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Review

A Systematic Review and Evolutionary Analysis of the Optimization Techniques and Software Tools in Hybrid Microgrid Systems

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Abstract: This study systematically reviews the optimization techniques (OTs) and software tools (STs) in hybrid microgrid systems (HMGSs) to enhance the efficiency, cost-effectiveness, and energy reliability. An advanced Scopus search was conducted using core keywords related to microgrids, renewable energy systems, and various OTs and STs, which identified 4134 relevant documents on OTs. These were classified into classical (16.87%), metaheuristic (47.12%), and artificial intelligence (AI)-based methods (36.01%), highlighting the dominance of metaheuristics and the growing role of AI-driven approaches in handling uncertainties and real-time decision-making. Additionally, 2667 documents on STs were analyzed, identifying MATLAB/Simulink (65.34%) and HOMER (22.08%) as the most widely used tools for simulation, modeling, and techno-economic analysis. This study identifies key research trends, highlights gaps in the optimization strategies, and emphasizes the need for AI integration, broader adoption of open-source tools, and scalable optimization frameworks. By mapping the evolution and effectiveness of OTs and STs, it provides valuable insights for researchers, policymakers, and industry professionals, supporting the development of sustainable and intelligent HMGS solutions.

Keywords: renewable energy systems; hybrid microgrid systems; optimization techniques; artificial intelligence (AI); metaheuristic algorithms; software tools

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1. Introduction

Energy is a pivotal element reflecting the social and economic growth of nations and the quality of life of their citizens. As societies grapple with changes in climate patterns and the rising costs of traditional fuels like gas and oil, the challenge of diversifying energy sources and reducing dependence on fossil fuels intensifies. Renewable energy sources (RESs) have emerged as a sought-after solution for electrical energy production due to their environmentally friendly nature compared to conventional methods. This transition toward renewables is further highlighted by reports from the International Energy Agency (IEA), which show a significant uptick in electricity generation using sustainable energy means. According to an IEA report, their central forecast suggests that between 2022 and 2027, the worldwide capacity of RESs will increase by approximately 2400 GW, which is an increase of almost 75%. Two key factors drive this surge in the adoption of RESs. Firstly, the global energy crisis has resulted in the increased costs of fossil fuels and electricity. Secondly, the incursion into Ukraine by Russia has made fossil fuel importers, especially those in Europe, recognize and value the benefits of RESs in enhancing energy security.

In response to the energy crisis, China, the European Union (EU), the United States, and India are rapidly implementing existing policies and introducing regulatory and market changes, as well as rolling out new measures faster than previously expected. This has been a significant factor in the growth trajectory shown in Figure 1. In this figure, the red bar represents the updated global forecast, while the light blue bars correspond to individual regional forecasts.

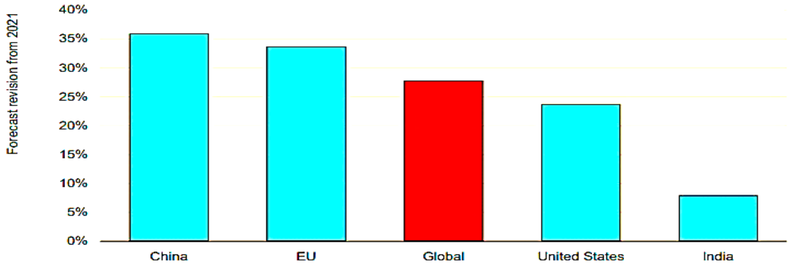


Figure 1. Predictions of the expansion of RES capacity between 2021 and 2027 [1].

Since the previous report, RES usage in the EU has seen a 30% increase, with Germany and Spain at the forefront, experiencing boosts of 50% and 60%, respectively [1]. As the need to diversify energy sources and reduce reliance on fossil fuels grows, the significance of RESs continues to increase. However, despite their sustainability, the intermittent nature of RESs such as wind and solar limits their ability to be used independently. To address this challenge, hybrid energy systems (HESs) combine multiple RESs, often integrating energy storage or conventional sources like diesel generators, to provide a more reliable and stable energy supply [2,3]. Microgrids (MGs), which can operate both connected to the grid and in isolation, are at the forefront of this innovation, offering flexibility in energy management [4]. The development of hybrid microgrid systems (HMGSs) further enhances this integration by optimizing the balance between renewable and conventional energy sources, achieving cost reductions, increased grid independence, and reduced environmental impact [5–8].

Within this context, HMGSs provide an advanced solution for energy management by integrating renewable and conventional power sources to reduce costs, enhance grid independence, and minimize environmental impacts. Due to the inherent complexity of HMGSs, advanced optimization techniques (OTs) are essential for achieving high efficiency, cost reduction, and system reliability. Recent advancements in artificial intelligence (AI) and metaheuristics have led to the development of powerful optimization algorithms that effectively address these challenges. Furthermore, specialized software tools (STs) such as HOMER and MATLAB/Simulink provide accurate modeling, simulation, and optimization capabilities, enhancing the practicality and feasibility of HMGSs for various applications.

Area of Study

Despite the rapid development of OTs and specialized STs, existing studies often focus on specific methods or tools without providing a holistic view of their integration in HMGSs. This review aims to fill this gap by analyzing and comparing the effectiveness and trends of various OTs and STs used in HMGSs, using Scopus records to assess their prevalence over time.

By reviewing the advancements and adoption trends, and identifying promising approaches, this study provides a comprehensive analysis of OTs and STs, offering actionable insights to improve the efficiency, reliability, and sustainability of HMGSs. Building on suggestions from our earlier investigation [9], the document is organized as illustrated in Figure 2, which outlines this study's workflow and key phases.

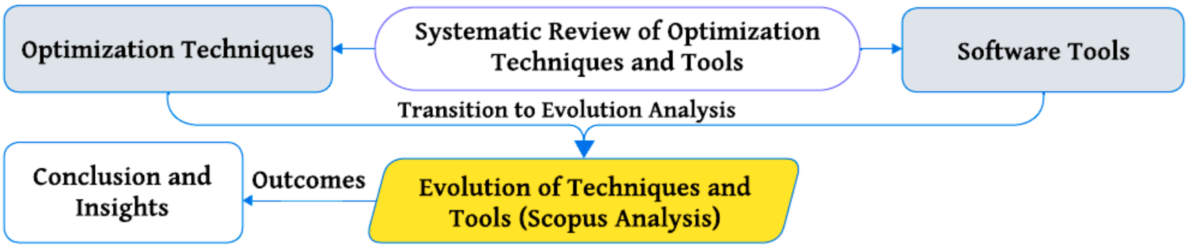


Figure 2. Workflow of this study.

The first section presents a systematic review of the OTs and tools, providing an in-depth analysis of various methods and tools employed in HMGSs. This section achieves our goal of delivering a comprehensive review, highlighting the latest advancements and identifying critical optimization approaches. The second section, Evolution of Techniques and Tools (Scopus analysis), examines the trends in the adoption of these techniques over time, providing a broader perspective on their evolution and impact. Finally, The Conclusion and Insights Section synthesizes the findings and presents valuable outcomes for researchers and practitioners.

2. Systematic Review of OTs and STs

Through the optimization process, the optimal value or solution can be identified. Optimization problems may involve one or more objectives, aiming to maximize, minimize, or address both in the case of multi-objective optimization. These problems are prevalent in diverse fields, such as mathematics, engineering, social studies, economics, agriculture, aviation, and RES, among many others [10–19]. To ensure the most efficient deployment of HMGSs, an optimization procedure is essential. Figure 3 highlights the critical OTs and STs utilized to solve problems and evaluate the effectiveness of HMGSs.

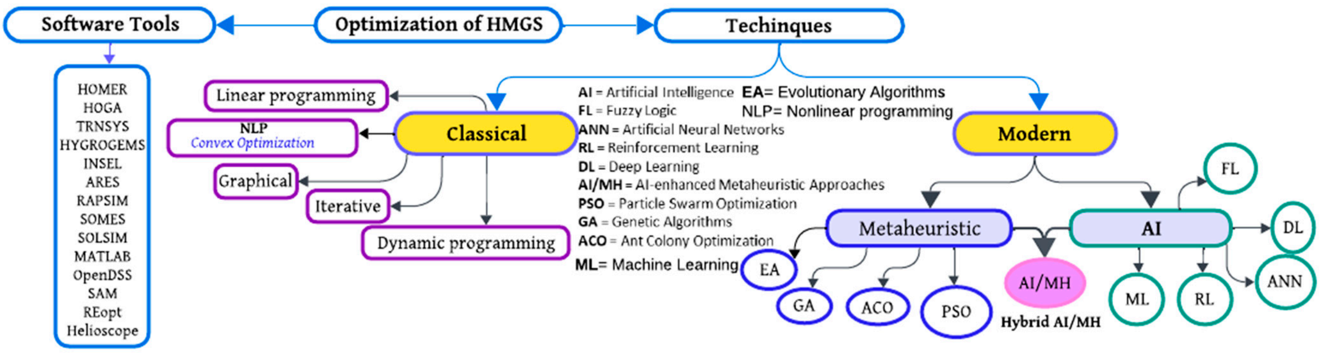


Figure 3. Key OTs and STs for HMGSs.

The OTs in HMGS studies are generally classified into the classical, metaheuristic, and AI-based approaches based on the methodologies used in the reviewed studies. These categories are defined as follows:

- Classical techniques: This category includes linear programming (LP), nonlinear programming (NLP) (with convex optimization as a subset), dynamic programming (DP), iterative methods, and graphical techniques. These methods rely on deterministic optimization models and predefined mathematical formulations to find optimal solutions.
- Metaheuristic techniques: These methods use stochastic, population-based, or evolutionary algorithms to explore large solution spaces efficiently. Genetic algorithms (GAs), particle swarm optimization (PSO), and ant colony optimization (ACO) are among the commonly used techniques in this category.

- AI-based techniques: This category includes optimization approaches that incorporate machine learning and neural networks to enhance decision-making and adaptation. Examples include artificial neural networks (ANNs), reinforcement learning (RL), deep learning (DL), and fuzzy logic (FL).

As a distinct subcategory within modern techniques, AI/enhanced metaheuristics (AI/MH) refers to cases where machine learning or AI components are integrated with metaheuristic algorithms to improve performance. Unlike pure metaheuristics, AI/MH techniques use AI-driven learning mechanisms to adapt the search strategies dynamically, increasing the convergence speed and solution quality.

This hybrid category differs from standalone AI-based techniques, which operate purely on data-driven learning models, and from traditional metaheuristics, which lack AI-driven adaptation.

The following sections provide an in-depth analysis of the OTs and STs most commonly used in HMGSs.

2.1. Optimization Techniques

The stochastic nature of natural resources, nonlinear variation in output power from solar photovoltaic (SPV) and wind turbine (WT), selection of component type and orientations, and economic modeling of energy generation costs in HMGSs all contribute to the complexity of the HMGS optimization problem [20]. This complexity has driven researchers to develop various methods and techniques for optimizing HMGSs, as detailed below.

2.1.1. Classical Techniques

Various OTs are employed to optimize the use of HESs integrated with MGs. This section reviews the research utilizing traditional OT methods, including iterative, graphical, linear, nonlinear, and dynamic programming, to address the optimization challenges in HMGSs. Table 1 provides a description of these techniques, along with the literature reviewed.

Table 1. Classical OTs applied in HMGS studies.

1. Iterative methods

In optimization processes, computer-driven simulations iteratively refine estimations by evaluating various factor combinations, retaining the most effective solutions while reducing the focus on less favorable ones. These methods play a crucial role in HMGSs, particularly in fine-tuning dispatch strategies and optimizing power flows in hybrid energy storage systems [21]. Their adaptability makes them effective for handling nonlinearity in real-time MG operations, especially in optimizing battery energy storage placement and unbalanced AC/DC power flow modeling [22]. However, iterative approaches can be computationally intensive, requiring proper calibration to prevent slow convergence or local optima trapping. Despite these challenges, they remain widely used due to their flexibility and reliability in solving complex MGs energy management problems.

Ref.	SPV	WT	Energy storage	DG	Other sources	Optimization Focus	Key Findings
[23]	✓	✓	✓	✓	✗	LCOE, LCOH	Investigated the sizing and economic evaluation of an HMGS SPV-WT-DG-battery system in islanded mode. Results demonstrated reduced life-cycle cost with low LPSP, outperforming HOMER in cost-effectiveness.
[24]	✓	✓	✓	✗	✗	Economic, reliability	Developed a multi-objective dispatching model using the MSIIO technique, optimizing energy storage utilization. Achieved 4.18% higher economic gains and 82.83% capacity utilization, outperforming PSO and differential evolution.

Table 1. *Cont.*

2. Nonlinear programming (NLP)							
Nonlinear programming (NLP) involves optimizing an objective function subject to nonlinear equality and inequality constraints, making it essential for solving real-world HMGS optimization problems with complex, nonlinear variable dependencies [25]. Unlike linear programming (LP), NLP provides greater flexibility, enabling the modeling of the dynamic energy dispatch, demand response programs (DRPs), and RESs integration in HMGSs. However, its challenges include the high computational complexity, sensitivity to initial conditions, and risk of converging to local optima rather than the global best solution [26]. NLP has been applied to optimize cost-efficiency, enhance demand-side management, and improve RES utilization in MG operations [27]. Similarly, stochastic MINLP methods have been used to effectively coordinate fuel-cell-based energy generation and energy storage under RES uncertainty, ensuring reliable MG operation even in the presence of fluctuating energy sources [28].							
[26]	✓	✓	✗	✓	✗	Revenue maximization, cost reduction	Applied a risk-aware mixed-integer nonlinear optimization approach to manage stochastic energy sources. Optimized DG, SPV, and WT operations under market price uncertainties, achieving cost minimization through fuel savings and energy sales. Enhanced energy dispatch and load-generation balance with robust scheduling techniques, including cubic spline interpolation.
To address the NLP limitations, convex optimization is widely used to reformulate complex nonlinear problems, ensuring global optimality and computational efficiency. It plays a crucial role in real-time MG energy management, decentralized optimization, and economic dispatch models, guaranteeing scalable and adaptive decision-making [29,30]. For instance, ref. [31] applies convex optimization in decentralized real-time energy management, optimizing economic dispatch under demand and RES uncertainties. Using Lagrangian dual decomposition, it minimizes the system-wide power costs in both grid-connected and islanded MGs. Similarly, ref. [32] addresses non-convex challenges in hybrid AC/DC MGs, transforming bidirectional converter models into convex formulations to improve the computational efficiency and solution time. Despite its advantages, convex optimization applies only to problems that can be mathematically transformed into convex structures. While researchers work to reformulate real-world problems for better computational efficiency, highly nonlinear or mixed-integer problems remain challenging to solve [30].							
3. Linear programming							
Linear programming is a mathematical optimization technique used to determine the optimal solution within defined linear constraints. It is widely applied in MG energy management, economic dispatch, and resource allocation due to its structured approach, computational efficiency, and ability to handle large datasets [33,34]. In MG applications, LP is frequently utilized for optimal scheduling of HESs [35], energy storage planning [36], and demand response integration [34]. Its key advantages include reliability, scalability, and guaranteed global optimality for problems with linear relationships. However, LP has limitations—it strictly adheres to a linear framework, which often fails to capture real-world complexities. Additionally, even small modifications can significantly impact the results, and solving large-scale problems can be computationally demanding [37].							
[33]	✓	✓	✓	✗	✗	Cost reduction, efficiency improvement	Modeled and optimized MG components using MILP, integrating demand response programming for standalone systems. Results demonstrated reduced mismatches, cost savings, and lower battery requirements via load scheduling. Validation performed with HOMER and GAMS using the CPLEX solver.
4. Dynamic programming							
Dynamic programming (DP) is an optimization technique that breaks down complex problems into smaller subproblems, solves each one only once, and stores the solutions for future use. This method is particularly effective for sequential decision-making and is widely applied in MG energy scheduling, storage management, and power flow optimization [38,39]. DP-based approaches have been successfully used to optimize real-time energy storage management in microgrids, addressing uncertainties in renewable generation while minimizing energy costs [38]. Additionally, adaptive DP methods have been implemented in dynamic energy management systems (DEMSs) for grid-connected and islanded MGs, ensuring efficient dispatch of RESs and storage resources [39]. In the residential sector, DP has been applied for solar energy scheduling, improving cost savings and enhancing electricity efficiency [40]. However, DP requires high computational resources, as it stores intermediate solutions, making it memory-intensive. Additionally, its application is best suited to problems that can be structured into interdependent subproblems, limiting its use in highly dynamic or large-scale real-time decision-making scenarios [41].							
[42]	✓	✓	✓	✓	MT, FC	Cost and emission minimization	Optimized standalone MG energy scheduling using advanced dynamic programming, achieving enhanced efficiency, reduced fuel costs, and decreased emissions. Implemented an optimal energy management system with a constrained single-objective model, minimizing operational and emission costs. Inclusion of battery storage significantly lowered the total costs and emissions, demonstrating system feasibility through simulation.

Table 1. *Cont.*

5. Graphical techniques				
Graphical optimization is an approach where objective functions and constraints are represented graphically to facilitate optimal decision-making. Graph-based methods are particularly useful for distribution network reconfiguration, energy storage scheduling, and resource allocation in MGs [43]. For instance, graph theory has been successfully applied to optimize MG topologies and distributed generation placement, ensuring radiality constraints and minimizing active power losses [44]. Additionally, graph-based P-Graph has been utilized for multi-period hybrid energy storage planning in MGs, enabling efficient energy dispatch and cost-effective hydrogen battery storage integration [45]. Graph theory is increasingly applied in MG power flow modeling and control, representing voltage/current relationships, energy transfer, and system connectivity. Its expansion has enabled alternative power flow methods and improved control strategies. However, graph-based optimization is most effective for structured graph problems. In highly dynamic microgrid scenarios with nonlinear, multi-objective, and stochastic constraints, advanced hybrid techniques may be required [43].				
[46]	Renewable electricity: Produced from localized HRES. -Non-renewable electricity: Generated from fossil fuels	Biogas, hydrogen generation, potential energy carriers (ammonia, urea)	LCOE, CO_2 reduction	Proposed a method for converting surplus renewable electricity, CO_2, and biogas into sustainable hydrogen using a P-Graph graphical optimization approach. Scenarios with 20%, 30%, and 40% demand increments showed annual cost increases of 32%, 27%, and 35%, respectively. Transition to non-renewable electricity began at 20% hydrogen demand, with natural gas usage starting at 40%. Sustainability was enhanced through Pareto frontier and TOPSIS analyses, optimizing the balance between environmental and economic factors.

Abbreviations: SPV = solar photovoltaic, WT = wind turbine, DG = diesel generator, MG = microgrid, HMG = hybrid microgrid, HRES = hybrid renewable energy system, LCOE = levelized cost of electricity, LCOH = levelized cost of hydrogen, MILP = mixed-integer linear programming, CPLEX = commercial optimizer by IBM, HOMER = hybrid optimization model for multiple energy resources, GAMS = general algebraic modeling system, MT = micro-gas turbine, FC = fuel cell.

The table above provides a comparative analysis of the optimization strategies for HMGSs, examining various computational methods, such as iterative processes, NLP, linear programming, and dynamic programming. Each method offers distinct advantages in enhancing the economic, reliability, and environmental outcomes. Iterative methods are often more cost-efficient than traditional models. Meanwhile, NLP addresses stochastic challenges, offering robust solutions in volatile markets. Linear optimization ensures structured problem-solving but may have limitations in handling complexity. In contrast, dynamic programming excels in decomposing complex issues, albeit at a higher computational cost. Overall, these studies highlight the importance of selecting optimization approaches that align with the specific characteristics, goals, and objectives of HMGSs.

2.1.2. Modern Optimization

Modern OTs in the context of HMGSs include metaheuristic and AI approaches that enhance energy system performance, efficiency, and sustainability by addressing complex challenges in real time or near real time.

Metaheuristics are high-level algorithms used to find good solutions for complex problems, especially when exact methods are impractical. Examples include genetic algorithms (GAs), particle swarm optimization (PSO), and ant colony optimization (ACO). These techniques mimic natural processes to explore and exploit solution spaces efficiently.

Artificial intelligence (AI) techniques, such as machine learning, reinforcement learning, and deep learning, learn from data to optimize energy systems. AI is adaptive and can improve system performance by predicting behaviors and making real-time decisions.

Metaheuristics and AI can be combined to leverage their strengths, creating AI-enhanced metaheuristics that improve the search efficiency and provide more effective solutions for HMGS optimization.

a. AI in HMGS optimization

In the context of HMGSs, AI OTs play a pivotal role in managing fluctuating energy sources and demands. These techniques enable dynamic, adaptive control strategies that enhance the stability, efficiency, and resilience of the grid. The key AI techniques used in HMGS optimization include artificial neural networks, reinforcement learning, and deep learning.

- Reinforcement learning

Dynamically adjusts control strategies to optimize the energy flow within HMGSs. Agents learn by performing actions, observing the outcomes, and adjusting their behavior to maximize a predefined reward. This adaptability makes it powerful for creating control policies that can adjust to varying conditions in real time [27]. The merits include its adaptability and proficiency in handling sequential decision-making. However, this approach often requires extensive data for training and presents challenges in designing an appropriate reward system. Unlike other AI techniques that rely solely on data, reinforcement learning learns directly from interactions within its environment, making it uniquely suited for complex, dynamic systems like HMGSs.

- Fuzzy logic

Fuzzy logic is a method of reasoning that handles approximate rather than fixed and exact conclusions, making it well suited for dealing with uncertainties and imprecise information in HMGSs. It is advantageous in HMG optimization due to its simplicity, transparency, and effectiveness in handling nonlinear systems under various conditions. Its main merits include the ease of understanding and implementation, as it relies on expert knowledge rather than extensive data for model training. However, a key challenge lies in defining precise membership functions and rules. Compared to data-driven methods like deep learning and artificial neural networks, fuzzy logic is easier to interpret and implement but may lack the depth and adaptability of those techniques.

- Deep learning

Deep learning, a subset of machine learning, leverages artificial neural networks with multiple layers to effectively recognize patterns and extract features from vast datasets. In HMGS optimization, it excels at forecasting energy consumption and generation, capturing complex nonlinear relationships [28]. Its primary merits include high accuracy in pattern recognition and the ability to handle unstructured data. However, this method requires substantial computational resources and large datasets, and it is often considered a “black box” due to its lack of interpretability. Compared to reinforcement learning and fuzzy logic, deep learning is more data-intensive and is particularly effective for modeling complex patterns.

- Artificial neural networks

Artificial neural networks are computational systems inspired by the biological neural networks in animal brains. They are highly effective at modeling nonlinear relationships, which is essential for predicting and optimizing energy flows in HMGSs [29,30]. A major advantage of these networks is their ability to learn from large datasets and generalize across various scenarios, enabling accurate forecasting and optimization in complex systems. However, a notable drawback is their “black box” nature, which can make the decision-making process challenging to interpret. Compared to fuzzy logic, artificial neural networks require more data for training but can model more intricate relationships than fuzzy logic or traditional AI/metaheuristic approaches.

- AI-enhanced metaheuristic (AI/MH)

AI-enhanced metaheuristic (AI/MH) methods integrate AI techniques, such as learning and adaptation, with metaheuristic algorithms to tackle optimization challenges. In

HMGSs, this approach facilitates more effective search strategies for energy management solutions. The key advantages include a balanced exploration and exploitation of the search space, along with faster convergence to high-quality solutions. However, integrating AI techniques with metaheuristic algorithms can be complex and may increase the risk of overfitting. While AI/MH can often achieve solutions more efficiently than traditional metaheuristics, it requires a more sophisticated design compared to standalone AI methods like deep learning or reinforcement learning.

Studies that utilize these techniques are detailed in Table 2, highlighting the applications, objectives, and findings associated with each AI approach in the context of HMGS optimization.

The collection of research spanning references [31–35] underscores the crucial role of AI-enhanced metaheuristic methods in HMGS optimization. Reinforcement learning and DRNN-LSTM models are notable for their capacity to perform demand-side management and predictive scheduling, leading to improved grid stability and reduced operational costs. The newly developed BWO algorithm exemplifies the efficacy of nature-inspired techniques in the strategic distribution of energy. These studies showcase how intelligent algorithms can adeptly navigate the complexities of energy management, yielding enhanced technical and economic outcomes.

While AI techniques offer advanced capabilities for managing complex, real-time decisions in HMGS optimization, metaheuristic approaches bring a complementary strength through their adaptive, nature-inspired algorithms. These techniques excel in solving multi-objective optimization problems within HMGSs due to their flexibility and robust capacity to navigate vast solution spaces. The following section explores the application of metaheuristic methods in HMGS optimization.

Table 2. Comparative analysis of AI algorithm utilization in autonomous MG optimization studies.

Ref.	SPV	WT	Energy Storage	DG	Other Sources	Optimization Method	Optimization Focus	Key Findings
[47]	✗	✓	✓	✗	✗	Reinforcement learning	Optimize battery scheduling, maximize battery and wind utilization, reduce grid dependence	Applied a 2-step-ahead reinforcement learning algorithm for optimized battery scheduling, addressing wind power uncertainties and mechanical failures to reduce grid reliance. Demonstrated a refined strategy for improved decision-making in MG energy management.
[48]	✓	✓	✓	✓	H_2 production, desalination, heating/cooling	Fuzzy logic, gray prediction algorithms	Intelligent demand side management	Utilized a multi-agent system with gray prediction for demand management in polygeneration MGs, maintaining effective operation even when demand exceeded design specifications. Optimized within capital constraints, ensuring adaptability for future conditions.
[49]	✓	✗	✓	✗	EVs	DRNN-LSTM for forecasting, PSO for load dispatch	Optimal load dispatch with forecasting integration	Applied the DRNN-LSTM model, outperforming MLP and SVM in forecasting the SPV output and residential load. PSO optimized the load dispatch, achieving an 8.97% daily cost reduction through peak load shifting. Coordinated EV charging contributed to cost savings and stability.

Table 2. *Cont.*

Ref.	SPV	WT	Energy Storage	DG	Other Sources	Optimization Method	Optimization Focus	Key Findings
[50]	✗	✓	✗	✗	✗	ANN-based fuzzy controller	Voltage stability in wind-fed isolated MG	The ANN-based fuzzy controller effectively maintained voltage stability in variable wind conditions, achieving stable system performance with acceptable THD levels. It successfully managed power distribution between critical and non-critical loads, ensuring near-nominal voltage throughout the system.
[51]	✓	✓	✓	✓	✗	BWO	Optimal MG energy management with DRPs	The stochastic day-ahead EMS, using price-driven DRPs, optimized the cost and energy coordination by incorporating a flexible price elasticity model for realistic customer responses. The BWO algorithm determined optimal resource scheduling in a 3-feeder MG system, effectively addressing renewable intermittency through stochastic scenario generation.

Abbreviation: SPV: photovoltaic solar, WT: wind turbine, DG: diesel generator, MG: microgrid, HMG: hybrid microgrid, HRES: hybrid renewable energy system, DRNN-LSTM: deep recurrent neural network with long short-term memory, PSO: particle swarm optimization, EVs: electric vehicles, ES: electric spring, AFC: artificial fuzzy controller, ES-AFC: electric spring–artificial fuzzy controller, ANN: artificial neural network, THD: total harmonic distortion, BWO: black widow optimization, DRPs: demand response programs, EMS: energy management system.

b. Metaheuristic techniques in HMGS optimization

Metaheuristic techniques are algorithmic strategies inspired by natural occurrences and animal behavior that are intended to tackle complicated optimization issues. They use a population-based method, repeatedly improving a collection of options to efficiently identify optimum or near-optimal solutions. These strategies are adaptable, able to solve a broad variety of situations when traditional methods may fail owing to the problem's size or complexity [36]. Here is an overview of the three well-known metaheuristic algorithms, particularly in the context of optimizing an HMGS:

- Particle swarm optimization (PSO): PSO is a metaheuristic that seeks solutions by optimizing particle placements based on natural social behavior. PSO is commonly used to assess HMGSs, as indicated by its inclusion in several research studies. For example, Ref. [37] identifies optimum system topologies and component sizes while considering dependability, cost, and environmental effect, and for enhancing energy management systems in MGs with optimized artificial networks for improved performance and renewable integration, as illustrated in reference [38]. Furthermore, Ref. [39] emphasizes PSO's application in designing and optimizing a smart DC MG's multi-objective function for an HMGS of SPV, WT, and biogas-based IC engine generators, with the goal of maximizing power availability while lowering costs, demonstrating PSO's superior performance in cost reduction and high availability when compared to other algorithms.
- Genetic algorithm (GA): A GA is a metaheuristic inspired by natural selection that use selection, crossover, and mutation to develop solutions toward optimality, which has been widely utilized in various studies to evolve candidate solutions toward optimality. For example, in Ref. [40], the GA improves HMGSs in order to reduce energy production costs while increasing dependability and environmental advantages. Ref. [41] demonstrates GA's use in designing energy management systems for MGs,

with an emphasis on maximizing the profit from energy exchanges and minimizing system complexity for improved smart grid integration. Another application of a GA, as detailed in Ref. [42], is optimizing a hybrid SPV/WT, addressing the loss of load probability (LLP) and system cost by selecting the optimal capacities for the SPV array, wind turbine, and battery, optimizing the SPV array tilt angle, and determining the ideal inverter size, demonstrating the GA's versatility in addressing complex optimization challenges in HMGSs.

- Ant colony optimization (ACO): ACO is a metaheuristic inspired by ant foraging behavior that efficiently solves discrete optimization problems such as routing and scheduling. ACO shows adaptability in HMGS optimization across several studies. Ref. [43] investigates the use of ACO for supervisory control in alternative energy distributed generation MGs, aiming to improve dispatch management while taking environmental and economic factors into account. Ref. [44] uses ACO for maximum power point tracking (MPPT) to enhance power quality in islanded MGs by optimizing HRESs units. Lastly, Ref. [45] applies ACO to an energy management system (EMS) in MGs, concentrating on cost-efficient scheduling and demonstrating significant cost savings over standard EMS and PSO approaches, demonstrating ACO's efficiency in complicated, multi-objective optimization tasks inside HMGSs.

In summary, metaheuristic techniques bring a flexible, adaptive approach to optimizing HMGS by drawing on nature-inspired algorithms to tackle complex, multi-objective challenges. While AI and metaheuristics both play critical roles in HMGS optimization, the need for dedicated STs becomes evident in scaling, simulating, and operationalizing these advanced techniques. The next section explores the STs commonly employed in HMGS optimization, detailing how they assist in system design, simulation, and analysis to achieve cost-effective, reliable, and sustainable energy management solutions.

2.2. STs for HMGS Optimization

The classification of STs for HMGS optimization is based on their primary roles in the design and optimization process [52]. These tools can be categorized into feasibility assessment tools, design and sizing tools, simulation and modeling tools, optimization tools, and comprehensive tools, as illustrated in Figure 4.

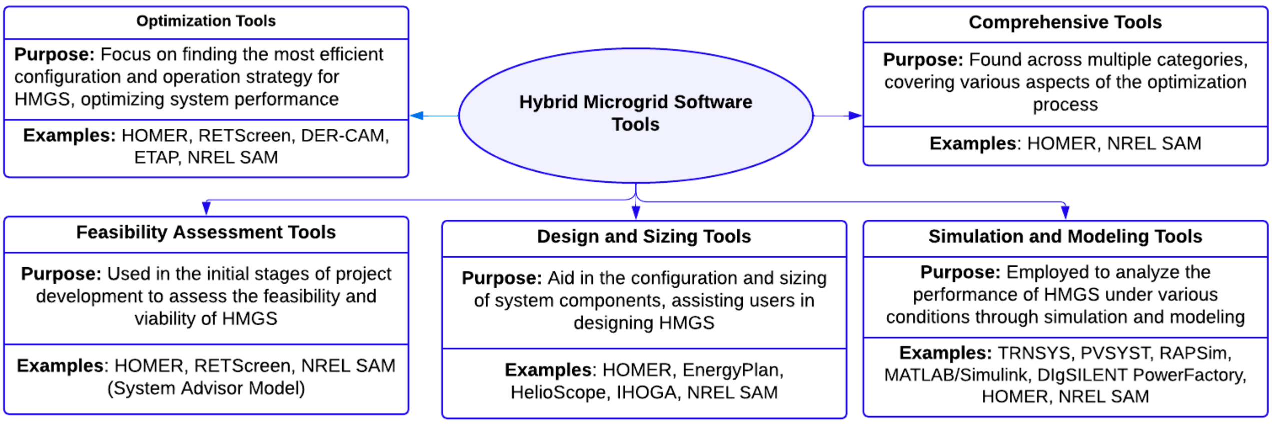


Figure 4. Classification of STs for HMGS optimization.

- Feasibility assessment tools: Used in the initial stages to assess the viability and potential of HMGS designs.
- Design and sizing tools: Aid in configuring and sizing system components to ensure they meet design requirements.

- Simulation and modeling tools: Analyze system performance under various conditions and predict behavior during operation.
- Optimization tools: Focus on improving the system's performance by finding the most cost-effective and energy-efficient operational strategies.
- Comprehensive tools: Integrate multiple functions, offering a holistic approach to designing, simulating, and optimizing HMGSs.

Each category serves a distinct purpose in guiding the development and optimization of HMGSs, ensuring that the designs are both technically sound and economically viable.

These tools have been applied in various studies, each emphasizing key economic performance metrics:

- Levelized cost of energy (LCOE): Represents the average cost per unit of electricity generated over the system's lifetime, serving as a critical metric for assessing long-term economic viability.
- Net present cost (NPC): Evaluates the total lifetime costs, including installation, maintenance, and operational expenses, providing a comprehensive assessment of the overall costs.
- Net present value (NPV): Assesses the profitability of a system by comparing the present values of the costs and revenues, helping to determine the project's economic feasibility.

These metrics are essential for designing cost-effective and technically sound HMGSs, particularly in isolated or grid-connected systems. Table 2 provides a summary of the research studies that utilize these STs, detailing each tool's functionality and primary findings.

Table 3 presents a diverse range of research studies that have utilized various STs to optimize HMGSs. These studies demonstrate how tools like HOMER, RETScreen, and NREL SAM have been employed for feasibility assessments, system design, and cost optimization. A common theme is the frequent integration of SPV with other energy sources such as WT, biomass, and DGs. Many of the studies prioritize reducing costs, particularly through the optimization of the LCOE, which has become a central performance metric. HOMER stands out as a widely used tool for its comprehensive ability to model, simulate, and optimize HMGSs, particularly in balancing technical performance with economic feasibility. As the table illustrates, the choice of software is crucial, depending on the system's complexity and the desired outcome, whether it is for off-grid or grid-connected configurations.

Building on these findings, the next section delves into the evolution of OTs and tools in HMGSs, highlighting the role of advanced AI and metaheuristic methods in achieving efficiency and reliability. This analysis also examines how STs have adapted to support increasingly complex technical and economic objectives in HMGSs, facilitating a balance between performance and cost-effectiveness.

Table 3. Research studies on HMGS optimization using different software programs.

Ref.	SPV	WT	Energy Storage	DG	Other Sources	Optimization Focus	Key Findings	Software Tool	Software Description
[53]	✓	✓	✓	✓	✗	LCOE, LCOH	Assessed HMG for green hydrogen production on a remote island. Scenario analysis revealed 80% RES as most cost-effective.	HOMER	Hybrid optimization of multiple energy resources (HOMER) was developed in 1993 by the National Renewable Energy Laboratory (NREL) [54]. It is designed to model and simulate various RESs, and it excels in cost analysis and sensitivity analysis, with integration capabilities for typical meteorological year (TMY2) data for weather and solar radiation, or user-provided data [55]. HOMER employs a proprietary simulation-based approach for optimization, using sensitivity analysis and a search algorithm to identify the lowest-cost system configurations across various input variables. It is widely used for the economic and technical assessment of large-scale HESs. Strength: Excellent for optimizing component sizing and conducting thorough cost analyses, with advanced sensitivity analysis capabilities. Weakness: May not capture all the dynamics of complex system behavior without precise, customized input data.
[56]	✓	✓	✓	✗	Biomass	Size, LCOE	Proposed SPV-WT-biomass storage system to meet remote area needs. ABC algorithm shortened simulation time vs. HOMER and PSO.	HOMER ABC PSO	
[57]	✓	✓	✗	✗	Biomass	Size, LCOE	HMGS for a 50 MW power plant in Pakistan; profitable with national grid integration, ideal for regions with frequent power outages.	HOMER	
[58]	✓	✓	✓	✗	✗	LCOE	Techno-economic assessment for off-grid HMGSs in the USA, Canada, and Australia; evaluated SPV-WT-battery with hydrogen storage. Minimum COE achieved with integrated SPV-WT battery, electrolyzer, and hydrogen tank, reducing costs to 0.50 USD/kWh compared to non-battery configurations at 0.78 USD/kWh.	HOMER	
[59]	✓	✓	✓	✓	✗	Cost, size	Assessed thermal energy storage in an islanded HMGS; DG contributed to higher COE.	IHOGA	IHOGA, developed by researchers at the University of Zaragoza, Spain, is designed for simulating and optimizing RES-based electric power systems. It has two versions: IHGO for systems up to 5 MW and MHOGA for larger systems without capacity limits. IHOGA's library includes diverse components like the SPV, WT, batteries, hydropower turbines, and various generators. It calculates the NPC, LCOE, NPV, IRR, and battery lifespan, using genetic algorithms to improve system efficiency and reduce costs over successive iterations [60]. Strength: Effective genetic algorithm for optimizing cost and sizing in HES. Weakness: Computationally intensive; may require fine-tuning for complex systems.

Table 3. *Cont.*

Ref.	SPV	WT	Energy Storage	DG	Other Sources	Optimization Focus	Key Findings	Software Tool	Software Description
[61]	✓	✓	✓	✓	Biomass	Cost, feasibility	Evaluated HMGSs for tourist regions in Europe, achieving 99% user demand coverage with RES in Gdansk, Poland, and 43% surplus in Agkistro, Greece.	TRNSYS	TRNSYS, developed in 1975 by France, Germany, and the United States, is a transient systems simulation tool used across various energy applications, including biomass, cogeneration, hydrogen fuel cells, wind and SPV systems, high-temperature solar, and geothermal heat pumps. It requires minimal data and computational resources, making it suitable for preliminary assessments [62,63]. Strength: High-fidelity transient simulation ideal for detailed technical system analysis. Weakness: Economic optimization is not the primary focus and may need additional modules for financial assessment.
[64]	✓	✓	✓	✗	Biomass hydropower	CO_2 reduction	Decarbonization study for Sichuan Province: Scenarios showed energy storage significantly reduced operational costs while requiring high investment, demonstrating feasibility for hydropower-rich regions.	EnergyPLAN	EnergyPLAN, developed by Aalborg University's Sustainable Energy Planning Research Group in Denmark in 2000, is a deterministic simulation tool for modeling national energy systems, including power, heating, cooling, industry, and transportation [65]. Strength: Effective for strategic policy scenario analysis. Weakness: Primarily a simulation tool, requiring additional software for detailed optimization.
[66]	✓	✗	✗	✗	✗	Modeling and simulation	Demonstrated RAPSim for optimal DG placement in an MG, considering SPV output variability influenced by solar radiation and time-dependent factors. Showcased the software's capabilities in data output, scenario management, and temporal/weather simulation.	RAPSim	Developed at Alpen Adria University Klagenfurt, RAPSim is an open-source tool for RES simulation in grid-connected and off-grid MGs. It prioritizes power production estimation for each source before conducting power flow analysis [67]. Strength: Detailed simulation for RES with scenario management. Weakness: Lacks built-in economic and sensitivity analysis; may require additional tools for comprehensive assessments.

Table 3. *Cont.*

Ref.	SPV	WT	Energy Storage	DG	Other Sources	Optimization Focus	Key Findings	Software Tool	Software Description
[68]	✓	✗	✗	✗	✗	Techno-economic, feasibility	Assessed the viability of a 500 kW SPV MG across 12 sites in Nigeria, including a techno-economic analysis. Findings showed economic feasibility at all sites, with payback periods ranging from 6.3 to 7.4 years based on NPC, internal rate of return, and payback period metrics.	RETScreen	Developed by Canada's Ministry of Natural Resources, RETScreen is a publicly available tool for assessing the costs and benefits of RE technologies worldwide. Released in 1998, RETScreen is particularly useful for on-grid feasibility analysis [69]. Strength: Comprehensive feasibility analysis, covering financial viability and risk assessment. Weakness: Limited in optimization capabilities; primarily focused on project feasibility rather than detailed system design.
[70]	✓	✗	✓	✗	✗	LCOE, feasibility	Evaluated a grid-connected MG with SPV and energy storage, comparing lead-acid (LA) and lithium-ion (LI) batteries. Findings showed that LI batteries are more feasible, with an LCOE of 6.75, compared to 10.6 for LA.	NREL SAM	The system advisor model (SAM), developed by NREL and Sandia National Laboratories, provides a robust platform for techno-economic analysis across various RESs, including CST, SPV, WT, fuel cells, biomass, and geothermal. It offers insights into CST technologies and RESs globally, available as a free, versatile tool for technical and financial assessments [71,72]. Strength: Highly versatile for techno-economic analysis and performance modeling across diverse RESs. Weakness: Broad capabilities may lack the specificity found in dedicated optimization tools.
[73]	✓	✓	✗	✓	✗	MG protection using communication-assisted digital relays	Proposed a protection scheme using digital relays with communication networks. Demonstrated detection of high-impedance faults in a high-penetration HMGS. Simulated in MATLAB/Simulink's SimPowerSystems toolbox.	MATLAB/ Simulink	MATLAB/Simulink, developed by MathWorks, is a high-performance environment for technical computing and simulation, extensively used for modeling, simulating, and analyzing dynamic systems, including MGs [74]. It enables integration with toolboxes like SimPowerSystems for RE applications, grid modeling, and fault detection in MGs [73]. Strength: Flexible and highly customizable, with extensive libraries for RES modeling and advanced fault analysis. Weakness: Requires expertise for custom implementation; computationally intensive for large-scale simulations.

Abbreviations: SPV: solar photovoltaic, WT: wind turbine, DG: diesel generator, HMGs: hybrid microgrid systems, LCOE: levelized cost of energy, LCOH: levelized cost of hydrogen, HOMER: hybrid optimization of multiple energy resources, CO_2: carbon dioxide, NPC: net present cost, ABC: artificial bee colony, PSO: particle swarm optimization, IHOGA: improved hybrid optimization by genetic algorithms, NPV: net present value, IRR: internal rate of return, NPC: net present cost, TRNSYS: transient system simulation, RAPSim: renewable alternative power systems simulation, SAM: system advisor model, CST: concentrating solar thermal, FC: fuel cell, LA: lead-acid battery, LI: lithium-ion battery.

3. Evolution of Techniques and Tools (Scopus Analysis)

The exploration of the scientific literature over time enables researchers to track the development and emerging trends within a specific field. This section investigates the evolution of OTs and STs for HMGSs, utilizing Scopus as the primary database. This analysis sheds light on the increasing complexity and advancements in the field, pinpointing key areas where OTs have gained significant traction and addressing insights noted in previous work.

Following the established best practices for systematic reviews, as shown in Figure 5, this study followed these steps:

1. Problem Planning and Formulation

- Defined research questions and objectives.
- Established criteria for selecting relevant literature.
- Outlined potential conclusions based on the findings.

2. Database, Keywords, and Search String Determination

- Selected Scopus as the primary database.
- Identified relevant keywords to ensure a comprehensive search.
- Developed a focused search string aligned with this study's objectives.

3. Literature Selection

- Applied the PRISMA methodology to screen and select relevant articles.
- Excluded unrelated studies, books, and non-English publications.

4. Analysis of Results

- Extracted insights from the selected studies.
- Analyzed trends, gaps, and emerging areas of focus in the field.

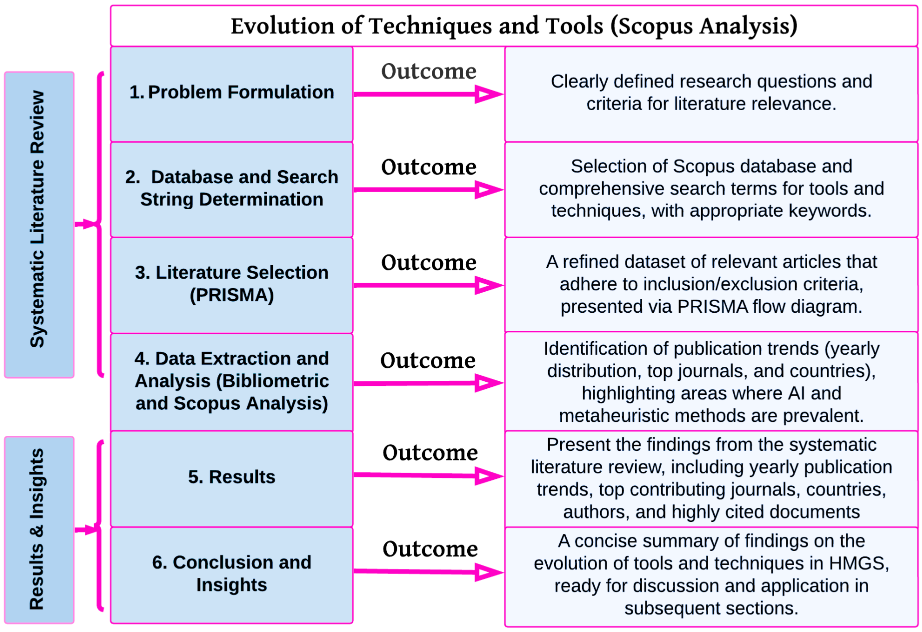


Figure 5. Systematic review process for the evolution of OTs and STs in HMGSs.

Figure 5 outlines the systematic review process for tracing the evolution of OTs and tools in the HMGS research. With this structured approach, we have gathered a comprehensive dataset of studies that reflect the trajectory and advancements in the field. The following sections present the results of our bibliometric and Scopus analyses, offering insights into the publication trends, leading journals, and geographic contributions in the domain of HMGS OTs and tools. These data reveal patterns and emerging areas of focus that highlight the growing role of AI and metaheuristic methods within HMGS research.

4. Systematic Review Framework and Results

This section presents the findings from the systematic review of OTs and STs in HMGSs, following the methodology outlined in Figure 5. It encompasses the structured review process (PRISMA) and the results derived from the analysis.

4.1. Problem Formulation

This study aims to map the current knowledge landscape surrounding OTs and STs in HMGSs through a systematic, category-specific analysis. By carefully selecting and applying relevant keywords in an advanced Scopus search, this study establishes a focused foundation for analyzing advancements in both techniques and tools, setting the stage for in-depth exploration and evaluation.

4.2. Database and Search String Determination

To ensure a comprehensive and targeted search, the keyword selection was based on three key criteria:

1. Relevance to HMGS optimization: Keywords were chosen to cover a broad range of OTs and STs commonly applied in HMGSs.
2. Coverage of classical and modern methods: The selection includes both classical approaches and widely adopted modern AI-enhanced metaheuristics to reflect proven advancements in optimization.
3. Scientific and practical significance: Keywords were derived from highly cited studies and standard industry practices, ensuring alignment with widely recognized methods in HMGS research.

Scopus was chosen for its vast collection of important scientific publications, ensuring thorough and reliable data collection. The search strategy focused on selecting relevant studies based on clear inclusion criteria while maintaining accuracy in identifying impactful research.

4.2.1. OTs

For this study, the Scopus database was selected due to its extensive repository of globally significant scientific publications across a wide range of fields. The review focused on core topics in relation to HMGSs, including MGs, renewable energy systems, and various OTs spanning both classical and modern approaches (as illustrated in Figure 3). To capture relevant studies, an advanced Scopus search was performed using the following search string: TITLE-ABS-KEY ((“microgrid” OR “micro grid” OR “micro-grid” OR “microgrids” OR “hybrid microgrid systems” OR “hybrid microgrid system” OR “rural microgrid” OR “urban microgrid”) AND (“renewable energy” OR “renewable energy sources” OR “renewable energy systems” OR “hybrid energy” OR “distributed energy resources” OR “hybrid energy systems” OR “hybrid energy sources” OR “hybrid power system”) AND (“optimization techniques” OR “metaheuristics” OR “genetic algorithm” OR “GA” OR “particle swarm optimization” OR “PSO” OR “ Ant Colony Optimization” OR “ACO” OR “evolutionary algorithms” OR “swarm intelligence” OR “Genetic programming” OR “Differential evolution” OR “Simulated annealing” OR “Tabu search” OR “Harmony search” OR “artificial intelligence” OR “Deep reinforcement learning” OR “fuzzy logic” OR “deep learning” OR “Deep reinforcement learning” OR “Support vector machine” OR “reinforcement learning” OR “machine learning” OR “artificial neural networks” OR “AI-enhanced metaheuristic" OR "linear programming" OR "non linear programming" OR "graphical technique" OR "iterative technique" OR "dynamic programming")).

4.2.2. STs

Similarly, the Scopus database served as the primary source for the literature on STs used in HMGS optimization. This segment of the review targeted topics related to microgrids, renewable energy systems, and specialized STs (as illustrated in Figure 3). The advanced Scopus search string applied to capture relevant software-focused studies was as follows: TITLE-ABS-KEY (("microgrid" OR "micro grid" OR "micro-grid" OR "microgrids" OR "hybrid microgrid systems" OR "rural microgrid" OR "urban microgrid" OR "hybrid microgrid system") AND ("renewable energy" OR "renewable energy sources" OR "renewable energy systems" OR "hybrid energy" OR "distributed energy resources" OR "hybrid energy systems" OR "hybrid energy sources" OR "hybrid power system") AND ("HOMER" OR "HOGA" OR "TRNSYS" OR "HYGROGEMS" OR "INSEL" OR "ARES" OR "RAPSIM" OR "SOMES" OR "SOLSIM" OR "MATLAB/Simulink" OR "OpenDSS" OR "System Advisor Model" OR "SAM" OR "REopt" OR "PVSYST" OR "Helioscope" OR "DIgSILENT PowerFactory" OR "PSCAD")).

4.3. Literature Selection (PRISMA Analysis)

The PRISMA flowchart methodology was rigorously followed, as illustrated in Figures 6 and 7, to systematically refine and select relevant articles for both OTs and STs. This process ensured that the final dataset included only the most relevant studies aligned with the objectives of this research.

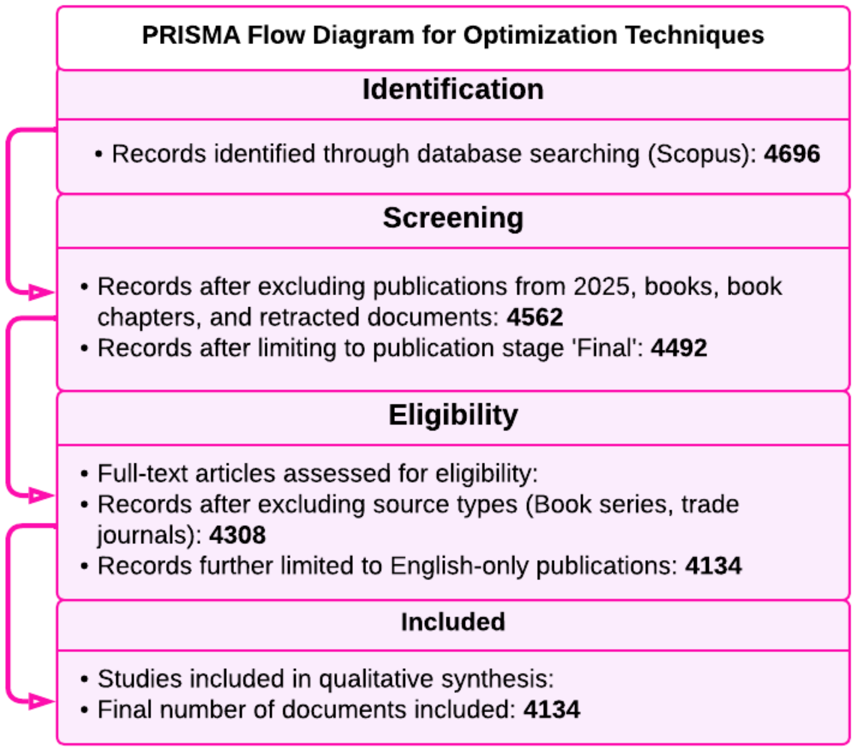


Figure 6. PRISMA flow diagram for the OT selection.

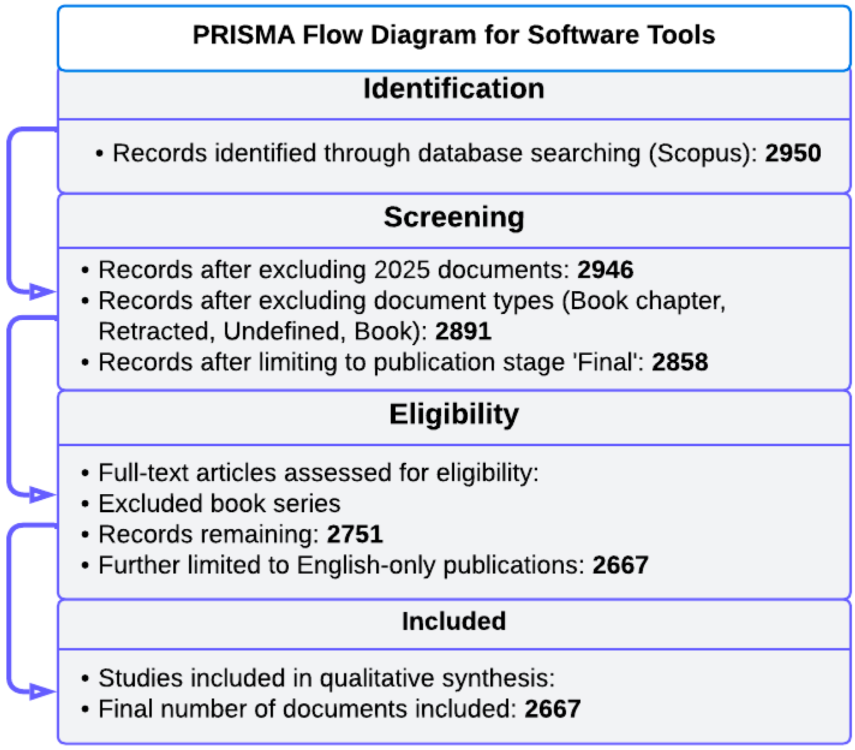


Figure 7. PRISMA flow diagram for the ST selection.

The selection process included four key stages:

- Identification—A total of 4696 OT-related and 2950 ST-related records were retrieved from Scopus.
- Screening—Duplicate entries, books, and retracted papers were removed. Additionally, only studies classified as "Final" publications were retained, reducing the count to 4492 OT-related and 2858 ST-related studies.
- Eligibility—Further refinement excluded book series for both OTs and STs. Additionally, trade journal papers were removed only for OTs, while no trade journal exclusions were applied to STs in this step. Finally, English-only publications were retained, resulting in 4134 OT-related and 2667 ST-related studies.
- Inclusion—The final dataset consisted of 4134 OT-related and 2667 ST-related studies used for the qualitative synthesis and analysis.

Note: The document count for the year 2024 includes publications retrieved up to November. Documents published beyond this date were excluded due to the review timeline.

To ensure a rigorous selection process, we applied the following inclusion and exclusion criteria:

Inclusion Criteria:

- Studies published in peer-reviewed journals and conference proceedings.
- Research that focuses on OTs and STs applied to HMGSs.
- Articles that include quantitative analysis, simulations, or case studies demonstrating the application of OTs and STs.
- Papers published in English to maintain consistency and accessibility.

Exclusion Criteria:

- Duplicate and irrelevant records removal

Initial filtering removed duplicate entries and irrelevant records, ensuring only unique and relevant studies were considered.

- Exclusion based on document type

Books, book chapters, retracted papers, and undefined document types were excluded.

- Exclusion based on publication stage

Only studies classified as "Final" publications were retained, removing preliminary or non-peer-reviewed works.

- Eligibility assessment and further refinement

Book series were excluded as they do not contribute original, peer-reviewed research.

Non-English publications were removed to maintain consistency and avoid translation inaccuracies.

The following subsections detail the application of PRISMA for each category.

4.3.1. Optimization Techniques

The selection process for OTs was conducted following the PRISMA flowchart guidelines, as depicted in Figure 6.

Initially, 4696 records were retrieved from the Scopus database. Screening excluded publications from 2025, books, book chapters, and retracted documents, narrowing the count to 4562. Limiting the results to "Final" publications further reduced this to 4492. In the eligibility phase, additional exclusions, including book series and trade journals, brought the total to 4308. Finally, limiting the results to English-only publications resulted in 4134 relevant papers for analysis.

4.3.2. STs

Following the PRISMA guidelines (Figure 7), the selection began with 2945 records from Scopus.

Initially, 2950 records were retrieved from Scopus. Screening excluded 2025 publications, books, chapters, retracted documents, and undefined documents, narrowing the count to 2891. Limiting the publication stage to "Final" reduced this to 2858. Further refinement in the eligibility phase excluded book series, bringing the count to 2751. Finally, limiting the results to English-language publications resulted in 2667 relevant papers for analysis.

5. Results

This section presents the findings from the systematic literature review, organized into key subsections reflecting the outcomes derived from the analysis. The results include the yearly publication trends, contributions from top journals, countries, authors, and insights into highly cited documents. These analyses provide an overarching view of the evolution and focus areas within the field of OTs and STs for HMGSs.

5.1. Yearly Distribution of Documents

The distribution of documents over the years highlights the growing interest in OTs and STs for HMGSs.

5.1.1. OTs

Figure 8 illustrates the yearly distribution of documents related to OTs in HMGSs.

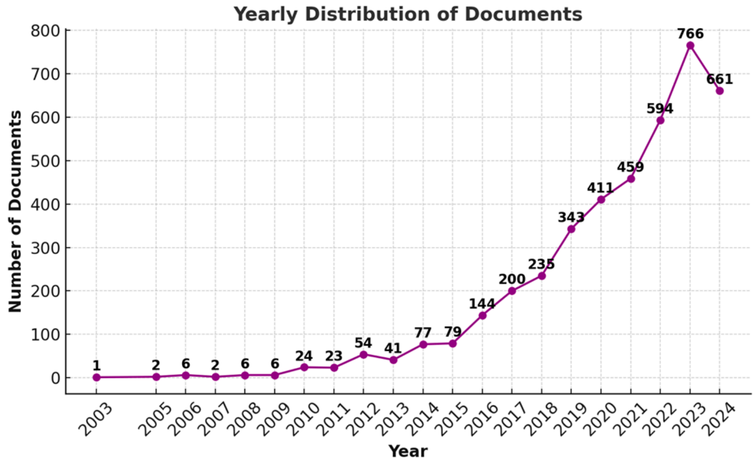


Figure 8. Yearly distribution of documents related to OTs in HMGSs (2003–2024).

A noticeable surge in the number of publications is observed, particularly after 2018, reflecting the growing academic and industrial interest in this field. This trend emphasizes the expanding research focus on optimizing HMGSs and the increasing adoption of advanced optimization methods.

To gain deeper insights into this collection of documents, our analysis quantified the percentage participation of each category of OT. The participation ratio of each category (P_c) was determined using the following equation:

$$P_c = \left(\frac{N_c}{N_t}\right) \times 100\%. \tag{1}$$

where:

P_c = Relative research weight (%) of a specific optimization technique category.

N_c = Number of documents in a specific category.

N_t = Total number of documents analyzed.

This measure provides a normalized representation of the research trends, allowing for comparative analysis across different optimization paradigms.

The results from our analysis indicate the following distribution:

- Classical techniques: P_c = 16.87% (N_c = 697, N_t = 4134)
- Artificial-intelligence-based techniques: P_c = 36.01% (N_c = 1489, N_t = 4134)
- Metaheuristic techniques: P_c = 47.12% (N_c = 1848, N_t = 4134)

The dominance of metaheuristic methods underscores their adaptability and effectiveness in addressing the complexities inherent in HMGS optimization, such as nonlinearity, uncertainty, and multi-objective constraints. This prevalence highlights a growing reliance on advanced algorithms capable of providing robust and efficient solutions for real-world energy systems.

5.1.2. STs

Figure 9 illustrates the yearly distribution of documents related to STs in HMGSs, highlighting a notable rise in publications, particularly after 2015.

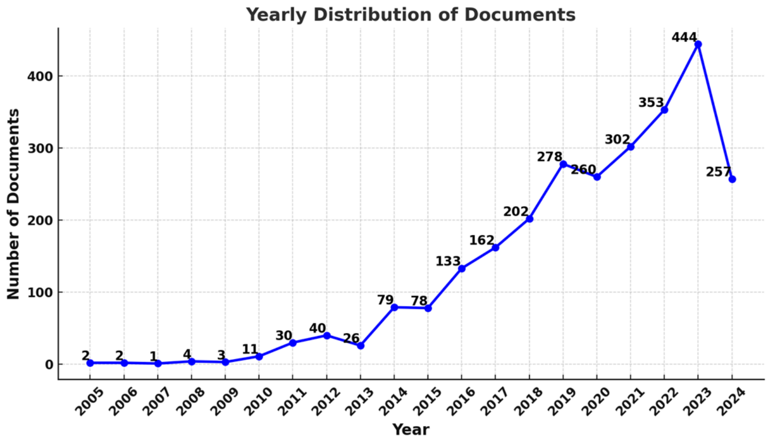


Figure 9. Yearly distribution of documents related to STs in HMGSs (2005–2024).

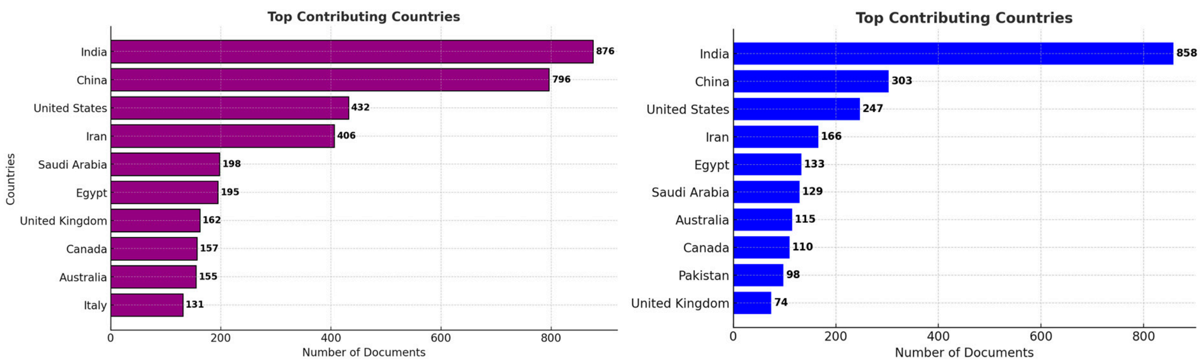
Among the 2667 documents analyzed, the distribution of ST utilization was assessed based on the relative research weight. MATLAB/Simulink exhibited the highest prevalence, appearing in 1743 documents (65.34%), while HOMER followed with 589 occurrences (22.08%). The participation ratios were derived using Equation (1), providing a comparative measure of the research focus across different STs. The dominance of MATLAB/Simulink and HOMER reflects the strong industry and academic preference for commercial tools in HMGS research. As discussed in Table 3, commercial software provides validated models, extensive libraries, and industry-standard simulation capabilities, making them reliable choices for HMGS analysis. However, licensing costs can limit accessibility, particularly for researchers in developing regions.

In contrast, open-source tools such as OpenDSS and RAPSim remain underrepresented in the dataset despite their potential advantages, including cost efficiency, transparency, and adaptability for specific MG applications. The lower adoption rate of these tools is often attributed to the limited technical support, fewer built-in optimization features, and steeper learning curve compared to commercial alternatives.

While MATLAB/Simulink continues to dominate, the increasing demand for cost-effective and customizable MG solutions may drive greater adoption of open-source tools in future research.

5.2. Top Contributing Countries

Figure 10a,b illustrate the top 10 contributing countries for OTs and STs, respectively.



(**a**) OTs (**b**) STs

Figure 10. Top contributing countries for (**a**) OTs and (**b**) STs.

India leads in both categories, followed by China and the United States. Other significant contributors include Iran, Saudi Arabia, and Egypt, along with notable participation from developed countries such as the United Kingdom and Canada. These results emphasize the global interest and collaborative efforts in advancing HMGS research.

5.3. Top Cited Documents

5.3.1. Top Cited Documents for OTs

The top 10 cited documents listed in Table 4 illustrate the diverse methodologies and advanced OTs applied in HMGSs.

Table 4. Top 10 highly cited documents for OTs in HMGSs.

Ref.	Authors	Journal	Year	Citations
[75]	Chaouachi, A., Kamel, R.M., Andoulsi, R., Nagasaka, K.	*IEEE Transactions on Industrial Electronics*	2013	575
[76]	Moghaddam, A.A., Seifi, A., Niknam, T., Alizadeh Pahlavani, M.R.	*Energy*	2011	540
[77]	Bevrani, H., Habibi, F., Babahajyani, P., Watanabe, M., Mitani, Y.	*IEEE Transactions on Smart Grid*	2012	519
[78]	Ahmad, T., Zhang, D., Huang, C., Song, Y., Chen, H.	*Journal of Cleaner Production*	2021	483
[79]	Morais, H., Kádár, P., Faria, P., Vale, Z.A., Khodr, H.M.	*Renewable Energy*	2010	476
[80]	Suganthi, L., Iniyan, S., Samuel, A.A.	*Renewable and Sustainable Energy Reviews*	2015	435
[81]	Long, C., Wu, J., Zhou, Y., Jenkins, N.	*Applied Energy*	2018	422
[79]	Ramli, M.A.M., Bouchekara, H.R.E.H., Alghamdi, A.S.	*Renewable Energy*	2018	421
[34]	Chakraborty, S., Weiss, M.D., Simões, M.G.	*IEEE Transactions on Industrial Electronics*	2007	403
[82]	Borhanazad, H., Mekhilef, S., Gounder Ganapathy, V., Modiri-Delshad, M., Mirtaheri, A.	*Renewable Energy*	2014	393

The most cited studies on HMGS optimization demonstrate significant advancements in optimization methodologies, including AI-based approaches, metaheuristics, and mathematical programming techniques. Chaouachi et al. [75] pioneered the integration of AI with linear programming and fuzzy logic for MG energy management, enhancing forecasting accuracy and battery scheduling to minimize operational costs and emissions. Moghaddam et al. (2011) [76] introduced the adaptive modified particle swarm optimization (AMPSO) algorithm, incorporating chaotic local search (CLS) and fuzzy self-adaptive (FSA) structures to improve the cost and emission minimization in MGs, outperforming traditional evolutionary algorithms. Bevrani et al. (2012) [77] developed an intelligent frequency control approach combining fuzzy logic with PSO, demonstrating superior adaptability in maintaining grid stability under uncertain renewable generation. Ahmad et al. [78] highlighted AI's transformative role in the energy sector, emphasizing its applications in smart grid optimization, predictive maintenance, cyberattack prevention, and real-time decision-making, positioning AI as a key enabler of the future digital energy market. Morais et al. (2010) [79] applied MILP for the optimal scheduling of generation units in an isolated DC-MG, proving its effectiveness in economic dispatch and real-time load balancing with rapid convergence. Collectively, these studies illustrate the evolution of advanced OTs, reinforcing their critical role in improving MG efficiency, reliability, and economic performance.

5.3.2. Top Cited Documents for STs

STs are indispensable for optimizing HMGSs, offering advanced capabilities in design, modeling, and management. Table 5 lists the top 10 highly cited articles in this domain, highlighting diverse applications of STs.

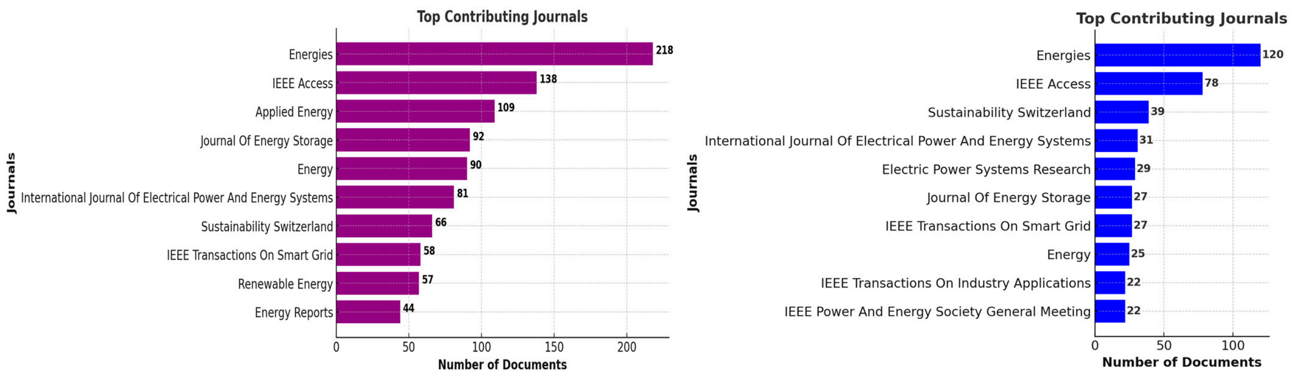
Table 5. Top 10 highly cited documents for STs in HMGSs.

Ref.	Authors	Journal	Year	Citations
[73]	Sortomme, E., et al.	*IEEE Transactions on Power Delivery*	2010	513
[83]	Hafez, O., Bhattacharya, K.	*Renewable Energy*	2012	489
[56]	Singh, S., et al.	*Energy Conversion and Management*	2016	383
[33]	Amrollahi, M.H., Bathaee, S.M.T.	*Applied Energy*	2017	340
[84]	Badal, F.R., et al.	*Protection and Control of Modern Power Systems*	2019	332
[57]	Ahmad, J., et al.	*Energy*	2018	282
[58]	Abdin, Z., Mérida, W.	*Energy Conversion and Management*	2019	268
[85]	Ou, T.-C., Hong, C.-M.	*Energy*	2014	221
[86]	Yu, X., et al.	*IEEE Transactions on Smart Grid*	2014	206
[87]	Li, J., et al.	*Applied Energy*	2017	202

One notable study introduced a communication-assisted digital relay protection scheme using MATLAB/Simulink, ensuring reliable fault detection in MGs with high DG penetration [73]. Another study utilized HOMER to minimize the life-cycle costs and assess the environmental impacts across various MG configurations, showcasing its versatility in HES analysis [83]. HOMER and GAMS software were combined to implement demand response programming, achieving substantial reductions in the battery and inverter requirements and total net present costs [33]. These studies collectively underscore the vital role of STs in enhancing the efficiency and reliability of HMGSs through robust optimization methodologies.

5.4. Top Contributing Journals

Figure 11a,b highlight the top contributing journals in the fields of OTs and STs for HMGSs, respectively. Both figures underscore the dominance of *Energies* and *IEEE Access* in terms of the document contributions. *Energies* leads the field with 218 documents for OTs and 120 documents for STs, reflecting its significant role in advancing HMGS research. Other key contributors include *Applied Energy*, *Journal of Energy Storage*, and *International Journal of Electrical Power and Energy Systems*, which consistently publish high-impact research.



(**a**) OT (**b**) ST

Figure 11. Top contributing journals for (**a**) OTs and (**b**) STs.

The top ten highly cited documents in Table 6 showcase cutting-edge OTs driving advancements in HMGSs.

Table 6. Top 10 contributing journals for OTs in HMGSs.

Rank	Journal Name	Number of Documents	Highly Cited Article	Citation Count
1	*Energies*	218	[88]	186
2	*IEEE Access*	138	[89]	172
3	*Applied Energy*	109	[81]	422
4	*Journal of Energy Storage*	92	[90]	244
5	*Energy*	90	[76]	540
6	*International Journal of Electrical Power and Energy Systems*	81	[91]	179
7	*Sustainability Switzerland*	66	[92]	127
8	*IEEE Transactions on Smart Grid*	58	[77]	519
9	*Renewable Energy*	57	[79]	476
10	*Energy Reports*	44	[93]	100

A novel energy management approach using DRL modeled as a Markov decision process (MDP) effectively addresses the challenges of uncertainty in the load demand, RESs variability, and electricity price fluctuations, achieving significant operational cost reductions [88]. To tackle the frequency stability in low-inertia MGs with high renewable penetration, self-adaptive virtual inertia control based on fuzzy logic dynamically adjusts the inertia constants in real-time, delivering an enhanced transient response and robust system stability [89]. Furthermore, a two-stage aggregated control framework for peer-to-peer (P2P) energy sharing within community MGs leverages constrained nonlinear programming (CNLP) optimization. This method achieves up to 30% cost savings for the community and notable economic benefits for individual prosumers [81]. These studies emphasize the essential role of advanced OTs in addressing critical challenges in HMGS design and operation.

The highly cited documents listed in Table 7 illustrate the critical role of advanced STs in modeling, simulating, and optimizing HMGSs. MATLAB/Simulink has been effectively used for load frequency control (LFC) in isolated MGs, leveraging multivariable generalized predictive control to stabilize the frequency amidst fluctuating RESs and continuous load disturbances [93]. HOMER Pro has been instrumental in conducting techno-economic feasibility analyses, identifying optimal configurations for HESs by evaluating parameters such as the NPC, COE, and greenhouse gas emissions across various sensitivity scenarios [94].

Table 7. Top 10 contributing journals for STs in HMGSs.

Rank	Journal Name	Number of Documents	Highly Cited Article	Citation Count
1	*Energies*	120	[93]	148
2	*IEEE Access*	78	[94]	125
3	*Sustainability Switzerland*	39	[95]	154
4	*International Journal of Electrical Power and Energy Systems*	31	[96]	130
5	*Electric Power Systems Research*	29	[97]	81
6	*Journal of Energy Storage*	27	[98]	59

Table 7. *Cont.*

Rank	Journal Name	Number of Documents	Highly Cited Article	Citation Count
7	*IEEE Transactions on Smart Grid*	27	[86]	206
8	*Energy*	25	[57]	282
9	*IEEE Transactions on Industry Applications*	22	[99]	142
10	*IEEE Power and Energy Society General Meeting*	22	[100]	48

Additionally, HOMER Pro was employed to assess the viability of hydrogen as a robust energy storage medium in a 100% renewable stand-alone MG, demonstrating its potential to electrify remote communities cost-effectively while reducing carbon footprints [97]. These studies underscore the indispensable role of tools like MATLAB/Simulink and HOMER Pro in advancing HMGS research and achieving sustainable energy solutions.

5.5. Top Contributing Authors

This section highlights the most prolific contributors to the HMGS research, categorized into two areas: OTs and STs. Tables 8 and 9 summarize the rankings based on the number of publications and key focus areas for each author.

Table 8. Top contributing authors in terms of OTs.

Rank	Author	No. of Publications	Key Focus Areas
1	Guerrero, J.M.	35	Distributed control, HMGS optimization, and intelligent energy management.
2	Gharehpetian, G.B.	19	Robust control, fault management, and resilient microgrid operation.
3	Dey, B.	18	Multi-objective optimization, renewable integration, and cost minimization in MGs.
4	Ustun, T.S	15	Cybersecurity, distributed control, and load frequency stability in MGs.
5	Marzband, M.	15	Stochastic optimization, demand response, and energy management in smart MGs.

Table 9. Top contributing authors in terms of STs.

Rank	Author	No. of Publications	Key Focus Areas
1	Guerrero, J.M.	24	Application of HOMER and MATLAB for hybrid systems, renewable integration, and grid stability.
2	Baghaee, H.R.	21	Fault-tolerant distributed control and resilience in islanded MGs.
3	Shahnia, F.	19	Stability analysis, system coupling, and optimization in sustainable MGs.
4	Gharehpetian, G.B.	18	Fault management, robust distributed systems, and islanded MG controls.
5	Ghosh, A.	14	Cooperative energy storage control, harmonic mitigation, and voltage regulation in MGs.

Table 8 identifies the leading authors contributing to the development and application of OTs in HMGSs.

These researchers have significantly advanced the field by introducing innovative methodologies to enhance system reliability, efficiency, and cost-effectiveness. Guerrero, J.M., leading the list with 35 publications, has been a pioneer in distributed control and HMGS optimization. Other prominent contributors, such as Gharehpetian, G.B., and Dey, B., focus on fault management and multi-objective optimization, respectively.

Table 9 showcases the authors most active in leveraging STs to design and analyze HMGSs. Their work has facilitated the integration of RESs and improved MG performance.

Guerrero, J.M., again ranks first, with 24 publications emphasizing the use of tools like HOMER and MATLAB for HESs. Baghaee, H.R., and Shahnia, F., follow closely, contributing to fault-tolerant systems and sustainable MG configurations.

6. Conclusions and Insights

6.1. Overview of Key Findings

This study provides a comprehensive evaluation of OTs and STs in the context of HMGSs.

- OTs: Advanced methodologies, such as AI-driven approaches, metaheuristics, and MILP, play a pivotal role in improving energy efficiency, reliability, and sustainability by addressing challenges like resource intermittency, load management, and cost optimization.
- STs: Tools like HOMER, MATLAB, and SAM are indispensable for designing, optimizing, and evaluating HMGS configurations, enabling researchers to analyze complex systems under diverse conditions.

6.2. Trends and Implications

The steady rise in research outputs, particularly after 2018, reflects the growing global emphasis on decarbonization and energy resilience, driven by key policy initiatives such as the Paris Agreement (2015) and the United Nations Sustainable Development Goals (SDGs), which have accelerated the adoption of RESs [101]. Additionally, the US Department of Energy (DOE) Smart Grid R&D Program has played a crucial role in advancing optimization strategies [102]. On the technological front, the declining costs of SPV and WT [103], along with the increasing role of OTs and STs, have further fueled research growth. Notably, DOE-led efforts, including the development of specific design tools and a solutions library by 2020, have enhanced the optimization capabilities. The high adoption of metaheuristic techniques, coupled with the integration of AI-based approaches, reflects a paradigm shift toward intelligent energy systems capable of adapting to dynamic conditions and uncertainties. These trends emphasize the critical role of advanced algorithms and modeling platforms in accelerating the transition to cleaner and more efficient energy systems.

6.3. Gaps and Opportunities

Despite significant advancements, several critical gaps remain in the optimization of HMGSs:

- Computational complexity and scalability: Many existing OTs struggle with scalability when applied to large-scale MGs. Future research should focus on developing lightweight AI models and hybrid AI–mathematical approaches to enhance real-time performance.
- Hybrid AI and traditional methods: The integration of AI with classical optimization techniques lacks standardization, making benchmarking and validation difficult. Developing benchmark datasets and hybrid frameworks is essential for improving model robustness and adoption.

- Regional disparities: Research has primarily focused on developed regions, with limited studies addressing cost-optimization strategies for low-resource settings and grid stability in high-penetration renewable systems.
- Emerging technologies: The role of blockchain, quantum computing, and the IoT in MG optimization remains largely unexplored. These technologies could enhance decentralized energy trading, security, and predictive maintenance.
- Cybersecurity and data privacy: As AI-driven energy management systems become more prevalent, addressing data privacy, security vulnerabilities, and resilience against cyber threats is crucial.

Future research should prioritize hybrid optimization frameworks, enhanced AI interpretability, and scalable real-time decision-making models. By fostering interdisciplinary collaboration, the HMGS community can develop more adaptive, secure, and efficient solutions for next-generation energy systems.

6.4. Final Takeaways

This work synthesizes critical insights into the HMGS research, providing an invaluable resource for academics, policymakers, and practitioners. It highlights the following:

- The transformative potential of combining advanced OTs with versatile STs.
- The contributions of leading researchers and journals in pushing the boundaries of HMGS innovation.
- The need for continued research into emerging technologies and their integration into energy systems.

By fostering innovation and collaboration, the HMGS community is well positioned to drive a sustainable energy future. This study serves as a roadmap, bridging knowledge gaps and paving the way for impactful advancements in energy systems optimization and management. By leveraging these insights, stakeholders can accelerate the adoption of resilient and sustainable MG solutions, contributing meaningfully to global energy objectives.

7. Conclusions

This comprehensive review provided a systematic analysis of the OTs and tools employed in hybrid microgrid systems (HMGSs), offering an in-depth evaluation of the methods and tools used in the field. This study analyzed 4134 documents for OTs and 2667 for STs. An advanced Scopus search was performed using core keywords for both OTs and STs, including microgrids, renewable energy systems, and the relevant tools and techniques from Figure 3, aimed at HMGS design and optimization.

The OTs were categorized into classical (16.9%), metaheuristic (48.3%), and AI-based methods (34.8%), demonstrating the dominance of metaheuristics while highlighting the transformative potential of AI-based approaches, particularly in predictive analytics and managing uncertainties. STs like MATLAB and HOMER have established themselves as critical enablers of HMGS design and optimization, facilitating detailed techno-economic assessments and offering scalable solutions for various configurations and geographic conditions. These findings underscore their indispensability in microgrid (MG) planning.

The results indicate a significant surge in research activity post-2018, driven by the global transition to renewable energy sources (RESs) and an increasing focus on energy resilience. Analysis of the top-contributing journals, authors, and countries highlights growing collaboration in this field. However, gaps remain in addressing cybersecurity, regional data limitations, and the integration of emerging technologies such as blockchain and the IoT. Future research should focus on addressing these gaps through interdisciplinary approaches and enhancing regional applicability.

This study serves as a guiding resource for advancing HMGS innovation. By leveraging the strengths of metaheuristic optimization and robust STs, stakeholders can drive sustainable energy solutions, address global energy challenges, and enhance energy resilience. By fostering innovation and collaboration, HMGS research can accelerate the global shift toward RESs, paving the way for significant advancements in energy systems optimization, resilience, and sustainable management.

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References

1. IEA. Renewables 2022. 2022. Available online: www.iea.org (accessed on 10 December 2022).
2. Deshmukh, M.K.; Deshmukh, S.S. Modeling of hybrid renewable energy systems. *Renew. Sustain. Energy Rev.* **2008**, *12*, 235–249. [CrossRef]
3. Krishna, K.S.; Kumar, K.S. A review on hybrid renewable energy systems. *Renew. Sustain. Energy Rev.* **2015**, *52*, 907–916. [CrossRef]
4. Tahir, K.A.; Ordóñez, J.; Nieto, J. Exploring Evolution and Trends: A Bibliometric Analysis and Scientific Mapping of Multiobjective Optimization Applied to Hybrid Microgrid Systems. *Sustainability* **2024**, *16*, 5156. [CrossRef]
5. Fathima, A.H.; Palanisamy, K. Optimization in microgrids with hybrid energy systems—A review. *Renew. Sustain. Energy Rev.* **2015**, *45*, 431–446. [CrossRef]
6. Hartono, B.S.; Budiyanto; Setiabudy, R. Review of microgrid technology. In Proceedings of the 2013 International Conference on QiR (Quality in Research)—Conjunction with ICCS 2013 2nd Int. Conf. Civ. Sp., Yogyakarta, Indonesia, 25–28 June 2013; pp. 127–132. [CrossRef]
7. Jha, P.; Sharma, N.; Jadoun, V.K.; Agarwal, A.; Tomar, A. Optimal scheduling of a microgrid using AI techniques. In *Control Standalone Microgrid*; Academic Press: Cambridge, MA, USA, 2021; pp. 297–336. [CrossRef]
8. Tahir, K.A.; Nieto, J.; Díaz-López, C.; Ordóñez, J. From diesel reliance to sustainable power in Iraq: Optimized hybrid microgrid solutions. *Renew. Energy* **2025**, *238*, 121905. [CrossRef]
9. Tahir, K.A.; Zamorano, M.; García, J.O. Scientific mapping of optimisation applied to microgrids integrated with renewable energy systems. *Int. J. Electr. Power Energy Syst.* **2023**, *145*, 108698. [CrossRef]
10. Calinescu, G.; Chekuri, C.; Pál, M.; Vondrák, J. Maximizing a monotone submodular function subject to a matroid constraint. *SIAM J. Comput.* **2011**, *40*, 1740–1766. [CrossRef]
11. Askarzadeh, A. A novel metaheuristic method for solving constrained engineering optimization problems: Crow search algorithm. *Comput. Struct.* **2016**, *169*, 1–12. [CrossRef]
12. Mete, H.O.; Zabinsky, Z.B. Stochastic optimization of medical supply location and distribution in disaster management. *Int. J. Prod. Econ.* **2010**, *126*, 76–84. [CrossRef]
13. Metters, R. Quantifying the bullwhip effect in supply chains. *J. Oper. Manag.* **1997**, *15*, 89–100. [CrossRef]
14. Ward, A.J.; Hobbs, P.J.; Holliman, P.J.; Jones, D.L. Optimisation of the anaerobic digestion of agricultural resources. *Bioresour. Technol.* **2008**, *99*, 7928–7940. [CrossRef] [PubMed]
15. Baquero, F.; Martínez, J.L.; Cantón, R. Antibiotics and antibiotic resistance in water environments. *Curr. Opin. Biotechnol.* **2008**, *19*, 260–265. [CrossRef] [PubMed]
16. Beume, N.; Naujoks, B.; Emmerich, M. SMS-EMOA: Multiobjective selection based on dominated hypervolume. *Eur. J. Oper. Res.* **2007**, *181*, 1653–1669. [CrossRef]
17. Tsikalakis, A.G.; Hatziargyriou, N.D. Centralized control for optimizing microgrids operation. *IEEE Trans. Energy Convers.* **2008**, *23*, 241–248. [CrossRef]
18. Atwa, Y.M.; El-Saadany, E.F.; Salama, M.M.A.; Seethapathy, R. Optimal renewable resources mix for distribution system energy loss minimization. *IEEE Trans. Power Syst.* **2010**, *25*, 360–370. [CrossRef]
19. Jiang, R.; Wang, J.; Guan, Y. Robust unit commitment with wind power and pumped storage hydro. *IEEE Trans. Power Syst.* **2012**, *27*, 800–810. [CrossRef]

20. Cagnano, A.; De Tuglie, E.; Marcone, F.; Porro, G.; Dauphin Rasolomampionona, D.; Klos, M.; Favuzza, S.; Zizzo, G. Experimental results on the economic management of a smart microgrid. In Proceedings of the 20th IEEE Mediterranean Electrotechnical Conference MELECON 2020—Proceedings, Palermo, Italy, 16–18 June 2020; pp. 459–463. [CrossRef]
21. Aziz, T.; Al Masood, N.; Deeba, S.R.; Tushar, W.; Yuen, C. A methodology to prevent cascading contingencies using BESS in a renewable integrated microgrid. *Int. J. Electr. Power Energy Syst.* **2019**, *110*, 737–746. [CrossRef]
22. Opathella, C.; Venkatesh, B. Three-Phase Unbalanced Power Flow Using a π-Model of Controllable AC-DC Converters. *IEEE Trans. Power Syst.* **2016**, *31*, 4286–4296. [CrossRef]
23. Bhuiyan, F.A.; Yazdani, A.; Primak, S.L. Optimal sizing approach for islanded microgrids. *IET Renew. Power Gener.* **2015**, *9*, 166–175. [CrossRef]
24. Zhu, J.-H.; Ren, H.; Gu, J.; Zhang, X.; Sun, C. Economic dispatching of Wind/photovoltaic/storage considering load supply reliability and maximize capacity utilization. *Electr. Power Energy Syst.* **2023**, *147*, 108874. [CrossRef]
25. Merabet, A.; Al-Durra, A.; El Fouly, T.; El-Saadany, E.F. Multifunctional energy management system for optimized network of microgrids considering battery degradation and load adjustment. *J. Energy Storage* **2024**, *100*, 113709. [CrossRef]
26. Jabari, F.; Zeraati, M.; Sheibani, M.; Arasteh, H. Robust Self-Scheduling of PVs-Wind-Diesel Power Generation Units in a Standalone Microgrid under Uncertain Electricity Prices. *J. Oper. Autom. Power Eng.* **2024**, *12*, 152–162. [CrossRef]
27. Gharehveran, S.S.; Shirini, K.; Khavar, S.C.; Mousavi, S.H.; Abdolahi, A. Deep learning-based demand response for short-term operation of renewable-based microgrids. *J. Supercomput.* **2024**, *80*, 26002–26035. [CrossRef]
28. Hai, T.; Aksoy, M.; Rezvani, A. Optimal energy management and scheduling of a microgrid considering hydrogen storage and PEMFC with uncertainties. *Int. J. Hydrogen Energy* **2024**, *88*, 1017–1033. [CrossRef]
29. Lesage-Landry, A.; Wang, H.; Shames, I.; Mancarella, P.; Taylor, J.A. Online Convex Optimization of Multi-Energy Building-to-Grid Ancillary Services. *IEEE Trans. Control Syst. Technol.* **2020**, *28*, 2416–2431. [CrossRef]
30. Lasemi, M.A.; Arabkoohsar, A.; Hajizadeh, A.; Mohammadi-ivatloo, B. A comprehensive review on optimization challenges of smart energy hubs under uncertainty factors. *Renew. Sustain. Energy Rev.* **2022**, *160*, 112320. [CrossRef]
31. Rahim, S.; Javaid, N.; Khan, R.D.; Nawaz, N.; Iqbal, M. A convex optimization based decentralized real-time energy management model with the optimal integration of microgrid in smart grid. *J. Clean. Prod.* **2019**, *236*, 117688. [CrossRef]
32. Liang, Z.; Chung, C.Y.; Zhang, W.; Wang, Q.; Lin, W.; Wang, C. Enabling High-Efficiency Economic Dispatch of Hybrid AC/DC Networked Microgrids: Steady-State Convex Bi-Directional Converter Models. *IEEE Trans. Smart Grid* **2024**, *16*, 45–61. [CrossRef]
33. Amrollahi, M.H.; Bathaee, S.M.T. Techno-economic optimization of hybrid photovoltaic/wind generation together with energy storage system in a stand-alone micro-grid subjected to demand response. *Appl. Energy* **2017**, *202*, 66–77. [CrossRef]
34. Chakraborty, S.; Weiss, M.D.; Simões, M.G. Distributed intelligent energy management system for a single-phase high-frequency AC microgrid. *IEEE Trans. Ind. Electron.* **2007**, *54*, 97–109. [CrossRef]
35. Li, Y.; Yang, Z.; Li, G.; Zhao, D.; Tian, W. Optimal Scheduling of an Isolated Microgrid with Battery Storage Considering Load and Renewable Generation Uncertainties. *IEEE Trans. Ind. Electron.* **2019**, *66*, 1565–1575. [CrossRef]
36. Atia, R.; Yamada, N. Sizing and Analysis of Renewable Energy and Battery Systems in Residential Microgrids. *IEEE Trans. Smart Grid* **2016**, *7*, 1204–1213. [CrossRef]
37. Bertsimas, D.; Tsitsiklis, J.N. *Introduction to Linear Optimization*; Athena Scientific: Belmont, MA, USA, 1997.
38. Rahbar, K.; Xu, J.; Zhang, R. Real-time energy storage management for renewable integration in microgrid: An off-line optimization approach. *IEEE Trans. Smart Grid* **2015**, *6*, 124–134. [CrossRef]
39. Venayagamoorthy, G.K.; Sharma, R.K.; Gautam, P.K.; Ahmadi, A. Dynamic Energy Management System for a Smart Microgrid. *IEEE Trans. Neural Netw. Learn. Syst.* **2016**, *27*, 1643–1656. [CrossRef]
40. Liu, D.; Xu, Y.; Wei, Q.; Liu, X. Residential energy scheduling for variable weather solar energy based on adaptive dynamic programming. *IEEE/CAA J. Autom. Sin.* **2018**, *5*, 36–46. [CrossRef]
41. Applied Dynamic Programming—Richard E. Bellman, Stuart E Dreyfus—Book Google. Available online: https://books.google.es/books?hl=ar&lr=&id=ZgbWCgAAQBAJ&oi=fnd&pg=PA3&dq=R.+Bellman,+%22Dynamic+Programming,%22+Princeton+University+Press,+1957.&ots=yg_fO3owFu&sig=i69XETEkYVak1DhWciYOlgEX__E#v=onepage&q=R.%20Bellman,%20%22Dynamic%20Programming,%22%20Princeton%20University%20Press,%201957.&f=false (accessed on 6 November 2023).
42. Moradi, H.; Esfahanian, M.; Abtahi, A.; Zilouchian, A. Optimization and energy management of a standalone hybrid microgrid in the presence of battery storage system. *Energy* **2018**, *147*, 226–238. [CrossRef]
43. Sierra, J.E.; Hernández, A.S.G.; Sierra, M.F.; Fernanda, M.; Carillo, S. Study of Graph Theory in Microgrids. 2022, p. 19. Available online: http://www.webology.org (accessed on 5 March 2025).
44. Salimon, S.A.; Fajinmi, I.O.; Adewuyi, O.B.; Pandey, A.K.; Adebiyi, O.W.; Kotb, H. Graph theory-enhanced integrated distribution network reconfiguration and distributed generation planning: A comparative techno-economic and environmental impacts analysis. *Clean. Eng. Technol.* **2024**, *22*, 100808. [CrossRef]
45. Mah, A.X.Y.; Ho, W.S.; Hassim, M.H.; Hashim, H.; Ling, G.H.T.; Ho, C.S.; Muis, Z.A. Optimization of photovoltaic-based microgrid with hybrid energy storage: A P-graph approach. *Energy* **2021**, *233*, 121088. [CrossRef]

46. Lim, J.Y.; How, B.S.; Rhee, G.; Hwangbo, S.; Yoo, C.K. Transitioning of localized renewable energy system towards sustainable hydrogen development planning: P-graph approach. *Appl. Energy* **2020**, *263*, 114635. [CrossRef]
47. Kuznetsova, E.; Li, Y.-F.; Ruiz, C.; Zio, E.; Ault, G.; Bell, K. Reinforcement learning for microgrid energy management. *Energy* **2013**, *59*, 133–146. [CrossRef]
48. Kyriakarakos, G.; Piromalis, D.D.; Dounis, A.I.; Arvanitis, K.G.; Papadakis, G. Intelligent demand side energy management system for autonomous polygeneration microgrids. *Appl. Energy* **2013**, *103*, 39–51. [CrossRef]
49. Wen, L.; Zhou, K.; Yang, S.; Lu, X. Optimal load dispatch of community microgrid with deep learning based solar power and load forecasting. *Energy* **2019**, *171*, 1053–1065. [CrossRef]
50. Mohanty, S.; Pati, S.; Sanjeeb; Kar, K. Persistent Voltage Profiling of a Wind Energy-Driven Islanded Microgrid with Novel Neuro-fuzzy Controlled Electric Spring. *J. Control. Autom. Electr. Syst.* **2023**, *34*, 609–623. [CrossRef]
51. Singh, A.R.; Ding, L.; Raju, D.K.; Kumar, R.S.; Raghav, L.P. Demand response of grid-connected microgrid based on metaheuristic optimization algorithm. *Energy Sources Part A Recover. Util. Environ. Eff.* **2021**, *52*, 917–928. [CrossRef]
52. Ross, M.M.D.; Turcotte, D.; Ross, M.; Sheriff, F. Photovoltaic Hybrid System Sizing and Simulation Tools: Status and Needs Optimal Design and Energy Management for Northern and Remote Microgrids View Project Dave Turcotte Natural Resources Canada Photovoltaic Hybrid System Sizing and Simulation Tools: Status and Needs. 2001. Available online: https://www.researchgate.net/publication/228496269 (accessed on 14 August 2023).
53. Hasan, T.; Emami, K.; Shah, R.; Hassan, N.M.S.; Belokoskov, V.; Ly, M. Techno-economic Assessment of a Hydrogen-based Islanded Microgrid in North-east. *Energy Rep.* **2023**, *9*, 3380–3396. [CrossRef]
54. HOMER—Hybrid Renewable and Distributed Generation System Design Software. Available online: https://www.homerenergy.com/ (accessed on 3 July 2023).
55. NSRDB | TMY. Available online: https://nsrdb.nrel.gov/data-sets/tmy (accessed on 3 July 2023).
56. Singh, S.; Singh, M.; Kaushik, S.C. Feasibility study of an islanded microgrid in rural area consisting of PV, wind, biomass and battery energy storage system. *Energy Convers. Manag.* **2016**, *128*, 178–190. [CrossRef]
57. Ahmad, J.; Imran, M.; Khalid, A.; Iqbal, W.; Ashraf, S.R.; Adnan, M.; Ali, S.F.; Khokhar, K.S. Techno economic analysis of a wind-photovoltaic-biomass hybrid renewable energy system for rural electrification: A case study of Kallar Kahar. *Energy* **2018**, *148*, 208–234. [CrossRef]
58. Abdin, Z.; Mérida, W. Hybrid energy systems for off-grid power supply and hydrogen production based on renewable energy: A techno-economic analysis. *Energy Convers. Manag.* **2019**, *196*, 1068–1079. [CrossRef]
59. Shezan, S.A. Design and demonstration of an islanded hybrid microgrid for an enormous motel with the appropriate solicitation of superfluous energy by using iHOGA and matlab. *Int. J. Energy Res.* **2021**, *45*, 5567–5585. [CrossRef]
60. iHOGA/MHOGA—Simulation and Optimization of Stand-Alone and Grid-Connected Hybrid Renewable Systems. Available online: https://ihoga.unizar.es/en/ (accessed on 6 July 2023).
61. Żołądek, M.; Kafetzis, A.; Figaj, R.; Panopoulos, K. Energy-Economic Assessment of Islanded Microgrid with Wind Turbine, Photovoltaic Field, Wood Gasifier, Battery, and Hydrogen Energy Storage. *Sustainability* **2022**, *14*, 12470. [CrossRef]
62. Mazzeo, D.; Matera, N.; Cornaro, C.; Oliveti, G.; Romagnoni, P.; De Santoli, L. EnergyPlus, IDA ICE and TRNSYS predictive simulation accuracy for building thermal behaviour evaluation by using an experimental campaign in solar test boxes with and without a PCM module. *Energy Build.* **2020**, *212*, 109812. [CrossRef]
63. TRNSYS 18. Available online: http://sel.me.wisc.edu/trnsys (accessed on 14 July 2023).
64. Wang, X.; Bamisile, O.; Chen, S.; Xu, X.; Luo, S.; Huang, Q.; Hu, W. Decarbonization of China's electricity systems with hydropower penetration and pumped-hydro storage: Comparing the policies with a techno-economic analysis. *Renew. Energy* **2022**, *196*, 65–83. [CrossRef]
65. Lund, H.; Thellufsen, J.Z.; Østergaard, P.A.; Sorknæs, P.; Skov, I.R.; Mathiesen, B.V. EnergyPLAN—Advanced analysis of smart energy systems. *Smart Energy* **2021**, *1*, 100007. [CrossRef]
66. Pochacker, M.; Khatib, T.; Elmenreich, W. The microgrid simulation tool RAPSim: Description and case study. In Proceedings of the 2014 IEEE Innovative Smart Grid Technologies—Asia ISGT ASIA, Kuala Lumpur, Malaysia, 20–23 May 2014; Volume 2014, pp. 278–283. [CrossRef]
67. RAPSim—Microgrid Simulator Download | SourceForge.net. Available online: https://sourceforge.net/projects/rapsim/ (accessed on 15 July 2023).
68. Mukhtar, M.; Obiora, S.; Yimen, N.; Quixin, Z.; Bamisile, O.; Jidele, P.; Irivboje, Y.I. Effect of Inadequate Electrification on Nigeria's Economic Development and Environmental Sustainability. *Sustainability* **2021**, *13*, 2229. [CrossRef]
69. RETScreen. Available online: https://natural-resources.canada.ca/maps-tools-and-publications/tools/modelling-tools/retscreen/7465 (accessed on 15 July 2023).
70. Alam, M.; Kumar, K.; Dutta, V. Analysis of lead-acid and lithium-ion batteries as energy storage technologies for the grid-connected microgrid using dispatch control algorithm. *Stud. Comput. Intell.* **2021**, *916*, 499–515. [CrossRef]

71. Nithyanandam, K.; Stekli, J.; Pitchumani, R. High-temperature latent heat storage for concentrating solar thermal (CST) systems. In *Advances in Concentrating Solar Thermal Research and Technology*; Woodhead Publishing: Sawston, UK, 2017; pp. 213–246. [CrossRef]
72. Home—System Advisor Model—SAM. Available online: https://sam.nrel.gov/ (accessed on 15 July 2023).
73. Sortomme, E.; Venkata, S.S.; Mitra, J. Microgrid Protection Using Communication-Assisted Digital Relays. *IEEE Trans. Power Deliv.* **2009**, *25*, 2789–2796. [CrossRef]
74. Simulink—Simulation and Model-Based Design—MATLAB. Available online: https://www.mathworks.com/products/simulink.html (accessed on 24 November 2024).
75. Chaouachi, A.; Kamel, R.M.; Andoulsi, R.; Nagasaka, K. Multiobjective Intelligent Energy Management for a Microgrid. *IEEE Trans. Ind. Electron.* **2012**, *60*, 688–699. [CrossRef]
76. Moghaddam, A.A.; Seifi, A.; Niknam, T.; Pahlavani, M.R.A. Multi-objective operation management of a renewable MG (micro-grid) with back-up micro-turbine/fuel cell/battery hybrid power source. *Energy* **2011**, *36*, 6490–6507. [CrossRef]
77. Bevrani, H.; Habibi, F.; Babahajyani, P.; Watanabe, M.; Mitani, Y. Intelligent frequency control in an AC microgrid: Online PSO-based fuzzy tuning approach. *IEEE Trans. Smart Grid* **2012**, *3*, 1935–1944. [CrossRef]
78. Ahmad, T.; Zhang, D.; Huang, C.; Zhang, H.; Dai, N.; Song, Y.; Chen, H.; Ahmad, T.; Zhang, D.; Huang, C.; et al. Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities. *JCPro* **2021**, *289*, 125834. [CrossRef]
79. Morais, H.; Kádár, P.; Faria, P.; Vale, Z.A.; Khodr, H.M. Optimal scheduling of a renewable micro-grid in an isolated load area using mixed-integer linear programming. *Renew. Energy* **2010**, *35*, 151–156. [CrossRef]
80. Suganthi, L.; Iniyan, S.; Samuel, A.A. Applications of fuzzy logic in renewable energy systems—A review. *Renew. Sustain. Energy Rev.* **2015**, *48*, 585–607. [CrossRef]
81. Long, C.; Wu, J.; Zhou, Y.; Jenkins, N. Peer-to-peer energy sharing through a two-stage aggregated battery control in a community Microgrid. *Appl. Energy* **2018**, *226*, 261–276. [CrossRef]
82. Borhanazad, H.; Mekhilef, S.; Ganapathy, V.G.; Modiri-Delshad, M.; Mirtaheri, A. Optimization of micro-grid system using MOPSO. *Renew. Energy* **2014**, *71*, 295–306. [CrossRef]
83. Hafez, O.; Bhattacharya, K. Optimal planning and design of a renewable energy based supply system for microgrids. *Renew. Energy* **2012**, *45*, 7–15. [CrossRef]
84. Badal, F.R.; Das, P.; Sarker, S.K.; Das, S.K. A survey on control issues in renewable energy integration and microgrid. *Prot. Control Mod. Power Syst.* **2019**, *4*, 1–27. [CrossRef]
85. Ou, T.C.; Hong, C.M. Dynamic operation and control of microgrid hybrid power systems. *Energy* **2014**, *66*, 314–323. [CrossRef]
86. Yu, X.; She, X.; Zhou, X.; Huang, A.Q. Power management for DC microgrid enabled by solid-state transformer. *IEEE Trans. Smart Grid* **2014**, *5*, 954–965. [CrossRef]
87. Li, J.; Xiong, R.; Yang, Q.; Liang, F.; Zhang, M.; Yuan, W. Design/test of a hybrid energy storage system for primary frequency control using a dynamic droop method in an isolated microgrid power system. *Appl. Energy* **2017**, *201*, 257–269. [CrossRef]
88. Ji, Y.; Wang, J.; Xu, J.; Fang, X.; Zhang, H. Real-Time Energy Management of a Microgrid Using Deep Reinforcement Learning. *Energies* **2019**, *12*, 2291. [CrossRef]
89. Kerdphol, T.; Watanabe, M.; Hongesombut, K.; Mitani, Y. Self-Adaptive Virtual Inertia Control-Based Fuzzy Logic to Improve Frequency Stability of Microgrid with High Renewable Penetration. *IEEE Access* **2019**, *7*, 76071–76083. [CrossRef]
90. Luo, L.; Abdulkareem, S.S.; Rezvani, A.; Miveh, M.R.; Samad, S.; Aljojo, N.; Pazhoohesh, M. Optimal scheduling of a renewable based microgrid considering photovoltaic system and battery energy storage under uncertainty. *J. Energy Storage* **2020**, *28*, 101306. [CrossRef]
91. Wu, H.; Liu, X.; Ding, M. Dynamic economic dispatch of a microgrid: Mathematical models and solution algorithm. *Int. J. Electr. Power Energy Syst.* **2014**, *63*, 336–346. [CrossRef]
92. Kerdphol, T.; Rahman, F.S.; Mitani, Y.; Hongesombut, K.; Küfeoğlu, S. Virtual inertia control-based model predictive control for microgrid frequency stabilization considering high renewable energy integration. *Sustainability* **2017**, *9*, 773. [CrossRef]
93. Wang, P.; Wang, D.; Zhu, C.; Yang, Y.; Abdullah, H.M.; Mohamed, M.A. Stochastic management of hybrid AC/DC microgrids considering electric vehicles charging demands. *Energy Rep.* **2020**, *6*, 1338–1352. [CrossRef]
94. Nurunnabi, M.; Roy, N.K.; Hossain, E.; Pota, H.R. Size optimization and sensitivity analysis of hybrid wind/PV micro-grids- A case study for Bangladesh. *IEEE Access* **2019**, *7*, 150120–150140. [CrossRef]
95. Dawood, F.; Shafiullah, G.M.; Anda, M. Stand-Alone Microgrid with 100% Renewable Energy: A Case Study with Hybrid Solar PV-Battery-Hydrogen. *Sustainability* **2020**, *12*, 2047. [CrossRef]
96. Baghaee, H.R.; Mirsalim, M.; Gharehpetian, G.B.; Talebi, H.A. A generalized descriptor-system robust H∞ control of autonomous microgrids to improve small and large signal stability considering communication delays and load nonlinearities. *Int. J. Electr. Power Energy Syst.* **2017**, *92*, 63–82. [CrossRef]
97. Shen, L.; Cheng, Q.; Cheng, Y.; Wei, L.; Wang, Y. Hierarchical control of DC micro-grid for photovoltaic EV charging station based on flywheel and battery energy storage system. *Electr. Power Syst. Res.* **2020**, *179*, 106079. [CrossRef]

98. Marzebali, M.H.; Mazidi, M.; Mohiti, M. An adaptive droop-based control strategy for fuel cell-battery hybrid energy storage system to support primary frequency in stand-alone microgrids. *J. Energy Storage* **2020**, *27*, 101127. [CrossRef]
99. Yuan, C.; Haj-Ahmed, M.A.; Illindala, M.S. Protection Strategies for Medium-Voltage Direct-Current Microgrid at a Remote Area Mine Site. *IEEE Trans. Ind. Appl.* **2015**, *51*, 2846–2853. [CrossRef]
100. Kumar, M.; Singh, S.N.; Srivastava, S.C. Design and control of smart DC microgrid for integration of renewable energy sources. In Proceedings of the 2012 IEEE Power and Energy Society General Meeting, San Diego, CA, USA, 22–26 July 2012. [CrossRef]
101. SDG Indicators—SDG Indicators. Available online: https://unstats.un.org/sdgs/metadata/ (accessed on 14 March 2024).
102. Ton, D.T.; Smith, M.A. The U.S. Department of Energy's Microgrid Initiative. *Electr. J.* **2012**, *25*, 84–94. [CrossRef]
103. IREA. *Renewable Power Generation Costs in 2020*; IREA: Frisco, TX, USA, 2020.