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Review

Meta-heuristics and deep learning for energy applications: Review and open research challenges (2018–2023)

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ABSTRACT

The synergy between deep learning and meta-heuristic algorithms presents a promising avenue for tackling the complexities of energy-related modeling and forecasting tasks. While deep learning excels in capturing intricate patterns in data, it may falter in achieving optimality due to the nonlinear nature of energy data. Conversely, meta-heuristic algorithms offer optimization capabilities but suffer from computational burdens, especially with high-dimensional data. This paper provides a comprehensive review spanning 2018 to 2023, examining the integration of meta-heuristic algorithms within deep learning frameworks for energy applications. We analyze state-of-the-art techniques, innovations, and recent advancements, identifying open research challenges. Additionally, we propose a novel framework that seamlessly merges meta-heuristic algorithms into deep learning paradigms, aiming to enhance performance and efficiency in addressing energy-related problems. The contributions of the paper include:
1. Overview of recent advancements in MHs, DL, and integration.
2. Coverage of trends from 2018 to 2023.
3. Introduction of Alpha metric for performance evaluation.
4. Innovative framework harmonizing MHs with DL for energy problems.

1. Introduction

The year 2021 saw a significant increase in renewable electricity generation, with a growth rate of 5.4%, or 402 TWh higher than the previous year [1]. This growth rate surpassed that of 2020, largely due to a sharp increase in renewable electricity generation in Asia. Overall, renewable energy sources generated a total of 7858 TWh of electricity in 2021. Renewable hydro was the largest contributor at 55%, with 4275 TWh, followed by wind energy at 23% with 1838 TWh, solar energy at 13% with 1034 TWh, bioenergy at 8% with 615 TWh, geothermal energy at 1% with 95 TWh, and marine energy at less than 1% with 1 TWh.

Solar and wind generation were the main drivers behind growth in the renewable energy sector, with increases of 23% and 16%, respectively. Together, they accounted for 80% of growth since 2017. Additionally, renewable hydropower generation fell by 82 TWh in 2021, compared to 120 TWh in 2019–20. Fig. 1 illustrates the comprehensive breakdown of renewable energy sources in 2021, encompassing hydro generation, solar power, wind generation, bioenergy generation, geothermal energy, and marine energy, categorized by continent. Fig. 2 displays the Regulatory Indicators for Sustainable Energy (RISE) and the overall renewable energy scores for 2021 across various countries. Here are the top ten countries in this ranking: Denmark, Germany, South Korea, United Kingdom, Hungary, Ireland, Portugal, Austria,

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List of Abbreviations

EAs	Energy Applications
RNN	Recurrent Neural Networks
MHs	Meta-Heuristics
DRL	Deep Reinforcement Learning
DL	Deep Learning
LSTM	Long Short-Term Memory
ML	Machine Learning
LCA	Laying Chicken Algorithm
TWh	Terawatt-hours
BBA	Big Bang Algorithm
RE	Renewable Energy
MVA	Multiverse Algorithm
PV	Photovoltaics
VEA	Volcano Eraption Algorithm
EV	Electric vehicles
CVA	Covid-19 Algorithm
RES	Renewable energy source
EGA	Evolutionary-Gradient Algorithm
RL	Reinforcement learning
PSO	Particle Swarm Optimization
CNN	Convolution Neural Networks
ACO	Ant Colony Optimization
ABC	Artificial Bee Colony
FA	Firefly Algorithm
LoRa	Short for long-Range
US	The United States of America
RISE	Regulatory Indicators for Sustainable Energy

Canada, and Slovak Republic. These nations have demonstrated significant progress and commitment to sustainable energy, earning them a place at the forefront of the RISE ranking for 2021.

Electricity capacity is a fundamental concept, signifying the maximum potential for electrical power generation at a specific moment. On the other hand, electricity generation refers to the actual amount of electrical energy produced within a defined timeframe. In this section, we provide a comprehensive analysis of countries' performance in total renewable energy, with a focus on the top and bottom 32 countries. We consider both their generation and capacity statistics for the year 2021, as illustrated in Fig. 3. The assessment scores have been computed using a performance metric, denoted as Alpha (α), calculated as follows:

$$\alpha = \frac{EG}{EC} \tag{1}$$

Here, EG represents the quantity of electrical energy generated in the year 2021, and EC corresponds to the electrical energy capacity of the respective nation at any given point in time. For example, Alpha values for three countries are as follows:

$$\begin{aligned} Iceland : \alpha &= \frac{19617}{2879} = 6.81 \\ Norway : \alpha &= \frac{156101}{39406} = 3.96 \\ Iran : \alpha &= \frac{15084}{11930} = 1.26 \end{aligned} \tag{2}$$

These Alpha values offer a valuable insight into how efficiently each of these countries utilized their renewable energy resources during 2021. Iceland stands out with an Alpha value of 6.81, indicating that it generated a substantial amount of electrical energy, exceeding the capacity provided by its renewable energy sources. In contrast, Iran's Alpha value of 1.26 suggests that it did not fully leverage its renewable energy potential during the same period, leaving room for improvement in its energy generation practices. Countries must address the following challenges and seize opportunities to enhance their efficiency in the future.

1.1. Background

One of the key advantages of transitioning to completely renewable energy is the potential to generate millions of jobs in the energy sector by 2050. This transition not only leads to a significant increase in job opportunities within the energy sector but also outpaces job losses in the fossil fuel industry. By embracing green energy sources, the renewable energy sector is projected to create a net increase of over 11 million jobs. This includes 19 million new jobs in renewables, energy conservation, grid improvement, and energy flexibility. On the other hand, the fossil fuel industry is expected to experience a decline of 7.4 million workers by 2050 [1–3]. To support this transition, education and training policies will play a crucial role in developing the necessary expertise and skills required for the renewable energy and energy-efficient industries. These industries hold tremendous potential for creating value and meeting the growing demand for renewable energies. By ensuring just and fair social and economic effects, resistance to the transition can be minimized. Moreover, this transition has the potential to transform the socioeconomic environment and bring about positive changes for society as a whole.

Countries around the world are beginning to recognize the immense potential of machine learning (ML) and are actively integrating it into their policies to advance their energy industries. Although countries are trying to restructure their energy strategies and rely more on cleaner energy sources, the intermittency of wind and solar power continues to pose a significant challenge. The power generation of wind turbines and solar panels is subject to fluctuations due to external factors such as cloud cover, solar radiation, and wind speed, which are beyond human control [4–6]. This variability presents a challenge for grid operators, who must balance energy supply and demand to ensure a stable and reliable energy supply. Whenever wind and solar farms generate less electricity, grid operators must turn to traditional power plants to compensate for the shortfall. Conversely, on windy and sunny days when renewable energy production exceeds demand, grid operators must reduce production from gas-fired and coal power plants to prevent overloading the grid. These changes to the energy supply can be costly and result in excessive carbon dioxide emissions when excess electricity is dissipated. Energy providers are compensated by grid operators for any adjustments made to their power system infrastructure, resulting in an annual savings of around $553 million for German consumers [7].

1.2. Bibliometric analysis

Accurately forecasting the health of energy distribution infrastructure is therefore a complex task that requires sophisticated techniques such as Deep Learning (DL) and Meta-heuristic algorithms which is a class of optimization algorithms to solve complex energy-related problems. DL has the potential to transform the energy sector by improving renewable energy distribution, forecasting, and the implementation of smart grids. Meta-heuristics are promising tool to optimize energy generation and distribution, reduce energy consumption, and improve the efficiency of energy systems. Although the combination of DL with meta-heuristic algorithms is still in its early stages of deployment, it has the potential to fundamentally transform the way we interact with energy resources [8–10]. Deep learning and meta-heuristic algorithms have exhibited substantial potential in tackling diverse energy-related challenges, owing to their capacity to discern intricate patterns, derive meaningful abstractions, and offer precise prognostications through the analysis of extensive datasets. As illustrated in Fig. 4, these methodologies can be harnessed to provide

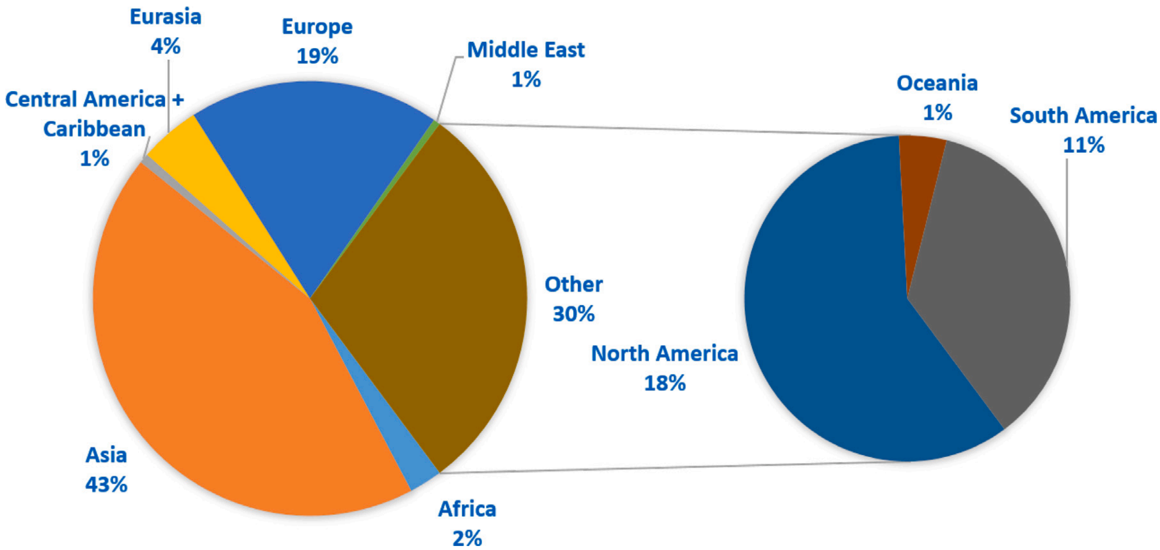


Fig. 1. Continental distribution of renewable energy sources in 2021.
Source: Based on data from [1–3].

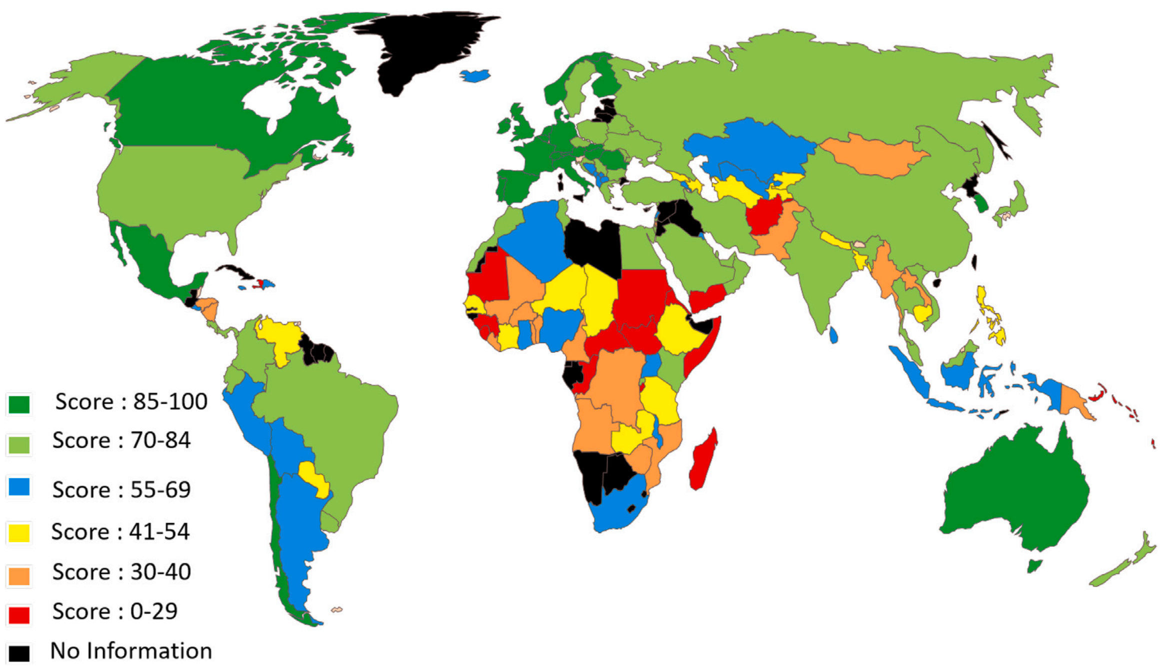


Fig. 2. Regulatory Indicators for Sustainable Energy (RISE), overall renewable energy score 2021.
Source: Based on data from [1–3].

solutions to different energy-related issues. Furthermore, Fig. 5 depicts the distribution of the utilization percentages of meta-heuristics and deep learning across various domains within the realm of energy applications.

The use of metaheuristic algorithms and deep learning for energy problems has been on the rise, as shown in Fig. 6. This figure represents the publication trend of papers in this field since 2018. Notably, it reveals that more than 75% of papers were published between 2021 and 2023, indicating a growing interest and emphasis on research in applying deep learning and metaheuristic algorithms to energy problems during this period.

During the data extraction phase, as part of the analysis of the chosen studies, a concise summary was crafted based on the collected data. As depicted in Fig. 7(a), the distribution of these selected studies across various subject areas is presented, with 30% of the studies falling within the domain of engineering. To be more specific, 19% of the articles were affiliated with the field of energy, 14% with computer science, and so forth. Fig. 7(b) illustrates the distribution of these selected studies across different databases, revealing that 50% of the studies originated from Springer, 35% from Science Direct, and 15% from IEEE Xplore. Meanwhile, Fig. 7(c) showcases the distribution of these studies across various publication types. Significantly, 84% of the studies were disseminated through peer-reviewed journals, 11% took the form of book chapters, and 5% were presented as conference papers.

We undertook an extensive bibliometric analysis to explore the research landscape within our field from 2018 to 2023. Figs. 5, 6, 7 showcase the outcomes of this analysis, which were derived using meticulous data collection and analysis techniques. Our methodology involved systematic keyword searches, database queries, and data

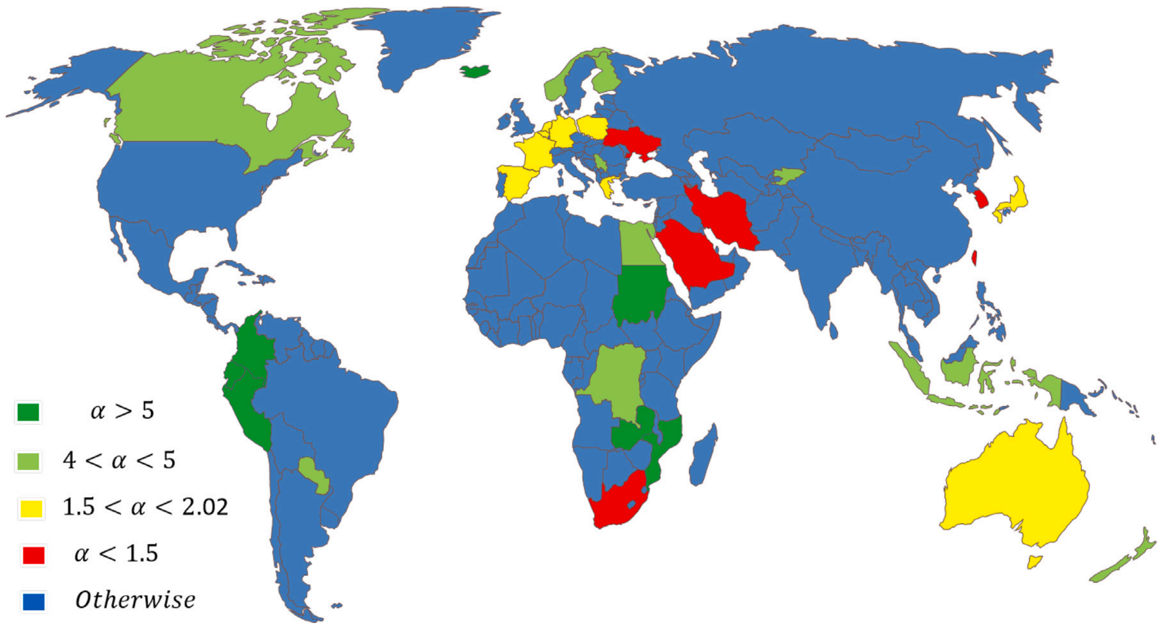


Fig. 3. Assessing renewable electricity capacity and generation in 2021: An analysis of countries with focus on top and bottom 32 countries utilizing the alpha ($\alpha = \frac{EG}{EC}$) performance metric.

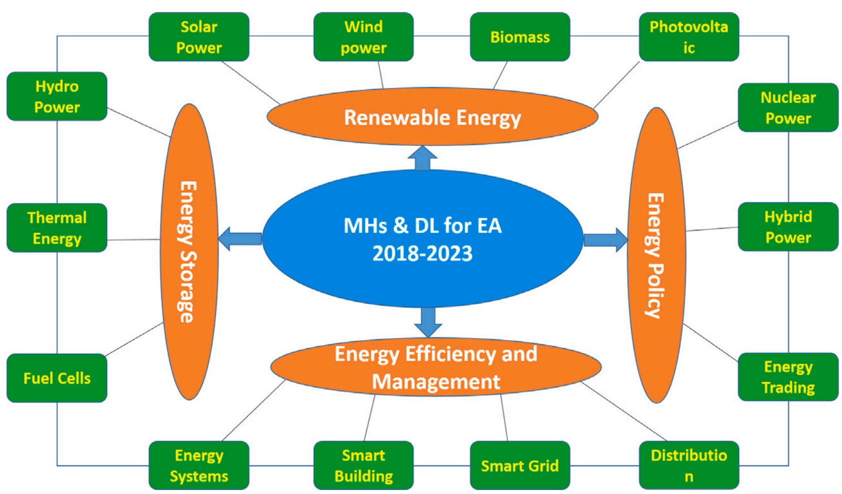


Fig. 4. Some applications of DL and MHs used during 2018–2023 for EAs.

extraction methods to ensure a thorough examination of pertinent literature within our research domain.

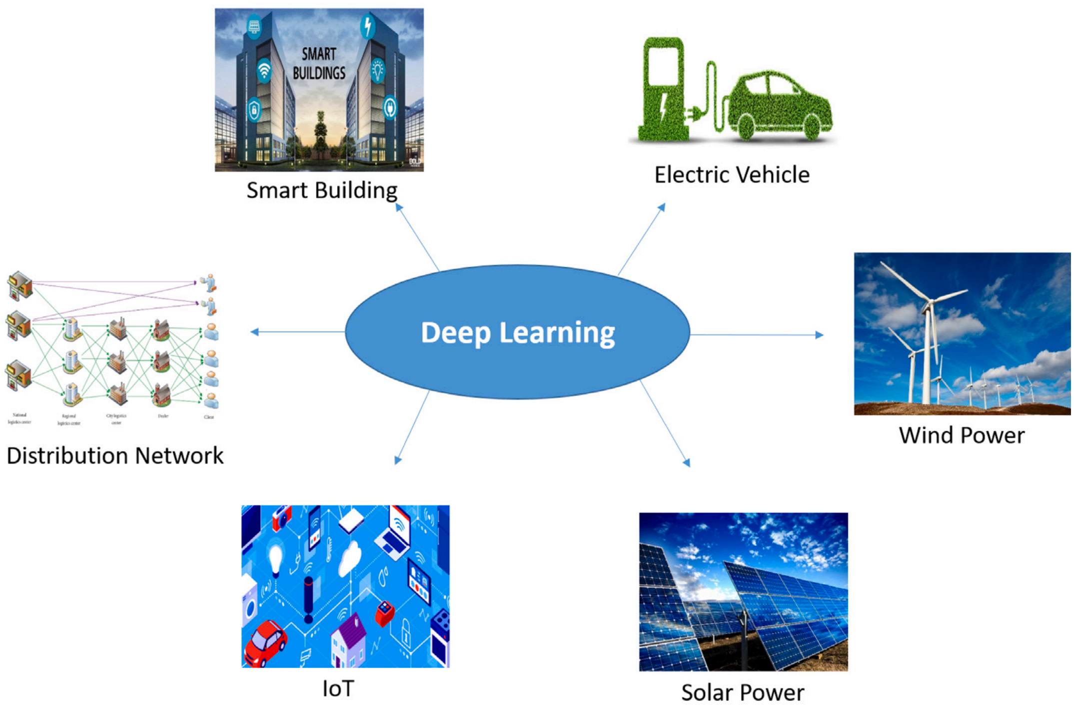
These figures offer valuable insights into various aspects of research trends, including the distribution of studies across subject areas, databases, and types of databases utilized. By employing robust methodology, we aimed to capture a comprehensive overview of research activities and trends within our field during the specified timeframe.

We conducted a series of targeted keyword searches encompassing terms like “renewable energy”, “Wind”, “Solar”, “Photovoltaic”, “Hydro”, “Bioenergy”, and “Geothermal”. In an effort to focus our exploration on the realm of optimization and deep learning, we supplemented these keywords with additional terms, including “meta-heuristics” and “deep learning”. As illustrated in Fig. 8, this word cloud was generated by analyzing the references employed in our study. The word cloud visually presents the top 50 most frequently occurring words, with the size of each word directly proportional to its frequency of appearance. Larger words within the cloud indicate a higher prevalence within the referenced material, offering an at-a-glance insight into the prominent themes and concepts driving our research.

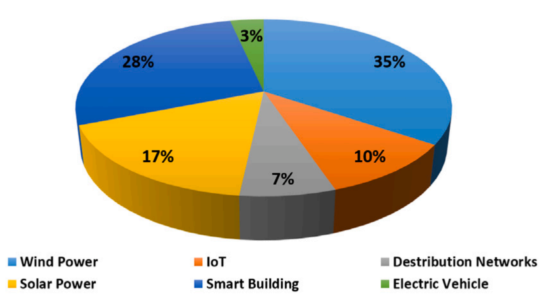
1.3. Contributions of this work

The purpose of this study is to examine recent advances and fundamental meta-heuristic algorithms in deep learning techniques as they apply to core energy technologies and energy distribution. This research first identifies the challenges that meta-heuristics and DL can address, reviews recent advances in the field, and assesses the impact of meta-heuristics and DL on energy applications. We then analyze the various classes of meta-heuristics in DL models that are used to tackle complex energy problems.

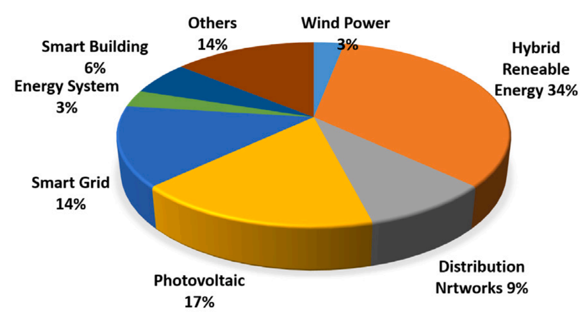
The novelty of this paper lies in its comprehensive exploration of the integration of meta-heuristic algorithms with neural networks for energy-related applications. Firstly, this paper consolidates and synthesizes the existing body of knowledge in the field, offering a holistic overview of state-of-the-art techniques and innovations. By



(a) DL in EA from 2018 - 2023

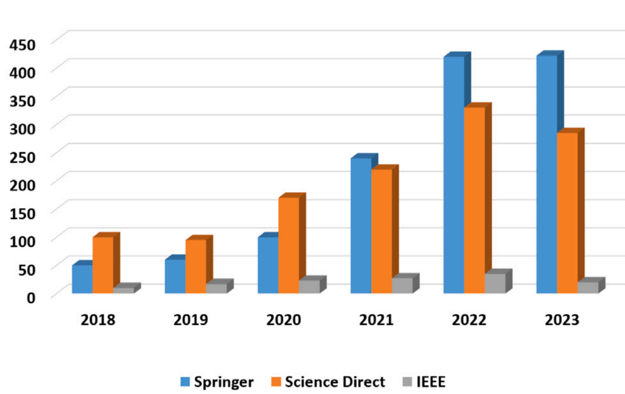


(b) Percentage of Deep Learning in Diverse Energy Applications

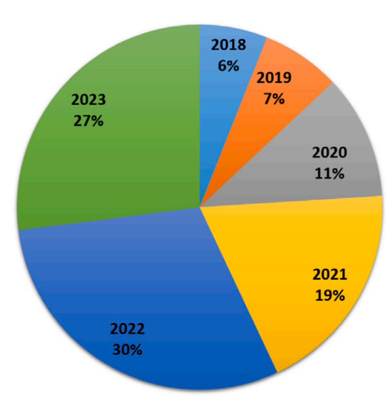


(c) Percentage of Meta-Heuristics in Diverse Energy Applications

Fig. 5. Utilization of meta-heuristics and deep learning in diverse energy applications from 2018 to 2023.



(a) Percentage of publications of metaheuristic algorithms and deep learning for energy



(b) All published papers in Science direct, IEEE explore and Springer

Fig. 6. Rate of publications in different data sets in area of meta-heuristics and deep learning (2018–2023).

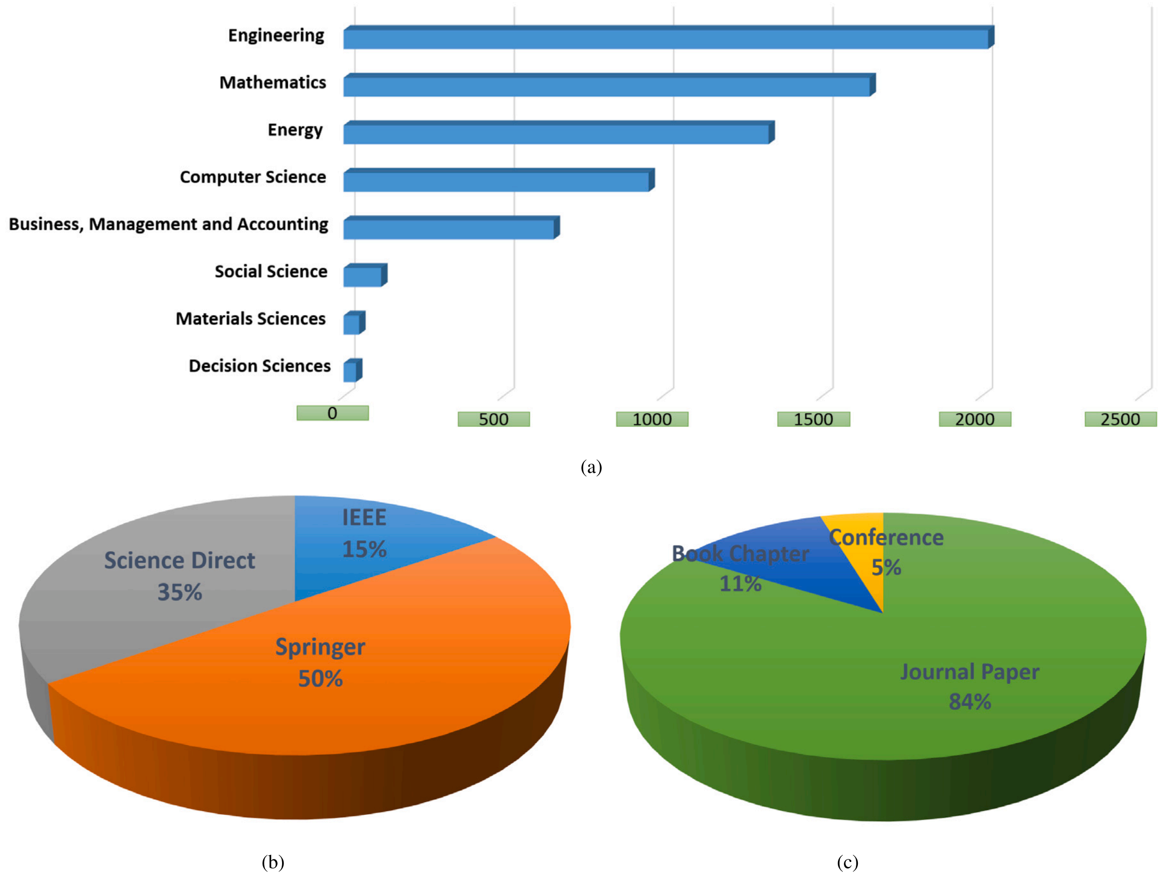


Fig. 7. (a) Rate of selected studies per subject area (b) Percentage of selected studies per data base. (C) Percentage of selected studies per type data base (2018–2023).

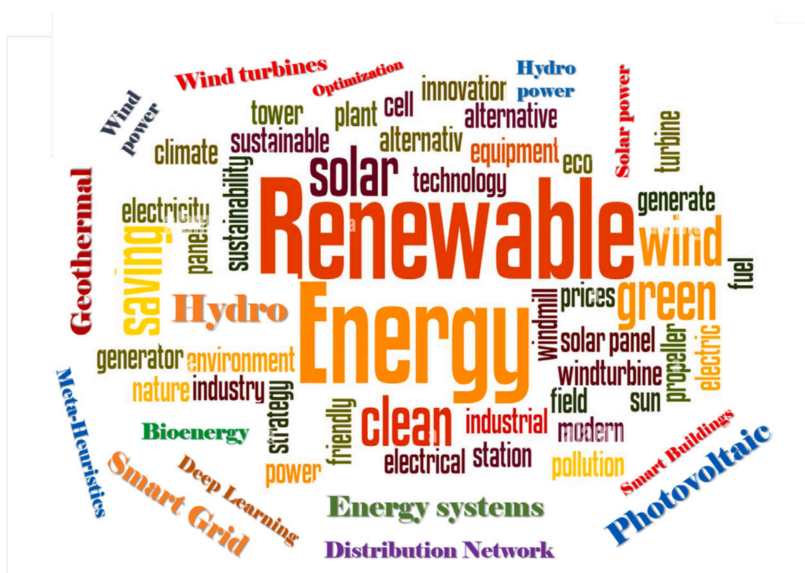


Fig. 8. Word cloud of 50 most frequently occurring words in the field of renewable energy 2018–2023.

doing so, it provides researchers and practitioners with a valuable resource for understanding the current landscape of meta-heuristic algorithms applied to neural networks in the context of energy phenomena. Secondly, this paper brings fresh insights by delving into recent developments within the realm of deep learning and meta-heuristic algorithms specifically tailored to energy applications over the past five years. This temporal focus ensures that the readers are not only equipped with a comprehensive understanding of the present state of the field but also gain access to the latest advancements and trends. By highlighting these recent developments, the paper fosters an environment of continuous learning and innovation, encouraging the exploration of novel approaches for addressing the challenges posed by complex and non-linear energy data. Consequently, this work contributes to the advancement of knowledge in the intersection of neural

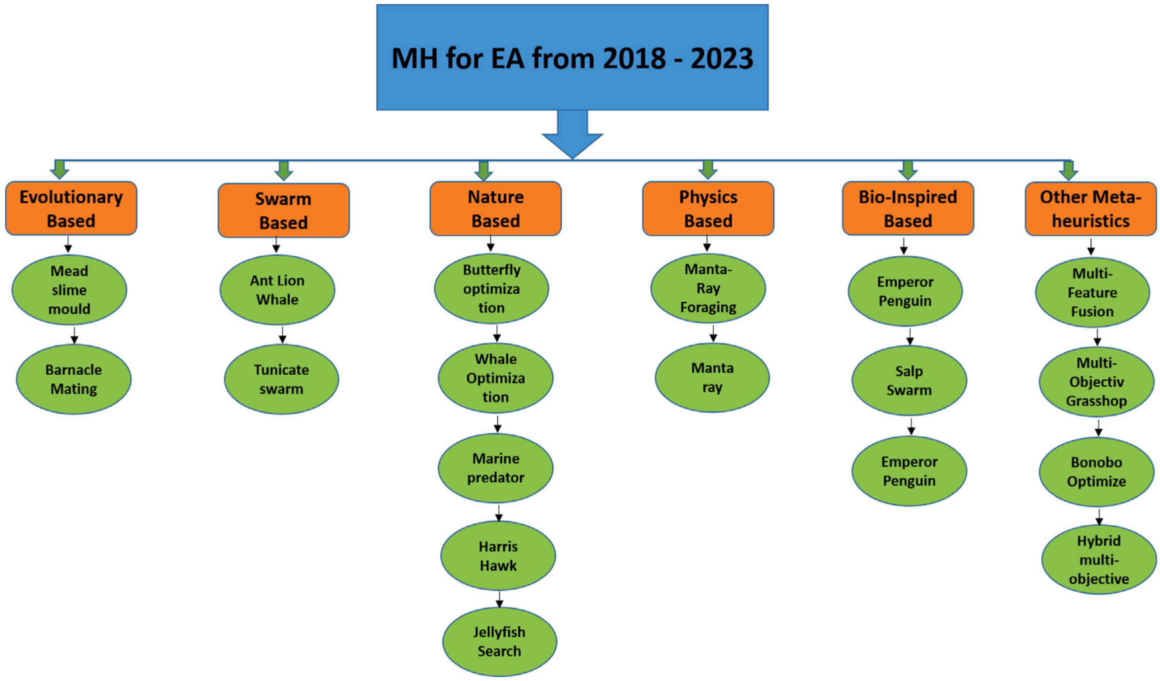


Fig. 9. Different kinds of MHs in EAs from 2018–2023.

networks, meta-heuristic algorithms, and energy modeling, offering a valuable resource for researchers, practitioners, and policymakers seeking to harness the power of artificial intelligence in the energy domain.

Finally, this paper presents an innovative framework that elegantly merges the capabilities of meta-heuristic algorithms with the vast domain of deep learning. This integration opens new avenues for enhanced problem-solving and optimization, promising to reshape the landscape of artificial intelligence and computational science.

The main contributions of this paper are as follows:

1. The study offers a comprehensive overview of recent advancements in MHs, DL, and their integration.
2. Focusing on developments from 2018 to 2023, it keeps researchers informed about the latest trends in this dynamic field.
3. The research introduces a performance evaluation method using the Alpha metric, offering a fresh perspective on the capabilities and generations of countries in the context of energy technologies.
4. The study introduces an innovative framework that harmonizes MHs with DL for energy problems.

In this study, our scientific aim is to explore the synergistic potential of deep learning (DL) and metaheuristic (MH) algorithms in addressing the complexities of energy-related modeling and forecasting tasks. Our research subject focuses on the integration of MH algorithms within DL frameworks for energy applications, aiming to enhance predictive accuracy and optimization efficiency. This study extends the existing research in the field by providing a comprehensive overview of recent advancements in MHs, DL, and their integration, covering trends from 2018 to 2023. Additionally, we introduce the Alpha metric as a novel method for performance evaluation in energy-related tasks, offering a fresh perspective on the capabilities and generations of countries in the context of energy technologies. Furthermore, we propose an innovative framework that seamlessly harmonizes MHs with DL, offering potential solutions to energy-related problems. Through these contributions, our work aims to advance the understanding and application of MHDL methodologies in the energy domain, paving the way for more efficient and effective energy management strategies.

Briefly, this article brings a new look to the existing literature in the following areas: (I) Recent advancements in MHs, DL, and their integration (II) The latest trends in this dynamic field, (III) Technology and (IV) Innovative framework that harmonizes MHs with DL for energy problems.

This study is structured around a comprehensive framework consisting MHs for EAs in Section 2. Then, Section 3 follows the core concept of energy technologies using DL. The use of MHs in DL for energy distribution utilities is elaborated in Section 4, Section 5 highlights challenges of MHs for EAs. Section 5.1 describes the analysis of the existing challenges of DL for EAs. Opportunities towards combined meta-heuristics and DL in the context of energy distribution systems is proposed in Section 6. Finally, Section 7 concluded the conducted study.

2. Meta-heuristics for energy applications

Meta-heuristics refer to a broad category of optimization methods aimed at finding optimal or near-optimal solutions for complex problems. They are versatile algorithms that efficiently explore solution spaces, often used when exact methods are impractical due to computational complexity [11]. This section focuses on the subject of Meta-heuristics (MH) techniques, which have garnered significant attention due to their remarkable effectiveness in solving a wide range of complex optimization problems. There are some classical optimization algorithms for energy applications, e.g. an efficient optimization technique was proposed a case study for small hydropower plant resource planning and development in [12]. Also [13] analyzes the operational and investment aspects of enhancing flexibility in power systems, focusing on fossil fuel generation, storage, and demand response. It discusses the role of power system flexibility in generation and planning, emphasizing simplified optimization methods and load profile effects. The authors implement an optimization model using MATLAB. Unlike traditional methods, MH techniques are gradient-free and have demonstrated superior performance in various applications [11]. They are also known for being easy to implement and often outpace classical optimization methods in terms of speed [14–16].

Furthermore, there are numerous metaheuristic algorithms that can be combined with deep neural networks to enhance their performance.

Remarkable examples of recent and efficient metaheuristic algorithms include Laying Chicken Algorithm (LCA) [17], Big Bang Algorithm (BBA) [18], Multiverse Algorithm (MVA) [19], Volcano Eraption algorithm (VEA) [20], Covid-19 Algorithm (CVA) [21], Evolutionary-Gradient Algorithm (EGA) [22], Particle Swarm Optimization (PSO) [23,24], Ant Colony Optimization (ACO) [25], Artificial Bee Colony (ABC) [26], Differential Evolution (DE) [27], Firefly Algorithm (FA) [28]. These algorithms encompass a diverse set of optimization techniques that can be used to optimize various aspects of deep neural networks. For instance, they can facilitate tasks such as weight initialization, hyperparameter tuning, architecture search, and many others, thereby contributing to the overall enhancement of deep neural network performance.

It is fascinating to witness the amalgamation of metaheuristic algorithms and deep neural networks, as it presents ample opportunities for achieving state-of-the-art results and pushing the boundaries of machine learning innovation.

Table 1 offers an extensive overview of research efforts within the field of meta-heuristics applied to energy-related scenarios, encompassing recent years. This table stands as an invaluable repository, facilitating a deeper understanding of the most recent advancements and developments within this dynamic field during this specific time frame. It features four informative columns. The first column, titled 'Meta-Heuristic Name', identifies the specific meta-heuristic techniques employed in each research paper. The second column, 'Energy Application Area', specifies the domain within energy applications that is addressed in each paper. The third column provides a concise summary of the research, offering a brief yet insightful description. Lastly, the fourth column, 'Year of Publication', presents the publication year of each referenced work. This comprehensive table acts as a focal point for researchers, practitioners, and enthusiasts, enabling them to navigate and access key insights, methodologies, and contributions that have shaped this exciting field during the specified timeframe.

Metaheuristic (MH) techniques are categorized into distinct classes, each drawing inspiration from diverse sources. These categories encompass evolutionary algorithms, swarm-based algorithms, nature-based strategies, physics-based algorithms, bio-inspired approaches, and an array of other innovative metaheuristics. Fig. 9 serves as an illustrative representation, showcasing the spectrum of proposed metaheuristics for energy applications spanning the years 2018 to 2022. This visual depiction provides a valuable snapshot of the diverse and evolving landscape of MH techniques tailored to address energy-related challenges during this specific period.

Recent meta-heuristic algorithms have been proposed to address a wide range of complex problems, such as IoT, image segmentation, the traveling salesman problem, multi-objective problems, and data clustering [29–35].

3. Deep learning for energy problems

3.1. Introduction to deep learning

Machine learning is a subset of artificial intelligence focused on developing algorithms that enable computers to learn patterns from data and make decisions or predictions without explicit programming. It encompasses various techniques such as supervised learning, unsupervised learning, and reinforcement learning, with applications spanning from image recognition to natural language processing. Deep learning refers to a type of machine learning that uses neural networks with multiple layers to learn from data. It is particularly effective for tasks like image recognition and natural language processing [36].

In the late 1980s, two significant breakthroughs reshaped the field of neural networks, setting the stage for the development of modern deep learning techniques. In 1986, Rumelhart, Hinton, and Williams introduced Recurrent Neural Networks (RNNs) [36]. RNNs, designed with feedback connections, possess the ability to process sequential data by retaining essential information in a hidden state. These networks employ the backpropagation algorithm to update their weights and learn representations from sequential data. Given their versatility, RNNs have found widespread use in applications such as natural language processing, speech recognition, and time series analysis [37].

In 1989, Yann LeCun and collaborators introduced Convolutional Neural Networks (CNNs) [38]. CNNs leverage the power of convolution to effectively handle grid-like data, including images. By utilizing filters, CNNs can extract pertinent features from input data, adapting their weights through backpropagation to enhance recognition performance. The impact of CNNs is particularly evident in their foundational role in image recognition and broad application in various computer vision tasks [39].

Another noteworthy advancement came in 1997 when Hochreiter and Schmidhuber introduced Long Short-Term Memory (LSTM) networks [40]. While RNNs excel at processing sequential data, they encounter challenges in capturing errors occurring over extended time intervals. LSTM networks address this limitation with memory cells and gating mechanisms, enabling them to retain context over prolonged time spans and identify inconsistencies within the data [41].

Over several decades, continuous advancements and refinements have been made in different types of deep learning approaches to simplify and enhance the resolution of complex problems. The introduction of LSTM networks exemplified the journey towards tackling challenges associated with error identification in long-term dependencies. These developments have significantly influenced the growth and application of deep learning methodologies across various domains.

Deep Reinforcement Learning (DRL) has emerged as a powerful combination of deep learning and reinforcement learning techniques. The integration of deep learning into reinforcement learning has gained substantial attention and made significant advancements in recent years. A notable milestone in this field was reached in 2013 with the introduction of the DQN algorithm by Volodymyr Mnih and colleagues [75]. This algorithm utilized deep neural networks to approximate Q-values within a reinforcement learning framework, demonstrating the potential of merging these approaches to tackle complex problems. Since then, numerous researchers and organizations have actively contributed to the advancement of Deep Reinforcement Learning, exploring various algorithms and applications, thereby driving innovation within the field [76].

In 2017, the Transformer architecture, introduced by Ashish Vaswani and the Google Research team, revolutionized sequence modeling [77]. Transformers excel in parallelizing computation, resulting in faster training times. Leveraging self-attention mechanisms, Transformers can handle variable-length input sequences without the need for padding. They have seen widespread adoption in natural language processing (NLP) tasks, outperforming RNN and LSTM-based models in applications like machine translation and language understanding. The success of Transformers has sparked the development of new architectures and advanced sequence modeling within Deep Learning [78].

Various common deep learning architectures are illustrated in Fig. 2, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), Deep Reinforcement Learning, Generative Adversarial Networks (GANs), Deep Belief Networks (DBNs), Autoencoders, Capsule Networks, Attention Mechanisms, and Transformers. Each architecture plays a specific role and influences the functionality of neural networks. Deep learning techniques have been continually refined and customized to suit specific applications. Recent advancements in deep learning have seen significant improvements achieved through experiments with various metaheuristic algorithms. For example, CNNs and RNNs have yielded superior accuracy and precision results, surpassing the performance of metaheuristics such as GA and PSO on different datasets. These ongoing improvements and explorations underscore the dynamic nature of deep learning algorithms and their pursuit of optimized outcomes.

Table 1
Meta-Heuristic (MH) algorithms for energy applications.

MH name	Energy Application Area	Description	Year
Improved butterfly optimization [42]	Smart buildings - Energy management strategy	This investigation introduces an enhanced iteration of the Butterfly Optimization Algorithm, tailored for optimizing the performance of a versatile energy system that combines cooling, heating, and power generation. This complex system comprises various key components, including a heat recovery system, a 5 kW proton exchange membrane stack, a compact absorption chiller, a humidifier, and a gas compressor. The algorithm leverages a comprehensive multi-criteria assessment approach, enabling the simultaneous attainment of an ideal design tailored for residential usage	2020
Ameliorative whale optimization algorithm (AWOA) [43]	Smart electric power and energy systems - Energy management strategy	In a quest to reduce energy consumption and emissions while enhancing the energy efficiency of hybrid electric ships, an enhanced iteration of the Whale Optimization Algorithm (AWOA) has been introduced. This AWOA algorithm plays a pivotal role in fine-tuning the fuzzy rules that govern the ship's hybrid power system, consisting of components such as a fuel cell, an accumulator battery, and a super-capacitor	2021
Multi-feature fusion-based algorithm [44]	Smart grid - Energy management strategy	An advanced method was proposed for improving the accuracy of mechanical fault identification in on-load tap changers within smart grids with electric vehicles (EVs). This technique combines multi-feature fusion, K-nearest neighbors (KNN), and an enhanced whale optimization algorithm. It assembles a high-dimensional feature set with time-domain, frequency-domain, energy, and composite multi-scale permutation entropy characteristics	2020
Nelder–Mead slime mould algorithm [45]	Solar power and photovoltaic models - Optimal sizing	To enhance the precision and efficiency of solar cell parameter estimation, the Improved Slime Mould Algorithm (ISMA) is introduced in this study. This approach synergizes the Nelder–Mead simplex (NMs) method with a random learning mechanism, optimizing the parameter estimation process to deliver more precise outcomes.	2021
Parallel slime mould algorithm (PSMA) [46]	Distribution network - Demand side management	This study offers a novel approach to tackle the distribution network reconfiguration (DNR) problem in the context of distributed generation (DG). A parallel slime mould algorithm (PSMA) as a solution is proposed, considering a range of DG types. The approach addresses the DNR problem by integrating four optimization objectives, encompassing active power loss, voltage stability index, load balance degree, and switching operation times	2022
Improved butterfly algorithm [47]	Smart grid - Smart buildings	An innovative and improved iteration of the butterfly algorithm is presented, designed to enhance home energy management systems in the realm of the Internet of Things (IoT). This approach embraces a multi-objective optimization strategy, with a primary focus on two key objectives: the reduction of energy consumption costs and the enhancement of user satisfaction. Our method is custom-tailored for seamless integration within the smart grid framework	2021
Multi-Objective Grasshopper Optimization Algorithm (MOGOA) [48]	Energy trading - Energy market trading	This paper introduces an approach called the Multi-Objective Grasshopper Optimization Algorithm (MOGOA) combined with the Deep Extreme Learning Machine (DELM) for short-term load prediction in Peer-to-Peer Energy Trading (ET) within Smart Grids (SGs). The proposed MOGOA-DELM model consists of four essential stages: data cleaning, Feature Selection (FS), prediction, and parameter optimization. By integrating these components, the model aims to enhance the accuracy and efficiency of short-term load prediction in P2P ET within SGs.	2022
Exponentially-Ant Lion Whale Optimization (E-ALWO) algorithm [49]	Yield optimization and energy efficiency - Optimal sizing	In pursuit of energy-efficient and trust-centric data packet routing, this research introduces an innovative routing model that harnesses the power of the Exponentially-Ant Lion Whale Optimization (E-ALWO) algorithm. The E-ALWO algorithm is a result of combining the Exponentially Weighted Moving Average (EWMA) principle with the Ant Lion Optimization (ALO) and Whale Optimization Algorithm (WOA). Through this amalgamation, the proposed model strives to optimize routing choices, thereby improving energy efficiency and maintaining trust in the reliable delivery of packets.	2021
Marine predators algorithm [50]	Wind, photovoltaic and solar thermal	In this paper, a comprehensive modern power grid paradigm is proposed to study the Load Frequency Control (LFC) issue. The study considers three types of renewable energy sources (RESs), namely wind, photovoltaic, and solar thermal. Additionally, the system paradigm integrates two types of energy storage units: superconducting magnetic energy storage and battery energy storage. The proposed approach aims to analyze and tackle the LFC issue in modern power grids more effectively.	2021

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Table 1 (*continued*).

MH name	Energy Application Area	Description	Year
Monarch butterfly optimization [51]	Distribution network - Optimal control strategy	This paper puts forward a formulation for addressing a multi-objective challenge associated with the integration of Distributed Energy Resources (DERs). The objective is to optimize the choice of suitable locations, capacities, and the balance between dispatchable and non-dispatchable DERs, all while accommodating multiple performance objectives. To efficiently tackle this complex decision-making problem, a hybrid method is introduced, which merges the monarch butterfly optimization algorithm with the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)	2020
Enhanced emperor penguin optimization algorithm [52]	Renewable energy sources - Energy management strategy	This paper introduces an enhanced version of the Emperor Penguin Optimization (EPO) algorithm for Dynamic Economic Dispatch (DED) in the presence of renewable energy sources and microgrids. The DED problem focuses on optimizing power allocation from committed generators to match variable load demands. By incorporating renewables and microgrids, the improved EPO algorithm aims to provide more accurate and efficient solutions for dynamic economic load dispatch, facilitating renewable energy integration into the grid.	2021
Chaos-opposition-enhanced slime mould algorithm [53]	Wind turbines - Optimal sizing	A Chaos-Opposition-Enhanced Slime Mould Algorithm (CO-SMA) for minimizing the cost of energy (COE) in wind turbines is proposed in this study. The COE model is established by considering the optimal design parameters such as rotor radius, rated power, and hub height. To address the limitations of classical SMA when dealing with nonlinear tasks, an improved variant named CO-SMA is proposed. CO-SMA leverages a chaotic search strategy (CSS) and crossover-opposition strategy (COS) to enhance its performance in optimizing wind turbine designs and minimizing COE.	2022
Enhanced salp swarm algorithm [54]	Wind turbines	This article introduces a novel modification and application of the Salp Swarm Algorithm (SSA) to improve the Maximum Power Point Tracking (MPPT) and fault-ride through ability of a grid-tied Permanent Magnet Synchronous Generator driven by a variable speed wind turbine (PMSG-VSWT). The multi-objective function, in the form of integral squared error, is minimized to determine the high-dimensional parameters of the Takagi–Sugeno–Kang fuzzy logic controllers (TSK-FLC) employed in the cascaded control of the grid-tied PMSG-VSWT.	2019
Integrated Harris Hawk Optimization algorithm (IH2OA) [55]	Photovoltaic, wind turbine, fuel cell and energy storage system	This paper outlines a hybrid strategy to efficiently manage power flow in a smart grid integrated with a Hybrid Renewable Energy System (HRES). The HRES includes photovoltaic panels, wind turbines, fuel cells, and energy storage like batteries. To optimize power flow, the Integrated Harris Hawk Optimization algorithm (IH2OA) is employed, which combines crossover and mutation functions within the Harris Hawk Optimization method, improving power flow management in the HRES-connected smart grid.	2021
Salp swarm optimization [56]	Hybrid power system - Optimal control strategy	An optimization algorithm has been proposed to determining the optimal combination of control parameters for a voltage source inverter, which integrates a photovoltaic (PV) power system with an electric vehicle (EV) charging station through a shared grid-connected AC bus. The optimization process utilizes the Salp Swarm Algorithm to minimize fluctuations in the DC-bus voltage by achieving a balance between active power flow and injected harmonics into the grid.	2020
Salp swarm algorithm [57]	Photovoltaic - Energy management	To achieve maximum power exploitation in grid-connected PV systems during fast-varying solar irradiation levels, this paper presents a novel configuration based on a modified Salp Swarm Algorithm. The proposed configuration employs a step-up boost converter for each PV panel, enabling independent control based on irradiation levels. This configuration results in multiple levels of DC voltage, which can be converted to AC using an active neutral point clamped (ANPC) inverter.	2020
Enhanced adaptive butterfly optimization algorithm [58]	Photovoltaic - Optimal sizing	In this study, we present an innovative iteration of the butterfly optimization algorithm, termed the Enhanced Butterfly Optimization Algorithm (EABOA). EABOA is designed to enhance the precision in determining the unidentified parameters of photovoltaic (PV) models. This improvement in EABOA involves introducing a novel position search equation and the utilization of a good-point set. These enhancements aim to strike a balance between exploration and exploitation, thereby boosting the algorithm's effectiveness in uncovering optimal solutions.	2021

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Table 1 (*continued*).

MH name	Energy Application Area	Description	Year
Modified manta ray optimization [59]	Hybrid power system - Energy management	This paper presents an enhanced version of the Manta Ray Foraging Algorithm for optimizing a hybrid power system comprising solar panels, a diesel generator, and a pumped water reservoir. The system utilizes excess solar energy to pump water into storage for future use. When solar energy is insufficient to meet demand, the diesel generator and pumped water reservoir supplement the power supply.	2021
Tunicate swarm algorithm (TSA) [60]	Photovoltaic - Optimal sizing	This paper introduces the Tunicate Swarm Algorithm (TSA) based on Maximum Power Point Tracking (MPPT) strategy to address the Partial Shading (PS) issue. The TSA is modeled with a Search and Skipping (SAS) scheme to minimize tracking time and search area effectively. By implementing the SAS scheme, the algorithm can efficiently discard voltage ranges that lack the Global Maximum Power Point (GMPP), resulting in reduced computation time and improved performance.	2021
Boosting slime mould algorithm [61]	Photovoltaic - Optimal sizing	An improved Slime Mould Algorithm (SMA) that incorporates both the Nelder–Mead simplex method and chaotic maps for estimating unknown parameters in photovoltaic models is introduced. The inclusion of chaotic maps enhances the location update strategy, replacing the random number component (rand), thus improving the algorithm's exploration patterns. Simultaneously, the Nelder–Mead simplex method is integrated to enhance the algorithm's ability to focus on refining solutions, leading to more precise parameter estimation within the photovoltaic model.	2021
Converged Barnacles Mating Optimizer (CBMO) algorithm [62]	Electric vehicles - Demand side management	This paper introduces a smart strategy to tackle the cost barrier in hybrid motors by proposing optimal sizing of the fuel cell stack and battery. The objective is to achieve a reliable and low-cost battery/fuel cell motor. To accomplish this, a novel metaheuristic algorithm, the Converged Barnacles Mating Optimizer (CBMO), is introduced to find the optimal configuration.	2020
Bonobo Optimizer (BO) [63]	Renewable energy sources - Energy management	This paper presents an enhanced approach to the Bonobo Optimizer (BO) by incorporating a quasi-oppositional method. The focus is on resolving the design challenge of hybrid microgrid systems, which include a combination of renewable energy sources (RES) such as PV panels, WT, batteries, and diesel generators. The proposed methodology aims to optimize the design process, enabling improved performance and efficiency of these systems.	2020
A mutated salp swarm algorithm [64]	Distribution network - Optimal control strategy	The objective of this paper is to enhance the operational efficiency of distribution systems by strategically assigning shunt capacitors (SCs) and distributed generations (DGs) like PV to efficiently manage reactive power compensation. To achieve the optimal sizing and placement of these devices, a robust optimization method is required. Thus, we introduce the Mutated Salp Swarm Algorithm (MSSA) in this research to address this intricate optimization challenge.	2019
Modified emperor penguin optimizer [65]	Energy storage system - Energy management strategy	A Modified Emperor Penguin Optimizer Algorithm (MEPOA) is proposed for the optimal allocation of Energy Storage Systems (ESS) and Phasor Measurement Units (PMU) in power distribution systems. The main objective of this study is to enhance voltage stability, taking into consideration power balance and voltage limit constraints.	2021
A hybrid squirrel search algorithm with whale optimization algorithm [66]	Renewable energy sources - Energy management strategy	An approach that combines the Squirrel Search Algorithm (SSA) with the Whale Optimization Algorithm (WOA) has been proposed to enhance power flow management (PFM) within a microgrid (MG) system connected to a hybrid renewable energy source (HRES). The SSA element is responsible for regulating voltage source inverter control signals, ensuring the balance of power exchange between the source side and load side.	2020
Salp swarm algorithm [67]	Energy management	An approach using the Salp Swarm Algorithm is introduced to tackle energy management and emission challenges involving storage devices. To address uncertainties linked to renewable energy sources, load requirements, and market prices, a probabilistic method based on the (2 m + 1) point estimate technique to resolve the energy management problem is employed. The proposed method is versatile, capable of addressing both deterministic and probabilistic energy management issues while combining the multi-objective optimization problem of cost and emissions into a single objective function focused on total cost.	2020

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Table 1 (*continued*).

MH name	Energy Application Area	Description	Year
Salp swarm algorithm-based optimal control scheme [68]	Photovoltaic - Optimal sizing	A salp swarm algorithm (SSA) is proposed to optimize the tuning of PV controllers, the objective function is enhancing the low voltage ride-through (LVRT) performance of grid-connected PV systems. The effectiveness of the LVRT improvement is evaluated in terms of percentage undershoots or overshoots, settling time, and steady-state error in the voltage response. The SSA is employed to optimize the fitness function and determine the ideal PI controller parameters that ensure an optimized design of the controllers.	2020
Jellyfish Search Optimization [69]	Renewable energy sources - Energy management strategy	This paper focuses on different sources of energy: thermal power generators, wind power generators (WPGs), and solar photovoltaic generators (SPGs). Uncertain WPG and SPG output powers are predicted using Weibull and lognormal probability distribution functions (PDFs), respectively. The objective function is designed to account for potential underestimations and overestimations in renewable energy sources (RES) output by integrating penalties and reserve costs. To demonstrate the viability of this approach, the study employs a Jellyfish Search Optimizer (JS) to optimize the modified IEEE 30-bus test system.	2021
Manta-Ray Foraging Optimization algorithm [70]	Smart buildings - Demand side management	In this research, the Manta-Ray Foraging Optimizer is used to ascertain optimal values for a range of variables aimed at enhancing envelope features and building design to reduce energy consumption in residential structures. The parameters under optimization encompass aspects such as window dimensions and type, foundation, wall and roof insulation, infiltration rate, building orientation, and thermal mass. Furthermore, the study explores various building shapes, including rectangles, trapezoids, T-shapes, H-shapes, crosses, L-shapes, and U-shapes.	2021
Emerging Harris Hawks Optimization [71]	Hybrid renewable energy system - Optimal sizing	Aiming to minimize the Annualized Cost of the System (ACS), this paper presents a combined algorithm for load forecasting and optimal sizing in a stand-alone photovoltaic (PV)/wind/battery hybrid renewable energy system. A hybrid method by integrating Support Vector Regression (SVR) with the emerging Harris Hawks Optimization (HHO) and Particle Swarm Optimization (PSO) techniques is proposed to predict load demand variability in remote areas of Kano and Abuja, Nigeria.	2021
Hybrid Salp Swarm Algorithm [72]	Hybrid renewable energy system - Demand side management	In the pursuit of identifying the best placements and dimensions for distributed renewable energy resources, covering both singular and multiple installations, a hybrid methodology has been introduced. This approach unites the Salp Swarm Algorithm (SSA) with the combined power loss sensitivity (CPLS) technique. The integration of photovoltaic (PV) and wind turbines (WT) into the distribution network is geared towards enhancing system voltage stability, loss reduction, and boosting system capacity.	2022
Harris Hawk Optimization Approach [73]	Smart grid - Energy management strategy	In the context of cost-effective operations and optimization within multi-source microgrids, a smart unit concept that leverages the Harris Hawk Optimization (HHO) algorithm to enhance cost efficiency has been proposed. The parameters under consideration encompass load demands, energy pricing, and generation capacities. The proposed method proceeds to validate the proposed unit across a range of microgrids, each equipped with distinct energy resources, operating in diverse scenarios is proceed.	2021
A hybrid multi-objective approach [74]	Smart grid - Energy management strategy	This paper introduces a hybrid multi-objective algorithm known as the Multi-objective Spotted Hyena and Emperor Penguin Optimizer (MOSHEPO), designed to address both convex and non-convex economic dispatch and microgrid power dispatch problems. MOSHEPO incorporates an array of non-linear characteristics and operational constraints pertaining to power generators, encompassing factors such as transmission losses, valve-point loading, multiple fuels, and prohibited operating zones.	2020

3.2. Deep learning applications for energy systems

Numerous DL applications have emerged to optimize smart grid operations. An innovative model that incorporates deep learning techniques for short-term load forecasting within the P2P energy trading domain of the energy market has been proposed in [79]. The proposed model leverages the oppositional coyote optimization algorithm (OCOA) for efficient feature selection, blending the principles of oppositional-based learning (OBL) with COA to enhance convergence rate. Additionally, accurate load prediction in P2P energy trading systems is achieved through the utilization of deep belief networks (DBN). [80] uses training of Bayesian models, dropout neural networks and stochastic variational Gaussian Process models, to emulate a challenging high-dimensional building energy performance simulation. The developed surrogate model harnesses 35 building design parameters as inputs to accurately estimate 12 annual building energy performance metrics as outputs. A pioneering approach has been presented in [81] for probabilistic day-ahead net load forecasting, leveraging Bayesian deep learning to effectively capture uncertainties. Using combining the principles of Bayesian probability theory with deep learning techniques, the methodological framework incorporates clustering in subprofiles and incorporates residential rooftop PV outputs as input features to significantly enhance the accuracy of aggregated net load forecasting. A novel incentive-based demand response program utilizing modified deep learning and reinforcement learning methods in [82] is proposed. The approach incorporates the use of a modified deep learning model which leverages recurrent neural networks to accurately forecast uncertainties including day-ahead wholesale electricity price, photovoltaic power output, and power load. [83]proposes profound domain of the smart grid, which stands as a vital component in the landscape of Industry 4.0. This investigation delves into the utilization and assessment of ML and DL models in terms of their efficiency and efficacy in smart grid applications. Moreover, significant trends and challenges in data analysis within the context of this new industrial era, such as scalability, cybersecurity, and big data, are examined, discussed, and emphasized.

Developments in DL have been unveiled for forecasting renewable energy. [84] presents a thorough and comprehensive review of deep learning-based renewable energy forecasting methods, aiming to assess their effectiveness, efficiency, and potential applications. The existing deterministic and probabilistic forecasting methods within the deep learning framework are categorized into four distinct groups: deep belief network, stacked auto-encoder, deep recurrent neural network, and other approaches. The utilization of diverse Deep Learning (DL) algorithms in the domain of solar and wind energy resources has been proposed by [85]. A comprehensive overview of the literature, highlighting the potential of DL techniques while assessing their performance. Additionally, the study addresses significant challenges and opportunities for future research within this domain. [86] presents a review of deep learning-based research in solar and wind energy forecasting, focusing on 2016 to 2020. The review extensively covers topics such as utilized data and datasets, data pre-processing methods, deterministic and probabilistic forecasting techniques, evaluation and comparison methods.

DL has been proposed in modeling renewable energy resources. A combined algorithm based on 3D-geographic information system and deep learning integrated approach was proposed by [87] to predict dynamic rooftop solar irradiance which the rooftop availabilities identify by a deep learning framework. [88] proposes a multi-objectives renewable energy-generation model to generate electrical energy from the wind. It also develops a multi-layer neural network model based on linear combination and multi-objective functions. Both model are evaluated to determine the best. Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) are proposed to solar energy in [89]. Reliable grid management and safe operation, and also cost-effectiveness of the photovoltaic system are addressed by the proposed methods which are based on real meteorological data series of Errachidia province, from 2016 to 2018. [90] presents a Mixed-Integer Linear Programming (MILP) approach to optimize a power system's includes a wind turbine, battery, and conventional grid. The aim is minimizing the daily operational cost and maximizing its resilience. A combined algorithm including deep learning and statistical models is proposed to forecast the 72 h ahead load demand and wind power output.

Advancements in renewable energy forecasting and optimization techniques were proposed by DL. A deep learning approach based on Long Short-Term Memory (LSTM), an adaptive neuro-fuzzy inference system (ANFIS) accompanied by fuzzy c-means (FCM) and ANFIS with grid partition (GP) were proposed in [91] to forecast 1 hour-ahead electrical energy producing from the solar-PV power plant. [92] presents a novel chronological time-period clustering algorithm that effectively identifies representative hours for each planning stage to address uncertainties in wind power and load demand. Furthermore, a deep learning approach is presented, utilizing bidirectional long short-term memory networks to provide accurate forecasts of yearly peak loads. The proposed model is then optimized using a mixed-integer linear programming formulation, and the Benders decomposition algorithm is employed to obtain the optimal solution. [93] offers a comprehensive survey of DL-based approaches for power forecasting in wind turbines, solar panels, and electric power load. It explores the datasets used, enabling researchers to identify appropriate datasets. Unlike previous surveys, it reviews forecasting schemes for both production and load sides simultaneously.

DL applications are emerging to enhance grid security and performance. A novel deep learning network designed specifically for analyzing ultra-short-term wind power data by [94]. The proposed method effectively handles large volumes of data in the smart energy era and mitigates the impact of random environmental variations. The approach involves decomposing the original sequence into sub-sequences using variational mode decomposition techniques. [95] proposes scenario-based two-stage sparse cyber-attack models for the smart grid and develops an innovative interval state estimation-based defense mechanism. Additionally, a stacked autoencoder is designed to extract nonlinear and nonstationary features from electric load data. A combined algorithm includes dynamic time warping and a bespoke gated recurrent neural network is proposed for accurate daily peak load forecasting in [96]. For forecasting aggregated power load and the photovoltaic (PV) power a deep neural network based on long short-term memory units model has been proposed in [97].

Proposed advancements in DL are enhancing energy forecasting and adaptation. A multistep wind speed prediction model that combines VMD (Variational Mode Decomposition), SSA (Singular Spectrum Analysis), LSTM (Long Short-Term Memory) network, and ELM (Extreme Learning Machine) is presented in [98]. The VMD is employed to decompose the original wind speed data into sub-layers, while SSA is used to extract trend information. LSTM performs forecasting for low-frequency sub-layers, and ELM handles forecasting for high-frequency sub-layers. Three algorithms are combined to predict wind speed in [99]. The proposed method is proposed be combination of wavelet packet decomposition, convolutional neural network, and convolutional long short term memory network. [100] presents a hybrid deep learning framework combined by convolutional neural networks and long short term memory to forecast consumption of energy in smart building by recording data of energy consumption at predefined intervals. [101] explores a deep learning-based method for short-term prediction of generated power in photovoltaic power plants. The effectiveness of the proposed method, which employs the Long Short-Term Memory (LSTM) algorithm, is evaluated and compared with the Multilayer Perceptron (MLP) network using performance metrics such as MAE, MAPE, RMSE. An approach for load forecasting that continuously learns from new data and adapts to evolving patterns is proposed in [102]. By employing RNN to capture time dependencies and updating weights with new data, the online aspect ensures real-time learning. Prediction of wind power using a high-frequency SCADA database with a 1-s sampling rate is proposed by a deep learning method in [103]. The predictive model initially included eleven features, such as wind speeds at different heights, pitch angles, nacelle orientation, yaw error, and ambient temperature.

Advancements in DL have been propose for policy modeling. [104] proposes peak wave energy period (TP) forecast model using lagged inputs derived from partial auto-correlation and an extreme learning machine. Its performance is compared to CNN, RNN, M5tree, MLR-ECM, and MLR models. [105] develops a renewable energy-driven forecasting model for policy, using Korea's energy policy as a case. Deep learning predicts demand shifts, with the gated recurrent unit as the base model for evaluating diverse renewable scenarios based on economic-environmental costs. A hybrid gated recurrent unit and CNN models is proposed in [106] to forecast typhoon-induced wind speed and wave height near port coasts. It designed two wind speed and four wave height models based on their combined outcomes. [107] proposes a long short-term memory to predict power generation of the "Searaser" wave energy converter using experimental and numerical simulation data. It addresses the wind speed-output power correlation lacking in previous research. A novel SD-BiGRU model that captures long-range dependencies and semantic data information is proposed in [108].

Some advancements in DL proposed for load prediction. Enhancing the GRU's directional nature, it establishes PSR-BiGRU for optimized subsequences using the CSO algorithm. A hybrid wind power prediction method using cascaded deep learning on mode-decomposed subseries, revealing implicit meteorological patterns has been presented in [109]. By employing empirical and variational mode decompositions, it enhances forecasting by extracting intrinsic mode functions and dissecting irregular sub-layers. A short-term wind speed prediction model to utilize double decomposition, error correction, and LSTM-based deep learning on decomposed wind speed and error sub-series for capturing memory characteristics was proposed in [110]. Using recurrent neural networks, an energy load forecasting method based on Sequence-to-Sequence (S2S) deep learning is proposed, adapting S2S architecture for gated recurrent unit and long short-term memory models [111]. [112] created and compared 12 data-driven models (7 shallow learning, 2 deep learning, and 3 heuristic methods) for building thermal load prediction. Among them, XGBoost and LSTM emerged as top performers, surpassing the best baseline model that utilizes previous day's data.

Proposed applications and methodological considerations in renewable energy highlight the potential of deep learning. [113] evaluates deep recurrent neural networks for predicting commercial building heating demand over a week, emphasizing their role in designing thermal storage tanks to meet longer-term needs and enhance distributed generation planning. A review of recent advancements in renewable energy using learning-based methods, particularly deep learning and machine learning in Solar and Wind domains was proposed. It introduces a novel taxonomy for evaluating method performance, highlighting challenges and emphasizing efficiency, robustness, accuracy, and generalization as key concerns [114]. Practical machine learning and deep learning applications in energy systems emphasizing the accuracy of DL algorithms for complex problem-solving is presented in [115]. The research highlights powerful but less explored DL algorithms such as RNN, ANFIS, RBN, DBN, WNN, and others.

A review of deep learning applications in wind and wave energy was proposed, comparing accuracy and highlighting their potential for optimization, management, forecasting, and behavior analysis [116]. A comprehensive overview of deep learning forecasting models in wind energy, including recurrent neural networks, restricted Boltzmann machines, convolutional neural networks, and auto-encoder approaches was presented, while also discussing future development directions [117]. An extensive review of deep learning for building energy use forecasting, covering literature, techniques, trends, applications, challenges, and potential future directions was proposed [118]. [119] proposed an integrated approach utilizing lab testing, real data, and neural networks to evaluate micro-scale photovoltaic panel performance for specific applications in defined environments, considering factors such as temperature, dust accumulation, and tilt angle.

Deep Learning (DL) techniques span a rich tapestry of specialized classes, each with its unique focus, including convolutional neural networks (CNNs) for image data, recurrent neural networks (RNNs) for sequential data, generative adversarial networks (GANs) for data generation, and more. Fig. 10 serves as an illustrative compass, unveiling the panorama of deep learning applications tailored explicitly for the energy sector between 2018 and 2023. This visual presentation provides a valuable snapshot of the diverse and evolving landscape of DL techniques, categorically organized to address the multifaceted challenges inherent to energy-related domains during this specific period.

Advancements in DL have been proposed for the energy sector. The paper in [120] proposed a systematic analysis and discussion of the most relevant examples for the energy sector. Conducting a comprehensive literature review on the applications of deep learning methods for image analysis, the study categorizes the results into macro-areas of application and examines emerging trends within energy-related cases. In [121], various architectures of deep recurrent neural networks (DRNNs) are investigated and customized specifically for predicting medium- and long-term energy demands. The authors aim to develop a tailored DRNN model for forecasting heating and electricity consumption with a 1-h resolution. Convolutional neural networks (CNNs), a type of deep learning technology, are employed to forecast future power usage. The performance of the models is evaluated using metrics such as mean absolute error, mean square error, root mean square error, and mean constant percentage error, as outlined in [122]. These metrics serve to rank the effectiveness of the models. The citation [123] presents an extensive literature and bibliometric review focusing on deep learning models specifically designed to enhance the accuracy and effectiveness of renewable energy forecasting methods. The Ref. [124] offers a comprehensive review of recent advancements and future prospects in the domain of forecasting renewable energy generation utilizing machine learning (ML) and deep learning (DL) methodologies. Given the rising integration of renewable energy sources (RES) into the electricity grid, precise forecasting of their generation is paramount for optimizing grid operations and energy management.

For the latest advancements in meta-heuristics and deep learning, we recommend exploring the following recent sources: [125–129]. These references delve into cutting-edge methodologies and innovations, offering valuable insights into the current state-of-the-art in both fields.

4. Meta-heuristics in deep learning for energy applications

Several metaheuristic algorithms have been introduced in recent studies to enhance the performance of deep learning (DL) models for various energy applications. The exploration of this emerging field has been conducted with meticulous attention to detail, culminating in a comprehensive understanding of the subject matter. The existing body of work in this nascent domain can be succinctly summarized as follows:

In [130], two metaheuristic algorithms were proposed for optimizing DL model weights to enhance the detection and prevention of cyberattacks. Another study, [131], introduced the Reptile Search Algorithm (RSA) to enhance Long Short-Term Memory (LSTM) and Bidirectional LSTM (BiLSTM) models through hyperparameter tuning. Furthermore, [132] applied a metaheuristic algorithm as a hyperparameter optimizer to improve the performance of Deep Belief Network (DBN) models used for converters and solar panels. In energy forecasting, [133] presented an enhanced Sine Cosine Algorithm (SCA) for hyperparameter tuning in Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) neural networks. A novel approach called Deep Learning with Metaheuristics based Data Sensing and Encoding (DLMB-DSE) was proposed in [134]. For estimating the state of charge (SOC) of batteries, [135] employed a recent metaheuristic algorithm to optimize deep learning parameters. Hybrid electric vehicle energy management with minimal fuel consumption was addressed in [136] using a combination of a new metaheuristic and deep learning. In the context of cyber threat detection in IoT-enabled Smart Cities, [137] utilized deep learning with hyperparameters optimized via the Multi-Versus Optimizer (MVO) algorithm. A novel metaheuristic-based clustering method combined with an optimal Gated Recurrent Unit (OGRU)-based network was introduced in [138] for IoT-enabled Wireless Sensor Networks (WSN) in 5G networks. [139] introduced a fusion of a new metaheuristic approach and deep learning for smart grid stability prediction models.

A novel hybrid short-term electric load forecasting model has been proposed in [140]. This model comprises three key components: data pre-processing and feature selection (utilizing a modified mutual information technique), training and forecasting (based on a factored conditional restricted Boltzmann machine), and optimization (facilitated by our genetic wind-driven optimization algorithm). These components collectively enhance the model's accuracy and performance for short-term electric load forecasting. The inclusion of the Jellyfish Search (JS)

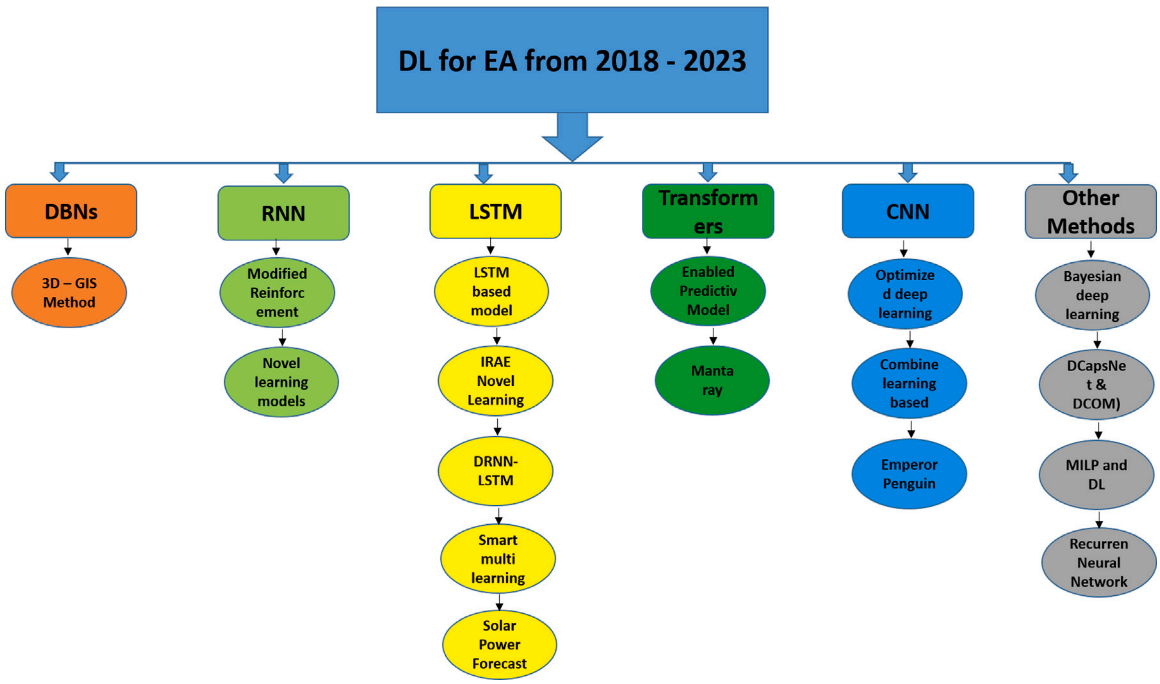
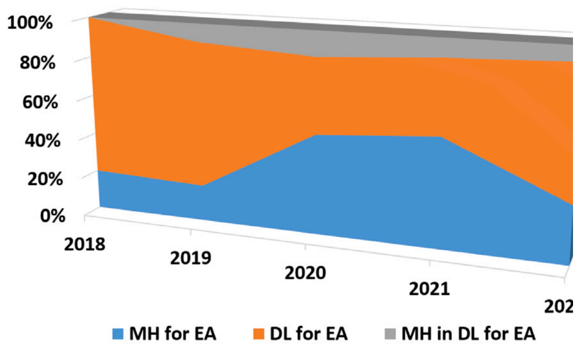


Fig. 10. Different kinds of DL techniques in EA from 2018–2023.

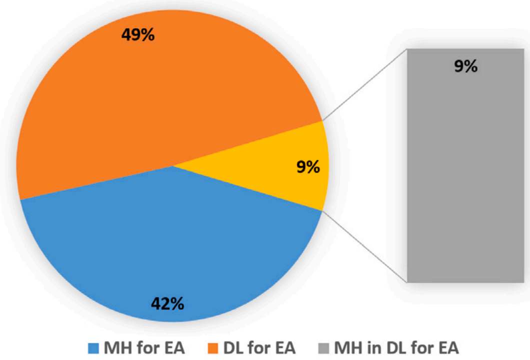
metaheuristic to fine-tune its hyperparameters was proposed in [141], thereby enhancing both the accuracy and stability of the model. Following the development of the hybrid JS-CNNs model, rigorous validation was conducted, yielding invaluable insights for shaping energy policy within management units and facilitating optimized regional power distribution strategies. This research substantially contributes to the prediction of future energy consumption trends and the elucidation of power consumption patterns in cities and counties across the nation. [142] introduces a novel approach by employing optimized deep learning neural networks for the accurate prediction of wave energy flux and various wave-related parameters. Notably, our methodology incorporates the innovative concept of "moth-flame optimization" as a pivotal component in determining the optimal configuration of the deep neural network architecture and the selection of pertinent input data. Furthermore, our work extends beyond conventional techniques, as we have enhanced the moth-flame optimization algorithm by refining its search space mechanisms, thereby advancing its efficacy in solving complex optimization challenges. An innovative forecasting system composed of three key modules: data preprocessing, individual forecasting, and weight optimization has been proposed in [143]. These modules work in concert to significantly enhance forecasting accuracy. The data preprocessing module employs decomposition techniques to obtain smoother sequences, while the prediction module utilizes deep learning algorithms to extract association features. In the weight optimization module, a unique combination strategy based on multi-objective optimization and nonnegative constraints is applied, greatly improving prediction accuracy, surpassing the limitations of individual models. [144] introduces an innovative hybrid algorithm that merges the realms of metaheuristics and machine learning to optimize daily operating schedules within building energy systems. Leveraging deep neural network machine learning, the proposed algorithm predicts the ideal operations for integrated cooling tower systems, while harnessing the power of metaheuristics to optimize the functionality of the remaining components. This synergistic approach ensures efficient and effective energy management. A mathematical modeling of a doubly fed induction generator (DFIG) and utilizes third-generation deep learning neural networks (DLNN) for controller design is presented by [145]. We regulate the torque of a variable-speed wind turbine generator using a PID controller with gains tuned by the DLNN model. To prepare the optimal dataset for DLNN training, we introduce the novel density-based grey artificial bee colony (D-GABC) algorithm. Additionally, D-GABC optimizes the neural network controller weights to prevent premature convergence and reduce computational time. This integrated approach enhances controller efficiency. To enhance climate-adaptive designs for the aerogel glazing system, a versatile optimization methodology was proposed in [146]. This approach seamlessly blends supervised machine learning with a cutting-edge teaching–learning-based optimization algorithm to determine optimal geometric and operating parameters. [147] proposes the Improved Slime Mould Algorithm (ISMA) to accurately and efficiently determine solar cell parameters. ISMA combines the Nelder–Mead simplex mechanism with random learning, enhancing both convergence and local search capabilities compared to traditional SMA approaches. [148] introduces an innovative approach to optimizing designs in the presence of stochastic uncertainties. A learning-based surrogate model to analyze and manage these uncertainties effectively is proposed. Moreover, we define a multi-level optimization function that accounts for uncertainty and seamlessly integrate it with a heuristic teaching–learning-based algorithm to identify the optimal design. [149] focused on data-driven machine learning techniques and their real-time applications in smart energy systems. Integrating machine learning into core energy technologies and its use in energy distribution utilities addressed. This review paper discussed identify common issues for future research and highlight opportunities and challenges in the field of machine learning for energy distribution. [150] proposes a hybrid CNN-LSTM-Transformer model, complemented by clustering and feature selection techniques, to forecast solar energy production efficiently. Using the Fingrid open dataset, the proposed model outperformed others, including LSTM-CNN, making it a trusted tool for seamless solar energy integration into grids.

5. Challenges of meta-heuristics and deep learning for energy applications

Both meta-heuristics and deep learning techniques present promising solutions for energy applications, yet they confront their own



(a)



(b)

Fig. 11. (a) Rate of selected studies per subject area (b) Percentage of selected studies per data base (2018–2023).

unique sets of challenges. Meta-heuristics face scalability issues in dealing with intricate, large-scale energy optimization problems, demanding efficient adaptation to high-dimensional variables and constraints. Additionally, ensuring convergence to global optima, managing computational efficiency, fine-tuning parameters, and addressing multi-objective optimization, robustness, real-time operation, constraint integration, and parallelization are paramount. Conversely, deep learning contends with data availability and quality concerns, interpretability as "black box" models, the need for extensive training data, computational complexity, generalization issues, and the intricate task of hybridization. Despite these challenges, both meta-heuristics and deep learning hold immense potential to revolutionize the energy sector, with researchers and practitioners continually striving to unlock their transformative capabilities.

5.1. Challenges of meta-heuristics

1. **Scalability:** Handling large-scale energy optimization problems is challenging due to the high dimensionality of variables and constraints involved. Developing scalable meta-heuristics that can efficiently explore the solution space and adapt to complex, real-world energy systems is crucial. Techniques like parallelization, surrogate modeling, and decomposition methods can help tackle scalability issues.
2. **Convergence:** Ensuring convergence to global optima is essential, especially when dealing with intricate energy systems. Meta-heuristics can sometimes get trapped in local optima. Advanced search strategies, such as diversity preservation mechanisms or hybridization with local search methods, can aid in escaping local optima and finding better solutions.
3. **Computational Efficiency:** Meta-heuristics can be computationally intensive, making them less suitable for real-time applications. Balancing computational efficiency with solution quality is essential. This can be achieved through algorithmic enhancements, such as adaptive parameter tuning, early termination criteria, and population control mechanisms.
4. **Parameter Tuning:** Tuning the parameters of meta-heuristics for specific energy optimization tasks is a challenging optimization problem itself. Automated parameter tuning techniques, like meta-heuristics for hyperparameter optimization or machine learning-based tuning, can assist in finding optimal parameter configurations for different scenarios.
5. **Multi-Objective Optimization:** Energy optimization often involves conflicting objectives, such as cost minimization and environmental impact reduction. Developing multi-objective meta-heuristics that can efficiently explore the trade-off between these objectives is essential. Pareto-based methods and preference-based selection mechanisms are useful for handling multiple, competing objectives.
6. **Robustness:** Energy systems are prone to uncertainties, and meta-heuristic solutions must remain reliable under changing conditions. Robust optimization techniques, scenario-based approaches, or robustness-enhancing meta-heuristics can be employed to ensure that solutions are resilient to variations in factors like renewable energy generation or demand fluctuations.
7. **Real-Time Operation:** Integrating meta-heuristics into real-time energy management systems demands algorithms capable of making rapid decisions in response to dynamic changes. Real-time meta-heuristics with adaptive search strategies and efficient data-driven decision-making processes are necessary to address sudden changes in supply and demand.
8. **Incorporating Constraints:** Energy optimization often involves various constraints, including physical, operational, and regulatory constraints. Effective handling of constraints within meta-heuristic algorithms is crucial to ensure that solutions are feasible and compliant with industry standards and regulations.
9. **Parallelization:** Leveraging parallel computing resources can significantly speed up meta-heuristic algorithms. Strategies like parallel meta-heuristics, distributed computing, or GPU acceleration can be employed to harness the power of multiple processors or computing nodes for tackling large-scale energy optimization problems efficiently.
10. **Hybridization:** Hybridization: Combining meta-heuristics with other optimization techniques or machine learning methods can lead to more robust and effective solutions. Developing hybrid algorithms that integrate different optimization paradigms effectively, like combining genetic algorithms with deep reinforcement learning or particle swarm optimization with neural networks, can be a challenge in itself but can yield powerful optimization tools.

5.2. Challenges of deep learning

1. **Data Quality:** Ensuring high-quality data involves not only accuracy, consistency, and reliability but also addressing issues like missing data, outliers, and data drift. Implementing robust data preprocessing and cleaning pipelines becomes imperative, and domain-specific data quality standards are essential for trustworthy results.
2. **Interpretability:** Enhancing the interpretability of deep learning models can be achieved through techniques like attention mechanisms, model visualization, and explainable AI. Bridging the gap between model complexity and human understanding is an ongoing challenge, especially for critical energy decisions.

3. **Training Data Size:** In scenarios with limited historical data, techniques such as semi-supervised learning, active learning, and synthetic data generation become indispensable to augment training datasets and facilitate model training and adaptation.
4. **Generalization:** Ensuring robust model generalization involves comprehensive data augmentation strategies, domain adaptation techniques, and model ensembling approaches to account for the inherent variability in energy systems.
5. **Model Complexity:** Managing model complexity necessitates the use of regularization methods, model compression techniques, and architecture search algorithms to strike a balance between model performance and resource efficiency.
6. **Energy Efficiency:** Designing energy-efficient deep learning models involves optimizing model architectures, quantization, and deploying model inference on energy-efficient hardware platforms, such as GPUs, TPUs, or specialized edge devices with low power consumption.
7. **Uncertainty Quantification:** Robust uncertainty quantification requires the incorporation of Bayesian neural networks, Monte Carlo dropout, and ensemble methods to provide probabilistic predictions and decision-making under uncertainty.
8. **Transfer Learning:** Effective transfer learning in the energy domain demands domain adaptation techniques, fine-tuning strategies, and model architectures that facilitate knowledge transfer from pre-trained models to specific energy tasks.
9. **Real-Time Processing:** Achieving real-time processing involves model optimization for low latency, hardware acceleration, and the development of edge AI solutions that can make rapid decisions based on dynamic energy conditions.
10. **Hardware Constraints:** Adapting models to resource-constrained hardware necessitates model quantization, model pruning, and hardware-aware neural architecture search to strike a balance between model complexity and hardware limitations.
11. **Privacy and Security:** Safeguarding sensitive energy data requires robust encryption, secure data sharing protocols, federated learning approaches, and rigorous security audits to protect against data breaches and adversarial attacks.
12. **Model Bias:** Identifying and mitigating biases in deep learning models requires fairness-aware training, debiasing techniques, and continuous monitoring to ensure equitable predictions and decision-making in energy applications.
13. **Data Fusion:** Effectively fusing heterogeneous data sources necessitates advanced data integration techniques, data quality validation methods, and noise reduction strategies to leverage the full potential of diverse data streams.
14. **Long-Term Forecasting:** Extending deep learning models for long-term forecasting requires the incorporation of time series analysis, trend modeling, and handling complex, multi-year dependencies within energy data to provide accurate long-term energy predictions and insights.

In Fig. 11, we present a comparative analysis of document counts spanning the years 2018 to 2023, focusing on the domains of meta-heuristics, deep learning, and the intersection of meta-heuristics within the realm of deep learning for energy applications.

6. MH in DL (MHDL) opportunities towards energy applications

Meta-heuristics represent a versatile and efficient approach in the domain of deep learning for energy applications. These optimization algorithms serve as robust tools to tackle intricate energy-related issues, optimizing neural network architectures, hyperparameters, and training methodologies. Their adaptability, proficiency in navigating high-dimensional search spaces, and knack for discovering near-optimal solutions establish them as indispensable assets for elevating energy efficiency and performance within deep learning applications. This section outlines many opportunities presented by the utilization of meta-heuristics in this context. Especially a comprehensive framework for utilizing MHs in conjunction with DL for improved energy management. MHDL framework comprises six interconnected steps:

Step 1: Data Acquisition

The first step focuses on collecting pertinent data from hybrid inventories of renewable energy sources. This foundational data forms the basis for subsequent analyses and model development, ensuring the representation of diverse and crucial information.

Step 2: Data Preprocessing

In the second step, data undergoes meticulous preprocessing. Extraneous information and noise are systematically identified and removed, resulting in a pristine dataset devoid of confounding elements.

Step 3: Data Enhancement through MHs

The third step involves harnessing the power of MHs to elevate data quality and relevance. MHs are employed to optimize the dataset, refining inputs for the subsequent DL phase. This step incorporates diverse data enrichment techniques and feature engineering to unlock latent insights within the dataset.

Step 4: DL Training Phase

The fourth step integrates the enriched dataset into the DL framework. Knowledge gained from MHs is seamlessly embedded into DL models, enabling them to make informed predictions and decisions. This training phase prepares the model for real-world energy applications.

Step 5: Prediction and Optimization

The fifth step is dedicated to prediction and optimization. DL models, trained on enhanced data, are deployed to manage energy-related tasks. Simultaneously, optimization techniques fine-tune various aspects of the energy problem, ensuring the efficient utilization of resources and offering forecasting capabilities.

Step 6: Evaluation and Validation

The sixth step rigorously assesses the effectiveness of integrating MHs with DL. Evaluation metrics and performance indicators scrutinize model accuracy, reliability, and overall performance in addressing energy-related challenges. This step serves as a crucial validation checkpoint for the approach.

A detailed visual representation of this comprehensive workflow is shown in Fig. 12 and the related Flowchart is shown in Fig. 13, which provides a graphical depiction of the entire process. This systematic framework offers a robust and versatile methodology for harnessing the potential of Meta-Heuristics within the realm of Deep Learning for advanced energy applications, with the promise of revolutionizing the field of renewable energy management.

6.1. Parameter sensitivity in enhanced MHDL framwork

We consider the following key parameters and their sensitivities to algorithm performance:

Population Size: The size of the population in meta-heuristic algorithms significantly influences convergence speed and solution quality. Larger populations may enhance exploration capabilities but incur higher computational costs. Conversely, smaller populations may lead to premature convergence and suboptimal solutions. We conduct sensitivity analyses to determine an optimal population size that balances computational efficiency with solution quality.

Parameterization for Data Refinement: Within the data refinement phase of our framework, parameters related to MHs play a crucial role in optimizing data quality and relevance. Sensitivity analyses are conducted to evaluate parameters such as refinement techniques, feature selection criteria, and optimization strategies, aiming to enhance the efficacy of data preprocessing and enrichment processes.

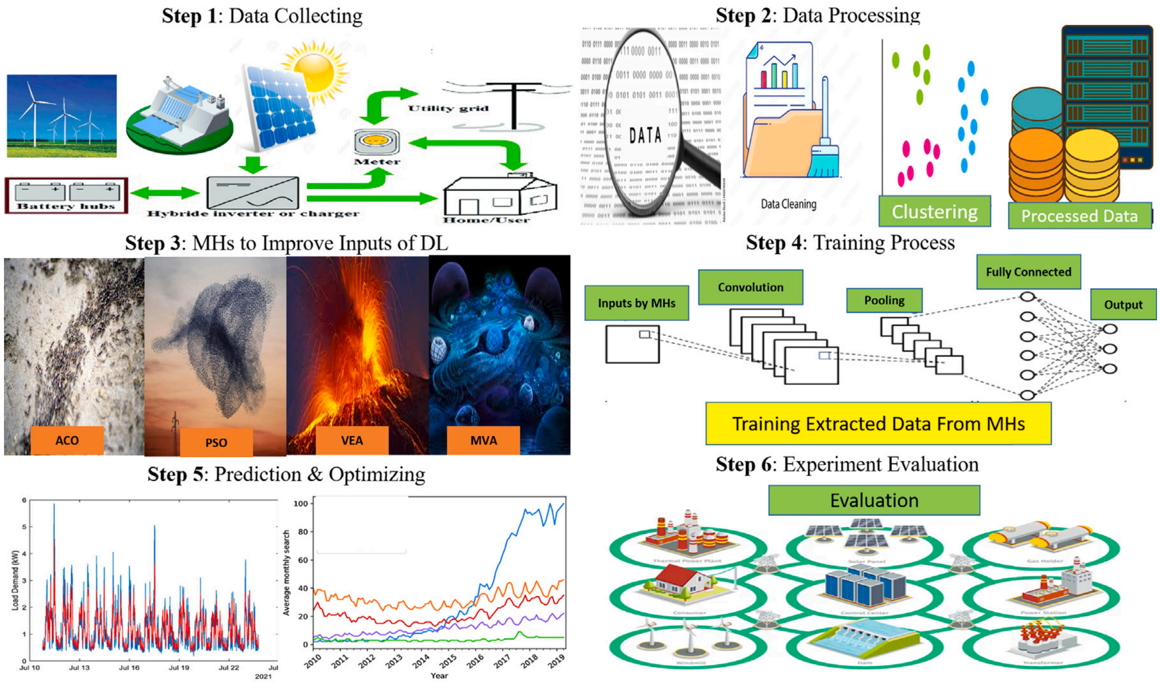


Fig. 12. The process of MHs in DL for energy applications.

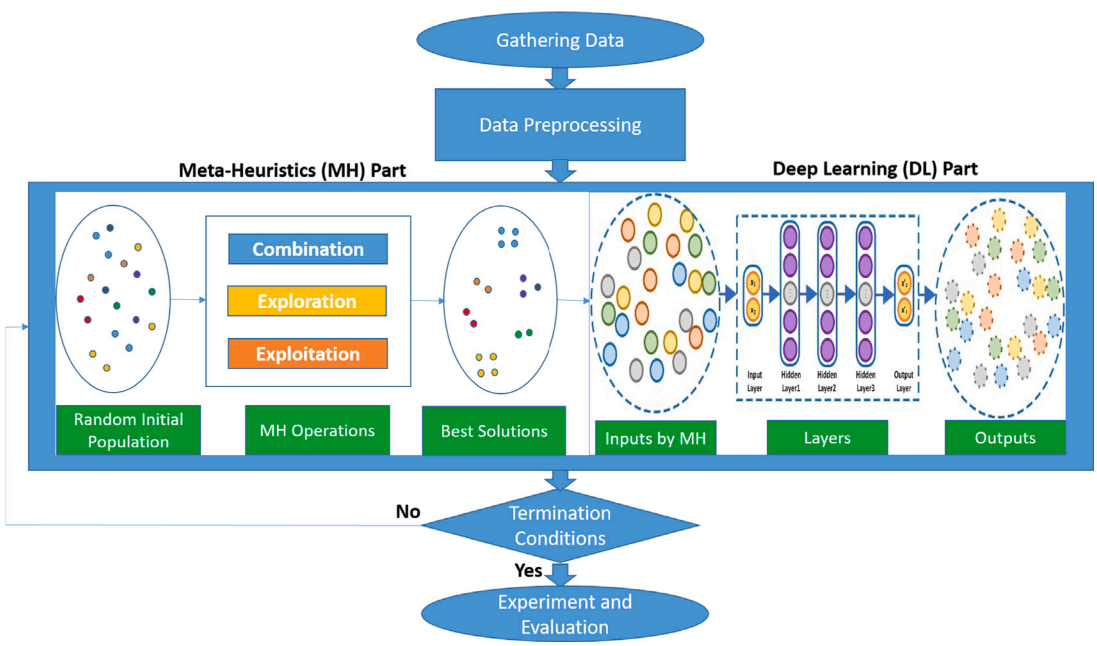


Fig. 13. Flowchart illustrating the proposed coupling framework.

Training Phase Optimization: Parameters during the optimization phase of deep learning models are pivotal in shaping model performance and generalization capabilities. Sensitivity analyses are conducted to assess parameters such as learning rate, batch size, regularization techniques, and network architecture, ensuring robust training and adaptation to diverse energy datasets.

Model Deployment and Fine-Tuning: In the deployment and fine-tuning phase, parameters governing model deployment and optimizatiton strategies are critical for achieving accurate predictions and efficient resource utilization. Sensitivity analyses are performed to evaluate parameters such as forecasting horizon, optimization objectives, and model evaluation metrics, guiding decision-making processes in energy management tasks.

Convergence Criteria: Convergence criteria define the conditions under which the algorithm halts, signaling convergence or reaching a predefined stopping criterion. Sensitivity analyses are conducted to evaluate the impact of different convergence criteria on algorithm performance, considering factors such as convergence speed, solution quality, and computational resources.

6.2. Computational complexity and practical applicability

The MHDL framework involves several computational steps, including data acquisition, preprocessing, data enhancement through MHs, DL training phase, prediction and optimization, and evaluation and validation. Each of these steps may incur computational overhead, particularly when dealing with large datasets and complex optimization problems. The integration of MHs with DL introduces additional computational requirements, such as parameter tuning and optimization convergence.

The computational complexity of the MHDL framework can vary depending on factors such as dataset size, model architecture, optimization algorithms used, and specific energy-related tasks addressed. Assessing the computational complexity involves analyzing factors like algorithm runtime, memory consumption, and scalability to handle increasing data volumes.

While addressing energy-related challenges, the practical applicability of the MHDL framework in path planning applications is crucial. Path planning often involves optimizing routes for energy-efficient navigation, resource allocation, or infrastructure deployment. The MHDL framework offers several advantages in this context:

Data-Driven Decision Making: By leveraging data acquisition and preprocessing steps, the MHDL framework enables data-driven decision-making in path planning applications. It utilizes historical data and real-time inputs to optimize path trajectories based on energy constraints and objectives.

Optimization and Prediction: Through the DL training phase and prediction and optimization steps, the MHDL framework enhances path planning by predicting energy consumption patterns, optimizing route selections, and refining navigation strategies. This facilitates more efficient resource utilization and improved performance in energy-constrained environments.

Evaluation and Validation: The evaluation and validation step ensures the robustness and reliability of path planning solutions generated by the MHDL framework. Performance metrics assess factors like energy efficiency, route accuracy, and computational efficiency, providing insights into the practical effectiveness of the proposed methods.

Some potential limitations of the proposed method in other real applications could include:

Scalability: The proposed method may face challenges when scaling to larger datasets or more complex systems outside of the energy domain.

Generalization: The effectiveness of the integrated framework may vary across different application domains due to differences in data characteristics and problem complexities.

Computational Resources: The computational requirements of the proposed method could be prohibitive for applications with resource constraints.

Domain-specific Challenges: Other real-world applications may pose unique challenges that the proposed method may not address effectively.

7. Conclusion and future work

In conclusion, this paper has provided an extensive and up-to-date examination of meta-heuristic algorithms and deep learning techniques in the context of energy applications spanning the years 2018 to 2023. While there exists a substantial body of work dedicated to both meta-heuristic algorithms (MHs) and deep learning (DL) techniques for energy-related problems, there is a noticeable gap in the literature when it comes to the integration of these two domains, particularly in the context of solving complex issues in renewable energy management.

Our study has not only shed light on the current challenges and limitations faced by MHs and DL in renewable energy management but has also introduced a novel framework that seeks to bridge these gaps. This innovative framework offers a promising avenue for addressing and optimizing renewable energy management problems in an efficient and effective manner. By harnessing the strengths of both MHs and DL, it presents a synergistic approach that can unlock new opportunities for advancing the field of sustainable energy management.

As we move forward into the future, the integration of MHs and DL is poised to play a pivotal role in addressing the pressing challenges associated with renewable energy generation, distribution, and utilization. The insights and methodologies presented in this paper pave the way for further research and development in this exciting and transformative field. By collaborating across disciplines and exploring the uncharted territories at the intersection of MHs and DL, we can unlock the full potential of renewable energy sources and contribute to a more sustainable and eco-friendly energy landscape. This paper marks a significant step towards realizing that vision, and we look forward to the exciting advancements that will undoubtedly emerge from this burgeoning field of study.

The paper contributes significantly in these areas:

(1) Providing a comprehensive overview of recent advancements in MHs, DL, and their integration.
(2) Offering detailed coverage of trends from 2018 to 2023.
(3) Introducing the Alpha metric for performance evaluation.
(4) Proposing an innovative framework that harmonizes MHs with DL for energy problems.

The integration of MHs and DL in energy applications offers a host of compelling benefits and promising opportunities for future works, including:

1. **Improved Optimization:** Meta-heuristics serve as powerful optimization tools when combined with deep learning in energy systems. They facilitate the discovery of optimal configurations and settings, enabling energy systems to operate at their peak efficiency. By fine-tuning parameters and exploring a vast solution space, meta-heuristics help uncover cost-saving opportunities and enhance overall system performance. This benefit is particularly valuable in scenarios where energy system optimization involves intricate variables and complex relationships, ultimately leading to significant cost reductions and operational improvements.
2. **Enhanced Efficiency:** The synergy between meta-heuristics and deep learning is instrumental in driving operational efficiency in energy management. Through continuous monitoring and real-time adjustment of energy usage and resource allocation, these techniques minimize wastage and maximize the productive use of resources. This heightened efficiency not only translates into cost savings but also plays a pivotal role in promoting sustainable energy practices. By optimizing energy utilization, systems become more environmentally friendly and economically viable in the long run.
3. **Cost Reduction:** Cost reduction is a central objective in effective energy management, and the integration of meta-heuristics with deep learning is a formidable strategy to achieve this goal. Predictive maintenance models, empowered by these techniques, anticipate equipment failures and strategically schedule maintenance activities, reducing the financial impact of unexpected breakdowns. Additionally, by optimizing resource allocation and operational processes, operational and maintenance costs can be substantially trimmed, bolstering overall cost-effectiveness in energy management strategies.
4. **Resource Allocation:** Optimal resource allocation is pivotal for achieving the highest efficiency and effectiveness in energy systems. Meta-heuristics embedded within deep learning frameworks excel in precisely this task. They ensure that critical resources, such as electricity, fuel, and manpower, are deployed where they can have the most significant impact. For instance, in the context of a power grid, these techniques help balance load distribution, preventing overloads and minimizing energy losses. In energy-intensive industries, this precise resource allocation can lead to substantial improvements in production efficiency and energy consumption.
5. **Grid Stability:** Grid stability is a fundamental prerequisite for an uninterrupted energy supply, particularly in today's context with the increasing integration of renewable energy sources.

The amalgamation of meta-heuristics and deep learning equips energy grids with the capability to respond in real-time to dynamic conditions. This ensures the grid's stability by mitigating potential issues, such as voltage fluctuations or line failures, before they can escalate into grid-wide failures. The outcome is a more reliable and resilient energy supply, essential for both consumer satisfaction and the seamless integration of renewable energy sources into the grid.

6. **Environmental Impact:** The implementation of meta-heuristics in deep learning for energy applications plays a pivotal role in mitigating the adverse environmental consequences of energy production and consumption. By optimizing energy usage patterns, these techniques contribute to a substantial reduction in greenhouse gas emissions and minimize the overall environmental footprint. This alignment with sustainability and environmental goals underscores the potential of meta-heuristics to foster a cleaner and greener energy ecosystem.
7. **Renewable Integration:** Meta-heuristics serve as a linchpin in the effective integration of renewable energy sources, such as solar and wind, into the energy landscape. Through their optimization capabilities, meta-heuristics enhance the generation and storage of renewable energy, reducing reliance on fossil fuels. This transition towards cleaner energy sources not only promotes environmental sustainability but also bolsters energy security by diversifying the energy mix.
8. **Real-Time Decision-Making:** The synergy between meta-heuristics and deep learning empowers real-time, data-driven decision-making in the face of ever-changing energy conditions. This dynamic responsiveness significantly improves the resilience of energy grids by enabling swift adjustments and adaptations. As a result, disruptions are minimized, and the grid can better accommodate fluctuations in supply and demand, enhancing overall grid stability.
9. **Optimal Load Balancing:** Efficient load distribution across the energy grid is a cornerstone of reliable energy delivery. Meta-heuristics excel in this domain by optimizing load balancing strategies. This optimization minimizes congestion, prevents overloads that can lead to outages, and ensures that energy resources are allocated effectively and sustainably. The result is a more resilient and robust energy infrastructure.
10. **Resource Management:** Effective management of energy resources, including batteries and storage systems, is essential for the long-term sustainability of the energy network. Meta-heuristics optimize the deployment and utilization of these resources, prolonging their lifespan and maximizing their contribution to grid stability. This careful resource management not only improves energy network efficiency but also extends the overall lifecycle of expensive infrastructure, making it a financially sound choice for energy providers and consumers alike.
11. **Predictive Maintenance:** Predictive maintenance utilizes advanced technologies like deep learning and meta-heuristics to monitor the condition of equipment in real-time. By analyzing data from sensors and historical maintenance records, it predicts when a piece of equipment is likely to fail. This proactive approach allows organizations to schedule maintenance before a breakdown occurs, minimizing downtime and avoiding costly repairs. It is a cost-effective strategy that ensures equipment reliability and operational efficiency.
12. **Energy Market Optimization:** Energy market optimization involves using sophisticated algorithms and data analysis techniques to make strategic decisions in the energy trading and pricing sectors. By optimizing energy trading strategies, it is possible to create a more equitable marketplace that benefits both energy consumers and suppliers. Fairer market conditions encourage competition and innovation while ensuring efficient use of energy resources, ultimately leading to better energy affordability and availability.
13. **Resilience:** Energy systems need to be resilient to withstand various challenges, such as extreme weather events or cyberattacks. The integration of meta-heuristics into deep learning models enhances the resilience of these systems. They can quickly adapt to changing conditions, making them more capable of withstanding disruptions and recovering rapidly from adverse events. This resilience is critical for maintaining a stable energy supply, especially in times of crisis.
14. **Energy Conservation:** Energy conservation is achieved by providing consumers with insights into their energy consumption patterns through data analysis and feedback mechanisms. By understanding their energy usage habits, consumers can adopt more energy-efficient practices, reduce energy wastage, and lower their utility bills. This benefits not only individual consumers but also contributes to the overall reduction of energy consumption, which is vital for environmental sustainability.
15. **Sustainability:** Sustainability in the energy sector involves optimizing the use of renewable energy sources like solar and wind while reducing reliance on non-renewable resources like fossil fuels. Deep learning and meta-heuristics play a crucial role in modeling and optimizing renewable energy generation. By aligning energy practices with global sustainability goals, we can reduce carbon emissions and mitigate the impact of climate change.
16. **Load Forecasting:** Accurate load forecasting is essential for energy planning and resource allocation. Deep learning and meta-heuristics help in analyzing historical data and predicting future energy demand. This ensures that energy providers can allocate resources efficiently, preventing shortages or surpluses. It also aids in long-term infrastructure planning to meet the growing energy needs of a region.
17. **Grid Integration:** Smart grid technologies combined with meta-heuristics enable better integration and coordination of diverse energy resources. This results in a more efficient distribution of energy across the grid, reducing transmission losses and improving overall energy reliability. It also supports the integration of intermittent renewable energy sources, such as solar and wind, into the grid.
18. **Distributed Energy:** Effective management of distributed energy resources, like residential solar panels and wind turbines, involves optimizing their operation to contribute to grid stability. By coordinating these resources efficiently, we can maximize their energy output and minimize fluctuations, ensuring a reliable and resilient energy supply.
19. **Consumer Empowerment:** Real-time information and control over energy consumption empower consumers to make informed decisions about how they use energy. This can include adjusting usage patterns during peak demand periods or investing in energy-efficient appliances. Empowered consumers have the potential to achieve cost savings and reduce their environmental footprint, contributing to a more sustainable energy future.
20. **Regulatory Compliance:** Energy providers can leverage meta-heuristics and deep learning to ensure compliance with regulations and standards. These technologies help in monitoring and optimizing energy operations, ensuring safety, legality, and reliability. Compliance not only avoids legal issues but also builds trust among consumers and regulators, fostering a stable energy market.

Declaration of competing interest

No conflict of interest exists. We confirm that there are no known conflicts of interest associated with this publication.

Data availability

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

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Research ethics

We further confirm that any aspect of the work covered in this manuscript involving human patients has been conducted with the ethical approval of all relevant bodies, and such approvals are acknowledged within the manuscript.

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