



Optimization and Control of Hybrid Renewable Energy Systems: A Short Critical Review

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Article Info	ABSTRACT
<i>Received:</i> 03 June 2026 <i>Revised:</i> 21 June 2026 <i>Accepted:</i> 23 June 2026 <i>Available online:</i> 30 June 2026 Keywords: Artificial Intelligence; Energy Management; Hybrid Renewable Energy Systems; Metaheuristic Optimization; Techno-Economic Analysis	The worldwide evolution towards cleaner and more sustainable energy infrastructures has fostered intense research on Hybrid Renewable Energy Systems (HRES) that combine two or more energy sources that are complementary to each other to tackle the limitations of individual renewables. This paper reviews the optimization, control, and energy management strategies used for the HRES and provides a critical short review of the same. This paper covers system classification, component modeling, classical and metaheuristic optimization techniques, AI-based energy management, and techno-economic assessment. The review also highlights key current challenges and offers directions for future research, including AI-based smart systems, hydrogen integration, digital twins, and blockchain-based energy trading.

1. Introduction

The global energy sector is undergoing a transformation due to increased energy demand, declining supply of fossil fuels, and greater awareness of climate change and greenhouse gas emissions. With rapid industrialization and population growth, the use of electricity has rapidly increased in the world, imposing a heavy burden on the traditional energy supply infrastructure system [1]. These have led to the development of renewable energy technologies as a major component of energy security and carbon emission reduction policies at a global level [1]. Solar photovoltaic (PV) and wind energy are among the renewables that have grown rapidly because of the maturity of these technologies and their decreasing installation cost. The installed capacity of solar and wind energy systems was 903.1 GW in 2017, which accounted for

approximately 41.4% of the total renewable energy capacity in the world. [2-4]

We have developed a lot in this area, but standalone renewable energy systems still face the disadvantage of the intermittent and stochastic nature of renewable resources. In contrast to solar energy, which can be produced only during the daytime, wind energy production is greatly susceptible to meteorological variations around the site, and the load demand profile is not really matched [5]. This leads to disruptions in supply, particularly in off-grid and remote areas with low cost of economic extension to the grid (Whiteman, 2024). These limitations can be mitigated to some extent with the help of energy storage systems and backup generators; however, they increase the complexity and cost of the overall system. [6-8]

To overcome these issues, the use of Hybrid Renewable Energy Systems (HRES) has been suggested as an alternative energy system that

involves the integration of different RE and/or conventional energy sources and energy storage systems. The use of different resources can improve the reliability of HRES for supply, energy efficiency, and cost effectiveness compared to single-source systems [9]. For instance, the complementarities of solar and wind resources could be a key factor in the stability of power generation and in reducing reliance on backup systems that rely on fossil fuels. This is because the relevance of HRES is rising in practice, as seen from the large-scale deployment of HRES all over the world; in 2000, HRES energy capacity was more than 700 GW and in 2021, it was more than 3100 GW. [10-12]

Besides technical benefits, HRES are essential and important in the context of sustainable rural electrification and decentralized access to energy in developing areas where the cost of traditional transmission infrastructure is economically not feasible [13]. In addition, HRES can also contribute to reducing the generation of greenhouse gas emissions when compared to diesel standalone power systems, thus making it an attractive solution over diesel standalone power systems. [14-16]

However, the design and operation of an HRES are extremely difficult owing to interactions among different energy sources, the intermittent availability of renewables, the nonlinearity of HRES component performance, and conflicting technical and economic targets. Thus, optimization and energy management methods are major research areas in the field of HRES development [17]. Optimization frameworks that are efficient, therefore, should consider various issues, including component sizing, operational scheduling, reliability enhancement, and economic considerations, such as minimizing the Levelized Cost of Energy (LCOE) and Net Present Cost (NPC). [18, 19]

This is a very brief and critical review of the recent developments relating to the optimization of HRES and Energy management strategies. The paper emphasizes the following: (1) main configurations and classification of HRES; (2) classical, metaheuristic, and AI-based optimization methods; (3) techno-economic and environmental assessment methods; and (4) challenges and new research directions. A literature review was carried out, and the literature

for the period 2015-2026 was mainly scientific journal articles published in scientific databases, focusing on literature related to the optimization of the HRES and literature on energy management and sustainability assessment.

2. Overview of Hybrid Renewable Energy Systems

2.1 Definition and Classification

Hybrid Renewable Energy Systems (HRES) are made of a combination of two or more energy sources, energy storage technologies, and power electronic converters that produce reliable and cost-effective electricity generation. HRES can help reduce the intermittency of standalone renewable energy systems and enhance the reliability and efficiency of the overall system by integrating complementary energy sources. [20]

Based on the criteria of their grid connectivity and internal power distribution architecture, HRES can be classified. [21]

2.1.1 Grid-Connected Systems

Grid-connected HRES work alongside the power grid as a secondary power supply and as an energy storage device for excess electricity. Typically, these systems need to store less energy than standalone systems, resulting in lower system costs and lower Levelized Cost of Energy (LCOE). They are widely used in urban and industrial settings, but must meet grid synchronization and stability requirements. [22]

2.1.2 Off-Grid Systems

Standalone or off-grid systems are not connected to the grid and are mainly used in areas where it is not economically viable to extend the grid. As there is no external power support, the system's reliability relies heavily on the appropriate sizing of the system and the management of energy. [2]

2.1.3 AC- and DC-Coupled Architectures

Alternatively, HRES can be classified according to the bus architecture as AC-coupled and DC-coupled. Typically, the DCW system reduces the losses associated with the conversion process, and the PV system is easier to integrate, whereas the ACW system enables the PV system to be connected to the existing AC system and grid. In the era of modern microgrid applications, hybrid AC/DC architectures, which are an

amalgamation of both configurations, are gaining popularity. [23]

2.2 Main HRES Components

The function of an HRES will rely on the joint operation of generation, storage, and backup.

2.2.1 Solar Photovoltaic Systems

In HRES, Solar PV technology is highly adopted because of its low maintenance cost, modularity, and reduced installation cost. However, PV generation is intermittent, and solar irradiation and environmental conditions are crucial in the determination of PV generation. [14]

2.2.2 Wind Turbines

Wind Turbines offer a generation profile that is often complementary to solar, which makes it more stable and effective to utilize renewable energy. However, the performance of wind energy continues to be site- and wind-specific. [24]

2.2.3 Battery Energy Storage

The most popular storage technology in HRES is battery systems because they serve to buffer the variability of renewable generation and load demand in the short term. System reliability and life cost are both affected by battery size and degradation. [25]

2.2.4 Diesel Generators

Diesel generators are often utilized as dispatchable backup generation in HRES to improve reliability when renewable generation is low. Although diesel-assisted systems enhance supply predictability and storage needs, they also contribute to higher fuel usage and greenhouse gas emissions.

2.2.5 Hydrogen and Fuel Cell Systems

Systems using hydrogen for storage are also long-duration storage technologies, available via

electrolyzers and fuel cells, which are suitable for seasonal energy storage applications. Although there are environmental advantages and they offer longer autonomy, the costs and low round-trip efficiency are still high and prevent them from being widely adopted. [26]

2.3 Common HRES Configurations

The literature is rich in studies of several HRES configurations investigated for their practicality and complementary operational features.

2.3.1 PV/Wind/Battery Systems

The PV/wind/battery system is the most commonly researched standalone HRES. Solar and wind resources complement one another, and battery storage can help deliver high renewable penetration and 'no compromise' in electricity supply in remote electrification. However, battery replacement is yet another issue, along with the cost of the initial purchase. [27]

2.3.2 PV/Diesel/Battery Systems

PV/diesel/battery systems are commonly used, where reliability and cost reduction are the priority. The diesel generator helps complement the low levels of renewable generation, lowers the need for battery storage, and stabilizes the system. However, this reliance on fossil fuels results in operational costs and environmental issues. [28]

2.3.3 PV/Wind/Hydrogen Systems

PV/wind/hydrogen systems include electrolyzers and fuel cells for storing excess renewable energy as hydrogen for future use. The capital cost and system complexity of hydrogen storage systems are significantly higher than those of battery-based systems; however, they offer far greater long-duration autonomy and reduced greenhouse gas emissions. [26]

Table 1. Comparative summary of common HRES configurations

Configuration	Typical Applications	Key Limitations	Key Advantages
PV/Wind/ Battery	Rural electrification; telecom stations; off-grid communities	High initial cost; battery degradation; limited long- duration storage	High renewable penetration; complementary resource utilization; low operational emissions
PV/Diesel/ Battery	Remote communities, mining sites, backup systems	Fuel consumption, emissions, and maintenance requirements	Improved reliability; lower storage requirements; moderate initial cost
PV/Wind/ Hydrogen	Seasonal storage; islanded microgrids; green hydrogen applications	High capital cost, low round-trip efficiency, complex control	Long-duration storage; high energy autonomy; reduced emissions

3. Sustainable Energy Management and Optimization Strategies

3.1 Optimization Objectives

Optimization is a very important part of the design and operation of HRES as system performance is influenced by the economic, technical, and environmental goals and under varying operating conditions. The majority of optimization studies concentrate on the minimization of the total system cost, improvement of supply reliability, and minimization of GHG emissions, which is often achieved using multi-objective optimization frameworks. [29]

Typical economic optimization objectives are to minimize the Net Present Cost (NPC) and Levelized Cost of Energy (LCOE), which includes capital, operation and maintenance, replacement, and fuel costs over the project life. LCOE is one of the most widely used economic indicators in HRES studies as it allows direct comparison between the different configurations of the system and energy technologies. [7]

$$LCOE = \frac{\sum_{t=1}^n \frac{C_t}{(1+r)^t}}{\sum_{t=1}^n \frac{E_t}{(1+r)^t}} \quad (1)$$

Reliability is optimized to guarantee that the system will meet the load demand with reasonable service continuity. Loss of Power Supply Probability (LPSP), Loss of Load Probability (LLP), and Energy Not Supplied (ENS) are among the common reliability indicators. A larger storage capacity and/or larger backup generation are generally required to achieve lower LPSP values, thus leading to higher system costs. Hence, there is always a compromise between economic performance and reliability for HRES optimization. [30]

Environmental targets are primarily to reduce carbon emissions, often in the context of diesel-assisted hybrid systems. Fully renewable configurations can also be used for achieving near-zero operational emissions, but are sometimes associated with increased storage sizes and initial investment. Recent studies increasingly employ multi-objective optimization methods that simultaneously consider cost, reliability, and

environment to achieve a balance between the three. [28]

3.2 Classical Optimization Methods

Classical optimization methods, which have been developed on the basis of simplified assumptions, give mathematically rigorous solutions to the problems of the design and operation of HRES. Among the various methods, linear programming (LP) and dynamic programming (DP) are the most widely used.

Linear programming has been used extensively for dispatching and scheduling energy problems, where the behavior of the system can be modeled by linear objectives and constraints. Although LP is beneficial for convex problems, the applications of LP in HRES are restricted because of the nonlinear properties of the renewable generation systems, storage dynamics, and degradation processes of the components. [31]

Sequential decision-making problems, such as battery energy management and operational scheduling, are well-suited for dynamic programming. DP can break the optimization problem into several decision points and therefore find the optimal operation strategy (also called a DP policy) over a finite time horizon. However, the computational complexity grows exponentially with the dimensionality of the problem, making DP impractical for large-scale and highly integrated HRES configurations. [32-34]

While classical optimization techniques are still relevant for simplified or deterministic cases, their inability to deal with nonlinear, stochastic, and multi-objective optimization problems has led to the increasing use of metaheuristic and artificial intelligence-based techniques. [35-37]

3.3 Metaheuristic Optimization Algorithms

Owing to their ability to solve nonlinear, non-convex, and multi-objective optimization problems without using gradient information or simplified mathematical formulations, metaheuristic algorithms have emerged as the most popular tools for solving optimization problems in HRES research. They are flexible and robust and are well-suited to component sizing, operating schedules, and energy management when renewable resources are highly variable. [38-41]

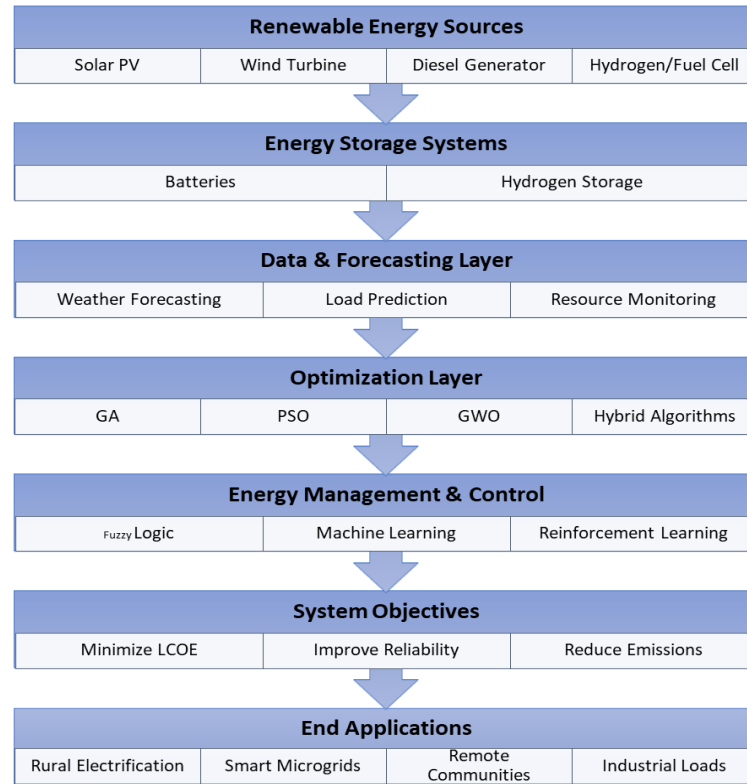


Figure 1. General framework of HRES optimization and energy management.

3.3.1 Genetic Algorithm (GA)

One of the oldest and most widely used optimization techniques in HRES studies is the genetic algorithm (GA). GA is an iterative evolution of candidate solutions to solve a problem globally and has been shown to be effective in multi-objective optimization problems involving cost, reliability, and emission reduction. The primary advantage is that it does not require explicit mathematical models, helping avoid premature convergence and efficiently exploring large search spaces. [18, 42]

GA has been applied successfully to the optimal sizing of PV/wind/diesel/battery systems for Remote Electrification. The GA resulted in simultaneous system cost and CO₂ emission reductions. However, GA can be very time-consuming and is sensitive to the parameters, size of the population, and mutation rate. [14, 43]

3.3.2 Particle Swarm Optimization (PSO)

One of the most commonly used algorithms in HRES optimization is Particle Swarm Optimization (PSO), which shows fast convergence, easy implementation, and has relatively low computational complexity. PSO has been proven to perform well in single-objective

and multi-objective optimization problems, particularly for the sizing and dispatch optimization of hybrid PV/wind/battery systems. [14]

In complex HRES setups, improved PSO variants have been reported to have lower LCOE and faster convergence than GA-based approaches in comparative studies. However, in a highly nonlinear optimization problem space, standard PSO algorithms may experience premature convergence and less search diversity, which urges the development of hybrid and modified PSO variants. [44]

3.3.3 Grey Wolf Optimization (GWO)

Grey Wolf Optimization (GWO) is a newer swarm-intelligence algorithm that has been gaining popularity for its ability to effectively balance exploration and exploitation, making it a promising option for HRES applications. In comparison to typical metaheuristic methods, GWO also provides better solution quality and requires less computational effort and fewer control parameters. [45]

Multi-objective GWO variants have been effectively tested and applied to sizing and operational optimization problems for a hybrid

microgrid, resulting in better solutions in terms of cost and reliability index in comparison to several classical optimization techniques. Owing to its ease of implementation and good convergence properties, GWO is becoming a potential optimization method for contemporary HRES applications. [46, 47]

Comparing different metaheuristics brings salient practical compromises to light. The GA is very powerful in solving a complex multi-objective optimization problem, but is time-

consuming. Although PSO has excellent convergence and ease of implementation, it may fail to converge to the global optimum in complex search spaces. However, GWO is a compromise between the convergence speed, solution quality, and simplicity of the parameters, which is why it has been increasingly used in recent HRES studies. Moreover, the hybridization of different algorithms has been shown to be a more efficient optimizer, such as PSO-GWO and GA-PSO, which use the complementary strengths of different algorithms. [38, 46]

Table 2. Comparison of common metaheuristic optimization methods for HRES

Algorithm	Main Advantages	Key Limitations	Typical HRES Applications
GA	Strong global search capability; effective for multi-objective optimization	High computational cost; sensitive parameter tuning	Component sizing; emission-cost optimization
PSO	Fast convergence; simple implementation; low computational complexity	Susceptible to local optima; reduced diversity in complex problems	Dispatch optimization; sizing of PV/wind/battery systems
GWO	Balanced exploration and exploitation; fewer tuning parameters; stable convergence	Relatively recent with limited long-term validation	Multi-objective microgrid optimization; hybrid system sizing

3.4 AI-Based Energy Management

The complexity of today's HRES has been growing and has led to the evolution of AI-based energy management systems that can adapt and make decisions in real time based on uncertain operating conditions. Unlike traditional techniques, AI techniques can better adapt to previous and current operational data, which enhances system flexibility and prediction accuracy. [48]

3.4.1 Machine Learning Approaches

Forecasting renewable energy generation, load forecasting, and intelligent dispatch of energy have been widely used applications of machine learning techniques, particularly artificial neural networks (ANN). ANN-based models can be developed to include the effect of weather variables on power generation, and this can boost the HRES's operational efficiency while dealing with the nonlinear relationships among weather variables and power generation. Hybrid methods involving machine learning and metaheuristic optimization have also been shown to yield better sizing and control performance in uncertain environments. [14]

3.4.2 Fuzzy Logic Control (FLC)

Fuzzy Logic Control (FLC) is frequently used in HRES energy management because it can be implemented in energy management systems to manage uncertain and changing operating conditions without the need for precise mathematical models. Using FLC-based controllers has been proven to control power flow between renewable resources, storage, and loads, and still maintain stable operation. These are the main advantages because of the low computational requirements and high interpretability; however, the performance heavily relies on the design of membership functions and expert-drawn rules. [18]

3.4.3 Reinforcement Learning (RL)

Reinforcement learning is a new paradigm of AI in autonomous HRES control and operational optimization. RL-based controllers can dynamically adjust energy dispatch strategies based on the variability of renewable availability, electricity demand, and market conditions, without the need to explicitly model the system. Advanced deep reinforcement learning approaches hold great promise for high-dimensional HRES applications that require complex state-action spaces and real-time decision-making. [48]

Although these AI-driven solutions have great promise, there are several practical challenges, such as data availability, computational needs, cybersecurity concerns, and the lack of interpretability of models. However, the use of AI to enhance HRES using sophisticated optimization methods is likely to be pivotal to the future evolution of intelligent and autonomous HRES.

4. Techno-Economic and Environmental Assessment

The key role of determining the feasibility and Sustainability of Hybrid Renewable Energy Systems (HRES) is techno-economic and environmental assessment. The assessments allow the comparison of different configuration options of the system to evaluate economic viability, operational performance, and environmental effects in different technical and climatic scenarios.

4.1 Key Assessment Metrics

The most commonly used economic indicators to evaluate HRES are the Net Present Cost (NPC) and Levelized Cost of Energy (LCOE) [49]. NPC is the total system cost over the project life span (capital investment, operation and maintenance, replacement, and fuel cost) discounted to the present value [7]. The LCOE, on the other hand, is the average cost of electricity generation per unit of useful electricity produced and can therefore be directly compared with other energy technologies and other configurations of the electricity generation system. [50]

FP is also commonly considered using other indicators like Total Annual Cost (TAC), Simple Payback Period (SPP), Internal Rate of Return (IRR), and Return on Investment (ROI). [7]

HOMER Pro is the most popular simulation and optimization software that allows component sizing, sensitivity analysis, and economic comparison across different resource and operational conditions for HRES techno-economic analysis. [49]

4.2 Cost–Sustainability Trade-Offs

One key fact that has appeared in all the HRES literature is the cost-benefit trade-off between economic efficiency and environmental health and safety. The higher the renewable

penetration, the lower the GHG emissions, but the larger the storage size and the higher the capital cost [28]. DieSel-assisted hybrid systems, on the other hand, are typically less expensive (per cycle) and more reliable but have higher fuel use and carbon emissions.

Sensitivity analyses show that both solar irradiance, fuel prices, and discount rates have significant impacts on economic performance. The changes in these parameters can drastically change the optimum system configuration, along with the feasibility of the project. Therefore, it has become necessary to conduct extensive sensitivity analysis as part of a contemporary HRES assessment study. [28]

4.3 Economic Feasibility Challenges

Even though they have good environmental and operational characteristics, HRES still face significant economic issues. A high initial capital cost remains one of the constraints for deployment, especially in regions with less money. Other combinations that are based on renewable resources with large battery banks usually have the highest upfront investment because of the high cost of storage technologies and power electronic components. [28]

However, the economic competitiveness of HRES has been greatly enhanced in the last few years owing to the reduction in the cost of photovoltaic modules and lithium-ion battery technologies [49]. Generally, systems connected to the utility grid have a lower LCOE owing to the utility grid's ability to decrease storage needs and increase the flexibility with which the system is operated. Moreover, it has been concluded that government incentives, subsidies, and policy support are key enablers that accelerate the adoption of HRES and economic Sustainability. [22]

4.4 The effect of Energy Storage Systems

Energy storage systems are an important factor in achieving the best design and optimization of an HRES. Battery systems are commonly used to achieve short-term balancing of energy demand and supply and to enhance energy supply reliability; however, replacement costs due to battery degradation can make energy-balancing systems quite costly over the life of a project.

Long-duration and seasonal storage is provided by hydrogen-based storage systems, but they currently incur much higher capital costs for electrolyzers, fuel cells, and hydrogen storage. Therefore, storage system selection and sizing are still major optimization challenges that play important roles in the economic and environmental aspects of systems. [26]

The research focus has been the search for a more efficient and cost-effective overall system, which has led to renewed interest in hybrid storage solutions that involve battery storage for short-term buffers and hydrogen storage for long-term storage [51]. These coupled solutions are promising candidates for improving energy autonomy while taking care of cost, reliability, and sustainability targets.

5. Present challenges and future research directions

5.1 Current Challenges

Although advancement in HRES development has been tremendous, some technical, economic, and operational hurdles persist for widespread implementation and sustained operation.

5.1.1 Renewable Intermittency

Although hybridization decreases the uncertainty of standalone renewable energy systems, solar irradiance and wind speed are still variable, which introduces uncertainty and instability in the system's operation. Reliable forecasting and adaptive energy management are still necessary for the reliability of the system, especially in isolated and off-grid applications. [52]

5.1.2 Battery Degradation

Degradation has a significant impact on HRES reliability and cost of ownership. The capacity of lithium-ion batteries decreases over time due to factors such as charge-discharge cycling, temperature fluctuations, and aging, which can make them more likely to need replacement [31]. However, many optimization studies still use simplified battery models that ignore the long-term degradation characteristics, which can lead to less representative economic and operational analyses.

5.1.3 The initial capital cost is high

The initial installation costs of renewable generation equipment, storage, and power electronic converters are still a challenge in the deployment of HRES, particularly in developing countries where financing mechanisms are limited [9]. While the costs of renewable technology have fallen significantly over the past few years, the high capital costs of storage technology still hinder economic use.

5.1.4 Lack of Real-World Validation.

Most HRES research activities are dominated by simulation-based analysis techniques using software tools such as HOMER Pro and MATLAB. Although simulation studies offer optimization lessons, experimental validation and field data are still relatively scarce [53]. Therefore, the differences between the simulated operating conditions and actual conditions are not always properly addressed.

5.1.5 Complex Control Architectures

HRES configurations are often a combination of renewable energy, storage, smart loads, and bidirectional grid interaction. Advanced hierarchical and adaptive control strategies are required to control these interconnected components, which must operate across multiple timescales. The complexity of these types of control systems is increasing, making their implementation and reliability difficult. [53]

5.1.6 Data Availability for AI Applications

Large amounts of accurate operational and meteorological data are required for AI-based optimization and energy management techniques. However, the application of machine learning and reinforcement learning is hindered in many deployment areas of rural and remote locations where historical data is either inaccessible or incomplete. [48]

5.2 Future Research Directions

New technical possibilities emerge to enhance the intelligence, flexibility, and Sustainability of HRES.

5.2.1 AI-Driven Smart HRES

The role of AI in the future operation and optimization of HRES is expected to be increasingly critical. Adaptive and autonomous energy management can be achieved through advanced machine learning and reinforcement

learning techniques, dynamically adapting to fluctuations in renewable energy supply and demand and market conditions (Kouihi et al., 2025). The interpretability, robustness, and feasibility of the models for real-world implementation should be enhanced in the future.

5.2.2 Hydrogen-Integrated Hybrid Systems

Long-duration and seasonal storage are promising options for hydrogen storage and green hydrogen production. There is a need for future research to be directed towards the integrated optimization of PV/wind/electrolyzer/fuel-cell energy autonomy to reduce LCOH and LCOE. [54]

5.2.3 Digital Twin Technology

Recently, the concept of digital twins has been highlighted as a valuable tool for real-time monitoring, predictive maintenance, and optimization of HRES, as outlined by Khan, et al. [55]. Digital twins can enable the ongoing synchronization of operational data with virtual system models, enhance fault diagnosis, increase system reliability, and optimize system operation under realistic operating conditions.

5.2.4 IoT-Enabled Predictive Control

HRES can integrate Internet of Things (IoT) technologies to monitor renewable generation, storage, and load demand in real time. For batteries and other critical components, such as wind turbines, IoT-based predictive control systems can provide more accurate forecasting, increased operational agility, and aid in condition-based maintenance. [56]

5.2.5 Blockchain-Based Energy Trading

The smart grid concept is gaining traction because of blockchain technology, which has the potential to facilitate decentralized energy management and peer-to-peer electricity trading in HRES-powered microgrids [55]. Blockchain technology can enhance the transparency of energy trading, enable smart contracts for automated energy transactions, and promote decentralized renewable energy participation in local energy markets.

In general, the integration of intelligent optimization, advanced storage technologies, digitalization, and decentralized energy management frameworks is likely to play a bigger role in future HRES research, to enhance system

reliability, economic viability, and environmental Sustainability.

6. Conclusions

This review provides a brief critical evaluation of Hybrid Renewable Energy Systems (HRES), focusing on the system configuration, optimization methods, energy management, and techno-economic analysis methods. HRES have proven to be useful tools to make renewable energy more reliable and to bring sustainable electrification to remote and off-grid applications.

Under current operating conditions, PV/diesel/battery systems are still providing good economic performance and reliability, even with high renewable integration, while PV/wind/battery systems are still the most popular configuration for low operational emissions with high renewable integration. The large-scale integration of hydrogen-integrated HRES is limited by the high upfront capital expenses, but it appears to be a viable option for long-duration energy storage and future green hydrogen applications.

As far as optimization is concerned, the ability of metaheuristic algorithms, such as GA, PSO, and GWO, to tackle the nonlinearity and multi-objectivity of the HRES design problems is found to be very good. Recent studies increasingly support hybrid and AI optimization frameworks with their enhanced performance of convergence and adaptation. In addition, the real-time autonomous HRES control of AI-based techniques, especially machine learning and reinforcement learning techniques, is anticipated to assume an ever-larger role.

The techno-economic analysis further demonstrates that the Levelized Cost of Energy (LCOE) and Net Present Cost (NPC) are the most important parameters for assessing the feasibility of HRES. However, there are substantial economic, reliability, and environmental trade-offs. More specifically, storage technologies still dominate the overall system cost and flexibility.

While significant strides have been made in research, there are still several key obstacles to overcome, such as the intermittent nature of renewables, battery degradation, high upfront investments, and limited data availability in the real world for advanced AI applications. Superior

integration of the optimization methods with intelligent control systems, advanced storage technologies, and field-scale implementation will be needed to overcome these challenges.

Overall, future developments for HRES will be mainly directed towards the intelligent and autonomous use of energy, where AI, hydrogen technologies, digital twins, IoT infrastructure, and decentralized approaches to energy management will play a key role. Progress in these areas will be key to moving towards reliable, sustainable, low-carbon energy systems.

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Conflict of interest

The authors declare no conflicts of interest concerning this research.

Conflict of Interest

The authors declare no conflicts of interest related to the publication of this manuscript.

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Author Contribution

D.Y. Taha proposed the research problem. T.W. Mohammed developed the theoretical framework. D.Y. Taha and T.W. Mohammed verified the analytical methods. All authors participated in the discussion of the results and contributed to writing the manuscript.

AI Declaration Statement

The authors confirm that the manuscript was written without the assistance of generative AI or AI-based writing tools.

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