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Review

A Systematic Review on Local Microgrids Optimization and Emerging Trends

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Abstract: Hybrid renewable energy systems (HRES) are increasingly recognized as viable solutions to the variability inherent in renewable energy sources, enhancing the reliability, resilience, and flexibility of power supplies. This review critically evaluates recent advancements in both on-grid and off-grid microgrids that incorporate renewable energy sources (RES), battery energy storage systems (BESS), and electric vehicle (EV) infrastructure. Particular emphasis was placed on two critical aspects: optimal system sizing and energy management systems (EMS). This review further investigates how current research addresses uncertainty, particularly concerning intermittent renewable generation, load demand fluctuations, and electricity market variability. Through a synthesis of the literature, it is evident that mathematical programming, meta-heuristic optimization, and machine learning have emerged as the predominant methodologies for component sizing, energy scheduling, power balancing, and reliability enhancement. In addition to summarizing existing studies, this review identifies major methodological trends, compares the strengths and limitations of current approaches, and highlights key research gaps and future priorities. This paper provides a focused and critical overview of current HRES-based microgrid design and control strategies, offering valuable insights for researchers, practitioners, and policymakers working towards more sustainable and intelligent energy systems.

Keywords: HRES; microgrid; optimal sizing; energy management system; EV

1. Introduction

1.1. Background

The growing dependence on fossil fuels for energy has significantly increased the demand for electricity in the residential, industrial, and commercial sectors. Currently, the global energy industry relies predominantly on fossil fuels, which account for over 80% of the total energy demand and are responsible for nearly 75% of emissions [1]. To address climate change and achieve planetary sustainability, the Earth must adopt RES such as solar power, hydroelectric energy, wind energy, biomass, and geothermal energy. Among the RES, solar energy is the fastest-growing renewable source at a reasonable cost [2,3]. Biomass control enables sustainable power solutions, whereas geothermal power delivers continuous, emission-free energy [4]. Furthermore [5], HRES are expected to reduce power sector emissions up to 90% of over the next five decades.

Worldwide energy consumption, as stated by [6], is outpacing population growth, raising concerns as demand surges, particularly in developing countries, where 759 million people lack access to electricity. HRES are dependable, carbon-free systems that reduce reliance on a single renewable source, an important advantage in areas with limited natural resources [7,8]. Beyond environmental benefits, HRES offers enhanced operational flexibility and resilience by exploiting the complementary characteristics of different renewable sources. For instance, solar and wind resources often exhibit inverse or weakly correlated generation profiles, which helps reduce overall power variability when combined within an MG architecture. This makes HRES particularly suitable for both off-grid and grid-connected MGs aiming to deliver reliable electricity under resource and demand uncertainty [5].

The effective deployment of integrated systems depends on resource availability, optimal system sizing, coordinated energy management, and the ability to handle uncertainty in renewable generation and load demands. Advanced optimization and control strategies, high renewable energy penetration compromise the system stability and economic performance [5,8]. Among these, off-grid MGs play a vital role in delivering reliable renewable energy to areas without grid access, supporting rural livelihoods and essential services such as healthcare, education, and agriculture [9]. Africa possesses vast renewable energy potential, particularly in solar, hydroelectric power (HEP), and wind energy; yet, the adoption of these clean energy sources is comparatively slow [7]. For instance, Ethiopia, located in the Horn of Africa at coordinates 9.14500 N 40.48970 E, has a population exceeding 130 million, with 78.1% residing in remote areas [10,11]. The majority of this capacity is generated from renewable sources, with HP supplying 89.9%, wind energy contributing 7.6%, and thermal power accounting for the remaining 2.5% [8,12]. And the government supports standalone MGs powered by a RES [12]. Despite the abundance of biomass, it remains underutilized for driving economic growth [5,13].

Moreover, the transportation sector, largely dominated by internal combustion engine (ICE) vehicles [14], is a significant and growing contributor to greenhouse gas (GHG) emissions, accounting for over 80% of East Africa's total emissions [13], particularly in Kenya, Tanzania, Ethiopia, and Uganda. As EV adoption grows, challenges such as securing an adequate renewable energy supply, managing grid demand, and expanding charging infrastructure arise [15]. EVs seek to reduce fossil fuel consumption and emissions by utilizing battery-powered transport supported by RES [16,17]. The transportation industry's reliance on oil and gas results in significant carbon dioxide emissions (CO_2) and environmental contamination [16]. To address this, EVs have been developed to reduce fossil fuel consumption and emissions by using batteries charged from RES. Various charging power levels and infrastructure setups are being designed and evaluated to support this transition [18,19]. Ethiopia has introduced supportive policies and incentives to encourage EV adoption and promote the adoption of EVs through a combination of incentives, supportive policies, and infrastructure development [20].

Regular technical inspections are crucial for identifying potential safety issues and maintaining the vehicle's operational efficiency [20,21]. Additionally, economic factors play a vital role in the maintenance of RES, particularly in the context of MG planning [10]. Therefore, the components of the MGs must be strategically selected to reduce power loss [22]. BESS and EVs play a critical role in enhancing grid and/or MG stability by mitigating variability and reducing peak loads [23,24]. An effective EMS is essential for efficient power generation, storage, and EV integration to ensure reliable and cost-effective energy [25].

1.2. Contribution and the Organization of the Review

This review provides a critical assessment of HRES based MGs, focusing on their sizing methodologies, mathematical modeling, optimization, and energy management. The contributions of this study are as follows: (1) It compares conventional, metaheuristic, and hybrid optimization algorithms for sizing HRES-based MGs, highlighting their strengths, limitations, computational complexities, and applicability across configurations. (2) It reviews mathematical models for renewable generation, battery energy storage systems (BESS), electric vehicles (EVs), and hybrid energy systems, emphasizing the assumptions and their effects on sizing accuracy and performance. (3) It synthesizes techno-economic, reliability, and environmental indicators used to evaluate HRES designs and provides a framework for assessing configurations. (4) It identifies key challenges in the literature, including uncertainty resilience, artificial intelligence, and machine learning for adaptive optimization, coordinated sizing with EVs and BESS, and underutilized renewable combinations. (5) The influence of energy policies, regulatory frameworks, and deployment considerations on the planning and adoption of HRES-based MGs is discussed. (6) It outlines research opportunities, including multi-objective optimization under uncertainty, AI-driven energy management, integrated sizing with advanced storage technologies, and scalable solutions for grid-connected and off-grid applications.

The remainder of this paper is organized as follows: Section 1 provides an overview of HRES components for stand-alone and grid-connected communities, together with the review procedure. Section 2 presents a literature review of relevant studies in this area. Section 3 discusses the foundations of MGs and their components. Section 4 examines the applications of MGs. Section 5 describes the key design parameters of MG systems. Section 6 presents the formulation of optimal power flow. Section 7 provides an overview of optimal sizing approaches for HRESs. Section 8 discusses the barriers, challenges, future research directions, and energy policy implications. Finally, Section 9 presents the conclusions.

1.3. Systematic Review Methodology

This review adopts a systematic literature review methodology to ensure transparency, reproducibility, and comprehensive coverage of relevant studies. Peer-reviewed journal articles published mainly between 2015 and 2025 were considered. The literature search was conducted using major scientific databases, including IEEE Xplore, Scopus, Web of Science, and ScienceDirect. Keywords such as "HRESs," "MGs," "optimal sizing," "EMS," and "EV integration" were used to identify relevant studies. Articles were selected based on relevance, methodological rigor, and applicability to off-grid and grid-connected MG contexts. The review procedure for this study is shown in Figure 1, which outlines a systematic review to evaluate HRES-related processes [26,27].

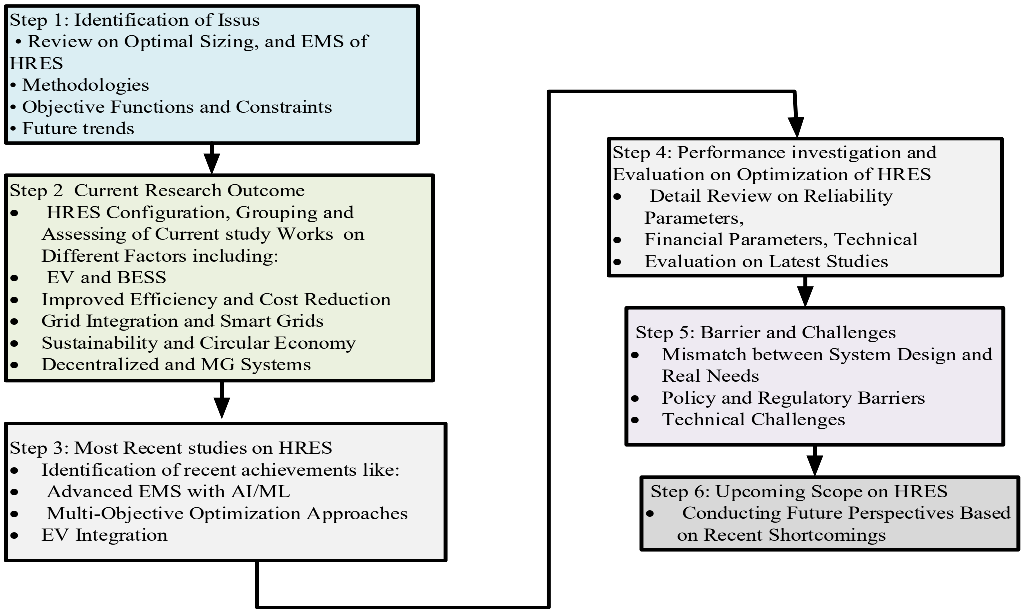

Figure 1. A general technique for assessing the research on HRES system sizing.

2. Literature Review

Recent technical evaluations and surveys have contributed to understanding energy management optimization in MG systems. Several studies modeled stand-alone wind-solar systems in MATLAB/Simulink using a maximum power point tracker (MPPT) and batteries to minimize costs [25]. However, these studies did not address EV integration, EMS, uncertainty handling, and full battery utilization for output stability. At Eskisehir Osmangazi University (ESOGU), a hybrid MG was optimized through HOMER Pro 3.14.2 and MATLAB R2022b software to include PV, wind turbine (WT), BESS, and grid connection, which achieved a 36% reduction in electric costs by integrating intelligent EV charging [28]. However, the evaluation did not account for system reliability alongside energy expenses. Also, a research team in Bangladesh developed a 300-kW solar EV station, which delivered favorable outcomes both environmentally and economically [29].

The study conducted in Bangladesh highlights the benefits of solar EV charging through smart grid integration and optimized battery utilization [23]. However, it lacks critical components such as EV technology, smart charging, and load control [30]. Other HRES studies focus on optimal sizing of WT, PV, BESS, and biomass resources. A new system combines WT, PV, battery management group (BMG), battery, and hydrogen (H_2) storage with advanced inverters to reduce total harmonic distortion (THD) and to improve power quality [31]. However, it neglects EVs, dynamic load management, fault tolerance, and comparative analysis, raising the risk of Loss of Power Supply Probability (LPSP). The study in Vietnam used HOMER Grid to assess solar EV charging;

however, the lack of battery storage limited its ability to address RES intermittency [18]. Research on Kutubdia Island applied fuzzy logic (FL) and non-dominated sorting genetic algorithm II (NSGA-II) for optimizing hybrid MGs in terms of cost and emissions, but did not address EV integration and policy factors. Hybrid energy storage system (HESS) boosts reliability in PV and MG systems by combining storage types, though these studies often lack EMS, control, and optimization, which are essential to sustainable energy success [18].

Several studies lack EMS, control techniques, and optimization, critical components required for improving HESS performance and promoting sustainable energy adoption [32]. This research provides an efficient power management system designed for lightweight EVs that combines HESS and container-based control to optimize PV-supercapacitor power transfers [33]. The combination of PV-wind HRES provides an environmentally friendly opportunity to recharge EVs by eliminating the need for fossil fuels [34]. Licensing NSGA-II is used as the optimal choice for achieving reliable renewable energy solutions in EV charging. PV efficiency is enhanced through an anzeta single-ended primary inductor converter (SEPIC) along with fuzzy MPPT methods, while hydrogen fuel cells maintain energy supply during solar or wind power deficits [33,35].

The integrated long-term energy alternative planning-logarithmic mean division index (LEAP-LMDI) provides a powerful analysis tool that breaks down historical data on energy consumption in a productive way into the important factors of activity, structure, and intensity to make scenario-based predictions. The variety of its applications in various national settings confirms its usefulness in developing specific energy policies and enhancing sector efficiency optimization based on combined socioeconomic and technological analyses [8]. In addition, this study [5] highlights the potential of Microbial fuel cells (MFCs) with paddy field soil substrates for simultaneous wastewater treatment and renewable energy production through enhanced electricity and methane generation. The review provides a comprehensive and insightful understanding of the recent trends in solar PV technology, emphasizing materials efficiency, global leadership in installations, supportive policy and funding environments, and detailed cost considerations [23]. This holistic perspective is vital for stakeholders aiming to further the development and deployment of solar PV technologies internationally. The work introduces renewable energy as one of the pillars of sustainable development and explains the technology, advantages, and use of such sources as solar, wind, and biomass [6]. Also, it highlights the importance of moving away from fossil fuels through the use of technological innovation, economic policies, and supportive policies to reduce climate change and establish a safe and resilient energy future.

Authors in [36] optimized a hybrid system using WT, BESS, and distributed generation (DG) with stochastic modeling and genetic algorithm- Monte Carlo simulation (GA-MCS) to reduce wind uncertainty and costs. However, it excluded EVs and operating expenses. For off-grid solar in Jos, Nigeria, high irradiance supports PV with batteries, charge controllers, and inverters, even though EV and wind integration are missing. Tools like HOMER or PVsyst could enhance performance analysis in [36,37]. Off-grid solar PV systems in Nigeria show strong economic viability, with a levelized cost of energy (LCOE) between \$0.106–\$0.14/kWh shown in [36,38]. Due to fuel subsidy removal, concentrated solar power (CSP) systems are now more cost-effective than traditional generators. These systems typically have 2–4-year payback periods, positive net present value (NPV), and an internal rate of return (IRR) of 20–38% [39]. Standalone solar PV in Jos, Nigeria, projects a strong technical and economic potential, with low operating costs and environmental benefits [31]. Solar PV-battery-diesel mini-grids are viable but lack EV integration and load uncertainty. A 20-kW solar-biogas electric vehicle charging station (EVCS) using fuzzy EMS reduces the costs by 74.67%, but it does not address economic uncertainty. Another study on standalone DC MGs with PV, WT, and BESS lacked validation, optimization, and cost-efficient control methods like particle swarm optimization (PSO) and genetic algorithm (GA) [40,41].

A critical examination of the reviewed studies reveals a recurring emphasis on cost minimization, often at the expense of reliability, uncertainty handling, and coordinated EV integration. While tools such as HOMER and MATLAB are widely used, many studies rely on deterministic assumptions and limited scenario analysis. These gaps highlight the need for multi-objective, uncertainty-aware optimization frameworks that jointly consider economic, technical, and environmental performance, as shown in Table 1.

Table 1 presents comparative studies on the optimal sizing of MGs, showing that most existing studies focus on hybrid configurations involving PV systems, WT, BESS, diesel generators (DG), fuel cells (FC), and other supporting sources such as biomass, biogas, and pumped hydro energy storage (PHES). The main objective functions considered in these studies include minimizing the cost, net present cost (NPC), cost of energy (COE), total harmonic distortion (THD), emissions, and EV charging demand. A few studies also aimed to maximize reliability, efficiency, energy access, or maintain the DC bus voltage. A wide range of optimization and control techniques has been applied, including MPPT, GAPSO, ANN/PWM, HOMER, fuzzy logic, genetic algorithm (GA), MOPSO, MILP, MOMVO, STELLA, Python 3.13-based methods, and game theory [1,42]. However, despite the diversity of approaches, many studies have significant limitations, such as neglecting EVs, EMS, uncertainty analysis, fault tolerance, reliability assessment, social and policy considerations, cost-benefit evaluation, and comparative optimization analysis. In addition, some methods suffer from high processing times, limited resource modeling, restricted renewable energy scopes, or long runtimes, indicating that a more comprehensive and integrated optimization framework is still needed for effective MG sizing.

Table 1. Various literature reviews on MGs' optimal sizing.

Ref.	Configuration	Objective Function	Algorithm (s)	Shortcomings
[28]	WT + PV	Minimize costs	MPPT	No reliability
[30]	WT + PV + BESS = Biomass	Minimize NPC	GAPSO	No EV, high LPSP & EMS
[31]	WT + PV	Minimize THD	ANN/PWM	No fault tolerance & comparison
[18]	PV	Minimize costs	HOMER	No BESS
[43]	PV + WT + BESS	Minimize costs	Fuzzy	Limited social/policy scope, no EV
[36]	WT + BES + DG + PV	Minimize COE	GA	M&O costs & EV excluded
[39]	PV + BE + DG	Optimize energy access	HOMER	No EV & load uncertainties
[44]	PV + Biogas	Minimization of EV charging	Fuzzy	Economic is ignored
[41]	PV + WT + BESS	Maintain DC bus voltage	MPPT	No comparison & optimization
[40]	PV	Maximize efficiency	Fuzzy	No EV & limited RES
[45]	PV	Minimize cost	MLA	Cost-benefit
[46]	PV	Minimize cost	STELLA	No optimization used
[47]	PV	Minimize costs	Python	Limited resources & reliability issues
[9]	PV + BESS + ROR + DG	Minimize costs	MOPSO	No EV & uncertainty
[48]	PV + WT + ESS	Minimize costs	MILP	No EMS & EV
[49]	PV + WT + BESS + EV	Minimize cost	SSR	No EMS & EVs
[22]	PV + WT	Maximize reliability	MOMVO	No DR/EVs & algorithms
[50]	PV + WT + FC + ESS + DG + MT	Minimize emissions & costs	MPSO	High processing time
[51]	PV + WT + BESS	DER & payback	NE & game theory	No EV & life expansion for RE
[52]	PV + WT + ESS + CHP + grid	Cost & CO_2 reduction	MILP	Long runtime
[53]	WT + PV + BESS = Biomass	Minimize NPC	GAPSO	No EV, high LPSP & EMS
[54]	WT + PV	Minimize THD	ANN/PWM	No fault tolerance & comparison
[34]	PV + WT + PHES + FC	Minimize cost	MOGOA	No storage & EVs

The research at Qatar University showed cost savings and reduced pollution compared to petroleum or grid-charged EVs [55,56]. A comprehensive cost analysis must include operating and maintenance expenses (O&M), insurance, depreciation, and interest rates, while also comparing rooftop, ground-mounted, and carport setups as well as the effects of feed-in tariffs**.** This study demonstrates a PV-biogas EV charging solution that uses HOMER optimization; however, it does not incorporate different storage components such as fuel cells, batteries, and supercapacitors [57]. An analysis conducted using Python programming evaluates various combinations of PV and EV charging stations, assessing their technical, economic, and environmental impacts on power systems [57]. These models analyze the performance of PV/grid/battery implementations using real systems data and trading specifications as described in [27,58].

Authors in [9] examine EV-connected MG EMS and system sizing for rural Southern Philippines through multi-objective PSO, optimization of power loss and LCOE, as well as GHG emissions associated with PV, WT, rate of return (ROR), HP, batteries, and diesel. This research does not analyse the stability of MGs along with their design flexibility. Artificial intelligence/machine learning (AI/ML) technologies enhance forecasting processes and control strategies, while DC MGs simplify the integration of EVs into networks. JAYA optimization enhances scheduling methods and raises rural energy access, but does not advance fundamental BESS technology required for stable MG operation and dependability [59,60].

3. Forecasting Methods and Uncertainty Analysis

In mathematical terms, uncertainty refers to the difference between the actual or estimated value and the true value, encompassing all errors [61]. Various elements of wind speed, PV battery systems are responsible for these uncertainties. Weather conditions, such as cloud cover and the surrounding air temperature, play a role in the unpredictability of PV power generation. Effective management of intermittent renewable energy generation requires accurate forecasting of such generation to ensure reliable power system operation and power planning.

The generation of conventional plants can be easily regulated; however, the generation of renewable energy cannot be easily regulated, and it is influenced by nature. In this scenario, forecasting power generation must precede the creation of a load schedule. Here are the different forecasting methods commonly used for power generation and load forecasting, depicted in Figure 2 [62,63]. Some of the forecasting techniques of the Statistical models and performance metrics are listed in Table 2 [63].

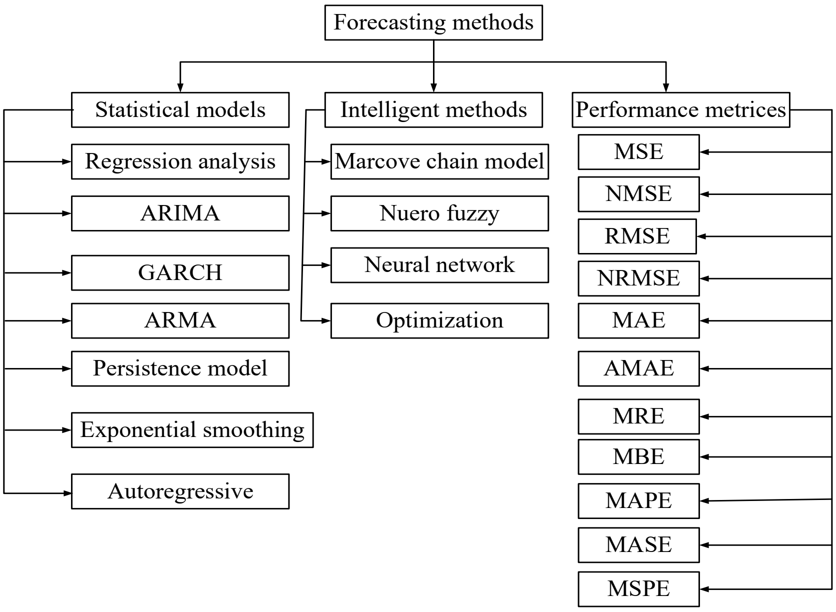

Figure 2. Types of forecasting methods.

Table 2. Statistical and performance metrics model.

Model Type	Mathematical Expression	Ref
Regression model	$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots . + \beta_n x_{ip}$, and $y = b * m_1^{x1} * m_2^{x2}$	[64]
ARIMA model	$Y_t = y_t + y_{t-1}$	[65]
AR model	$Y_t = \emptyset_1 Y_{t-1} + \emptyset_1 Y_{t-2} \dots + \emptyset_p Y_{tp1}$	[65]
MA model	$x_t = \sum_{j=0}^{n} \theta_j \omega_{t-j} = \omega_t + \theta_1 \omega_{t-1} + \cdots + \theta_n \omega_{t-n}$	[62]
ARMA model	$X = \sum_{i=1}^{m} \varphi_i x_{t-i} + \sum_{j=0}^{n} \theta_i \omega_{t-j}$	[62]
MAE model	$\mathrm{MAE} = \frac{1}{N} \sum_{t=1}^{N} \lvert P_t - M_t \rvert$	[62]
MAPE model	$\mathrm{MAPE} = \frac{100\%}{N} \sum_{t=1}^{N} \left\lvert \frac{P_t - M_t}{P_t} \right\rvert$	[65]
RMSE model	$\mathrm{RMSE} = \sqrt{\frac{1}{N} \sum_{t=1}^{N} (P_t - M_t)^2}$	[62]
MBE model	$\mathrm{MBE} = \frac{1}{N} \sum_{t=1}^{N} (P_t - M_t)$	[62]

This section offers an overview of articles that employ time series techniques, either on their own or as part of hybrid algorithms, for predicting wind speed/power and solar forecasts, as depicted in Table 3.

Table 3. Statistical model for HRES.

Model Used	Error	Duration	Brief Description	Ref
Solar time-based analog ensemble method	NMAE = 4.659% NRMSE = 7.356%	1-day	This model gives a short-term forecast based on past data.	[62]
Symbolic aggregated approximation	RMSE = 2.57 MAE = 1.86	120-days	This method is highly applicable to big data sets and is typically executed with the help of ANN and SVM algorithms.	[66]
Continuous conditional random fields	RMSE = 8.92	4-months	CCRF combines relationship learning, optimization, and probabilistic forecasting advantages effectively.	[66]
Gaussian process	RMSE improvement 100%	48-h	They proposed a new prediction model using a Gaussian process.	[66]
ARMA	Absolute error	3-years	The prediction of wind energy is carried out using a regression model with adaptive parameters based on a window approach.	[67]
Combined probability prediction	RMSE = 0.322 MW MAPE = 2.712%	3-months	Raw wind data preprocessed via energy-optimized documentation.	[68]

In real-world MG operation, uncertainty quantification is not merely theoretical but directly influences system reliability and economic outcomes. Stochastic and probabilistic methods enable operators to anticipate renewable variability, while robust optimization ensures feasibility under worst-case conditions. Recent studies increasingly combine probabilistic forecasting with machine learning techniques to enhance decision-making under uncertainty, depicted in Table 4 [69–72].

Table 4. Encompassing taxonomy of uncertainty quantification and risk management methods.

Method Category	Mathematical Foundation	Uncertainty Type Addressed	Computational Complexity	Primary Output
Stochastic modeling	Probability theory, stochastic processes	Primarily aleatory	Medium-high	Probabilistic distributions of outcomes
Bayesian inference	Bayesian probability, decision theory	Both aleatory and epistemic	high	Posterior distributions, credible interval
Ensemble forecasting	Dynamical systems, statistics	Both	Medium	Prediction intervals, scenario distributions
Sensitivity analysis	Variance decomposition, regression	Epistemic	Low-medium	Importance measure, parameter rankings
Robust optimization	Convex optimization, Game theory	Epistemic worst case	high	Optimal decisions under uncertainty
Evidence theory	Dempster-Shafer calculus	Epistemic ignorance	medium	Plausibility intervals
Fuzzy systems	Fuzzy set and possibility theory	Linguistic/ambiguity	low	Membership functions, linguistic rules

Table 5 presents a summary of the installed capacities of significant grid-connected power plants in Ethiopia, providing context for the national energy landscape of Ethiopia. This information is crucial for understanding the rationale behind the development of decentralized microgrids and the deployment of hybrid renewable energy systems. Ethiopia's renewable energy endowment is considerable, featuring vast hydropower capacity, significant geothermal potential related to its position on the East African Rift System, expanding wind corridors, particularly in the Somali and Afar regions, and increasing solar irradiation. The government has recognized this potential and initiated ambitious programs aimed at scaling the installed power capacity from approximately 4300 MW to over 17,000 MW by 2020. These efforts involve large-scale projects in the wind, geothermal, and solar sectors, developed through collaboration with private sector actors to spur Ethiopia's industrial base and economic transformation [25,73].

Table 5. Capacity of existing plants linked to the national grid in megawatt (MW) [25].

Power Plant	Installed MW	Remarks
Hydro	~1947.5	A massive HP potential with major projects like the Grand Ethiopia Renaissance Dam (GERD)
Wind	~324	Strong wind corridors in the Rift Valley and the Northern Highlands
Solar	50	Great Rift Valley
Diesel	89	Stable, but limited by feedstock
Thermal	~7.3	Great Rift Valley
Biomass	15	High deforestation due to overreliance on traditional biomass

The geographical coordinates of the country lie between 3^0 and 15^o north of the equator and 33^0 to 48^o east of the Greenwich Meridian, which makes it lie in the GMT^{+3} time zone, as shown in Figure 3 [74]. It is in the northeastern part of the Horn of Africa and covers an area of 1.1 million km^2. It borders East and southeast with Somalia, east with Djibouti, North and northeast with Eritrea, south with Kenya, southwest with South Sudan, and West with Sudan, hence it is a landlocked country. Ethiopia is a nation with diverse terrain and climates, three main climatic areas, high temperature and evapotranspiration, and a rapidly growing population of approximately 130 million, making it the second most populous country in Sub-Saharan Africa [73].

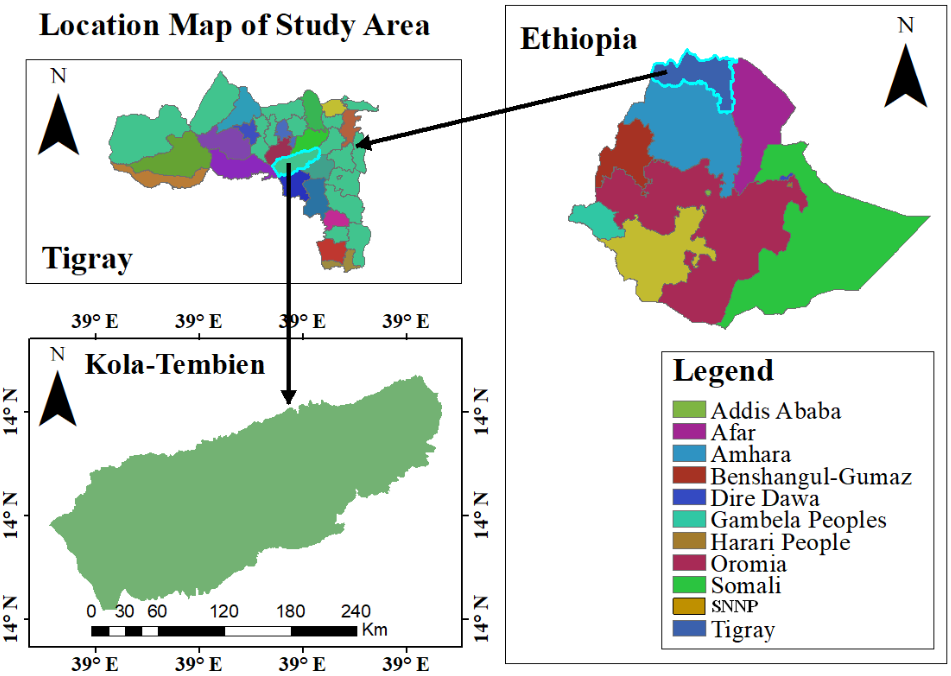

Figure 3. Map of Wereda Kolatemben in the Tigray Region, Ethiopia, East Africa.

HRES is a type of power production system that uses a combination of two or more RES to supply a reliable and constant power supply. These varied sources are intelligently managed in the system to eliminate intermittency in individual renewable technologies [75]. Table 6 values were derived from an extensive review of literature, encompassing both scientific articles and data from government and electricity companies. In certain instances, it was necessary to consider national or regional demand per capita to estimate the island demand.

Table 6. Implemented MGs in Ethiopia found in the literature.

Project Locations	Capacity (KW)	Configuration	Ref
Welega	7.95	WT + PV + BESS	[42]
Tigray region	19,530	WT + hydro + geothermal + PV + biomass + gas	[13]
Bahir Dar city	1250	WT + PV + BESS	[76]
Somalia region	1651	WT + PV + diesel generator	[77]
Kabi/Jaldu district	26.186	WT + PV + Batteries	[78]
SNNPR region	83	PV + Diesel generator	[79]
Sasu-Adigrat	96	PV + WT + DSI + BESS	[80]
Nifasso	205	WT + PV + FC	[75]

4. MG Current Trend and Topology

MG is a small energy system that unites renewable systems, storage, and intelligent controllers to work either grid-connected or stand-alone to the central grid. These systems are becoming smarter and more resilient with modern trends such as HRES, AI optimization, and new models such as community ownership and the MG as a Service. Having developed out of the centralized models, the modern topology is now characterized by decentralized control, which can be flexible and provide the ability to network systems and aggregate them into Virtual Power Plants. Finally, MGs are evolving beyond their role as backup power to critical and smart, decentralized, digital, and sustainable energy platforms of the future [42].

The coordinated system of loads and generators that operates independently from the national grid is called an MG. The development of MGs continues to advance, as they play a critical role in enhancing grid resilience against extreme weather and cyberattacks [81].

Projects like the Consortium for Electric Reliability Technology Solutions (CERTS) in the U.S. and European Union (EU) MG initiatives began in 1999 to integrate distributed energy resources (DERs), focusing initially on reliability over emissions [82,83]. Key challenges such as energy management and safe operation remain central today. The EU's MGs project addressed similar issues related to energy management, safety in both grid-connected and standalone conditions, and communication rules [55]. Many of the challenges identified in these studies continue to be a focus of ongoing research and development efforts [15,84]. Figure 4 shows the schematic diagram of MG [27].

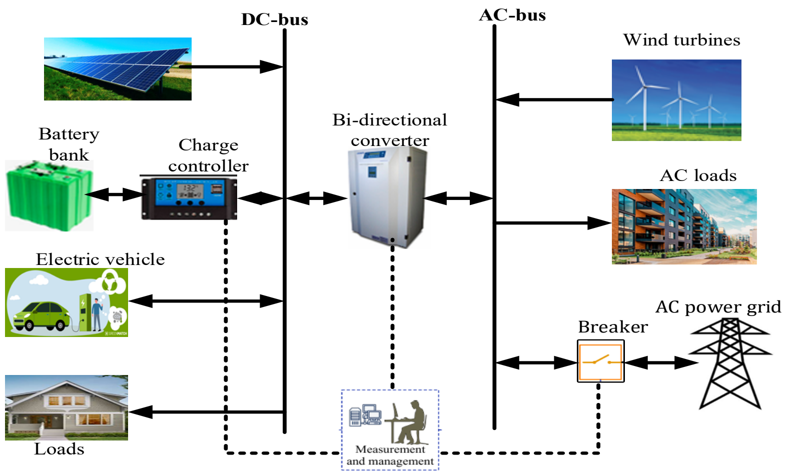

Figure 4. Schematic diagram of MG.

EMS for grid-connected MGs helps coordinate operation between MGs and the main grid by regulating power exchanges and improving the use of power imports, exports, and distributed resources. Whereas, off-grid regions operate to maximize their existing resources for self-maintenance [27].

4.1. Component of MG

MG is a small-scale, localized energy system that can be operated independently or grid-connected to the national grid. As shown in Figure 5, MG systems incorporate both dispatchable and non-dispatchable sources [85]. The system's load demands are represented by residential, industrial, and commercial sectors, and the rest of society, which represent load demands in the system. Supported by diesel or gas fuel generators, the system utilizes and integrates smart meters with Internet of Things (IoT) functionality for monitoring and operational excellence [86]. It utilizes solar power combined with wind, hydro, and biogas, which has become popular in rural areas due to the availability of biomass [82].

The components of MGs depicted in Figure 5 HRES include storage elements, combined batteries, and hydrogen storage as well as power generators by using wind, solar, HP, and biogas energy [87].

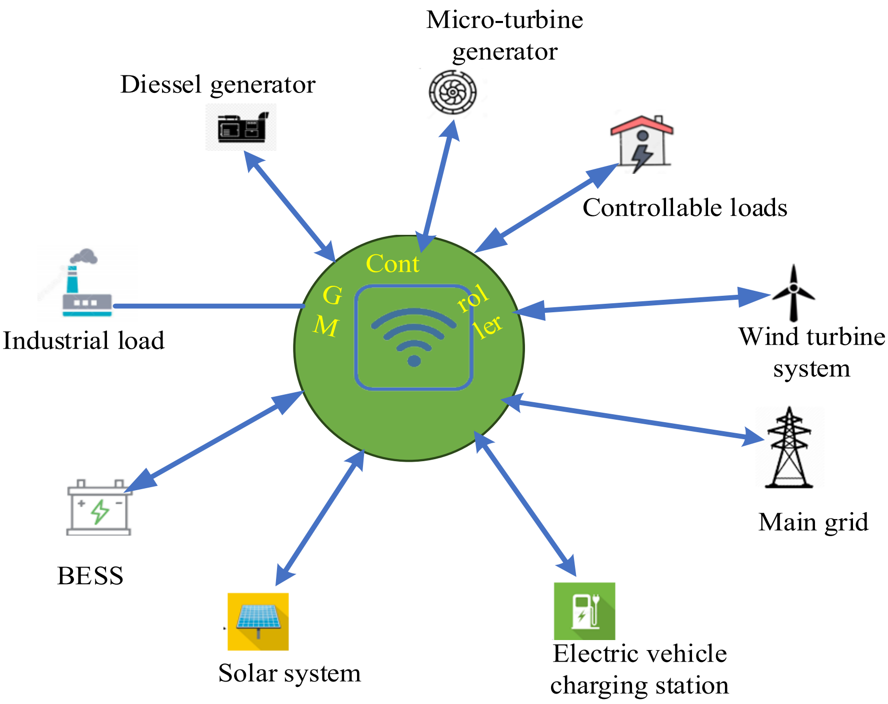

Figure 5. Component of MG.

4.2. Classifications of MG

MG can be classified based on several factors, like how they are connected, what kind of loads they support, and where they are located. HRES began operating in rural areas in 1978, with the integration of diesel and solar PV power introduced by 1983. These systems were eventually connected to the national grid [27,88]. Modern hybrid energy systems that unite PV systems with WT generators, joined by BESS and EVs, provide dependable off-grid power, which allows flexible autonomous system designs [28]. Understanding common power generation technologies is essential to evaluating the MG scheme [89]. The classification of small/MG is illustrated in Figure 6.

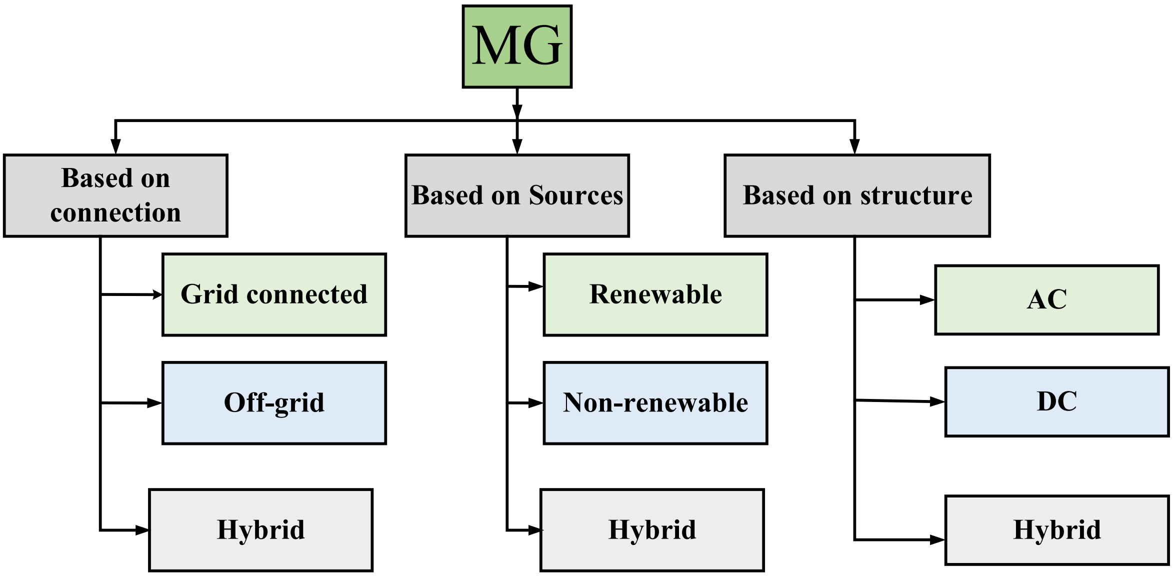

Figure 6. Classification of MGs.

4.3. Energy Management System of MG

EMS is the central brain of MG, and it serves as the core component of HRES. It plays a critical role in controlling, monitoring, and optimizing energy production, storage, and consumption within HRES. In an off-grid setting, EMS is vital in balancing intermittent renewable energy with demand, particularly when national grid access is unavailable. Various optimization techniques support the efficient scheduling of energy resources and storage that ensure stability and promote economic benefits [90].

Numerous researchers have employed various solution algorithms to address EMS challenges, aiming for the efficient and optimal operation of MGs under different scenarios. These methods are employed to plan HRES and loads, reduce system operational expenses, losses, and outages, manage the intermittency and volatility of RES, and sustain RES penetration levels, predict generation, load demand, energy storage system conditions, and energy prices, as illustrated in Figure 7. The subsequent subsections will detail these methods and solution algorithms following a thorough critical review of recent research studies [91,92]. The following subsections will present these strategies and solution algorithms based on a thorough and critical review of recent research studies.

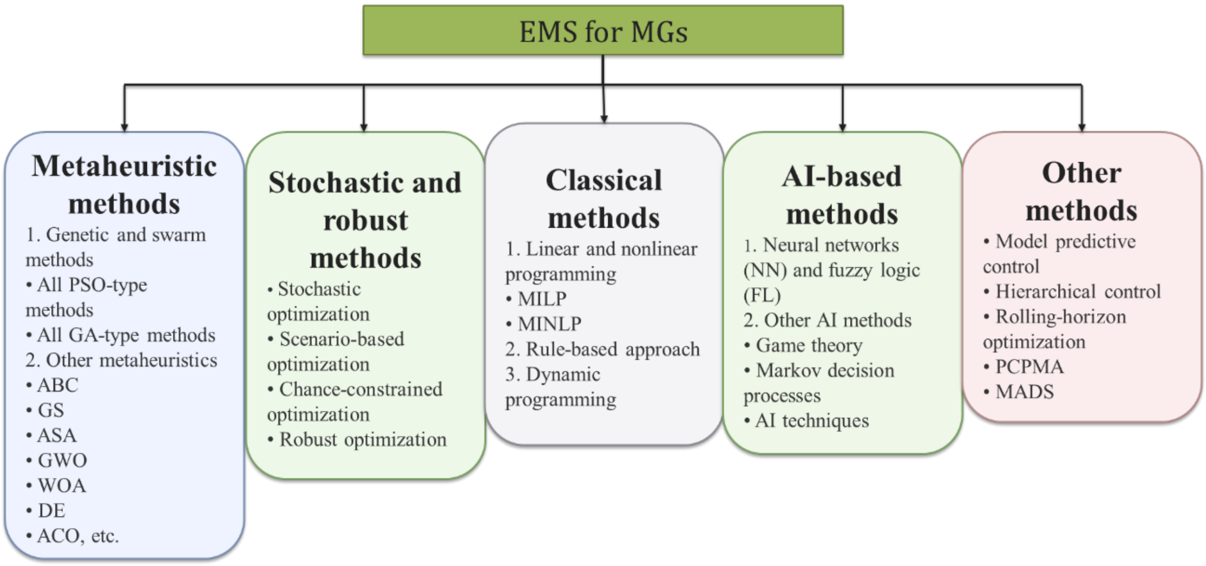

Figure 7. EMS approach for MGs.

4.3.1. EMS Using Stochastic and Robust Control

The coordination of their operations becomes increasingly challenging due to rising uncertainties, such as the variability in RE generation and demand. Robust optimization provides a framework for systematically addressing these uncertainties and variations [93] A Robust Data Predictive Control framework for EMS (RDPC-EMS) is proposed to overcome the uncertainty of retail electricity price transactions and minimize the operating cost of HRES [94]. The first layer has DMPC, which coordinates electricity forecasting and energy scheduling between the distribution network operator and cooperative MGs to reduce daily operating costs based on the forecasted energy prices. In the second layer, it predicts the result of the first layer to get the result of the HRES and balance supply and demand [95]. A two-stage adaptive robust optimization approach, as developed in [96], leverages the collaborative functioning of MG with PV under worst-case uncertainties. This model proved effective not only in reducing operational costs but also in sustaining frequent energy exchanges among MGs.

4.3.2. EMS Using the Classical Approach

Classical optimization methods typically involve mathematical strategies to address both linear and non-linear challenges with limited space and action EMS in MG planning and operation [37].

The MILP approach has been suggested to reduce the daily energy production costs. As the integration of RES increases, the energy cost decreases linearly. Economic optimization targets minimal cost or maximal revenue, bounded by battery state-of-charge and generator capacity constraints. This method presupposes a predictable, quasi-static environment and provides one, repeatable solution of a given set of inputs, which makes it easy to understand, verifiable, and prefers its use where rigorous operational determinism and regulatory adherence are necessary [96]. All variable parameters, including energy prices, WT, PV input data, and demand, are accurately forecasted using Long-Short Term Memory neural networks to manage the uncertainties in RES. MILP has effectively lowered the operating costs of clustered MGs by incorporating storage batteries [97].

The FL system is employed to forecast load demand and RES generation for efficient scheduling. Reference [97] introduces an EMS based on MILP to reduce daily operating costs through a multi-layer approach. By energizing multiple layers in the EMS execution, the overall system's operating expenses can be decreased. An MG based on HRES is discussed in [98]. The MILP algorithm was utilized in bi-level EMS, aiming to exchange information and power through the grid, and to schedule energy following the isolation of MGs, considering uncertainties and demand response programs.

4.3.3. EMS Using Artificial Intelligence

This section examines AI techniques related to soft computing and machine learning that are utilized in the EMS of MGs. As outlined in [99], the proposed approach utilizes deep neural networks (DNNs) and model-free reinforcement learning techniques for an EMS aimed at optimizing MGs/DNO profits through energy trading while also, reducing the peak-to-average ratio on the demand side by employing a peak shaving storage system. The privacy of individual MG is safeguarded using DNN, without requiring direct access to MG's data. The combination of both DNNs and MC is suggested as a hybrid strategy to take advantage of the specific strong sides. Although DNNs are effective in finding complicated patterns in data, MC simulation is useful in trying out data with uncertainty, although it is computationally intensive. A deep CNN-based model has been suggested to estimate the daily operating costs of several interconnected MGs [83,100].

The approach has successfully lowered operational expenses and, when compared to MPC, the greedy policy method, and ADP, it excels in cost reduction while maintaining a relatively low computational load. The MGs Energy Trading Bayesian Game (METBG) is introduced to synchronize MGs and optimize profits, taking into account the unpredictable nature of plug-in EVs [101]. Authors in [93], introduced a method for optimizing benefits among multiple stakeholders using Stackelberg game theory (SGT). This approach is designed to model local energy transactions, aiming to maximize the profits of the MMG system and enhance the autonomy of MGs.

4.3.4. EMS Using a Metaheuristic Approach

A dynamic networking model utilizing the NSGA-II has been created, effectively reducing the daily operational expenses of interconnected MGs through the application of graph theory [102]. Metaheuristic optimization techniques, such as Harmony Search Algorithm (HSA), Bacterial Foraging Optimization (BFO), Enhanced Differential Evolution (EDE), and ant colony optimization, have been effectively applied in EMS to balance multiple objectives, including minimizing electricity costs, reducing energy consumption, peak-to-average load ratios, and maintaining user comfort in home energy management systems (HEMS) [103]. These methods specifically help manage trade-offs among conflicting objectives, which are common in energy systems.

In MGs, EMS must handle the integration of intermittent RES, BESS, and load demands while ensuring system stability and economic operation. Metaheuristic algorithms are among the most used optimization techniques due to their robustness and adaptability in handling multi-objective problems where cost minimization is a major goal [104]. PV and WTs dominate as renewable generation sources, with batteries commonly used for energy storage, optimized through metaheuristic methods for improved economic and operational outcomes. Metaheuristic approaches are also popular in power systems beyond MGs, where they have been applied to problems such as power flow optimization, reactive power dispatch, economic and emission dispatching, and Volt/Var control, demonstrating effective performance in solving these complex power system challenges [105]. Their flexibility makes them suitable for real-time and large-scale systems with varying constraints.

Moreover, research confirms that combining metaheuristic algorithms with computational intelligence techniques, often seen in energy load forecasting, enhances prediction accuracy and supports better demand-side management within EMS frameworks for smart grids [8,23,106]. Hybrid forecasting methods, which include metaheuristic optimization, provide advantages over single-model approaches by improving the reliability and efficiency of load management decisions. While metaheuristics present powerful optimization capabilities, it is important to note challenges such as the need for proper customization to specific problem constraints and rigorous benchmarking to avoid weak comparative claims in the literature [107]. Sound methodological practices are crucial to leverage the full potential of metaheuristic EMS solutions.

Generally, EMS uses advanced computational tools to enhance power system resilience and efficiency [108–110]. It plays a crucial role in meeting the power demands of EVs while simultaneously enhancing system efficiency [1]. It manages power distribution from each source, targeting to ensure good acceleration, range, noise control, fuel efficiency, low emissions, and cost reduction. It is integrated into the vehicle's central controller, which analyzes circumstances and modifies components in real-time [111,112].

4.4. Evolution of MG

Early electric grids were highly centralized systems, placed around large fossil fuel-based power plants. The power flow was unidirectional, moving from generation to transmission lines, to the distribution systems, and finally reaching the customers. MGs enhance power quality while offering financial, environmental, and technical benefits to both consumers and providers. In grid-connected modes, local demand is met via the main grid, while off-grid systems must maintain their demand-generation balance to ensure stability. Figure 8 shows the previous, current, and future trends in EV electricity use [113].

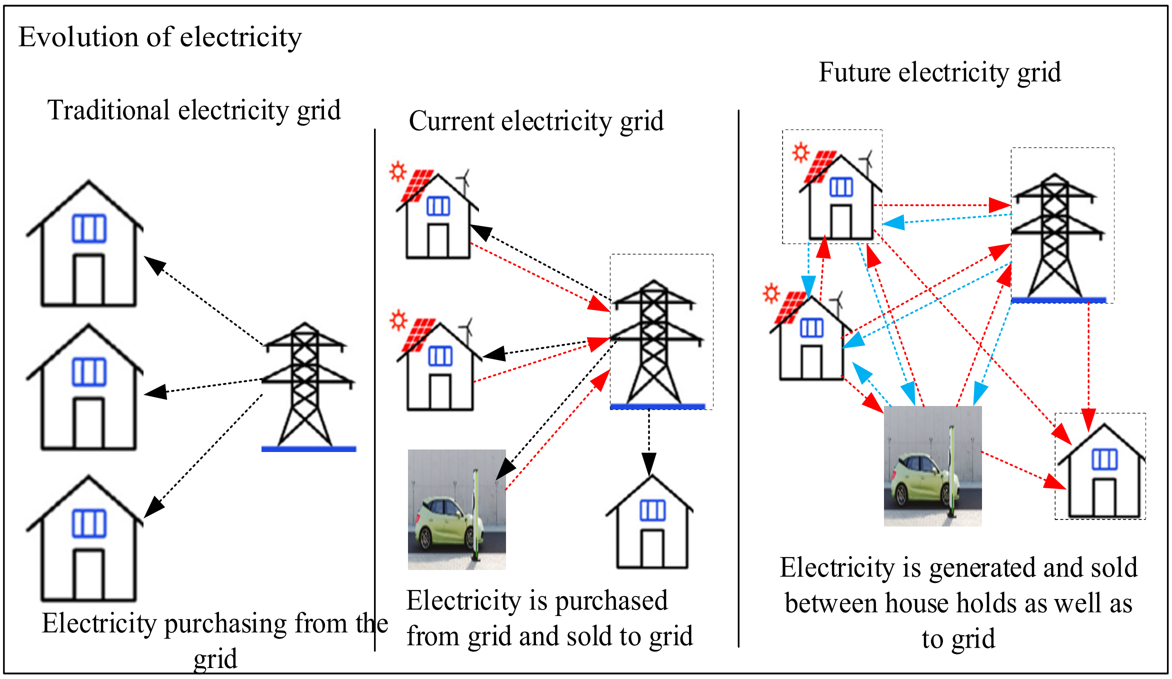

Figure 8. Evolution of the electricity grid infrastructure.

As depicted in Figure 9, the DC output from the PV is linked to the DC bus through DC-DC converters, while the WT output is connected to the DC bus via an AC-DC converter [114]. The BESS and EV are integrated with the DC bus using a bi-directional converter, facilitating both charging/discharging operations. Moreover, the possible arrangements of a typical WT/PV system, such as WT with PV, WT with PV and BESS, and other RES, WT with PV, BESS, and fossil sources, PV with WT, BESS, and other RES, or fossil sources, are shown in Figure 9.

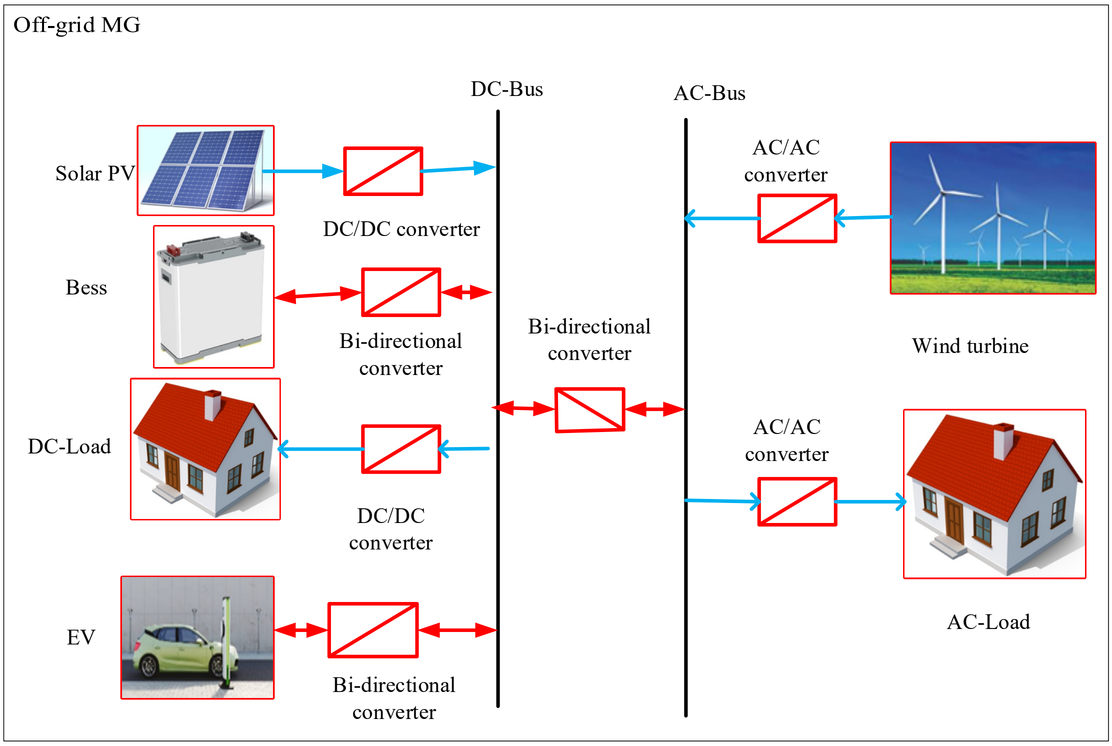

Figure 9. Isolated microgrids [113].

Figure 10 compares different PV/WT-based HRES configurations and highlights their difference in reliability, cost, and environmental impact. Also, it focuses on the sustainability of EVs is directly linked to how the electricity used to charge them is produced. EVs are better for the environment if the electricity is generated from clean, renewable sources. All EV types, plug-in electric vehicle (PEV), hybrid electric vehicle (HEV), and plug-in hybrid electric vehicle (PHEV), produce low emissions when charged with clean, RES [115]. The energy transition poses a dual challenge: integrating intermittent renewables such as solar and wind without large-scale storage while maintaining a stable grid that can rapidly meet rising EV demand [26].

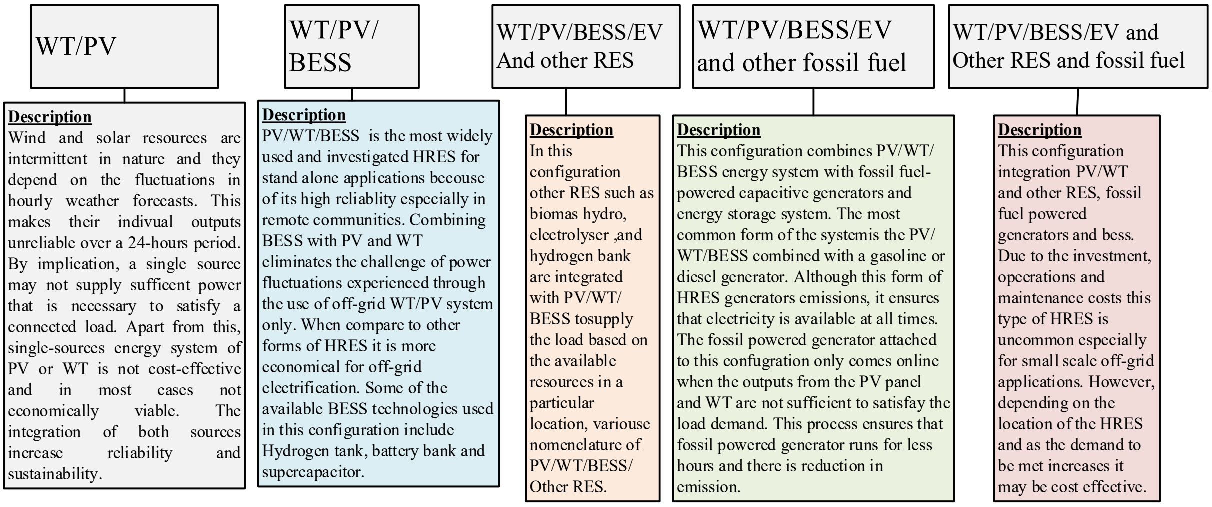

Figure 10. PV-Wind HRES configuration.

A grid-connected hybrid AC/DC microgrid that integrates wind turbines, solar photovoltaic panels, energy storage systems, and electric vehicles via AC/DC, DC/AC, and bidirectional converters connected to a common AC bus is shown in Figure 11. This microgrid provides AC and DC loads while facilitating flexible power exchange with the utility grid and effective energy management.

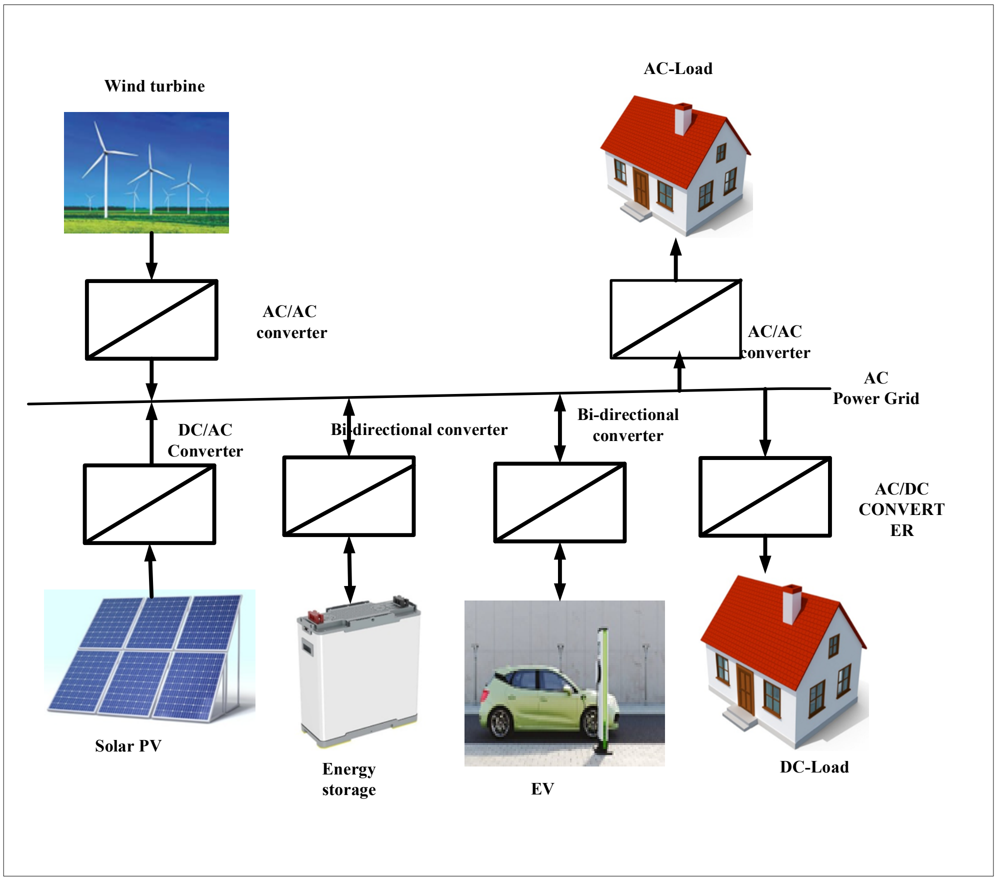

Figure 11. Grid-connected microgrids.

The charging/discharging of EVs can be divided into two key categories: unidirectional/bidirectional charging. In unidirectional charging, the energy flow is only from the grid into the EV. Whereas bi-directional charging flows include vehicle-to-grid (V2G), grid-to-vehicle (G2V), and V2H Figure 12 illustrates the classification of charging/discharging methods.

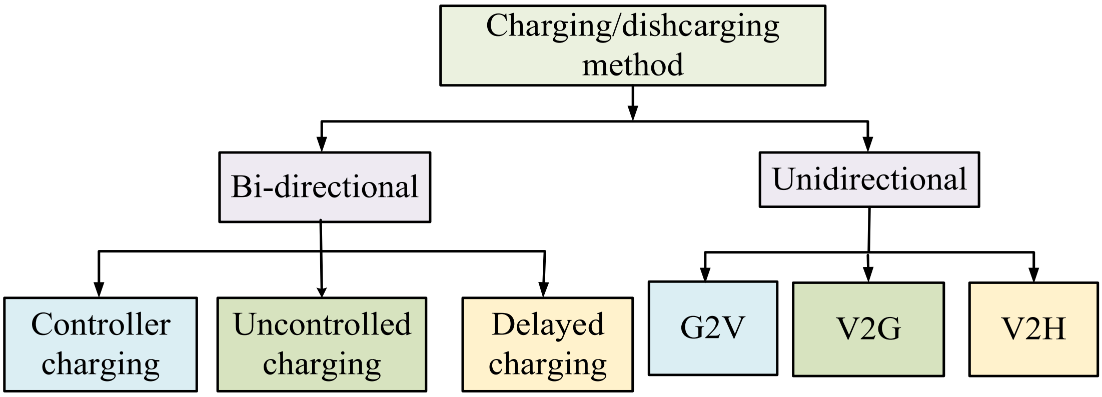

Figure 12. Classification of charging and discharging methods.

4.4.1. PV Generation Modelling of MG

PV generation modeling involves creating a predictive framework using algebraic methods to forecast the energy output of solar PV systems based on the environmental conditions. Solar MGs provide an attractive renewable energy solution owing to their adaptability for use at different scales and their potential for future growth [116]. The power output of a PV array is influenced by the size and efficiency of its solar modules and solar irradiance (G) when MPPT is employed. Solar generation modeling calculates the electricity generated over time, with the PV output expressed by Equation (1) [117,118]:

$$P_{pv} = \eta_s * A * G\left(1 - \beta(T_c - T_{ref})\right) \tag{1}$$

where P_{pv} is the PV system's output power (W); A is the total area of the PV panels (m^2); η_s is efficiency of the PV system under standard conditions; G is solar irradiance (W/m^2); T_c is PV cell temperature (°C); T_{ref}; reference temperature (25 °C), and β is the temperature coefficient of power (in 1/°C). To calculate the efficiency of a PV system, apply the following formula [10].

$$\eta_{pv} = \eta_r * \eta_t\left[1 - \beta_T * (T_c - 25) - \beta_T * G\left(\frac{T_{nom} - 20}{800}\right) * (1 - \eta_r * \eta_t)\right] \tag{2}$$

The terms η_r and η_t represent the reference and MPPT efficiency system, respectively. The temperature coefficient is indicated by T_c and T_{nom} refer to the actual operating and current cell temperatures, respectively [10].

4.4.2. Modelling of Wind Power of MG

Wind energy is unpredictable and is produced through systems that convert kinetic energy using components such as wind towers, blades, and turbines. Consequently, the output of wind energy that largely depends on wind speed and varies with the height of the tower can be converted and measured as hub height using Equation (4) [113]. Many people utilize variable-pitch or speed control loads. In 1887, Charles in Scotland built the first wind-powered generator to produce electricity [119]. Wind speed and thus power output vary with tower height, measured as hub height, and can be modeled using Equation (3) [53].

$$P_{wT} = \frac{1}{2}\rho * A * \eta_{gb} * \eta_{gen} * V_{hub}^3 \tag{3}$$

The height at a certain measurement point is determined using Equation (4).

$$V_{hub} = V_a\left[\frac{\ln\left(\frac{h_{hub}}{h_s}\right)}{\ln\left(\frac{h_a}{h_{hs}}\right)}\right] = \frac{v}{v_0} = \left(\frac{h}{h_a}\right)^{\alpha} \tag{4}$$

Here, α represents the Hellmann exponent, which can be calculated with Equation (5) [110].

$$\alpha = \frac{0.37 - 0.088 * \ln(v_0)}{1 - 0.088 * \ln\left(\frac{H_{10}}{10}\right)} \tag{5}$$

The power law exponent (α) is typically 1/7 for open space designs [21].

$$P_{wind} = \begin{cases} 0 & \text{if } v_f \leq v \\ P_r * \dfrac{v^3 - v_c^3}{v_r^3 - v_c^3} & \text{if } v_c \leq v \leq v_r \\ P_r & \text{if } v_r \leq v \leq v_f \end{cases} \tag{6}$$

4.4.3. BESS and State of Charge (SoC) Modeling

Figure 13 shows the classification of ESS by chemical storage, electrochemical storage, electrical storage, and hybrid storage, providing a list of the common technologies in each category. The use of BESS in MGs improves power quality, manages demand during peak hours, regulates frequency, smooths renewables, and provides backups [120,121]. Its main role is balancing energy supply and demand, aiding cost optimization [122,123].

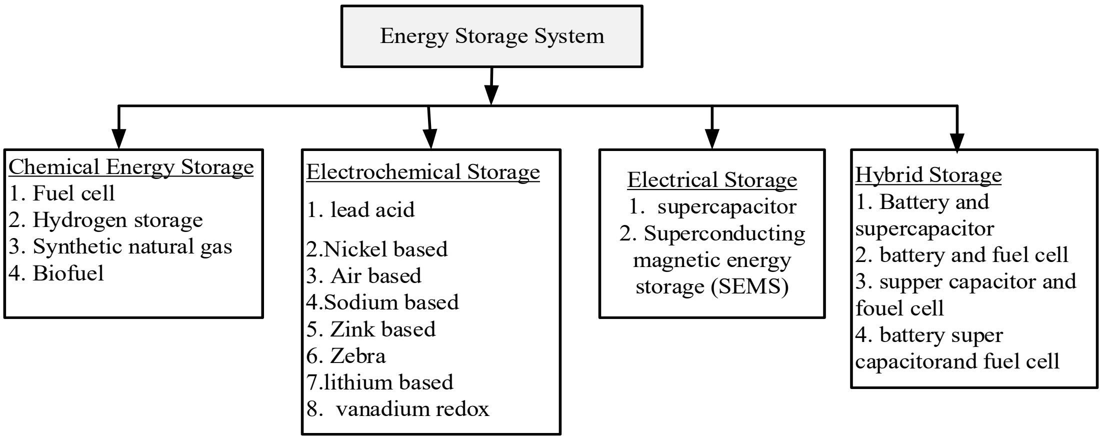

Figure 13. Overview of ESS.

BESS is used to smooth intermittent power from renewable sources and helps shave peak demand, enhancing grid stability and efficiency [21].

$$C_{BESS} = \frac{AD * P_{load}}{\eta_{inv} * \eta_{BES} * DoD} \tag{7}$$

where: AD/DoD stands for autonomy day and depth of discharge, respectively, while η_{inv} and η_{BESS} stand for efficiencies of the inverter and the battery, respectively [21]. When the power produced by each resource surpasses the demand, the energy is utilized to charge the BESS, and the battery power can be described by [111,124]:

$$P_{BESS} = P_{pv}(t) + P_{wind}(t) - \frac{P_{load}(t)}{\eta_{inv}} \tag{8}$$

where: P_{BESS} is a power exchange by BESS, P_{pv} is power generated by PV, P_{wind} is power generated from wind, P_{load} is the power demand at time t, and η_{inv} is inverter efficiency. In BESS, the state of charge, SoC(t), is a fundamental parameter influencing the battery's performance, which is determined by the excess or deficiency of power generated by RESs with the demand [125]. The mathematical equation of SOC under charge and discharge will be expressed as flows [111].

$$\mathrm{SoC(t)} = \begin{cases} \mathrm{SoC(t-1)} + \left\{\mathrm{P_{pv}(t)} + \mathrm{P_{wind}(t)} - \frac{\mathrm{P_{load}(t)}}{\eta_{\mathrm{inv}}}\right\}\eta_{\mathrm{BESS}} \\ \quad \mathrm{P_{pv}(t)} + \mathrm{P_{wind}(t)} > \mathrm{P_{load}(t)} \\ \mathrm{SoC(t-1)} + \left\{\frac{\mathrm{p_{load}(t)}}{\eta_{\mathrm{inv}}} - \mathrm{P_{pv}(t)} + \mathrm{P_{wind}(t)}\right\}\eta_{\mathrm{BESS}} \\ \quad \mathrm{P_{pv}(t)} + \mathrm{P_{wind}(t)} < \mathrm{P_{load}(t)} \end{cases} \quad (9)$$

where SoC(t − 1) is the state of charge at the previous time step, P_{load}/η_{inv} is the load demand adjusted for inverter efficiency, η_{BESS} battery efficiency.

4.4.4. Converters Modeling

Power converters such as DC/AC and AC/DC converters are necessary when a system has both AC and DC components [126]. Although the load is AC, the output from solar PV panels and batteries is DC. The size of the converter is calculated by combining the peak load demand P_L^m with the inverter efficiency η_{inv}. Meanwhile, the inverter rating $P_{inv}(t)$ is determined using Equation (10).

$$\mathrm{P_{inv}(t)} = \frac{\mathrm{P_L^m}}{\eta_{\mathrm{inv}}} \quad (10)$$

where $P_{inv}(t)$ drawn power from the inverter at time t, P_L^m load demand and η_{inv} inverter efficiency.

4.4.5. Modeling of EV

The mathematical modelling of EVs integrates with mechanical dynamics, electrical systems, and energy storage to simulate real-world behaviour. It enables system design, energy consumption prediction, battery sizing, charging strategy, and performance optimization [127]. The energy balance at time t of the system is given by:

$$\mathrm{P_{net}(t)} = \mathrm{P_{wind}} + \mathrm{P_{pv}} + \mathrm{P_{BESS}} + \mathrm{P_{EV}} - \mathrm{P_{load}} = 0 \quad (11)$$

The mathematical modeling of EV is as follows:

$$\mathrm{P_{EV}(t)} = \mathrm{N_{EV}} * \begin{cases} \eta_{\mathrm{ch}}^{\mathrm{EV}} . \mathrm{P_{ch}^{EV}} & \text{if charging conditions} \\ \frac{\mathrm{P_{dis}^{EV}}}{\eta_{\mathrm{dis}}^{\mathrm{EV}}} & \text{if disccharging conditions} \end{cases} \quad (12)$$

where P_{EV} is the total power exchange by EVs, N_{EV} is number of EVs connected, η_{ch}^{EV} and η_{dis}^{EV} are charging and discharging efficiency of EV batteries, respectively, and P_{ch}^{EV}, P_{dis}^{Ev} are power per EV during charging and discharging, respectively. The EV battery's state of charge evolves according to Equation (13).

$$\mathrm{SoC^{EV}(t)} = \mathrm{SoC^{EV}(t-1)} + \frac{\mathrm{P_{EV}(t)} . \Delta \mathrm{t}}{\mathrm{E_{max}^{EV}}} \quad (13)$$

Five research studies that use MATLAB-based optimization for energy management and smart EV charging are summarized in Table 7. Reduced billing, cost minimization, and peak shaving are among the goals. Methods like fuzzy logic, mixed-integer programming, linear programming, and rule-based approaches are used. Results show that microgrid systems are more cost-effective, have lower emissions, save operating costs, and use more energy.

Table 7. Summary of literature related to smart charging of EV-PV and WT systems.

Ref.	Objectives	Software	Optimization Techniques	Finding
[120]	Peak-shaving and valley-filling	MATLAB	Linear programming	Effective peak shaving and valley filling
[128]	Minimizing charging costs	MATLAB	Fuzzy logic	The optimization algorithm does not form the basis of its operation. Such optimizations consist of multiple objectives (minimizing charging cost and system losses).
[118]	Minimize operational cost	MATLAB	Mixed-integer linear programming	Implementing smart charging can result in the parking lot owner minimizing operational costs associated with charging PV consumption.
[117]	To minimize costs	MATLAB	Mixed-linear integer programming	Reduced GHG emission and MG degradation battery cost.
[84]	Reducing the billing cost	MATLAB	Rule-based algorithm	Rule-based charging demonstrates better cost efficiency and lower power consumption.

5. Application of MG

MGs improve energy reliability and sustainability by integrating renewables, supporting grid stability, and enabling independent power management [1]. Figure 14 explains the application of MG and is also used for:

(i) RE integration**:** MGs facilitate the incorporation of WT, solar PV, BESS, and other RS to ensure a consistent and reliable power supply to both off-grid and grid-connected systems.
(ii) Energy resilience and reliability: supplying the community during power outages.
(iii) Maritime MGs: installed on ships, ferries, and marine vessels, operate in stand-alone at sea and on-grid mode at ports. As ships increasingly adopt electric systems, maritime MGs are emerging as a promising and growing business opportunity.
(iv) Biological: Artificial ecosystems function as life support systems for long space missions, providing Earth-based food and waste support systems in open setups [45].
(v) Space: Reliable power systems are vital for space missions. Space MGs offer a sustainable means to meet energy needs in space applications [119].

MGs are local energy systems that integrate distributed energy production, energy storage, and load control. They stand out by operating independently from the main grid. Energy management uses algorithms for optimization, and MGs can be classified according to connection, operation mode, power type, and monitoring systems [121].

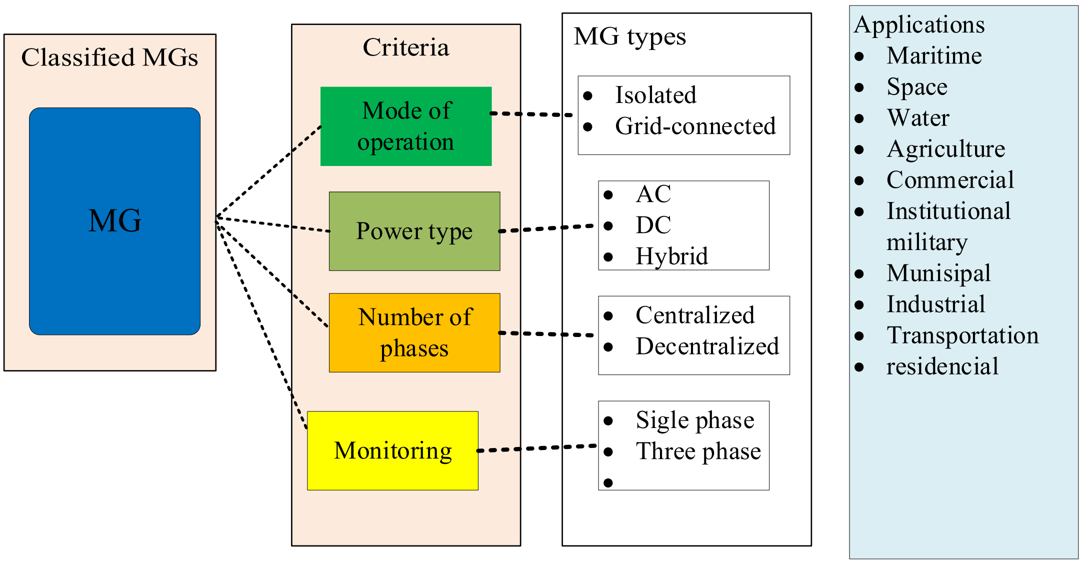

Figure 14. Standard application of MGs in terms of operation.

Optimal sizing of HRES systems involves selecting component capacities while ensuring feasibility and reliability. This analysis focuses on implementing HRES grids with efficient energy generation and storage units using optimization methods [129,130]. Optimal sizing of HRES systems involves estimating component capacities while meeting feasibility and reliability constraints [27]. Governments often develop HRES networks, but cost data for grid installation is limited. However, HRES grids are generally more cost-effective than traditional systems, especially in rural areas where generation and storage units are located [85]. Figure 15 outlines the HRES sizing optimization process. It starts with system input data, followed by system configuration. The sizing problem is defined using an optimization method. Subsequently, the system's performance is assessed, feasibility constraints are verified, and the objective function is computed to determine the optimal solution using [44].

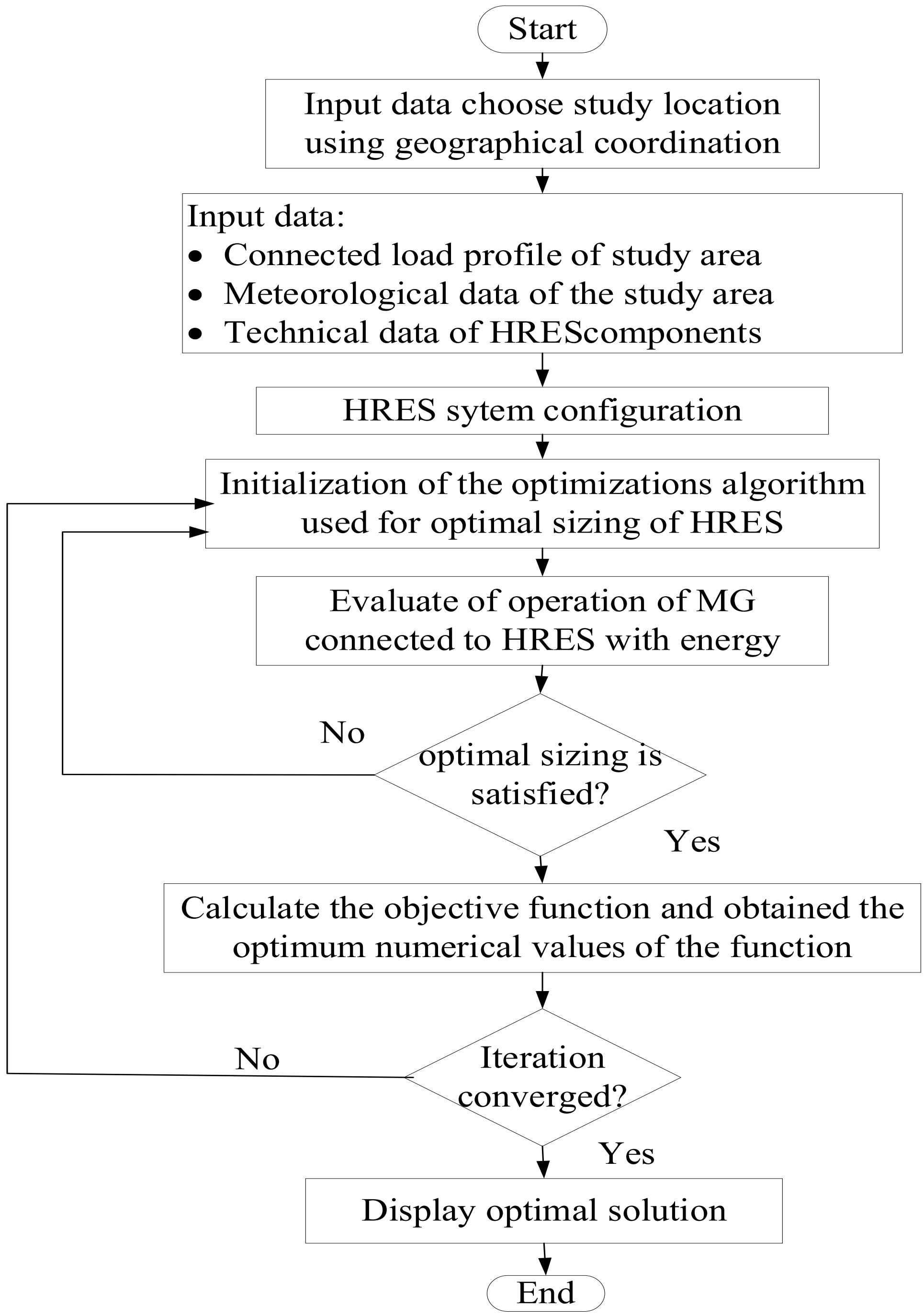

Figure 15. Overview of HRES optimal sizing using metaheuristic optimization algorithm.

6. Problem Formulation

6.1. Formulation of Optimal Power Flow

This review examines the optimal design of EMS for MGs based on DERs, aiming to reduce cost and enhance reliability through a multi-objective strategy and day-ahead scheduling. It considers the uncertainties associated with renewable load and pricing. The primary objective is to balance the generated energy and load power as shown in Equation (14) [42].

$$\mathrm{P_{balance}} = \mathrm{P_{load}} - \mathrm{P_{WT}} - \mathrm{P_{PV}} - \mathrm{P_{BESS}} - \mathrm{P_{EV}} = 0 \tag{14}$$

Because of the BESS, EV charging/discharging operations, the main grid will reduce the net imbalance in the equation, as illustrated in Equation (15).

$$\mathrm{P_{MG}} = \mathrm{P_{balance}} \pm (\mathrm{P_{bess+}P_{EV}}) \tag{15}$$

The EMS problem seeks to reduce the cost of energy over 24 h, factoring in system costs such as initial investment, O&M, and replacement costs, as shown in Equations (16)–(19) [42].

$$C_t^{PV} = N_{PV}\left(C_c^{PV} + C_{o\&m}^{PV}\frac{(1+i)^n - 1}{i(1+i)^n}\right) \tag{16}$$

$$C_t^{WT} = N_{WT}\left(C_c^{WT} + C_{o\&m}^{WT}\frac{(1+i)^n - 1}{i(1+i)^n}\right) \tag{17}$$

$$C_t^{BESS} = N_{BESS}\left(C_c^{BESS} + C_{o\&m}^{BESS}\frac{(1+i)^n - 1}{i(1+i)^n}\right) \tag{18}$$

$$C_t^{EV} = N_{EV}\left(C_c^{EV} + C_{o\&m}^{EV}\frac{(1+i)^n - 1}{i(1+i)^n}\right) \tag{19}$$

where C_t^x is the total discounted cost of component X (PV, WT, BESS, and EV) over the project lifetime, C_c^x capital cost per unit of component x, N_x is number of units of component x, $C_{o\&m}^x$ annual operation and maintenance cost per unit of component x, i is the discount rate, and n project lifetime (years).

Cost and reliability are the most vital factors to consider when constructing HRES. These aspects are linked to emissions and technological hurdles. These aspects are linked to emissions and technological challenges [42]. Due to the distinct nature of the goals, optimal sizing in HRES can be achieved by addressing a single or multi-objective optimization problem [120].

The main function combines initial capital and maintenance costs to minimize the system's annual LCOE, as shown in Figure 16. The review explores scenarios with solar + PHES, wind + PHES, and hybrid solar-wind + PHES to compare and identify the best setup. Objective functions and constraints guide the optimization process [131]. In off-grid HRES, components must operate within specific constraints, ensuring an optimal power balance between the generated power supply and the demand of the system performance [37,109]. Figure 16 illustrates various types of objective functions. Researchers often prioritize economic, dependability, technological, and emission aspects. A detailed description of the types of objective functions is given in Figure 16.

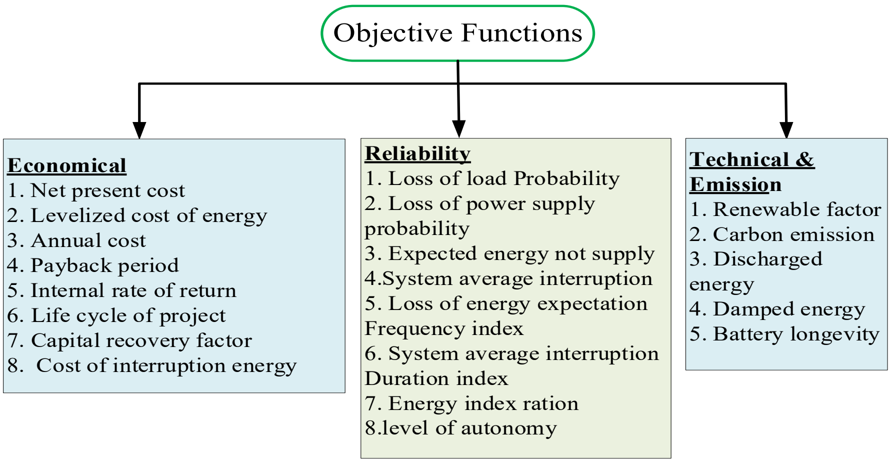

Figure 16. Objective functions of the HRES system.

6.2. Objective Functions of Economics for MG

The economic evaluation of the system has been conducted using conventional techno-economic indicators. These include net present cost (NPC), LCOE, annual cost (AC), payback period (PP), internal rate of return (IRR), annualized cost of the system (ACS), total annual cost (TAC), lifecycle cost of the project (LCP), and capital recovery factor (CRF). The NPC of the generator is determined by summing the present value of the cost of capital, maintenance, replacement, salvage, and fuel consumption [105,128]. To compute the LCOE, the CRF is applied to multiply the NPC by the system's yearly energy usage [132,133].

The optimization problem seeks to minimize the total NPC by adjusting the decision variables, including the number of PV panels, wind turbines, batteries, and EV units. This objective is followed under constraints related to component limits, the probability of loss of power supply (LPSP), and energy efficiency and flexibility limits.

6.2.1. NPC

It refers to the presence of the value of future benefits and costs for a project over its lifetime [10].

$$\text{Minimize of } N_{NPC}\ \{N_{PV}, N_{WT}, N_{bat}, N_{EV}\} \tag{20}$$

Subject to:

$$N_{PV}^{mini} \leq N_{PV} \leq N_{PV}^{max}$$

$$N_{WT}^{mini} \leq N_{WT} \leq N_{WT}^{max}$$

$$N_{bat}^{mini} \leq N_{bat} \leq N_{bat}^{max}$$

$$N_{EV}^{mini} \leq N_{EV} \leq N_{EV}^{max}$$

$$0 \leq LPSP \leq LPSP_{Max}$$

$$0 \leq EEF \leq EEF_{Max}$$

The calculation of the system's net present cost is as follows:

$$C_{NPC} = \sum\nolimits_x C_I + C_R + C_{O\&M} - S \tag{21}$$

$$C_{NPC} = \sum\nolimits_{n=0}^{N_{proj}} \left(C_I(n) + C_R(n) + C_{o\&m}(n) - S(n)\right) * \frac{1}{(1+I_r)^n} \tag{22}$$

$$C_I = \sum N_{PV}C_{IPV} + N_{bat}C_{Ibat} + N_{wt}C_{Iwt} + N_{EV}C_{IEV} \tag{23}$$

$$C_R = \sum N_{PV}C_{RPV} + N_{bat}C_{Rbat} + N_{wt}C_{Rwt} + N_{EV}C_{REV} \tag{24}$$

$$C_{O\&M} = \sum N_{PV}C_{O\&MPV} + N_{bat}C_{O\&Mbat} + N_{wt}C_{O\&Mwt} + N_{EV}C_{O\&MEV} \tag{25}$$

$$S = \sum N_{PV}S_{PV} + N_{bat}S_{bat} + N_{wt}S_{wt} + N_{EV}S_{EV} \tag{26}$$

where C_I, C_R, and $C_{o\&m}$ are capital, replacement, operation, and maintenance costs. S-salvage value, N_{pv}, N_{bat}, N_{wt}, N_{EV}, number of PV, batteries, wind turbine, and electric vehicles. Also, C_{Ipv}, C_{ibat}, C_{Iwt}, C_{IEV} investment cost per unit for PV, batteries, WT and EVs. Fisher's formula calculates the real interest rate as follows:

$$I_r = \frac{i - i_f}{1 + i_f} \tag{27}$$

The following formula is used to calculate S:

$$S = C_R \left(\frac{N_{comp}\left(N_{proj} - N_{comp} * INT\left(\frac{N_{proj}}{N_{comp}}\right)\right)}{N_{comp}} \right) \tag{28}$$

where N_{comp} is the component lifetime, N_{proj} the total project lifetime in years, and INT integer part function.

6.2.2. COE

It represents the yearly cost per kWh for accessible electrical energy [10], and indicates the actual or immediate expense of energy obtained from DERs. For planning purposes, the grid can be evaluated over short-term periods, daily, monthly, or yearly, as shown in Equation (29).

$$COE = \frac{NPC}{\sum_{i=1}^{8760} P_{gen}} * CRF \tag{29}$$

6.2.3. LCOE

Used to compare the cost-effectiveness of different energy technologies. It indicates the average cost per unit of electricity generated, taking into account all costs over the lifetime of the energy-generating assets, as shown in Equation (30).

$$\mathrm{LCOE} = \frac{\mathrm{I} * \mathrm{CRF} + \mathrm{O} + \mathrm{F} + \mathrm{M}}{\mathrm{E_{Gen}}} \tag{30}$$

where I is the initial capital investment, O, F, and M are annual O and M fuel costs, E is electricity generation, and CRF is the capital recovery factor.

LCOE can also be evaluated as flows:

$$\mathrm{LCOE} = \frac{\mathrm{LCC}}{\mathrm{E_{Generation}}} \tag{31}$$

where $E_{Generation}$ indicates the energy output produced by the system, while LCC represents the lifecycle cost of the project. The replacement cost is less than the salvage value, indicating that the total cost of the project throughout its duration corresponds with its value at the end of the system's life. This assessment also takes into account the initial capital investment, as well as operation and maintenance costs [134]. The LCC can be computed using Equation (32).

$$\mathrm{LCC} = \mathrm{C_{cap}} + \sum\nolimits_{\mathrm{T=1}}^{\mathrm{T=8760}} \mathrm{C_{O\&M}} + \sum\nolimits_{\mathrm{T=1}}^{\mathrm{T=8760}} \mathrm{C_R} - \mathrm{C_{Sal}} \tag{32}$$

In this scenario, C_{cap}, $C_{O\&M}$, C_R, and C_{Sal} represent the expenses related to capital, operation and maintenance, replacement, and the project's end-of-life value, respectively. The salvage cost (C_{Sal}) indicates the value of the components of an integrated system at the time the project is finalized. This cost is calculated as follows in [53,135].

$$\mathrm{C_{sal}} = \mathrm{C_R} * \frac{\mathrm{R_{rem}}}{\mathrm{R_{PL}}} \tag{33}$$

where R_{PL} and R_{rem} represent the project's lifespan and the component's remaining life, respectively.

The economic study considers the system's TAC which is expressed in Equation (34) [136].

$$\mathrm{TAC} = \mathrm{C_{ann,cap}} + \sum\nolimits_{\mathrm{i=0}}^{\mathrm{T=8760}} \mathrm{C_{O\&M}} + \sum\nolimits_{\mathrm{i=0}}^{\mathrm{T=8760}} \mathrm{C_R} \tag{34}$$

where C_R represents the cost to replace each subsystem, $C_{O\&M}$ denotes the expenses for operating and maintaining each subsystem, and $C_{ann,cap}$ refers to the annual interest on the capital cost. The net present cost (NPC) indicates the current value of both the capital investment and the operational expenses throughout the project's duration and is defined as follows [136].

$$\mathrm{NPC} = \frac{\mathrm{TAC}}{\mathrm{CRF}} \tag{35}$$

6.2.4. CRF

The capital recovery factor can be represented by Equation (36).

$$\mathrm{CRF} = \frac{\mathrm{i}(1+\mathrm{i})^{\mathrm{n}}}{(1+\mathrm{i})^{\mathrm{n}} - 1} \tag{36}$$

6.2.5. Simple Payback Period (SPP)

It is the time required to repay the investment's cost.

$$\mathrm{F_1} = \mathrm{Minif(SPP)} = \frac{\mathrm{PC_c}}{\mathrm{AP}} \tag{37}$$

6.2.6. IRR

In a discounted cash flow analysis, it is a discount rate that makes the NPV of all cash flows zero [120].

$$\mathrm{F_2} = \mathrm{Maxf(IRR)} = -\mathrm{PC_c} + \sum_{\mathrm{y=1}}^{\mathrm{Y}} \mathrm{M_Y} * (\mathrm{IRR})^{\mathrm{Y}} = 0 \tag{38}$$

6.3. Objective Functions of Reliability and Technical Evaluations for MG

System reliability refers to the ability of an electrical power system to supply adequate energy to a quantified load without experiencing shortages or service interruptions [2,53]. The most prevalent metrics and target functions for ensuring the dependable sizing of HRES include EMS, which is determined at certain times by optimizing the operational costs through a day-ahead scheduling. This process aims to minimize the LCOE, loss of load probability (LOLP), LPSP index, expected energy not supplied (EENS) index, and reliability index (RI) [137].

6.3.1. LOLP

Power systems use reliability indices to measure the probability of consistently supplying enough electricity to meet consumer demand at any given time [76,124].

$$\mathrm{LOLP} = \mathrm{y}\{\mathrm{f(x)} \leq 0\} = \frac{1}{\mathrm{N}}\sum_{1}^{\mathrm{T}} \mathrm{F_y} \tag{39}$$

6.3.2. LPSP

It is a key reliability index ranging from 0 to 1. An LPSP of 0 means the system is fully reliable with no power shortages, while 1 indicates complete failure to meet demand [53].

$$\mathrm{LPSP} = \frac{\sum_{t=1}^{8760} \mathrm{P_{load}(t)} - \mathrm{P_{pv}} - \mathrm{P_{wind}}}{\sum_{t=1}^{8760} \mathrm{P_{load}}} \tag{40}$$

6.3.3. EENS

The most commonly used measures and goal functions for HRES sizing dependability are listed below [111].

$$\mathrm{EENS} = \begin{cases} \mathrm{P_{Load}} - \int_{\mathrm{P_{min}}}^{\mathrm{P_{max}}} \mathrm{P.\,f_p(p)dp} & \mathrm{P_{Load}} > \mathrm{P_{max}} \\ \int_{\mathrm{P_{min}}}^{\mathrm{P_{max}}} (\mathrm{P_{Load}} - \mathrm{P}).\,\mathrm{f_p(p)dp} & \mathrm{P_{min}} \leq \mathrm{O_{Load}} \leq \mathrm{P_{max}} \\ 0 & \mathrm{P_{Load}} \leq \mathrm{P_{min}} \end{cases} \tag{41}$$

The following are the primary metrics and target functions for HRES optimal sizing with respect to reliability. (1) level of autonomy (LA), (2) load demand uncertainties (LDU), (3) loss of load expectation (LOLE), (4) loss of energy expectation (LOEE), (5) minimization of customer damage function (CDF), (6) maximization of the reliability index (RI) or availability index, (7) System average interruption frequency index (SAIFI), (8) System average outage interruption duration index (SAIDI), (9) LOLP, the number of hours per year that energy exceeds the capacity of the HRE generation system, and (10) The LOEE that represents the total energy the grid-connected or stand-alone HRES does not deliver [138].

7. Performance Benchmarks for HRES-Based Microgrids

Researchers have applied various solution techniques to tackle energy management challenges, enabling efficient and optimal MG operation under different conditions. These methods help schedule DERs and loads, lower operational costs, reduce losses and outages, manage RES intermittency, maintain penetration levels, and forecast generation, demand, storage status, and energy prices. The following subsections provide detailed algorithms and techniques drawing on a comprehensive review of recent studies [139]. Based on the literature review, the simulated results for various scenarios used to validate system performance are presented in Table 8.

Table 8. Comparative literature on HRES applications and studies.

Ref.	Title of the Article	Objective	Scenarios
[99]	Research on energy management strategies for fuel cell commercial vehicles based on a model-predictive control strategy	Address the problems of lacking economic efficiency and the short driving range of electric commercial vehicles by developing an improved EMS for fuel cell hybrid vehicles.	The fuel cell hybrid vehicle operates through extremely distinct operational states.
[140]	Hybrid Renewable Energy Systems for Off-Grid Electrification: A Comprehensive Review of Storage Technologies, Metaheuristic Optimization Approaches and Key Challenges.	Review storage technologies and optimization methods for reliable off-grid hybrid systems	Off-grid hybrid PV-wind-storage systems for rural electrification.
[141]	Advancements in Hybrid Energy Storage Systems for Enhancing Renewable Energy-to-Grid Integration	Explore hybrid energy storage solutions to improve renewable penetration and grid stability	On-grid integration of solar and wind with advanced hybrid storage systems.
[43]	Assessing the Economic and Technical Feasibility of Off-Grid Renewable Hybrid Systems in Remote Communities	Evaluate the cost-effectiveness and technical viability of hybrid PV-wind-biomass systems	Off-grid electrification for remote communities using PV-wind-biomass hybrid models.

As shown in Table 9, the reviewed HRES microgrid studies highlight several important technical and economic performance metrics. Renewable penetration levels were reported to range from 70% to 95% in some studies, demonstrating the strong potential of HRESs to supply a substantial portion of the load demand while reducing the diesel generator runtime, fuel consumption, and associated emissions [108]. In addition, the performance of core system components, including PV (18–22%), wind turbines (35–45%), Li-ion batteries (85–95%), and electrolyzers (60–70% efficiency), was identified as a critical factor influencing the simulation accuracy, system sizing, energy yield, and storage losses [142]. From an economic perspective, optimized HRES configurations achieved an LCOE in the range of 0.08–0.2 USD/kWh, which is significantly lower than diesel-only generation (0.3–0.6 USD/kWh) and grid extension options (0.25–0.4 USD/kWh), indicating the economic viability of well-designed remote microgrids [86]. Furthermore, advanced EMS can reduce annual operational costs by 10–25%, mainly through improved predictive control and optimization strategies that minimize fuel usage [143].

Table 9. Key technical and economic metrics of reviewed HRES microgrid studies.

Ref	Range Penetration Level	Significances
[108]	70% to 95%	Annual RF indicates renewable load coverage and can greatly reduce diesel runtime, fuel costs, and emissions. Key HRES components are crucial inputs for simulation and optimization that influence system sizing, energy production, and storage losses.
[142]	PV: 18–22% WT: 35–45% Li-on battery: 85–95% Electrolyser: 60–70% (Efficiency)	Core HRES component efficiency ranges are key inputs for simulation and optimization, directly affecting system sizing, energy yield, and storage losses.
[86]	Optimized HRES:0.08–0.2 $/KWh Diesel generator: 0.3–0.6 $/KWh Grid extension: 0.25–0.4 $/KWh	LCOE results demonstrate HRES economic, with well-designed remote MGs cheaper than a diesel-only system.
[143]	10–25% reduction from annual operational cost	Advanced EMS reduces fuel consumption by minimizing the use of predictive control and optimization algorithms.

8. Challenges and Future Directions

Insufficient rural electrification leads to challenges that hinder the development and improvement of the standard of living. Bringing electricity lines to isolated regions is challenging because of rugged landscapes, which increase the cost of infrastructure development. Communities that set up solar systems and MGs in rural areas are usually burdened with buying costly equipment and finding skilled professionals to install them. Problems in storing renewable energy often lead to operational instability in renewable energy systems.

Several challenges affect the adoption of EVs, including limited charging infrastructure, high purchase prices, extended recharge times, challenges in battery durability, and limited availability of diverse and affordable models. However, innovations in battery technology, rapid charging, and V2G systems are solving these problems and making EVs more efficient and convenient for use. The coming years may see an increase in the range of available EVs and enhanced efforts from governments to support this shift into a more environmentally friendly manufacturing platform, and promote the integration of advanced autonomous systems.

To address the challenges associated with optimizing the adoption of HRESs with BESS integration, the following measures are recommended:

(i) Public-Private Partnerships should allow government organizations to connect with NGOs and private businesses to share development costs and risks related to infrastructure construction.
(ii) Greater emphasis should be placed on developing solar-powered mobile healthcare and educational units that can provide transportable and self-sustaining services to remote and underserved communities.
(iii) Expanding the use of renewable energy can significantly reduce greenhouse gas (GHG) emissions and other harmful pollutants. In this context, the integration of hybrid BESS and EVs can help compensate for the intermittency of HRESs, reduce fuel consumption, and improve environmental performance. Simultaneously, efforts should continue to lower the installation and maintenance costs associated with achieving fully renewable energy systems.
(iv) The organization should develop international partnerships to seek funding and deploy rural energy initiatives across the globe, and establish platforms to exchange proven successful techniques.
(v) Recent research utilizes stochastic and resilient optimization techniques to address uncertainties in the operation, control, and scheduling of MG. Future research should focus on ML and AI-based uncertainty management to identify and model sources of uncertainty, ensuring the smooth functioning of the next generation of MGs.
(vi) In addition to RES, load, and electricity price uncertainty, BESS and DSM techniques, such as the DR program, should be considered in MG scheduling. These techniques use AI or soft computing to predict variable states and maximize system benefits through peak shaving and filling activity.
(vii) The development of customized cybersecurity protocols alongside the investigation of protective frameworks against natural disasters and supply chain disruptions will improve MG's resilience and security performance, and Virtual Power Plant-Expanding MG cooperation beyond the local boundary.
(viii) Network MG-Distributed control and cooperative power exchange, and Mobile MG-Enhancing resilience through portable power solutions.
(ix) Overall, the integration of new HRES technologies with BESS has the potential to overcome many of the limitations of earlier systems and shows strong promise for future MG operation. Key research areas include optimal sizing, cost reduction, safety enhancement, and advanced system management.

Policy plays a key role in leading a nation to the effective exploitation of its energy resources in socio-economic development. So, it is necessary to emphasize that the existence of an energy policy is vital. The presence of policy, however, does not ensure the responsible management of energy resources of a nation [144].

Ethiopia has seen an end to its archaic hydropower-centered policy of 1994, and a diversified energy policy of 2018, with priorities of decentralized rural accessibility and renewable energy diversification shown in Table 10. This new policy is carried out by the modified National Electrification Program, which seeks to have all the people have access to electricity by the year 2025 to enable the country to have middle-income status [145].

Table 10. Key energy policies and strategies in Ethiopia [144,145].

Name of Policy	Year	Description
National Energy Policy of Ethiopia	1994	The federal republic's first national energy policy addressed all sectors, aiming to harness energy resources for development. Although electricity receives limited focus, it provides a comprehensive framework for national energy objectives.
Climate Resilient Green Economic Strategy	2011	The initiative outlines energy and economic strategies to tackle climate change to become a climate-resilient economy and reach the middle-income status by 2025.
Ethiopia National Energy Policy	2012	An amended 1994 policy addressing economic development, global environmental changes, and broader inclusions.
National Electrification Program Implementation Road Map and Financing Prospectuses	2017	A government program that spells out plans and programs to be implemented to enable the attainment of universal electricity accessibility by the year 2025 through the nationwide expansion of the national grid and increasing off-grid programs across the nation.
National Energy Policy	2018	An updated energy policy addressing previously overlooked challenges, while aligning with other strategies and maintaining the national ambition of reaching middle-income status by 2025.
National Electrification Program: Integrated Planning for Universal Access	2019	Revised and updated NEP 2017, with revisions that provide the progress in place at the time, and recommendations based on analysis to be aligned by 2025 to achieve universal access.

Authors in [146] present the World-Wide Fund for Nature's (WWF) Global Energy Policy Framework, outlining an urgent, holistic strategy to transition the world to a 100% RES by 2050. It emphasizes five key action areas: reducing energy demand through efficiency and sufficiency; phasing out fossil fuels; generating electricity exclusively from renewables; electrifying all possible sectors; and developing renewable solutions for hard-to-electrify industries. The framework advocates for a transformation that is faster, greener, and fairer, accelerating deployment, minimizing harm to nature, and ensuring equitable access and climate justice. It also calls for supportive global and regional policy landscapes, including targeted incentives, ambitious regulations, carbon pricing, streamlined permitting, and financial mechanisms to drive renewable energy integration and grid modernization. WWF positions itself as a neutral, global catalyst, leveraging its expertise and network to guide policies, investments, and community actions toward a sustainable energy future that mitigates climate change and reverses biodiversity loss.

9. Conclusions

The review comprehensively examines the global implementation of HRES-based MGs in both off-grid and on-grid settings, with particular emphasis on the optimization techniques employed for their optimal sizing and operation. This demonstrates that HRES-based MGs are integral to providing sustainable, reliable, and resilient energy access by integrating solar, wind, biomass, hydropower, and energy storage technologies. These systems have significant potential to reduce reliance on fossil fuels, decrease greenhouse gas emissions, and promote energy equity, particularly in remote and rural areas of developing countries. Despite considerable technological advancements and the promising outcomes of numerous pilot projects worldwide, several challenges remain. These include system optimization, real-time control, economic viability under uncertainty and risk, and long-term policy and regulatory integration. This review also addresses relevant mathematical models, optimization methods, and the increasing role of EVs in supporting utility grids and power systems. Based on these findings, future research should focus on developing hybrid AI-stochastic optimization frameworks for real-time MG control, enhancing EV participation through V2G strategies, modeling uncertainty-aware EMSs for high renewable penetration, incorporating cybersecurity and resilience metrics into MG planning, and validating proposed models using real operational MG data. In conclusion, HRES-based MGs represent a promising pathway toward a cleaner, smarter, and more inclusive energy future.

Glossary of Acronyms

ACS	Annualized cost of the system
AI	Artificial intelligence
BESS	Battery energy storage systems
BL	Battery longevity
BMG	Battery management group
CCSA	Chaotic Map-Based Chameleon Swarm Algorithm
CDF	Customer damage function
CE	Carbon emission
CERTS	Consortium for Electric Reliability Technology Solutions
CRF	Capital recovery factor
CSP	Concentrated solar power
DE	Discharged energy
DERs	Distributed energy resources
DG	Distributed generation
EENS	Expected Energy not Supplied
EMS	Energy management systems
EVCS	Electric vehicle charging station
EVs	Electric vehicles
G2V	Grid to vehicle
GA	Genetic algorithm
GA-MCS	Genetic algorithm-Monte Carlo simulation
GERD	Grand Ethiopia Renaissance Dam
GHG	Greenhouse gas
HESS	Hybrid energy storage system
HEV	Hybrid electric vehicle
HP	Hydropower
HRES	Hybrid renewable energy systems
ICE	Internal combustion engine
IRR	Internal rate of return
LA	Level of Autonomy
LCOE	Levelized cost of energy

LCP	Lifecycle cost of the project
LDU	Load Demand Uncertainties
LOEE	Loss of energy expectation
LOLE	Loss of Load Expectation
LOLP	Loss of load probability
LPSP	Loss of power supply probability
MGs	Micro-grids
MILP	Mixed-integer linear programming
MPC	Model Predictive Control
MPPT	Maximum Power Point Tracker
NPC	Net present cost
PEV	Plug-in electric vehicle
PHEV	Plug-in hybrid electric vehicle
PP	Payback period
RES	Renewable energy sources
RF	Renewable factor
RI	Reliability index
SAIDI	System average outage interruption duration index
SAIFI	System average interruption frequency index
SEPIC	Single-ended primary inductor converter
SPP	Simple payback period
TAC	Total annual cost
THD	Total harmonic distortion
V2G	Vehicle to grid
V2H	Vehicle to home
WT	Wind turbine
WWF	World Wide Fund

Author Contributions

F.M.G.: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Resources; Software; Validation; Visualization; Writing—original draft; Writing—review and editing. C.W.; Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Supervision; Resources; Software; Validation; Visualization; Writing—original draft; Writing—review and editing. P.M.M.; Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Supervision; Resources; Software; Validation; Visualization; Writing—original draft; Writing—review and editing. All authors have read and agreed to the published version of the manuscript.

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