applied sciences

MDPI

Review

Hybrid Renewable Energy Systems—A Review of Optimization Approaches and Future Challenges

Akvile Giedraityte *, Sigitas Rimkevicius , Mantas Marciukaitis , Virginijus Radziukynas and Rimantas Bakas

Lithuanian Energy Institute, Breslaujos St. 3, 44403 Kaunas, Lithuania
* Correspondence: akvile.giedraityte@lei.lt

Abstract: The growing need for sustainable energy solutions has propelled the development of Hybrid Renewable Energy Systems (HRESs), which integrate diverse renewable sources like solar, wind, biomass, geothermal, hydropower and tidal. This review paper focuses on balancing economic, environmental, social and technical criteria to enhance system performance and resilience. Using comprehensive methodologies, the review examines state-of-the-art algorithms such as Multi-Objective Particle Swarm Optimization (MOPSO) and Non-Dominated Sorting Genetic Algorithm II (NSGA-II), alongside Crow Search Algorithm (CSA), Grey Wolf Optimizer (GWO), Levy Flight-Salp Swarm Algorithm (LF-SSA), Mixed-Integer Linear Programming (MILP) and tools like HOMER Pro 3.12–3.16 and MATLAB 9.1–9.13, which have been instrumental in optimizing HRESs. Key findings highlight the growing role of advanced, multi-energy storage technologies in stabilizing HRESs and addressing the intermittency of renewable sources. Moreover, the integration of metaheuristic algorithms with machine learning has enabled dynamic adaptability and predictive optimization, paving the way for real-time energy management. HRES configurations for cost-effectiveness, environmental sustainability, and operational reliability while also emphasizing the transformative potential of emerging technologies such as quantum computing are underscored. This review provides critical insights into the evolving landscape of HRES optimization, offering actionable recommendations for future research and practical applications in achieving global energy sustainability goals.

Keywords: hybrid renewable energy systems; optimization techniques; optimization criteria; computation efficiency; sustainable energy; innovations

Academic Editors: Xinyan Wang, Mengdi Pan and Parisa Naeiji

Received: 9 January 2025
Revised: 29 January 2025
Accepted: 5 February 2025
Published: 8 February 2025

Citation: Giedraityte, A.; Rimkevicius, S.; Marciukaitis, M.; Radziukynas, V.; Bakas, R. Hybrid Renewable Energy Systems—A Review of Optimization Approaches and Future Challenges. *Appl. Sci.* **2025**, *15*, 1744. https://doi.org/10.3390/app15041744

1. Introduction

The configuration of energy systems has changed over decades during the 20th century from individual energy devices and small sub-systems into complex centralized systems with enormous power generation capacities [1]. At the beginning of the 21st century, it was recognized worldwide that we need to drastically reduce greenhouse gas emissions to avoid catastrophic consequences for our planet and humanity. The Paris Agreement is a good illustration of understanding this challenge—196 countries have committed to reduce emissions under the framework of this Agreement on climate change [2]. The Paris Agreement declares the ambitious target—to limit global temperature increases to as close as possible to 1.5 degrees Celsius. The energy transition is unavoidable; therefore, climate-neutral energy generation and energy storage technologies play a vital role in achieving this target.

The combination and integration of different renewable energy generation technologies in an optimal way, considering technical, environmental, economic, and social criteria, becomes an important challenge. The development of hybrid renewable energy systems (HRESs), the robust design of various RES technologies, the algorithms of their optimization, and comprehensive considerations of the above-mentioned criteria are needed to address this challenge. This diverse body of research reveals the importance of interdisciplinary research on the evolution of HRESs and the importance of interdisciplinary approaches in achieving sustainable energy solutions. There is a lot of research investigating the performance of energy systems, but the adequacy and suitability of various analysis methods and tools for the optimization of HRESs are often questioned.

The objective of this paper is to review the latest scientific papers on HRES optimization analysis and define its advantages, challenges, and future perspectives. The optimization focuses on technology selection and development assessment.

This article further integrates insights from various studies on innovative approaches to HRES optimization. It provides an overview of the developments in this field and the ongoing challenges and innovations that continue to drive its evolution. It presents an extensive examination of HRES optimization, highlighting critical advancements in design, performance evaluation, and optimization methodologies.

HRES optimization will remain critical for addressing the growing global demand for clean, reliable, and affordable energy. As renewable energy sources like solar and wind become more prevalent, their inherent intermittency and variability necessitate advanced optimization techniques to ensure stability and efficiency in energy systems [3,4]. By integrating energy storage solutions, such as batteries and hydrogen, with robust control strategies, HRESs can meet energy demands even during fluctuating environmental conditions [5–7]. Furthermore, as energy systems grow in complexity, combining multiple renewable sources in a single hybrid configuration offers opportunities to improve resilience, reduce dependency on fossil fuels, and optimize cost-effectiveness [8,9].

In the future, the role of HRESs will expand beyond technical performance to include broader considerations such as environmental sustainability, social acceptance, and economic feasibility. Existing multi-objective optimization frameworks, like those highlighted in [10,11], will be essential research objects for balancing diverse criteria. Moreover, the integration of advanced technologies, such as machine learning and artificial intelligence [12], will enable real-time adaptability and predictive maintenance, ensuring that these systems can evolve alongside advancements in technology and policy [13,14]. As climate change and energy equity continue to drive global energy transitions, optimizing HRESs will be pivotal for meeting sustainability goals while providing reliable energy access to underserved regions [15,16]. By fostering local participation, renewable energy adoption, and decentralized energy sharing, energy resilience is significantly strengthened, making these approaches not only practical but essential for a sustainable and equitable energy future [17]. Therefore, the ongoing analysis and improvement in optimization methodologies and tools for HRESs are crucial to determine optimal configurations of integrated energy systems in terms of reliability, safety, environmental, and economic parameters by achieving long-term sustainability goals.

2. Methodology

The authors developed a literature selection methodology to perform a comprehensive literature review. The Scopus, ScienceDirect, and Google Scholar databases were utilized to search for relevant scientific papers published since 2017. Initially, a literature search was performed to find articles by title, abstract, and keywords. The search was primarily based on the use of logical combinations presented in Figure 1.

Moreover, the search results have a multi-stage filtering process based on criteria such as publication year, citation ranking, abstract, conclusions, scheme of the system, and focus on system optimization tools. A systematic review database was created for all prioritized studies. Based on the mentioned data, only articles analyzing HRESs, with at least two renewable energy sources, not thorough reviews, and with system optimization tasks, were selected and cited in Section 3. In total, from 182 downloaded articles, journals, books, papers, and technical reports, just 55 are cited in Section 3 for the selection of commonly used optimization methods for HRESs. Furthermore, all relative information, such as computation efficiency and optimization limits, was selected using direct queries in scientific literature databases, skipping Step 1 "Literature search" and finishing with Step 2 "Selection".

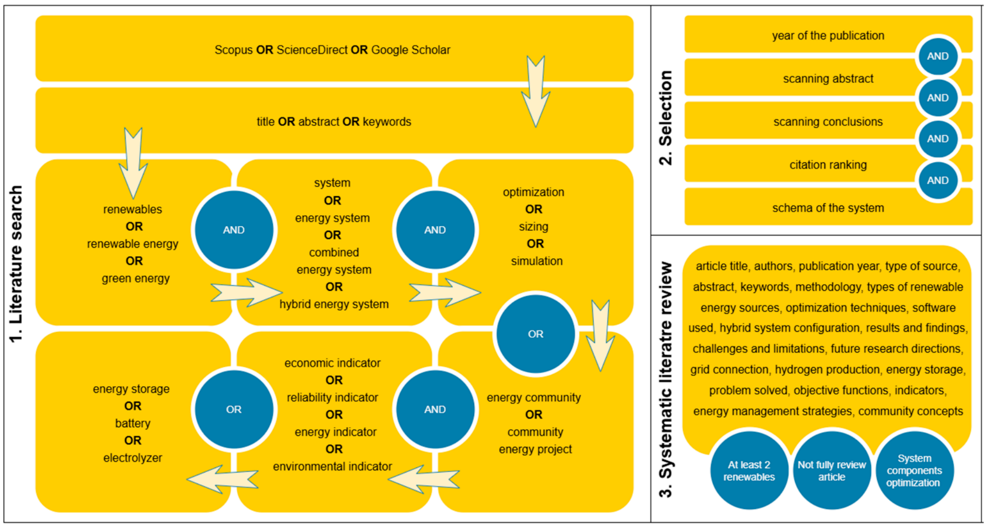

Figure 1. Literature selection process (developed by the authors).

Integrating different renewable energy and energy storage technologies into one HRES achieves more reliable and sustainable energy generation. Sections 3.1–3.3 analyze recent research publication trends regarding the diversity of renewable energy technologies, energy storage solutions and grid connection type. This analysis indicates the likely development trajectory of HRESs in the future and amplifies the importance of optimizing diverse technologies.

3. HRES Design

HRESs represent an innovative approach to utilizing the diverse potential of renewable energy sources. Taking each type of renewables, the vast majority are characterized by inherent variability and intermittency. To enhance the stability and usability of these systems, pumped hydro, battery, and hydrogen solutions play a pivotal role, offering mechanisms to store excess energy during peak production periods and supply power during deficits. Additionally, the incorporation of grid connection technologies serves as a critical bridge, allowing HRESs to balance local energy demands with the distribution or transmission energy networks, improve power quality, and provide backup during periods of extended shortfall.

3.1. Renewables Diversity

The main part of an HRES belongs to renewable energy technologies. Figure 2 illustrates the distribution of renewable energy sources in cited articles published from 2017 to 2024. Each bar represents the total number of articles per year, with individual contributions from six renewable energy categories: solar, wind, biomass, geothermal, hydropower, and tidal energy. Figure 2 also demonstrates an increase in the number of scientific articles analyzing HRESs.

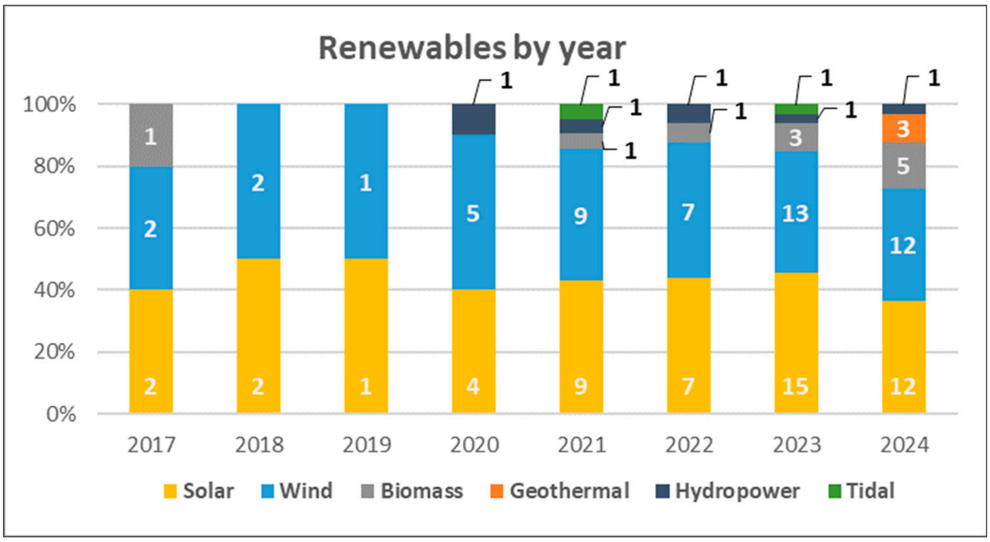

Figure 2. Distribution of renewable energy sources in cited references, each number represents the amount of the identified renewable energy sources in HRES in a given year(developed by the authors).

The most typical composition of HRESs includes solar and wind energy (see Table 1). The most difficult structures combine solar, wind, biomass/geothermal and hydro components [8,9,18,19]. The structured data indicates a growing diversification in research focus, with hydropower and biomass gaining prominence in recent years. This trend underscores an increasing interest in broadening the scope of renewable energy technologies beyond the dominant solar and wind sources.

3.2. Energy Storage Solution

The energy produced from renewables with fluctuating generation needs energy storage solutions to compensate for the imbalance between energy generation and demand and ensure a more resilient and cost-effective system. Figure 3 illustrates the number of articles published each year from 2017 to 2024 that focus on different energy storage solutions (ESS), including various energy storage technologies.

Furthermore, the most innovative ESS contains pumped hydro, battery and hydrogen technologies (see Table 1). Additionally, given data highlights a clear shift in focus over time, with battery and hydrogen storage technologies becoming increasingly prominent in academic research while pumped hydro remains relatively underrepresented. The rapid rise in articles on hydrogen storage, especially in recent years, reflects growing interest in its potential for long-term energy storage and decarbonization efforts. Moreover, nearly half of the articles do not incorporate energy-saving solutions. HRESs with storage components have been implemented worldwide to address energy needs in diverse contexts. For instance, a solar–wind–biomass HRES was deployed in Northeast China, integrating advanced energy storage solutions to address frequent power shortages in rural areas [20]. Similarly, in Algeria, off-grid HRESs combining PV, wind, diesel generators, and battery storage have been installed to provide electricity to residential buildings in remote rural regions [21]. Another notable example is the hydrogen-based HRES in Jeju Island, South Korea, which integrates wind turbines, PV panels, and biomass gasifiers to supply hydrogen for transportation and industrial uses [22].

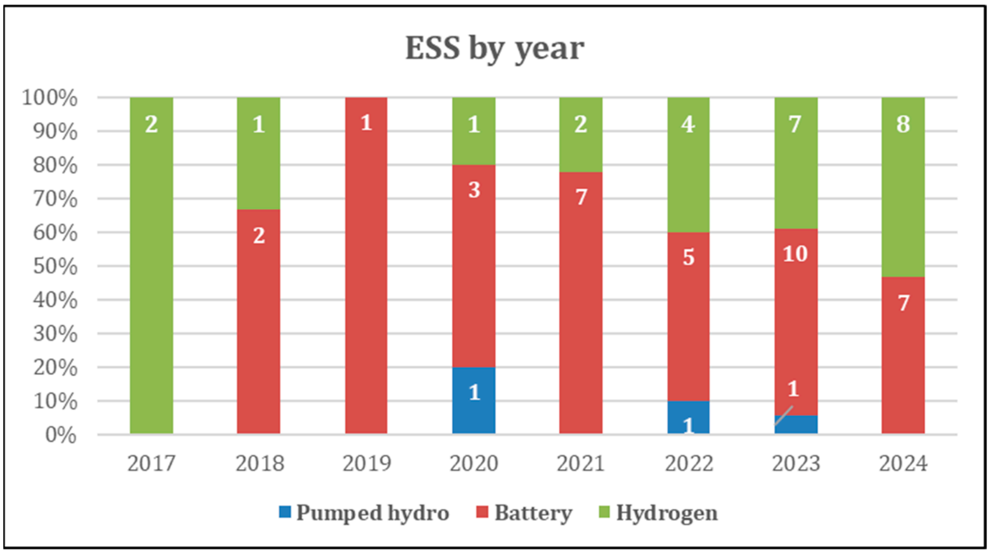

Figure 3. Distribution of energy storage system in cited references, each number represents the amount of the identified energy storage components in HRES in a given year (developed by the authors).

Almost half of the articles addressing ESS usually integrate hybrid storage solutions, including battery and hydrogen components. This solution gains among researchers every year, demonstrating a growing recognition of the importance of hybrid energy storage systems to meet diverse energy needs and enhance system flexibility and resilience.

3.3. Grid Connection

Not only energy storage solutions but also grid connection type influence the optimization model, so Figure 4 shows the number of articles published annually from 2017 to 2024, focusing on grid-connected ("on") and off-grid ("off") energy systems.

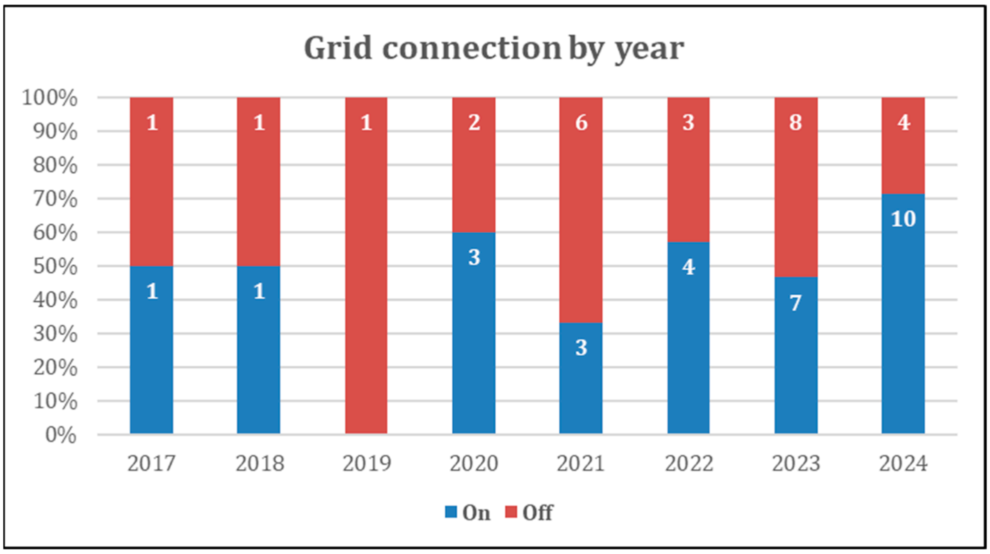

Figure 4. Distribution of grid connection type in cited references, each number represents the amount of the identified grid connection types in HRES in a given year (developed by the authors).

The growing interest in grid-connected systems has been captured, particularly in recent years. It indicates a shifting research focus towards the integration of energy systems with existing grids, gradually moving away from islanded grids and reflecting the global expansion of electricity networks. Grid integration offers several advantages, such as improved access to renewable energy resources, reduced reliance on localized energy generation, and enhanced system efficiency through centralized management and load balancing. Successful examples include the European Union's push for cross-border electricity markets [23] and the integration of large-scale renewable plants in China and the United States, which leverage grid connectivity to meet national energy targets [24,25]. These advancements demonstrate how grid-connected systems support energy demand and foster technological innovation, economic growth, and environmental sustainability, making them a cornerstone of modern energy infrastructure development [26].

The practical applications of HRESs extend far beyond residential power supply. Some telecommunication towers, which require continuous and reliable energy to maintain connectivity, all around the World have been powered using core renewables, such as sun and wind. Hydrogen and methanol fuel cells are incorporated in a grid-connected and islanded HRES [27]. A notable real-world example is the microgrid on Kodiak Island. In remote areas, HRESs are crucial for rural electrification, ensuring access to clean energy where grid extension is economically unfeasible [21]. In industrial contexts, HRESs stabilize the energy supply for manufacturing plants and support green hydrogen production, as seen in large-scale projects in Queensland, Australia [28]. This example also provides pelagic discrete energy trading system between Australia and Japan [29].

Additionally, HRESs are increasingly integrated into urban microgrids to improve grid resilience and support demand-side management, leveraging real-time optimization algorithms [20,30]. These diverse applications highlight the flexibility of HRESs in addressing global energy challenges while promoting sustainability and energy equity.

Many grid-connected systems also support island mode operation, ensuring flexibility and reliability during grid outages or disruptions (see Table 1). This dual-mode capability highlights the importance of resilience in modern energy systems while emphasizing the benefits of integration with broader electricity networks.

The synergy between renewable diversity, storage solutions, and grid integration helps optimize system cost and energy utilization in a diverse geographical area and paves the way for developing resilient and adaptable energy infrastructures from remote areas to urban environments. These trends emphasize the dynamic nature of energy research as it adapts to emerging challenges and opportunities in the energy transition to a sustainable future.

3.4. Energy Community Framework

The reviewed articles (see Table 1) provide opportunities to identify the approach of the energy communities, which can be characterized with five main characteristics: local focus [20,31,32], member-driven [15], renewable energy [22,28], decentralization and energy sharing [19,33,34]. However, the authors neither explicitly distinguish the concept nor address the specific characteristics of the energy communities. This article underlines the exploration of energy community integration specifics as an area of growing importance for enhancing local energy resilience and independence. By combining HRES with demand response measures and collaborative energy-sharing strategies, energy communities can address challenges such as privacy-preserving energy management and real-time optimization [30,35]. Additionally, papers highlight the need for electric vehicle charging station analysis, emphasizing their potential contributions to the advancement of energy communities.

Energy community status empowers members with collective access to clean, affordable energy while fostering economic savings, energy independence, and environmental sustainability. It promotes local job creation, innovation, and social cohesion, enabling communities to take charge of their energy needs and benefit from favorable policies and incentives. This status strengthens resilience, supports modern energy technologies, and ensures a greener, fairer future [36].

4. HRES Optimization

Building on the foundational aspects of HRES design, optimization is a critical process that ensures these systems operate efficiently and reliably in real-world scenarios. While the design phase lays the groundwork by selecting components and defining configurations, optimization empowers these components to achieve maximum performance under specific constraints such as cost, emissions, and reliability. Furthermore, the general principles of energy system optimization, exploring techniques with their criteria, and identifying patterns in reviewed scientific articles are provided in this article. Moreover, providing guidance on selecting suitable optimization methods enables tailored solutions that account for the unique characteristics of HRES. Lastly, synthesizing insights from reviewed studies, this chapter bridges the gap between design and operation, identifies best practices, and highlights opportunities for future research, particularly in multi-objective optimization.

4.1. General Principle of Energy System Optimization

The general principle of energy system optimization provides a structured process that requires clear and systematic representation to ensure transparency and ease of understanding. Among the reviewed articles, flowcharts and pseudo-codes are the most predominant methods for describing optimization algorithmic steps [37,38]. The energy community framework of the research object is also discussed here.

4.1.1. Flowchart

The most widely used structure is the flowchart, it can visually represent many different processes, algorithms and strategies: energy management strategy [31,39]; Aspen Plus process flow diagram of the Anion Exchange Membrane (AEM) water electrolyzer [15]; structure of Back Propagation Neural Network (BPNN) algorithm [40]; solution flow of two-stage robust optimization model [41]; PV–wind–H2 system energy flow [42]; optimization and simulation flowchart [43]; strategy architecture of Bi-level gaming program [44]; Improved CSA implementation flowchart for solving the problem [45]; power management of the HRES with charge and discharge strategies; and Flowchart of the Archimedes optimization algorithm (AOA) [32]; block diagram of HRES energy production operation; and block diagram of whale optimization algorithm (WOA) implementation strategy for HRES designing [46]; 2 flowcharts of Monte Carlo simulation (MCS) method [35]; NSGA-II optimization flowchart [19]; flow diagram of the proposed design approach of 100% renewable electricity supply and the framework of the developed hybrid Multi-Criteria Decision Making (MCDM) approach [9]; Hybrid Grey Wolf Optimizer-Sine-Cosine Algorithm (HGWO-SCA) algorithm flowchart is employed for the design of a PV/WT/FC [47]; simplified flow chart of the proposed hybrid energy system [48], Gravity Energy Storage sizing and implementation methodology [49]; operation strategy of HRES composed of PV, WT, Bio-diesel generator, and battery; and flowchart and steps of the emerging metaheuristic optimization method based on Harmony Search (HS) [33]; proposed framework for the robust planning of an IHS; Flowchart of the solution process of the Hybrid Metaheuristic Algorithm; HMA-based Adaptive Robust Optimization (ARO) [50]; flowchart of the optimization procedure [51]; Modified Multi-Objective Salp Swarm Optimization Algorithm (MMOSSA) flowchart [31]. All mentioned flowcharts provide a high-level visual representation of the decision-making process.

Flowcharts for HRES in the reviewed literature vary widely in design and focus, reflecting distinct methodologies and objectives. A comparison can be drawn based on three key aspects: optimization frameworks, energy management strategies, and component integration. For instance, flowcharts using metaheuristic algorithms like Particle Swarm Optimization (PSO) and genetic algorithms (GA) focus on cost and efficiency optimization, often visualizing iterative processes for the sizing and placement of components [20,28]. In contrast, some studies emphasize energy management, illustrating real-time control strategies for balancing supply and demand in microgrids, such as using hybrid algorithms for load sharing and grid support [22,48]. Lastly, regarding component integration, flowcharts differ by the extent of renewable and storage technologies included, with some incorporating advanced hydrogen storage and electrolyzers alongside traditional PV and wind setups [21,22]. As a result of this analysis, the most straightforward energy system sizing flowchart of an off-grid 100 percent HRES is shown in Figure 5.

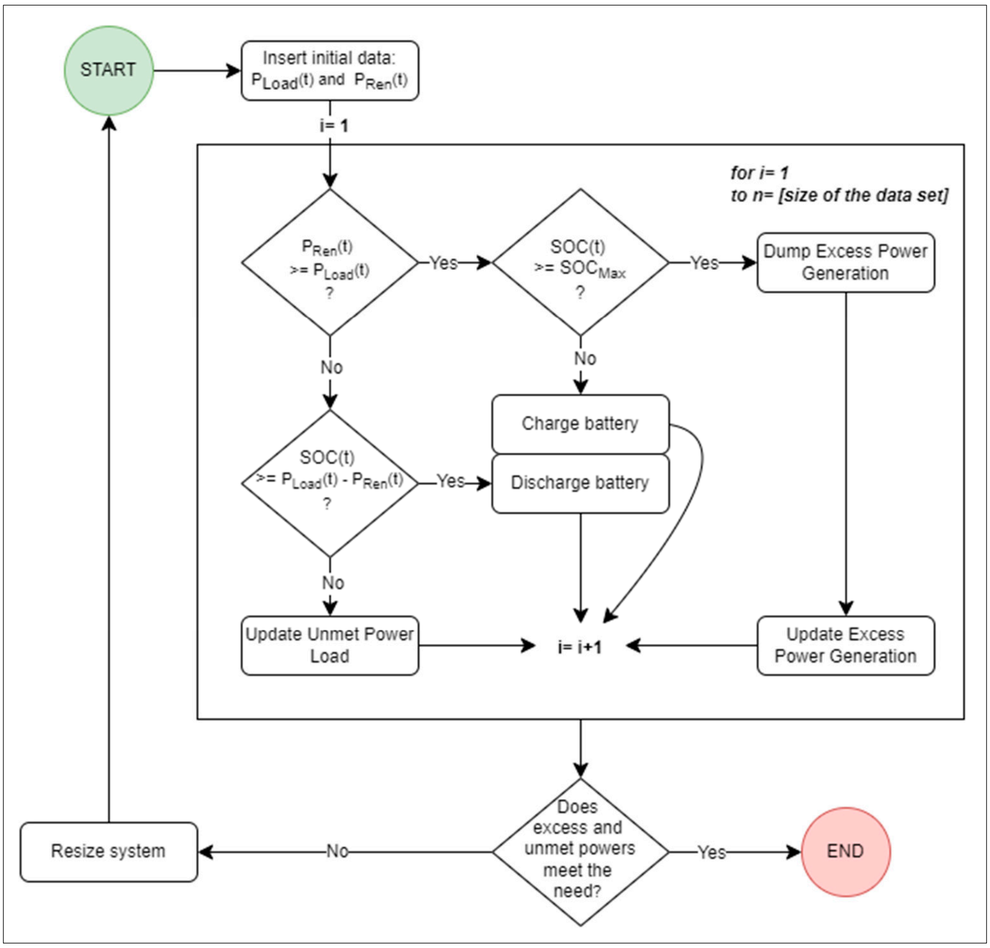

Figure 5. Energy system sizing flowchart (developed by the authors).

4.1.2. Pseudocode

The second tool used to describe the operation of the system is the following pseudocode: PSO algorithm processes [24], GA-PSO algorithm processes [29], PSO algorithm processes [41], Improved CSA algorithm process [31], Temporal Difference (TD) Lambda within a Reinforcement Learning framework for HRES optimization [42], MOPSO solving procedure [34], HGWO-SCA algorithm implementation methodology [35], and LF-SSA implementation methodology [36]. It bridges the gap between visual diagrams and detailed programming, offering a simplified, language-independent outline of the computational logic behind the optimization. As a result of the literature analysis, the pseudo-code for the same system as the flowchart is provided in Figure 6.

```
START
P_Load(t), P_Ren(t)
i = 1

for i in range(1, n + 1):
    if P_Ren(t) >= P_Load(t):
        if SOC(t) >= SOC_Max:
            Dump_Power()
        else:
            Charge_Battery(P_Ren(t) - P_Load(t))
    else:
        if SOC(t) >= (P_Load(t) - P_Ren(t)):
            Discharge_Battery(P_Load(t) - P_Ren(t))
        else:
            Update_Unmet_Power(P_Load(t) - P_Ren(t) - SOC(t))

    Update_Excess_Power(max(0, P_Ren(t) - P_Load(t)))

    i += 1

if Excess_Power_Generation and Unmet_Power_Load meet requirements:
END
else:
        Resize_System()
        Go to START
```

Figure 6. Energy system sizing pseudo-code (developed by the authors).

In detail, the flowchart and the pseudo-code illustrate a simplified process for optimizing an HRES by balancing energy supply, demand, and storage. The process starts by initializing input data: $P_{\_(Load(t))}$, which represents the power demand, and $P_{\_(Ren(t))}$, the renewable energy generation at a given time step. The iteration begins with i = 1, showing the first step. The system first checks if the renewable energy generation is enough to meet the load $P_{\_(Ren(t))} \geq P_{\_(Load(t))}$. If the generation exceeds the demand, the surplus energy is used to charge the battery, provided the battery's state of charge (SOC) is below its maximum capacity SOC_Max. The excess power generation is dumped if the battery is fully charged [52]. When renewable energy is insufficient to meet the load $P_{\_(Load(t))} < P_{\_(Ren(t))}$, the system evaluates whether the battery can discharge enough energy to cover the deficit $SOC \geq P_{\_(Load(t))} - P_{\_(Ren(t))}$. If not, the unmet load is recorded for later analysis. After each time step, metrics such as unmet load and excess generation power are updated, and the system moves to the next step i = i + 1. Once all time steps have been processed, the system evaluates whether the combined excess and unmet power meet predefined operational requirements. If the requirements are satisfied, then the process ends; otherwise, the system is resized, components like battery capacity or renewable generation are adjusted, and the process begins again. This iterative framework efficiently balances energy supply, battery storage, and demand, minimizing energy losses and enhancing reliability.

In detail, the flowchart and the pseudo-code illustrate a simplified process for optimizing an HRES by balancing energy supply, demand, and storage. The process starts by initializing input data: $P_{\_(Load(t))}$, which represents the power demand, and $P_{\_(Ren(t))}$, the renewable energy generation at a given time step. The iteration begins with i = 1, showing the first step. The system first checks if the renewable energy generation is enough to meet the load $P_{\_(Ren(t))} \geq P_{\_(Load(t))}$. If the generation exceeds the demand, the surplus energy is used to charge the battery, provided the battery's state of charge (SOC) is below its maximum capacity SOC_Max. The excess power generation is dumped if the battery is fully charged [52]. When renewable energy is insufficient to meet the load $P_{\_(Load(t))} < P_{\_(Ren(t))}$, the system evaluates whether the battery can discharge enough energy to cover the deficit $SOC \geq P_{\_(Load(t))} - P_{\_(Ren(t))}$. If not, the unmet load is recorded for later analysis. After each time step, metrics such as unmet load and excess generation power are updated, and the system moves to the next step i = i + 1. Once all time steps have been processed, the system evaluates whether the combined excess and unmet power meet predefined operational requirements. If the requirements are satisfied, the process ends; otherwise, the system is resized, components like battery capacity or renewable generation are adjusted, and the process begins again. This iterative framework efficiently balances energy supply, battery storage, and demand, minimizing energy losses and enhancing reliability.

Flowcharts and pseudo-codes are key tools for describing optimization processes in HRES. The flowchart describes an energy management strategy, an optimization workflow, an algorithmic implementation, an energy flow, a system design approach and a decision-making framework. The pseudo-code complements flowcharts by detailing computational logic in a structured, replicable format. Additionally, their integration enhances clarity and reproducibility by creating a comprehensive framework for understanding and implementing optimization strategies [39,43].

4.2. Optimization Techniques

Following the creation of flowcharts and pseudo-codes, the next critical step in energy system optimization is selecting appropriate optimization methods and establishing the criteria for the mathematical model. The inherent complexity of HRES components and interactions necessitates careful selection of optimization techniques. The adoption of the right method ensures efficient system performance while optimizing the objective functions, whether economic [31,53,54], environmental [31,55,56], technical [45,57], or multi-objective [10,58,59]. Furthermore, this section delves into the methodologies used, captured scientific principles, and the relationship between criteria identified in the reviewed studies.

Additionally, the methods summarized in Table 1 represent a wide range of optimization and simulation techniques widely applied in various areas, including renewable energy integration [31], energy storage optimization [45], power system reliability improvement with uncertainty analysis [44], cost reduction in energy systems [43]. HOMER Pro 3.12–3.16 and MATLAB 9.1–9.13 are prominent simulation tools in this field. HOMER Pro 3.12–3.16 are extensively used for microgrid design [53], while MATLAB 9.1–9.13 provides a flexible programming environment for implementing diverse optimization algorithms [60]. MILP is a deterministic optimization technique, is well-suited for handling discrete and continuous decision variables in linear energy planning and scheduling [61]. On the other hand, metaheuristic algorithms like MOPSO excel in solving complex, non-linear, and multi-modal problems and are effective for multi-objective optimization [43]. PSO is frequently applied to optimize continuous variables [8]. CPLEX commercial is a robust optimization solver for linear and integer programming problems [41]. NSGA-II, a genetic algorithm, is particularly well-suited for multi-objective optimization, where generating a Pareto front ensures that no single objective can be improved without degrading another [35]. Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), a widely used multi-criteria decision-making method, ranks solutions based on their proximity to an ideal solution [62]. Nature-inspired algorithms, such as the CSA, GWO, and LF-SSA, are gaining popularity due to their ability to balance exploration and exploitation in solving non-linear, multi-modal optimization problems [45,47,48]. Additionally MCS is a powerful tool for probabilistic and uncertainty analyses [30], while the ε-Constraint Method is instrumental in converting multi-objective problems into single-objective ones [21].

Moreover, the analyzed articles reveal scientific principles for HRES optimization techniques:

- *Simulation tools are combined with optimization techniques*. MATLAB 9.1–9.13 is paired with algorithms like MOPSO, demonstrating their utility in combining simulation-based scenario analysis with robust optimization for better system design [58]. Also, its HOMER Pro 3.12–3.16 is used to solve the optimization problem using GA [49]. HOMER 3.14 simulates system configurations and compares the results with GWO [37]. MATLAB's 9.1–9.13 computational capabilities are incorporated with PSO to optimize energy system planning parameters [8].
- *Metaheuristic algorithms are blended with decision-making methods*. Firstly, the MOPSO and TOPSIS combination effectively balances optimization with multi-criteria decision-making, highlighting its use for selecting optimal Pareto solutions in multi-objective problems [62]. Secondly, NSGA-II and Linear Programming (LP) adaptation effectively apply bi-level optimization for capacity planning and environmental impact reduction [10].
- *HRES performance improved by combining metaheuristic algorithms*. Hybridized GA-PSO and MOPSO algorithm balances global and local exploration, optimizing renewable energy penetration while minimizing costs [43].
- *Multi-Objective Optimization is used together with Pareto Analysis*. The aim is to use NSGA-II [10], [19] or MOPSO [59] algorithms to determine the minimum energy cost and lifecycle emissions and to maximize job creation indicators. The best solution for the multi-objective optimization task was chosen by employing the Pareto front.

This article focuses on MATLAB 9.1–9.13 and HOMER Pro 3.12–3.16 software. In the time domain simulation, ten of the most typical examples were identified using HOMER Pro 3.12–3.16, where the HRES simulation took 1 year [15,34,37,38,48,53–56,63,64]. Seven cases were found using MATLAB 9.1–9.13. The major part [41,49,55,58] simulated 1 year period of HRES, 1 article [65] presents week-long results widely analyzing the problem and 2 articles [8,60] focus on more precise security and real-time modeling. So, more precise results are required as the shortest period is simulated. This manuscript focuses on sizing HRES components based on averaged prognosis data, so the significant number of articles the time domain is extended to 1 year because it captures the full range of seasonal variations in renewable energy availability, load demand, and environmental conditions.

4.3. Optimization Criteria

Furthermore, the reviewed studies also emphasize a wide array of the most used broad-spectrum criteria in HRES optimization (see Table 1), categorized into economic, environmental, energy, and social dimensions. Economically, Total Net Present Cost (TNPC) [28,38,42] and Levelized Cost of Energy (LCOE) [10,20,63,66] appear as dominant measures, complemented by Operation and Maintenance Cost (OMC) [15,58,67]. Environmentally, CO_2 emissions [35,50] and Renewable Fraction (RF) [32,53] are recurrent metrics, reflecting sustainability concerns. In terms of energy performance, key metrics include Loss of Power Supply Probability (LPSP) [19,48,64,68] and Energy Not Supplied (ENS) [57,58,68], which evaluate system reliability and efficiency. On the social front, criteria like Job Creation Potential (JOBC) [9,10] are used. These widely adopted criteria underscore a comprehensive approach to balancing economic feasibility, environmental sustainability, operational reliability, and social benefits in HRES optimization.

To conclude, here are some observed relationships between criteria and optimization methods across the reviewed articles:

- *Economic indicators on multi-objective approaches*. Economic optimization criteria like TNPC and LCOE are most frequently paired with MOPSO [31,43,59,62]. This technique is used in studies focusing on cost optimization and energy management.
- *Environmental criteria on evolutionary algorithms*. CO_2 emissions [21,39,50] and Renewable Fraction (RF) [32,53] as a part of environmental indicators are often used together with nature-inspired algorithms like PSO, CSA and Strength Pareto Evolutionary Algorithm 2 (SPEA2). These methods provide robust solutions to highly non-linear, multi-modal optimization problems where ecological considerations are crucial.
- *Reliability criteria on simulation-driven techniques*. Reliability measures like Loss of Power Supply Probability (LPSP) [37,48,59] and ENS [58], are predominantly optimized through a combination of simulation tools such as HOMER Pro 3.12–3.16 and MATLAB 9.1–9.13. These criteria are addressed within multi-criteria decision-making solutions like TOPSIS and Evaluation Based on Distance from Average Solution (EDAS), highlighting their adaptability.
- *Social criteria on emerging frameworks*. During the analysis 2 social indicators were found: the JOBC [9] and the Composite Sustainability Index (CSI) [10] are addressed within multi-criteria decision-making solutions like TOPSIS and EDAS, highlighting their adaptability.

4.4. Computation Efficiency

Several critical factors influence the computation efficiency and speed in HRES optimization (see Figure 7).

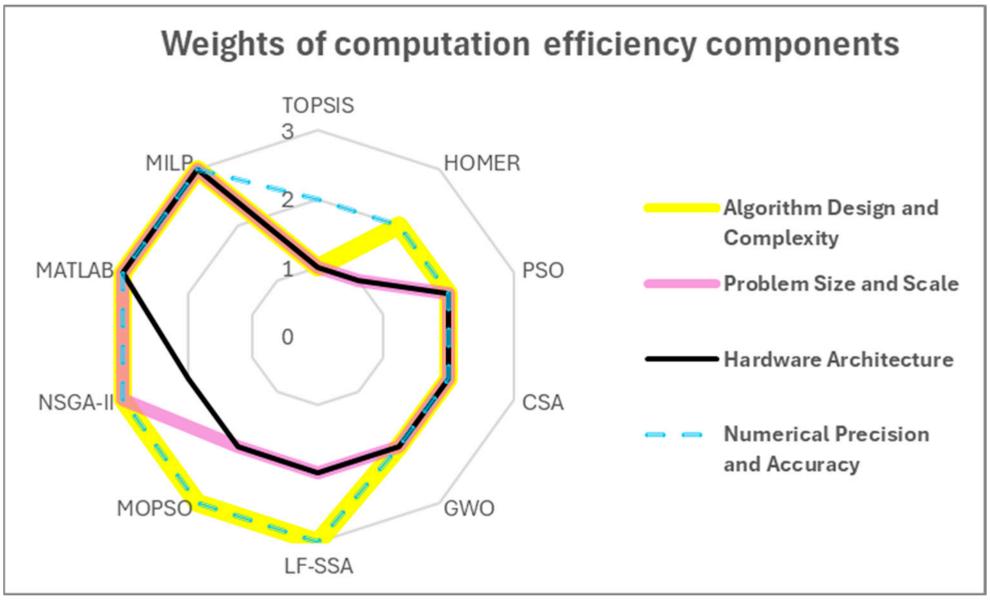

Figure 7. Optimization tools computations efficiency components weights, where 1 represents low, 2 represents medium and 3 represents high impact on an efficiency component(developed by the authors).

The design and complexity of the algorithm play a pivotal role, with iterative processes, large solution spaces, and non-linear problems significantly increasing computation time. Problem size and scale, including the number of variables, constraints, and objectives, directly affect resource demands, with large-scale tasks such as grid-wide simulations requiring extensive computational resources. Leveraging parallel computing techniques can mitigate these challenges by distributing tasks across multiple processors, although efficient task decomposition and minimizing synchronization overhead are essential for success.

Hardware architecture greatly influences performance, as do factors such as processor speed, memory bandwidth, and I/O capabilities. Software optimization enhances speed through efficient data structures, memory management, and load balancing, especially in high-performance computing environments. However, data communication overhead in distributed systems can be a bottleneck, making its minimization essential. Additionally, numerical precision affects computational resources, requiring a balance between accuracy and efficiency. In addition, energy-efficient systems, while conserving power, may impose performance limits that also affect computational speed [69]. Besides, it was decided to rank optimization methods based on four key criteria: Numerical Precision and Accuracy, Hardware Architecture, Problem Size and Scale, and Algorithm Design and Complexity. Each of these criteria was assessed and rated on a scale of 1 to 3, with corresponding values: 1—"Low", 2—"Medium" and 3—"High". Where a higher value indicates a more significant impact or higher complexity for that component.

4.4.1. Algorithm Design and Complexity

Methods were evaluated based on their computational and structural demands. MILP, MATLAB 9.1–9.13, NSGA-II, MOPSO and LF-SSA ranked "High", as their relies on rigorous mathematical formulations and complex constraint handling, making it highly accurate but computationally intensive [16,70], and its ability to support diverse and complex optimization algorithms. These methods require advanced algorithmic sophistication [71,72]. In contrast, simpler heuristic-based approaches like GWO, CSA, PSO and HOMER Pro 3.12–3.16 scored "Medium" as they rely on relatively straightforward iterative frameworks ([71,73,74]). TOPSIS was the least complex and was assigned to "Low", as it focuses on simple ranking metrics rather than intricate optimization processes [9,62].

4.4.2. Problem Size and Scale

The ability of methods to handle larger datasets and increasingly complex problems is considered. MILP, MATLAB 9.1–9.13 and NSGA-II were again among the top performers, with scores of "High", respectively, due to their ability to solve high-dimensional problems, whilst with increased computational effort [70,72], and its parallelization capabilities allow it to handle extensive simulations effectively [71,73]. MOPSO and LF-SSA, GWO, CSA and PSO utilize multi-objective capabilities, included in "Medium", while heuristic methods like PSO and GWO achieved moderate scalability [75,76]. Simpler methods like HOMER Pro 3.12–3.16 and TOPSIS are more appropriate for small-scale or less computationally intensive tasks, attached to "Low", highlighting its limited applicability to larger datasets [9,74].

4.4.3. Hardware Architecture

Here assessed the dependence of methods on computing resources. MILP and MATLAB 9.1–9.13 are both assigned to "High", reflecting their reliance on high memory capacity for large-scale computations, leverage advanced hardware capabilities such as parallel processing but are not inherently optimized for graphics processing units or distributed computing environments [69,70]. NSGA-II, MOPSO and LF-SSA, GWO, CSA, PSO are in group "Medium", as they require robust hardware for managing multi-objective optimization problems but can perform adequately on less advanced systems with minor adjustments [72,76], heuristic-based methods, as they operate efficiently on standard hardware, making them more accessible [71,74], though they lack specialized hardware designs [20,74,77]. HOMER Pro 3.12–3.16 and TOPSIS are a part of "Low", as they require minimal hardware resources, reflecting their lightweight computational nature [9,62].

The advent of new quantum artificial intelligence (AI) processors has the potential to revolutionize the scientific world, particularly in the domain of HRES optimization. Quantum computing's unparalleled ability to perform parallel computations and solve complex optimization problems exponentially faster than classical processors could drastically reduce computation time for resource-intensive methods like PSO, Genetic Algorithms (GA), and machine-learning-based predictive models. On conventional processors, calculations that traditionally require hours or days could be completed in seconds or minutes on a quantum chip, enabling real-time simulations and optimizations for HRES design and operation. This speed-up would allow scientists to explore larger solution spaces, refine multi-objective optimization problems more effectively, and model more complex systems without the bottleneck of computational delays [78–80].

4.4.4. Numerical Precision and Accuracy

The computational methods and tools exhibit varying levels of precision and accuracy depending on their design and intended applications. It was ranked on its ability to deliver precise and accurate solutions to reviewed articles. MILP, MATLAB 9.1–9.13, NSGA-II, MOPSO and LF-SSA ranked as "High", as excel in precision, offering highly accurate solutions, particularly for complex energy systems multi-objective optimization. This group has precise mathematical formulations [16,70–72] and offers robust accuracy and balances between precision and heuristic adaptability [72,76]. GWO, CSA, PSO, and HOMER Pro 3.12–3.16 got "Medium", as they achieve moderate precision, focusing on approximate or heuristic solutions [37,77], delivered acceptable results without requiring high precision [20,74], especially TOPSIS, designed for simplicity, as it prioritizes approximate, but acceptable solutions over precision [74]. Based on the selected papers, researchers generally focus on developing hybrid frameworks that combine quantum and classical computing for maximum efficiency.

4.5. Weakness and Limits of Optimization Methods

The reviewed methods, referenced in more than one article from 2017 to 2024, reveal significant limitations in addressing complex optimization challenges in energy systems. HOMER Pro 3.12–3.16 struggles with modeling advanced utility billing structures, multi-objective optimization, and machine learning capabilities, while MILP, despite its efficiency, faces scalability issues and lacks integration with energy management systems (EMS). PSO and Constrained Multi-Objective Particle Swarm Optimization (CMOPSO)-Multi Strategy Integration (MSI) algorithms are hindered by slower convergence, sensitivity to parameter settings, and high computational demands. NSGA-II and SSA suffer from weak convergence and high computational costs, with SSA particularly limited in mitigating local optima and optimizing load-shifting tasks. GWO and CSA exhibit challenges in scalability, dynamic adaptation, and balancing exploration with exploitation. Additionally, TOPSIS lacks a robust distance-weighting mechanism, further had the need for more comprehensive and efficient approaches to solving real-world energy system problems (see Table 1).

Table 1. Weakness and limits of optimization methods (structured by the authors).

Article	Method	Weakness/Limits
[81]	HOMER Pro 3.12–3.16	The system faces significant limitations, including an inability to model various electric utility billing structures and complex pricing methodologies and the absence of machine learning-based predictive modeling capabilities. It lacks novel storage systems and advanced thermal modules utilizing heat pumps, along with optimization and modeling for these systems. High costs restrict accessibility for low-resource laboratories and individuals, while the system cannot perform multi-objective optimization or support innovations in HRES design and operation. Users encounter challenges in defining specific prices and costs in inputs, further limiting their flexibility and practicality.

Table 1. *Cont.*

Article	Method	Weakness/Limits
[16,70,82]	Mixed-Integer Linear Programming	The MILP method, while highly efficient in achieving optimality and reducing computational effort, sacrifices some accuracy due to linearization, though this trade-off is generally acceptable. However, it faces challenges such as computational complexity, extensive data requirements, and scalability issues, particularly in problems involving complex non-linear interactions among variables. The method's practicality diminishes with an increasing number of time steps and binary variables, pushing it to the limits of applicability. Additionally, MILP does not account for energy management systems and becomes computationally intensive and difficult to manage when addressing large-scale problems.
[71,83,84]	Particle Swarm Optimization	The randomness is determined by the default settings of the MATLAB 9.1–9.13 function. Moreover, the PSO-Proportional-Integral-Derivative (PID) controller tends to have slower convergence and higher computational complexity compared to the traditional PID controller. Additionally, it may converge to local optima, and its performance is highly sensitive to parameter settings, such as inertia weight and cognitive and social parameters, which require careful tuning to achieve optimal results.
[85]	Multi-Objective Particle Swarm Optimization	The CMOPSO-MSI algorithm demonstrates superior performance by being closer to the origin and exhibiting a more favorable distribution, while also achieving the smallest voltage fluctuations compared to other approaches. This algorithm demonstrates the most negligible voltage fluctuations, but its overall performance improvement is limited despite an upward trend with increased training time.
[72,84,86]	Non-Dominated Sorting Genetic Algorithm	The model requires significant computational resources to simulate the necessary data sets, which can restrict its applicability in certain scenarios. Similarly, genetic algorithms face challenges, including the need for a large number of iterations to converge in complex problems or large search spaces, as well as the time-consuming process of fine-tuning multiple parameters for optimal performance. Additionally, the high computational costs and weak convergence in complex real-world problems, along with the lack of consideration for energy management systems, further limit the practicality of these approaches.
[87]	TOPSIS	It uses the weighting of normalized performance ratings and does not explicitly apply the distance weighting concept.
[84]	Crow Search Algorithm	The CSA algorithm occasionally gets stuck in local optima, particularly in high-dimensional search spaces where it also exhibits slow convergence. Its performance is affected by an imbalance between exploitation and exploration at various levels, which can hinder optimization.
[73,88]	Grey Wolf Optimizer	The GWO algorithm faces several limitations, including its lack of consideration for energy management systems and reliability, as well as its computational complexity. It struggles to manage multiple variables and has not yet been adapted for dynamic situations. Exploring appropriate operators, such as multi-swarm approaches, repositories, or performance measures, is essential in evolving dynamic search spaces. Additionally, addressing uncertainties in inputs, outputs, objective functions, and constraints is critical for effectively solving real-world problems, which the GWO method has yet to achieve comprehensively.
[75,76,89]	Salp Swarm Algorithm	The SSA algorithm suffers from low convergence and precision, and its performance in optimizing load-shifting, reducing delays, and minimizing electricity cost reduction is often inferior to that of GA. While the incorporation of Leavy Flight algorithm has improved its search trends, the initial SSA cannot effectively perform well-distributed or focused searches. Furthermore, it struggles to mitigate the impact of local optima on its search direction, often falling into regional areas and failing to maintain the right balance between diversification and intensification.

5. Suggestions from Previous Research

While Section 4 presents the weaknesses and limits of optimization techniques, researchers have also proposed valuable future directions, which might cover a few negative issues. This chapter compiles research suggestions from 2020 to the present, categorizing them into nine key areas: system optimization and modeling; reliability and uncertainty analysis; integration of renewable energy sources; data and monitoring systems; demand-side management; advanced optimization techniques; technology improvements; economic and policy implications; and future scope for specific systems (see Table 2).

Table 2. Suggestions for future research (structured by the authors).

Topic	Article, Year of the Publication	Suggestions for Future Research
System Optimization and Modeling	[90], (2021)	Optimization of component sizes and control strategies via Genetic Algorithm.
	[62], (2021)	Supply chain optimization and advanced system integration theories.
	[68], (2024)	Development of grid-connected microgrid systems.
	[31], (2024)	Continuous search space and thermal energy storage modeling for energy and economic benefits.
Reliability and Uncertainty Analysis	[57], (2020)	Expansion to larger-scale systems with advanced energy conversion/storage technologies for reliability and stability.
	[50], (2021)	Reliability/cost assessment under uncertainties in load and renewable resources using computationally intensive and time-consuming algorithms like MCS.
	[67], (2022)	Probabilistic reliability assessment and control strategies in distributed generation.
	[91] (2024)	Risk and uncertainty analysis for microgrid reliability evaluation.
Integration of Renewable Energy Sources	[56], (2020)	Feasibility of energy systems in other locations.
	[49], (2022)	Optimization of solar–wind HRES for electric vehicle charging stations.
	[7], (2023)	Integration of biomass and geothermal energy in multigenerational systems.
	[53], (2023)	Involving geothermal heat and wave power in RES analysis.
	[60], (2024)	Implementation of combined heat and power in industrial HRES.
Data and Monitoring Systems	[38], (2023)	Importance of monitoring solar and tidal resources for system optimization.
	[48], (2024)	Continuous monitoring of battery charging and discharging rates.
Demand-Side Management	[47], (2021)	Incorporating interactive community responses and incentive-based demand response.
	[37], (2021)	Game-theory-based demand response for realistic microgrid scheduling.
	[60], (2024)	Demand-side management in hybrid industrial systems.
	[83], (2022)	To stagger the demand with proportional increases, the stochastic variation of resources and their repercussions on the electrical network capacities.
Advanced Optimization Techniques	[92], (2020)	Multi-objective optimization for green hydrogen energy systems.
	[20], (2023)	Application of advanced algorithms to improve energy system optimization accuracy such as MOPSO and NSGA-II algorithms.
	[40], (2023)	Combining MOPSO with harmony search and cuckoo search algorithms.
Technology Improvements	[44], (2023)	Focus on advanced battery technologies for power management.
	[48], (2024)	Incorporation of Zn-ion batteries in energy storage systems.
	[63], (2024)	Transition from polymer electrolyte membrane to alkaline electrolyzers.
Economic and Policy Implications	[33], (2023)	Impact of weather patterns on economic and energy systems.
	[55], (2023)	Job creation assessment for battery storage systems.
	[93], (2024)	Methodology application to address economic concerns in hotels.
Future Scope for Specific Systems	[93], (2022)	Updating route tables for better system exploitation.
	[94], (2024)	Development of prototypes for experimental investigations.

6. Discussion

The reviewed articles offer a comprehensive analysis of HRES design, optimization techniques, and future insights. Its scope is illustrated in Figure 8.

Optimization approaches advantages:

- This research highlights the trade-offs between complexity, scalability, hardware dependence, and accuracy for each optimization technique. MILP and MATLAB 9.1–9.13 are the most flexible and suitable for HRES multi-objective optimization for their precision and versatility, but they require significant computational resources (see Section 4.4).
- Four scientific principles for HRES optimization are revealed: simulation tools are combined with optimization techniques, metaheuristic algorithms are blended with decision-making methods, metaheuristic methods are combined in between, and multi-objective optimization is used together with Pareto Analysis (see Section 4.2). These principles are crucial for HRES optimization as they enable precise modeling of complex systems, efficient exploration of solution spaces, and practical decision-making.
- Four relationships between criteria and optimization methods were identified: economic indicators for multi-objective approaches, environmental criteria for evolutionary algorithms, reliability criteria for simulation-driven techniques, and social criteria for emerging frameworks (see Section 4.3). Incorporating social criteria, such as job creation and public acceptability, alongside traditional metrics like carbon emissions ensures technically robust and socially beneficial HRES designs. Balancing competing objectives like cost, efficiency, and sustainability ensures innovative, scalable, and actionable solutions for real-world energy challenges.

Optimization techniques challenges:

- As the diversity of renewable energy sources in HRESs increases, along with the integration of more energy storage solutions and the development of both islanded and grid-connected HRESs (see Section 3), the demand for innovative optimization solutions, their integration, and the selection of appropriate criteria is growing.
- This article collects challenges (see Table 1) that researchers faced, so the directions clearly emphasize advancing HRES optimization, control, and integration of renewable resources [62,68,90]. Reports are increasingly addressing uncertainties [50,67,91], improving demand-side management [47,60], and developing advanced optimization techniques [20,40,92] to enhance system efficiency and scalability. HRES integration is often coupled with innovative technologies like advanced batteries and AI-based optimization [44,48,63]. Optimization challenges underscore a growing need for sustainable and resilient solutions. Economic and policy considerations are also gaining prominence, particularly in evaluating job creation [55,93]. Robust monitoring systems and dynamic modeling remain crucial for ensuring adaptability and precision in HRES performance [38,48].

Future perspectives:

- The roadmap for future research consisting of nine areas (see Table 2) was developed to address existing issues and foster advancements in HRESs, enabling efficient integration, improved reliability, and broader adoption in diverse energy landscapes.
- Future advancements in HRESs will likely focus on dynamic optimization that incorporates high-resolution renewable resource forecasting and real-time adaptability of HRESs [31,68]. Scaling these systems to integrate diverse energy sectors, including industrial and agricultural loads, will further enhance their applicability and impact [57,68]. Efficient algorithm designs will play a role as HRESs expand globally, emphasizing the need for lightweight and scalable algorithms.

- The future lies in integrating quantum computing, which can drastically accelerate complex tasks and enable the exploration of previously unfeasible problems such as real-time dynamic pricing in HRESs, microgrid control, or detailed life cycle assessments of HRESs [79,80]. The speed of quantum computing compensates for the low performance of the optimization methods, its real benefit lies in tackling complex problems that require high computational depth, expanding the scope of HRES research.
- The growing importance of enhancing local energy resilience and independence underlines the need to integrate and explore energy sustainability at local and regional levels. It can be done using an energy community framework to get additional benefits for community members and ensure a resilient, efficient, and sustainable energy future (see Section 3.4).

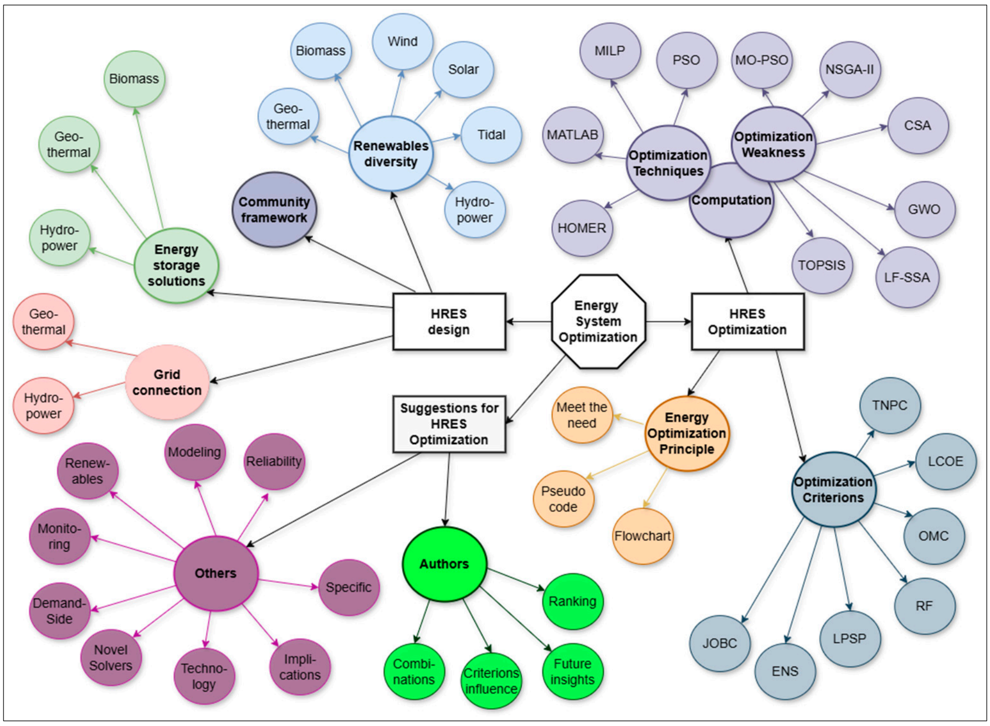

Figure 8. Structured scope of this article (developed by the authors).

Author Contributions: Conceptualization, S.R. and A.G.; methodology, A.G.; resources, A.G.; writing—original draft preparation, A.G.; writing—review and editing, M.M., V.R. and R.B.; visualization, A.G.; supervision, S.R. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AEM	Anion Exchange Membrane
AI	Artificial Intelligence
AMS	Annual Money Savings
AOA	Archimedes Optimization Algorithm
AREA	Total Area Required

ARO	Adaptive Robust Optimization
ASAI	Average System Availability Index
BFS	Breadth-First Search
BPNN	Back Propagation Neural Network
C & CG	Column Constraint Generation Algorithm
CAIDI	Customer Average Interruption Duration Index
CAPS	Probability of Unmet Load
CMOPSO	Constrained Multi-Objective Particle Swarm Optimization
COE	Cost of Electricity; Cost of Energy
CRF	Capacity Recovery Factor
CSA	Crow Search Algorithm
DPP	Deficit Power Probability
EAC	Equivalent Annual Costs
ECSR	Electricity Capacity Shortfall Rate
EDAS	Evaluation Based on Distance from Average Solution
EF	Electrolyzer Efficiency
ELF	Equivalent Loss Factor
EMS	Energy Management System
EMV	Energy Matching Variance
ENS	Energy Not Supplied
EPC	Energy Purchase Cost
ESOA	Ebola Optimization Search Algorithm
ESS	Energy Storage System
GA	Genetic Algorithm
GWO	Grey Wolf Optimizer
HGWO-SCA	Hybrid Grey Wolf Optimizer—Sine Cosine Algorithm
HMA	Hybrid Metaheuristic Algorithm
HRES	Hybrid Renewable Energy System
HS	Harmony Search
IP	Interruption Probability
JOBC	Number of Manpower; Employment Opportunities; Job Creation Potential
LCE	Life Cycle Emission
LCOE	Levelized Cost of Energy
LCOH	Levelized Cost of Hydrogen
LDP	Load Deficit Probability
LF-SSA	Hybrid Levy Flight-Salp Swarm Algorithm
LIP	Load Interruption Probability
LOLE	Loss of Load Expected
LOLP	Loss of Load Probability
LPSP	Loss of Power Supply Probability
MCDM	Multi-Criteria Decision Making
MCS	Monte Carlo simulation
MHOGA	MegaWatt Hybrid Optimization by Genetic Algorithms
MILP	Mixed-Integer Linear Programming
MMOSSA	Modified Multi-Objective Salp Swarm Optimization Algorithm
MOMFO	Multi-Objective Optimization Metaheuristic Algorithm
MOORA	Multi-Objective Optimization on the Basis of Ratio Analysis
MOPSO	Multi-Objective Particle Swarm Optimization
MSI	Multi-Strategy Integration
NPV	Net Price Value
NSGA-II	Non-Dominated Sorting Genetic Algorithm II
OMC	Operation and Maintenance Cost
PCOE	Penalty Cost of Emission

PDR	Power Discard Rate
PESA II	Pareto Envelope-Based Selection Algorithm II
PID	Proportional-Integral-Derivative
PRER	Primary Renewable Energy Rate
PSO	Particle Swarm Optimization
PSP	Power Supply Probability
RC	Replacement Cost
REC	Renewable Energy Contribution
REU	Renewable Energy Utilization
RF	Renewable Fraction; Renewable Energy Fraction
RFI	Renewable Fraction Index
RI	Reliability Index
RSM	Statistical Approach of the Response Surface Method
SAIDI	System Average Interruption Duration Index
SAIFI	Average Interruption Frequency Index
SOC	State of Charge
SPEA2	Strength Pareto Evolutionary Algorithm 2
TAC	Total Annual Cost
TD	Temporal Difference
TFC	Total Fixed Cost
TIC	Total Investment Cost
TLCC	System Total Life Cycle Cost
TNPC	Total Net Present Cost
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
UEL	Unmet Electricity Load
WOA	Whale Optimization Algorithm Anion Exchange Membrane

Appendix A

Table 1. A detailed review of literature sources (developed by the authors).

Article, Year	Renewables	Energy Storage System	Grid	Optimization Technique	Criteria
[22], 2017	Solar/Wind/Biomass	Hydrogen	On	Mixed-integer linear programming (MILP)	Total Annual Cost (TAC)
[58], 2017	Solar/Wind	Hydrogen	Off	Multi Objective Particle Swarm Optimization (MOPSO), MATLAB 9.1	Total Annual Cost (TAC), Replacement Cost (RC), Operation and Maintenance Cost (OMC), Total Investment Cost (TIC), Loss of Load Expected (LOLE), Energy Not Supplied (ENS), Loss of Power Supply Probability (LPSP), Equivalent Loss Factor (ELF)
[54], 2018	Solar/Wind	Battery/Hydrogen	On	HOMER Pro 3.12	Levelized Cost of Hydrogen (LCOH), Levelized Cost of Energy (LCOE), Electrolyzer Efficiency (EF)
[43], 2018	Solar/Wind		Off	Genetic Algorithm Particle Swarm Optimization (GA-PSO), Multi-Objective Particle Swarm Optimization (MOPSO)	Total Net Present Cost (TNPC), Levelized Cost of Energy (LCOE), Loss of Power Supply Probability (LPSP)
[45], 2019	Solar/Wind		Off	Crow Search Algorithm (CSA)	Total Net Present Cost (TNPC), Power Supply Probability (PSP), Loss of Power Supply Probability (LPSP), Loss of Load Probability (LOLP), Deficit Power Probability (DPP), Interruption Probability (IP)
[39], 2020	Solar/Wind	Hydrogen	On	Particle Swarm Optimization (PSO)	Total Net Present Cost (TNPC), CO_2 Emissions, CH_4 Emissions
[57], 2020	Solar/Wind		Off	Breadth-First Search (BFS), Inverse Transform Method, Mixed-Integer Multi-Objective Particle Swarm Optimization (MOPSO)	System Average Interruption Duration Index (SAIDI), System Average Interruption Frequency Index (SAIFI), Customer Average Interruption Duration Index (CAIDI), Average System Availability Index (ASAI), Energy Not Supplied (ENS), Total Investment Cost (TIC)
[92], 2020	Wind/Hydro		On	Ant Colony Optimization, Simulated Annealing Method	System Average Interruption Duration Index (SAIDI), System average interruption frequency index (SAIFI), Customer Average Interruption Duration Index (CAIDI)
[56], 2020	Solar/Wind		On	Non-Dominated Sorting Genetic Algorithm II (NSGA-II), HOMER Pro 3.12	Total Net Present Cost (TNPC), CO_2 Emissions, Environmental footprint
[65], 2020	Solar/Wind		Off	Mixed-Integer Linear Programming (MILP), MATLAB 9.7, INTLINPROG	Equivalent Annual Costs (EAC)
[90], 2021	Solar/Wind		On	Stochastic Optimization Theory, Monte Carlo Simulation (MCS)	Energy Purchase Cost (EPC), Maintenance Cost, Carbon Emission Cost, Daily Operation Cost
[62], 2021	Solar/Wind		On	Multi-Objective Particle Swarm Optimization (MOPSO), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method	Cost of Electricity (COE)

Table 1. *Cont.*

Article, Year	Renewables	Energy Storage System	Grid	Optimization Technique	Criteria
[46], 2021	Solar/Wind/Tidal	Hydrogen	Off	Whale Optimization Algorithm (WOA)	Total Net Present Cost (TNPC), Levelized Cost OF Energy (COE), Load Deficit Probability (LDP)
[21], 2021	Solar/Wind		Off	Particle Swarm Optimization Algorithm, ε-constraint Method	Cost of Electricity (COE), Capacity Recovery Factor (CRF), Loss of Power Supply Probability (LPSP), CO_2 Emissions, Renewable Energy Contribution (REC), Renewable Fraction (RF)
[9], 2021	Solar/Wind/Biomass/Hydro		On	Fuzzy Analytical Hierarchy Process, Multi-Objective Optimization on the basis of Ratio Analysis (MOORA), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method, Evaluation Based on Distance from Average Solution (EDAS), Data-Driven methodology and Quality Management Approach (Six Sigma)	System Total Life Cycle Cost (TLCC), Probability of Unmet Load (CAPS), CO_2 emissions, Total Area Required (AREA), Number of Manpower (JOBC)
[59], 2021	Solar/Wind		Off	Multi-Objective Particle Swarm Optimization (MOPSO), Pareto Envelope-Based Selection Algorithm II (PESA II), Strength Pareto Evolutionary Algorithm 2 (SPEA2)	Total Net Present Cost (TNPC), Penalty Cost of Emission (PCOE), CO_2 Emissions, Loss of Power Supply Probability (LPSP), Availability, Renewable Fraction, Levelized cost of energy (LCOE)
[47], 2021	Solar/Wind	Hydrogen	Off	Hybrid Grey Wolf Optimizer—Sine Cosine Algorithm (HGWO-SCA)	Total Life Cycle Cost (TLCC), Load Interruption Probability (LIP)
[37], 2021	Solar/Wind		Off	Grey Wolf Optimizer (GWO), HOMER Pro 3.14	Loss of Power Supply Probability (LPSP), Levelized Cost of Energy (LCOE)
[50], 2021	Solar/Wind		Off	Sine-Cosine Algorithm, Crow Search Algorithm (CSA), ε-Constraint Method	Total Annual Cost (TAC), Nox Emissions, CO_2 Emissions, SO_2 Emissions
[34], 2022	Solar/Wind	Battery/Hydrogen	Off	HOMER Pro 3.14, Criteria-COPRAS	Levelized Cost of Energy (LCOE), Levelized Cost of Hydrogen (LCOH), Operation Cost, Nox Emissions, Capacity shortage, Excess electricity
[67], 2022	Solar/Wind	Battery/Hydrogen	On	Mixed-Integer Linear Programming (MILP), GAMS, CPLEX	Operation and Maintenance Cost (OMC)
[93], 2022	Solar/Wind	Hydrogen	On	CPLEX	Levelized Cost of Energy (LCOE), Levelized Cost of Hydrogen (LCOH), Utilization Efficiency of Renewables
[30], 2022	x		Off	Jaya algorithm, Interior Point Method (IPM), CPLEX, Particle Swarm Optimization (PSO), Monte Carlo Simulations (MCS)	Total Net Present Cost (TNPC), Present Confidence level
[35], 2022	Solar/Wind	Battery/Hydrogen	On	Multi-Objective Particle Swarm Optimization (MOPSO), Non-Dominant Sorting Genetic Algorithm II (NSGA-II)	Life Cycle Cost (LCC), Loss of Power Supply Probability (LPSP), CO_2 Emissions
[19], 2022	Solar/Wind/Biomass/Hydro		Off	Non-Dominated Sorting Genetic Algorithm (NSGA-II)	Cost of Energy (COE), Life Cycle Emission (LCE), Job Creation Potential, Loss of Power Supply Probability (LPSP)

Table 1. *Cont.*

Article, Year	Renewables	Energy Storage System	Grid	Optimization Technique	Criteria
[49], 2022	Solar/Wind		On	Genetic Algorithm (GA), MATLAB 9.10	Total Net Present Cost (TNPC)
[18], 2023	Solar/Wind/Biomass/Hydro	Battery/Hydrogen	Off	Multi-Period P-Graph	Levelized Cost of Hydrogen (LCOH), Gross Profit, Environmental Cost
[61], 2023	Solar/Wind/	Battery/Hydrogen	Off	Mixed-Integer Linear Programming (MILP)	Total Net Present Cost (TNPC), CO_2 Emissions
[38], 2023	Solar/Tidal		Off	Particle Swarm Optimization (PSO), Cuckoo Optimization, HOMER Pro 3.15	Total Net Present Cost (TNPC), Excess Electricity, Unmet Electricity Load (UEL), Capacity Shortage
[15], 2023	Solar/Wind/Biomass	Hydrogen	On	HOMER Pro 3.15	Levelized Cost of Energy (LCOE), Operation and Maintenance Cost (OMC), Total Net Present Cost (TNPC). CO_2 Emissions, CO Emissions, Unburned Hydrocarbons Emissions, Particulate Matter Emissions, SO_2 Emissions, NOx Emissions
[40], 2023	Solar/Wind	Pumped hydro/Battery/Hydrogen	Off	Equilibrium Optimizer Algorithm, Artificial Bee Colony, Lightning Search Algorithm, Gray Wolf Optimizer (GWO)	Levelized Cost of Energy (LCOE), Exergy Efficiency
[44], 2023	Solar/Wind		On	Master-Followers Bi-Level Gaming Model	Gross Profit, Loss of Power Supply Probability (LPSP)
[7], 2023	Solar/Wind		On	Loss Reduction Method, Voltage Improvement Method	System Average Interruption Duration Index (SAIDI), System average interruption frequency index (SAIFI), Customer Average Interruption Duration Index (CAIDI), Average System Availability Index (ASAI)
[66], 2023	Solar/Wind		On	Multi-Objective Optimization Metaheuristic Algorithm (MOMFO), Taguchi Method, fuzzy decision-maker-based multi-objective optimization algorithm	Levelized Cost of Energy (LCOE), Loss of Power Supply Probability (LPSP), Renewable Energy Fraction (RF)
[32], 2023	Solar/Wind		Off	Archimedes Optimization Algorithm	Total Net Present Cost (TNPC), Renewable Fraction Index (RFI), Loss of Power Supply Probability (LPSP)
[74], 2023	Solar		On	Non-Dominated Sorting Genetic Algorithm (NSGA-II), TOPSIS method	Renewable Energy Fraction, Loss of Power Supply Probability (LPSP), Total Life Cycle Cost (TLCC), Waste of Energy, Energy Matching Variance (EMV)
[20], 2023	Solar/Wind/Tidal	Battery/Hydrogen	Off	Chameleon Swarm Algorithm	Total Net Present Cost (TNPC), Levelized Cost of Energy (LCOE), Loss of Power Supply Probability (LPSP), Cost-benefit index
[33], 2023	Solar/Wind		Off	Harmony Search (HS)	Total Annual Cost (TAC), Loss of Power Supply Probability (LPSP)
[51], 2023	Solar/Wind	Battery/Hydrogen	Off	TRNSYS, Design of Experiments (DOE) Technique, Statistical Approach of The Response Surface Method (RSM)	Total Life Cycle Cost (TLCC), Predicted Mean Vote (PMV)
[55], 2023	Solar/Wind	Battery/Hydrogen	On	HOMER Pro 3.16, MATLAB 9.13	Total Net Present Cost (TNPC), CO_2 Emissions, Loss of Power Supply Probability (LPSP)

Table 1. *Cont.*

Article, Year	Renewables	Energy Storage System	Grid	Optimization Technique	Criteria
[53], 2023	Solar/Wind/Biomass		On	HOMER Pro 3.16	Net Present Cost (NPC), Levelized Cost of Electricity (LCOE), Renewable Fraction (RF)
[28], 2024	Solar/Wind	Hydrogen	On	Sizing Based on Peak Power	Levelized Cost of Hydrogen (LCOH), Total Net Present Cost (TNPC)
[41], 2024	Solar/Wind	Battery/Hydrogen	On	Column Constraint Generation Algorithm (C & CG), MATLAB 9.8, CPLEX	Operation and Maintenance Cost (OMC), Flexible Electric Load Dispatch Compensation Cost, Transaction Cost In Between System and Power Grid, Total Net Present Cost (TNPC)
[42], 2024	Solar/Wind	Hydrogen	On	MegaWatt Hybrid Optimization by Genetic Algorithms (MHOGA)	Levelized Cost of Hydrogen (LCOH), Total Net Present Cost (TNPC)
[64], 2024	Solar/Wind/Biomass	Battery/Hydrogen	Off	HOMER Pro 3.16	Total Annual Cost (TAC), Loss of Power Supply Probability (LPSP)
[94], 2024	Solar/Wind		On	Ebola Optimization Search Algorithm (ESOA), Particle Swarm Optimization.	Grid Reliability, Levelized Power Supply Price
[68], 2024	Solar/Wind/Biomass		Off	Markov Reliability Process	Failure rate, Reliability index (RI), Repair time, Unavailability, Energy not Supplied (ENS), Loss of Power Supply Probability (LPSP), Availability
[91], 2024	Solar/Wind		On	TD Lambda Algorithm	Fuel Cost, Battery Depletion Expenses, Renewable Energy Utilization (REU)
[8], 2024	Solar/Wind/Geothermal/Hydro		On	Particle Swarm Optimization (PSO), Mixed-Integer Linear Programming (MILP), MATLAB 9.10	Operation Cost, Share of Renewables
[60], 2024	Biomass/Geothermal		Off	Multi-Objective Grey Wolf Optimization, Engineering Equation Solver (EES), MATLAB 9.14	Exergy Efficiency, Annual Money Savings (AMS), Total Fixed Cost (TFC), Net Price Value (NPV)
[10], 2024	Solar/Wind	Hydrogen	On	Non-Dominated Sorting Genetic Algorithm (NSGA-II) with Linear Programming	Primary Renewable Energy Rate (PRER), Loss of Power Supply Probability (LPSP), Power Discard Rate (PDR), Levelized Cost of Energy (LCOE), Total Net Present Cost (TNPC), CO_2 Emission, SO_2 Emissions, NOx Emissions, PM25 Emissions, Employment Opportunities (JOBC), Composite Sustainability Index (CSI)
[48], 2024	Solar/Wind/Biomass	Battery/Hydrogen	Off	Levy Flight-Salp Swarm Algorithms (LF-SSA), HOMER Pro 3.16	Total Annual Cost (TAC), Levelized Cost of Energy (LCOE), Loss of Power Supply Probability (LPSP)
[31], 2024	Solar/Wind		On	Modified Multi-Objective Salp Swarm Optimization Algorithm (MMOSSA)	Total Net Present Cost (TNPC), Levelized Cost of Energy (LCOE), Energy loss, Frequency Deviation, Voltage Stability Indicator, CO_2 Emissions

Table 1. *Cont.*

Article, Year	Renewables	Energy Storage System	Grid	Optimization Technique	Criteria
[93], 2024	Biomass/Geothermal	Hydrogen	On	Bi-Objective Optimization	Levelized cost of product, Total Net Present Cost (TNPC), CO_2 Emissions, Exergo-Environmental Index (EEI)
[63], 2024	Solar/ Wind	Hydrogen	On	HOMER Pro 3.16	Total Net Present Cost (TNPC), Investment Cost, Operation Cost, Levelized Cost of Energy (LCOE), Electricity Capacity Shortfall Rate (ECSR), Hydrogen Capacity Shortfall Rate, Excess Power Rate

References

1. Kabeyi, M.J.B.; Olanrewaju, O.A. Smart grid technologies and application in the sustainable energy transition: A review. *Int. J. Sustain. Energy* **2023**, *42*, 685–758. [CrossRef]
2. United Nations Framework Convention on Climate Change (UNFCCC). Paris Agreement. 2015. Available online: https://unfccc.int/sites/default/files/resource/parisagreement_publication.pdf (accessed on 5 January 2025).
3. Bamisile, O.; Cai, D.; Adun, H.; Dagbasi, M.; Ukwuoma, C.C.; Huang, Q.; Johnson, N.; Bamisile, O. Towards renewables development: Review of optimisation techniques for energy storage and hybrid renewable energy systems. *Heliyon* **2024**, *10*, e37482. [CrossRef] [PubMed]
4. Mancò, G.; Tesio, U.; Guelpa, E.; Verda, V. A review on multi-energy systems modelling and optimisation. *Appl. Therm. Eng.* **2024**, *236*, 121871. [CrossRef]
5. Bornemann, L.; Lange, J.; Kaltschmitt, M. A rigorous optimisation method for long-term multi-stage investment planning: Integration of hydrogen into a decentralized multi-energy system. *Energy Rep.* **2025**, *13*, 117–139. [CrossRef]
6. Hannan, M.A.; Wali, S.B.; Ker, P.J.; Rahman, M.S.A.; Mansor, M.; Ramachandaramurthy, V.K.; Muttaqi, K.M.; Mahlia, T.M.I.; Dong, Z.Y. Battery energy-storage system: A review of technologies, optimisation objectives, constraints, approaches, and outstanding issues. *J. Energy Storage* **2021**, *42*, 103023. [CrossRef]
7. Haldia, P.; Kumar, S.; Negi, S.; Sagar, N. Reliability Improvement Technique Considering Various Renewable Energy Sources. In Proceedings of the IEEE International Conference on Industrial Electronics: Developments and Applications (INDUC 2023), Imphal, India, 18–22 August 2023; IEEE: New York, NY, USA, 2023; pp. 372–380. [CrossRef]
8. Zhang, H.; Liao, K.; Yang, J.; Zheng, S.; He, Z. Frequency-Constrained Expansion Planning for Wind and Photovoltaic Power in Wind-Photovoltaic-Hydro-Thermal Multi-Power Systems. *Appl. Energy* **2024**, *356*, 122401. [CrossRef]
9. Ullah, Z.; Elkadeem, M.R.; Kotb, K.M.; Taha, I.B.M.; Wang, S. Multi-criteria decision-making model for optimal planning of on/off-grid hybrid solar, wind, hydro, biomass clean electricity supply. *Renew. Energy* **2021**, *179*, 885–910. [CrossRef]
10. Liu, L.; Zhai, R.; Xu, Y.; Hu, Y.; Liu, S.; Yang, L. Comprehensive sustainability assessment and multi-objective optimisation of a novel renewable energy-driven multi-energy supply system. *Appl. Therm. Eng.* **2024**, *236*, 121461. [CrossRef]
11. Oliveira, G.C.; Bertone, E.; Stewart, R.A. Optimisation modelling tools and solving techniques for integrated precinct-scale energy–water system planning. *Appl. Energy* **2022**, *318*, 119190. [CrossRef]
12. Nutakki, M.; Mandava, S. Review on optimisation techniques and the role of Artificial Intelligence in home energy management systems. *Eng. Appl. Artif. Intell.* **2023**, *119*, 105721. [CrossRef]
13. Alabi, T.M.; Aghimien, E.I.; Agbajor, F.D.; Yang, Z.; Lu, L.; Adeoye, A.R.; Gopaluni, B. A review on the integrated optimisation techniques and machine learning approaches for modeling, prediction, and decision making on integrated energy systems. *Renew. Energy* **2022**, *194*, 822–849. [CrossRef]
14. Mukelabai, M.D.; Barbour, E.R.; Blanchard, R.E. Modeling and optimisation of renewable hydrogen systems: A systematic methodological review and machine learning integration. *Energy AI* **2024**, *18*, 100455. [CrossRef]
15. Gul, E.; Baldinelli, G.; Farooqui, A.; Bartocci, P.; Shamim, T. AEM-Electrolyzer Based Hydrogen Integrated Renewable Energy System Optimisation Model for Distributed Communities. *Energy Convers. Manag.* **2023**, *285*, 117025. [CrossRef]
16. Song, Y.; Mu, H.; Li, N.; Wang, H. Multi-objective optimisation of large-scale grid-connected photovoltaic-hydrogen-natural gas integrated energy power station based on carbon emission priority. *Int. J. Hydrogen Energy* **2023**, *48*, 4087–4103. [CrossRef]
17. Abu, S.M.; Hannan, M.A.; Rahman, S.A.; Long, C.Y.; Ker, P.J.; Wong, R.T.K.; Jang, G. An effective optimisation algorithm for hydrogen fuel cell-based hybrid energy system: A sustainable microgrid approach. *Int. J. Hydrogen Energy* **2025**, *98*, 1341–1355. [CrossRef]
18. Ji, M.; Zhang, W.; Xu, Y.; Liao, Q.; Klemeš, J.J.; Wang, B. Optimisation of Multi-Period Renewable Energy Systems with Hydrogen and Battery Energy Storage: A P-Graph Approach. *Energy Convers. Manag.* **2023**, *281*, 116826. [CrossRef]
19. Hassan, R.; Das, B.K.; Hasan, M. Integrated off-grid hybrid renewable energy system optimisation based on economic, environmental, and social indicators for sustainable development. *Energy* **2022**, *250*, 123823. [CrossRef]
20. Zhou, J.; Xu, Z. Optimal sizing design and integrated cost-benefit assessment of stand-alone microgrid system with different energy storage employing chameleon swarm algorithm: A rural case in Northeast China. *Renew. Energy* **2023**, *202*, 1110–1137. [CrossRef]
21. Mokhtara, C.; Negrou, B.; Settou, N.; Settou, B.; Samy, M.M. Design optimisation of off-grid Hybrid Renewable Energy Systems considering the effects of building energy performance and climate change: Case study of Algeria. *Energy* **2021**, *219*, 119605. [CrossRef]
22. Won, W.; Kwon, H.; Han, J.H.; Kim, J. Design and operation of renewable energy sources-based hydrogen supply system: Technology integration and optimisation. *Renew. Energy* **2017**, *103*, 226–238. [CrossRef]
23. European Commission. *Clean Energy for All Europeans Package*; European Commission: Brussels, Belgium, 2019; pp. 1–33. Available online: https://energy.ec.europa.eu/document/download/4d355bf1-1381-4d95-9c48-3b5b8c58469e_en?filename=cleanenergy_com_en.pdf (accessed on 5 January 2025).

24. International Renewable Energy Agency (IRENA). *Renewable Energy Integration in Power Grids*; IRENA: Abu Dhabi, United Arab Emirates, 2020; pp. 1–72. Available online: https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2020/Jul/IRENA_Renewable_Energy_Statistics_2020.pdf (accessed on 5 January 2025).
25. U.S. Department of Energy (DOE). *Grid Modernization Initiative*; DOE: Washington, DC, USA, 2021; pp. 1–30. Available online: https://www.energy.gov/sites/prod/files/2021/02/f82/GMI_Strategy_FINAL%20as%20of%201.20.21.pdf (accessed on 1 January 2025).
26. International Energy Agency (IEA). *World Energy Outlook 2021*; IEA: Paris, France, 2021; pp. 1–386. Available online: https://www.iea.org/reports/world-energy-outlook-2021 (accessed on 1 January 2025).
27. Deevela, N.R.; Kandpal, T.C.; Singh, B. A Review of Renewable Energy-Based Power Supply Options for Telecom Towers. *Environ. Dev. Sustain.* **2024**, *26*, 2897–2964. [CrossRef] [PubMed]
28. Rezaei, M.; Akimov, A.; Gray, E.M. Economics of Renewable Hydrogen Production Using Wind and Solar Energy: A Case Study for Queensland, Australia. *J. Clean. Prod.* **2024**, *435*, 140476. [CrossRef]
29. Queensland Government. New Green Hydrogen Investment Set to Boost Queensland Economy. 2024. Available online: https://statements.qld.gov.au/statements/101665 (accessed on 3 January 2025).
30. Li, Y.; Li, K.; Yang, Z.; Yu, Y.; Xu, R.; Yang, M. Stochastic optimal scheduling of demand response-enabled microgrids with renewable generations: An analytical-heuristic approach. *J. Clean. Prod.* **2022**, *330*, 129840. [CrossRef]
31. Abid, M.S.; Ahshan, R.; Al Abri, R.; Al-Badi, A.; Albadi, M. Techno-economic and environmental assessment of renewable energy sources, virtual synchronous generators, and electric vehicle charging stations in microgrids. *Appl. Energy* **2024**, *353*, 122028. [CrossRef]
32. Kharrich, M.; Selim, A.; Kamel, S.; Kim, J. An effective design of hybrid renewable energy system using an improved Archimedes Optimisation Algorithm: A case study of Farafra, Egypt. *Energy Convers. Manag.* **2023**, *283*, 116907. [CrossRef]
33. Fan, J.; Zhou, X. Optimisation of a hybrid solar/wind/storage system with bio-generator for a household by emerging meta-heuristic optimisation algorithm. *J. Energy Storage* **2023**, *73*, 108967. [CrossRef]
34. Babatunde, O.M.; Munda, J.L.; Hamam, Y. Hybridized Off-Grid Fuel Cell/Wind/Solar PV/Battery for Energy Generation in a Small Household: A Multi-Criteria Perspective. *Int. J. Hydrogen Energy* **2022**, *47*, 6437–6452. [CrossRef]
35. Sadeghi, D.; Ahmadi, S.E.; Amiri, N.; Marzband, M.; Abusorrah, A.; Rawa, M. Designing, optimizing and comparing distributed generation technologies as a substitute system for reducing life cycle costs, CO_2 emissions, and power losses in residential buildings. *Energy* **2022**, *253*, 123947. [CrossRef]
36. European Commission. Energy Communities. Available online: https://energy.ec.europa.eu/topics/markets-and-consumers/energy-consumers-and-prosumers/energy-communities_en (accessed on 3 January 2025).
37. Emad, D.; El-Hameed, M.A.; El-Fergany, A.A. Optimal techno-economic design of hybrid PV/wind system comprising battery energy storage: Case study for a remote area. *Energy Convers. Manag.* **2021**, *249*, 114847. [CrossRef]
38. Khare, V.; Khare, C.J.; Bhuiyan, M.A. Design, Optimisation, and Data Analysis of Solar-Tidal Hybrid Renewable Energy System for Hurawalhi, Maldives. *Clean. Energy Syst.* **2023**, *6*, 100088. [CrossRef]
39. HassanzadehFard, H.; Tooryan, F.; Collins, E.R.; Jin, S.; Ramezani, B. Design and Optimum Energy Management of a Hybrid Renewable Energy System Based on Efficient Various Hydrogen Production. *Int. J. Hydrogen Energy* **2020**, *45*, 30113–30128. [CrossRef]
40. Ghandehariun, S.; Ghandehariun, A.M.; Ziabari, N.B. Performance Prediction and Optimisation of a Hybrid Renewable-Energy-Based Multigeneration System Using Machine Learning. *Energy* **2023**, *282*, 128908. [CrossRef]
41. Xia, L.; Wu, B.; Zhou, L.; Liang, T.; Liu, Z. Scheduling of Renewable Energy Hydrogen Production System Based on Two-Stage Distribution Robust Optimisation. In Proceedings of the 10th Hydrogen Technology Convention (WHTC 2023), Foshan, China, 22–26 May 2023; Springer: Singapore, 2024; Volume 1, pp. 222–243. [CrossRef]
42. Dufo-López, R.; Lujano-Rojas, J.M.; Bernal-Agustín, J.L. Optimisation of size and control strategy in utility-scale green hydrogen production systems. *Int. J. Hydrogen Energy* **2024**, *50*, 292–309. [CrossRef]
43. Ghorbani, N.; Kasaeian, A.; Toopshekan, A.; Bahrami, L.; Maghami, A. Optimizing a hybrid wind-PV-battery system using GA-PSO and MOPSO for reducing cost and increasing reliability. *Energy* **2018**, *154*, 581–591. [CrossRef]
44. Chen, B.; Chen, Y.; Zhou, H.; Bai, X.; Li, B.; Guo, X. A bi-level gaming programming for regional integrated energy system considering the users' reliability incentive. *Reliab. Eng. Syst. Saf.* **2023**, *229*, 108839. [CrossRef]
45. Moghaddam, S.; Bigdeli, M.; Moradlou, M.; Siano, P. Designing of Stand-Alone Hybrid PV/Wind/Battery System Using Improved Crow Search Algorithm Considering Reliability Index. *Int. J. Energy Environ. Eng.* **2019**, *10*, 429–449. [CrossRef]
46. Naderipour, A.; Abdul-Malek, Z.; Arabi Nowdeh, S.; Kamyab, H.; Ramtin, A.R.; Shahrokhi, S.; Klemeš, J.J. Comparative evaluation of hybrid photovoltaic, wind, tidal, and fuel cell clean system design for different regions with remote application considering cost. *J. Clean. Prod.* **2021**, *283*, 124207. [CrossRef]

47. Jahannoosh, M.; Nowdeh, S.A.; Naderipour, A.; Kamyab, H.; Davoudkhani, I.F.; Klemeš, J.J. New hybrid meta-heuristic algorithm for reliable and cost-effective designing of photovoltaic/wind/fuel cell energy system considering load interruption probability. *J. Clean. Prod.* **2021**, *278*, 123406. [CrossRef]
48. Modu, B.; Abdullah, M.P.; Bukar, A.L.; Hamza, M.F.; Adewolu, M.S. Operational strategy and capacity optimisation of standalone solar-wind-biomass-fuel cell energy system using hybrid LF-SSA algorithms. *Int. J. Hydrogen Energy* **2024**, *50*, 92–106. [CrossRef]
49. Emrani, A.; Berrada, A.; Bakhouya, M. Optimal sizing and deployment of gravity energy storage system in hybrid PV-Wind power plant. *Renew. Energy* **2022**, *183*, 12–27. [CrossRef]
50. Yang, Z.; Ghadamyari, M.; Khorramdel, H.; Seyed Alizadeh, S.M.; Pirouzi, S.; Milani, M.; Banihashemi, F.; Ghadimi, N. Robust multi-objective optimal design of islanded hybrid system with renewable and diesel sources/stationary and mobile energy storage systems. *Renew. Sustain. Energy Rev.* **2021**, *148*, 111295. [CrossRef]
51. Assareh, E.; Dejdar, A.; Ershadi, A.; Jafarian, M.; Mansouri, M.; Roshani, A.S.; Azish, E.; Saedpanah, E.; Lee, M. Techno-economic analysis of combined cooling, heating, and power (CCHP) system integrated with multiple renewable energy sources and energy storage units. *Energy Build.* **2023**, *278*, 112618. [CrossRef]
52. Sanajaoba, S.; Fernandez, E. Maiden application of Cuckoo Search algorithm for optimal sizing of a remote hybrid renewable energy system. *Renew. Energy* **2016**, *96*, 1–10. [CrossRef]
53. Abdelhady, S. Techno-economic study and the optimal hybrid renewable energy system design for a hotel building with net zero energy and net zero carbon emissions. *Energy Convers. Manag.* **2023**, *289*, 117195. [CrossRef]
54. Gökçek, M.; Kale, C. Techno-economical evaluation of a hydrogen refuelling station powered by Wind-PV hybrid power system: A case study for Izmir-Çeşme. *Int. J. Hydrogen Energy* **2018**, *43*, 10615–10625. [CrossRef]
55. Yazdani, H.; Baneshi, M.; Yaghoubi, M. Techno-economic and environmental design of hybrid energy systems using multi-objective optimisation and multi-criteria decision-making methods. *Energy Convers. Manag.* **2023**, *282*, 116873. [CrossRef]
56. Mayer, M.J.; Szilágyi, A.; Gróf, G. Environmental and economic multi-objective optimisation of a household level hybrid renewable energy system by genetic algorithm. *Appl. Energy* **2020**, *269*, 115058. [CrossRef]
57. Yahaya, A.A.; AlMuhaini, M.; Heydt, G.T. Optimal Design of Hybrid DG Systems for Microgrid Reliability Enhancement. *IET Gener. Transm. Distrib.* **2020**, *14*, 816–823. [CrossRef]
58. Baghaee, H.R.; Mirsalim, M.; Gharehpetian, G.B. Multi-objective optimal power management and sizing of a reliable wind/PV microgrid with hydrogen energy storage using MOPSO. *J. Intell. Fuzzy Syst.* **2017**, *32*, 1125–1135. [CrossRef]
59. Kharrich, M.; Mohammed, O.H.; Alshammari, N.; Akherraz, M. Multi-objective optimisation and the effect of economic factors on the design of the microgrid hybrid system. *Sustain. Cities Soc.* **2021**, *65*, 102646. [CrossRef]
60. Zhu, C.; Wang, M.; Guo, M.; Deng, J.; Du, Q.; Wei, W.; Zhang, Y.; Mohebbi, A. An innovative process design and multi-criteria study/optimisation of a biomass digestion-supercritical carbon dioxide scenario toward boosting a geothermal-driven cogeneration system for power and heat. *Energy* **2024**, *292*, 130408. [CrossRef]
61. He, H.; Huang, Y.; Nakadomari, A.; Masrur, H.; Krishnan, N.; Hemeida, A.M.; Mikhaylov, A.; Senjyu, T. Potential and Economic Viability of Green Hydrogen Production from Seawater Electrolysis Using Renewable Energy in Remote Japanese Islands. *Renew. Energy* **2023**, *202*, 1436–1447. [CrossRef]
62. Sun, B. A multi-objective optimisation model for fast electric vehicle charging stations with wind, PV power, and energy storage. *J. Clean. Prod.* **2021**, *288*, 125564. [CrossRef]
63. Yang, T.; Yan, X.; Cai, W.; Luo, H.; Xu, N.; Tong, L.; Yan, F.; Chahine, R.; Xiao, J. Parametric Study and Optimisation of Hydrogen Production Systems Based on Solar/Wind Hybrid Renewable Energies: A Case Study in Kuqa, China. *Sustainability* **2024**, *16*, 896. [CrossRef]
64. Sadeghi, A.; Maleki, A.; Haghighat, S. Techno-economic analysis and optimization of a hybrid solar-wind-biomass-battery framework for the electrification of a remote area: A case study. *Energy Convers. Manag. X* **2024**, *24*, 100732. [CrossRef]
65. Kiptoo, M.K.; Lotfy, M.E.; Adewuyi, O.B.; Conteh, A.; Howlader, A.M.; Senjyu, T. Integrated approach for optimal techno-economic planning for high renewable energy-based isolated microgrid considering cost of energy storage and demand response strategies. *Energy Convers. Manag.* **2020**, *215*, 112917. [CrossRef]
66. Heydari, A.; Nezhad, M.M.; Keynia, F.; Fekih, A.; Shahsavari-Pour, N.; Garcia, D.A.; Piras, G. A Combined Multi-Objective Intelligent Optimisation Approach Considering Techno-Economic and Reliability Factors for Hybrid-Renewable Microgrid Systems. *J. Clean. Prod.* **2023**, *383*, 135249. [CrossRef]
67. Corengia, M.; Torres, A.I. Coupling time-varying power sources to production of green hydrogen: A superstructure-based approach for technology selection and optimal design. *Chem. Eng. Res. Des.* **2022**, *183*, 235–249. [CrossRef]
68. Gupta, M.; Bhargava, A. Optimal Selection and Analysis of Microgrid Energy System Using Markov Process. *Sustain. Energy Technol. Assess.* **2024**, *62*, 103623. [CrossRef]

69. Al-Shafei, A.; Zareipour, H.; Cao, Y.A. Review of High-Performance Computing and Parallel Techniques Applied to Power Systems Optimisation. *arXiv* **2022**, arXiv:2207.02388.
70. Nozarian, M.; Seifi, H.; Sheikh-El-Eslami, M.K.; Delkhosh, H. Hydro-Thermal Unit Commitment involving Demand Response resources: A MILP formulation. *Electr. Eng.* **2023**, *105*, 175–192. [CrossRef]
71. Kumar, S.; Gupta, A.; Bindal, R.K. Load-frequency and voltage control for power quality enhancement in a SPV/Wind utility-tied system using GA & PSO optimisation. *Results Control Optim.* **2024**, *16*, 100442. [CrossRef]
72. Abdoulaye, M.A.; Waita, S.; Wekesa, C.W.; Mwabora, J.M. Optimal sizing of an off-grid and grid-connected hybrid photovoltaic-wind system with battery and fuel cell storage system: A techno-economic, environmental, and social assessment. *Appl. Energy* **2024**, *365*, 123201. [CrossRef]
73. Sultan, H.M.; Menesy, A.S.; Kamel, S.; Korashy, A.; Almohaimeed, S.A.; Abdel-Akher, M. An improved artificial ecosystem optimisation algorithm for optimal configuration of a hybrid PV/WT/FC energy system. *Alex. Eng. J.* **2021**, *60*, 1001–1025. [CrossRef]
74. Huang, Y.; Masrur, H.; Lipu, M.S.H.; Howlader, H.O.R.; Gamil, M.M.; Nakadomari, A.; Mandal, P.; Senjyu, T. Multi-objective optimisation of campus microgrid system considering electric vehicle charging load integrated to power grid. *Sustain. Cities Soc.* **2023**, *98*, 104778. [CrossRef]
75. Hou, G.; Guo, Z. Maximum power point tracking of solar photovoltaic under partial shading conditions based on improved salp swarm algorithm. *Electr. Power Syst. Res.* **2025**, *241*, 111316. [CrossRef]
76. Ren, H.; Li, J.; Chen, H.; Li, C. Adaptive levy-assisted salp swarm algorithm: Analysis and optimisation case studies. *Math. Comput. Simul.* **2021**, *181*, 380–409. [CrossRef]
77. Huangpeng, Q.; Huang, W.; Gholinia, F. Forecast of the hydropower generation under influence of climate change based on RCPs and Developed Crow Search Optimisation Algorithm. *Energy Rep.* **2021**, *7*, 385–397. [CrossRef]
78. Huo, D.; Gu, W.; Guo, D.; Tang, A. The service trade with AI and energy efficiency: Multiplier effect of the digital economy in a green city by using quantum computation based on QUBO modeling. *Energy Econ.* **2024**, *140*, 107976. [CrossRef]
79. Ghaemi Asl, M.; Ben Jabeur, S.; Nammouri, H.; Bel Hadj Miled, K. Dynamic connectedness of quantum computing, artificial intelligence, and big data stocks on renewable and sustainable energy. *Energy Econ.* **2024**, *140*, 108017. [CrossRef]
80. Khumsikiew, J.; Netthong, R.; Yingngam, B. Research advancements in quantum computing and digital twins. *Digit. Twins Smart Cities Villages* **2025**, *5*, 103–118. [CrossRef]
81. Moss, R.; Pearson, D.; Preece, R. A Free and Open-Source Microgrid Optimisation Tool. *Energy AI* **2024**, *18*, 100455. [CrossRef]
82. Karbasforoushha, M.A.; Khajehzadeh, M.; Jearsiripongkul, T.; Keawsawasvong, S.; Eslami, M. A comprehensive review of building energy optimisation using metaheuristic algorithms. *J. Build. Eng.* **2024**, *98*, 111377. [CrossRef]
83. Gonzalez Gabriel, L.F.; Ruiz-Cruz, R.; Coss y Leon Monterde, H.J.; Zúñiga-Grajeda, V.; Gurubel-Tun, K.J.; Coronado-Mendoza, A. Optimizing the penetration of standalone microgrid, incorporating demand-side management as a guiding principle. *Energy Rep.* **2022**, *8*, 2712–2725. [CrossRef]
84. Papari, B.; Timilsina, L.; Moghassemi, A.; Khan, A.A.; Arsalan, A.; Ozkan, G.; Edrington, C.S. An advanced meta metrics-based approach to assess an appropriate optimisation method for Wind/PV/Battery based hybrid AC-DC microgrid. *e-Prime-Adv. Electr. Eng. Electron. Energy* **2024**, *9*, 100640. [CrossRef]
85. Xu, X.-F.; Wang, K.; Ma, W.-H.; Wu, C.-L.; Huang, X.-R.; Ma, Z.-X.; Li, Z.-H. Multi-objective particle swarm optimisation algorithm based on multi-strategy improvement for hybrid energy storage optimisation configuration. *Renew. Energy* **2024**, *223*, 120086. [CrossRef]
86. Shi, Y.; Chen, P. Energy retrofitting of hospital buildings considering climate change: An approach integrating automated machine learning with NSGA-III for multi-objective optimisation. *Energy Build.* **2024**, *319*, 114571. [CrossRef]
87. Chakraborty, S. TOPSIS and Modified TOPSIS: A comparative analysis. *Decis. Anal. J.* **2022**, *2*, 100021. [CrossRef]
88. Liu, Y.; As'arry, A.; Hassan, M.K.; Hairuddin, A.A.; Mohamad, H. Review of the grey wolf optimisation algorithm: Variants and applications. *Neural Comput. Appl.* **2024**, *36*, 2713–2735. [CrossRef]
89. Panda, S.; Samanta, I.S.; Rout, P.K.; Sahu, B.K.; Bajaj, M.; Blazek, V.; Prokop, L.; Misak, S. Priority-based scheduling in residential energy management systems integrated with renewable sources using adaptive Salp swarm algorithm. *Results Eng.* **2024**, *23*, 102643. [CrossRef]
90. Li, P.; Wang, Z.; Wang, J.; Yang, W.; Guo, T.; Yin, Y. Two-stage optimal operation of integrated energy system considering multiple uncertainties and integrated demand response. *Energy* **2021**, *225*, 120256. [CrossRef]
91. Karthikeyan, M.; Manimegalai, D.; RajaGopal, K. Power Control of Hybrid Grid-Connected Renewable Energy System Using Machine Learning. *Energy Rep.* **2024**, *11*, 1079–1087. [CrossRef]
92. Suyono, H.; Hasanah, R.N.; Mudjirahardjo, P.; Purnomo, M.F.E.; Uliyani, S.; Musirin, I.; Awalin, L.J. Enhancement of the Power System Distribution Reliability Using Ant Colony Optimisation and Simulated Annealing Methods. *Indones. J. Electr. Eng. Comput. Sci.* **2020**, *17*, 877–885. [CrossRef]

93. Wang, D.; Ali, M.A.; Alizadeh, A.; Singh, P.K.; Almojil, S.F.; Alali, A.F.; Almoalimi, K.T.; Almohana, A.I. Thermoeconomic appraisal of a novel power and hydrogen cogeneration plant with integration of biomass and geothermal energies. *Int. J. Hydrogen Energy* **2024**, *52*, 385–400. [CrossRef]
94. Zhu, G.; Yan, G.; Garmroudi, D. Optimizing Solar-Wind Hybrid Energy Systems for Sustainable Charging Stations and Commercial Applications: A Two-Stage Framework with Ebola-Inspired Optimisation. *Expert Syst. Appl.* **2024**, *246*, 123180. [CrossRef]