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An Overview of Current Optimization Approaches for Hybrid Energy Systems Combining Solar Photovoltaic and Wind Technologies

Ibrahim Seidu[1] | Sani Salisu[1] | Abdullahi Abubakar Mas'ud[2] | Umar Musa[1] | Adamu Halilu Jabire[3] | Firdaus Muhammad-Sukki[4] | Ibrahim Abubakar Mas'ud[5]

[1]Department of Electrical Engineering, Faculty of Engineering, Ahmadu Bello University, Zaria, Nigeria | [2]Department of Electrical Engineering, Jubail Industrial College, Jubail, Saudi Arabia | [3]Department of Electrical Engineering, Taraba State University, Jalingo, Nigeria | [4]School of Computing, Engineering and the Built Environment, Edinburgh Napier University, Edinburgh, Scotland, UK | [5]Department of Mechanical Engineering, Shibaura Institute of Technology, Koto City, Tokyo, Japan

Correspondence: Sani Salisu (salisus02@gmail.com) | Firdaus Muhammad-Sukki (f.muhammadsukki@napier.ac.uk)

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ABSTRACT

This study reviews recent developments in optimization techniques for hybrid solar photovoltaic and wind energy systems, particularly those using artificial intelligence (AI) and hybrid algorithms. Due to the global need for sustainable energy, the study compares both traditional and modern optimization techniques. It shows that hybrid algorithms, like, Gray Wolf–Cuckoo Search Optimization (GWCSO), can speed up convergence and reduce costs by up to 25% compared with other conventional methods, such as linear programming. The study groups optimization techniques into traditional, software-based, AI-driven, and hybrid approaches; assessing how well they improve system efficiency, reliability, and cost. It also outlines sizing methods and their economic, technical, and environmental effects, with results showing that AI-driven methods can lower the levelized cost of energy by 10%–15% in complex microgrids (MGs). The study further provides a structured way to size MGs, addressing a gap in optimization methods for independent hybrid systems in remote locations. Greater flexibility of hybrid algorithms in handling complex optimization problems was emphasized. Ultimately, this study offers new insights into combining AI with traditional methods, suggesting future research directions for both smart grid and MG design.

1 | Introduction

Due to the continuously growing energy demand across various sectors, including commercial, industrial, agricultural, and residential, fossil fuel resources are becoming increasingly scarce. As a result, there exists a notable upward trend in the adoption of renewable energy (RE) sources for electricity production in recent times [1]. Although wind and solar energy systems provide both autonomous and grid-connected options, the inherent stochastic nature of these resources can impact their efficiency. One way to address the challenge of unpredictable availability is by integrating them into hybrid systems that are grid-connected [2]. Standalone solar and wind systems provide a dependable option in remote locations far from the power grid, such as rural areas or regions with challenging terrain. These systems typically include integrated storage to compensate for periods when weather conditions restrict energy production [3, 4]. Additionally, economic considerations can hinder access to the grid, underscoring the significance of these standalone solutions. The hybrid renewable energy system (HRES) combines RE and traditional energy sources; additionally, it has the capability to integrate multiple RE sources that are operational either independently or linked with the grid. A hybrid system based on RE offers a more advantageous alternative compared with a system reliant on a single energy source, considering factors like expense, reliability, and effectiveness. Hybrid systems utilizing RE have the flexibility to utilize single or multiple energy sources, and they have the ability to function in isolation or be grid-connected [2]. The global shift toward dependable and practical HRES is primarily motivated by the promising technical and economic advantages of combining different energy sources and the rapid decline of traditional energy sources [5]. Various arrangements of hybrid systems can be implemented based on specific prerequisites and resource accessibility in different locations; this study exclusively focuses on photovoltaic (PV)–wind turbine (WT) hybrids. The emphasis is due to the intrinsic compatibility of solar and wind assets, which positions them as the most promising duo for sustainable power generation.

Solar irradiation reaches its peak during the summer months, and wind resources often intensify during the winter in certain regions. This temporal complementarity presents significant potential for hybrid systems. However, the inherent unpredictability of both energy sources, caused by seasonal and weather fluctuations, adds complexity to system design and optimization [1, 6]. To maximize the reliability of a hybrid PV–wind system, the strategic integration of additional alternative energy sources, like, diesel generators (DGs) and fuel cells (FCs), can be implemented [7]. By incorporating these augmented systems, it becomes possible to meet vital power needs in remote, non-electrified regions where access to the grid is unavailable [8]. However, beyond reliability, comprehensively evaluating microgrids (MGs) necessitates considering their economic and environmental impacts. Although some systems boast perfect reliability, they may not be economically feasible or environmentally sound due to potential pollutant emissions or excessive resource consumption [9–11]. There is no single-objective function universally applicable to the MG sizing problem. Instead, the optimization objectives for best MG sizing are developed considering various factors, like the location and type of the MG, the preferred mode of operation, the required reliability level, and specific needs related to economics, operation, and the selection of components (e.g., energy and storage sources). An additional critical factor that distinguishes current techniques for optimal MG sizing is the choice of the optimization techniques used to solve the sizing problem. Existing studies have discussed various algorithms, including classical, evolutionary, machine learning, and multiobjective algorithms. Although optimal MG sizing is crucial for ensuring efficient operation from both technical and economic perspectives, no standardized framework for addressing the issue has been reported. To propose a framework for addressing the MG sizing issue, this study presents an extensive review of current approaches used for MG sizing.

This review introduces a novel method for optimizing standalone solar PV–wind HRESs in remote locations by systematically combining traditional and advanced techniques, particularly artificial intelligence (AI)–driven and hybrid algorithms. Unlike previous studies that primarily focused on grid-connected systems or single optimization goals [1, 5], this study offers a comprehensive framework for MG sizing using multiobjective optimization.

A typical hybrid solar–wind system includes PV arrays, WT systems, energy storage systems, control units, power converters, and other essential auxiliary components [11–13]. When energy production exceeds demand, the excess is strategically used to charge storage. Conversely, during periods of insufficient renewable generation, the storage system discharges to supplement the available energy and reliably meet load demands [14, 15]. The findings of this review are crucial for designing affordable, dependable, and environmentally friendly HRES for rural and remote communities, improving energy access in off-grid locations, and guiding smart grid development. Ultimately, this study benefits RE researchers, engineers, policymakers, and rural development professionals by providing practical insights for deploying HRES in underserved areas, thereby promoting global energy equity and sustainability.

While previous studies have extensively explored HRESs, particularly those connected to the grid and utilizing solar PV, WTs, and auxiliary power like DGs [1, 5, 7], the optimization of independent HRES for remote areas has received less attention. Specifically, the integration of advanced AI and hybrid optimization techniques tailored for these unique challenges remains underexplored [2, 8]. Although software tools like Hybrid Optimization Model for Electric Renewable (HOMER) and improved hybrid optimization by genetic algorithm (iHOGA) are frequently employed for sizing grid-tied systems [16, 17], their application to standalone systems is limited by their lack of customization and inability to dynamically adapt to varying environmental factors [18]. Moreover, existing reviews typically focus on optimizing a single objective, such as cost reduction [1, 3], neglecting the crucial multifaceted optimization (economic, technical, environmental, and social) necessary for remote deployments [9, 12].

To address these gaps, this review systematically investigates both traditional and advanced optimization methods for independent PV–wind hybrid systems, emphasizing AI-powered and hybrid algorithms. Unlike prior research that mainly focuses on urban or grid-integrated systems [5, 13], the present study specifically targets remote locations without grid connections. This study presents a comprehensive framework for sizing MGs that integrates AI-based techniques (like Gray Wolf–Cuckoo Search Optimization [GWCSO]) with traditional methods, resulting in up to 25% quicker convergence and better cost efficiency compared with conventional approaches [19]. By underscoring the versatility of hybrid algorithms in handling multiple optimization goals, this review provides a guide for developing reliable, cost-effective, and environmentally sustainable HRES for neglected regions, thereby differentiating itself from existing literature. Figure 1 shows the classification of optimization techniques used in HRES.

In terms of energy systems, the optimization and design processes face inherent constraints stemming from factors, such as the availability of resources, technological limitations, considerations of efficiency, and the intricacies of complex mathematical models [2]. However, the landscape has been significantly transformed by recent breakthroughs in computational techniques. The utilization of advanced optimization algorithms and sophisticated simulation tools has substantially enhanced our capacity to grapple with these challenges. Consequently, it is possible to navigate the intricacies of energy system optimization more effectively, leading to the creation of

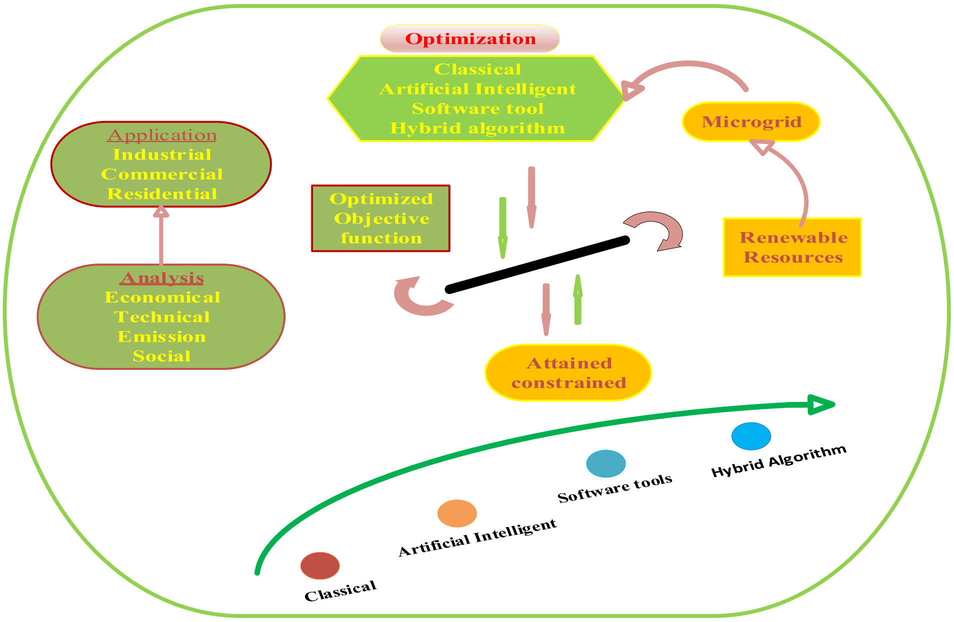

FIGURE 1 | Classification of optimization techniques used in hybrid renewable energy system [2].

TABLE 1 | Techniques for determining hybrid energy system's cost.

Reference	System cost analysis	Method description
[32]	NPC	It is determined by deducting the current value of all expenses accrued across the system's lifespan from the total revenue presently generated during the same period. This computation entails aggregating the discounted cash flows for every year throughout the project's timeline.
[1]	Total annualized cost (TAC)	It is a comprehensive annual cost that covers all financial responsibilities associated with the system throughout its complete lifespan, encompassing both initial investments and ongoing expenditures.
[1, 33]	Life cycle cost	This entails a comprehensive assessment of all expenses associated with an asset, encompassing both recurring and one-time costs, over its complete lifespan or a designated period.
[34, 35]	LCOE	The TAC of the MG significantly influences the COE. The LCOE is calculated as the ratio of the total system cost to the total energy generated over a specific period.

Abbreviations: COE, cost of energy; LCOE, levelized cost of energy; MG, microgrid; NPC, net present cost.

systems that are not only more optimized but also more resilient [20, 21]. Various simulation tools, like HOMER, Hybrid Optimization using Genetic Algorithm (HOGA), and Hybrid Power System Simulation Model (HYBRID2), and so forth, have become indispensable tools for designing, optimizing, and assessing the effectiveness of PV–WT hybrid systems, as extensively explored in [16, 17]. While these software programs offer valuable features, limitations arise. Compatibility issues with specific operating systems may constrain usability. Accessibility challenges and reduced adaptability compared with customization optimization techniques are noteworthy drawbacks.

To attain cost-effectiveness and power sufficiency, deploying meticulous sizing and optimization techniques is crucial. Factors such as system reliability, cost, PV system size, panel tilt angle, WT hub height and size, and the battery capacity and demand thorough examination. This comprehensive approach mitigates the risks of under sizing, resulting in an inadequate power supply or over sizing, leading to excessive cost [18]. From a comprehensive analysis conducted by multiple authors [18, 22–31], Table 1 highlights the key findings regarding sizing and optimization techniques, while Figure 2 gives a pictorial representation of an islanded MG.

Below is an outline of the work's structure: Section 2 gives an outline of sizing methodologies for PV–WT hybrid systems. In Section 3, an extensive survey of the literature is presented, focusing on the several optimization techniques utilized in the work of PV–wind hybrid systems; Section 4 delves into the current trends in optimization; and Section 5 serves as the concluding part of the paper.

2 | Comprehensive Overview of Solar PV–WT Hybrid MG Systems

This section provides a concise outline of the Solar PV–WT-based MG. Figure 2 provides a conceptual illustration of the

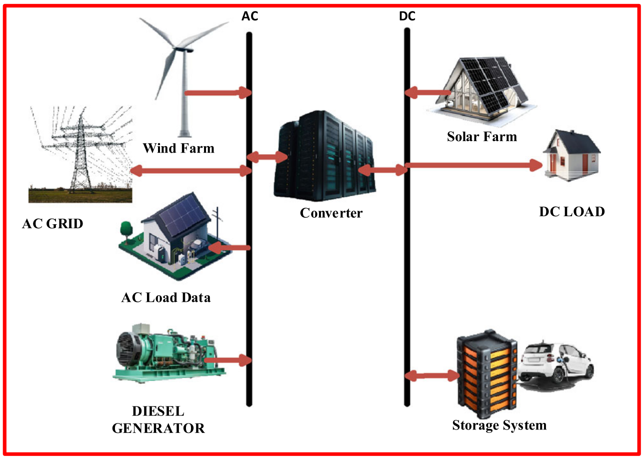

FIGURE 2 | Grid-connected microgrid [23]. AC, alternating current; DC, direct current.

intended MG. The primary components of the system are the PV and WT systems. The power from both the PV and WT systems is heavily influenced by weather conditions, specifically solar irradiance, temperature, and wind speed. The intermittency of solar irradiance and wind speed leads to fluctuations in the generated power [16]. Typically, solar PV power peaks around midday, while WT power generation is higher during cooler periods and can even produce excess energy depending on the load demand.

To mitigate the intermittent nature of these systems and maximize power utilization, Energy Storage Technologies (EST) have become a critical component of HRES MGs [17]. With significant improvements in battery technology and substantial cost reductions, battery storage systems have emerged as a better EST in HRES MGs. However, to ensure reliability, flexible power sources like DG and generators powered by hydrogen FCs are often integrated as power sources [18, 22–24]. Power electronic interfaces—including DC–DC, DC–AC, and AC–DC converters—facilitate the smooth integration of diverse energy sources and loads within an MG. These converters enable different types of energy systems, whether renewable, storage, or traditional, to work harmoniously by converting power into compatible forms for efficient distribution and use. This adaptability allows for effective energy management and stability within MGs, making it easier to meet demand flexibly and ensure reliable operation across various power sources and consumption needs.

The adoption of HRES MGs is on the increase globally, addressing diverse load demands with improved efficiency and resilience.

2.1 | Criteria for the Enhancement of PV–Wind Systems

The optimization of a PV–wind model necessitates the following input parameters.

2.1.1 | Location and Meteorological Data

The identification of a suitable location and its meteorological assessment are critical for effective MG design [36]. These factors provide valuable insights into the optimal generation mix and storage technology needed for the MG, ultimately minimizing transmission losses [2]. Meteorological parameters such as solar irradiation, wind speed, ambient temperature, and relative humidity play a crucial role in determining the MG's performance [3, 5, 7].

2.1.2 | System Configuration

Preliminary studies using meteorological information such as sunlight intensity, wind velocity, and temperature can determine the appropriate sizing of equipment. However, it is crucial to take into account the relative resource potential of both PV and wind energy at the specific location. In areas where the potential for solar energy exceeds that of wind energy, the hybrid system configuration should prioritize PV, allocating a smaller share to WTs [37].

2.1.3 | Load Profile

A proper analysis of load demand is crucial in the design process of an MG, as its primary objective is to meet local energy needs [2]. To accurately assess the load patterns of the MG, the system's yearly load profile, with hourly and daily time steps, must be considered [5]. This detailed approach provides a better understanding of the MGs energy demand over time, ensuring efficient and reliable operation.

2.1.4 | System Framework

In energy systems analysis, system frameworks serve as crucial mathematical representations, accurately simulating diverse energy-related challenges [4]. Researchers utilize these models across various computational platforms to dissect and solve intricate energy issues [20]. Specifically concerning the optimization of PV and wind systems, the precision of underlying component models holds paramount importance. This demands the inclusion of all pertinent variables affecting energy conversion—meteorological conditions, resource availability, component specifics, and operational limitations [38]. While a simple model structure is preferred, maintaining accuracy to the actual system may entail added complexity [39]. Neglecting key factors or oversimplifying can lead to inaccurate predictions and suboptimal results.

2.1.5 | Optimization Results

To obtain accurate optimization results that avoid overgeneration or undergeneration of power, it is crucial to diligently follow the four aforementioned steps. Although power generation from PV–wind systems naturally varies based on location-specific factors, it is important to investigate the possibility of generalizing optimization outcomes to neighboring areas for scalability and cost-effectiveness purposes. Figure 3 provides a synopsis of the critical design aspects for PV–WT-based MGs. These considerations serve as the foundation for formulating the MG optimization problem.

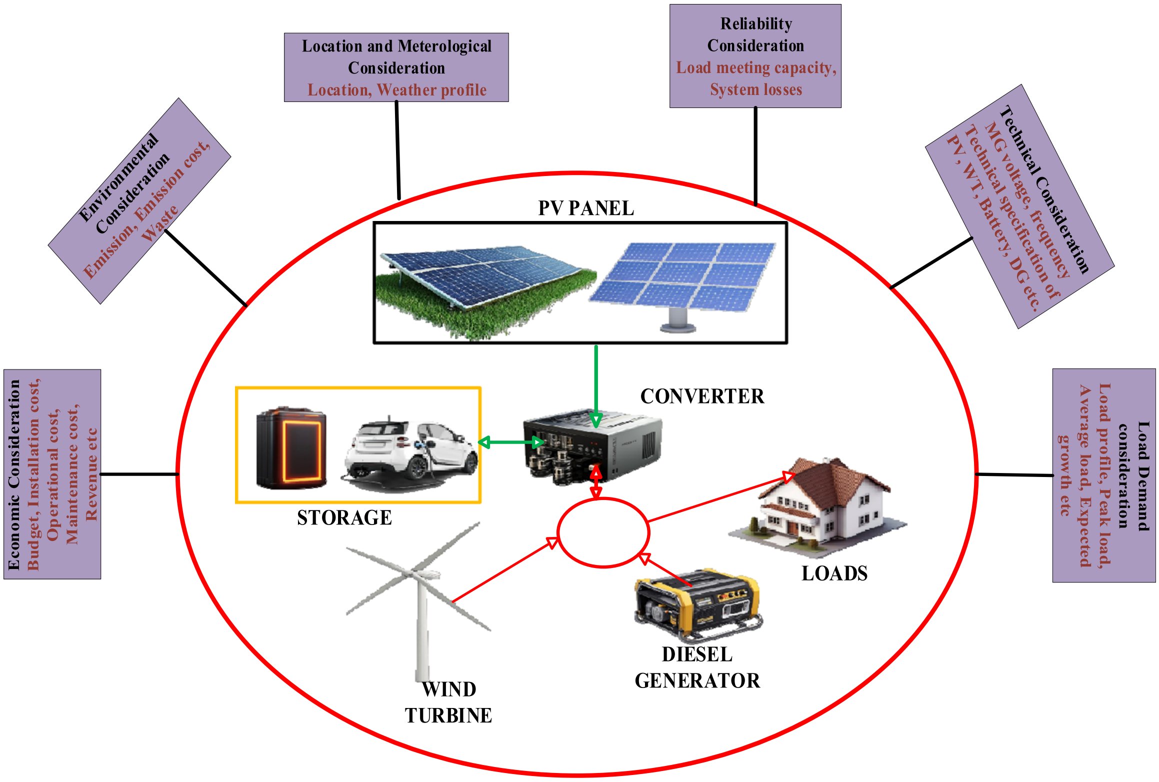

FIGURE 3 | Common consideration for PV–WT-based MG [40]. DG, diesel generator; MG, microgrid; PV, photovoltaic; WT, wind turbine.

2.2 | Criteria for Optimizing MG Systems

Objective formulation, or the cost function, is a critical aspect of MG sizing problem formulation, as it aims to integrate economic, technical, environmental, and reliability considerations of the MG [40]. Common objectives in designing a hybrid PV–WT MG include reducing costs and environmental emissions while enhancing system reliability. The following sections briefly discuss the key objectives from the economic, environmental, and reliability perspectives.

2.2.1 | System Cost Analysis

Cost analysis plays a crucial role in optimizing PV–wind power systems by focusing on reducing average expenses associated with system implementation, which includes acquisition, installation, operation, maintenance, and replacement costs, as well as fuel costs for backup generators. Commonly used techniques such as life cycle cost (LCC), net present cost (NPC), and cost of energy (COE) provide critical information about the financial viability and long-term implications of these systems [41]. Additionally, revenue generation may be considered as an objective to be maximized during MG sizing. For further details, refer to Table 1.

2.2.2 | Environmental Objectives

A critical motivating factor driving the adoption of HRES is minimizing greenhouse gas (GHG) emissions from electricity generation [42] DGs, which emit GHGs, often serve as backup power sources to enhance the MG's reliability. The primary environmental objective when optimizing an HRES is to minimize GHG emissions from the MG. The greenhouse gas emission cost (GEC), which accounts for the total emissions expenses over the project's lifetime, is a commonly used environmental metric in the sizing of PV–WT-based MGs. The GEC is expressed as follows:

$$\mathrm{GEC} = \left[\frac{f+1}{i-f}\right]\cdot\left[1-\left(\frac{f+1}{i+1}\right)^{p}\right]\cdot\left[\sum_{i=1}^{m}\sum_{j=1}^{n}\mathrm{PF}_j E_{ij} P_i\right]. \tag{1}$$

In (1), P_i signifies the power generated by the DG, while PF_j indicates the outlying impact cost for emission type j from the DG unit. The variable m refers to the emission type, such as CO_2, sulfur dioxide (SO_2), or nitrogen oxides (NO_x). E_{ij} is the emission factor for the ith DG and emission type j, and n represents the total number of DGs in the MG [43].

Another key environmental metric used in MG optimization is the Levelized Emission (LE) [43]. The LE is outlined as the ratio of the overall GHG emissions from the MG over a year to the entire power produced by the MG during that the same period, and is represented by Equation (2′).

$$\mathrm{LE} = \frac{\sum \mathrm{GHG}_{\downarrow \mathrm{year}}}{\sum E_{\mathrm{g}\downarrow \mathrm{year}}}. \tag{2}$$

In Equation (2′), $\sum \mathrm{GHG}_{\downarrow \mathrm{year}}$ represents the total greenhouse gas emissions in a year, and $\sum E_{\mathrm{g}\downarrow \mathrm{year}}$ denotes the summation of the energy produced by the MG in that the same year. LE denotes the GHG emissions per unit of power produced by the system. The goal is to minimize LE as much as possible. Preferably, for a

PV–WT-based MG, if no fossil fuel-based backup generator is included, the LE should ideally be zero.

2.2.3 | System Reliability Analysis

Reliability in hybrid power-generating systems, such as PV–wind MGs, is a crucial factor due to the inherent unpredictability of solar and wind resources, which can lead to inconsistent power generation, particularly during intervals of low sunlight or wind [37]. A system is deemed reliable if it can consistently meet the energy demand within a specified timeframe. During MG sizing, reliability indices like Loss of Load Supply Probability (LPSP), Loss of Load Probability, Loss of Power Supply Probability (DPSP), and Expected Energy Not Supplied (EENS) are incorporated in the objective formulation [38]. Various techniques for assessing system reliability have been discussed in the literature and are outlined in Table 2.

Table 3 shows some of the latest techniques and software that have been implemented previously.

2.3 | Hybrid System Modeling

Modeling is the first stage of the design process, offering a comprehensive understanding of various parameters and constraints before the practical implementation occurs [53]. The efficiency of a wind and solar hybrid system is contingent upon its components. This segment outlines the modeling equations for the wind, PV, and battery systems.

2.3.1 | PV System Modeling

Various models have been utilized in previous studies to determine the energy output of PV systems [23]. A simplified model was utilized in this study, considering solar irradiance and temperature, expressed by (1) [2, 25, 45].

$$PV = PV_{rated} \times [1 - T_{STC} + \beta(0.0256G + T_{aT})] \times \frac{G(t)}{1000}. \quad (1')$$

PV represents the module's power output, PV_{rated} represents the power rating (W) under standard test conditions, G denotes the solar irradiance (W/m^2), T_{aT} denotes the ambient temperature (°C), and β is the temperature coefficient defined by $(-3.7 \times 10^{-3}\ [1/°C])$ [4, 54].

2.3.2 | Wind System Modeling

To compute the power output from the WT, the wind speed value at the desired height is transformed to the WT hub height associated with the power law equation in (2) [55].

$$V_2 = V_1\left(\frac{h_2}{h_1}\right)^{\alpha}. \quad (2')$$

Here, V_2 and V_1 denote the wind speed at the WT hub height h_2 (m) and at the desired height h_1, respectively, with α representing the power law exponential.

Equation (3) was utilized to calculate the output power of the WT [56].

$$P_w = \begin{cases} 0, & V < V_{in}, V > V_o, \\ V^3\left(\frac{P_r}{V_r^3 - V_{in}^3}\right) - P_r\left(\frac{V_{in}^3}{V_r^3 - V_{in}^3}\right) & V_{in} \leq V < V_r, \\ P_r V_r \leq V < V_o. & \end{cases} \quad (3)$$

In this context, V (m/s) signifies the wind speed, P_r (kW) represents the rated power, and V_{in} (m/s), V_o and V_r denote the

TABLE 2 | Technique for determining a hybrid energy system's reliability.

Reference	Criteria	Definition
[34]	DPSP	It is a reliability metric that measures the probability of the energy supply failing to meet the demand, resulting from system malfunctions or insufficient generation from RE systems.
[44]	LHSP	It is an indicator of the percentage of unmet heat demand in relation to the total heat demand within the hybrid energy system.
[2]	LPSP	It is a frequently utilized method, which assesses probability of insufficient energy supply meeting the load during the design of a hybrid system. It is computed as the ratio of the deficits power supply to the load requested within specified timeframe.
[45]	Renewable factor (RF)	This is a metric indicating the ratio of energy provided by RE sources to the total load. RF ranges from 0 to 1.
[46]	EENS	It represents the total amount of electricity the microgrid is expected to be unable to supply within a given timeframe. This metric is used to assess the security of the electricity supply.
[1, 47]	Unmet load	The proportion of the load that remains unmet in comparison to the total load over a specified duration, usually 1 year.

Abbreviations: DPSP, loss of power supply probability; EENS, expected energy not supplied; LHSP, loss of heat supply probability; LPSP, loss of load supply probability.

TABLE 3 | A breakdown of latest techniques implemented in the hybrid PV–WT system model.

Reference	System Type	Load/location	Technique/software	Objective function	Findings
[18]	PV/wind/DG/battery		Iterative approach	DPSP, COE, and TNPC	In response to the substantial initial cost associated with an oversized battery in the MG system, a comparative study to the selection of a DG alternator energy supply.
[22]	PV/Wind/DG/battery/biogas	Industrial load (Pakistan)	HOMER	Cost minimization, fuel saving, and improved environmental emissions	Integrating a PV tracking system within a microgrid system can significantly enhance its power output compared with operating as separate systems.
[23]	PV/WT/DG/battery	Rural healthcare facilities (Iseyi, Sokoto, Jos, Maidugori, Enugu, and Portharcourt)	HOMER	NPC and COE	Systems integrating PV/WT/DG/batteries are deemed, optimal for health centers in rural areas located in Iseyin, Sokoto, Maiduguri, Jos, and Enugu. Meanwhile, PV/DG/battery hybrid systems are considered ideal for Portharcourt.
[24]	PV/DG/battery	Rural healthcare services (Madhya)	HOMER	NPC	The PV/DG/battery energy systems provide a cost-effective and environmentally friendly solution for supplying energy to remote healthcare centers. This leads to a strong conclusion that REs are a superior choice for healthcare facilities in these regions.
[25]	PV/WT/DG/battery	Household (Iran)	MOPSO	COE and LPSP	Integrating renewable energy solutions in distant regions of Iran transcends mere energy provision; it signifies a transformative move toward a sustainable, prosperous, and equitable future for all stakeholders.
[26]	PV/WT/DG/battery	Household (Sundarbans)	PSO	POE, LPSP, and RF	The results suggest that Hybrid Microgrid Systems in the Sundarbans area predominantly depend on the usage of solar and wind power, harnessing the region's abundant renewable resources.
[27]	PV/WT/DG/battery	Household (Southern Denmark)	Taguchi and MOMFO	LCOE and LPSP	The proposed technique has demonstrated exceptional performance, outperforming established techniques such as Non-Dominated Sorting Algorithm II (NSGA-II), MOPSO, and Multiobjective Social Engineering Optimizer in two crucial metrics: LCOE and LPSP.
[28]	Grid/electric campus vehicle		Monte Carlo (MC) and NSGA-II optimization algorithm.	LPSP, LCC, and WE	The MG system can function with the incorporation of electric vehicles (EVs) in an economical and dependable way. Furthermore, it leads to a significant reduction in peak-to-valley value and CO_2 emissions, while also boosting the income of EV users.

(Continues)

TABLE 3 | (Continued)

Reference	System Type	Load/location	Technique/software	Objective function	Findings
[29]	PV/P2H2P/ battery	Rural and urban load (Australia)	HOMER pro	NPC and COE	The combination of hydrogen and battery storage presents an innovative and efficient approach to solely power standalone Microgrid systems using renewable energy sources.
[30]	PVT, WT, MT, EES, TES, and GB	Rafsanjani (Iran)	E-PSO	TAC	Through the combination of two separate combined heat and the standalone multicarrier MG, the decrease is by more than 25%.
[31]	PV/WT/battery		Jaya and Gray Wolf optimization (JGWO)	LOPS and TAC	To tackle the issues of ensuring reliable renewable generation in the face of changing weather conditions and the associated costs, a highly efficient sizing method has the associated costs, a highly efficient sizing method has been developed. This method utilizes a hybrid algorithm called JGWO, which does not depend on algorithm-specific parameters. It achieves ideal sizing solutions and outperforms traditional techniques.
[48]	PV/WT/battery		Controlled elitist GA approach		The outcomes indicate this approach is suitable by providing both economic and environmental factors simultaneously.
[49]	PV/WT/FC/ battery	South Africa	Quasioptimal control search using pattern search optimization	Operating and capital cost	The study presents a model for an HRE system with four configurations, replacing the traditional two-stage stochastic programming with a quasioptimal control based on differential equations to minimize operational and capital costs.
[50]	PV/WT/DG/ battery	Saudi Arabia	Reinforcement learning neural network algorithm (RLNNA)	Annual System Cost (ASC) and reliability	The suggested RLNNA method outperforms SDO, MRFO, and PSO in terms of ASC and achieves a 0% LPSP. It also demonstrates faster convergence than PSO, MRFO, and SDO, although these algorithms can still reach the best solution. Overall, the study underscores RLNNA's effectiveness in optimizing HES sizing for off-grid power systems in islanded areas.

(Continues)

TABLE 3 | (Continued)

Reference	System Type	Load/location	Technique/software	Objective function	Findings
[51]	PV/WT/DG/battery	Saudi Arabia	Harris Hawk Optimizer (HHO)	ASC	The effectiveness of HHO was examined and compared with seven other techniques: GOA, CSO, GA, Big Bang–Big Crunch, Coyote Optimizer, Crow Search, and Butterfly Optimization Algorithm. This comparison aimed to achieve optimal sizing for the HRE MG by reducing the ASC.
[52]	PV/WT/DG/biogas/battery	Southern Iraq	Hybrid Gray Wolf–Cuckoo Search Optimization (GWCSO)	TAC	The results were compared with those achieved using PSO, GA, GWO, CSO, and Antlion Optimization to evaluate the optimal sizing results with reduced costs. The adopted GWCSO has the lowest deviation and found to be more robust than the other algorithms.

Abbreviations: COE, cost of energy; CSO, cuckoo search optimization; DG, diesel generator; DPSP, loss of power supply probability; EES, electrical energy storage; E-PSO, evolutionary particle swarm optimization; FC, fuel cell; GA, genetic algorithm; GB, gas boiler; GOA, grasshopper optimization algorithm; HOMER, hybrid optimization model for electric renewable; HRE, hybrid renewable energy; LCC, life cycle cost; LCOE, levelized cost of energy; LOPS, loss of power supply; LPSP, loss of load supply probability; MG, microgrid; MOMFO, multi-objective moth flame optimization; MOPSO, multiobjective particle swarm optimization; MRFO, manta ray foraging optimization; NPC, net present cost; POE, price of electricity; PSO, particle swarm optimization; PV, photovoltaic; PVT, photovoltaic thermal; RF, renewable factor; SDO, supply demand optimization; TAC, total annualized cost; TES, thermal energy storage; TNPC, total net present cost; WE, waste energy; WT, wind turbine.

minimum, maximum, and nominal speeds of the WT, respectively.

2.3.3 | Battery System Modeling

The battery is employed for storing excess generated power, maintaining system voltage, and supplying power to the load when the hybrid system produces deficient energy. Battery size is influenced by factors like temperature, battery lifespan, and maximum depth of discharge (DOD). The capacity of the battery is expressed in (4) [1, 18].

$$C_B = \frac{D_a \times L_d}{V_B \times \mathrm{DOD}_M \times \eta_B}, \tag{4}$$

where

- DOD_M, battery maximum depth of discharge,
- V_B, battery's tension,
- L_d, electricity usage per day,
- D_a, battery autonomy,
- η_B, efficiency of the battery.

The charging and discharging status of the battery is represented using (5) and (6) [57].

$$\mathrm{SOC}(t) = \mathrm{SOC}(1-\tau)(t-1) + \eta_B \times \left(P_{pv}(t) + P_w(t) - \frac{P_{load}(t)}{\eta_{inv}}\right), \tag{5}$$

$$\mathrm{SOC}(t) = \mathrm{SOC}(1-\tau)(t-1) + \eta_B \times \left(\frac{P_{load}(t)}{\eta_{inv}} - P_{pv}(t) + P_w(t)\right), \tag{6}$$

where

- τ: hourly discharge rate of the battery,
- η_{inv}: the inverter's efficiency,
- P_{load}: the load demands,
- SOC: the battery's state of charge (SOC).

The battery's performance is influenced by three factors: the presence of sustainable energy sources, the limits of discharging and charging, and the DOD. It is important to state that the battery's SOC must adhere to the specified constraints outlined in (7), while the battery's status in terms of maximum and minimum SOC is expressed by (8) and (9).

$$\mathrm{SOC}_m(t) \le \mathrm{SOC}(t) \le \mathrm{SOC}_M(t), \tag{7}$$

$$\mathrm{SOC}_M = V_B \times C_B, \tag{8}$$

$$\mathrm{SOC}_m = (1 - \mathrm{DOD}_M) \times (V_B \times C_B). \tag{9}$$

The battery power is given in (10):

$$P_B = P_{pv} + P_w - \frac{P_{load}(t)}{\eta_{inv}}. \quad (10)$$

The most effective hybrid solar–wind system can reach the ideal equilibrium between its overall efficiency and system cost. The cost-efficiency strategy motivates reducing the overall expenses of RES by focusing on key components, like, solar panels, batteries, and WTs [58]. The approach includes minimizing capital investments, maintenance costs, and replacement costs throughout the system's lifespan, which is expressed in (11) [58].

$$C_T = \min\{C_{pv} + C_w + C_B + C_{other}\}. \quad (11)$$

The initial step in the optimal sizing methodology for a PV–WT MG involves gathering the energy demand and the meteorological information. This is followed by system modeling that takes into account cost considerations and reliability. Finally, an optimization technique is utilized for meeting system configuration criteria.

3 | Optimization Approaches for PV–WT Systems

Optimizing PV–wind hybrid systems is essential for achieving maximum efficiency, reliability, and cost savings while minimizing environmental harm [58]. Previous research has investigated various optimization methods, ranging from traditional techniques like linear programming (LP) to modern AI-driven methods, such as Particle Swarm Optimization (PSO) [1, 2, 58]. However, a significant gap exists in addressing the specific challenges of standalone HRES in remote regions, where fluctuating resources and the absence of a grid necessitate customized solutions.

Optimization [59] is the process of identifying the most efficient method to either maximize or minimize a problem's objective formulation. For any given problem, optimization involves determining the best approach to achieve this maximization or minimization of the objective function. This function represents the desired outcomes to be maximized or the undesired outcomes to be minimized. Various optimization techniques have been developed to tackle engineering problems within defined constraints and conditions, enabling the identification of the optimal strategy or conditions [60]. A mathematical relationship exists between constraints, objectives, and decision variables, which aids in selecting the appropriate algorithm and assessing the complexity of finding the best possible solution in an optimization problem.

An optimization problem can be classified into distinct types considering factors, like, the quantity of objectives, variable types, constraints, optimization nature, equations, and problem structure [61]. It is essential to emphasize that as the number of optimization variables increases, the required simulations grow exponentially, leading to a substantial rise in computational time and effort for the optimization process. Hence, designers must identify an effective optimization approach capable of efficiently and accurately determining the optimal system configuration. Research literature has documented various optimization approaches for solar–wind systems, encompassing modern and traditional approaches [58, 62, 63]. Nevertheless, the present study classified optimization techniques into four broad categories: traditional/classical, AI, software tool, and hybrid techniques. Figure 4 gives a pictorial representation of the classification of optimization techniques adopted in this study. Utilizing these techniques allows the attainment of optimal configurations that meet load requirements.

3.1 | Classical Optimization Technique

Traditional optimization techniques, including graphical, probabilistic, analytical, and numerical methods, have historically been used for HRES sizing [64–74]. For example, graphical techniques [64, 65] optimize PV and battery configurations using long-term weather data set but are limited to analyzing only two variables, thus overlooking crucial parameters like WT hub height or PV tilt angle. Probabilistic methods [66, 68] account for uncertainties in solar and wind resources but often fail to represent dynamic system behavior, potentially leading to inefficient sizing in fluctuating conditions. Analytical techniques [71–73, 75] offer fast calculations but struggle with intricate, nonlinear systems. Lastly, numerical methods like mixed-integer linear programming (MILP) [76–79] are effective for well-defined scenarios but become computationally demanding for problems with multiple objectives.

3.1.1 | Graphical Technique

A graphical technique, proposed by [65], enables the identification of the most suitable setup for an independent solar–wind hybrid system by considering data sets of wind speed and solar irradiation spanning over three decades, collected at hourly

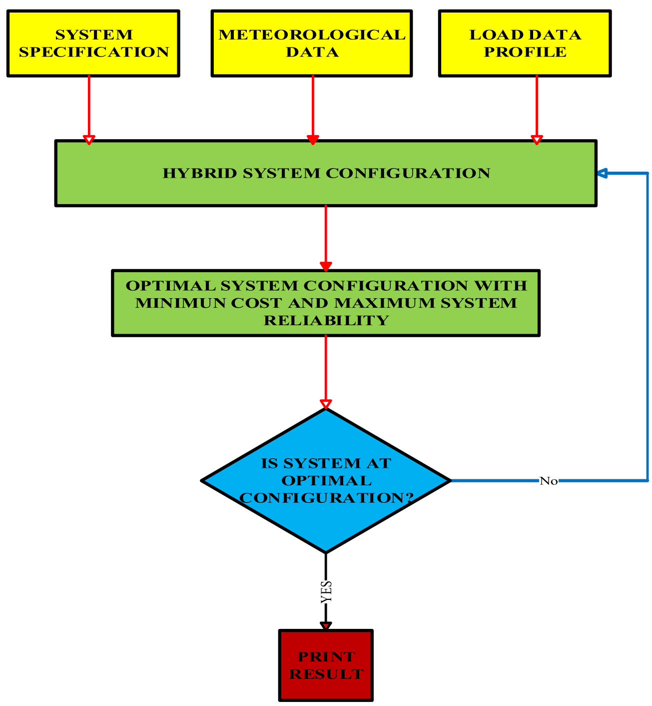

FIGURE 4 | Typical procedure for optimizing the sizing of hybrid systems [64].

intervals. The electricity usage requirements, derived from the typical consumption pattern of a standard household in Massachusetts, serve as the system's load requirements. The technique, designed to achieve a specified LPSP and given load, computes the optimal arrangement in relation to the number of PV modules and batteries, aiming to minimize system costs. Reference [65] assumes a linear correlation among the overall system cost, the number of PV modules, and batteries. The intersection point on the curve representing this correlation denotes the minimum cost, facilitating the computation of the optimal setup for the PV array and battery bank.

Furthermore, a graphical technique was presented by [64] for the best arrangement of a solar–wind power generation set. This method considers the average monthly values of wind and solar energy. Although both graphical methodologies concentrate exclusively on two variables, either PV and battery or WT and PV, in the optimization process, they neglect critical aspects such as the installation height of WT and the slope angle of PV modules.

3.1.2 | Probabilistic Technique

The sizing approaches that incorporate probability considerations for solar–wind systems account for the influence of fluctuations in both solar irradiance and wind speed and are considered during the system design phase. Probability-centric approach was introduced by [66] employing the LPSP technique for standalone PV system design. This methodology allows for the calculation of the least required sizes necessary for both the storage capacity and PV system, guaranteeing a dependable power supply to the demanded load. The quantification of power supply reliability involves evaluating the total annual hours during which the power demand of the consumer surpasses the available PV supply. The research covers a duration of a year to gather the SOC data of the battery. Afterward, the overall distribution function of the battery's SOC is determined, and the LPSP is calculated as [1 − (The cumulative time the battery SOC exceeds the minimum)]. Studies akin to those in [67–69], incorporating wind generators, have investigated an ideal battery bank storage size in autonomous systems utilizing both PV and wind power. Hourly data spanning a long duration regarding wind velocity and solar irradiation is utilized to create the probability density function (PDF) for hybrid generation. Subsequently, the PDF for storage is determined based on the load distribution in question. Ultimately, the battery bank size is computed to guarantee the desired system reliability state using the LPSP technique. Table 4 shows a selection of the articles that implemented probabilistic techniques.

3.1.3 | Analytical Technique

An analytical technique was utilized in [72] to integrate factors such as the likelihood of loss, clarity index, and power consumption, and the cost per unit of each component within the system. Furthermore, its accuracy and feasibility were demonstrated in a separate study [75]. Additionally, it necessitated substantial meteorological data and provided a quick processing time, combined with simplified calculations [73]. However, the process of estimating the position coefficient of the mathematical equation using this particular technique presented a significant challenge [74]. Table 5 shows some of the articles that implemented analytical techniques.

3.1.4 | Numerical Approach

System design using numerical techniques relies on mathematical analysis and computations, considering uncertainties related to power sources. The power balance of the system has the potential to be simulated on a daily or hourly basis [70]. Acquiring extended meteorological data time series is essential for calculating the output energy from the PV panel, and the wind power setup is good for evaluating the battery capacity. Common numerical methods for optimizing the size of HRESs include techniques that repeat calculations, random and fixed methods, and MILP [76]. These techniques are employed to

TABLE 4 | List of some of the works that implemented probabilistic approach of size optimization.

Reference	System elements	Objective	Description
[80]	Islanded PV/ battery grid	LCC and LPSP	The available solar irradiance to the PV was modeled, and the calculation of the generated power was carried out, followed by an assessment of the battery charge.
[81]	Islanded PV	LCOE and LPSP	Taking into account the probabilistic fluctuations in demand and the locations meteorological conditions, size optimization was accomplished by reducing the objective functions.
[82]	PV/WT/DG/ battery	EENS and NPV	A mixture of probabilistic methods, including Monte Carlo simulation and ANN, is employed. The main constraints for developing the optimization model are the uncertainties in solar irradiance, wind speed, fuel prices, and battery life, with the objective functions taken into account.
[83]	PV–WT	LPSP	The size optimization of the MG in a Hong Kong location is detailed using hourly meteorological data, with the objective function serving as the reliability parameter.

Abbreviations: ANN, artificial neural network; DG, diesel generator; EENS, expected energy not supplied; LCC, life cycle cost; LCOE, levelized cost of energy; LPSP, loss of load supply probability; MG, microgrid; NPV, net present value; PV, photovoltaic; WT, wind turbine.

TABLE 5 | List of some of the works that implemented the analytical technique of size optimization.

Reference	System components	Objective	Description
[84]	Autonomous PV system		Size optimization is performed in light of two climate cycles. The sizing curve is derived by superimposing the sizing lines corresponding to each climate cycle. An exponential function is applied to fit the sizing curve and determine the system size.
[85]	PV–battery	LCC, COE, and LPSP	The prime configuration of PV size and battery capacity was ascertained based on the defined objective functions.
[86]	PV/biomass/biogas/ micro hydro	COE, EENS, and EIR	The selection of various components in the MG system is based on the demand and the availability of each energy source. Optimization was performed by minimizing the objective functions.
[87]	PV/battery	LCOE	A technoeconomic model for the size optimization of the system for a location in Italy is presented. The system cost optimization was performed by minimizing the objective function.

Abbreviations: COE, cost of energy; EENS, expected energy not supplied; EIR, effective interest rate, LCC, life cycle cost; LCOE, levelized cost of energy; LPSP, loss of load supply probability; MG, microgrid; PV, photovoltaic.

enhance the sizing of various components, including solar PV, WT, FC, electrolyzes, and storage devices, to accomplish zero energy shortfalls, minimize system expenses, and ensure a consistent electricity supply. For instance, in [71], researchers utilized an iterative method to minimize the gap between the produced and required power within a defined timeframe. The study focused on optimizing the capacity of the PV panels, its optimal tilt angle in a PV–battery system implemented in Oman.

Many research studies have used LP methods to improve the sizes of self-operating HRESs with solar panels and WTs [77]. Additionally, reference [78] utilized a deterministic optimization method called MILP to determine the optimal configuration of PV–WT–BS–DG while minimizing the levelized cost of energy (LCOE) over a 20-year period. The optimal system, according to the results, consists of 90% RE sources.

Furthermore, the researchers in [79] introduced a technique that utilizes MILP and a precise method to identify the best size and placement of the PV and WT system components, considering the energy requirements at points of consumption. The optimization's objective function aims at minimizing the initial cost of the system, which also serves as a factor for evaluating the system. The research concluded that optimizing both the location and size contributes to reducing the initial investment costs.

3.1.5 | Overview and Assessment

Traditional optimization techniques utilize mathematical models for seeking the best overall solution in a predictable manner, but they encounter challenges when dealing with complex environments involving a high quantity of variables. In contrast, numerical techniques that provide approximate solutions are commonly utilized. For example, when optimizing the size of HRESs, numerical techniques like iterative optimization, stochastic and deterministic approaches, and MILP are frequently employed. Additionally, graphical and probabilistic approaches have been utilized. Research has been dedicated to optimizing the size of islanded PV/WT/FC HRES to meet power needs, with objectives including reducing overall capital expenditure, lowering the LCOE during a 20-year lifespan, and minimizing the initial system expenses. These optimization methods allow for the adjustment of the prime configuration of the hybrid system based on load demand and location.

3.2 | Simulation Tool Technique

Software tools like HOMER, iHOGA, and RETScreen are popular for HRES optimization due to their user-friendly interfaces [16, 17, 88–95]. For instance, HOMER has been used to size PV–wind systems in the UAE and Ethiopia [89, 90], but its lack of calculation transparency restricts customization [74]. Similarly, while iHOGA is good for multiobjective optimization, it does not handle probabilistic study [95]. RETScreen, applied in studies like [93, 94], facilitates quick feasibility studies but is less effective for dynamic, standalone systems. Figure 5 highlights some of these popular software options [96].

HOMER software, created by the National Renewable Energy Laboratory, is commonly utilized for the analysis and design of MG and off-grid power systems [97–99]. It assists users in optimizing energy system configurations by taking into account various factors like RESs, storage technologies, and conventional generators. By inputting data on energy resources, load profiles, and economic parameters, users can determine the most economical and reliable solution for their specific requirements. HOMER holds significant value for engineers, researchers, and decision-makers involved in the design and improvement of decentralized power systems [100].

Researchers have utilized the HOMER software for various studies, including determining the optimal dimensions for a PV–wind MG in the western region of the UAE and Saudi Arabia [89, 91]. Additionally, the software was utilized in assessing the feasibility of a self-sufficient PV–wind–hydro setup deployed in Ethiopia, demonstrating its ability to supply

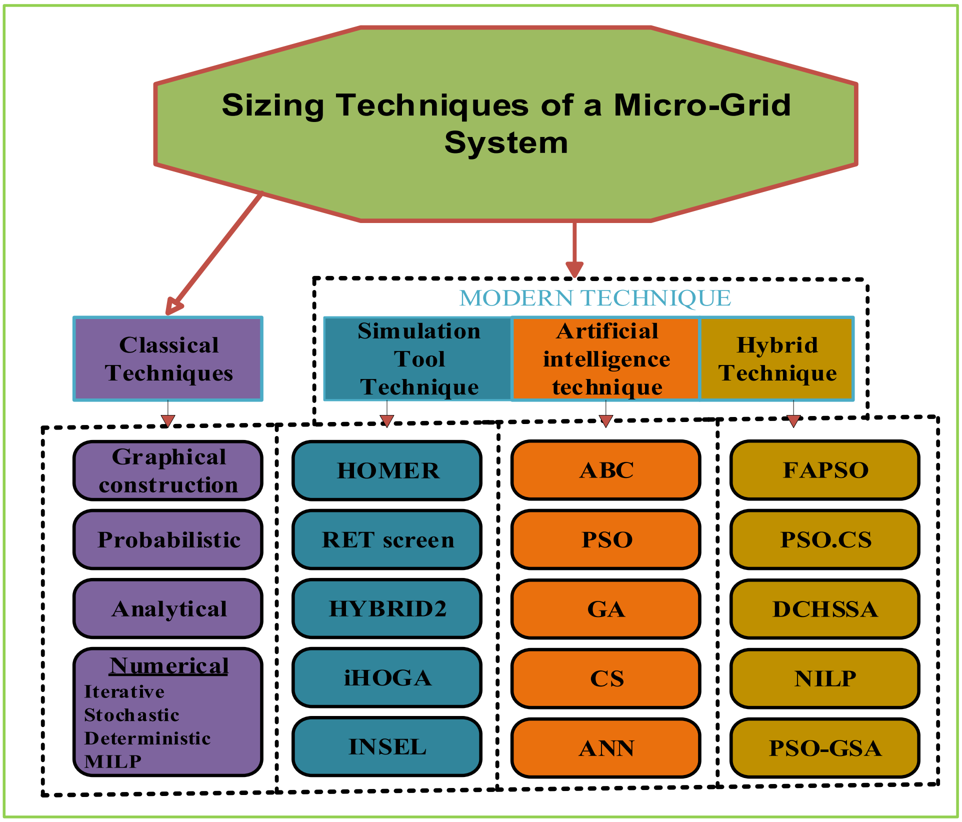

FIGURE 5 | Optimization technique classification [88–94]. ABC, artificial bee colony; ANN, artificial neural network; CS, chaotic search; DCHSSA, dynamic crowding hybrid salp swarm algorithm; GA, genetic algorithm; GSA, gravitational search algorithm; HOMER, hybrid optimization model for electric renewable; MILP, mixed-integer linear programming; NILP, nested integer linear programming; PSO, particle swarm optimization.

energy to remote locations [88, 90]. However, a drawback was identified in the software's lack of transparency in the calculation process, limiting users from adjusting the details of the system parts [74].

In a different study, researchers used the HOMER to look into whether a standalone hybrid solar, DG, and battery system would be viable for Pratas Island in Taiwan. Additionally, the authors used the HOMER software to look at the RE sources in a certain location, assessing the costs, technical aspects, and environmental impacts of various power options. Another research study focused on technical and economic considerations of a PV/DG/battery setup for households in Nigeria, utilizing HOMER optimization software to enhance the system's efficiency [101].

The HOMER software has been widely recognized for its capabilities in optimizing and analyzing various RE systems, rendering it an invaluable resource for scholars and professionals in the field of sustainable energy.

The iHOGA and MHOGA are distinct variations of the HOGA software, created by scholars affiliated with the Zaragoza University in Spain [102]. These versions, constructed using C++, are customized specifically for simulating and optimizing power generation setups that focus on utilizing RESs. The iHOGA software is suitable for power systems with capacities ranging from a few watts to 5 MW, while the MHOGA software was specifically developed for power systems in the MW range without any limitations [92].

In a study referenced [95], the HOGA software was utilized to optimize a self-sustaining PV/WT/battery system. The HOGA technique enabled simultaneous sensitivity analysis. However, it is crucial to emphasize that this specific application did not take into account the net measurements and probability analysis [37].

Another study referenced as [103] utilized iHOGA software to perform the optimization of single or multiple objectives of HRES for a standard residential complex in France. The multiple objective optimizations are intended to decrease emissions and unfulfilled energy requirements while maintaining a slightly higher NPC in contrast to the single goal of reducing only the NPC.

Furthermore, in a different context, iHOGA software was applied to optimize an HRES for the inhabitants of Mucura island, showing the potential to reduce operational expenses by minimizing reliance on fuel, optimizing the use of local RESs, and guaranteeing year-round power accessibility. The findings highlight the possibility of ecofriendly and financially feasible energy alternatives [104].

The HYBRID2 software package is designed to facilitate detailed analysis of the long-lasting effectiveness and financial viability of different energy setups. It offers a user-friendly interface and utilizes a computer model based on probabilistic/time series analysis. It integrates time series data for wind velocity, temperature, solar intensity, and loads with the user-defined energy system [105]. It has the capability to accurately forecast the performance of a power system integrating different sources of energy. It considers variations in load demand and wind data within each time step, allowing for more precise performance predictions.

The RETScreen energy management software platform provides a comprehensive solution for low-carbon planning, execution, monitoring, and reporting. People widely use it to quickly assess and calculate PV electricity generation and other RE systems [106]. The software has been employed in various studies and feasibility assessments, showcasing its versatility and effectiveness in evaluating RE projects.

In a study referenced as [93], the significant variations in utilization and outcomes of three well-known free tools, including RETScreen, PV Geographical Information System, and PVWatts, were examined. People commonly use these tools for rapid approximations and computations related to PV electricity generation.

In a study referenced as [94], the RETScreen software was deployed to assess the potential of a PV/bioenergy/WT/hydrogen storage setup for Al-aroub Technical College in Palestine. The results from the simulation clearly indicated that the HRES, which comprises PV, bioenergy, and a small-scale FC generator, is more economically viable for the school. Additionally, the RETScreen software was utilized to evaluate four distinct scenarios concerning the implementation of PV systems in neighborhoods, in light of new regulations [107]. The tool was also used to determine the optimal scale for RES in two varied problem situations, encompassing both instances with and without subsidies for RES [108].

The results from these studies highlight the diverse applications of the RETScreen software in assessing the financial and ecological consequences of RESs, making it a precious tool for sustainable energy strategy and execution.

In summary, this section covers five categories of software tools for HRES: pre-viability, dimensioning, modeling, and flexible design investigation tools. It also provides an overview of software tools suitable for research studies on HRES, particularly those involving RE components. Additionally, the article incorporates case studies that employ diverse software applications like HOMER, RETScreen, HYBRID2, integrated simulation environment language (INSEL), and iHOGA to improve the technical and financial performance of HRESs.

3.3 | AI Technique

AI-based techniques, such as Genetic Algorithms (GA), PSO, and Cuckoo Search (CS), have become increasingly popular for tackling complex, nonlinear optimization problems [25, 109–111]. For example, GA has been used to optimize PV–wind systems considering both LPSP and cost [112], while PSO was applied in Saudi Arabia for sizing remote HRES [111]. Recent research (2023–2024) further highlights AI's capabilities, with the Fire Hawk Optimizer showing superior performance to PSO in Turkey [90] and the Chameleon Swarm Algorithm optimizing standalone systems in China [113]. Nevertheless, these studies often concentrate on optimizing a single objective or on grid-connected systems, with limited focus on multiobjective frameworks for standalone HRES [114–116]. Methods of AI, like, ANN, GA, and Fuzzy Logic, are extensively employed to improve the efficiency of hybrid systems with the goal of maximizing their financial benefits [117].

Researchers utilized Typical Meteorological Year data to propose a sizing technique that is optimized using GA [112]. The aim of this optimization framework was to compute the best system that can attain the intended LPSP while reducing the TAC of the system. The scholars introduced two optimization variables that are typically not considered: the elevation of the WT and the tilt angle of the PV panel array.

Another study presented an optimization scheme that utilizes the CS technique for energy management and optimal configuration of an MG [110]. The study introduced a proposed system that combines PV and wind power sources with battery storage and a DG. The Multiobjective Particle Swarm Optimization method was utilized in identifying the optimal arrangement of MG for an electrification project in Iran [25]. Additionally, a study conducted in Saudi Arabia employed PSO to ascertain the best system arrangement, which included PV/wind/DG integration and a backup battery system, for a remote area. The results obtained from this approach were compared with those from an iterative technique used to evaluate the effectiveness of the suggested method [111]. Ant Colony Optimization (ACO) stands out as a strong competitor for minimizing TAC in various setups that include PV technology, WT generators, DG, and battery banks [118]. The mine blast algorithm (MBA) demonstrates its adaptability by efficiently tackling the minimization of TAC in systems combining PV/WT/DG/FC and hydrogen tank technologies [8]. The Preference-Inspired Coevolutionary Algorithm is good at reducing both the Annual Cost of Supply and LPSP, while also minimizing fuel emissions in configurations involving PV/DG/WT/battery systems [119]. The Improved Escaping-Bird Search Algorithm (IEBSA) was utilized to determine the best configuration for PV, WT, and battery systems [120]. This optimization process focuses on reducing energy losses, increasing the voltage profile, taking into account the associated system costs, and improving the Energy-Not-Supplied (ENS) index [119]. The Harris Hawk Optimization technique was employed to discover the most optimal design for the HES, with a primary focus on reducing the Annual Supply Cost (ASC) and improving the reliability of the power network [52]. The Improved Fruit Fly Algorithm proves to be effective in dealing with cost and emissions concerns within PV/WT/DG/battery systems [121]. A neural network (NN) shows it can effectively lower the chances of losing power supply in PV/WT/battery/utility grid systems [122]. The NN algorithm, inspired by ANNs, has demonstrated exceptional global search capabilities [123]. Incorporating the MBA [124] introduces a fresh perspective in minimizing the ASC for PV/WT/FC systems compared with other metaheuristic techniques. Research incorporating the Crow Search Algorithm [125, 126] highlights its emphasis on minimizing NPC while considering constraints, such as Energy Loss Fraction and COE. The Improved Firefly Algorithm [125] tackles the challenges of minimizing ASC and reducing CO_2 emissions within a configuration consisting of PV/WT/DG/battery. Using the Flower Pollination

Algorithm in PV/WT/FC systems [127] focuses on reducing NPC, Loss of Load Expectation, and Loss of Energy Expectation, providing a thorough evaluation of how well the system works. Using the Grasshopper Optimization Algorithm (GOA) in PV/WT/battery/DG systems [34] focuses on improving the COE and the likelihood of Diesel Power Supply (DPSP), highlighting the need to consider both costs and how reliable the system is.

Furthermore, an analysis was carried out to assess the efficiency of the Improved Artificial Bee Colony (IABC) in comparison to other techniques, such as ABC and ABC–ABC. The comparison findings demonstrated that the suggested technique is the most efficient approach for identifying optimal bidding parameters that satisfy the demand at a reduced fuel cost. The effectiveness of the GOA in dealing with an optimization challenge was illustrated. The authors applied GOA to an autonomous MG setup to identify the best system configuration capable of reliably meeting energy demands. The optimization focused on two criteria: the COE and the probability of power supply deficiency. Simulation results affirm that, when compared with alternative algorithms, such as CSOA and PSO, GOA demonstrates the ability to optimally size the system [34]. A different study proposed a PSO method to optimize the operation of HRE-based MGs while considering reserve margins for critical loads. This marks the first study of its kind to investigate reserve margins for critical loads and suggest that surplus RE should exclusively charge batteries [128]. Another study carried out an optimum configuration of a hybrid system integrating PV, WT, and FC to meet the energy requirement for a case study in Egypt using a modified version of the Ruddy Turnstone algorithm. The results from this study were compared with those using the Hybrid Firefly/harmony search (HS) technique [113].

An analysis of the technoeconomic feasibility of sizing grid configurations for HRE systems was conducted in Turkey. The study, conducted using Python and three metaheuristic algorithms (Fire Hawk Optimizer, PSO, and Gray Wolf Optimizer), concludes smaller systems are deemed more appropriate for systems with stringent limitations. Additionally, it suggests that the Fire Hawk Optimizer is usable for solving optimal power distribution and optimal system dimensioning problems. Overall, the study emphasizes the significance of system size in relation to constraints and highlights the potential applicability of the Fire Hawk Optimizer in addressing optimal power flow and system sizing challenges. However, the results of the suggested technique slightly outperformed those of the Hybrid Firefly/HS technique in terms of cost [129].

Lastly, a framework for designing the optimal size and evaluating the cost benefits of a standalone HRE MG system utilizing the chameleon swarm algorithm was proposed by researchers. They intended to provide power to a rural area in northeastern China [115]. Another study examined the optimal dimensioning of a rural MG system utilizing a two-stage stochastic programming approach that incorporates a scenario-based method, taking into account more than one energy system and various EV technologies involved in operations involving grid and vehicle interactions [130]. Additionally, the implementation of a modified cuckoo search optimization technique was carried out to ascertain the ideal dimensions of components for an HES that integrates PV/WT/DG/battery systems for an isolated region. The primary objective was to reduce the COE and the probability of load loss [131].

In summary, a diverse range of optimization methods has been utilized to enhance HRES, integrating both PV and WT technology. These optimization techniques encompass classical methods, software tools, AI, and hybrid optimization approaches. While traditional methods are linked with disadvantages like inflexibility and lengthy calculation times, AI techniques like PSO, GA, and HS have been employed to enhance the efficiency of solar and wind energy. These optimization methods have played a great role in reducing costs, CO_2 emissions, and optimizing the dimensions as well as operational approaches of PV/WT/battery storage systems. Additionally, a variety of optimization techniques have been introduced in determining the optimal scale of HRES with a focus on reducing the total system costs and also meeting reliability conditions.

3.4 | Hybrid Technique

Hybrid techniques integrate multiple optimization methods to capitalize on their advantages and compensate for their limitations [132]. For instance, the GWCSO achieved lower NPC and LCOE compared with using Gray Wolf Optimization (GWO) alone [111], while a hybrid Simulated Annealing–Tabu Search (SA–TS) approach outperformed individual methods in minimizing cost [133]. Recent progress includes the Particle Swarm Optimization–Gravitational Search Algorithm (PSO–GSA) for MG energy trading [120] and the Dynamic Crowding Hybrid Salp Swarm Algorithm (DCHSSA) for PV–wind sizing [134]. However, despite these advancements, hybrid techniques are seldom applied to standalone HRES in remote areas, where multiobjective optimization is particularly important [8, 112, 117]. In their study [19], researchers applied a hybrid GWCSO technique to attain the best configuration for a grid-connected MG. The GWCSO approach outperformed the GWO algorithm, showcasing reduced total component units, annual cost, NPC, and LCOE. Additionally, the GWCSO algorithm displayed minimal deviation, underscoring its heightened accuracy and robustness compared with the GWO algorithm.

Another study [134] performed a technoeconomic evaluation of PV energy connected to the grid. The system aimed at fulfilling the electricity demands of a designated area by the Centre for Solar Energy Research and Studies in Tripoli, Libya. The research employed a hybrid methodology that integrated the Binary Bat Algorithm (BAT) and ABC algorithms. Harmony-search-based simulated Annealing is a strong choice for lowering the LCC in systems that use solar panels, WTs, hydrogen, and batteries.

Furthermore, researchers combined SA and TS to optimize the sizing of an independent energy system [133]. Their goal was to minimize energy costs by considering various design variables, like, WT, PV setups, DG, FC, batteries, converters, and dispatch strategies. The authors found that the hybrid SA–TS approach outperformed using SA or TS individually, resulting in improved solutions in terms of quality and convergence. In their investigation [135], researchers presented an optimal design methodology aimed at determining the ideal quantity of PVP, WT, and batteries in a hybrid system. The aim was to reduce the aggregate yearly expenses of the system while adhering to specific limitations. To achieve this objective, the researchers integrated three algorithms: chaotic search, SA, and HS. This combination led to the creation of a new hybrid algorithm termed the discrete chaotic harmony search-based simulated annealing algorithm (DCHSSA).

Other researchers proposed a hybrid fuzzy adaptive GA to optimize the configuration of a HES integrating PV, WT, and a battery backup system [136]. Historical hourly data were used to stochastically model the PV generation, WT and energy demand. The hybrid approach provided an optimal quantity of PVP, WT, and storage units, ensuring minimal system costs and satisfying the load demand. A nested integer linear programming technique was proposed by [137] to compute for the ideal configuration of a nanogrid system for a residential estate in Kano State, Nigeria. This technique effectively addressed the complex computational challenges encountered by the MILP technique. Genetic Algorithm Particle Swarm Optimization has gained acceptance for its ability to minimize the NPC in PV/WT/battery systems [135]. Hybrid approaches, such as combining GA with PSO [122], and utilizing the CS algorithm alongside GA and PSO [138], showcase the potential synergies in optimizing the NPC and LPSP. Hybrid GWCSO is utilized to ascertain the optimal sizes of PV/WT/biomass gasifiers/batteries/DG with a focus on minimizing the TAC [52].

Lastly, a proposed technique, the PSO–GSA technique, is a new hybrid optimization technique that combines the capabilities of PSO and GSA to tackle the intricacies and uncertainties associated with MG energy trading. Figure 6 depicts the current sizing methods utilized for independent HRES [120].

In summary, researchers have utilized hybrid techniques to optimize energy systems, combining techniques such as GWCSO, BAT, ABC, SA, TS, and hybrid fuzzy adaptive GA. These approaches aimed overcoming the limitations of individual algorithms and achieving improved results in configuring PV, WT, and battery systems, as well as addressing the complexities of MG energy trading.

3.5 | Knowledge Gap and Novel Contribution

The existing literature highlights a significant gap in optimizing standalone PV–wind HRES for remote areas. The majority of studies concentrate on grid-connected systems or optimizing a single objective, often overlooking the multifaceted requirements of standalone systems, such as balancing cost, reliability, and emissions [1, 5, 11]. Furthermore, despite the rising popularity of AI and hybrid techniques, their application to remote HRES remains limited. Few studies address the customization challenges of software tools or the dynamic characteristics inherent in standalone systems [18, 114]. While recent reviews (e.g., [36, 39, 41, 96, 139], cover HRES optimization broadly, they lack a specific focus on standalone systems in remote regions (Table 6).

The novelty of this review lies in its specific focus on standalone HRES, where it integrates AI-driven hybrid techniques with traditional techniques to tackle the unique challenges of remote areas. By offering a roadmap for future research, including the exploration of emerging algorithms like the Fire Hawk Optimizer [129], this study aims at advancing sustainable energy solutions for remote regions. Table 7 shows the existing gaps in previous studies, with recommendations for further improvement.

4 | Discussion on Optimization Techniques

This review presents concise methodologies for sizing hybrid PV–wind systems. These approaches consider diverse needs, encompassing criteria, conditions, and the execution procedure. Furthermore, they incorporate mathematical representations of PV systems, WT, and battery storage. The design of HRES in this study employs a multitude of well-established optimization approaches. It is well known that the growing complexity of optimization problems within the sustainable power system arises from the increased integration of diverse RESs.

Optimization techniques are classified into four categories: traditional, simulation software tool-based, AI, and hybrid techniques. While traditional methods follow a rigorous process, they have certain drawbacks such as inflexible iterations, slow convergence speed, computational time requirements and limited ability to handle dynamic changes. On the other hand, the modern approach which is subclassified into three: demonstrated a higher speed and flexibility compared with the traditional techniques, offering an efficient convergence speed, and effective global search solutions. To provide a clear and comprehensive understanding, a detailed breakdown of all optimization methods, including their respective strengths and weaknesses, is presented in Table 4. The results indicate a growing acceptance and utilization of modern techniques in recent literature.

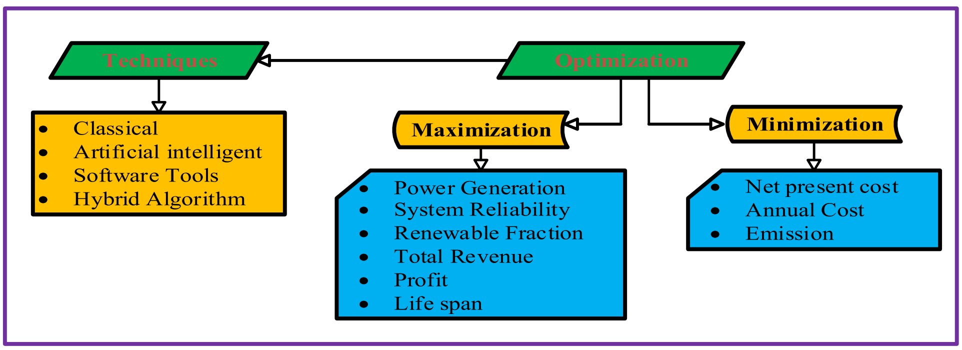

FIGURE 6 | Existing size optimization techniques for the hybrid renewable energy system [76].

TABLE 6 | Merits and demerits of some optimization techniques.

Type	Technique	Advantages	Drawbacks
Traditional	Iterative	Is simple to implement	Ignored some important parameters, for example, PV tilt angle. Typically leads to higher computational demands and less than optimal outcomes.
	Probabilistic	Simple to use and eliminate the requirement for time series data	Incapable of showcasing the dynamic capabilities of the hybrid system.
	Graphical		The optimization process can only incorporate two parameters.
	Analytical/ numerical	Rapidly	Low flexibility.
Software tool	HYBRID2	The models are characterized by	It necessitates a higher level of understanding of the system configuration
	HOGA	Can be single or multiobjective their comprehensive optimization variables	
Artificial intelligence	PSO, GA, CS, ABC, MSCS, and SAO	Efficiency, adaptability, customization, Fast response, can solve complex problem	Complexity, data dependency, and cost
Hybrid	MOPSO–ABC FAPSO	Solve a multiobjective and complex tasks	

Abbreviations: ABC, artificial bee colony; CS, chaotic search; FAPSO, firefly algorithm and particle swarm algorithms; GA, genetic algorithm; HOGA, hybrid optimization using genetic algorithm; MOPSO, multiobjective particle swarm optimization; MSCS, multi-strategy cuckoo search; PSO, particle swarm optimization; PV, photovoltaic; SAO, smell agent optimization.

TABLE 7 | Comparison of existing studies with our review.

Study	System type	Optimization focus	Key method	Limitations	Recommendation
[1]	Grid-connected HRES	Cost minimization	Classical, software tools	Limited to single-objective, urban focus	Multiobjective framework, standalone focus
[5]	Grid-connected HRES	Technoeconomic analysis	HOMER and GA	Ignores remote applications	Tailored to remote areas, hybrid AI integration
[19]	Grid-connected MG	Cost and reliability	GWCSO	Limited to grid-connected systems	Applies GWCSO to standalone systems
[129]	Grid-connected MG	Power flow and sizing	Fire Hawk Optimizer	Single-objective focus	Multiobjective, remote HRES emphasis
Present study	Standalone PV–WT	Cost, reliability, and emissions	Hybrid AI, traditional	N/A	Comprehensive framework, remote focus, and multiobjective

Abbreviations: AI, artificial intelligence; GA, genetic algorithm; GWCSO, gray wolf–cuckoo search optimization; HOMER, hybrid optimization model for electric renewable; HRES, hybrid renewable energy system; MG, microgrid; PV, photovoltaic; WT, wind turbine.

The review further highlights that approximately a decade ago, conventional methods, including graphical, iterative, probabilistic, and analytic approaches, held considerable popularity. Yet, due to their constraints, they have significantly declined in usage among researchers. Presently, the predominant focus revolves around leveraging AI-based nature-inspired metaheuristic and heuristic techniques, like, SA, GCA, TS, BBO, GA, HS, ACO, ICA, and so forth, to optimize hybrid PV–wind systems. Among these AI-driven techniques, GA stands out as the most frequently utilized approach. However, when dealing with complex issues, a basic AI algorithm might prove inadequate in arriving at the target solution and may encounter challenges in achieving a satisfactory result. This situation underscores the importance of effectively hybridizing more than one technique. The application of hybrid techniques has been shown to enhance reliability and improve accuracy. By incorporating hybrid techniques, researchers have observed accelerated convergence rates and achieved a more accurate result.

Despite the inherent complexity of single algorithms, there is a noticeable rise in the application of hybrid algorithms in the study of PV–wind hybrid systems. Understanding these hybrid algorithms is important for future research, as it seeks to address the challenges and complexities involved in combining and designing hybrid systems.

Furthermore, various supplementary algorithms, including the Bat algorithm [140], CS [141], Chaotic Ant swarm optimization [142], Firefly algorithm [143], Cultural Algorithm [142], Memetic Algorithm [144], smell agent algorithm [145–147], and multistrategy serial CS algorithm [148], alongside other nature-inspired methodologies, have demonstrated the ability to solve diverse optimization problems. These techniques have the prospect of contributing to the progression of future research in optimizing HESs reliant on RESs.

While traditional optimization techniques such as LP are reliable for smaller systems, AI-based approaches like GA outperform them in larger, more complex systems due to their ability to handle nonlinearities and multiobjective functions. For example, hybrid approaches like Gray Wolf Cuckoo Search show a 25% improvement in convergence speed when optimizing multisource energy systems. However, there are still challenges with the computational complexity, highlighting the need for more efficient hybrid algorithms.

5 | Conclusion

In this study, a comprehensive review of optimization techniques for hybrid energy systems was presented, specifically focusing on solar PV and WT combinations. It shows that the growing complexity of HRES requires sophisticated optimization methods to address the challenges of intermittent resource availability, cost management, and system reliability. While traditional optimization methods like graphical, probabilistic, and analytical techniques played a crucial role in early developments, they have largely been replaced by more advanced approaches.

The emergence of AI-driven optimization algorithms, such as PSO and GA, has significantly enhanced the ability to efficiently explore large solution spaces and manage complex, multiobjective optimization problems. Additionally, hybrid algorithms, which combine strengths from multiple techniques, have demonstrated superior performance in terms of convergence speed, solution accuracy, and handling the complexities of PV–WT system design. This study shows that hybrid techniques, such as the GWCSO and PSO–GSA, offer enhanced capabilities for managing the intricate balance between cost, reliability, and environmental considerations. It also highlighted that while software tools like HOMER and RETScreen are indispensable for practical applications, they have certain limitations, such as lack of flexibility in system customization. To address this, researchers have increasingly turned to hybrid and AI techniques, which allow for more tailored optimization and decision-making in real-time applications.

In conclusion, the future of HRES optimization lies in further development and application of hybrid algorithms that integrate AI with traditional methods, along with advancements in computational power and data availability. These techniques not only promise more efficient, reliable, and cost-effective solutions but also open the door for innovations in smart grid and MG configurations. However, technical complexity and the need for specialized knowledge continue to be barriers to widespread adoption, indicating a need for further research focused on simplifying these advanced techniques for broader use.

5.1 | Limitations and Future Directions

Although this review thoroughly examines optimization methods for independent solar PV–wind HRES, mainly for remote areas, it has some limitations. First, it only focuses on standalone systems and the results might not directly apply to HRES connected to the grid or MG in cities. While this study fills an important gap in the current research, it is obvious that the proposed framework might not be suitable for all types of systems. Second, since the review utilizes information and results from other studies, there is a likely chance of bias. This is because the reviewed studies may have used different methods, looked at systems of different sizes, and been conducted in different environments. Third, even though the review highlights AI and hybrid algorithms, it does not include new experiments or detailed simulations for specific situations. This could have provided more evidence on how well the proposed framework operates.

Addressing these limitations will enable future research to build upon this review, leading to more robust, adaptable, and evidence-based optimization frameworks for HRES. The present study intends to accelerate the implementation of sustainable energy solutions, especially in remote communities, and provide global energy equity and environmental sustainability.

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