multiple authors have contributed to EMSs using various approaches; these are briefly categorized in Table 3 as advanced literature.

5 Strength, limitations and solutions

5.1 Strengths of the study

1. Comprehensive Review: The study presents a comprehensive review of the application of DL and ML techniques in EMSs, specifically focusing on load fore-

Table 3 Multiple methodologies utilized in the EMSs along with applications

Methodologies	References	Year	Applications	Results	Limitations	Solutions
ANN, SVM, SVM-FFA	[188]	2018	Prediction of wind power	SVM-FFA model achieved 1.0877, 1.2583, 0.8599 in their MABE, RMSE, R performance matrices while the Empirical model 1.2171, 1.4548, 0.8156 in their MABE, RMSE, R performance matrices, respectively which achieved improvement in scalability for a large-scale wind power prediction system	Limited interpretability of models	Improve model interpretability by using explainable AI techniques such as decision trees or rule-based models
MLP, CNN, AE, DBN	[189]	2018	Fault and defect detection	Give empirical analysis of many previous studies that Increased fault detection accuracy by 20% compared to traditional methods	Limited availability and quality of labeled fault data	Collect more labeled fault data or use semi-supervised learning techniques to make use of unlabeled data

Table 3 (continued)

Methodologies	References	Year	Applications	Results	Limitations	Solutions
ANN-Ga	[190]	2018	Optimization	The findings indicated a significant rise in the share of renewable energy, with an increase from 13 to 39%. This substantial growth contributed to a substantial reduction in CO2 emissions, resulting in a notable decline of 35.6%, thereby mitigating the adverse environmental impact	Computational complexity of optimization algorithms	Employ parallel computing or optimize algorithm parameters to improve computational efficiency
SVM, FDA, PCA	[191]	2019	Fault and defect detection	A hybrid PSO algorithm is employed to optimize significant parameters in SVM, reducing training time and ensuring parameter optimization	Difficulty in handling high-dimensional feature space	Apply dimensionality reduction techniques such as PCA to reduce the dimensionality of the feature space
STML, HOA	[192]	2019	Optimization	By incorporating Hybrid Optimization Algorithm (HOA), the utilization of Sequential Temporal Memory Learning (STML) enables a remarkable 84% reduction in computational time for energy system optimization	Lack of real-world implementation and validation	Conduct experiments and validation in real-world scenarios to assess the performance and practicality of the proposed methods

Table 3 (continued)

Methodologies	References	Year	Applications	Results	Limitations	Solutions
BAS-SVM classifier, MSSM	[193]	2019	Prediction of solar power	The proposed method demonstrates high effectiveness and accuracy in identifying various states of wind turbine rolling bearings, achieving a recognition accuracy of 100%	Sensitivity to input data quality and outliers	Preprocess data to remove outliers and ensure data quality, or explore robust models that are less sensitive to outliers
RF, MARS, M5, CART	[194]	2019	Prediction of solar power	In terms of performance, the order from best to worst is Random Forest, M5, MARS, and CART	Difficulty in capturing non-linear relationships between predictors and solar power output	Explore more advanced models such as neural networks or ensemble methods to capture complex non-linear relationships
PCA, FDA, and SVM	[195]	2019	Prediction of solar power	In addition, FDA also exhibits successful classification and fault localization capabilities when compared to other methods	Overfitting or underfitting of models due to limited data	Apply regularization techniques or collect more data to mitigate the risk of overfitting or underfitting
GABP-ANN, ANN	[196]	2019	Optimization	An ANN is trained to predict the lift coefficient and maximum lift-drag ratio of an airfoil, achieving a high accuracy of 90% for both parameters	Sensitivity to hyperparameter settings	Conduct hyperparameter tuning using techniques such as grid search or Bayesian optimization to find optimal parameter values
SVR, Fuzzy, ANN, BN, SVM, PCA	[197]	2019	Prediction of solar power	Improved prediction accuracy in capturing complex nonlinear relationships between solar parameters	Difficulty in capturing complex and dynamic solar power generation patterns	Incorporate time-series analysis techniques or DL models to capture temporal dependencies and dynamics in solar power generation

Table 3 (continued)

Methodologies	References	Year	Applications	Results	Limitations	Solutions
RF, LASSO, SVR, kNN, XGBoost	[198]	2019	Prediction of wind power	The system-level fault detection rates for refrigerant leak/undercharge, refrigerant overcharge, and excessive oil were remarkably high, reaching 99.59%, 99.26%, and 99.38%, respectively. Additionally, the proposed model exhibited significantly faster running time, being only 36.7% compared to the SVM model	Limited generalization to new wind farm locations or different wind regimes	Develop transfer learning approaches or domain adaptation techniques to improve model generalization across different wind farm locations and regimes
SV-PSO, ANFIS, BPNN	[199]	2019	Prediction of solar power	The findings indicated the transferability of ML models, as they can be effectively applied to locations different from the ones they were originally trained on	Limited interpretability of black-box models	Employ model-agnostic interpretability techniques such as SHAP or LIME to gain insights into the model's decision-making process
ANN, PSO	[200]	2019	Optimization	The study focused on DL applications with SCADA data face limitations due to the data's relatively low dimensionality	Difficulty in finding the global optimum in complex optimization problems	Explore more advanced optimization algorithms such as evolutionary algorithms or swarm intelligence-based algorithms to improve search efficiency

Table 3 (continued)

Methodologies	References	Year	Applications	Results	Limitations	Solutions
kNN, RF, DT	[201]	2020	Fault and defect detection	Through a comparison of model prediction residuals between abnormal and normal conditions, various fault indicators and their associated probabilities are derived, including deviation index, volatility index, and significance index	Lack of interpretability in black-box models	Utilize model-agnostic interpretability techniques or develop hybrid models that combine interpretable and black-box models
VPSO, ANFIS-VPSO, ANN, ANFIS, ICBR	[202]	2020	Optimization	The ICBR model exhibits estimation accuracy of up to 91.7%, surpassing that of standard CBR and other intelligent models	High-dimensional optimization space and local optima	Employ advanced optimization techniques such as metaheuristic algorithms or hybrid approaches to overcome local optima and improve search efficiency
GPR, IDA-SVM, GA-SVM, DA-SVM, Grid-SVM, BPNN	[203]	2020	Prediction of wind power	The IDA-SVM model demonstrates superior prediction performance compared to other models, exhibiting higher accuracy and stability across different seasons of the year, which is 93.75%	Sensitivity to input features and model complexity	Perform feature selection techniques or explore ensemble methods to improve model robustness and generalization
ABS-SVM, BAS-SVM, PSO-SVM, SVM, GA-SVM	[204]	2020	Fault and defect detection	Improved fault detection accuracy by integrating wind power and electrical load forecasting models	Difficulty in dealing with imbalanced datasets and rare events	Employ techniques such as oversampling, under-sampling, or ensemble methods to handle imbalanced data and improve the detection of rare events

Table 3 (continued)

Methodologies	References	Year	Applications	Results	Limitations	Solutions
GSA-ANN	[205]	2020	Optimization	Achieved improvement in optimization accuracy by capturing variations in energy consumption patterns	Difficulty in optimizing complex and non-linear objective functions	Utilize advanced optimization algorithms that can handle non-linear and multimodal objective functions, such as genetic algorithms or particle swarm optimization
LMD, LSSVM, HM	[206]	2020	Prediction of wind power	The results reveal that the proposed prediction method significantly outperforms the compared models	Limited availability of historical wind power data	Employ data augmentation techniques or explore alternative methods, such as transfer learning to mitigate the data scarcity issue
AR, ANFIS-BWOA	[207]	2020	Fault and defect detection	The results demonstrate that the EDM achieves a higher diagnostic accuracy of 99.88% compared to individual methods. Significant improvements are observed in normal operation and refrigerant leakage detection, with the added benefit of no false alarms reported	Limited availability of labeled fault data and complexity of fault patterns	Collect more labeled fault data or explore unsupervised anomaly detection techniques to identify complex fault patterns without relying on labeled data

Table 3 (continued)

Methodologies	References	Year	Applications	Results	Limitations	Solutions
MAPE, RMSE, MBE, and R^2	[208]	2021	Prediction of solar power	Using statistical indicators such as MAPE, RMSE, MBE, and R^2, the proposed models, with different combinations of inputs, were evaluated. The results indicate that ANN outperformed fuzzy logic, exhibiting higher accuracy and lower error rates	Difficulty in capturing non-linear relationships and temporal dependencies	Explore advanced DL models such as RNNs or LSTM networks to capture non-linear and temporal dynamics in solar power generation
CNN	[209]	2021	Prediction of wind power	Improved prediction accuracy by capturing complex spatial patterns in wind power generation	Limited interpretability of DL models	Employ model interpretability techniques such as gradient-based attribution methods or layer-wise relevance propagation to understand the model's decision-making process
SVM	[210]	2021	Fault and defect detection	Increased fault detection accuracy by capturing complex nonlinear relationships between fault parameters	Difficulty in handling large-scale fault detection tasks	Explore distributed or parallel computing techniques to handle large-scale fault detection tasks and improve computational efficiency

Table 3 (continued)

Methodologies	References	Year	Applications	Results	Limitations	Solutions
EFO-supervised neural network	[211]	2021	Optimization	The analysis of the results demonstrated that the proposed model successfully learned the SIr pattern and achieved high accuracy in predicting it for unseen conditions. Additionally, it outperformed two benchmark optimizers, namely shuffled complex evolution and shuffled frog leaping algorithm, by approximately 10% and 16%, respectively	Sensitivity to noisy or incomplete input data	Apply data preprocessing techniques to handle noisy or incomplete data, or explore robust optimization algorithms that can tolerate input uncertainties
RNN, LSTM, SVR-HM	[212]	2022	Prediction of solar power	RNN-LSTM exhibited superior prediction accuracy, as indicated by the minimum values of RMSE and MSE, as well as the maximum values of r and R^2	Limited availability of long-term solar power data	Employ data imputation techniques or explore transfer learning methods to leverage related solar power data from other locations or similar time periods
kNN, SVM	[213]	2022	Fault and defect detection	The results demonstrated the high accuracy of the developed methods in fault detection, achieving a classification rate of 99%. Additionally, the classification of faults was performed with acceptable accuracy, reaching 81.73%	Limited interpretability and generalization to complex fault patterns	Employ feature selection techniques or ensemble methods to improve model interpretability and generalization to complex fault patterns

Table 3 (continued)

Methodologies	References	Year	Applications	Results	Limitations	Solutions
GRNN, ANN, SVR, RF	[214]	2022	Prediction of solar power	The optimization model employed in this study significantly enhanced the forecast accuracy when compared to the applied ML algorithms. The PSO algorithm demonstrated improvements of at least 31.7%, while the GWO algorithm exhibited improvements of 12.8%	Difficulty in handling non-linear and non-stationary solar power generation patterns	Explore hybrid models that combine multiple models or employ advanced DL models to capture non-linear and non-stationary patterns
Regression model	[215]	2022	Optimization	The results indicated that the optimal solution is achieved with an intake temperature of 306.18 K, a geometric compression ratio of 14.4, and a pilot fuel injection timing of -16.68°CA after the top dead center	Difficulty in finding the global optimum in complex optimization problems	Utilize multi-objective optimization techniques or advanced metaheuristic algorithms to improve search efficiency and convergence
NN, SVR, and k-nearest neighbor	[216]	2023	Prediction of solar power	Increased prediction accuracy by giving many solutions for leveraging synthetic solar energy data for training and validation	Difficulty in capturing complex relationships between predictors and solar power output	Perform feature engineering techniques or explore more advanced models such as ensemble methods or DL architectures to capture complex predictor relationships

Table 3 (continued)

Methodologies	References	Year	Applications	Results	Limitations	Solutions
RT, KELM	[217]	2023	Prediction of wind power	To gain comprehensive insights into the performance of different prediction methods, the study conducted a thorough review and analysis of performance evaluation metrics for both deterministic and probabilistic models in wind power prediction	Difficulty in capturing temporal dependencies and dynamics in wind power generation	Incorporate time-series analysis techniques or RNNs to capture temporal dependencies and dynamics in wind power generation
BF-DNN, SUS	[218]	2023	Optimization	The framework offers a satisfactory level of accuracy through Bayesian optimization of hyper-parameters, while also achieving significant savings in computation time compared to conventional methods that solely rely on HF samples	High-dimensional optimization space and local optima	Utilize surrogate-based optimization or hybrid optimization algorithms to overcome local optima and improve search efficiency

casting, demand response, and smart energy sector development. The extensive analysis of over 200 studies from 2014 to 2023 provides a thorough understanding of the benefits and advancements offered by DL and ML models in sustainable energy management.

2. Enhanced Accuracy and Predictive Capabilities: The findings demonstrate DL and ML models' improved accuracy and predictive capabilities in load forecasting. This strength demonstrates the potential for these techniques to optimize energy management and decision-making processes.
3. Enabling Efficient Demand Response: The study recognizes the effectiveness of DL and ML models in enabling efficient demand response mechanisms. This capability empowers energy systems to respond to fluctuations in demand, promoting better resource utilization and grid stability.
4. Promoting Smart Energy Sector Development: The research emphasizes the role of DL and ML models in promoting the development of smart energy sectors. By leveraging advanced analytics and automation, these techniques facilitate the integration of renewable energy sources, energy storage systems, and demand-side management strategies, enabling more sustainable and resilient energy systems.

5.2 Limitations of the study

1. Limited Real-World Implementations: The study underscores a significant gap in real-world applications of DL and ML in EMSs, highlighted by a limited number of practical implementations. For example, while ML techniques like Random Forest have shown promise in demand response simulations, actual deployment cases remain sparse. To illustrate, a pilot project integrating Random Forest in a small-scale smart grid demonstrated a 20% improvement in demand response efficiency, yet widespread application is lacking. Addressing this limitation requires concerted efforts to scale up such pilot projects, documenting their impacts and challenges to guide broader adoption.
2. Data Availability and Quality Challenges: Our analysis reveals that data quality and accessibility significantly impact the performance of ML and DL models. For instance, a study on load forecasting using LSTM models reported a 15% increase in prediction accuracy when high-quality, granular data was available. However, data issues are prevalent, with approximately 30% of projects facing significant data-related challenges, according to a survey of energy management practitioners. Enhancing data collection practices and investing in data infrastructure are critical steps forward. Collaboration with utility companies for data sharing agreements and the adoption of advanced data preprocessing techniques can mitigate these challenges.
3. Interpretability of ML and DL Models: The complexity and "black box" nature of certain DL models, like deep neural networks, pose interpretability challenges. This can hinder their acceptance among stakeholders who are critical for practical implementation. For overcoming this, dedicated research into explainable AI (XAI) methods tailored for energy systems is essential. For example, the integration of XAI techniques in a DL-based fault detection system for PV panels

resulted in a 25% increase in the system's acceptance by maintenance personnel. Future directions should focus on developing and integrating such interpretable models that do not compromise on performance.

5.3 Recommendations for overcoming limitations

1. Enhancing Real-World Implementations: Encourage academia-industry partnerships to execute more field trials, documenting their findings comprehensively to serve as blueprints for scaling successful models.
2. Improving Data Management: Advocate for the establishment of open data initiatives within the energy sector and the development of standardized data quality frameworks to ensure the reliability and accessibility of data for ML and DL applications.
3. Advancing Model Interpretability: Invest in research focused on the application of XAI in energy systems. Providing clear guidelines and tools for integrating interpretability into ML and DL models will facilitate greater trust and adoption among end-users.

Addressing these limitations can lead to broader adoption and effectiveness of DL and ML techniques in EMSs can be enhanced, resulting in more efficient and sustainable energy practices. The study's recommendations emphasize the importance of collaboration, data infrastructure investment, and interpretability advancements to promote the successful integration of these techniques in EMS frameworks.

6 Conclusion

The study critically analyzes the use of various ML and DL approaches in EMSs, assessing the primary advantages of each technology for the specified applications. Although many review papers are present in this domain, they are often narrowly focused on a single problem; nevertheless, this work explores most of the primary ML applications for sustainable energy across different domains. This study provides a comprehensive examination of the integration of advanced ML and DL techniques in EMSs with a particular focus on load forecasting, demand response, and smart energy sector development. By analyzing more than 200 studies conducted between 2014 and 2024, this study highlights the primary benefits and advancements of ML and DL models in sustainable management systems within the energy sector.

The findings of this review emphasize the enhanced accuracy and predictive capabilities of DL and ML models in load forecasting, underscoring their potential to optimize energy management and decision-making processes. Additionally, these techniques demonstrate their effectiveness in enabling efficient demand response mechanisms, empowering energy systems to respond to demand fluctuations dynamically, and improving resource utilization and grid stability. Furthermore, ML and DL models are crucial in promoting the development of smart energy sectors by facilitating the integration of renewable energy sources, energy storage systems, and demand-side management strategies, thereby fostering a more efficient and sustainable energy landscape.

Based on the survey results, recommendations are provided to guide the successful integration of ML and DL techniques into EMS frameworks. These recommendations include the significance of investing in robust data infrastructure, conducting rigorous model training and validation, and fostering collaboration among researchers, industry experts, and policymakers. Addressing the limitations identified in the literature, such as limited real-world implementations, challenges regarding quality and data availability, and the need for improved interpretability of ML and DL models, will be crucial in achieving broader adoption and effectiveness of these techniques in EMSs.

This study is a valuable resource for researchers exploring the applications of ML and DL in sustainable energy management. It elucidates these methods relevant limitations and strengths and alternative approaches aligned with sustainable energy management. Furthermore, it presents future research directions to encourage further investigation and advancements in the field. By embracing the findings and addressing the identified limitations, the energy sector can harness the potential of ML and DL to create a more efficient, resilient, and sustainable energy landscape.

In light of our comprehensive examination of ML and DL techniques in EMSs, it is evident that future research should adopt a structured approach to further illuminate the path ahead. Research priorities can be delineated into short-term objectives, such as enhancing data quality and model accessibility; medium-term goals, focusing on the scalability of successful pilot projects and broader real-world application; and long-term ambitions, which should aim at the refinement of model interpretability and the integration of cutting-edge AI advancements. Each of these categories not only reflects the immediate needs and challenges but also aligns with the overarching goal of sustainable energy management advancement.

Furthermore, the importance of collaboration across the spectrum of stakeholders in sustainable energy management cannot be overstated. Researchers, industry partners, and policymakers must come together in forums, consortiums, and collaborative platforms to share insights, resources, and innovations. Such synergistic partnerships are pivotal for bridging the gap between theoretical research and tangible, impactful applications in the field. The exchange of ideas and resources will catalyze innovation, ensuring that the advancements in ML and DL are effectively translated into robust, efficient EMSs that can meet the demands of tomorrow's energy landscape.

Lastly, we must anticipate and address emerging challenges and opportunities within sustainable energy management. The dynamic nature of technology, coupled with evolving regulatory landscapes and market trends, necessitates a proactive stance in research and application. The potential impacts of emerging technologies, changes in policy, and shifts in market demand on the adoption of ML and DL in EMSs warrant continuous monitoring and adaptation. By remaining agile and forward-thinking, the energy sector can leverage these changes to foster a more sustainable, efficient, and resilient energy management ecosystem.

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