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Review

Current Status, Sizing Methodologies, Optimization Techniques, and Energy Management and Control Strategies for Co-Located Utility-Scale Wind–Solar-Based Hybrid Power Plants: A Review

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Abstract: The integration of renewable energy sources, such as wind and solar, into co-located hybrid power plants (HPPs) has gained significant attention as an innovative solution to address the intermittency and variability inherent in renewable systems among plant developers because of advancements in technology, economies of scale, and government policies. However, it is essential to examine different challenges and aspects during the development of a major work on large-scale hybrid plants. This includes the need for optimization, sizing, energy management, and a control strategy. Hence, this research offers a thorough examination of the present state of co-located utility-scale wind–solar-based HPPs, with a specific emphasis on the problems related to their sizing, optimization, and energy management and control strategies. The authors developed a review approach that includes compiling a database of articles, formulating inclusion and exclusion criteria, and conducting comprehensive analyses. This review highlights the limited number of peer-reviewed studies on utility-scale HPPs, indicating the need for further research, particularly in comparative studies. The integration of machine learning, artificial intelligence, and advanced optimization algorithms for real-time decision-making is highlighted as a potential avenue for addressing complex energy management challenges. The insights provided in this manuscript will be valuable for researchers aiming to further explore HPPs, contributing to the development of a cleaner, economically viable, efficient, and reliable power system.

Keywords: control strategies; energy management strategies; hybrid power plant; optimal sizing; optimization; utility-s

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1. Introduction

The importance of sustainable energy sources in mitigating global greenhouse gas emissions and ensuring a reliable energy supply is underscored by both the Paris Agreement and the United Nations Sustainable Development Goals [1]. Adopting new, clean, and renewable energy sources (RESs) helps decarbonize the transportation and power generation industries. Research and development, economies of scale, and government policies have driven recent improvements in wind and solar energy technology. As a result, wind and solar are becoming more cost-competitive with conventional fossil fuels [2,3], and traditional power plants are gradually decommissioning [4].

There is limited market penetration for wind and solar energy, resulting in a lesser need for dispatchable renewable energy plants. As renewable energy usage increases, these facilities will play a crucial role in providing grid services, ensuring a consistent electricity supply [3], and addressing any issues arising from unknown resources, grid problems, or unusual situations [5]. Unpredictable weather patterns and geographical location-dependent availability limit the effectiveness of renewable energy, severely impacting the reliability and stability of their power supply and necessitating the use of complementary sources like batteries.

Several studies have looked into ways to deal with the problem that wind and solar resources change over time. These have included storing and limiting resources [6–8] to make them more useful, combining hybrid resources like hydropower [9], bioenergy [10], hydrogen/fuel cells [11], and the possibility of wind and solar resources working together [2,12–14]. Previous studies [13,15–18] have highlighted that researchers mainly studied wind and solar hybrid systems for off-grid environments, focusing on small-scale generation units to reduce reliance on fossil fuel generators and fulfill specific energy needs. Therefore, this study refers to HPPs (>1 MW) as co-located utility-scale wind farms and solar farms with or without battery storage connected at the point of common connection (PCC). Several key factors drive the main motivations behind HPPs compared with standalone renewable power plants or standalone energy storage [2,7,12,14]. Wind and solar power combine to counteract each energy source's intermittent power output, ensuring stable, continuous power output. Wind turbines generate power on windy days with limited sunlight, while solar panels produce electricity on cloudy or low-wind days, ensuring a stable electricity supply. The negative correlation between wind and solar resources helps provide more consistent power for hybrid plants [2]. In markets with no direct correlation between wind and solar resources, HPPs can benefit from power dispatching. If electricity market prices show a negative correlation with wind power, HPPs can capitalize on their solar resources to generate revenue during high market prices [2]. They promote energy independence by reducing reliance on centralized power plants and distant energy sources, ensuring a reliable and stable electricity supply. Therefore, HPPs that consist of wind, solar, and energy storage have been active in research.

Manufacturers and project developers are currently developing HPPs to ensure their economic viability in markets with a high demand for predictable and manageable energy supply to maintain grid reliability and dispatchability [13]. However, the installation costs remain high. On top of this, combining these technologies intensifies the complexity, requiring additional models specific to each discipline, understanding power generation sources, and accommodating supplementary design variables [2]. Therefore, efficient sizing and optimization methodologies, as well as energy management and control strategies, are essential to exploring the optimal configuration of parameters such as system cost, reliability, and the size of photovoltaic systems, batteries, and wind turbines.

Researchers have documented numerous methodologies in the literature related to sizing [3,19–22], optimization [23,24], and various tools [2,25–27] that consider economic and reliability factors. The economic assessment of renewable energy entails an analysis of total expenses, cost of energy (COE), annualized system cost (ASC), levelized cost of energy (LCOE), and life cycle cost (LCC) [21,22,28]. It takes into account initial investment, operational and maintenance costs, as well as replacement expenses. The assessment of reliability involves examining the disparity between the supply of renewable energy and the corresponding demand, employing several metrics such as loss of load probability (LLP), loss of power supply probability (LSSP), renewable fraction (RF), energy unmet, and renewable energy factor (REF).

Constraints related to minimizing grid-injected power, decreasing fluctuation rates, and improving the utilization factor guide system size optimization. These considerations, along with the main objective of minimizing costs, collectively shape the optimization process [29]. Achieving the best possible design of an HPP requires careful consideration of technical, economic, reliability, environmental, and social factors to ensure the best possible design feasibility. The Appendix A (Table A1) provides a detailed description of these factors.

Recent research has shown a preference for hybrid methodologies over traditional methods, as well as an increase in modern algorithmic techniques [30], relying on individual artificial intelligence (AI) algorithms and hybrid methods, which are gaining prominence compared with traditional methods because of their capabilities in resolving intricate optimization challenges. These techniques primarily consider multi-objective functions, mainly cost and LPSP [31,32], with other criteria like COE, LPSP, REF, etc., as constraints [33].

Iterative, graphical, probabilistic, and analytical techniques, including algorithms like the genetic algorithm (GA) and particle swarm optimization (PSO) [23,24], achieved the objectives. Commercially available software tools, such as HOMER, aid in sizing and optimizing standalone solar photovoltaic and wind-based systems, identifying optimal energy system sizes, and conducting sensitivity analyses to explore varying input variables or uncertainties. Energy management [11,34,35] and control strategies [3,13,34,36–42] drive the effective functioning of HPPs, enhance system performance, and meet energy demands. Various methods, such as centralized, distributed, and hybrid, control hybrid renewable power systems. Most energy management methods focus on power requirements and economic, technical, and techno-economic-oriented strategies [42,43], making it critical to establish a well-defined and suitable management approach. Figure 1 illustrates the overall scope of this study. Appendix A (Table A2) summarizes the essential findings from the review studies.

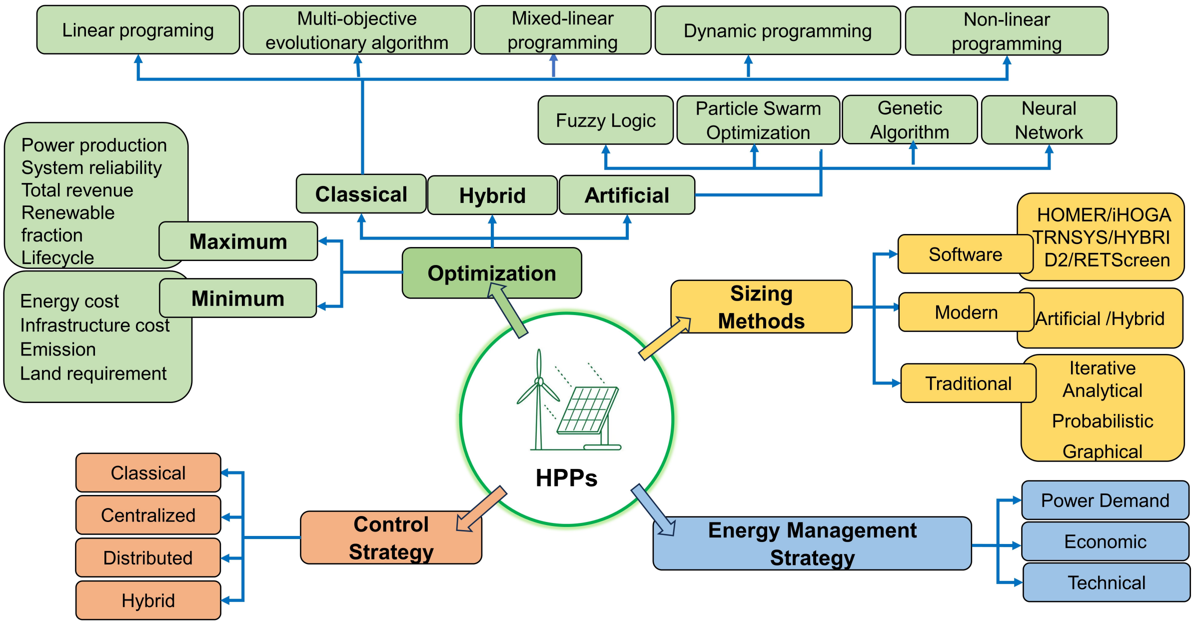

Figure 1. Graphical representation of the scope of this study.

Contribution of this Review Paper

The absence of a universally agreed-upon definition for HPPs presents a challenge in exploring this emerging field. This discrepancy could lead to misleading conclusions, given the limited literature on co-located utility-scale HPPs. Despite the potential benefits of HPPs, particularly in co-locating wind and solar farms, their long-term economic viability remains uncertain. However, the studies conducted thus far have not placed significant attention on the exploration of optimization, size, and energy management, specifically within the context of utility-scale operations. This study aims to fill this research gap by examining various energy management and control tactics, optimization techniques, and sizing methodologies employed by the research community over the past decade using wind and solar energy. Researchers use an interdisciplinary approach to bridge the knowledge gap and enhance the efficiency of utility-scale HPPs in the renewable energy sector. This study also serves as a valuable resource for developers and researchers engaged in HPPs, providing them with the means to evaluate decision-making tools, energy management, and control strategies to optimize the financial performance of these projects. This assessment considers various factors, including local resources, land availability, costs, and market prices. Recent developments in HPPs are comprehensively analyzed in this article, offering readers a convenient source of information categorized according to their specific interests. Additionally, this study aims to enhance knowledge and foster discussions among policymakers, academics, and industry professionals.

This study includes sections that cover a review approach, exploration of various available topologies in the scientific literature, the global status of HPPs, optimization techniques, sizing methodologies, energy management systems and control strategies, discussions, challenges, and future aspects of HPPs, and conclusions.

2. Review Approach

The evaluation of the existing literature on the sizing, optimization, energy management, and control strategies of utility-scale HPPs involved the following procedure: The first stage involved gathering a wide range of scholarly articles from several databases and online platforms, such as Science Direct, Google Scholar, IEEE Xplore, and Web of Science. Since utility-scale HPPs are in their early stages, there is limited research, which mainly comprises wind and solar. By extrapolating key findings and methodologies from HRES studies, the authors intend to shed light on the potential applicability and viability of these insights within the context of HPPs. The data collection process involved a four-step approach, as shown in Figure 2. Initially, a Boolean search was conducted, utilizing the following combination of keywords: ("large-scale hybrid power plant" OR "hybrid renewable energy system") AND ("optimization software tools" OR ("optimal sizing" OR sizing") OR ("energy management" AND "control strategies"). The focus was limited to the database's topic section, encompassing article titles, abstracts, and keywords, as well as all possible combinations thereof. All articles chosen exclusively covered hybrid systems that incorporated both wind and PV elements.

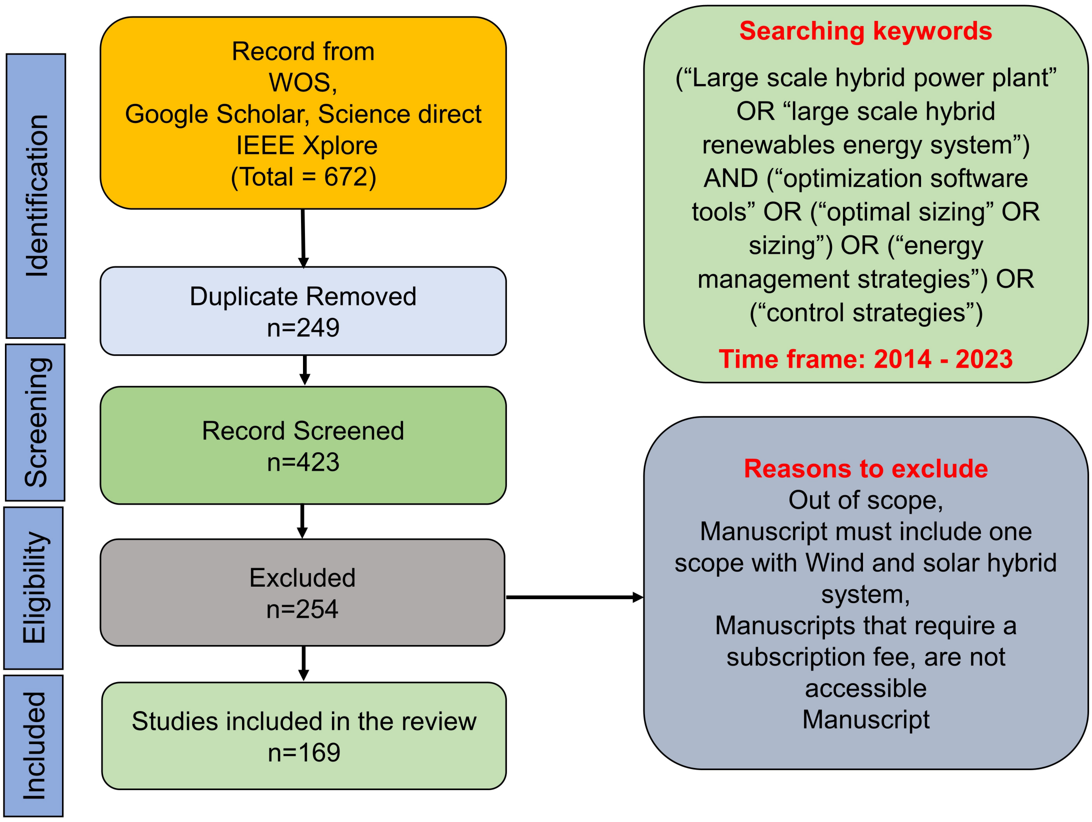

Figure 2. PRISMA model for the literature selection.

Subsequently, the acquired research papers underwent a screening process adhering to predetermined criteria for inclusion and exclusion. Inclusion criteria encompassed studies focused on co-located wind and solar plants coupled with or without energy storage. This hybrid must include either optimization techniques, sizing methodologies, energy management systems, or control strategies. Exclusion criteria pertained to studies out of scope, centered on single-source renewable energy systems, and those that did not employ optimization techniques or energy management systems and control strategies. This study also excluded the hybrid system used for residential applications, papers that required a paid subscription, and papers not published in the English language. The results from the chosen studies were then put together to give a full picture of the latest progress in system optimization, EMS, and control strategies for HPPs that store energy.

Utility-scale HPPs are in the early stages of implementation compared with the hybrid renewable energy system (HRES); therefore, the authors mainly focused on a decade-long timeframe, i.e., 2014–2023. Initially, the search yielded 672 articles from the IEEE Xplore, Google Scholar, Science Direct, and Web of Science (WoS) databases, as illustrated in Figure 2. Endnote software version 20 was used to merge the results and eliminate duplicates. The abstract and conclusion sections of the remaining articles were scrutinized to ascertain the relevance to the objectives of this review study. This narrowed down the number of articles to 171. To summarize, each collected article was meticulously studied to acquire a comprehensive grasp of the research findings.

3. Topologies and Configuration

The basic components of the reviewed HPPs mainly comprise wind farms, solar farms, and battery storage. Several studies have analyzed the arrangement of co-located wind–solar hybrid power facilities. Petersen et al. [36] described two different configurations for co-located wind solar-based HPPs, in which wind is the main energy source. These configurations provide choices for either grid connection or off-grid operation. Additionally, Vivas illustrated different topologies based on grid connection and integration techniques [11]. The deployment of HPPs as standalone or grid-connected operations depends on the application's requirements and available funds. Standalone HPP systems continue to meet load demands while operating independently from the grid. However, because of resource constraints and excess energy waste, this strategy poses performance and reliability issues [11]. Technically and economically, it works best when connecting to the grid is either too expensive or unfeasible.

On the other hand, a grid-connected system allows for bidirectional power flow by integrating an HPP with the main electrical grid. When the production of renewable energy is inadequate, this feature enables the system to take power from the grid and return excess energy when the need for renewable energy is greater [11,44]. Solar and wind power plants can be set up in three different ways, as explained in [7,11,45,46], including the following: an AC-coupled topology (Figure 3), a DC-coupled topology (Figure 4), or a hybrid DC/AC-coupled topology (Figure 5). Several studies have noted the AC-coupled system as the most common form of hybrid power plants [3,8,37–39]. Table 1 compares the advantages and disadvantages of each method with the coupling topology.

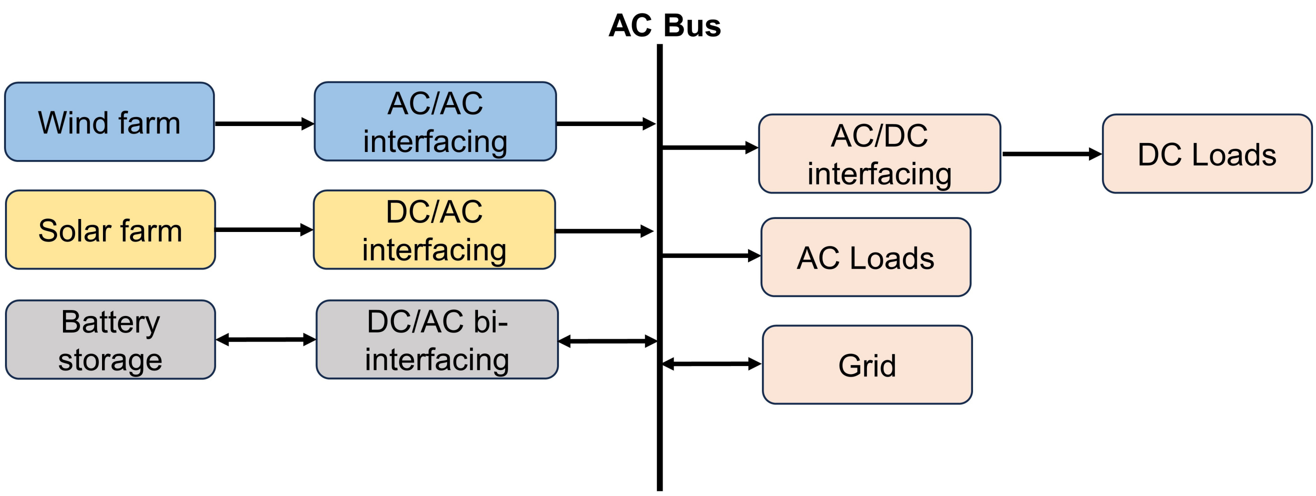

Figure 3. Grid-connected AC-coupled configuration.

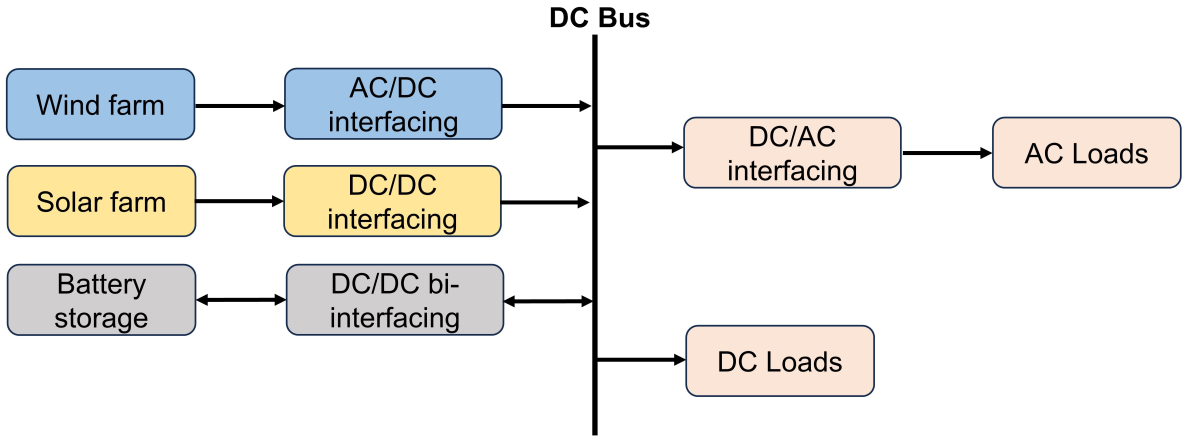

Figure 4. Grid-connected DC-coupled configuration.

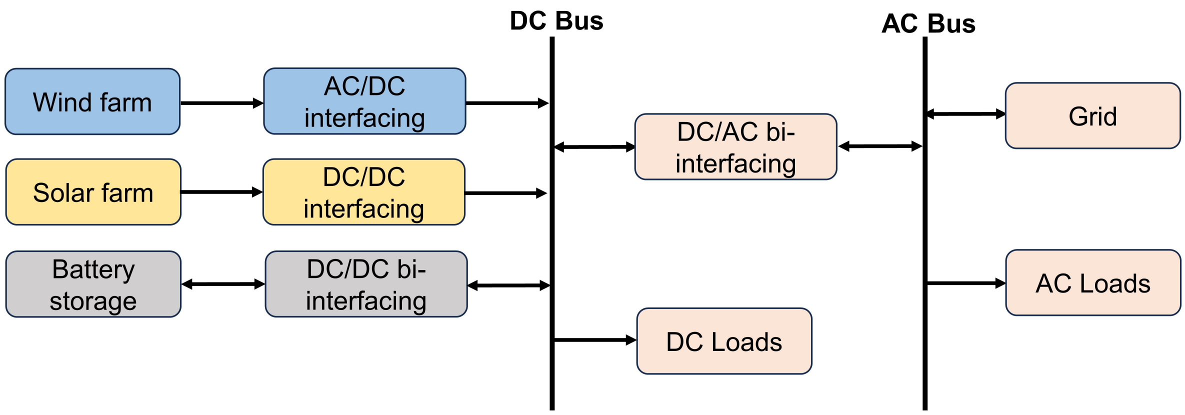

Figure 5. Hybrid configuration.

Table 1. A comparison of coupling topologies with advantages and disadvantages [7,17,46].

Configuration	Advantage	Disadvantage	Application
DC-coupled	• Synchronization not needed. • Fewer components used.	• Requires a large number of conversion components. • If converter is out of order, the whole supply is disturbed.	• Low voltage. • DC microgrid. • Long-distance transmission.
AC-coupled	• Standard interface and modular structure. • Protection system is easier. • Ready to grid connection.	• Potential risks to system stability and integrity due to the need for power quality correction elements. • Synchronization required. • Not suitable for long transmission.	• Medium- and high-production applications. • AC microgrid.
Hybrid	• Flexible system compared with AC and DC. • High efficiency.	• Controlling and managing energy is complex.	• Domestic and industrial applications.

In the AC-coupled topology, all HPP resources are interconnected to a common AC bus using dedicated power electronics interfacing [7,11,17]. The wind farm is connected to the AC bus, but the solar farm utilizes a system inverter (DC-AC) to convert the DC output into AC. Using a bidirectional DC-AC converter, the Battery Energy Storage System (BESS) is linked to the AC bus, guaranteeing a consistent supply–demand balance at its pre-established capacity. An AC/DC rectifier can power DC loads. In the AC-coupled architecture, the only bidirectional energy transfer takes place between the grid and the AC bus [36]. In certain cases, if the hybrid installation is located close to a grid source, the inverter may provide an on-grid or off-grid option that permits grid connection. When the BESS is completely charged, excess electricity generation may be sent to the grid. Alternatively, the inverter connects to the grid to maintain energy balance at times when daily output from renewable energy sources is small and BESS discharge is fully used.

In the DC-coupled topology, all energy sources are linked to a shared DC bus via power electronics interfacing, offering cost savings in capital expenditure [11,36]. DC loads receive direct power from the DC bus, while AC loads require a DC/AC inverter for operation. In this setup, wind and solar farms generate variable electric energy, while the electronic interface helps regulate electric energy to meet system demands. The bidirectional DC-DC converter connects BESS to the DC bus, ensuring a consistent supply–demand balance at its designated capacity.

In the DC/AC-coupled topology, a combination of DC and AC-coupled features is utilized. The solar farm is connected through a DC-DC converter, while the wind farm is linked to the DC bus through a rectifier and DC/DC converter. A bidirectional DC/AC inverter facilitates energy conversion between the DC and AC buses. The AC bus can power multiple AC loads and connect to the grid when available. The hybrid configuration offers higher efficiency and lower system cost for domestic and industrial applications [7,11,17], but managing energy can be challenging as a result of accommodating AC and DC loads/grid.

4. Global Status of HPPs

Hybrid plants are becoming more and more popular because of advancements in battery technology, variable renewable energy, and cost reduction. For many years, different hybrid configurations and the integration of multiple energy sources have been an essential part of the energy landscape. Most of the current emphasis has been on connecting solar plants with batteries. The wind-based hybrid power plant (HPP) has acquired significant traction lately [12,13,47]. An updated list of co-located HPPs that are now operating and planned throughout the world—particularly those that are using solar and wind energy—is provided in this section. Plants with a capacity of one megawatt or more are the main emphasis; smaller projects are becoming more common but are not included in this data synthesis. In 2017, WindEurope [12] shared a database on co-located power plants integrating wind and storage technologies. To further promote awareness and knowledge about HPPs, WindEurope expanded this database to include HPPs that combined both wind and solar technologies, with or without storage components, as shown in Figure 6.

There are presently only a small number of operating or in-development HPPs based on solar and wind energy in the world, and these projects' business cases are still in the planning or assessment phases. Utility-scale HPPs have attracted interest throughout the last five years, especially in the USA and Europe [12,13,47]. HPPs aim to maximize energy production, improve grid stability, and ensure a steady supply of electricity by using wind, solar sources, and energy storage. This section highlights these fundamental features, which are explained briefly in the following paragraphs. Table 2 summarizes some of the innovative initiatives undertaken by HPP developers.

Vattenfall has developed a commercial PV–wind hybrid project in Cynog Park, U.K., to evaluate the feasibility of combining solar and wind technologies. In 2016, the project underwent upgrades to incorporate a 4.95 MWp solar PV farm and a 3.6 MVA onshore wind farm, showcasing the advantages of integrating a battery storage system to optimize energy production. Manufacturers emphasize the need for regular curtailment simulations to manage output and ensure efficient energy utilization, such as every 10 or 15 min, according to WindEurope [12] and Klonari [47].

Haringvliet, a Dutch project integrating wind (21 MW), solar (41 MW), and battery power capacity (12 MW), aims to stay competitive and generate revenue by participating in the wholesale electricity market and Guarantees of Origin. The plant provides frequency containment reserves and time-shifting services, ensuring its sustainability and competitiveness [12,47]. The Kennedy Energy Park in northwest Queensland, Australia, is a 60.2 MW hybrid renewable energy facility that combines 19.3 MW solar PV, 43.2 MW wind, and 4 MWh lithium-ion energy capacity to meet local energy demand without excessive storage capacity [12,48].

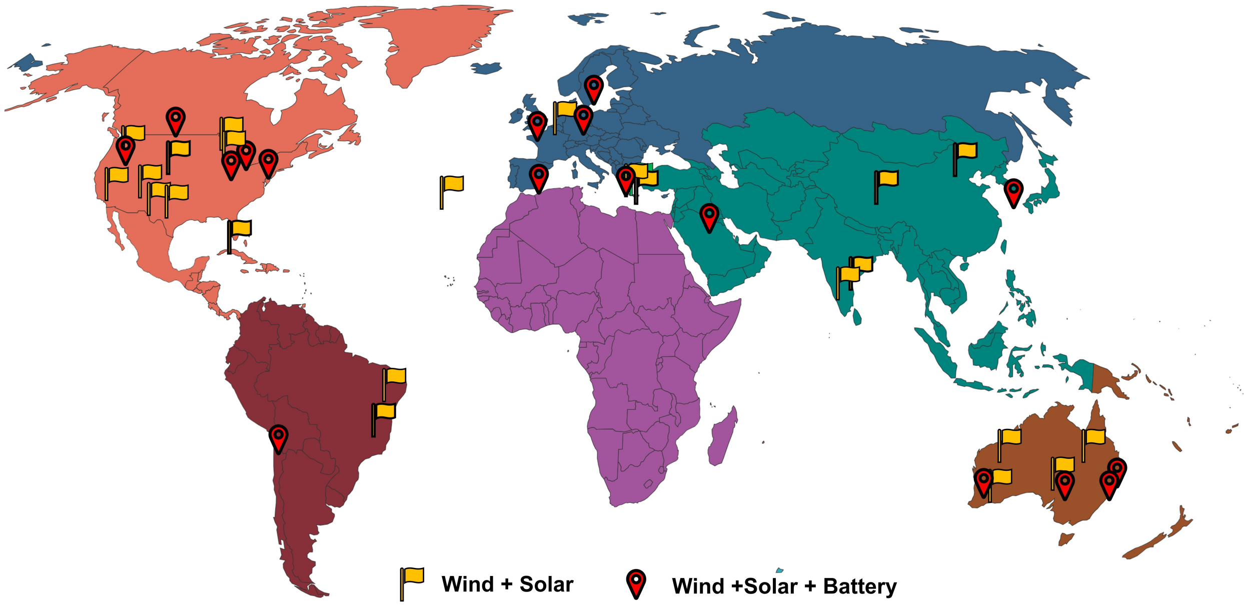

Figure 6. Wind–solar hybrid power plants (adopted and in addition to WindEurope).

The Minnesota Community Site in the USA is the first U.S. wind and solar HPP, combining wind (5 MW) and solar (0.5 MW) to generate electricity for a local municipality, but ensuring grid connection compliance remains a significant challenge [12,47]. The Kavithal Solar Wind Project in Raichur, India, combines a 50 MW wind farm with a 28.8 MW solar PV site to create a hybrid system to address grid-integration challenges with fluctuating renewable energy output and benefits from shared transmission infrastructure and operations, leading to cost reductions [49].

Siemens Gamesa in La Muela, Spain, developed a PV–wind hybrid initiative, combining an 850 kW wind turbine, a 245 kW PV module, 222 kW diesel generators, and a 429 kW battery power capacity system to provide dependable green power to remote areas without access to the main electricity grid and minimize diesel consumption [50]. The Ollague Microgrid in Chile uses wind (0.3 MW), PV (0.205 MW), lithium-ion battery power capacity (0.3 MW), and a diesel generator to provide a continuous 24-h energy supply. Storing the grid's surplus energy in the BESS for nighttime use in an off-grid village results in significant energy and cost savings compared with relying solely on a diesel generator [47].

The Tilos hybrid plant in Greece is the first energy-self-sufficient island, consisting of wind (0.8 MW), PV (0.16 MW), and storage power capacity (0.8 MW) systems [12]. It will meet 70% of the island's energy needs, reducing costs and enhancing stability. Excess energy will charge electric vehicles for local transportation [51]. Wheatridge Renewable Energy Facilities in the USA are the first utility-scale HPP plant in North America, featuring a 300 MW wind farm, 50 MW solar facility, and 30 MW storage power capacity system aiming to reduce greenhouse gas emissions by at least 80% by 2030 [52].

The Grand Ridge Project in Illinois, USA, combines 210 MW of wind, 20 MW of solar, and 36 MW of battery storage power, offering advantages like shorter development timelines, reduced construction costs, enhanced energy supply stability, and optimized infrastructure productivity [53]. Graciosa, Portugal, uses a hybrid plant that combines wind (4.5 MW), PV (1 MW), storage power capacity (6 MW), and a diesel generator to meet 70% of the island's power needs, with diesel generators serving as backup plants.

Table 2. HPP projects operating, under development, or approved.

Project	Location	Wind (MW)	Solar (MW)	Storage (MW/MWh)	Main Function	Status	Reference
Wind + Solar Project							
Cynog park	U.K.	3.6	5		Maximizing grid utilization	Operating (2016)	[47]
Minnesota Community Site	U.S.	5	0.5		Local municipality, but ensuring grid connection compliance	Operating (2018)	[12]
Kavithal Solar Wind Project	India	50	28.8		Enhanced and flatter power output, shared transmission infrastructure	Operating (2018)	[49]
Louzes	Greece	24	1			Operating (2012)	[12]
Wind + Solar + Battery							
Haringvliet	Netherlands	21	41	12	Frequency containment reserve services and time-shifting services	Operating (2020)	[12,47]
Kennedy Energy Park	Australia	43.2	15	2/4 *	Meet local energy demand without excessive storage capacity	Operating (2017)	[12,47]
La Plana	Spain	0.85	0.245	0.4/0.5 *	Support remote areas without access to the gird and minimize diesel consumption	Operating (2017)	[50]
Tilos Hybrid Plant	Greece	0.8	0.16	0.8	Power demand and enhanced stability	Operating (2018)	[51]
Wheattridge Renewable Energy	USA	300	50	30	Contribution to GHG reduction	Operating (2020)	[52]
Graciosa	Portugal	4.5	1	6	Meet power demand	Operating (2020)	
Grand Ridge	USA	210	20	36	Enhanced energy supply stability	Operating (2020)	[53]
Upcoming, under development, and approved [12]							
Kendinin	Australia	120	50	N/A	Enhanced and flatter power output	Under feasibility study	[12]
Clarke Creek	Australia	800	N/A	N/A	Enhanced and flatter power output	Under feasibility study	
Andra Pradesh hybrid project	India	16	25	10	Enhanced and flatter power output	Contracted	
Tender Project	India	N/A	N/A	N/A	Enhanced and flatter power output	Approved	
Three Gorges, Inner Mongolia	China	2.7 GW	300	880	Enhanced and flatter power output	Under construction	
Northwest Ohio	USA	105	3.5	1	Enhanced and flatter power output	Under development	
Megisti hybrid project	Greece	1	0.85	1.44	Weak power grid	Under licensing	
Angios Elestratios Green Island	Greece	1	0.101	0.72	Weak power grid	Under development	
Endesa	Portugal	264	365	168	Enhanced and flatter power output	Under Planning	

* Battery storage energy capacity.

5. Optimization Techniques

Optimization in energy systems aims to achieve optimal outcomes within specific conditions and constraints, considering stakeholders' needs. Optimization entails optimizing resource utilization, including energy sources, sizing, financial means, control, and energy management, while adhering to grid requirements and constraints. Selecting multiple parameters to maximize or minimize can achieve optimization (as depicted in Figure 7). Common optimization approaches include classical methods, artificial methods, and hybrid methods (as depicted in Figure 8), which are used in various applications [11,20,34,42,43,54,55]. The main objectives of optimizations could be to optimize existing infrastructure by combining multiple energy sources in a single power plant, reduce redundant infrastructure, maximize land use efficiency, achieve higher profitability, and minimize energy loss [12,13].

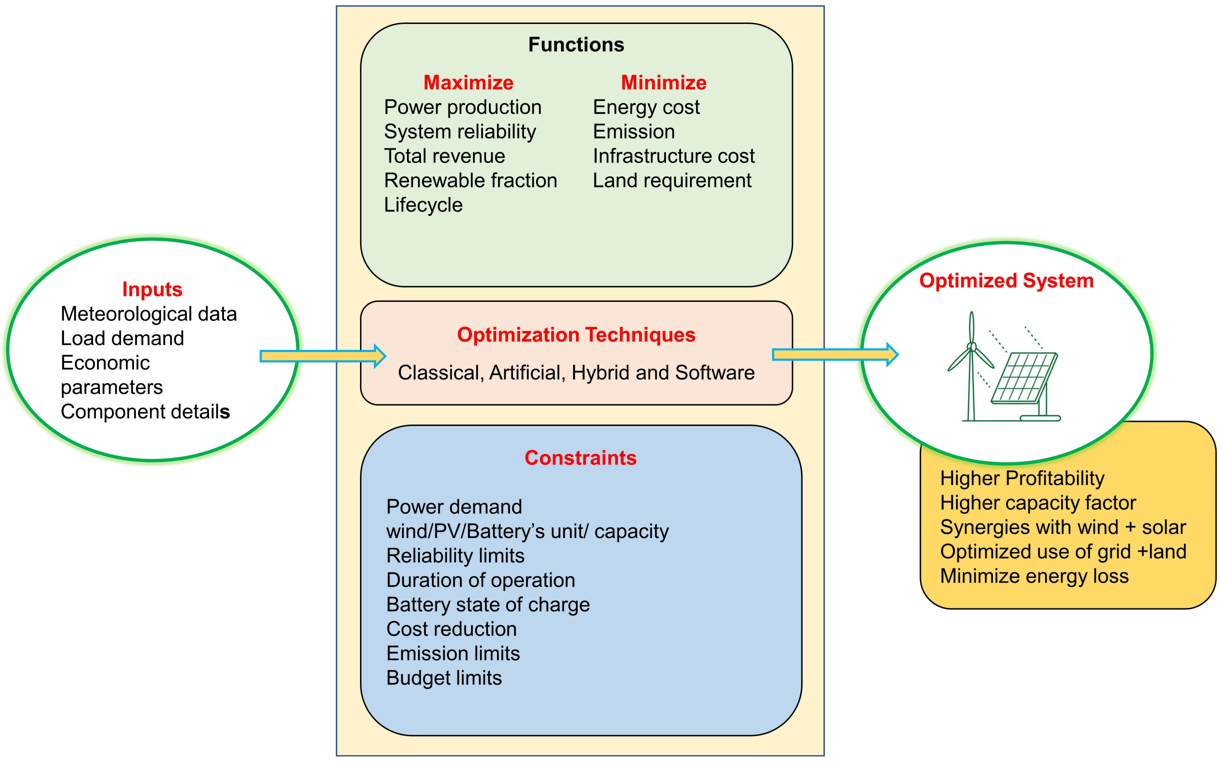

Figure 7. Optimization procedures for HPPs.

Classical optimization methods use mathematical formulations to determine globally optimal solutions in a deterministic fashion, but they face challenges when dealing with complex variables. Classical approaches, such as iterative, analytical, graphical, and probabilistic analyses, use differential calculus to compute energy models. Methods are limited by objective functions that lack continuity or differentiability. Examples of iterative techniques include the linear programming model (LPM) [25], multi-choice goal programming [56], multi-objective evolutionary algorithms (MOEAs) [57], mixed-integer linear programming (MILP) [58–60], and nonlinear programming (NLP) [61]. These techniques aim to achieve outcomes like null energy deficits, minimized system costs, and consistent power supply. The optimal arrangement for a hybrid system varies depending on factors such as location and demand patterns. However, because of their limited optimization capacity, these methods are limited in use among researchers. Probabilistic approaches provide statistical explanations for variable designs, whereas deterministic approaches view load demand and resources as predictable quantities with known time-series variation. Graphical construction procedures are created when optimization functions and outlines are drawn in the same graph, focusing on the implementation region.

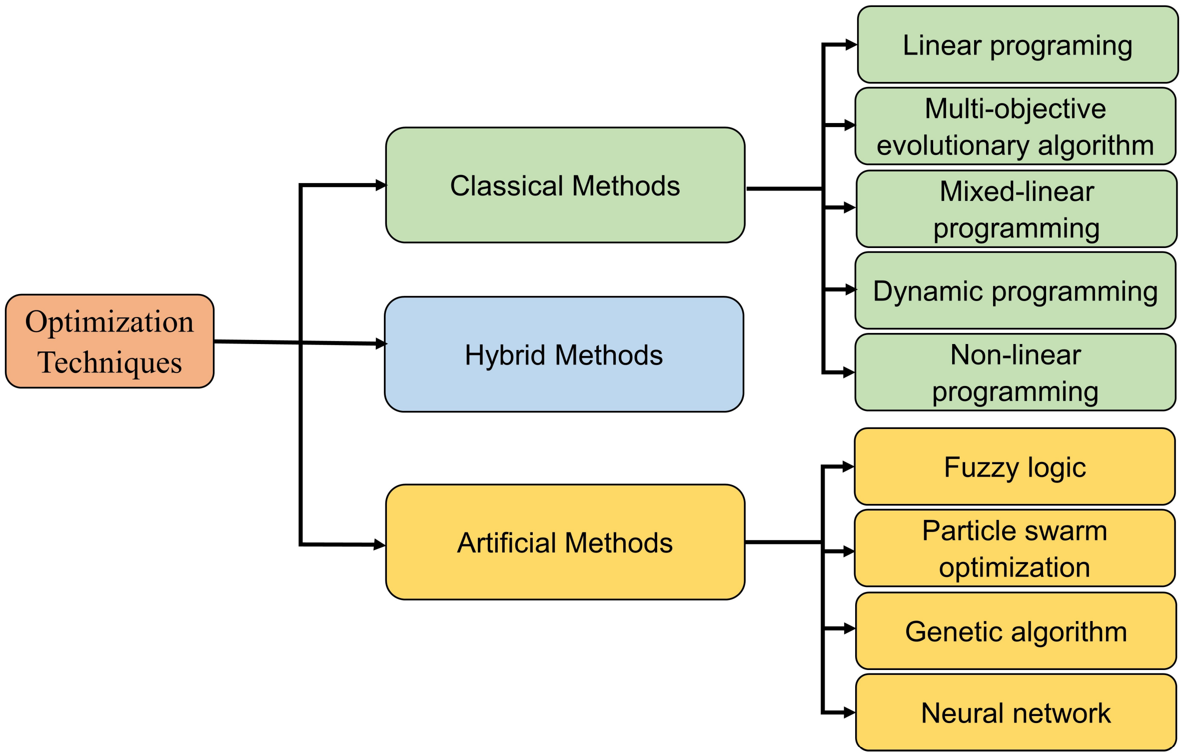

Figure 8. Optimization techniques for HPPs.

In the literature [11,34,42,43,55], many artificial techniques, including GA, PSO, the harmony search algorithm (HSA), simulated annealing (SA), the ant colony algorithm (ACA), the bacterial foraging algorithm (BFO), the artificial bee colony algorithm (ABC), and cuckoo search (CS), have been reported for sizing renewable sources. These algorithms are capable of addressing the non-linear characteristics of renewable energy system components or the intermittent behavior of solar and wind energy sources. These algorithms have shown reduced computation times, improved accuracy, and superior convergence rates compared with conventional methods. However, the focus in this section is directed solely towards the methods that have been commonly and recently employed by researchers.

In hybrid renewable energy systems, evolutionary heuristic search methods use GA to optimize dimensions. Researchers have successfully used it in several different areas, such as planning day-ahead schedules for hybrid plants [62], optimizing the design and layout of hybrid wind–solar-storage plants [21], and balancing life cycle cost, system embodied energy, and the chance of losing power supply in PV–wind–battery hybrid systems [63]. However, the success of these approaches depends on steady wind speeds and consistent voltage output from PV cells, which can be challenging in real renewable energy setups. PSO is an optimization search algorithm that minimizes LCOE while maintaining a suitable production range. It has been used for many things, like lowering the cost of energy storage [64] in HPPs, lowering the cost of energy (COE) [65], LPSP, total annual cost (TAC), and emissions [66], solving multi-objective optimization problems, making sure the system works reliably, and lowering the total cost, unmet load, and fuel emissions [67].

Artificial neural networks (ANNs) are dynamic adaptive computing systems that can process information in parallel. Enhancing HPP performance has resulted in improved efficiency, reliability, and cost-effectiveness [68]. These methods enable better resource allocation, load management, and overall system operation. They also improve energy capture, reduce energy waste, and optimize power generation. Neural network optimization also shows promise in predictive maintenance, preventing costly breakdowns and downtime. Faria et al. [69] and Singh and Lather [70] introduced ANNs as a power management approach for hybrid PV–energy storage systems, analyzing the State of Charge

(SOC) of individual ESSs. Mohandes et al. [71] used neural networks to predict hourly energy distribution for renewable energy sources and battery storage systems. However, this approach did not consider the gradual deterioration of energy storage systems, which can significantly impact an HPP's operational performance.

Fuzzy logic control (FLC) is a method that is easier to understand and less affected by changes in parameters compared with ANNs. It operates based on rules [11] defined by membership functions. Athari and Ardehali [72] used FLC to analyze the impact of changing electricity prices on energy storage performance in a grid-connected HRES. The shuffled frog leap algorithm was used to fine-tune membership functions, aiming to minimize operational expenses and improve the performance of HRES energy storage components. Fuzzy logic has been used to manage energy flux in hybrid systems with solar, wind, and battery components, demonstrating successful control of energy flux [73]. Yahyaoui and De La Peña [74] used fuzzy logic to enhance energy management systems for wind, solar, battery, and diesel generator systems. Ammari et al. [34] identified various fuzzy logic algorithms, such as the adaptive neuro-fuzzy inference system (ANFIS), the fuzzy analytic hierarchy process (FAHP), ANP, fuzzy clustering, the genetic algorithm, fuzzy particle swarm optimization, fuzzy honeybee optimization, and quantum-behaved particle swarm optimization.

Hybrid methods are techniques that combine multiple algorithms to address the limitations of a single algorithm. This flexibility allows soft computing approaches to manage complex optimization problems more effectively, leading to more accurate results [42]. Tito et al. [75] optimized a hybrid PV, WT, and battery system using GA and an exhaustive search. Singh et al. [76] used enhanced differential evolution and PSO to determine the best sizes for each component of their sizing model. Hybridization can take various forms; a few examples include Monte Carlo simulation with multi-energy balance and financial equations [77] or the fusion of GA and PSO (GAPSO) [32]. Alshammari and Asumadu [78] used Harmony Search, Jaya, and particle swarm optimization to find the best configuration for an HRES comprising wind, photovoltaic, biomass, and battery technologies. The primary goal was to meet customers' electricity needs in a cost-effective and reliable manner while ensuring efficiency.

Furthermore, many approaches to optimizing hybrid renewable resources focus on cost reduction, including LPSP constraints to lower system expenses. Other constraints include minimizing grid-injected power, decreasing fluctuation rates, and enhancing the utilization factor. These considerations drive the optimization process, with cost reduction as the single objective [29,79]. In contrast to single-objective and multi-criteria decision-making techniques, multi-objective optimization methods offer a range of optimal solutions. Modern techniques using AI algorithms and hybrid methods are gaining popularity over traditional methods for resolving complex optimization challenges. These techniques consider multi-objective functions, primarily cost and LPSP, with constraints like COE, LPSP, and REF [31–33].

Summary and Evaluation

HPPs are complex because of uncertainties and limitations, leading to the adoption of soft computing methods with meta-heuristic algorithms. These techniques, which come in single-objective optimization (SOO) and multi-objective optimization (MOO), offer increased adaptability and accuracy. However, their complexity is a common drawback. Traditional methods are highly effective but have limitations due to parameters. Contemporary optimization approaches require robust hardware performance because of their intricate procedures and codebase. Their strengths include efficiency, rapidity, and accuracy. Combining conventional and modern optimization techniques creates an approach with remarkable speed and resilience, requiring sophisticated design and code creation. Table 3 and the Appendix A (Tables A3 and A4) outline the advantages and disadvantages of each method and summarize the study of single and multiple objective functions.

Table 3. Advantages and disadvantages of optimization methods adapted from [25,43,54].

Techniques	Advantage	Disadvantage
Classical	• Efficient multi-objective solutions that are valuable for investment decision-making. • Quicker processing time.	• Limitations in optimizing space, and exhibit linear relationships with the variables. • Require a mix of discrete and continuous probability.
Artificial	• Offer more efficiency. • More accurate. • Fast convergence.	• Complex solving process. • Require more memory space.
Hybrid	• High convergence. • Offer time efficiency. • Robustness. • Quick convergence.	• Design complexity. • Code generation challenges.

6. Sizing Methodologies

In HPPs, determining the appropriate wind farm, solar farm, and battery storage energy capacity is crucial for establishing the system's capacity. Incorrect sizing can lead to undersized or oversized systems. Designing HPPs considers factors like cost reduction, reliability enhancement, and emissions reduction [28]. Accurately assessing real loads as well as wind and solar metrological data is critical, as climatic conditions affect energy availability at specific locations [54]. Researchers often rely on average data from hours [75,80] or months [17] to analyze system performance. Figure 9 shows how size optimization methodologies fall into classical, modern, and software-based approaches. Traditional methods use iterative, numerical, analytical, probabilistic, and graphical methods based on differential calculus, simplifying the process of identifying optimal continuous and differentiated solutions, while modern techniques use artificial and hybrid methods [43,46,54]. Commercially available software tools, such as HOMER, aid in sizing and optimizing standalone solar photovoltaic and wind-based systems, identifying optimal energy system sizes, and conducting sensitivity analyses to explore varying input variables or uncertainties.

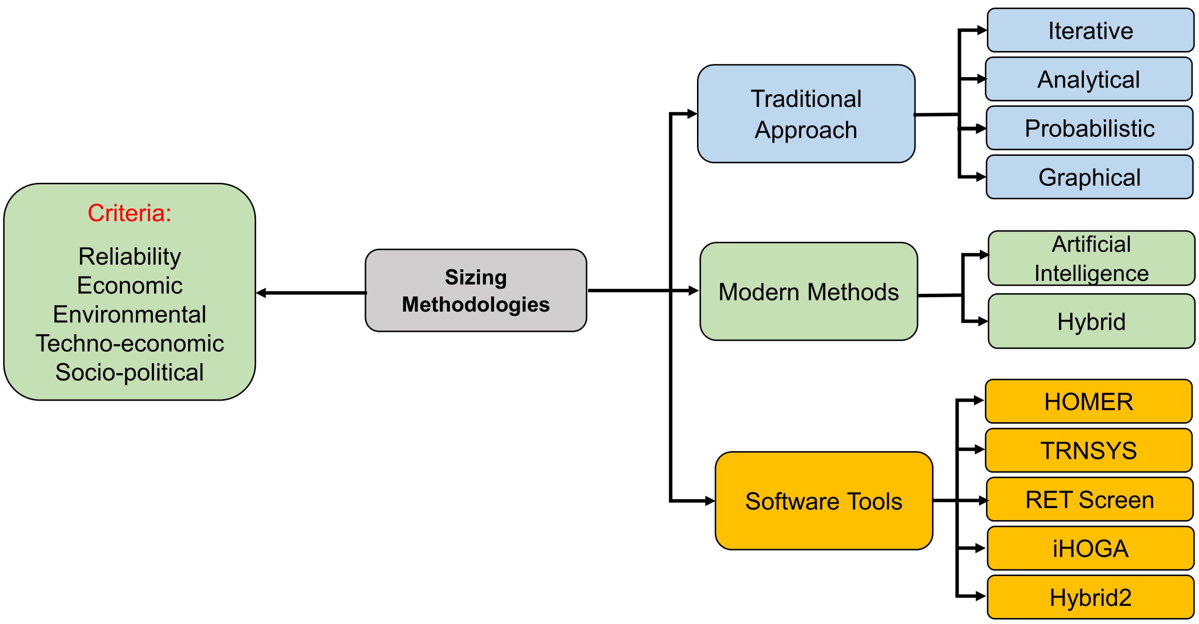

Figure 9. Sizing methodologies.

6.1. Sizing HPPs Using the Classical Approach

Several studies [33,54,81] explored various approaches for sizing solar and wind-based hybrid systems. A classical approach includes probabilistic, graphical, analytical, numerical, and iterative methods. However, only widely used approaches are considered in this study. Iterative methodologies are used to evaluate performance in HPPs using a recursive process. The framework uses the LPSP model for power reliability and integrates LCOE and net present value (NPV) models to account for system costs. Identifying the optimal system configuration is based on achieving the lowest LCOE/NPV, leading to cost reduction through linear parameter adjustments or linear programming methods. Akram et al. [80] presented two iterative search algorithms for optimal sizing components in a grid-connected microgrid configuration for maximum reliability and minimum cost.

The probabilistic approach is a method for determining system size, but its results may not be suitable for identifying the optimal solution. Li et al. [82] proposed a new probabilistic method for optimizing an off-grid hybrid energy system, estimating power distribution probability in the South China Sea region. Lian et al. [83] highlighted the use of probabilistic methodologies for assessing reliability simultaneously. Analytical methods describe HPPs using computational models that determine the size of the hybrid system based on feasibility [84]. The approach is faster than the Monte Carlo simulation and requires less time. This approach views the hybrid system as a numerical model and defines its size as a function of viability [15]. Karve et al. [85] used mathematical methods and improved particle swarm optimization (IPSO) to find the best size for a hybrid PV–wind–battery system that could work on its own. They performed the study to lower the system's annual costs.

6.2. Modern Methods

Modern methods utilize artificial intelligence and hybrid methodologies, enhancing their adaptability and ability to handle complex optimization challenges with more accurate results [43,55]. The design of renewable HPPs is complex because of uncertainties, technical considerations, and site limitations. Conventional methods are inadequate, leading to a shift towards soft computing techniques, often relying on meta-heuristic algorithms [42,43,55]. Contemporary techniques incorporate both single and hybrid algorithms to address a wider range of challenges, enabling more efficient and refined optimization outcomes [42]. Numerous techniques have been documented in the literature [11,28,34,42,46,54,55], including GA, PSO, HSA, SA, ACA, BFO, ABC, and CS. These algorithms can address the non-linear characteristics of renewable energy system components or the intermittent behavior of solar and wind energy sources. Kiehbadroudinezhad et al. [86] used a division algorithm and an enhanced genetic algorithm to model, design, and optimize wind, PV, and battery hybrid systems for water desalination. Muthukumar and Balamurugan [87] used a bee algorithm and neural architecture to optimize wind and solar hybrid systems, as well as test various solar irradiance and wind velocities. Roy et al. [64] used PSO in HPPs to reduce energy storage costs by utilizing multiple energy storage systems.

Hybrid techniques combine different methods to achieve optimal design outcomes. Riaz et al. [88] presented a hybrid of PSO with grey wolf optimization (GWO) used for optimal power flow. Ghorbani et al. [32] used the fusion of GA and PSO (GAPSO). Zhang et al. [89] developed a hybrid approach that combined the Harmony Search Optimization (HSO) method with the simulated annealing (SA) technique, enhancing chaotic search and demonstrating better results for optimizing HRES sizing than either method individually. Abdelshafy et al. [90] used a PSO-GWO approach to find the best HRES design. The method converges optimally faster and better.

6.3. Sizing HPPs Using Software Tools

Software tools efficiently and cost-effectively design, analyze, optimize, and assess HPPs. These tools are designed to operate under optimal conditions for investment and power reliability [17,34,35,43,83,91]. The National Renewable Energy Laboratory (NREL) developed HOMER to evaluate energy based on resource costs and availability. Several studies [92–96] have used HOMER software (Homer Pro) to determine the most cost-effective configuration for hybrid systems, with some finding a combination of solar panels and wind turbines as the optimal approach. Other software tools used for sizing include IHOGA, HYBRIDS2, TRNSYS, and RETScreen.

The Renewable Energy Research Laboratory (RERL) at the University of Massachusetts developed Hybrid2 software (version 1.3), a computer model for analyzing hybrid power systems that include electrical loads, wind turbines, photovoltaic installations, diesel generators, battery storage units, and power conversion devices [34]. The Electric Engineering Department at the University of Zaragoza developed HOGA as a hybrid system optimization tool, while HYBRIDS is a Microsoft Excel spreadsheet-based application used for renewable energy assessments [97].

For simulation purposes, TRNSYS software (version 18) from the University of Wisconsin allows programmers to define time steps ranging from 0.01 s to 1 h. TYRSYN optimizes generation system combinations and sizes energy storage capacity to achieve the LCOE across renewable energy fractions [98]. RETScreen evaluates the technical and financial viability of renewable energy, energy efficiency, and cogeneration projects.

Table 4 displays a comparison of various tools, revealing their respective qualities and limitations [25,26,34,43,99]. Table 5 provides a comprehensive overview of various size methodologies, including the system components and objective functions.

Table 4. Summary of the input and output for sizing optimization software tools.

Software	Input	Output	Limitations	Availability
HOMER	• Load demand. • System control. • Resource input. • Component details. • Emission data. • Constraints. • Capital and maintenance cost.	• Sizing optimization. • Techno-economic analysis. • Environmental analysis. • Risk assessment and sensitivity analysis. • Analytical probability.	• Use first order linear equations. • Time series data cannot be used. • Needs more information to get started.	Free access www.homerenergy.com (accessed on 15 Decmeber 2023)
HYBRID2	• Load demand. • Resource input. • Component details. • Financial data.	• Sizing optimization. • Percentage of GHG emissions. • Techno-economic analysis.	• Simulations take a long time. • Only one configuration can be simulated at a time.	Free access https://www.umass.edu/windenergy/research/topics/tools/software/hybrid2 (accessed on 7 Februaryr2024)
HYBRIDS	• Component details.	• Cost of energy. • Percentage emission of GHGs.		-
IHOGA	• Resource input. • Constraints. • Economic data. • Component details. • Emission data.	• Cost of energy. • Multi-objective optimization. • Life cycle emission. • Sizing optimization. • Analytical probability.	• Only one configuration can be simulated at a time. • Lacks sensitivity analysis and probability analysis.	The EDU version is free, while the PRO version is priced www.ihoga.unizar.es/en/ (accessed on 7 February 2024)
RETScreen	• Resource input. • Load data. • Project database. • Product database.	• Costs. • Techno-economic analysis. • Emission reduction. • Sensitivity and risk analysis. • Analytical probability.	• Input data are reduced. • Time series data cannot be used.	Free access www.retscreen.net (accessed on 22 Decmeber 2023)
TRNSYS	• Resource input. • Inbuilt model/	• Dynamic simulation behavior. • Technical evaluation. • Thermal behavior.	• No option for optimization.	Priced www.trnsys.com (accessed on 20 Decmeber 2023)

Table 5. Summary of various studies conducted on HPPs/HRES using sizing software tools.

Software	Energy Resources				Objective of the Study	Reference
	Wind	Solar	Battery	Other		
HOMER	✓	✓	✓		Cost-effective configuration of HRES	Muller et al. [92]
	✓	✓		FC	Evaluate technical and financial performance	Al-Badi et al. [100]
	✓	✓	✓		Sizing design of HRES	Hoarca et al. [101]
HYBRID2	✓	✓	✓		Sizing method of standalone RES based on techno-economic analysis and object-oriented programming	Belmili et al. [102]
IHOGA	✓	✓			Optimal sizing of RES	Fadaeenejad et al. [103]
	✓	✓	✓		Sizing design of HRES	Hoarca et al. [101]
HOMER PRO	✓	✓			Minimize LCOE, life cycle cost	Ranaboldo et al. [104]
HOMER	✓	✓	✓		Energy production, net present cost, and levelized cost of electricity	Baker [105]
HOMER	✓	✓	✓	Hydrogen	Total net present cost	Babatunde et al. [106]
RETScreen	✓	✓	✓	Biomass	Feasibility study based on economics and the environment	Hossen and Shezan [107]
TRNSYS	✓	✓			Optimal sizing of wind–PV-based hybrid system	Anoune et al. [17]
	✓	✓	✓		Energy performance of the system	Mazzeo et al. [108]

Summary and Evaluation

The speed and ease of use of traditional methods for scaling hybrid systems may be overcome by using artificial intelligence techniques. AI techniques leverage multi-objective functions to tackle complex challenges. Iterative approaches, which use recursive processes, can mitigate the constraint but may overlook critical parameters. Artificial intelligence offers versatility and favorable outcomes for complex tasks, but the complexity of the codes in the algorithms poses challenges. Table 6 presents a comparison of various sizing methods used in hybrid systems.

Table 6. Comparison of various studies on sizing methods/tools.

Techniques/Tools	Advantage	Disadvantage	Reference
Iterative	• User-friendly and capable of early-stage threat detection. • Easy to code. • Use of linear variable parameters or linear programming techniques is highly efficient in achieving cost minimization.	• Suboptimal solutions result from linear adjustments in decision variables, not optimizing factors like PV module slope angle and wind turbine installation height, which have a more significant effect on cost.	Chauhan and Saini [109]
Probabilistic	• The system is stochastic and can randomly identify the optimal solution based on the provided data. • Simple sizing methods do not require time-series data.	• Optimization considers limited performance parameters, potentially not suitable for identifying optimal solutions. • Less efficient in representing the dynamic nature of performance changes within a hybrid system.	Ganguly et al. [84]; Lian et al. [83]
Analytical	• Size determination is simpler and requires less computational resources than Monte Carlo simulation.	• System design becomes less flexible as performance is evaluated using computational models. • Model is unable to predict the coefficient of the mathematical equation related to position.	Lian et al. [83]
Graphical	• The most straightforward method for depicting complex problems or situations involving numerous mathematical equations.	• The method is limited to handling problems with multiple dimensions because of scale and graphical interpretation complexities, making its reliability uncertain. It faces difficulties in graphing non-linear, exponential, logarithmic, and trigonometric expressions and is impractical when combined with other approaches.	Rathore and Patidar [110]
LP	• The model exhibits a linear relationship among variables, is renowned for its favorable convergence, and is less stringent.	• The system may become stuck in a local search, reducing accuracy and confidence over time, and not considering variable evolution and changes.	Saiprasad et al. [111]

Table 6. *Cont.*

Techniques/Tools	Advantage	Disadvantage	Reference
GA	• GAs are powerful tools that can manage multiple parameters, including integers, discrete values, and non-differential attributes, simultaneously. Their parallelism allows for simultaneous evaluation of multiple strategies, enhancing the likelihood of achieving optimal solutions. GA has proven superior in cost and environmental analysis compared with HOMER Pro software and SA.	• GAs are time-consuming but less computationally intensive than the analytical method, as they are specifically designed for local searches.	Iweh et al. [35]; Riaz et al. [88]
PSO	• Proficient in executing parallel computations, achieving rapid convergence, efficiently finding the optimal global solution, and effectively resolving complex problems.	• The system exhibits poor local search performance when dealing with complex problems with numerous dimensions, with a notable tendency towards premature convergence.	Dubey et al. [112]; Gad et al. [113]; Wang et al. [114]; Gupta and Srivastava [115]
ACO	• The algorithm quickly identifies optimal solutions through feedback mechanisms, demonstrates parallelism, is adaptable, and can be combined with another algorithm for a potent, reliable approach. It achieves the global minimum with fewer iterations compared with particle swarm optimization.	• Insufficient parameter selection can lead to stagnation, premature convergence, and inability to reach optimal solutions, especially when addressing discrete problems, with potential challenges in continuous problems.	Gupta and Srivastava [115]
CS	• The algorithm, which incorporates Levi's flight trait, enhances its performance by enabling convergence towards global optimal solutions, boasts robust random searching paths and optimization capabilities, and is highly prone to hybridization with other algorithms.	• Incorrect initial parameters can lead to a local search trap and slow convergence rate.	Shen et al. [116]
SA	• The process of achieving optimal outcomes is methodical and predictable, with programming being straightforward, resilient, and flexible, enabling smooth transitions between local and global search modes.	• The system exhibits limited efficiency and prolonged computational durations.	Iweh et al. [35]

Table 6. *Cont.*

Techniques/Tools	Advantage	Disadvantage	Reference
HS	• The method requires fewer adjustable control parameters, no initial decision variable configuration, and operates without requiring derivative information.	• Exhibits gradual and premature convergence, with limited ability to constrain and adjust search ranges.	Dubey et al. [112]
GWO	• Fewer parameters. • Easy to implement.	• The algorithm's precision and accuracy have been reduced because of a slow convergence pace during later iterations, resulting in a lack of local search presence.	Wang et al. [114]
HOMER	• An expedient approach to obtaining a desired solution for a singular objective.	• The linear equation model's initial attributes are undefined, and it assumes a fixed state throughout the investigation. It does not allow users to choose suitable equipment, does not consider future developments, and is constrained by input parameters. It does not support control strategies like iHOGA and is overshadowed by nature-inspired algorithms. A well-informed criterion is needed for a satisfactory solution in the optimization process.	Saiprasad et al. [111]; Kavadias et al. [117]
iHOGA	• Ability to directly implement a control strategy during the sizing of HRES.	• The focus is on achieving individual objectives and addressing non-linear problem scenarios.	Saiprasad et al. [111]
RETScreen	• Drastically lowers the expenses linked to the identification and evaluation of potential energy projects in comparison with Homer Pro.	• The task involves manually compiling data into a workbook or Excel sheet.	Ramli et al. [118]

7. Control and Energy Management Strategies

HPPs, which combine wind and solar power, face challenges such as power quality, voltage fluctuations, network stability, frequency disparities, and efficient dispatch. To ensure system reliability, effective power management, and optimal performance, an effective control system and an energy management strategy (EMS) are crucial. The approach can regulate power allocation from generators, stabilize voltage and frequency, optimize resource utilization, minimize operational costs, and prolong the system's lifespan.

7.1. Control Strategies

The literature [3,7,8,36–40] presents a variety of control systems for wind turbines, with few studies focusing on the combination of HPPs with batteries. The typical composition of HPP controllers includes a plant model and an embedded dispatch function. The plant model includes power-generating units (PGUs) that contribute to power production at the PCC. The controller is programmed with predefined reference values and can be adjusted to parameters like curtailment set-points, grid limitations, or frequency variations [3,38,39]. The dispatch function optimizes power utilization from different PGUs by processing the output. Few have adopted a supervisory hierarchical control framework with multiple levels dedicated to specific objectives, such as active power management [39], frequency regulation, reactive power and voltage control [38,39], and maximizing revenue [119]. This structure aims to optimize power management, maintain frequency stability, and regulate voltage levels effectively. Petersen et al. [7] developed and verified a reduced-order performance model for wind turbines, photovoltaic parks, and BESS, testing it in two scenarios. For controller design, comprehensive resource simulations are essential.

HPPs can be controlled using various methods, such as centralized, distributed, and hybrid [11,34,35], as shown in Figure 10, and proportional-integral control [8,39]. Moreover, another study by Olatomiwa et al. [120] classifies control strategies into classical and intelligent control. Traditional approaches include ANNs, FLC, multi-objective PSO, and adaptive neuro-fuzzy inference systems. These strategies can enhance the cost-effectiveness of the system and ensure seamless energy flow.

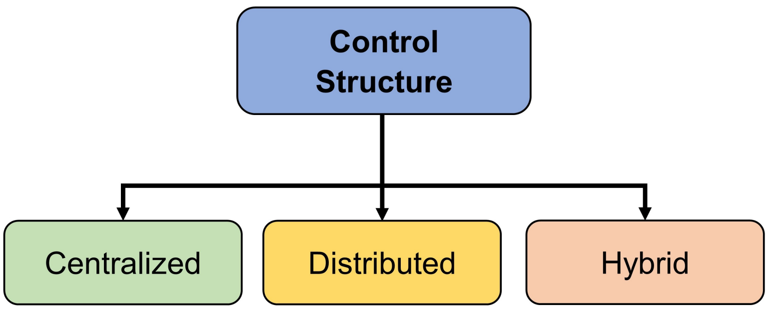

Figure 10. HPP control strategies.

Intelligent control algorithms drive the centralized approach for conventional energy coordination control [80]. The STATCOM (Static Synchronous Compensator) system is critical to efficiently managing power in multisource energy systems because it regulates reactive power [80]. However, as wind farms, photovoltaic arrays, and composite energy storage systems become more prevalent, the limitations of this centralized approach pose challenges for large-scale integrated power-generation systems.

To overcome these drawbacks, the multi-agent system has emerged as a viable alternative, offering intelligent and adaptable responses to varying working conditions and demands [121]. Wu and Hua [121] created a multi-agent-based energy coordination control system (MA-ECCS) to make large-scale wind–photovoltaic energy storage power-generation units more stable, efficient, and good at making decisions. It enables non-fixed client–server cooperation among agents by using a negotiation model inspired by the contract net protocol.

The flow chart algorithm [8,39], linear programming [122], model predictive control [123], the Pareto algorithm [124], and the adaptive neuro-fuzzy inference system [125] are some of the control algorithms that are used. However, these algorithms require precise models of the entire system, as well as accurate demand and weather resource data. Hybrid systems often use distributed or hybrid control strategies for efficiency, system failure minimization, and incorporating multiple control methods. Agrawal et al. [126] developed a two-tier optimization approach to improve the operational efficiency of HRESs, while Hashemi and Zarif [127] introduced a two-phase method to manage reactive power in power systems. Shibl et al. [128] introduced a dual-phase energy dispatch management framework for HPPs, integrating machine learning techniques.

Summary and Evaluation

Control methods in practical applications are chosen based on system complexity, optimization, robustness, communication capabilities, and potential failure consequences. Real-world systems employ various strategies to balance efficiency, adaptability, and reliability, ensuring a harmonious equilibrium. Hybrid systems widely use distributed or hybrid control methods because they effectively decentralize control, reduce system failures, and integrate multiple control strategies, although the interconnection and processing codes are complex. Table 7 provides a comprehensive overview of the various control categories, outlining their advantages and disadvantages.

Table 7. A comparison of various control methods [28,34,35,43].

Control Method	Advantage	Disadvantage
Centralized	• Efficient optimization and coordination. • Easier implementation and management for simpler systems. • Maintaining the lowest possible energy costs.	• Single point of failure. • Scalability issues in complex systems. • Lack of robustness in the face of controller malfunctions.
Distributed	• Scalability for complex systems. • Adaptability to environmental changes. • Robustness against failures.	• Necessitate more intricate communication and synchronization mechanisms. • Most solutions are not optimal. • Coordinating decisions among distributed agents can be challenging.
Hybrid	• Combines the advantages of centralized and distributed approaches. • Customized control strategies for various system components. • Local controllers are seldom utilized.	• Management of both central and local decision-making processes is complex. • Present potential integration challenges.

7.2. Energy Management Strategies

Effective energy management of HPPs aims to achieve optimal efficiency and reliability while minimizing costs, ensuring a continuous energy supply throughout the year [11]. This can lead to benefits such as extended component lifespan, reduced economic parameters, and enhanced overall system performance [15]. Energy management methods include rule-based, optimization-based, reinforcement-based, and learning-based methods [35,42,129]. This review provides an overview of different EMSs studied in the literature [11,34,35,42]. Figure 11 illustrates the major management strategies.

The power-oriented strategy aims to meet energy demand by controlling the power balance and battery state of charge, which define the operational limits of major energy storage systems [11,34,42]. This strategy is simple and controlled through algorithms in flowchart diagrams, guided by flowchart diagrams. Similarly, the technical objective-oriented strategy aims to optimize the technical parameters of a hybrid system to meet load demand [130,131], prolong equipment lifespan [132], enhance system performance, ensure stability [133], extend storage component lifespan [134], and optimize generator parameters. This involves using various algorithms like predictive control [135], PSO [136], real-time optimization [137], neural network techniques [138], and software tools like HOMER [137]. Implementing these strategies requires design constraints, power storage system state management, and consideration of degradation parameters. Depending on the optimization objectives, these strategies offer medium complexity and promising system performance and lifespan outcomes. Brka et al. [139] employ a flowchart algorithm, while Cano et al. [140] use model predictive control and fuzzy logic. A strategy's effectiveness is dependent on precise forecasting and reliable system models for accurate operations, which affect the system's performance.

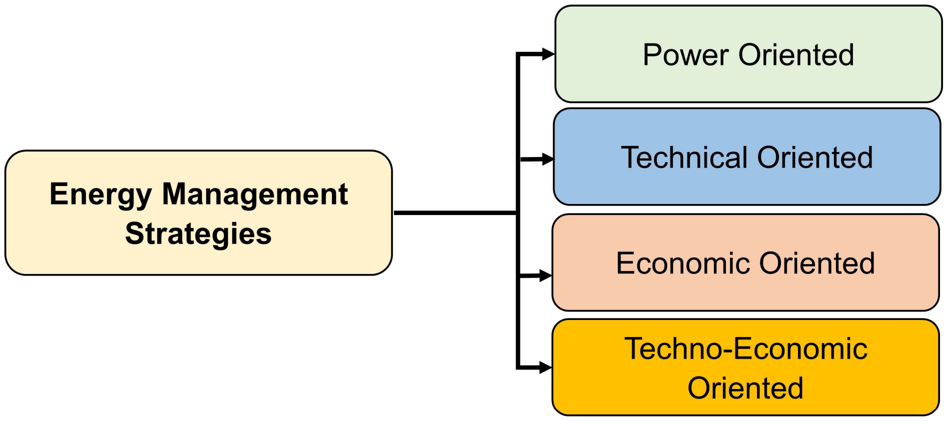

Figure 11. Energy management strategies.

An economic-oriented strategy involves assessing energy demand and minimizing system expenses. Research in this area uses various algorithms, including genetic algorithms, differential evolution algorithms, model predictive control, mixed-integer linear programming, fuzzy logic, and commercial software like HOMER. A dual-tier energy management system for microgrids was developed using a hierarchical dispatch framework, focusing on reducing operational expenses and mitigating forecast inaccuracies, as outlined in Ju et al. [141]. However, the model does not account for stochastic variations in renewable energy output.

Finally, a techno-economic objective-oriented approach improves system performance by balancing supply and demand, taking into account technical and economic factors to extend equipment lifespan and reduce maintenance costs [11,43]. It offers an ideal solution compared with conventional generation alternatives. Existing approaches involve solving nonlinear optimization problems by incorporating costs and equipment depreciation into a multi-objective function. Various techniques ensure a harmonious power distribution for optimal system functioning by determining the power output from each component. The solution to extreme energy shortages depends on the system's configuration. Hamdi et al. [142] implemented an ANN and MATLAB program to examine LCOE, zero power loss supply probability, and curtail energy for a wind- and solar-based hybrid system.

Summary and Evaluation

EMS is essential for managing power movement across various components. Utilizing strategies such as rule-based, optimization-based, learning-based, and reinforcement learning (RL) enhances the efficiency of hybrid energy systems. Rule-based strategies commonly handle practical scenarios, while optimization-based approaches address complex optimization issues using algorithms. Machine learning techniques train controllers in RL-based energy management, enabling decisions based on system status and objectives. This approach minimizes maintenance costs and prolongs the lifespan of equipment. However, complex optimization algorithms may increase the complexity of the system in real-world scenarios. Table 8 provides a comprehensive examination of the optimization objectives, design constraints, and control algorithms associated with energy management strategies.

Table 8. Management methods and their characteristics [11,34,43].

Management Strategy	Design Constraint	Control Algorithm	Advantages	Disadvantages
Power requirements	• Power balance. • Battery state of charge.	• Flow chart algorithm. • SOC based on the algorithm. • Supervisory centralized control algorithm. • Distributed control algorithm. • Artificial intelligence method. • Linear programming. • Predictive control.	• Simplicity in design and control.	• Lifetime not optimized. • O and M not optimized. • Performance not optimized.
Technical-oriented	• Power balance. • Battery state of charge. • Battery degradation.	• Flow chart algorithm. • SOC based on the algorithm. • Supervisory centralized control power algorithm. • Battery short time.	• Increase performance. • Improve lifetime. • Less complex.	• Operation and maintenance cost are not optimized.
Economic-oriented	• Power balance. • Battery state of charge. • Cost function.	• Cost minimize algorithm. • Power reference and priority algorithm.	• Optimal system response. • Minimize system cost.	• Complex algorithm. • Increases operation and maintenance costs. • Not optimized for lifetime.
Techno-economic-oriented	• Power balance, • Battery state of charge. • Cost function. • Battery degradation.	• Optimization algorithm is used to determine the power reference of a multi-objective function.	• High performance.	• Complex algorithm. • Increases operation and maintenance costs.

8. Discussion

The lack of a universally accepted definition of HPPs poses a challenge to exploring this emerging field. This disparity can lead to misguided conclusions, as there is limited literature on co-located utility-scale HPPs. HPPs offer potential advantages, especially from co-locating wind and photovoltaic facilities. However, their long-term economic viability is uncertain because of a lack of standardized definitions and existing park instances. Previous research has improved the understanding of hybrid systems on a small scale, but there is a noticeable lack of comprehensive review articles on energy management and control strategies and optimization methodologies for HPPs at the utility scale. This study aims to address this gap by extrapolating key findings and methodologies from HRES studies. The Discussion Section is categorized by the topics explored in this manuscript, considering its structure and issues.

Topologies: Regarding the topologies and configurations of HPPs, there exists limited research into the consequences of varying topologies on the outcomes of dimensioning. Each topology, including AC-coupled, DC-coupled, and hybrid, has unique converters and equipment, potentially affecting the system's technological and economic efficiency. As a result, it is imperative to undertake a comprehensive comparative assessment of distinct HPP topologies.

Optimization: The primary goal of employing optimization techniques in HPP is to achieve superior overall performance while also meeting grid requirements and constraints. Optimization studies primarily focus on three methodologies including classical, artificial, and hybrid approaches. Classical methods are quick and efficient but limited in optimization space. Artificial methods are efficient, precise, and fast, but they require complex processing procedures. Research has shifted towards hybrid algorithms for multi-objective optimization, with HOMER software becoming popular for its robustness and cost-effectiveness. Artificial intelligence-based optimization models have shown superiority over conventional methods because of their adaptability, enabling solutions for both single and multi-objective design problems, but they face usability challenges and involve complex implementation processes. Hybrid methods combine the strengths of conventional and advanced optimization techniques to improve efficiency and reduce processing time. However, the design and code delivery add to the complexity and the need for a specific code. Based on the literature reviewed, most of the research is carried out using SOO, while there has been an increase in the use of hybrid algorithm techniques to solve MOO problems in the last five years, as shown in Figure 12.

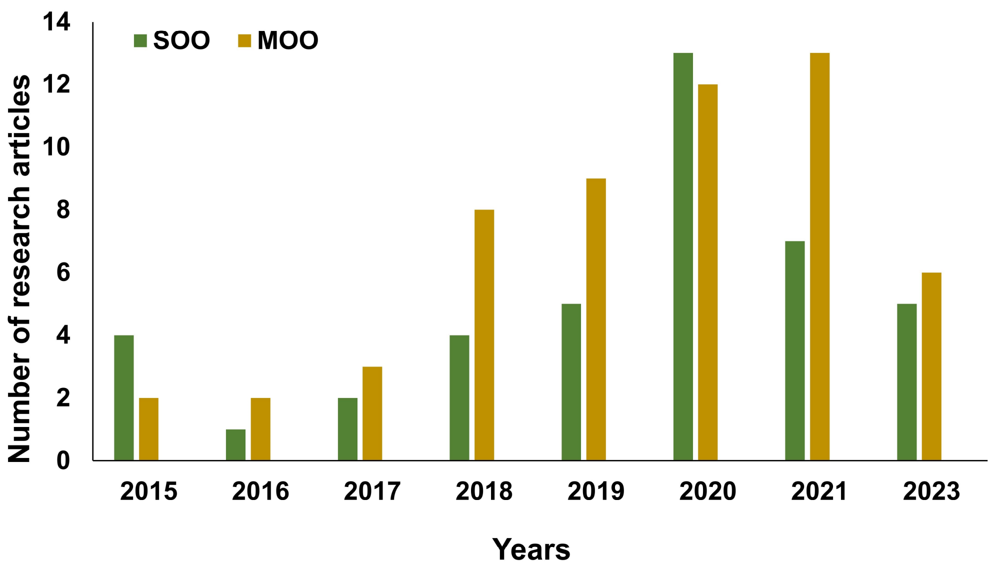

Figure 12. The use of SOO vs. MOO in the reviewed research articles.

Sizing: The optimization of sizing and proportions for solar–wind hybrid system components is crucial for cost reduction and operational satisfaction. However, as system complexity increases because of uncertainties such as output fluctuations, load variation, and constraints, a single algorithm may not be effective. A novel approach that combines the strengths of multiple methods holds promise for optimized sizing with increased precision and reduced computational time, addressing complex system dynamics challenges. Future optimization of HPP sizes involves considering not only minimizing annual and fuel costs but also enhancing reliability through factors like the human development index and job market, as well as bolstering sustainability and resilience. Exploring sizing methodologies that incorporate operational safety, sustainability, and resilience indicators could help address these challenges. Figures 13 and 14 show the sizing methodologies and evaluation criteria used in the literature. The occurrence frequency of meta-heuristic algorithms and software tools is the highest.

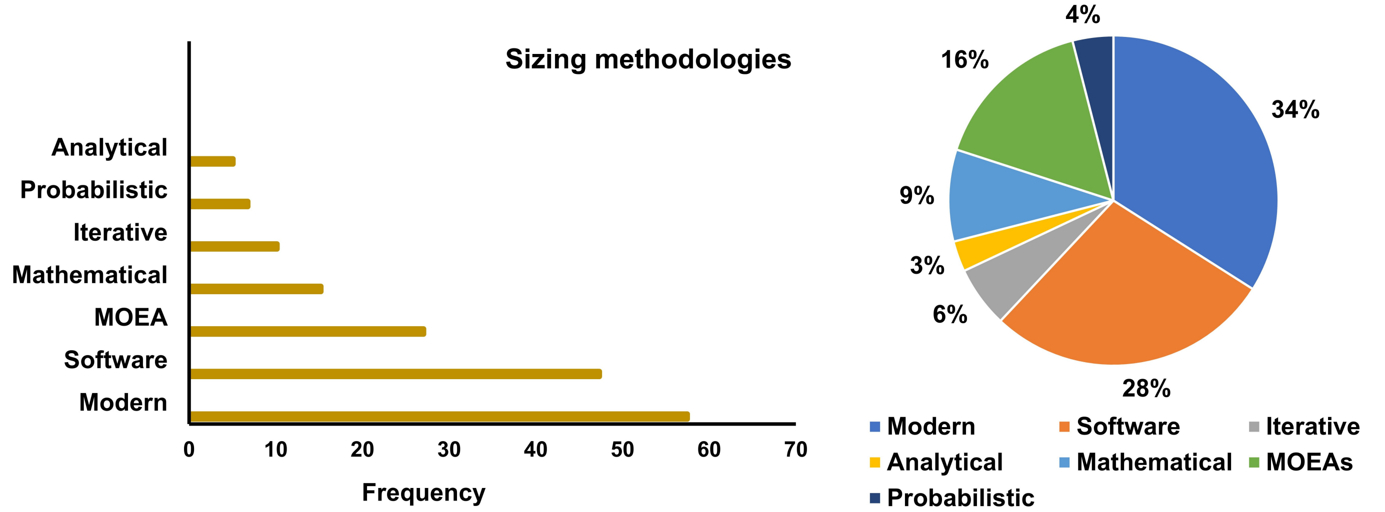

Figure 13. Summary of sizing methodologies used in the literature.

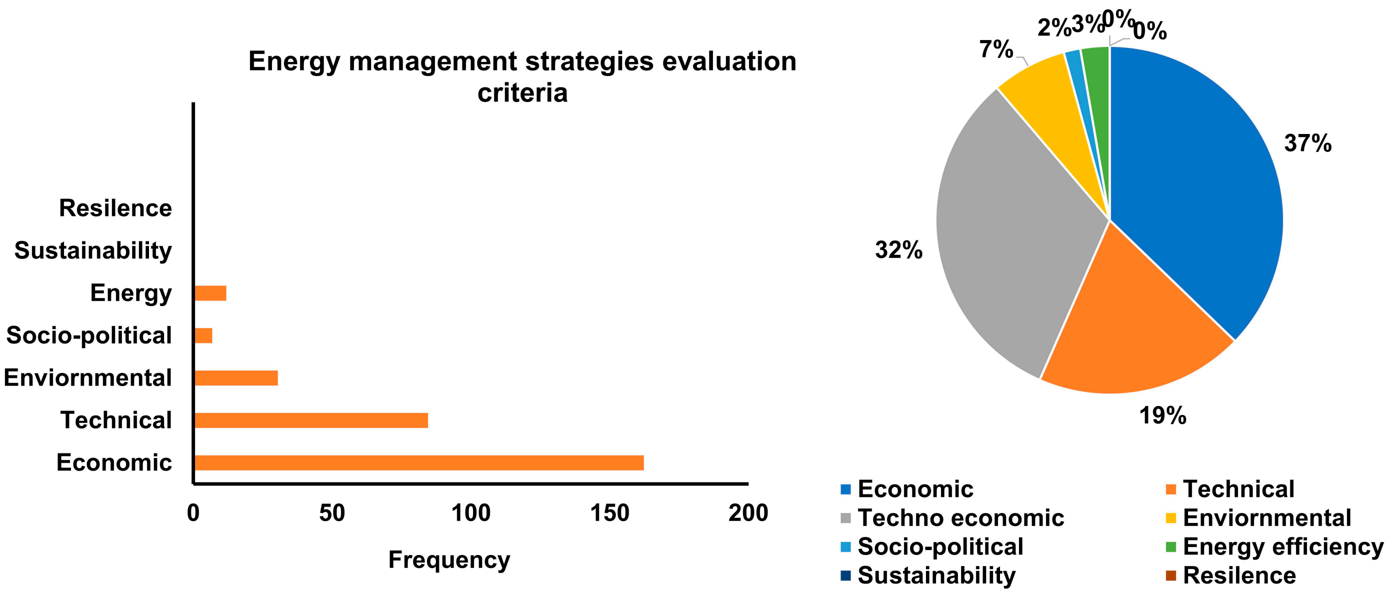

Figure 14. Summary of optimization evaluation criteria used in the literature.

Control and Energy Management Strategies

Control strategies for HPPs employ various control strategies, including centralized, distributed, and hybrid. Distributed and hybrid control methods are effective in managing generators autonomously, reducing system failure risk, extending system lifespan, and enabling advanced control techniques. However, the most challenging aspect lies in the complexity of interconnections or programming logic processing within the system. Energy management strategies are designed to optimize energy flow and determine operational equipment and power levels. The complexity of a strategy depends on optimization goals, system topology, and configuration. This study reveals that researchers favor rule-based energy management strategies over complex optimization techniques because of their ease of application and quick calculations. Economic considerations are a key factor in sizing optimization models for HPPs. Simplistic strategies focus on demand fulfillment but lack optimization parameters considering operating costs and equipment degradation. Technical strategies aim to amplify the system response and minimize equipment wear, while economic strategies aim to minimize cost functions by establishing priority and reference power levels for system elements. However, these strategies require intricate optimization algorithms, introducing an extra layer of complexity. Despite this complexity, these strategies yield optimal solutions for energy storage systems, aiding in the design of effective energy control systems to enhance overall system performance. In general, the developed sizing optimization model is used to assess the HPP characteristics that characterize a feasible project from the beginning. However, more sophisticated strategies must be developed to take into consideration several variables, including battery deterioration, the choice of turbine technology, uncertainties, diverse market engagement, and more. The research community should focus on refining artificial intelligence techniques and strategically integrating them to address various objective functions. As autonomous microgrid systems grow, robust communication and real-time energy management strategies are crucial. Table 9 summarizes control algorithms, optimization objectives, limitations, and descriptions of EMS from the recent literature.

Table 9. Summary of the control algorithms, optimization goals, constraints, and EMS descriptions obtained from the recent literature.

Anagement Strategies	Control Algorithm/ Approach	Energy System	Design Constraints	Objectives	Reference
Power requirement	Flowchart	Wind/solar/FC	Power balance, SOC, H_2 stock	Ensure demand sizing	Cozzolino et al. [143]
	Flowchart	Wind/solar/H_2	Power balance, SOC, H_2 stock	Ensure demand	Zhang et al. [144]
	Flowchart	Wind/solar/battery	Power balance, SOC	Ensure demand	Bade et al. [40]
Technical	ANN	Wind/solar/battery	Power balance, SOC, battery degradation	Redue LPSP, ensure demand	Q. Li et al. [145]
	Flowchart	Wind/solar/battery	Power balance, SOC	Ensure demand, quality of service	Long et al. [39]
	PMC/multi-objective approach	Wind/solar/battery/FC	Power balance, SOC, battery degradation, H_2	Increase reliability, ensure demand	Eriksson and Gray [135]
	PSO Recurrent neural network	Wind/solar/battery/FC	Power balance, SOC, battery degradation, H_2	Reduce LPSP, ensure demand	Yan et al. [137]
	Flowchart Multi-stage machine learning	Wind/solar/battery/FC	Power balance, SOC, battery degradation, H_2	Ensure demand, reliability	Shibl et al. [128]
Economical	Linear programing and simulation	Wind/solar/battery	Power demand, SOC, cost	Reduce system cost	Nogueira et al. [146]
	MLIP	Wind/solar	Power demand, SOC, cost	Reduce total operating cost	Lamedica et al. [147]
	FL	Wind/solar/battery/FC	Power demand, SOC, cost, H_2	Ensure demand	Rouholamini and Mohammadian [148]
	Flowchart, supervisory hierarchical control system	Wind/solar/battery/auxiliary	Power demand, SOC, cost	Ensure demand, increase revenue	Long et al. [39]
Techno-economic	FL	Wind/solar	Power balance, cost	Increase reliability and reduced loss	García-Triviño et al. [149]
	PSO	Wind/solar/battery/FC	Power demand, SOC, cost, H_2, battery and electrolyzer degradation	Ensure demand, minimize operating and maintenance cost, increase reliability and performance	Valverde et al. [150]
	Lyapunov technique, simultaneous perturbation stochastic approximation	Wind/solar/battery	Power demand, SOC, cost, battery degradation	Increase reliability and performance	Ciupageanu et al. [151]
	GA	Wind/solar/battery/thermal load	Cost	Cost reduction and sustainability	Das et al. [152]
	ANN, MATLAB	Wind/solar/battery/electrolyzer/ FC/	LCOE	Reduce LCOE, reduce power curtail	Hamdi et al. [142]
	HOMER	Wind/solar/battery/electrolyzer/ FC/thermal load	Power demand, SOC, cost, battery/FC/electrolyzer degradation,	Ensure demand, cost of energy	Priyanka et al. [153]
	Improve search space reduction	Wind/solar/battery	power demand, SOC, cost	Ensure demand, reduce levelized cost of energy	Nirbheram et al. [154]

9. Research Opportunities

Research gaps in hybrid power plants (HPPs) have been discovered, emphasizing the need for more study to solve operational issues related to solar intermittency and wind output curtailment. Because of the lack of long-term performance data from such systems, research papers that use modeling tools for system design and optimization of hybrid systems incorporating solar photovoltaic and wind turbine technologies frequently have limitations because they are not always compared to real-world results.

HPP systems work in a complex way, with several controllers and control loops that are connected via connections. Communication breakdowns may have a significant effect on how well HPPs operate as a whole. The control architecture, goals, and topology of the HPP determine how data are exchanged and communicated. Grid compliance and auxiliary services need appropriate data exchange and communication frameworks, as well as time resolution, management of communication failures, and determination of variables transferred.

Moreover, with differing control techniques and flexibility in manipulating various variables, the integration of controllers from multiple suppliers increases complexity. As such, it is essential to examine these problems while designing the control architecture and fine-tuning control settings.

Artificial intelligence (AI) has proven useful in several renewable energy-related fields. Advanced dynamic modeling and the identification of various causes of uncertainty may be accomplished via the application of AI and machine learning techniques. Notably, AI-driven model-free methods for HPPs have not yet been investigated in the field of regulating unknown parameters. The incorporation of such methodologies may affect HPPs' control structure, hence augmenting its dependability and resilience to uncertainties.

10. Future Trends

Anticipated advancements, government incentives, and policies in solar and wind technologies are expected to decrease costs for renewable energy sources, contrasting with the annual increase in expenses for traditional energy resources. As a result, this combination of energy sources will become more cost-effective in the future, and the positive environmental impacts are likely to promote its adoption.

Additionally, the integration of artificial intelligence into energy management is expected to enhance the hybrid system's performance in the near term. This involves optimizing resource allocation based on demand and predicting renewable resource availability, which can significantly cut down operational expenses. The future optimization of HPP sizes involves considering not only minimizing annual and fuel costs but also maximizing the profit and utilization of the infrastructure and environmental aspects like the human development index and job market, as well as bolstering sustainability and resilience. This requires implementing sophisticated control methods through a distributed and hybrid controller, which holds the potential to enhance the efficiency of modular HPPs. Lastly, applying modern control techniques to monitor the operation of these modular HPPs further optimizes the utilization of renewable resources and enhances energy management.

11. Conclusions

This paper reviewed and analyzed the available research articles on sizing, optimization, energy management, and control strategies to develop co-located wind- and solar-based HPPs. This review shows that the number of published papers on HPPs has increased because of growing interest from both the industry and the scientific community in recent times. There are a large number of review articles related to the scope of this paper; however, only a few of them have considered utility-scale wind- and solar-based HPPs without explicitly covering them. Therefore, a comprehensive comparative assessment is needed. This paper reviewed various approaches used by academics to optimize these systems, whether grid-tied or not. Meta-heuristic algorithms are the most popular methods for sizing wind–solar hybrid systems. No single approach has outperformed across all problem types. Using a hybrid approach that combines two or more meta-heuristic optimization techniques helped find the global best system configurations and made risk assessments more thorough by taking into account more factors. HOMER stands out as the most widely used software tool because of its comprehensive incorporation of renewable energy systems. It facilitates optimization and sensitivity analyses, streamlining the evaluation process for a multitude of potential system configurations. In terms of control and energy management strategies, hybrid centralized and distributed control strategies appear to be effective for efficient operation, meeting demand, and improving performance. Centralized control optimizes local groups, while distributed control ensures global coordination among groups, minimizes system failure risks, and enables the integration of multiple control methods within a single system. The findings suggest the need for further advancements in algorithms and multi-objective strategies for widespread use in distributed energy applications. Comparative studies are also needed to draw general conclusions about co-locating wind and PV farms. Future research should address larger-scale challenges, complex objective spaces, and inherent uncertainty, as well as incorporate a diverse range of methods to develop robust hybrid algorithms.

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Abbreviations

HPP	hybrid power plant
RES	renewable energy sources
MW	mega watt
PCC	point of common connection
COE	cost of energy
ASC	annualized system cost
LCOE	levelized cost of energy
LCC	life cycle cost
LLP	loss of load probability
LPSP	loss of power supply probability
RF	renewable fraction
REF	renewable energy factor
AI	artificial intelligence
GA	genetic algorithm
PSO	particle swarm optimization
HOMER	hybrid optimization of multiple energy resources
EMSs	energy management strategies
PV	photovoltaic
WT	wind turbine
HRES	hybrid renewable energy system
WoS	Web of Science
AC	alternate current
DC	direct current
LPM	linear programming model

MOEA	multi-objective evolutionary algorithms
MILP	multi-integer linear programming
NLP	non-linear programming
HSA	harmony search algorithm
SA	simulated annealing
ACA	ant colony algorithm
BFO	bacterial foraging algorithm
ABC	artificial bee colony algorithm
CS	cuckoo search
ANN	artificial neural network
SOC	state of charge
FLC	fuzzy logic control
FL	fuzzy logic
ANFIS	adaptive neuro-fuzzy inference system
FAHP	fuzzy analytic hierarchy process
GAPSO	generic algorithm particle swarm optimization
SOO	single-objective optimization
MOO	multi-objective optimization
NPV	net present value
IPSO	improved particle swarm optimization
GWO	grey wolf optimization
NREL	National Renewable Energy Laboratory
HOGA	hybrid optimization of generic algorithm
TRNSYS	transient system simulation software
RETSCreen	renewable-energy and energy-efficiency technology screening software
FC	fuel cell
PGUs	power generating units
STATCOM	static synchronous compensator
MPC	model predictive control
TLBO	teaching learning-based optimization
EDE	enhanced differential evolution
SSA	slap swarm algorithm
FPA	flower pollination algorithm
GSA	gravitation search algorithm
CSA	crow search algorithm

Appendix A

See Tables A1–A4.

Table A1. Economic, reliability, social, energy efficiencies, and environmental indices, and their main formulas (adapted from: [129]).

Assessment	Preferred Indicators	Functions
Technical indicator	LPSP	$LPSP = \frac{\sum_{t=1}^{T} \lvert P_{load}(t) - P_{supply}(t) \rvert}{\sum_{t=1}^{T} P_{load}(t)}$
Economic indicator	NPC	$NPC = C_{ini} + \sum_{n=1}^{N_s} \left(\frac{C_{annual}}{(1+r)^n} + \frac{C_{replace}}{(1+r)^{N_R}} + \frac{C_{salvage}}{(1+r)^{N_s}} \right)$
	ACS	$ACS = C_{ini} + C_{replace} x \frac{r(1+r)^{N_s}}{(1+r)^{N_s} - 1} + C_{annual}$
	LCOE	$LCOE = \frac{C_{ini} + \sum_{n=1}^{N_s} \left(\frac{C_{annual}}{(1+r)^n} + \frac{C_{replace}}{(1+r)^{N_R}} + \frac{C_{salvage}}{(1+r)^{N_s}} \right)}{\sum_{n=1}^{N_S} \frac{E_{first}(1-d)^n}{(1+r)^n}}$
Social political indicator	HDI	$HDI = 0.0978 \; x \; ln\left(\sum_{t=1}^{8760} E_{load}(t) \right) - 0.0319$
	JC	$JC = \sum_{m=1}^{M} jC_m . C_{renew.m}$
Energy Efficiency indicator	ECR	$ECR = \frac{\sum_{t=1}^{T} \lvert P_{renew}(t) - P_{load}(t) \rvert}{\sum_{t=1}^{T} P_{renew}(t)}$
Environmental indicator	E_{carbon}	$E_{carbon} = \sum_{t=1}^{T} \sum_{n=1}^{N} \theta_n \cdot P_{fossil}(t)$
	LCCF	$LCCF = E_{carbon} + \sum_{n=1}^{N} \delta_n \cdot C_{fossil \cdot n} + \sum_{m=1}^{M} \delta_m \cdot C_{renew \cdot m}$
	LEOE	$LEOE = \frac{E_{carbon} + \sum_{n=1}^{N} \delta_n \cdot C_{fossil \cdot n} + \sum_{m=1}^{M} \delta_m \cdot C_{renew \cdot m}}{\sum_{n=1}^{N_S} E_{first}(1-d)^n}$

HDI = human development index. JC = job creation. $P_{load}(t)$ = load demand at time t. $P_{supply}(t)$ = power supply of HPP at time t. T = simulation period. C_{ini} = initial investment cost. C_{annual} = operation and maintenance cost. $C_{replace}$ = replacement cost. $C_{salvage}$ = salvage value at the end of lifetime. N_R = year of component replacement. N_s = design lifetime. r = discount rate. E_{first} = first-year energy production. d = degradation rate. $E_{load}(t)$ = load demand at time t. jc_m = job creation factor of renewable installed capacity. jc_n = job creation coefficient of electricity generated by fossil-based technologies. $C_{fossil \cdot n}$ = rated capacity of the n-th fossil-based technology. $C_{renew \cdot m}$ = rated capacity of the m-th renewable energy technology. $P_{renew}(t)$ = renewable energy generation at time t. $P_{load}(t)$ = load demand at time t. E_{carbon} = direct carbon emissions produced by non-renewable energy technologies. θ_n = direct carbon emission coefficient of fossil-based technologies per kilowatt-hour. $P_{fossil \cdot n}(t)$ = power output of the n-th fossil-based technology at time t. δ_m and δ_n = indirect carbon emission coefficients of renewable and fossil-based technologies per kilowatt-hour. $C_{fossil \cdot n}$ = rated capacity of the n-th fossil-based technology. $C_{renew \cdot m}$ = rated capacity of the m-th renewable energy technology.

Table A2. Highlights of review studies on sizing and optimization and energy management strategies of renewable energy-based hybrid systems from 2014 to 2023.

Reference/Year of Study	System Studied	Topic Covered	Highlights
Chauhan and Saini [109]	HRES	• Reviewed various configurations (AC/DC) and energy storage technology options for system control and management. • Mathematical models for wind, micro-hydro, solar, and biomass gasifier energy systems. • Sizing techniques including AI, multi-objective design, iterative approaches, analytical methods, probabilistic approaches, and graphical construction methods. • Software tools including HOMER, HOGA, RETScreen, HYBRIDS, and TRNSYS for assessing and analyzing hybrid energy systems.	• DC-AC-coupled is efficient and the least-cost scheme. • A combination of centralized and distributed control approaches is acknowledged as optimal to ensure strong control in IRES without single point failure issues.
Siddaiah and Saini [25]	HRES	• Review on planning, configurations, and modeling and optimization techniques of hybrid renewable energy systems for off-grid applications. • Mathematical model for cost minimization. • Optimization models including classic, artificial intelligence, and hybrid. • Sizing methodologies including classical techniques, artificial intelligence, and hybrid techniques.	• Reliability-centric models improve system performance and reduce uncertainty in renewable energy resources.
Al-falahi et al. [55]	HRES	• Various combinations of wind/solar. • Sizing techniques including single algorithms and hybrid algorithms. • Software tools including HOMER and iHOGA.	• AI algorithms are increasingly popular for solving complex optimization challenges, while hybrid algorithms are increasingly preferred because of their favorable results in recent times.
Khan et al. [28]	Solar photovoltaic and wind hybrid energy systems	• Economic feasibility, sizing strategies, and future prospects. • Optimization techniques including graphical construction, iterative methodologies, direct programming, multi objectives optimization function, and probabilistic. • New approach including GA, PSO, SA, ACA, and ABC.	• Artificial intelligence and hybrid algorithms performed better than traditional approach. However, the hybridization of more than two algorithms is recommended for better performance.
Anoune et al. [17]	PV–wind based HRES	• Various configurations of hybrid renewable energy systems. • Hybrid systems' performance metrics including reliability and system cost. • Sizing methods including AI, GA, PSO, SA, CS, MOO, HSA, iterative, probabilistic, and analytical. • Software tools including HOMER, HYBRID2, HOGA, HYBRIDS, TRNSYS, etc.	• The literature shows hybrid renewable energy systems lack cost competitiveness compared with conventional fossil fuel-based power systems. • Methods of optimization, such as those centered around artificial intelligence algorithms and heuristic techniques, are more favorably received compared with conventional approaches. Among these, HOMER stands out as the predominantly utilized tool.

Table A2. *Cont.*

Reference/Year of Study	System Studied	Topic Covered	Highlights
Lian et al. [83]	HRES	• Various configurations of hybrid renewable energy systems. • Sizing methodologies including analytical, probabilistic, iterative, numerical, graphic construction, GA, PSO, SA, ACO, ABC, CS, and hybrid methods. • Software tools including HOMER, iHOGA, HYBRIDS, and HYBRID2.	• Hybrid optimization techniques are recommended because of their adaptability and optimization capabilities, enabling a comprehensive exploration of the subject.
Lindberg et al. [13]	Wind–solar battery HPP	• Co-located wind and solar park modeling methodologies. • Physical design, control strategies, market participation, and quantification of possible synergies.	• Energy management systems require intelligence and dispatch models to optimize resource utilization and maximize resource utilization.
Ammari et al. [34]	HRES	• Reviewed sizing, optimization, and control and energy management. • Sizing methods including traditional and software, • Optimization techniques including classical, artificial, and hybrid methods. • Control methods including centralized, distributed, and hybrid control. • Energy management objectives including technical, economic, and techno-economic.	• Highlighted that the use machine learning, commercial software, and neural networks is a good option for hybrid systems. • Hybrid renewable energy systems utilize fuzzy logic, particle swarm optimization, neural networks, and commercial software like HOMER for overseeing components.
Emad et al. [91]	Wind–solar battery	• Reviewed mathematical formulations for wind, solar and energy storage • Economic aspects including NPC, LCC, TAC, and COE TLBO. • Sizing approaches including classical techniques, meta-heuristic techniques, and hybrid techniques. • Software tools including HOMER.	• Meta-heuristic optimization methods offer higher precision and reduced computational time compared with conventional techniques.
Thirunavukkarasu et al. [81]	HRES	• Reviewed various optimization techniques. • Optimization techniques including classical, artificial, hybrid, and software tools. • Types of optimization problems included constraints, variables, problem structure, nature of equations, permissible value of the design variables, separability of the function, and the number of objective functions.	• Hybrid optimization algorithms provide a faster, more reliable, and efficient method for problem-solving.
Iweh et al. [35]	HRES	• Reviewed hybrid system performance indicators. • Optimization methods including classical, meta-heuristic, and software. • Software tools including HOMER, iHOGA, RETScreen, TRNSYS, HYCROGEM, HYBRIDS, and INSEL.	• AI-based hybrid methodologies offer superior system optimization effectiveness.

Table A3. Summary of various studies on optimization methods for a single objective.

Optimization Method	System Configurations	Optimization Function	Constraints	Reference
GA FL	Wind/PV/battery	Minimize total cost	Power balance State of charge	Adbelhak et al. [155]
ACA, Integer LPM	Wind/PV	Minimize total cost	Number of PV panels, wind turbines, and batteries	Fetanat et al. [156]
PSO SA	Wind/PV/battery	Minimize total present cost	Number of hybrid components, energy not supplied, battery SOC	Ahmadi et al. [157]
CS	Wind/PV/battery	Minimize total cost	Seasonal variation in the load	Sanajaoba and Fernandez, [158]
SA, CS, Improved HS	PV–wind–reverse osmosis–battery	Minimize total LCC	Surface area of PV arrays, wind turbine blades, quantity of batteries, LPSP, and SOC	Peng et al. [159]
TLBO, EDE, and SSA	Wind–PV	Minimize TAC, reliability	Number of hybrid system components, LPSP, DOD	Khan et al. [20]
Jaya, TLBO	Wind/PV/battery	Minimize TAC	Number of hybrid system components, LPSP, SOC	Khan et al. [160]
AC, firefly algorithm, PSO, GA	Wind/PV/battery	NPC	Number of hybrid system components, SOC	Javed et al. [161]
Crow and PSO	Wind/PV/battery	Minimize COE	Distribution of power supply and demand planning	Guneser et al. [162]
GWO Sine cosine Algorithm	Wind/PV/H_2	Minimize LCC	Number of hybrid system components	Jahannoosh et al. [163]

Table A4. Summary of various studies on optimization methods for multiple objective functions.

Optimization Method	System Configurations	Optimization Function	Constraints	Reference
FPA SA	Wind/PV/battery	Minimize LPSP Maximize cumulative saving	PV panel tilt angle, number of PVs, wind turbines, and batteries	Tahani et al. [164]
PSO GA	Wind/PV/battery	Minimize LPSP Minimize LCC Minimize fluctuation rate Minimize loss of energy probability	Numbers of PVs, wind turbines, and batteries	Ma et al. [165]
PSO Nelder Mead Algorithm	PV/wind/fuel cell	Minimize power loss	Power balance, bus voltage	Senthil et al. [166]
PSO GSA	PV/wind	Minimize total energy loss Maximize voltage profit	Power flow m bus voltage, load constraints, PV/wind capacity	Radosavljevic et al. [167]
Biogeography-based optimization, PSO	Wind/PV/battery	Minimize cost Minimize system index reliability	Power balance between supply and demand	Abuelrub et al. [168]
CSA, PSO	Wind/PV/battery	Minimize cost Minimize loss Minimize voltage profile	Number of hybrid system components, size of batteries, network bus voltage constraint, allowable current constraint, peak capacity of each renewable DG constraint, and power balance constraint	Aliabadi et al. [169]

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