Energy Conversion and Management: X 24 (2024) 100724

Contents lists available at ScienceDirect

Energy Conversion and Management: X

journal homepage: www.sciencedirect.com/journal/energy-conversion-and-management-x

A comprehensive review of artificial intelligence approaches for smart grid integration and optimization☆

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ARTICLE INFO

Keywords:
Artificial intelligence
Scheduling energy sources
Machine learning
Multi-agent system
Deep learning
Renewable energy sources
Load forecasting
Renewable energy forecasting
Micro grid
Smart grid

ABSTRACT

Technological advancements, urbanization, high energy demand, and global requirements to mitigate carbon footprints have led to the adoption of innovative green technologies for energy production. The integration of green technologies with traditional grids offers huge benefits. This amalgamation may bring a power mismatch dilemma due to intermittent renewable energy production and nonlinear energy consumption patterns which can affect the whole system's reliability and operational efficiency. An efficient Energy Management System (EMS) is essential to deal with uncertainties associated with renewable energy production and load demand while optimizing the operation of distributed energy generation sources. This state-of-the-art review presents artificial intelligence-based solutions to improve EMS, focusing on optimal scheduling of generation sources, forecasting load and renewable energy production, and multi-agent-based decentralized control. The review's finding suggests that the advanced metaheuristic algorithms can overcome challenges of trapping in local optima and premature convergence and due to this, they are now widely adopted and effectively utilized in scheduling problems. To mitigate uncertainties of renewable energy production and load demand, the long short-term memory and convolutional neural networks can manage spatiotemporal characteristics of renewable and load datasets and forecast highly accurate results. The multi-agent-based system offers a distributed control to complex problems that are computationally less expensive and outperforms centralized approaches. The increased use of advanced metaheuristic optimization techniques and hybrid machine learning and deep learning models is observed for optimization and forecasting applications. The advanced metaheuristic algorithms are a good addition to the literature, they are still in emerging stages and their performance can further be improved. This review also presents the decentralized and centralized EMS-based energy-sharing mechanism between interconnected micro grids. The use of advanced forecasting and metaheuristic algorithms can potentially handle the stochastic nature of renewable energy production and load demand.

1. Introduction

A report on population in a twenty-seventh edition of the United Nations (UN) projected that the world's population would rise to 8.5 billion in 2023 and 10.4 billion in 2100 [1]. This significant population growth poses many challenges, including increased energy demand, potential energy shortages, and continued reliance on traditional energy production methods. These aspects will likely lead to soaring energy

☆ The publication of the article is financially supported by the University of Palermo, "Piano straordinario per il miglioramento della qualità della ricerca e dei risultati della VQR Cofinanziamento spese di pubblicazione di prodotti scientifici (Misura C) - Anni 2024-2026". This manuscript is part of the project PON ''Ricerca e Innovazione'' 2014-2020, Asse IV ''Istruzione e ricerca per il recupero'' con riferimento all'Azione IV.4 ''Dottorati e contratti di ricerca su tematiche dell'innovazione'' e all'Azione IV.5 ''Dottorati su tematiche green''. DM 1061/2021

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https://doi.org/10.1016/j.ecmx.2024.100724

Available online 10 October 2024

prices and heightened carbon footprints. Due to technological advancement with regard to efficiency and low cost, it has been a common practice in the current realm to integrate renewable-based generation with traditional grids. Alongside this, the idea of Micro Grid (MG) has emerged [2], which is the small-scale and low-voltage electricity grid. The MG can effectively address issues like high energy demand and reduce carbon emissions by controlling and managing its Distributed Energy Resources (DERs). The DERs include distributed generating units, distributed storage devices, and electrical load [3]. Considering its economic and environmental advantages, the MG has the potential to lower the reliance on fossil fuel-based energy generation by maximizing the amalgamation of highly renewable energy generation sources. A market analysis and forecasting report published by the International Energy Agency claimed that renewable energies will provide nearly 80% of global energy demand by 2050 [4]. It is clearly evident that renewable technologies such as solar Photovoltaic (PV), and Wind Turbine (WT) will be widely adopted in traditional grids. Acknowledging the advancements in power converters and storage devices, replacing 100% fossil fuel-based energy generation with renewables is now possible. Depending on such a significant amount of energy portion from renewables brings some challenges such as a mismatch between demand & supply due to intermittency and variability of renewable energy production, which may lead to blackouts, grid instability, and lack of system reliability. The MG when operating in off-grid mode, has the ability to overcome the mismatch dilemma by increasing the generation capacity, which increases the system cost. The other solution is adopting energy management strategies that utilize storage devices such as battery storage and hydrogen-based storage [5] to store energy during high generation periods and generate otherwise, provide some stability. The power mismatch problem intensifies as the number of households increases in the MG environment, creating a non-uniform consumption pattern and the utilization of more Renewable Energy Sources (RESs) further complicates the energy management strategies.

Although the integration of innovative green technologies with traditional grids can revolutionize the energy landscape. The intricate amalgamation is full of challenges and state-of-the-art approaches possess inherent limitations, necessitating inventive solutions. By leveraging the potential of Artificial Intelligence (AI), the Smart Grid (SG) can monitor, control, and optimize the operation of MG, promoting energy efficiency, and aiding the transition to sustainable energy solutions [6]. The SG is characterized by features like Demand Response Programs (DRPs), which employ AI algorithms to shift energy consumption patterns from on-peak hours to off-peak hours or shifting where the energy from renewables is high. These algorithms make intelligent decisions by analyzing historical energy consumption patterns or by forecasting future energy production. Several innovations such as AI-based optimization techniques, AI-based forecasting methods, and Multi-Agent System (MAS) have all been designed to improve SG, aiding to improve energy efficiency and promote sustainability [7]. This study intends to investigate the role of AI-based algorithms in improving energy management strategies and provide solutions using state-of-the-art approaches, laying the foundation for affordable and sustainable energy solutions for end-users.

In literature, traditional mathematical optimization techniques have significantly been used to optimize the operation of MG including linear programming [8], Mixed Integer Linear Programming (MILP) [9], and Quadratic Programming (QP) [10]. In [11], the authors developed an optimization framework based on MILP for analyzing and optimizing the energy sources of MG. The optimization framework supports the integration of RESs, including Wind Energy (WE), PV systems, and Energy Storage Systems (ESSs). The intended model is expected to minimize grid's operational costs. Another study employed MILP for optimal scheduling of energy sources ensuring the Economic Load Dispatch (ELD) [12]. Optimization with traditional mathematical approaches can be cumbersome as energy demand, market prices, and weather conditions change regularly, showing nonuniform or nonlinear trends that are difficult to solve using these techniques [13]. Other traditional optimization techniques such as Iterative method [14], Gradient Descent [15], Quasi-Newton [16], etc have the limitation of slow convergence, scalability problem, and are computationally expensive. Some popular classical metaheuristic algorithms including Genetic Algorithm (GA) [17], Particle Swarm Optimization (PSO) [18], Ant Colony Optimization (ACO) [19], Simulated Annealing (SA) [20], and Cuckoo Search Algorithm (CSA) [21] can integrate RESs, and optimize the charging and discharging of ESSs. The authors in Ref. [22] proposed a GA to maximize energy utilization from renewables, aiming to minimize energy costs and carbon footprints. In [23], PSO was proposed to optimize the charging and discharging of ESS. Although classical methods have shown superior performance in overcoming the challenges associated with MG optimal operation. They confront the issues of premature convergence and may easily fall into local optima. In the current realm, advanced Metaheuristic Optimization Techniques (MOTs) with small modifications are being used in literature for solving energy management problems in MG and can address difficulties faced by classical methods. Some of these algorithms are the Promoted Remora Optimization algorithm, Golden Jackal Optimization algorithm, Artificial Gorilla Troops optimizer, Gradient Pelican Optimization algorithm, improved Moth Flame Optimization algorithm with decreasing inertia weight strategy, Gradient Pelican Optimization algorithm, and improved Grey Wolf Optimization (GWO) algorithm. In Ref. [24], the authors made small modifications in the Pelican Optimization algorithm by introducing the local escaping operator and proposed a new version called the Gradient Pelican Optimization algorithm which can resolve the issue of premature convergence and local optima fall. Another study introduced a local escaping operator in GWO and proposed an improved version of GWO in Ref. [25]. The findings demonstrated 15% reduction in operational cost. The newly proposed MOTs are a good addition to the literature, they are still in emerging stages and their performance can further be improved.

To ensure accurate and optimized scheduling of energy sources and overcome the variability effect of renewable-based energy generation, utility companies heavily rely on factors such as future load demand, energy generation from RESs, and weather conditions. Traditional forecasting methods such as statistical methods and physical methods have been employed to predict future patterns [26]. Statistical methods like Auto-Regressive Integrated Moving Average (ARIMA), Seasonal ARIMA (SARIMA), and exponential smoothing have the limitations of handling non-stationary and high dimensional renewable data and are unable to capture complex patterns [27]. Physical methods, like the Numerical Weather Prediction method take atmospheric data as input to forecast wind speed, whereas the Solar Radiation method takes into account cloud cover to predict solar irradiance. Both these methods are used to forecast renewable energy. These methods fail to generate precise results due to uncertainty associated with weather prediction and are computationally intensive. The AI-based forecasting algorithm, including Machine Learning (ML) algorithms [28], and Deep Learning (DL) [29] can be used to forecast with high precision and accuracy. Some studies including regression techniques for day-ahead load forecasting [30], Random Forest (RF) for Short-Term Load Forecasting (STLF) [31], and Multi-Layer Perceptron (MLP) for predicting grid stability [32], have shown excellent results in overcoming the uncertainties and improving the system reliability. Other state-of-the-art techniques such as Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs) particularly the Long Short-Term Memory (LSTM) model can also mitigate uncertainties associated with renewable energy production by capturing spatiotemporal characteristics of datasets [33]. These techniques are discussed in detail in later sections.

Dynamic changes in load & renewable energy production increase the complexity of integrating RESs and storage devices. These challenges can be resolved through distributed control approaches. The AI-based MAS offers several advantages including scalability, robustness, adaptability, and decentralized decision-making. In [34], the authors proposed MAS-based distributed control for regulating complex energy management and controlling DERs. The findings demonstrated robust and excellent control considering fluctuating renewable energy, grid disturbances, and dynamic load behavior.

The integration of RESs into the grid faces challenges due to randomness and variabile nature of renewable energy production. The dynamic nature of load demand is another crucial factor, that creates power mismatch problems. An efficient Energy Management System (EMS) is essential which can handle uncertainties associated with load demand and renewable energy production while optimizing the operation of DERs. The Ref. [35] presented the idea of integrated EMS to overcome the issue of power mismatch through predictive or real-time energy management. The authors focused only on PV energy forecasting while ignoring the aspect of load forecasting and little attention was given to optimization. Another study in Ref. [36] tried to address the power mismatch dilemma by proposing an idea of interconnected MG. The proposed solution was solely based on optimization techniques while disregarding the forecasting of energy consumption and renewable energy production. To improve the reliability and operational efficiency of home EMS, the authors in Ref. [37] proposed a solution targeted only on load forecasting and load scheduling. In Ref. [38], the authors focused on forecasting renewable energy production to ensure efficient and reliable grid operation. A DL-based technique for load forecasting was discussed in Ref. [39] to improve energy management, infrastructure planning, and budgeting. The Table 1 demonstrates the uniqueness of this review for improving EMS in comparison with other recent reviews.

Addressing the uncertainties associated with load demand and renewable energy production through the selection of efficient optimization and forecasting techniques produces a critical research gap. In this review, an efficient EMS is discussed that employs advanced forecasting algorithms and optimization techniques to overcome the power mismatch problem and optimize the operation of MG. Given the broad applications of AI, the rapid advancements of RESs, and the growing interest in incorporating new technologies into a grid, this review aims to present the use of various AI-based approaches for different applications in MG, particularly in the contexts of optimization, forecasting load demand and renewable energy production, and distributed control operation. These approaches are comprehensively discussed, and their significance in improving the reliability and efficiency of EMS is reviewed.

1.1. Review methodology

To conduct a comprehensive review, the keyword ”energy management” was searched on 01 August 2024 on the Scopus database. It was found that 51,266 research studies have been published from 2015 to 2024. These papers include 23,384 research papers, 22,871 conference proceedings, 1,611 review articles, and 1,942 book chapters. Other documents are very limited in numbers. These documents can be found in the Scopus database using comprehensive search criteria. The search criteria include minor relative inclusions and reiterations. This research utilizes the Scopus database to look at the AI-based methodologies utilized in ”energy management,” primarily from 2015 to 2024. A search methodology for determining the relevant literature is illustrated in Fig. 1. It began with filtering search keywords using the title, abstract, and keywords search bars. The search keywords and findings are given below:

- The first search terms, (”heuristic” OR ”nature-inspired”) AND ”energy management” AND ” optimization” yielded 459 research articles, 246 conference papers, 20 review articles, and 52 book chapters.
- The second search on ”machine learning” AND ”energy management” returned 1,908 total papers, 902 of which are research

Table 1
The distinctiveness of the current work in comparison with other reviews published in recent times.

Ref	Year	Techniques	Objectives
[40]	2018	• Statistical forecasting methods (Regression, Exponential Smoothing, ARMA). • ANN, machine learning-based SVM, some hybrid methods.	Focused on PV power forecasting to ensure stable, reliable, and effective grid operation & planning.
[36]	2022	• ANN, MAS, DP, fuzzy logic, MILP, and others. • PSO, ACO, CSA, GA, DE, and others	Presented AI-based approaches in interconnected MGs to handle power mismatch problems.
[38]	2023	• ML algorithms such as linear regression, support vector regression, SVM, and RF. • DL algorithms including ANN, CNN, RNN, auto-encoders, and deep belief neural network.	Focused on forecasting renewable energy production to ensure efficient and reliable grid operation.
[41]	2024	• Statistical forecasting methods (Multiple Regression, Exponential Smoothing, AR, MA, ARMA, ARIMA) for load forecasting. • Optimization methods (Linear Programming, MILP, GA, PSO, SA, ACO, Fuzzy logic) for load scheduling.	Discussed two important aspects of home EMS such as load forecasting and load scheduling. Comparison was made between various load forecasting and optimization techniques.
[39]	2024	• RNN, LSTM, GRU, CNN, autoencoders	Presented various DL-based techniques for STLF to improve energy management, infrastructure planning, and budgeting.
[42]	2024	• ANN, SVM. • Deep learning models such as LSTM, CNN, GRU, and some hybrid methods. • Other statistical methods, ensemble methods, probabilistic approaches.	The work targeted to minimize the variability effect of renewable energy production which improves grid integration and power production. Discussed various forecasting models including statistical methods, machine learning, and deep learning methods.
[35]	2024	• Physical models such as NWSP. • DL and ML models such as LSTM, RF, SVM, ANN, and some hybrid methods.	Aimed to improve integrated EMS through the combination of solar power forecasting, demand-side management, and supply-side management.
[37]	2024	• Statistical forecasting methods (Multiple Regression, Exponential Smoothing, AR, MA, ARMA, ARIMA) for load forecasting. Other than this, SVM,	Enhanced peer-to-peer energy trading between various components of home EMS. Compared various load forecasting and scheduling

(continued on next page)

Table 1 (*continued*)

Ref	Year	Techniques	Objectives
		ANN, expert systems, adaptive demand, and fuzzy logic are also included. • Optimization methods (Linear Programming, MILP, GA, PSO, SA, ACO, Fuzzy logic) for load scheduling.	techniques that are most suitable for home EMS.
This paper	2024	• Comprehensively discussed five nature-inspired optimization approaches such as GA, PSO, CSA, SA, ACO, and some newly proposed optimization methods. • ML algorithm including supervised learning. unsupervised learning and reinforcement learning. • DL methods such as ANN, CNN, and LSTM. • Multi-Agent System featuring Cooperative Game Theory and Non-Cooperative Game Theory.	Addresses challenges of power mismatch and uncertainties associated with load demand and renewable energy production.
Comprehensively discussed the AI-based optimization techniques in resource scheduling.			
Discussed advanced ML and DL-based forecasting applications including load forecasting, weather prediction, and renewable energy production forecasting to overcome uncertainties in energy system.			
Explored the role of MAS in solving problems such as scalability, robustness, adaptability, and decentralized decision-making.			

articles, 733 of them are conference papers, 89 are review articles and 71 are book chapters.

- The keywords "deep learning" AND "energy management" were used in our third search, which provided 790 research articles, 471 conference papers, 48 review articles, and 32 book chapters.
- The fourth search term, "multi-agent systems" AND "energy management" provided 396 research articles, 336 conference papers, and 23 review articles, and 16 book chapters.

Based on the search and available data, AI approaches are grouped into four major types: metaheuristic optimization techniques, machine learning methods, deep learning approaches, and multi-agent systems. During the keyword-based search, it was observed that research articles and conference papers are published in large numbers in every keyword search, indicating the significance of AI-based approaches in energy management.

This paper is organized as follows. This review starts with Section 2 where it discusses the origin of AI and its brief introduction in energy systems. Section 3 discusses the role of AI-driven nature-inspired algorithms in energy management. Steps for dataset preparation before applying ML or DL models and some important performance evaluation metrics are presented in Section 4. Section 5 explores the role of ML and DL approaches in forecasting applications, followed by a discussion on MASs in Section 6. Recommendations, challenges, and open issues of all reviewed AI approaches are addressed in Section 7, and Section 8 concludes the work. The list of symbols & abbreviations of long terminologies is presented in Table 2.

2. Exploring the Background of AI: From Origins to Advancements

In the 1950s, a young British mathematician, Alan Turing, initially floated the idea of solving problems using machine intelligence in his research article "Computing Machinery and Intelligence" [43]. In 1956, John McCarthy coined the term "Artificial Intelligence" for the very first time in a historic conference named "Dartmouth Summer Research Project on AI". The conference was aimed to emulate human problem-solving abilities [44]. By definition, an AI system simulates the functioning of the human mind, making computers, robots, and software think intelligently like humans [45]. It works by studying brain patterns and examining cognitive processes. Two scientists Russell and Norving defined AI as [46],

Definition: "Any entity that perceives its environment from sensors and acts in that environment from actuators can be described as an agent".

Since the birth of AI in the 1950s, the development of intelligent machines has been driven by a diverse array of approaches. Statistical learning [47], knowledge-based systems [48], soft computing [49], and symbolic reasoning [50] are among those approaches. In the field of energy management, it can potentially manage energy by making the system more intelligent and automatic without human participation. Researchers and industry experts have explored various areas in which AI contributes to enhancing the performance and efficiency of EMS. The potential areas include integration of RESs, optimizing MG operation, battery charging, and discharging management, forecasting applications, network security, anomaly detection, predictive maintenance, system restoration, and energy-efficient operation, etc. The AI-based optimization algorithms can optimize scheduling, regulate energy flow among MG components, and select the optimal size of DERs [51]. When considering the integration of RESs into the electrical grid, the AI-based forecasting algorithms play a crucial role in optimizing the variables including weather parameters, energy generation patterns, and demand forecast, which ensures effective energy distribution. Accurate forecasts guarantee utility companies to optimize energy production, prepare for emergencies, and offer grid integration with renewable energy. The AI-based algorithms can also identify anomalies and monitor grid components' operation through real-time data analysis [52]. This ensures a more rapid reaction to grid disturbances, more compelling power distribution, and less downtime. This makes MG more dependable and effective, supporting the transition towards a cleaner energy mix. By analyzing real-time data like energy price, electricity demand, and storage performance, AI methods are capable enough to optimize the operation of ESSs, enhancing charging and discharging schedules [53]. This promotes MG stability, maximizes the use of stored energy, and can effectively integrate the intermittency of RESs. Based on sensor data, maintenance logs, and performance indicators, AI-based approaches are utilized for predictive maintenance, and suggesting preventive procedures [54].

Some notable international organizations and projects that have already implemented AI in energy systems are General Electric, National Renewable Energy Laboratory (NREL), Tesla, and IBM Watson. General Electric utilizes AI algorithms that analyze sensor data to timely predict

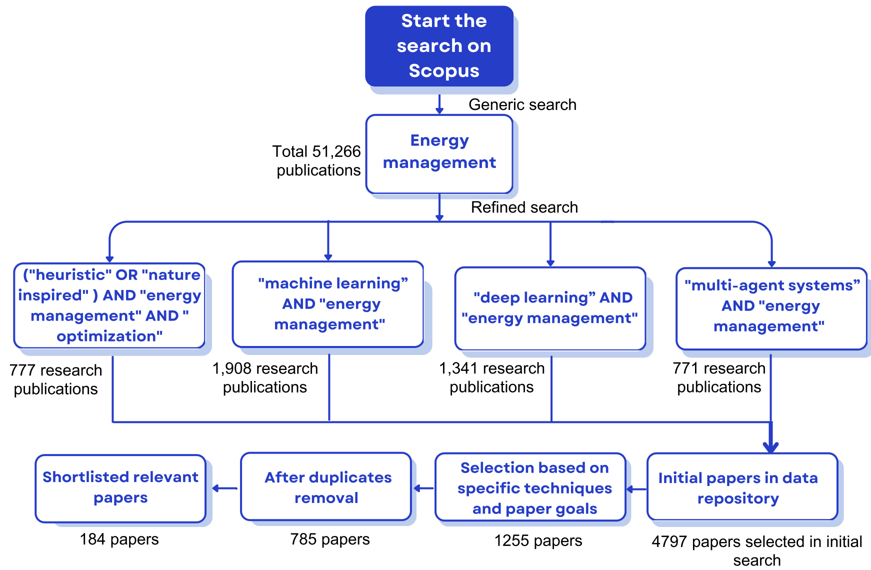

Fig. 1. A step-by-step methodology of keyword-based search using Scopus database for finding relevant literature.

maintenance requirements of the machinery before faults occur [55]. The AI algorithms help improve the performance and reliability of power-generating equipment. The NREL in the United States has made forecasting tools using AI approaches to predict energy production from renewables [56]. This helps the grid operator to optimize energy flow by analyzing fluctuations in energy production. To perform intelligent peer-to-peer energy trading, Tesla's auto bidder employs advanced AI algorithms, which can optimize the operation of DERs by continuously monitoring weather conditions and energy consumption profile [57]. Another notable organization is IBM's Watson detects anomalies to prevent cyber threats in power generation and depends on AI algorithms. These algorithms work based on finding suspicious activities by analyzing network traffic and system behavior [58].

This paper focuses on the data-driven, non-symbolic, and soft computing paradigms of AI. The four categories of AI approaches for energy management and optimization including metaheuristic methods, ML approaches, DL techniques, and MAS are discussed as illustrated in Fig. 2. The following sections present a comprehensive analysis of these approaches, describe their working process through textual and graphical illustrations, and how they overcome the issues related to MG operations.

3. AI-driven metaheuristic approaches for improving energy management system

The advancement in optimization techniques has given power to energy systems that can monitor and control energy generation, consumption, and storage while keeping energy costs low, and balancing energy demand and supply. The ultimate requirement for optimizing MG's operation is to make an efficient and reliable EMS. The AI-based MOTs are a possible solution to complex energy management challenges and dynamic constraints. These techniques mimic the behavior of natural processes, like swarm intelligence, genetic evolution, and cognitive behavior of various animals. The MOTs utilize three types of searches random, local, and global to identify optimal solutions [59]. These algorithms analyze the vast amount of data, identify intricate patterns, and make intelligent decisions to optimize the energy system. By motivating from diverse contributions of MOTs in energy system, this study focuses on following techniques, including GA [17], PSO [18], ACO [19], SA [20], CSA [21], and some latest approaches. The following subsection will discuss the working process of each algorithm and their applications in mitigating MG challenges in detail.

3.1. *Evolutionary algorithms*

3.1.1. *Genetic algorithm*

A GA is a nature-inspired approach that simulates Darwin's natural evolution theory [60]. A key characteristic of this algorithm is its ability to solve difficult and complex problems. It enables the optimization by selecting the fittest individuals through the fitness function and applies simple crossover and mutation operators [61]. The optimization process starts with randomly searching the solution space through strings of integers called chromosomes. An integer within a chromosome/individual is known as a gene and represents as a string of 0's and 1's. An initial random population of chromosomes or individuals is created. A fitness function applies to a randomly generated population, and the best individuals are identified based on the fitness score. These individuals further go through crossover, mutation, and reproduction processes. In reproduction, the most useful chromosomes are kept for the following population, while others are replaced with new chromosomes through crossover and mutation. Crossover is a process in GA where a few entities of parent chromosomes are interchanged depending on the crossover point to form two new offspring chromosomes. The mutation applies to newly formed offspring chromosomes, where specific gene values alter. For more clear depiction, a step-by-step evolution process of GA is illustrated in Fig. 3.

Early in the 1990s, GA was employed for the first time to determine optimal generation patterns of thermal generating units [62]. To deal with Unit Commitment (UC) and ELD, Ponciroli et al. suggested an enhanced GA-based strategy called EDGAR [17], in which authors considered 65 units, including gas, coal, and nuclear plants. The authors compared the results with previously developed reference codes from the Argonne National Laboratory. The authors of [63] proposed a combined sizing and energy management methodology using GA with MILP to optimize the sizing of MG components and address energy management problems. A GA with MILP was implemented to optimize the sizing of MG components and address energy management problems. Borce et al. proposed a real GA (a variant of GA) to schedule 2 hydro and 4 thermal power units optimally [64], and estimated its performance on 30 Bus Systems. The suggested method outperformed two hybrid methodologies, the dragonfly algorithm/PSO and GWO/PSO. In [65], authors employed GA for determining the optimal size and location of battery storage and PV system with the aim of reducing the system's losses. For this purpose, GA was simulated sequentially through a multi-phase Optimal Power Flow (OPF) problem, considering dynamic

Table 2
Frequently used abbreviations and variables in the manuscript.

Nomenclature			
Variables	*Description*	*Variables*	*Description*
i	Iteration	x_n^*	Minimum cost a MG achieves (without energy trading).
n	A single MG	$C_{n,g}$	Energy purchasing price from the electricity grid.
N	Set of MG	$C_{n,u}^k$	The cost of user discomfort.
w	Inertia factor	$C_{n,s}$	The cost of operating energy storage.
r_1, r_2	Random numbers	$C_{n,e}$	The payment cost to other MG
j	Particle	δ_n^α	Priority Factor
ν	Total sample values	K_n	Set of users within a Particular MG
ρ_i	Actual values	$\mathbf{E}$	Energy allocation
$\widehat{\rho}_i$	Predicted values	$P_j(i)$	Best position of particle j at iteration i.
c_1	Social rates	$Y_j(i)$	Current position of a particle j at iteration i.
c_2	Cognitive rates	$V_j(i)$	Velocity of a particle j at iteration i
Abbreviations			
Acronym	*Description*	*Acronym*	*Description*
AI	Artificial Intelligence	ACO	Ant Colony Optimization
ANNs	Artificial Neural Networks	CSA	Cuckoo Search Algorithm
CNNs	Convolutional Neural Networks	CGT	Cooperative Game Theory
DRPs	Demand Response Programs	DP	Dynamic Programming
DG	Distributed Generation	DL	Deep Learning
DERs	Distributed Energy Resources	DA	Dragonfly Algorithm
DR	Demand Response	DWT	Discrete Wavelet Transform
ELD	Economic Load Dispatch	ESS	Energy Storage System
EV	Electric Vehicle	ELF	Electric Load Forecasting
EMS	Energy Management System	GA	Genetic Algorithm
GWO	Grey Wolf Optimization	IoTs	Internet of Things
LSTM	Long Short Term Memory	ML	Machine Learning
MILP	Mixed Integer Linear Programming	MSE	Mean Squared Error
MOTs	Metaheuristic Optimization Techniques	MAS	Multi-Agent System
MLP	Multi-layer Perceptron	MG	Micro Grid
MAPE	Mean Absolute Percentage Error	MAE	Mean Absolute Error
NSGA-II	Non-dominated Sorting Genetic Algorithm II	NCGT	Non-Cooperative Game Theory
OP	Optimization Problem	OPF	Optimal Power Flow
PV	Photovoltaic	PSO	Particle Swarm Optimization
PEVs	Plug-in Electric Vehicles	QP	Quadratic Programming
RMSE	Root Mean Square Error	RF	Random Forest
RESs	Renewable Energy Sources	RNNs	Recurrent Neural Networks
RL	Reinforcement Learning	SVM	Support Vector Machine
SA	Simulated Annealing	SSA	Singular Spectrum Analysis
STLF	Short Term Load Forecasting	SG	Smart Grid
UNs	United Nations	UC	Unit Commitment
WE	Wind Energy	WT	Wind Turbine

load and PV production curves. The study demonstrated the effectiveness of GA in finding the optimal location of these distributed resources despite the varying load and PV conditions. One study proposed a LSTM model with hybrid parameter optimization approaches, including GA, adaptive weight PSO, and a global attention mechanism for optimal MG operation. This model can effectively manage the uncertainties associated with renewable energy production, electricity demand, and energy prices [66].

The GA can be used for multi-objective optimization problems. In one study [67], a multi-objective approach dealing with cost minimization, pollution reduction, and power losses was proposed. The authors employed a modified GA named Non-dominated Sorting Genetic Algorithm-II (NSGA-II). Due to various operational constraints, one-point crossover and mutation are used to improve the convergence and computing time. The proposed MG integrates RESs such as PV and WTs with a diesel generator, and stores surplus energy using storage options, aiming to power household loads. Ahmad et al. proposed a multi-objective GA to take into account the maximum energy contribution from MG consisting of PV and biomass, aiming to minimize energy cost and carbon footprints [22]. In another study [68], an NSGA-II was presented for optimal scheduling of multiple generation sources while minimizing the energy cost and power losses as a multi-objective problem. The authors implemented the proposed approach on an IEEE 33-bus test network consisting of 10 PV units and 4 battery storage units.

The GA has been widely applied in energy systems to integrate RESs, manage battery charging and discharging, and optimize energy management operations. It surpasses conventional techniques like Lambda Iteration and can integrate with other mathematical and heuristics methods to boost performance. The variant NSGA-II is particularly effective in solving multi-objective optimization problems. It is computationally efficient and capable of handling the non-linear dynamics of energy systems. Its convergence properties and computational complexity can be further improved by carefully selecting crossover and mutation values. Despite GA's implementation in the energy system, it has few inherent limitations. It does not always guarantee the global minimum and provides a solution closer to the ideal, may fall into local minima, and takes a longer time to converge to the final solution [69]. These challenges of GA can be addressed by other variants like NSGA-II and other straightforward adjustments. In Ref. [70], the binary-real coded GA with k-means clustering was proposed to optimize the scheduling of generating units. The k-means clustering algorithm resolves the issue of local minima trapping by partitioning the population size into dynamically sized sub-populations.

3.2. *Swarm algorithms*

3.2.1. *Particle swarm optimization*

Eberhart and Kennedy 1995 proposed PSO, inspired by the flocking behavior of birds, and called it a swarm intelligent algorithm [71]. In PSO, flying birds refer to particles; a group of birds/particles is called a swarm. Each particle in the swarm is a candidate solution having a fitness function and flies to search for the best solution (food) that is with best fitness value by exploring the search area. Throughout the search process, each particle records its local value and global best value from other particles in a swarm for its fitness function and modifies its velocity and position accordingly. The particles keep updating their velocity and position in every iteration until reach to global solution and stop changing the position [72]:

$$V_j(i+1) = wV_j(i) + c_1 r_1 (P_j(i) - Y_j(I)) + c_2 r_2 (P_j(i) - Y_j(i)) \tag{1}$$

$$Y_j(i+1) = Y_j(i) + V_j(i+1) \tag{2}$$

The velocity and current position of particle j at iteration i is represented in the above Eqs. 1 and 2 by V and Y. The hyperparameters c_1 and c_2 stand for the respective social and cognitive rates whereas r_1 and r_2 are any random numbers in the range of 0 and 1. The inertia factor is represented as w. The whole working process of the PSO algorithm is illustrated in Fig. 4.

In [73], the authors used an adaptive binary PSO to solve and optimize the generating unit, which is formulated using MILP. The authors

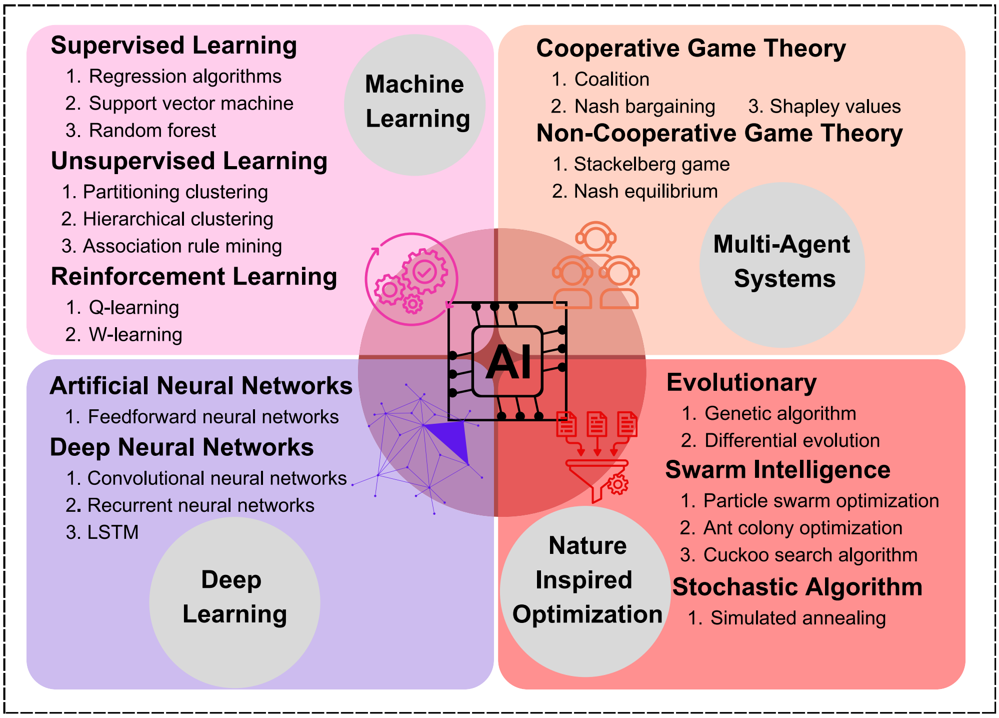

Fig. 2. The pictorial representation of four major AI-based approaches used in improving EMS.

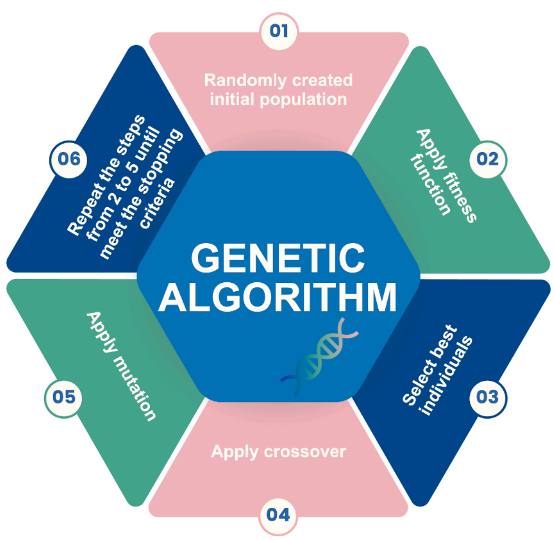

Fig. 3. A step-by-step graphical illustrations of GA evolution process.

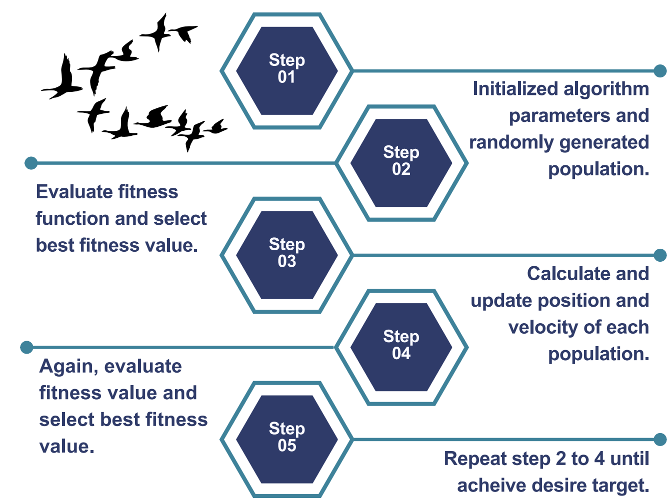

Fig. 4. Sequential process of PSO: A visual breakdown of each algorithmic step.

included constraints such as operating zone limits, spinning reserves capacity, and ramp rates minimum up and down time limits. The proposed technique was tested on various standard systems, including the RTS system, and IEEE 118 bus system considering variable units. A modified PSO with an equilibrium optimizer is presented in [18] for solving UC problems. The authors considered deterministic and stochastic loads to test the proposed hybrid approach. A trade-off was observed between cost minimization and computational time. The suggested method outperformed the Standard Equilibrium optimizer by saving 309.95$ and 1951.5$ for the 10-unit and the 20-unit system under deterministic load. It also performed better than the Standard Equilibrium under the 10-unit system during a stochastic load and saved 40.93$. The proposed algorithm takes a considerably longer computational time to complete a desired task. Ibrahim et al. proposed a hybrid Salp Swarm algorithm and PSO for MG that stabilizes the DC-bus voltage and provides a constant power supply despite fluctuating load [74]. The performance is highly dependent on DC-bus voltage. The PSO can be utilized to find the optimal location of the battery, and its charging and discharging cycles to ensure optimal and stable power supply. In [75], the authors proposed a solution for battery location and selection type to overcome the power mismatch problem through a master–slave methodology that employs a Vortex Search algorithm. The PSO was used in the slave stage to determine the operational scheme for the batteries, recommended by the master stage. In [23], a cost analysis of the MG's optimal operation is discussed using PSO. The authors determined the optimal size of battery storage to manage the charging/discharging cycle and WE. In a recent study, a unique approach utilizing weight-aggregated PSO was presented to improve the performance and reliability of the distribution system for battery size and charging/discharging scheduling [76]. To overcome the stochastic behavior of renewable energy production and ensure optimal operation of MG, the authors proposed a day-ahead PV forecasting model together with scheduling operation [77]. A variety of cost optimization techniques are examined and compared, including PSO, GA, and Harmony Search Algorithm.

In [78], the authors developed a Multi-stage EMS for smart MG that integrates PV, ESS, and electrical grid. The Multi-stage EMS is structured in two layers: the Anticipative Layer, and the Reactive Layer. The first one utilizes Multi-objective PSO for optimizing power set points based on predicted energy demand and PV power generation whereas the latter one compensates for prediction uncertainties by employing real-time data and Extremum-Seeking optimization. The proposed method demonstrated significant improvements over existing energy management strategies, including reductions in the energy bill, battery degradation cost, and Peak-to-Average Ratio. Another similar study [79], employed Multi-stage EMS that optimizes power distribution using a combination of PSO and Extremum-Seeking Controller, resulting in a 10.8% increase in energy bill savings and a 56.1% reduction in Peak-to-Average Ratio compared to traditional methods. One study proposed binary social learning PSO (a variant of PSO) in conjunction with a Parallelization framework to address the UC problem. It allows the integration of PV & WE with new energy generation technologies, such as Plug-in Electric Vehicles (PEVs) for charging & discharging [80]. The proposed methodology improved intelligent PEV charging and discharging management while optimizing resource allocation. To avoid the local optima problem, an elitist-based PSO was employed with the characteristics of SA in [81]. The objective was to solve the UC problem in two layers. The authors employed elitist-based PSO and SA in the upper layer to mitigate local optima issues, while the lower layer enhances search efficiency.

The literature review reveals that PSO integrates RESs and PEVs efficiently, reduces the operation cost of the generation source, and optimizes ESSs which reduces the power mismatch problem. It can manage the charging and discharging mechanism of intelligent PEV at the cost of high computational complexity, which can be mitigated through parallelization. Other challenges in its implementation include local minima trapping, premature convergence, and sub-optimal control parameter selection that can lead to poor solutions [82].

3.2.2. Ant colony optimization

The ACO is a population-based metaheuristic approach that mimics the behavior of ants when searching for food. This technique was proposed in the 90's by Marco Dorigo and was initially used to solve the traveling salesman's problem [83]. An ant is a social insect that interacts with other ants to find food. Ants roam around their colonies looking for food. When an ant finds food, it spits a liquid called pheromone on the ground on its way home. Other ants communicate using this pheromone by smelling it and following the same path to reach the final destination (food). Every ant spits out a pheromone and as the pheromone amount increases, it is more likely to get the food. Fig. 5 illustrates the algorithmic step of ACO.

The ACO is effective in solving combinatorial optimization problems by finding optimal solutions for the cost function. Lakshmi et al. presented an ACO approach in [19] for tackling the UC problem and reducing the system's cost. The authors implemented a 4-unit system and determined the best combination of generating units in terms of cost reduction. To check the efficacy of the presented algorithm, the results are compared with Dynamic Programming (DP), and findings revealed that ACO performs better than DP. In [84], the authors implemented ACO with GA named as evolving ACO, and the goal was to determine the optimal mix of generating units. The GA was employed to optimize the ACO parameters and then the later method identified the best schedule for generating units. This approach was tested on 10 and 20-unit systems, showing it as a highly cost-effective solution. The proposed methodology performed better, as it employed evolving parameters rather than a fixed set. Another study proposed a modified version of ACO for addressing the UC problem on two different systems [85]. One

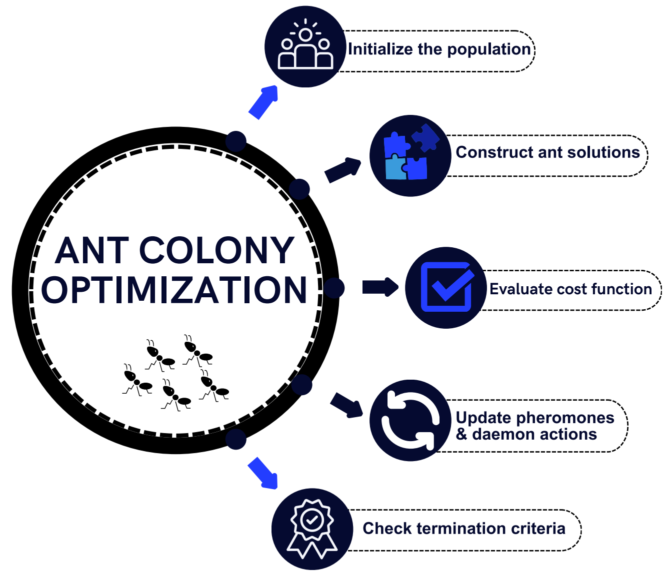

Fig. 5. A stepwise process of ACO: Describing the behavior of ants for searching food.

with 10 generating units running for 24 h and the other with 4 generating units running for 8 h. The modified ACO showed better results than the original version in optimizing the problem and improving the convergence speed. A nodal ACO that eliminated the shortcomings of ACO and addressed the UC problem in Ref. [86]. The proposed methodology was tested on the 1996 IEEE Reliability Test System, characterized by 26 generating units. and validation of results showed 0.08% energy savings than SA and GA. Mengyi et al. proposed an economic load dispatch strategy using niche ACO for building-integrated MG, considering the variable generation pattern of RESs [87]. The proposed method intends to maximize the use of renewable energy while keeping the balance between demand and supply. The performance of the niche ACO was compared with traditional methods, and demonstrated significant improvements, leading to a decrease of 12.96% environmental costs, and 14.25% operational costs. To overcome energy shortage risks and provide energy balancing operation among MG components, the authors in [88] proposed an ACO-tuned super-twisting sliding mode controller. The proposed approach has the capability to handle nonlinearities and improves the system response under uncertainties and variability of load conditions and renewables.

The ACO offers several advantages: it can tackle large-scale UC problems to solve combinatorial optimization problems and outperforms mathematical optimization methods like DP by avoiding local minima traps.

3.2.3. Cuckoo search algorithm

Yang et al. proposed CSA, a nature-inspired algorithm [95], works based on the parasitism strategy found in some species of cuckoos. The Lévy flight is added to this algorithm, which enables it to perform better than simple isotropic random walks [96]. Unlike other birds, the cuckoo lays its eggs in other birds' nests and controls the hatching rate by choosing nests that hold newly laid eggs. The parasitic cuckoo bird lays its eggs after eating the eggs of its host bird. Some hosts resist this behavior and build a new nest somewhere else or toss out the foreign eggs. This cuckoo breeding analogy is utilized for designing CSA, and each step of this algorithm is described in Fig. 6. Yang divides cuckoo reproduction into three parts, as described in [97]:

- Eggs act as solutions and are kept in nests.
- The cuckoo keeps its eggs (solution) in a suitable place with a higher probability of survival. For instance, if the cuckoo's eggs are more

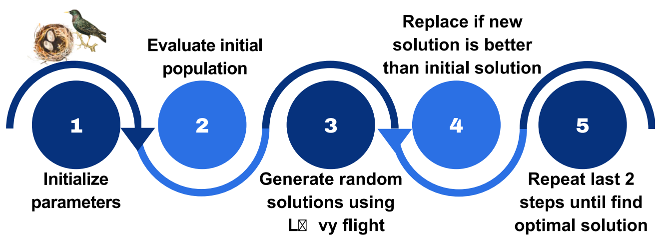

Fig. 6. A pictorial representation of CSA: Describing the phenomena of hatching cuckoo eggs.

familiar with the host bird's eggs (best solution), there is a higher chance of hatching (next generation).

- The number of host nests is fixed, indicating the population size. The host birds may find alien eggs (worst case scenario), which they may toss out of the nest. If not, the eggs mature and pass to the next generation.

Zhao et al. solved the UC problem using an improved binary CSA to reduce the fuel and start-up cost of generating units while balancing the constraints such as minimum up and down time, generation limits, power balance, and spinning reserve constraints [21]. The algorithm is designed to choose the right search direction by following a binary updating mechanism. A heuristic search methodology based on a novel priority list prevented the algorithm from being stuck in local optima. The authors validated the performance of the proposed algorithm on four generating units, and it showed good performance in terms of cost savings compared to numerical methods. One study solved heat and power dispatch problems using an adaptive CSA with exponential evolution mutation in [92] to minimize the cost. The authors used an adaptive parameter approach to enhance its exploration and exploitation capabilities. For this purpose, the authors used Gaussian sampling during the global search phase and an exponential evolution mutation approach during a local search. This small modification showed outstanding performance when compared with simple CSA and exponential evolution mutations on 7, 24, and 48 units.

The authors solved the congestion management problem by scheduling generating units using CSA [93]. This work aims to reduce line overloading while keeping minimum scheduling costs. A study addressed the UC problem considering vehicle-to-grid integration via binary real-coded based CSA [94]. This algorithm offers several advantages, including ease of use and fewer tuning parameters. It can easily fall into local optima and exhibits a slow convergence [98]. The overview of AI-based MOTs for improving EMS is summarized in tabular form in Table 3.

3.3. Stochastic algorithm

3.3.1. Simulated annealing

An SA algorithm is a method that stochastically improves global searches as it uses randomness in its searching process [99]. This algorithm is based on a metallurgical annealing process, which boosts metal's strength by rapidly heating it and then gently cooling it, improving its flexibility [100]. The annealing process involves excitation of the atoms at high temperatures, followed by gradual cooling of excitation, which allows them to settle into a new, more stable structure. It can solve nonlinear objective functions where other existing local search algorithms are less efficient. Like the Hill Climbing algorithm, it explores a relatively tiny portion of search space and updates single solutions until local optima reaches. Unlike Hill Climbing, it can accept poorer solutions as workable answers [101]. A visual representation of each SA algorithmic step is presented in Fig. 7.

Zhuang et al. applied the SA method to the UC problem in [89]

Table 3
Overview of AI-based metaheuristic algorithm for optimal scheduling of generation sources in improving EMS. [Part-1].

Technique	Ref	Key idea	Objective	Simulation tool
GA	[17]	Solved UC/ED problem using a GA variant called "EDGAR".	EDGAR findings are compared with other methods as per total cost in the summer and winter periods.	Python, CPLEX
GA	[67]	The NSGA-II is used to solve a multi-objective optimization problem where the reduction of operational costs, overall emissions, and power losses are all simultaneously sought.	Minimize the operational cost and power losses and improve the convergence rate by providing a solution within 15 min.	GridLab-D
PSO	[18]	This study suggested a hybrid approach called MPSO-EO for resolving the UC problem, which enhances the particle position update process to increase population diversity.	Output power generation, Cost of generating units, Optimal scheduling operation of generating units	MATLAB
PSO & ACO	[81]	The authors combined the attributes of PSO and SA and proposed the ISAPSO algorithm to solve the UC problem.	Cost comparison with other algorithms for 4 and 10 generating units	MATLAB
PSO	[80]	The proposed approach named SLPSO optimizes the operation of generating units while taking into account the integration of energy sectors	Cost comparison between other algorithms for 10 generating units, Power generation from renewables, Optimal scheduling operation of generating units with and without renewables	NG
ACO	[19]	Implemented ACO on four unit systems and found the optimal scheduling pattern	Reduced the overall operational cost of the system	NG
GA & ACO	[84]	GA and ACO were combined to create the hybrid methodology known as evolving ACO, which was then tested on systems with 4 and 10 units.	Minimize the cost compared to other algorithms considering 10 and 20-unit systems.	MATLAB
ACO	[85]	Modified ACO was used to address the UC problem for two systems—one with 10 generating units running for 24hrs and another with 4 generating units running for 8 h.	Cost comparison with state-of-the-art methods, Achieving optimal generating scheduling pattern.	MATLAB
ACO	[86]	To solve the UC issue and eliminate ACO's drawbacks, nodal ACO is adopted. The authors investigated the effectiveness of the recommended methodology using	Compare generating unit cost to various approaches and perform better than GA and SA.	MATLAB

(continued on next page)

Table 3 (*continued*)

Technique	Ref	Key idea	Objective	Simulation tool
		26 producing units and found a 0.08 percent energy savings over SA and GA.		
SA	[20]	The scheduling of generating units while integrating RESs and optimized by the SA approach.	Determine the best-generating unit scheduling strategy, taking RESs into account.	Not Given
SA	[89]	The SA was suggested to solve the UC problem, where the authors used 100 generating units as test systems.	Regarding cost savings, the proposed method outperformed existing algorithms and was more effective at meeting the challenging constraint.	FORTRAN
SA	[90]	Presented a hybrid approach for determining the best scheduling scheme for producing units based on QP and simulated annealing.	Maximum cost saving as compared to other approaches	Expert Systems
SA	[91]	Applied simulated annealing and an adaptive schedule on 10 generating units to solve the UC problem.	Minimize the cost level while satisfying the constraints	MATLAB
CSA	[21]	The UC problem is addressed by a suggested enhanced binary CSA. The algorithm is given a binary update mechanism to assist in selecting the proper search direction, and a heuristic search technique can keep it from getting stuck in local optima.	Outclass the conventional state-of-the-art methods while lowering the network's overall cost.	MATLAB
CSA	[92]	A combined adaptive CSA and Differential Evolution (DE) method is proposed for solving heat and power dispatch problems.	Compared to other CSA-based variations, lessen the cost and time complexity.	MATLAB
CSA	[93]	Congestion management problem was resolved using CSA through rescheduling generating units	Reducing the congestion cost	MATLAB
CSA	[94]	Addressed the UC problem considering vehicle-to-grid integration using binary real coded based CSA.	Reduce the operating costs and compare the performance with other algorithms.	MATLAB

considering 100 units of the test system. The authors considered 100 units as test systems. The approach did not presume any particular issue structure and is quite flexible in handling UC. The suggested method produced near-ideal results and demonstrated faster convergence than DP. In [20], the SA approach integrated RESs and optimized generating unit operations, aiming to reduce system costs and significantly cut execution time compared to the DP method, while maintaining

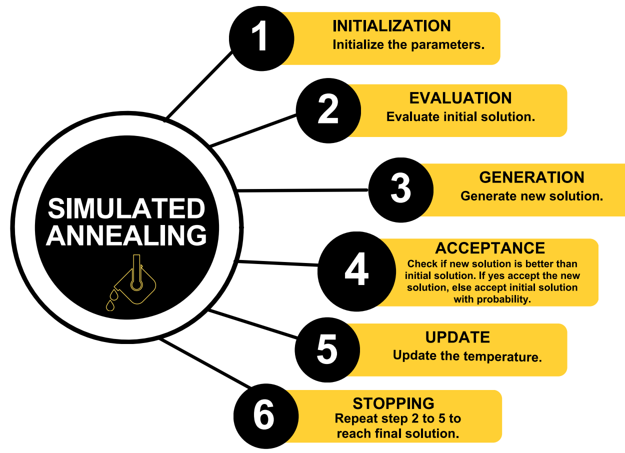

Fig. 7. A visual representation of each SA algorithmic step.

generation plans. A hybrid approach proposed in [90], employed SA and a mathematical technique named QP to address the generating unit scheduling problem. In [91], the authors combined SA with an adaptive schedule to address the UC problem. Adjusting the temperature level according to the cost enhanced the solution quality and improved the convergence speed. Test results demonstrated significant improvements with adaptive schedules as compared to algorithms with static schedules such as SA and GA.

The intermittent nature of renewable energy production and the variability of the EV's load could disrupt the stable power supply operation of MG. Mei et al. proposed a multi-objective optimization model for MG design to minimize the economical and environmental problem using adaptive SA & PSO, considering the stochastic renewables-based energy production and EV's load [102]. The suggested methodology used the linear weighting method to utilize the full potential of renewables and fulfill the energy demand. This approach employed a two-person zero-sum game, providing better balance in both objectives. The outcomes of the simulation demonstrated that the multi-objective linear weighting method approach can reduce the impact of uncertainties, encouraging full absorption of renewable energy with full load. A stochastic model considering the regulatory capacity of hydro-power plants and the stochastic behavior of WE and PV units was presented in [103]. Hydro-power plants are characterized by nonlinear behavior and use linearization methods to transform an original model into a MILP formulation. Then, a two-stage approach was implemented to solve the UC problem using a heuristic approach. Peddakapu et al. addressed similar issues of fluctuating power production from renewables, leading to inconsistent power supply and power shortages in [104].

3.4. Advanced metaheuristic approaches

Some newly proposed metaheuristic optimization algorithms can effectively handle the power mismatch problem. Most of these algorithms follow swarm behavior in finding the optimal solution.

Hua et al. proposed an energy management strategy for grid-connected and independent systems using swarm intelligence-based Promoted Remora Optimization algorithm [105]. The proposed algorithm is the advanced version of the Remora Optimization algorithm (introduced in 2021), addressing the limitations of local minimum entrapment and slow convergence. Another swarm intelligence-based algorithm called the Golden Jackal Optimization algorithm was proposed in [106] to solve multi-objective optimization problems for optimal scheduling of DERs, aiming to minimize the system cost. The proposed algorithm resolved the issues of being trapped in local optima and ensured faster convergence compared to traditional algorithms. The algorithm depicted satisfactory results in terms of achieving less cost than PSO, Artificial Bee Colony, and Tabu Search algorithm. One study proposed an Artificial Gorilla Troops optimizer for finding the optimal sizing of MG's components [107]. The study aimed to minimize the energy cost while estimating the probability of loss of power supply.

The Pelican Optimization Algorithm, a newly proposed method presented in Ref. [108], suffers premature convergence and has the issue of imbalance between exploitation and exploration capabilities. These challenges were addressed using the local escaping operator in another swarm-based algorithm called the Gradient Pelican Optimization Algorithm. The proposed algorithm is implemented in Ref. [24], aiming to determine capacity planning and optimize the operation of energy units in order to meet the energy demand of isolated areas. One study integrated emerging technologies including RESs, ESS, EVs, and DRP within the traditional grid using an improved version of GWO [25], which utilizes the power of the local escaping operator. The incorporation of these technologies illustrated the reduction of 15% operational cost. A recent study applied the GWO [109] demonstrating that it is highly effective in MG operations. The findings indicate significant achievements in reducing system costs and carbon footprints, enhancing system stability, and maximizing the use of renewable energy. An evolutionary approach named the QRUN algorithm was proposed in Ref. [110] for energy trading and finding the optimal capacity of distributed generation components including PV, biomass, and battery storage.

A swarm-based Improved Moth Flame Optimization algorithm with a decreasing inertia weight strategy was implemented in Ref. [111], aiming to determine the optimal size of PV, WT, and battery storage systems. The results showed the supremacy of the proposed algorithm as it can effectively reduce the net present cost and carbon emission in comparison with PSO and the original version of the Moth Flame Optimization algorithm. A Grasshopper Optimization algorithm with rule-based energy management strategies was proposed in [112], to determine the optimal size of MG located in Nigeria and to ensure OPF among its components. To find the optimal economic operation of interconnected MGs, an Archimedes Optimization algorithm was proposed by Kamel et al. in [113]. The novel feature of the study is the ability of interconnected MGs to exchange power with each other and with utility.

To overcome the mismatch problem in MG, authors in Ref. [114] proposed a dual approach that first forecasts day-ahead PV power and energy demand using a hybrid approach stationary wavelet transform and GWO-based least-square Support Vector Machine (SVM). Then scheduling of MG's components was performed using the Salp Swarm algorithm, aiming to minimize the operational cost. The approach can effectively manage the intermittency of renewable-based energy production. A hybrid methodology called Whale Optimization algorithm and Pattern Search was proposed in Ref. [115] to optimize the MG operation while considering the stochastic effect of PEVs and RESs. A multi-objective optimization problem was solved using the Sparrow Search algorithm proposed in Ref. [116], that aims to minimize the carbon emission and operating cost of MG to optimize the operation of MG. The overview of AI-based advanced metaheuristic algorithm for optimal scheduling of generation sources is presented in Table 4.

In [117], the authors developed a smart energy management unit to control the energy coming from a multi-energy system, intending to minimize the operation cost. The control unit employed the Harris Hawk optimization algorithm that made intelligent decisions based on the energy demand, electricity price, and generation capacities. One study proposed the idea of clustering and interconnecting MG in Ref. [118], where the authors optimize the operation of MG using the Marine Predator algorithm. The clustering and interconnected feature of the proposed study allows MG to exchange energy with each other or within the MG components, enhancing the system's reliability and stability.

By reviewing the above-mentioned literature, several insights can be drawn and are listed below:

Table 4
Overview of AI-based advanced MOT for optimal scheduling of generation sources in improving EMS. [Part-2].

Ref.	Technique	Objective	Features
[105]	Promoted Remora Optimization	Provide energy supply at minimum cost.	
Maintain constant DC bus voltage.			
Protect batteries from overcharging and depletion.	Components included in the study are PV, battery, Fuel cells, and load.		
Maximize the utilization of renewable energies.			
Reduce carbon emissions.			
Fast convergence towards an optimal solution.			
The incorporation of a Levy flight operator helps avoid local minima falling.			
[106]	Golden Jackal Optimization	Resolve the issues of MG energy management problem.	
Minimize the operating cost.	Components included in the study are PV, WT, battery, PEVs, diesel generator, Fuel cells, and load.		
Effective manages non-linear and non-convex optimization functions.			
Proposed approach generates 96% accurate results.			
Fast convergence speed.			
[24]	Gradient Pelican Optimization Algorithm	Determine the optimal size of MG components.	Components included in the study are PV, battery, diesel generator, biomass, and load.
Incorporate local escaping operator which helps the algorithm to avoid optima problem.			
The proposed algorithm outperformed other metaheuristic optimization techniques in terms of accuracy and computational efficiency.			
[25]	GWO	Optimal scheduling of multi-energy MGs, considering maximum energy from RESs	

(*continued on next page*)

Table 4 (*continued*)

Ref.	Technique	Objective	Features
Minimize the operational cost of multi-energy MGs.	Components included in this study are combined heat and power systems, WTs, boilers, EVs, and ESSs.		
The proposed algorithm integrated with the local escaping operator, helping the algorithm to not fall in local optima.			
The proposed study effectively incorporates uncertainties associated with stochastic wind energy production, energy price, and load demand.			
[110]	QRUN Optimization	Determine the optimal size of the energy system while meeting the electricity demand of Alrashda village.	Components included in this study are PV, biomass, and batteries.
The proposed study integrated the RUN algorithm with quantum mechanics to enhance the exploration and exploitation capabilities.			
The algorithm provides faster convergences towards the desired goal.			
[111]	Improved Moth Flame Optimization	Determine the optimal size of generation sources while minimizing net present cost, loss of load, and carbon emission.	Components included in this study are PV, WTs, and batteries.
The proposed study integrated the RUN algorithm with quantum mechanics to enhance the exploration and exploitation capabilities.			
The proposed algorithm considers decreasing inertia weight strategy which avoids the problem of premature convergence.			
[112]	Grasshopper Optimization Algorithm	The proposed algorithm aims to find the optimal configuration of MG components.	Components included in this study are PV, WTs, diesel generators, and batteries.
The proposed algorithm outperforms other optimization techniques by significantly reducing the capital cost of the designed system.			
[114]	Salp Swarm Algorithm	To reduce overall energy cost, the proposed study ensures the optimal operation of MG components by handling the intermittency of renewable energy production and scheduling generating units.	Components included in this study are PV, WTs, diesel generators, grid, and ESSs.
Forecasts day-ahead PV power and energy demand using a hybrid approach stationary wavelet transform and GWO-based least-square SWM.			
The proposed algorithm is compared with PSO which determines the optimal scheduling pattern.			

- The swarm-based MOTs are significantly employed in energy management strategies in order to optimize the operation of MG and showed excellent results while effectively resolving the issue of premature convergence and local minima entrapment.
- Considering the outstanding capabilities of classical metaheuristic algorithms such as GA and PSO, they are commonly used as benchmarks in various studies.
- Small modifications or improved versions of metaheuristic algorithms have shown considerable results and can be used in energy management strategies.
- In energy management, along with determining the optimal size of DERs, finding an optimal location of DERs is also a crucial element to guarantee the cost-optimized energy operation.

3.5. Discussion

MOTs are advanced search methods crafted to discover optimal or near-optimal solutions for intricate optimization challenges, even when faced with incomplete information and resource constraints. Extensive literature reviewed in the preceding section demonstrates their effectiveness in tackling complex optimization problems such as RES integration, hybridization and resource allocation, energy efficiency and stability, cost optimization, constraint management, and multi-objective optimization.

3.5.1. Integration of technologies

MOTs can effectively optimize the operation of MGs enabling seamless integration of cutting-edge technologies such as PV, WT, ESSs, and PEVs. This integration and optimized operation ensure cost-effective energy production, enhance efficiency, and boost system reliability. In [110], the authors utilized battery storage to store surplus energy during off-peak periods for later discharge during peak demand. One notable study incorporated PEVs and optimized their charging and discharging strategies using PSO [80]. Despite their ability to generate clean and cost-efficient energy, RESs are constrained by intermittent power supply due to weather dependency. Solar energy stands out for its low maintenance, stable operation, and high irradiance during peak times, yet faces challenges such as year-round sunlight availability and insufficient grid infrastructure for bidirectional power flow. In [5], the authors explored the integration of AI with smart grids to optimize hydrogen energy usage, highlighting advancements, challenges, and potential breakthroughs in generating, distributing, and utilizing energy.

3.5.2. *Hybridization and resource allocation*

Hybridization involves blending multiple techniques to harness the strengths of each while mitigating their weaknesses. Numerous studies have applied hybrid methodologies, such as combining GA with MILP to optimize MG component sizes and devise energy management strategies [63]. Another approach utilized a binary social learning PSO with a Parallelization framework to optimize generation patterns and integrate technologies like PV, WE, and PEV charging/discharging [80]. In [92], proposed an adaptive CSA with exponential evolution mutation to minimize costs in heat and power dispatch, enhancing both exploration and exploitation capabilities. In the reviewed literature, it is observed that hybrid methods provide better results than individual techniques by taking advantage of the novel features of each technique and overcoming the challenges. They optimize the MG operation by selecting the appropriate source size and their optimal location. It also includes energy storage optimization to balance demand and supply, lower reliance on costly energy sources, and minimize carbon emissions by choosing the optimal size and position of storage devices.

3.5.3. *Energy efficiency and stability*

Based on the literature reviewed, combining a traditional grid with RESs is proposed to enhance overall efficiency and could prove economically viable at a large scale. The integration of RESs brings the dilemma of variability and intermittent nature of energy production in different weather conditions. ESSs, act as reliable backup options by storing excess energy during periods of high generation and providing energy in low generation period [110], countering the intermittency of RESs. The energy storage optimization plays a crucial role in balancing energy supply and demand. The key considerations in optimizing ESSs include cost, lifespan, and matching energy demand with supply. Optimizing the utilization of these energy sources can address the challenges associated with high penetration of renewables, potentially improving grid reliability, flexibility, and stability issues [119]. Additional benefits include reduced power losses [120], lower carbon footprints [121], minimized upfront costs [122], and prevention of feeder overloads [123]. Meanwhile, diesel engines offer low initial investment costs but are burdened with high operational expenses and substantial carbon emissions.

3.5.4. *Cost optimization*

Many reviewed studies considered it as a primary objective function aiming to save money by reducing energy costs with the incorporation of DERs in traditional grid. It helps the utilities by lowering the burden on generating sources. Cost optimization refers to identifying the optimal operational cost of energy-generating sources, including traditional energy sources, RESs, and ESSs, while satisfying the constraints and fulfilling the consumer's energy demand. Better EMS and resource allocation are required to get the full economic advantage.

3.5.5. *Constraints management*

MOTs can effectively solve complex optimization problems considering some diverse real-world constraints. These algorithms can optimize problems with equality & inequality constraints, as well as non-linear & non-convex constraints, making them excellent for practical applications. In the MG domain, one study employed PSO to determine optimal generation patterns while satisfying constraints including spinning reserves capacity, operating zone limits, and ramp rates minimum up and down time limits [73]. In [21], the authors addressed the generating unit's scheduling problem while respecting the constraints of minimum up and down time, generation limits, power balance, and spinning reserve. The advantages and disadvantages of AI-based nature-inspired optimization techniques and suitable tools for solving optimization problems are discussed in Table 5.

3.5.6. *Multi-objective optimization*

According to the studied literature, the improved or modified versions of MOTs are significantly being used for addressing multi-objective optimization problems. These objectives involve the minimization of power loss, and carbon emissions along with the primary objectives of grid efficiency and stability. A variant of GA called NSGA-II has been extensively employed in literature for solving various optimization problems [68]. The enhanced version of the GA improves issues related to premature convergence and computing complexity.

The upcoming section thoroughly discusses the role of ML and DL approaches in improving energy management strategies through load forecasting, renewable energy prediction, and weather forecasting. It starts with an explanation of essential prerequisites such as dataset preparation and a discussion of performance evaluation metrics.

4. Data Collection and Preparation

ML and DL models are predominantly being utilized in energy systems for forecasting applications. These include predicting energy demand, energy generation from RESs, electricity prices, and weather-related parameters such as wind speed and solar irradiance. Before delving into the discussion of each application, it is essential to address several key steps and terminologies necessary for ML and DL models. These involve dataset collection, pre-processing, feature engineering, and some performance metrics for model evaluation.

4.1. *Dataset collection*

Data collection is a fundamental and costly task in ML and DL applications. The quality and quantity of data significantly impact the model's performance. As data quality and quantity increase, the model produces fewer erroneous results and improves accuracy. In forecasting applications, data can be collected directly through specific devices or from publicly accessible historical datasets, such as meteorological and past energy consumption data. In many cities, weather stations are built to measure and monitor various weather-related parameters using Supervisory Control and Data Acquisition systems [124]. The collected data at this stage is in raw form, often containing missing values, outliers, and duplicates. It must undergo a pre-processing step to be converted into a suitable form for model training, which will be discussed in the next section.

4.2. *Dataset pre-processing*

After data collection, data pre-processing transforms raw data into a usable format. This process encompasses several steps, including data normalization, filling in the missing values, removing outliers and duplicates, adjusting data resolution, and data decomposition.

4.2.1. *Data normalization*

Data normalization is converting all the features of a dataset to a

Table 5
Advantages, and disadvantages, of AI-based nature-inspired optimization techniques and suitable tools for solving optimization problems.

Aspect	Detail									
Advantages										
Robustness & Flexibility	Address complex constraints and minimize objectives, considering the dynamic nature of RESs.									
Scalability	They can be used in both small residential and large grid-connected renewable energy systems.									
Multi-Objective Optimization	Many HOTs can solve multi-objective optimization problems, optimizing criteria like cost, power losses, and environmental impact simultaneously.									
Parallel Processing Capability	Combining optimization techniques can accelerate the optimization process.									
Ease of Implementation	These techniques are easy to implement which can reduce both time and cost.									
Disadvantages & Limitations										
Computationally Intensive	Can be computationally expensive for high dimensional problem size.									
Convergence Speed	Many techniques converge slowly, reaching to the ideal solution.									
Parameter Sensitivity	Performance depends on carefully selecting parameters.									
Stochastic Nature	These techniques yield stochastic results that may be incorrect, necessitating multiple runs for accuracy.									
Type of Optimization Problem (OP)	**Tools**									
	MATLAB	**R**	**APOPT**	**MOEA Framework**	**Microsoft Excel**	**Python**	**GAMS**	**AMPL**	**IBM ILOG CPLEX**	**Gurobi**
Nonlinear OP	✓	✓	✓	×	×	✓	✓	✓	✓	×
Linear OP	✓	✓	×	×	✓	✓	✓	✓	✓	✓
Single Objective OP	✓	✓	×	×	✓	✓	✓	✓	✓	×
Multi Objective OP	✓	✓	×	✓	×	✓	✓	✓	✓	×
OP with Non-linear/Linear Constraints	✓	✓	✓	×	×	✓	✓	✓	✓	×
OP with Large Decision Variables	✓	×	×	×	×	✓	✓	✓	✓	✓

common range, typically between 0 and 1, to ensure uniformity. This involves adjusting the mean to 0 and the standard deviation to 1. In ML, unnormalized data can negatively impact the model's learning, potentially causing issues such as overshooting. The model may require more time to converge to a local minimum or may exhibit unstable convergence [125].

4.2.2. *Filling the missing values*

There are essentially two strategies for handling missing values in a dataset. One approach is to ignore the missing values if their proportion is relatively small. The other strategy involves imputing the missing values of each input feature with its mean value.

4.2.3. *Changing data resolution*

The term "data resolution" refers to the frequency at which data is collected such as per second or minute. Adjusting data resolution is often necessary when a learning model needs to be trained for predictions over longer time horizons. The literature commonly discusses the averaging method for this purpose [125]. The authors in [126] utilized the averaging technique to transform data resolution from 15 min to 1 h, enhancing the model's performance.

4.2.4. *Data decomposition*

Data decomposition is primarily used for time series data, involving the breakdown of this data into various components to capture seasonality and trends [125]. Many methods for decomposing time series data have been proposed in the literature, with the Discrete Wavelet Transform (DWT) being the most efficient and widely applicable. For example, Mishra [127] and Memarzadeh [128] successfully utilized DWT to decompose PV power and wind speed data into additional subcategories.

4.3. *Feature engineering*

Feature engineering is a critical phase in developing predictive applications with ML algorithms. This process entails transforming raw data features into representations that optimize the performance of the model [129]. It addresses challenges such as data sparsity, feature redundancy, and high dimensionality. Feature engineering is categorized into feature extraction and feature selection, which are explained in the subsequent section.

4.3.1. *Feature extraction*

Feature extraction is the process of extracting relevant information or features from the raw data and transforming them into a supported format for ML or DL algorithms. It aims to keep the most important information intact, offering computational advantages. It may involve manipulating the dataset by adding new features or separating irrelevant information.

4.3.2. *Feature selection*

This step represents the final stage, crucially involving the selection of a compact subset of features from high-dimensional datasets and the elimination of extraneous and irrelevant features. Three principal approaches for feature selection exist: filter, wrapper, and embedded [130]. The filter method assesses and categorizes features based on their correlation with the target value. The wrapper method also called the closed-loop approach, selects random features, evaluating their performance based on the predictive accuracy. The iterative process continues until the optimal features are identified. The embedded approach is seamlessly integrated within the ML algorithm, exclusively selecting features that significantly contribute to the model's performance. Recent literature has proposed various methods for performing dimensionality reduction, including Principal Component Analysis [33] and the Fourier Transform Frequency Spectrum [131].

4.4. *Performance metrics*

Performance metrics evaluate the effectiveness of ML/DL models. They provide insights into how well a model performs on a specific task. ML tasks are typically divided into two categories: regression and classification. Regression models are utilized in forecasting applications, where the output consists of continuous values. The primary evaluation metrics for regression include Mean Squared Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and R-squared error [132]. The subsequent section discusses these metrics and their respective formulations.

4.4.1. *Mean squared error*

The MSE computes the average of the squared differences between the actual and predicted values, as represented by the following formula. The primary drawback of MSE is that its squaring component disproportionately amplifies small errors.

$$MSE = \frac{1}{\nu}\sum_{i=1}^{\nu}(\rho_i - \widehat{\rho}_i)^2 \quad (3)$$

In the given equation, ν represents the total sample values. The actual values are denoted by ρ_i, while the predicted values are denoted by $\widehat{\rho}_i$.

4.4.2. Root mean square error

The RMSE is obtained by taking the square root of the MSE. This error metric mitigates the effect of the squaring factor in MSE, providing a more interpretable measure of error. Mathematically, it is represented as follows:

$$RMSE = \sqrt{\frac{1}{\nu}\sum_{i=1}^{\nu}(\rho_i - \widehat{\rho}_i)^2} \quad (4)$$

4.4.3. Mean absolute error

This evaluation metric measures the average absolute difference between the actual and predicted values and is represented by the formula below. It is more robust toward outliers, providing a more accurate representation of the degree of error.

$$MAE = \frac{1}{\nu}\sum_{i=1}^{\nu}|\rho_i - \widehat{\rho}_i| \quad (5)$$

4.4.4. Mean absolute percentage error

It is also an important measurement of error and is calculated by taking the percentage of MAE.

$$MAPE = \frac{1}{\nu}\sum_{i=1}^{\nu}\left|\frac{\rho_i - \widehat{\rho}_i}{\rho_i}\right| \times 100 \quad (6)$$

4.4.5. R squared error

It describes the proportion of total variation in dependent variables and can be explained by the independent variables. It is calculated using the following equation.

$$R^2 = 1 - \frac{\sum_{i=1}^{\nu}(\rho_i - \widehat{\rho}_i)^2}{\sum_{i=1}^{\nu}(\rho_i - \overline{\rho}_i)^2} \times 100\% \quad (7)$$

$\overline{\rho}$ is the mean of total sample values.

5. Machine Learning and Deep Learning Approaches for Improving Energy Management System

ML is a sub-field of AI focused on developing algorithms that enable computers to learn autonomously from historical data and experiences. ”Machine learning” was coined in 1959 by an American scientist Arthur Samuel [28]. The primary goal of ML is to simplify human tasks, especially those that are challenging for humans to accomplish accurately and promptly. Whereas DL is another subfield of AI that is based on Artificial Neural Networks (ANNs) where higher-level features are automatically extracted from data using multiple layers. In literature, the ML and DL techniques have been widely applied in smart grids, aiming to provide stable power operation, maximize the utilization of renewable energy, and reduce energy costs. The ML and DL models improve energy management strategies by contributing to load demand forecasting, UC, scheduling energy resources, and forecasting renewable energy generation.

In order to predict accurate results using ML or DL models, it is required to train the models with enough data. The dataset characterized by weather-related parameters and energy demand values is partitioned into three sub-datasets for model training, validating, and testing. This partitioning can be in different ratios. In most cases, 70% data is allocated for model training, whereas the remaining 30% data is further divided into 15% for model validation and 15% for model testing [133]. Model deployment is performed in the last stage that renders the predicted estimated renewable energy production, and energy demand. The complete workflow process from data acquisition to model deployment is elucidated in Fig. 8.

5.1. Load forecasting

To ensure accurate scheduling of energy sources, utility companies heavily rely on factors such as STLF (hourly and day ahead prediction), the minimum and maximum up and down times of generating units, and capacity. In load demand forecasting, utilizing input data from the preceding year or several days before the energy consumption data is common. A fuzzy linear regression model was proposed in [134] for STLF during summer and winter weekdays and weekends. Model results indicated variations of 5% for weekdays and 20% for weekends between forecasted and actual values. In [30], the authors utilized polynomial regression techniques to forecast a day ahead hourly load demand, comparing the results with those obtained through linear regression. Statistical parameters were employed to identify anomalies within the dataset based on forecasted errors. Moshoko et al. introduced a supervised learning-based linear regression methodology for STLF [135]. Leveraging forecasted results, the authors employed MILP to optimize scheduling patterns for power-generating units. Such ML techniques exhibit the potential for computational time reduction. The authors in Ref. [136] proposed a DL-based load forecasting method to optimize energy production planning during the years 2020 to 2040. This model was designed for Mexico’s electrical system. Through accurate load forecasting, the proposed study achieved multiple targets such as cost reduction of up to 11.02%, 28.27% of emission reduction, and 20.23% of low water usage.

The authors in Ref. [31] presented a hybrid approach to amalgamate RF with kernel density estimation for short-term hourly load demand forecasting. An RF-based model is trained on historical data, followed by probability prediction using kernel density estimation, leveraging individual tree outputs from the forest. To manage the charging and discharging of EV loads, Zafeirios et al. forecasted EV load curves using a range of methodologies, including statistical, ML, and DL approaches, implemented on various datasets [137]. The authors evaluated the performance of each approach and the findings revealed that the ML approaches are better suited for this task. Fig. 9 illustrates the performance trend of each approach using the performance metrics MAE and RMSE across two different datasets. XGBoost and the MLP are efficient and reliable methods, producing lower error rates.

Zulfiqar et al. proposed a hybrid approach that combines deep residual CNN and LSTM networks to forecast the short-term electricity load of individual households [33]. The deep residual CNN extracts spatial features while the LSTM learns through temporal information presented in the electricity dataset. The authors evaluated the proposed approach using two datasets and compared its performance with several state-of-the-art ML and DL models. The error rates of the forecasted results are illustrated in Fig. 10, demonstrating that the proposed approach achieved significantly lower error rates in load forecasting. High penetration of renewable energy causes the power instability problem in the traditional grid. A study proposed a novel intelligent wild geese algorithm optimized DL approach (IWGADL-STLF) for STLF in MGs [138]. This approach used an attention-based Bi-directional LSTM model and achieved RMSE of 0.307, MSE of 0.094, MAPE of 1.198, MAE of 0.082, and R-squared score of 0.988.

5.2. Renewable energy forecasting

The uncertainty associated with predicting RESs accurate output can significantly impact the UC problem, posing a significant challenge to MG planning and operation. RESs provide significant environmental and economic benefits. Their integration into smart grids is hindered by the

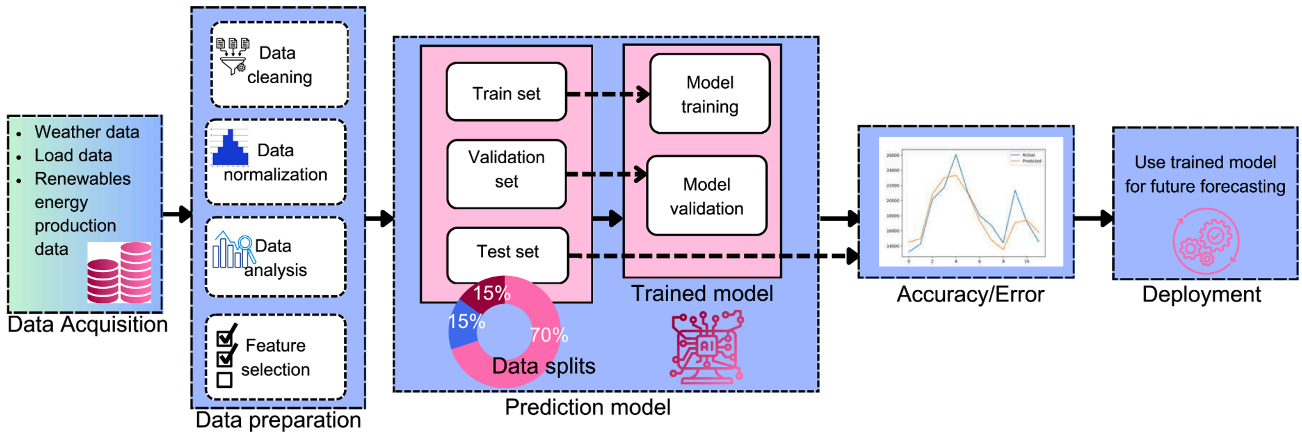

Fig. 8. The flow process of machine learning life cycle from data acquisition to model deployment.

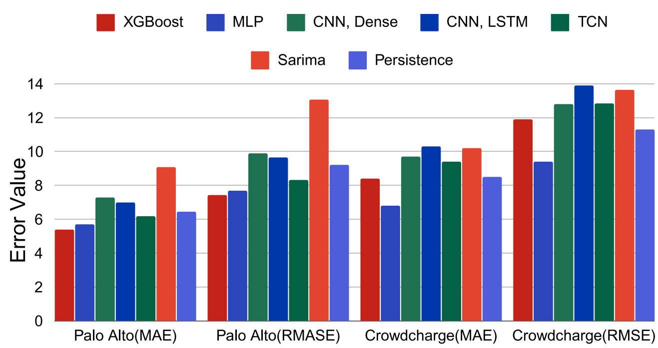

Fig. 9. Performance analysis of various forecasting approaches to forecasting EV load curve using Palo Alto and Crowdcharge datasets [137].

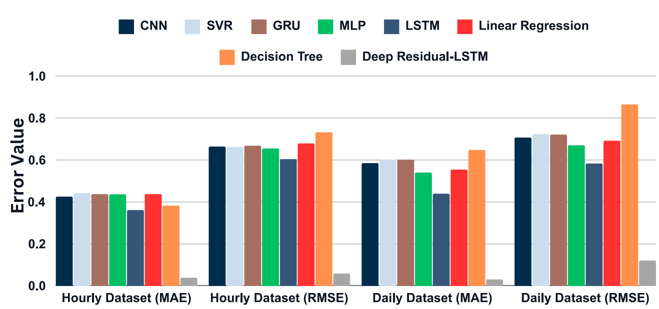

Fig. 10. Performance analysis of various forecasting approaches to forecasting energy consumption evaluating on hourly and daily datasets [33].

data's volatility and randomness. In [139], a hybrid approach combining the features of Singular Spectrum Analysis (SSA), CNN, and LSTM was proposed to forecast solar power generation for 1-h, 2-h, and 24-h ahead intervals. This approach aimed to leverage the spatial–temporal dependencies present in the solar power generation dataset. The proposed approach demonstrated excellent results by effectively utilizing three distinct methods. The SSA was employed in multiple stages, embedding the data into a higher-dimensional space, extracting salient components through singular value decomposition, and reconstructing the data using those extracted elements. The data was processed through a 1D convolutional layer (second method), which extracts sub-sequences from sequences using filters or kernels, identifying local trends and enhancing the network's ability to recognize temporal characteristics. The authors implemented an LSTM architecture (third method), which learns long-term dependencies in the data and predicts solar power generation using three gating mechanisms. To ensure the efficacy of the proposed method, it was compared with three other hybrid methodologies: CNN-LSTM, SSA-LSTM, and SSA-CNN. The forecasting error rates of the SSA-CNN-LSTM model, illustrated in Fig. 11, demonstrate the excellent performance of the proposed approach. A fundamental LSTM architecture is illustrated in Fig. 12. The LSTM network is a variant of RNN designed to mitigate the vanishing gradient problem inherent in traditional RNNs. This is achieved through the use of three gates: the input gate, the forget gate, and the output gate, which collectively regulate the flow of information within the network. The input gate ensures which information should be kept in the memory cell. The forget gate decides which information is less relevant and should not be added to the memory cell. The output gate controls the memory cell by only giving the relevant information. These gates enable the LSTM to determine the extent of information to retain or discard from the input sequence, making it particularly effective for capturing long-term dependencies.

An accurate renewable energy prediction is essential for effective planning and management. The authors in the study [140] combined Echo State Networks for nonlinear mapping with CNNs (ESNCNN) for accurate renewable energy prediction. The model outperformed existing methods and reduced the MAE by 5.49%, MSE by 5.01%, and RMSE by 3.76%. A day-ahead forecasting is crucial for autonomous control of energy systems. The study [141] proposed an ensemble model with CNN, gated recurrent unit, and BiLSTM for day-ahead forecasting of multi-energy systems. These models were evaluated using real-world data from Arizona, USA and the ensemble approach achieved the lowest RMSE of 1.98 and MAE of 4.12. Recent research emphasizes deploying ramping products to mitigate uncertainties in energy demand and RESs. A study by Yurucsen et al. [142] proposed a methodology for grid development arrangements and formulating grid balancing strategies, considering PV power integration. The authors devised association rules by employing an apriori algorithm for PV ramp power direction maps to analyze spatiotemporal patterns.

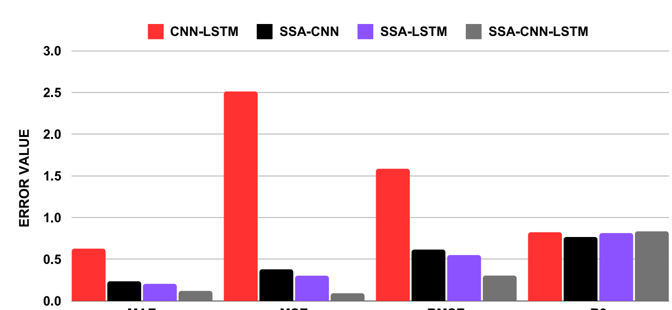

Fig. 11. Performance analysis of various DL approaches to forecasting solar power, employing different metrics [139].

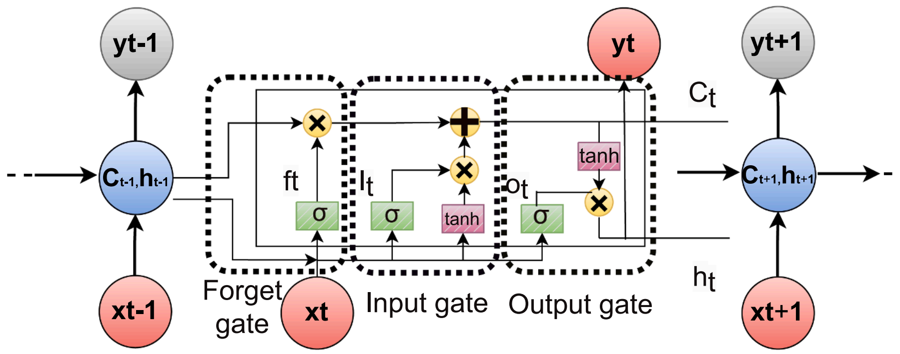

Fig. 12. An internal fundamental structure of LSTM model.

In Ref. [143], the authors addressed the variable and intermittent nature of the energy production by developing a short-term WE forecasting model for a 400-MW offshore wind farm. This study showed the effective integration of multiple DL techniques utilizing the Laser Imaging Detection and Ranging (LiDAR) and SCADA data, achieving a prediction accuracy loss of 6.8% and an error ranging from 2.11 to 10.95%. The study demonstrated that the integrated approaches enhance the robustness and generalization of the prediction model by considering the environmental factors and mechanical data of Wind WTs. The UC problem was addressed in Ref. [144] to minimize production costs while incorporating renewable energy and storage units with traditional grid. The authors developed forecasting models to predict renewable energy such as a Markov-based model for solar radiation prediction and a statistical method named auto-regressive integrated moving average model for wind speed forecasting. Based on the forecasted results the DP optimization technique with ANN was used to optimally schedule the generating units.

5.3. Weather forecasting

Weather resources such as solar irradiance, ambient temperature, and wind speed vary from location to location at different times of the day. An accurate weather forecast is essential for energy management applications to take into account spatiotemporal dependencies in weather data. In Ref. [145], the authors forecasted solar irradiance and wind speed through a multi-headed Convolutional LSTM (CLSTM) that uses three CNNs combined with PSO, referred to as MHCLSTM-PSO, which supports solar and wind energy generation prediction. The dataset used in this study consisted of temperature, pressure, wind speed, wind direction, solar irradiance, and other periodic measurements such as day of the year, month of the year, and season of the year. Each of the three CNNs extracts features from the data and learns complex patterns. The output of each CNN is then separately fed into three LSTM networks, which learn long-term dependencies in the data and forecast solar irradiance and wind speed. The temporal data are trained using the MHCLSTM layer. The outputs of all LSTM networks are concatenated and optimized using PSO. The proposed approach achieved a significant accuracy of 93.54%, which is considerably high as compared to the 72.52% of CNN, 78.16% of LSTM, and 85.56% of CLSTM. The comparative analysis of each approach with the proposed MHCLSTM-PSO in terms of lower error rates is presented in Fig. 13.

Feng et al. proposed a hybrid PSO and extreme learning machine algorithm to predict the global solar radiation in China [146]. After rigorous training and testing of the model, the findings demonstrated that the northwestern region has more potential for solar energy production, having abundant solar radiation. One study employed a hybrid K-nearest neighbors and ANNs approach for short-term hourly solar irradiance prediction [147], focusing on optimizing MG operation while integrating PV energy. The proposed methodology achieved MAE of 42 W/m^2 and RMSE of 242 W/m^2. Jasmin et al. addressed the stochastic variability inherent in solar irradiance and its impact on power generation [148], proposing a Reinforcement Learning (RL) based ANNs approach to optimize day-ahead schedules for generating units. This methodology adeptly manages the intermittent nature of PV energy production.

5.4. Scheduling energy sources

Unit scheduling problem often faces computational burdens when integrating large number of energy resources. A logistic regression model was proposed in Ref. [149] to mitigate computational burdens. This model was trained on past energy demand data and UC scheduling patterns and demonstrated efficacy across various power system standard test cases, including IEEE 24, 73, and 118 bus systems, notably

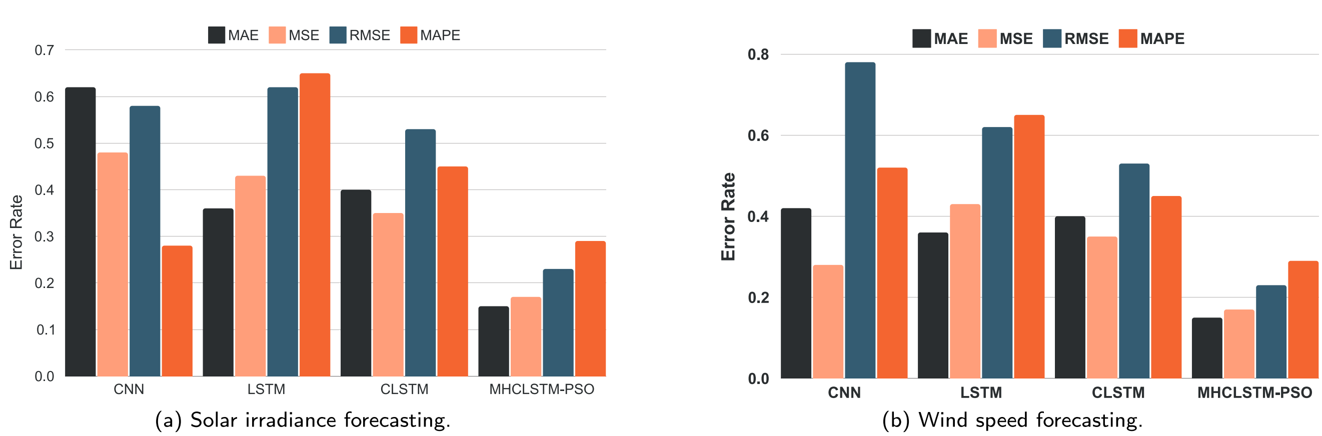

Fig. 13. Performance analysis of various DL and hybrid approaches to forecasting solar irradiance and wind speed, using different metrics [145].

excelling in computational efficiency. In Ref. [150], the authors utilized RL for real-time scheduling optimization in EMS. They employed deep Q-learning and deep policy gradient methods to execute multiple actions simultaneously. The proposed approach incrementally updates the Q-value to mitigate the computational cost. The findings indicated that real-time feedback mechanisms can promote efficient energy usage behaviors among consumers. A multi-step strategy employing deep Q-learning and MILP techniques for solving the UC problem was proposed in [151]. Despite the advancements, it is important to acknowledge that Q-learning approaches encounter scalability issues when used with more than 10 generating units.

In Ref. [152], a deep RL algorithm was proposed for scalable power scheduling optimization. The problem was modeled as a Markov decision process in a multi-agent simulation and achieved superior performance across various test systems with up to 100 generating units. Another study in [153] also applied a deep RL algorithm using MILP and deep Q-networks for optimal energy scheduling to enforce strict operational constraints like power balances. Navin et al. introduced a novel solution to the UC problem leveraging fuzzy RL technique [154], termed as a multi-agent fuzzy RL. This framework empowers individual generating units to optimize their operations over 24 h to fulfill load demands. This approach eliminates the need for prior system knowledge. The methodology involves fuzzification of the UC problem followed by RL-based optimization. Experimental validation across 10 generating units demonstrated the superiority of this approach over existing methodologies.

Several studies have suggested RL-based tree search techniques for the UC problem. Patrick et al. proposed a guided tree search RL-based

Table 6
Overview of DL approaches in forecasting applications.

Ref.	Model(s)	Architecture	Data resolution	Outcome	Application area
[158]	ANN	☆Three-layer architecture Levenberg–Marquardt approach Hyperbolic tangent Number of neurons in the hidden layer is determined using heuristic simulation. Input layer size depends on the number of input parameters. Output layer had one node.	10 min	The model topology with only one measurement of wind speed and the latest wind power showed excellent results in comparison with other topologies. The calculated MAPE are 3.6502%, 3.0706%, and 5.7557% in August 2002, November 2002, and January 2003.	Wind energy forecasting and incorporated forecasting results into UC scheduling.
[159]	ANN & GA	☆Three-layer fully connected network Sigmoid activation function The number of neurons in the input layer depends on the number of hours. Output layer neurons are determined by the total number of generators and hours. Model trained by backpropagation using gradient descent.	3 h	This hybrid approach can significantly reduce the processing time and cost in comparison with SA. Provides a near-optimal solution.	Provides optimal schedules of generating units.
[160]	ANN	☆Six-layer architecture 4 hidden layers are used. The sigmoid activation function is employed to smoothen the input of the first hidden layer. Weights are updated by back-propagation using gradient descent. Swish activation function is used at the end of the last hidden layer to classify the output.	1 h	In comparison to the scenario-based stochastic approach, the simulation findings indicate that using the forecasting method reduced operational expenses by 10.84%.	Predict wind speed. Forecast solar irradiance. Forecast energy demand.
[161]	ANN	☆Single-layer architecture An input layer includes a unit for each element of the data set. The hidden layer contains 30 neurons, and the output layer has one neuron. Sigmoid activation function. The model is trained by the decomposition algorithm DEC.	1 h	The suggested method performs better than other techniques. For instance, in one situation, the error of the suggested method is 6.63%, which is lower than ARIMA's error of 10.18%, support vector regression's error of 9.66%, and long short-term memory networks' error of 12.51%.	Forecast short-term hourly energy consumption of the hospital building, and the whole campus of Politecnico di Milano.
[162]	ANN	☆Three-layer architecture Levenberg–Marquardt approach Haar and Daubechies wavelet time–frequency analysis is used to fix the neurons.	10 min	In 90.60% of the analyzed sample days, the recommended forecaster's deviation was under 4%. The final forecaster's RMSE was 35.77 W/m2, which was a 37.52% improvement in accuracy over the persistent benchmark model.	Forecasted solar irradiance and solar energy for various day conditions including sunny days, partially cloudy days, and cloudy days.
[163]	RNN-LSTM	☆Three-layer architecture One input layer, one hidden layer with a feedback loop, and one output layer. Hyperbolic tangent activation function.	1 h	The RNN outperforms the SVM method by providing more reliable and safe results with an average error of less than 5%.	Forecast the wind power generation.
[164]	LSTM	☆Long short term memory The learning rate of 0.005. The look-ahead horizon and batch size are 6 and 64. Confidence level of 0.95. Time step of 1.	15 min	Make a comparison between deep learning methods and ARMA (conventional time series method). ARMA provides less satisfying results. LSTM gives a minimal average cost (4.56 × 106$) than RNN and GRU	Forecasts the future energy consumption and wind power generation.
[165]	LSTM & SARIMAX	☆Long short term memory The number of hidden layers is 3. The number of neurons per hidden layer is 60. Batch size = [1, 32, 64] Optimizer types= [Adam, RMSprop] Activation function is Sigmoid.	1 h	The suggested hybrid model (LSTM-SARIMAZ) could forecast both the load and wind speed more precisely than existing models. It could lower the RMSE for both wind speed prediction and load forecasting by 10.5% to 16.6% and by 22% to 44%.	Forecast the 3 days ahead energy demand and wind speed.
[33]	Deep Residual CNN & LSTM	☆Deep Residual CNN & LSTM The architecture contains 9 Conv layers, 2 LSTM layers, and 2 Dense layers.	1 h	The proposed approach showed excellent forecasted results with an MAE of 15.65%, MSE of 8.77%, and RMSE of 14.85%.	Short-term load forecasting.
[139]	CNN & LSTM	☆CNN & LSTM The architecture consists of Conv1D, MaxPooling1D, LSTM, dropout, and Dense layer.	1 h	The proposed approach showed excellent forecasted results with 1 h ahead prediction and MAE of 0.1202, with 2 h ahead prediction and MAE of 0.1400, and with a day ahead prediction and MAE of 0.1774.	1 h, 2 h, and day ahead prediction of solar power.

approach to mitigate the exponential explosion resulting from the escalating number of generators [155]. The authors accounted for the unpredictable nature of the load and tested the method on 30 generators. According to the findings, the guided tree search consumes less computational time while yielding optimal solutions regarding operating expenses. This approach faces challenges such as shallow search depth and run-time variability, which was addressed in [156]. The authors employed guided A* and guided IDA* to tackle these challenges. Guided A* utilizes a unique heuristic function and a priority list, resulting in a 94% reduction in runtime. Guided IDA* addressed runtime variability by replacing the fixed parameter depth with a time budget constraint, leading to 1% cost savings over Guided UCS despite similar computational costs. In [157], two RL-based algorithms, namely tree search and approximate policy iteration methods were presented to solve the day-ahead UC problem while considering 12 generating units. The UC problem is formulated as a Markov decision process to find a low-cost solution for generation scheduling. The proposed methodology demonstrated promising results by significantly reducing the runtime (2.5 min) compared to SA, achieving a 27% cost reduction. An overview of discussed studies of ML and DL in the context of energy management is presented in Table 6.

By reviewing the above literature in the context of forecasting and optimal scheduling of generation sources, several useful insights are deduced and described below:

- STLF instead of long-term forecasting is the widely adopted type of forecasting in the context of achieving optimal scheduling operation.
- Forecasting renewable generation such as solar and wind energy significantly depends on the spatiotemporal characteristics of the dataset which can affect the prediction accuracy of renewable energy production. The hybrid DL methods such as CNN for local temporal patterns and LSTM which remembers long-term dependencies, can effectively address this challenge to support the optimized energy production.
- In order to improve DL model's performance, metaheuristic algorithms are now being used for hyperparameter tuning.
- Reinforcement learning can address the exponentially increasing computational cost associated with an increasing number of generation sources through continuous Q quality value.

5.5. Discussion

The reviewed literature demonstrates that DL architectures exhibit exceptional performance owing to their ability to identify highly complex and nonlinear relationships between inputs and outputs. Several technical aspects must be considered when implementing a DL architecture, which are discussed in the subsequent sections.

5.5.1. Data quality and security

In forecasting applications, data quality, and quantity play crucial roles in training ML or DL models, with their performance significantly depending on these attributes. Data availability is often limited in real-world environments due to security and privacy concerns. When building a forecasting model, access to a large volume of high-quality data is essential, as poorly measured or incomplete data can lead to inaccurate predictions. Data is typically gathered using sensors, which may generate duplicate values and can experience interruptions due to sensor blockages. Incorporating advanced technologies such as IoT and blockchain into MG can enhance the data collection process and provide robust data security.

5.5.2. Feature engineering

Feature engineering is a crucial concept that enhances model prediction accuracy. It involves incorporating additional features into datasets beyond the primary ones, which significantly influence the prediction. Weather parameters such as solar irradiance and wind speed are primary factors when considering energy generation from PV and WE. Additional parameters like humidity, air temperature, atmospheric pressure, wind direction, and other weather conditions can significantly impact forecasting results and should be considered in the forecasting model.

5.5.3. Computational cost

Most of the literature employed DL-based approaches, especially ANNs for energy system applications. Other popular architectures in the literature are RNNs [163] such as LSTM [166]. In forecasting applications, many RNNs suffer a vanishing gradient problem. The LSTM networks can overcome vanishing and exploding gradient problems, by capturing long-term dependencies, and retaining important information despite gaps between relevant data points. These characteristics make LSTM an ideal choice for time series forecasting. Its complex structure leads to computationally expensive forecasting and makes the training process time-consuming. This problem can be attributed to redundant or unnecessary dataset features and duplicate values. To mitigate these issues, various computing techniques, such as parallel processing and in-database processing, can be employed to reduce computational complexity. Data reduction techniques, such as principal component analysis, can further accelerate the training process.

5.5.4. Hybridization

It is observed in the literature that hybrid methodologies are extensively employed in forecasting applications, leveraging the strengths of each approach to improve prediction accuracy. In [33], LSTM and deep residual networks were used to forecast electricity load. The forecasting errors of hybrid approaches were significantly lower compared to their original methods and other ML approaches. Figs. 11 and 13 also validate this observation where the forecasting errors of the hybrid approaches are much lower than their original versions.

The following section discusses the role of MAS for distributed control for effective energy distribution and management in decentralized networks.

6. AI-based Multi-Agent Systems for Improving Energy Management System

When designing hybrid energy systems, it is crucial to carefully determine an appropriate control strategy to fully leverage the system's inherent adaptability and resilience. The control strategy of these systems becomes more complex as the number of different sources increases significantly. Distributed control, which allows decisions to be made locally within each power source, facilitates coordination among sources competing for the same power. In this context, the MASs offer a suitable solution for the autonomous control of various elements in the hybrid energy system, enhancing scalability and robustness [167]. This technology has been successfully applied in many fields such as traffic and transportation [168], business process management [169], and various industrial applications [170]. The same principle can be utilized to regulate power sharing among multiple sources in a hybrid energy system. One study proposed an intelligent energy management strategy for multiple MGs connected with a grid using MAS to provide cost-effective scheduling for connected MGs [171]. In a recent study, the authors compared the performance of centralized and decentralized energy storage for achieving optimal energy management operation of MG [172]. The decentralized approach demonstrated excellent cost saving by approximately 72.78% compared to the centralized approach in terms of cost. Agents, which may be physical or virtual entities, can interact with each other and respond to environmental changes, making decisions autonomously without external control. Agents can directly manage each energy source in energy systems based on available resources and requirements. The surplus energy can charge batteries during low energy demand. The MAS determines the optimal time for charging through each resource based on its criteria and objectives, rather than relying on external instructions. Agents also communicate and cooperate with each other to accomplish tasks efficiently. Consider a system where the PV system charges the battery when sunlight is available, and the battery discharges to provide power when sunlight is not available. Two approaches such as Cooperative Game Theory (CGT) and Non-Cooperative Game Theory (NCGT) have been employed to optimize these tasks. The overall strategy for power sharing among various energy sources using MAS is illustrated in Fig. 14. In the following subsection, two approaches of MAS are discussed such as CGT and NCGT to study coalitions and non-binding relationships between participants. The Tables 7 and 8 show the applications, advantages, and disadvantages of MAS.

6.1. Cooperative game theory

The CGT allows each MG component to benefit more from cooperatively running under effective controlling techniques, as opposed to operating separately. In [173], the authors used a coalitional game theory approach to provide an optimal share of renewable energy to households and minimize MG's overall costs. The success of a coalition is determined by how much cost is saved, which is distributed among its members depending on a fairness principle. The authors utilized the Shapley value as a fairness measure to determine each coalition member's contribution and cost savings. Also, MAS can be used for energy trading between multiple interconnected MGs. Various coalitional game theory-based algorithms have been used in the literature to enhance the benefits of MGs with cooperative structures [174]. The authors proposed an incentive mechanism based on Nash bargaining to facilitate fair and efficient energy trading between MGs. The Nash bargaining formula involves multiplying the improved performance of all MGs to distribute the benefits of a cooperative structure equally. This can be done under the constraints of exchanging energy with the electricity grid and other MGs. The objective function involving this strategy can be written as [175]:

$$max : \Pi_{n\in N}\left[x_n^* - \left(c_{n,g} + \sum_{k\in k_n} c_{n,u}^k + c_{n,s} + c_{n,e}\right)\right] \tag{8}$$

The above equation represents the additional benefits of cooperation, divided into two main components. The term, x_n^*, indicates the minimum cost an MG can achieve without engaging in energy trading with other MG. The second term encompasses the cost incurred by a MG when exchanging energy with another MG. In the equation, terms such as $C_{n,g}$ denotes the energy purchasing price from the electricity grid, $C_{n,u}^k$ is user discomfort cost, $C_{n,s}$ is the cost of operating energy storage, and $C_{n,e}$ represents the payment costs to other MG. Here, N represents the set of MG, and K_n denotes the set of users within a particular MG, denoted by n. The Nash product ensures equitable treatment of each MG regarding sharing the benefits of collaboration. The difference between the two terms reflects the cost reduction achieved by a MG.

6.2. Non-cooperative game theory

In NCGT, participants are not required to make binding agreements with each other. This strategy involves various decision-making bodies that aim solely to maximize their profits [176]. The authors in [34] proposed a decentralized controller, based on NCGT to manage the energy consumption of a MG while taking into account intermittent energy production from RESs, seasonal demand changes, and grid interruptions. Similarly, MAS-based NCGT can be employed for energy trading between various MGs. In an interconnected system of multiple MGs, the Nash equilibrium is utilized to address competition among buyer MGs [177]. The Nash equilibrium applies to systems in which all MGs are interconnected in such a way that they share energy equally and simultaneously. Each buyer MG adopts the Nash equilibrium strategy based on its priority factor, enabling fair energy sharing among multiple MGs. The overall satisfaction level of each MG is measured using a logarithmic function, as presented below:

$$S_n = \delta_n^\alpha . log\left(1 + \frac{E_n}{T_n}\right), \qquad n\in N \tag{9}$$

As a result, the utility function which is utilized to identify the best strategies for each buyer MG is provided below.

$$U(S) = \underset{\mathbf{E}}{argmax}\left[\sum_{n\in N}\delta_n^\alpha . log\left(1 + \frac{E_n}{T_n}\right)\right] \tag{10}$$

$$\sum_{n\in N} E_n \leqslant E \tag{11}$$

E is the vector representing the energy allocation, with elements E_n. The energy allocation to MG n must always be less than the total available energy. As described below, a non-cooperative strategy is employed to formulate competition for energy among multiple MGs.

In [178], the authors considered the priority factor for energy allocation to buyer MGs, denoted as δ_n^α. Priority factors include each buyer MG's past efforts to sell surplus energy to nearby MGs and their load demand. This mechanism encourages MGs to engage in energy trading with each other proportionally to the energy they have contributed in the past, along with their local energy demands. This strategy can reduce reliance on grid energy, reducing the grid's burden. The Stackelberg game is another well-known NCGT approach used to regulate energy trading between interconnected MGs. A seller MG is seen as the leader in the competition, while buyer MG is regarded as the follower [179]. Buyers are allocated energy based on their bids. In [180], the regional control unit is depicted as the leader, whereas the village MG is depicted as the follower.

7. Recommendation, Challenges and Open Issues of AI in Energy Management

Based on the literature on AI-driven methodologies, this section

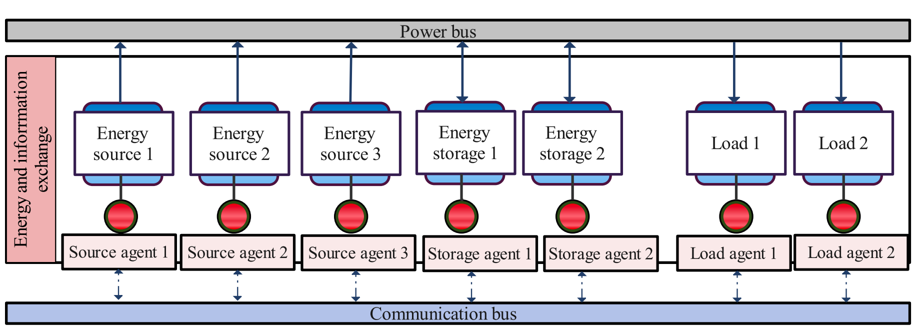

Fig. 14. A multi-agent system for sharing energy among multiple agents.

Table 7
Applications of machine learning, deep learning, and multi-agent system in EMS.

Energy System Applications	Methods									
Applications	**Machine Learning Algorithms**					**Deep Learning Algorithms**			**Multi-agent System**	
	Fuzzy Linear Regression	**SVM**	**RF**	**K-Means Clustering**	**Q-Learning**	**FNNs**	**LSTM**	**DNNs**	**CGT**	**NCGT**
Load Forecasting	✓	✓	✓	✓	×	✓	✓	✓	×	×
Predicting Renewable Energy Production	✓	✓	✓	✓	×	✓	✓	✓	×	×
Energy Consumption Modeling	✓	×	✓	×	×	×	×	×	×	×
Energy Price Forecasting	✓	✓	✓	×	×	✓	✓	✓	×	×
Fault Detection and Diagnosis	×	✓	✓	✓	×	✓	×	✓	×	×
Energy Theft Detection	×	✓	×	✓	×	×	×	×	×	×
Energy Efficiency Analysis	✓	✓	✓	✓	×	×	×	×	×	×
Energy Storage Management	×	✓	×	✓	✓	✓	✓	✓	✓	✓
Demand Response Optimization	✓	×	×	×	✓	×	×	×	✓	×
MG Energy Management	✓	✓	×	✓	✓	×	×	×	✓	✓
Predictive Maintenance	×	×	✓	×	×	×	✓	✓	×	×

Table 8
Advantages, and disadvantages, of machine learning, deep learning, and multi-agent systems.

Methods	Advantages	Disadvantages/ Limitations
Fuzzy Linear Regression	Can handle imprecise and uncertain data.	
More robust against outliers and easy to interpret.	Complex interpretation than simple linear regression.	
More computationally intensive than linear regression.		
SVM	Has the ability to process high-dimensional datasets, dealing with non-linear relationships.	
Not prone to overfitting.	Limited effectiveness in dealing with multi-class problems.	
High computational cost and precise adjustment of parameters.		
K-Means Clustering	Straightforward and quick.	
Suitable for data exploration and classification.	Requires specifying the number of clusters in advance and can be sensitive to the starting conditions.	
RF	High precision, less susceptible to overfitting.	More computationally intensive than DT and harder to interpret.
ANN	Handle complex patterns, adaptable to various data types, and highly accurate.	Overfitting due to limited data and Black-box nature.
RNN	Can manage sequential and time series data as well as long-term dependencies.	It may be susceptible to overfitting and slow training and can experience issues like vanishing or exploding gradients.
LSTM	Capable of managing long-term dependencies, making it valuable for time series data.	Susceptible to overfitting, requiring diligent tuning.
CGT-based Multi-Agent System	Enhance the system's stability and reliability by dividing the task among multiple agents.	
This approach can be extended to include multiple agents, making it suitable for large-scale applications.	Complex formation makes the system computationally intensive.	
Necessitates robust communication and coordination among multiple agents which is resource intensive.		
NCGT-based Multi-Agent System	Lowers the possibility of single-point failure, as agents operate autonomously.	
Has the ability to adapt to changing environments and varying tactics of other agents.	The non-cooperative behavior provides sub-optimal outcomes.	
It offers multiple equilibria, making it difficult to predict which one will be selected.		

presents the fundamental challenges and potential opportunities associated with each approach in the context of energy management. The advantages and disadvantages of all MOTs, ML approaches, DL architectures, and MAS are summarized in Tables 7–9. These state-of-the-art techniques have the potential to revolutionize the development of an optimized EMS. Due to the rising world population, energy demand and cost have increased considerably, and to deal with these issues, the local communities are shifting their priorities of energy usage towards local DERS. The amalgamation of DERs into electrical grid systems is beneficial in terms of reducing energy costs and minimizing carbon footprints. This integration has few inherent limitations as energy generation from renewables is highly stochastic and depends on favorable weather conditions which generates non-linear energy production patterns. This may cause a power mismatch dilemma as the individual households or whole communities always follow an irregular consumption pattern and can lead to blackouts or instability of the whole system. The inappropriate behavior necessitates energy management strategies that can manage the stochastic nature of renewable energy production while optimizing the operation of DERs. The current electrical grid system is an old-age infrastructure and in the past few decades, it has shown very little progress. There is a need to upgrade outdated grid infrastructure with a modern power system that takes the leverage of advanced green technologies and techniques to satisfy the energy demand locally at the lowest cost while taking into account the uncertainties.

The challenges of power mismatch, and uncertainties of renewable

Table 9
Advantages and disadvantages of AI-based techniques used for energy management applications.

Ref.	Methods	Disadvantages	Advantages
[17,67,84,181,69]	GA	The initial population's initialization is a complex and time-consuming task.	
Computation time is a critical issue for GA. Less certain convergence. Possibility that the final solution is not what is expected from it as it generates heuristic solutions. Provide smooth and simple convergence for finding optimal solutions. Can easily be implemented.	Versatile when simulating constraints.		
[82,18,182]	PSO	Premature convergence and high computational time are major failures of PSO.	
The final solution may not meet your expectations as it holds heuristic characteristics. The high tendency of being stuck into local optima limits its application. More stable convergence compared with other methods.	Simpler implementation with minor tuning.		
[84,85,183]	ACO	Slow convergence.	
Solution accuracy decreases as data size increases.	Can apply to large-scale UC problems.		
[101,20] [89,91]	SA	Temperature parameter is difficult to control. Because the cooling process is so slow, it takes ten times as many iterations.	More computationally efficient than DP.
It can accept the worst solution to find the optimal global solution.			
[21,92,93,98]	CSA	Slow convergence.	
Required some modification to get full advantage of it. Provide global optima solution as cuckoo lays eggs to other bird's nest. Less tuning parameters.	Easy implementation.		
[105,107,108,24,109]	Advanced metaheuristic algorithm	Can effectively overcome challenges like premature convergence, and fall into local minima.	Support the integration of a large number of MG's components while reducing the system's operational cost.
[184,149,185,151,155,157]	ML	RL based Q-learning method has dimension problem. Simple RL-based methods can not be applied to a large number of generators.	SVM and k-means clustering avoid the problem of being stuck in local optima.
Logistic regression and nearest neighbor reduce computational time in UC. RL-based guided tree search does not suffer exponential explosion problem while considering 30 generators in solving UC problem [155].			
[158,186]	ANN	A network that is too small or too large may experience precise mapping and over-fitting problems.	
Capable of extracting correlation b/w variables without describing system equations.	Require less computational resources.		
[139,33]	CNN & LSTM	CNN requires large labeled datasets.	
Because of complex architecture, LSTM needs large datasets for model training.	The hybrid DL methods such as CNN for local temporal patterns and LSTM which remembers long-term dependencies, can be employed in forecasting applications.		
[34]	Multi-Agent System	Provides limited control and error-prone system.	Offers a distributed control strategy to multiple energy sources, reducing computational and communication burden.

energy production can be resolved by adopting multiple technologies together and the system can be recognized as a futuristic model as presented in Fig. 15. The idea of interconnected MGs comes to light in which each MG can optimize the operation of the local home through decentralized-based multi-agent control and can share information and energy with nearby MGs and with centralized EMS. To mitigate uncertainties associated with load demand and renewable energy production, the EMS which is installed inside each home can leverage of advanced forecasting algorithms to predict future load demand & renewable energy generation. Based on predicted values, the multi-agent control can optimize the operation of generation sources. This system fulfills the local demand of each MG by utilizing local RESs and ESSs in a decentralized way. The excess energy is traded off to other directly connected MGs using a peer-to-peer energy-sharing approach to fulfill their energy demand. The extra energy after fulfilling the requirement of directly connected MG is shared with centralized EMS to fulfill the demand of those MGs that are not directly connected. The centralized EMS system is also connected to the grid to manage the energy demand of any MG in case of more energy requirements. This trading mechanism can use different priority scheduling algorithms for energy sharing, some of which are described in the review. This system utilizing decentralized-based multi-agent control, forecasting techniques, and optimization techniques can handle the uncertainties, overcome the power mismatch problem, and optimize the generation source while meeting the high energy demand. There are still some challenges present in this hybrid centralized and decentralized approach. A detailed description of these challenges is given below.

7.1. Challenges of AI-based metaheuristic algorithms

- **Renewable Integration:** In recent years, power systems have been enhanced with modern technologies and infrastructure, leading to improvements in transportation systems, environmental pollution reduction, and the efficient management of energy resources. This innovative power infrastructure encompasses emerging technologies such as PEVs, RESs, ESSs, and demand-side management. Some studies have addressed these innovative technologies, but considerable work remains.
- **High Dimensionality:** In the power systems, numerous decision variables and constraints generate a high-dimensional search space, complicating the task for metaheuristic approaches to explore and exploit the entire space effectively. This complexity often results in slow convergence, causing algorithms to require numerous iterations before arriving at a satisfactory or optimal solution.
- **Premature Convergence:** This phenomenon occurs when metaheuristic algorithms become trapped in sub-optimal solutions and fail to explore better solutions in other regions of the search space. This issue arises due to insufficient exploration or the algorithm's inability to escape local optima, resulting in sub-optimal decision-making.
- **Black-box Solution:** Metaheuristic algorithms often provide challenging black-box solutions to interpret and explain. Understanding the rationale behind optimization decisions is crucial for energy management applications. This lack of interpretability can pose significant challenges for various stakeholders in accepting the outcomes of metaheuristic algorithms.
- **Dynamic Environments:** EMS operates in dynamic and uncertain environments where various parameters such as load demand, energy prices, and the availability of renewable energy fluctuate continuously. Metaheuristic algorithms face challenges in swiftly adapting to these dynamic conditions, necessitating careful modifications to enhance their responsiveness and effectiveness.
- **Computational Complexity:** The optimal solution for the integration of hybrid energy sources with minimal computational effort remains a critical challenge. Researchers and policymakers are continually seeking methods to address the complexities inherent in non-linear systems. This review discusses several emerging optimization algorithms aimed at identifying optimal solutions for energy management problems. The variation in case studies and computational systems complicates selecting a single superior approach for efficient energy management.

7.2. Challenges of ML and DL

- **Interpretability:** ML algorithms often result in a "black box" phenomenon, where the inner workings of the models are difficult to interpret or comprehend. Understanding the outcomes or predictions

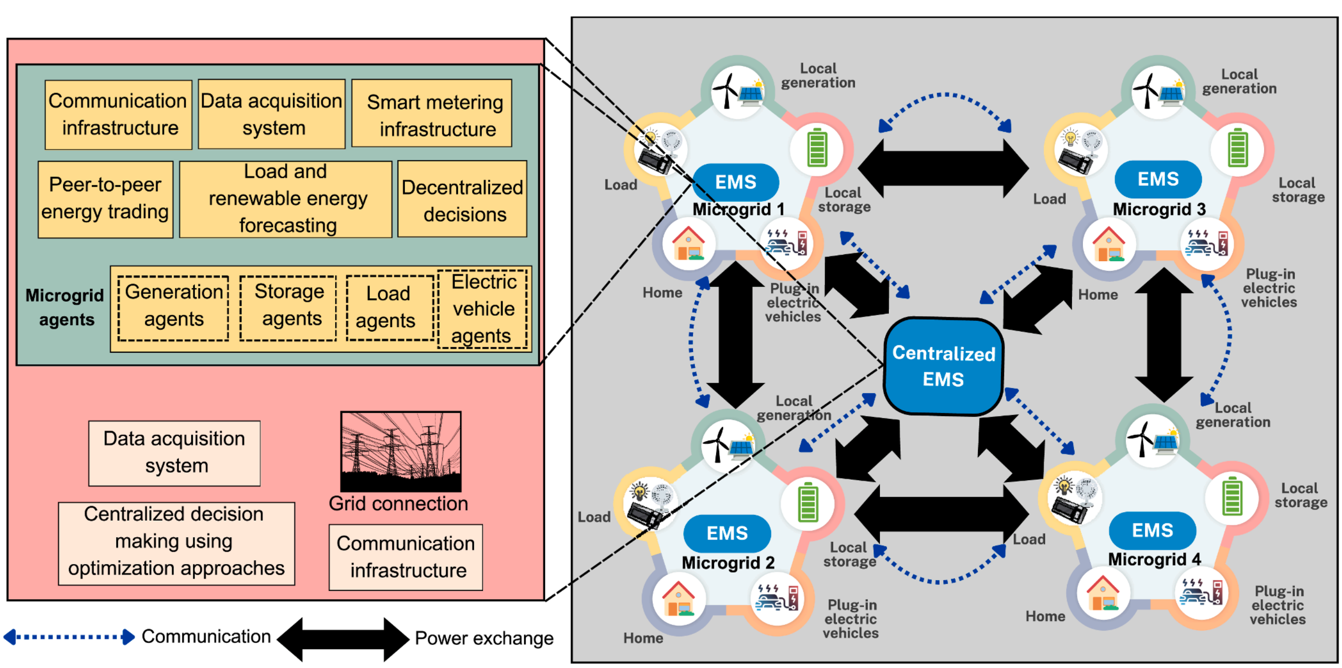

Fig. 15. Optimized EMS with hybrid centralized and decentralized energy sharing mechanism.

generated by these models can be a challenging task. This lack of interpretability poses significant challenges when justifying predictions to regulatory authorities or other stakeholders.

- **Data Quality and Availability:** Ensuring data quality and availability is one of the most challenging tasks in ML. ML models generate accurate predictions when trained on extensive, and high-quality datasets. Obtaining reliable and meaningful data for predictive applications can be difficult. Data may suffer from missing values, inconsistencies, or biases, which can result in erroneous outcomes.
- **Overfitting:** Overfitting represents a prevalent challenge encountered in ML algorithms, particularly in deep neural networks, wherein models tend to capture intricate patterns specific to the training data rather than discerning generalized patterns. While exhibiting satisfactory performance on the training set, such models fail when presented with unseen data during testing, leading to erroneous predictions and diminished generalization capabilities. Mitigating the overfitting phenomenon necessitates striking a judicious equilibrium between model complexity and its generalization ability across diverse datasets.
- **Scalability:** In forecasting applications, scalability emerges as a significant challenge, particularly when dealing with vast datasets. Certain ML techniques may incur considerable computational overhead or prove ineffective when confronted with intricate forecasting tasks. The imperative of employing efficient feature selection and dimension reduction methodologies and strategies arises to address scalability concerns.
- **Concept Drift:** This phenomenon occurs when the statistical characteristics of data change over time, thereby diminishing the precision of predictive models. The underlying correlations and patterns in forecasting applications may change due to various variables, such as shifting customer preferences or altering market conditions. To ensure the accuracy of projections, it is imperative to address concept drift in ML models through continuous monitoring, retraining, and updating.
- **Model Selection and Hyperparameter Tuning:** Choosing the appropriate model and tuning hyperparameters in ML can be challenging and often requires extensive testing and validation. It is crucial to carefully select the most suitable algorithms and optimize their hyperparameters to ensure reliable forecasting. In time series forecasting, the target variable often strongly correlates with various factors, including trends, periodic measurements, and seasonality. Traditional ML algorithms typically fail to capture these patterns effectively. Advanced DL architectures, such as LSTM and CNN, are used to efficiently model these trends by managing spatiotemporal features.

7.3. Challenges of MAS

- **Communication Infrastructure:** Various agents communicate with each other, thereby generating large volumes of data. A fast and efficient communication network is required to support real-time data exchange between agents. Data security is a significant concern. The data may include information about end-user behavior, the condition of the MG, and the generation status of energy sources, all of which must be kept confidential. Adopting advanced technologies, such as creating an IoT environment and implementing blockchain, can address these challenges effectively.
- **End-user Preferences:** The demands and interests of users significantly differ from those of power utilities. It is essential to consider these differences when managing energy in multiple interconnected MGs while ensuring the privacy of both users and power utilities. Optimal techniques must be developed to achieve fair energy allocation within the system.
- **Adaptability:** Elements within MG are inherently dynamic. Load demand fluctuates at different intervals throughout the day, and energy production from RESs varies correspondingly. Agents must effectively respond to these changing behaviors to enhance energy sharing among the various components of the MG.
- **Compliance:** Effective energy management and privacy concerns are significant issues when providing cost-effective solutions for both utilities and end-users. MASs should meet the energy management and cyber-security requirements in compliance with local and international standards.

8. Conclusion

The increasing energy demand with nonlinear behavior and the stochastic nature of renewable energy production create the power mismatch problem. Efficient EMS is essential that consider these factors while optimizing the operation of DERs. This review suggests that the integration of forecasting techniques with optimization techniques can significantly enhance the performance of EMS. Generally, the EMS leverages forecasting algorithms to predict renewable energy production and load demand which helps to overcome the power mismatch problem and optimally regulate the power flow to satisfy peak demand at minimum possible cost. The reliability and efficiency of EMS heavily depend on the accuracy of forecasting algorithms and scheduling techniques. The selection of both forecasting and scheduling techniques depends on several factors including the complexity of the problem, type of energy sources, accuracy, and adaptability which together can achieve the goal of high operational efficiency and reliability. For optimal scheduling of generating units, the classical metaheuristic algorithms often face premature convergence and can trap in local optimal which may cause erroneous results. The finding of this review suggests that these challenges can be mitigated through careful parameter selection, algorithmic modifications, and hybridization of techniques. It is also observed that the advanced metaheuristic algorithms are now widely being adopted and can be employed for optimal energy scheduling applications that offer cost-effective energy management solutions while effectively utilizing the DERs. The review of forecasting approaches reveals that combined DL-based architectures such as CNN and LSTM are being employed in a large number of studies due to their ability to manage spatiotemporal characteristics of renewable energy sources and load datasets and forecast highly accurate results. Except to centralized control energy management approaches that manage energy in a centralized manner and are vulnerable to single-point failure, there exist some decentralized energy control approaches.

The review of state-of-the-art studies suggested that MAS provides a distributed control strategy in complex problems to manage and control energy sources in a decentralized way, ensuring affordable and sustainable energy solutions to end-users. A recent study utilizing a distributed approach for energy storage in Ref. [172] demonstrates excellent cost saving by approximately 72.78% compared to the centralized approach. The MAS-based distributed control approaches are computationally less expensive, support the integration of intermittent renewable sources, handle dynamic changes in load and renewable energy production, and enhance scalability. In the end, a hybrid decentralized and centralized EMS is presented in interconnected MGs network that can optimize the operation of local DERs while dynamically managing the intermittent renewable energy production and load demand. The interconnected MGs are intended to overcome challenges such as power mismatch, and high energy demand. They provide affordable electricity to end users by leveraging the potential of advanced forecasting algorithms, scheduling algorithms, and multi-agent-based decentralized control. This review can significantly help researchers and EMS development authorities in the selection of best optimization and forecasting techniques with hybrid centralized and decentralized control.

Declaration of Competing Interest

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

Data availability

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

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