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Comprehensive Review of Sizing Methodologies for Optimal Design of Hybrid Renewable Energy Systems

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Abstract- Hybrid Renewable Energy Systems (HRES) are becoming a viable method to provide the ever-increasing energy demands with less reliance on traditional fossil-fuel power generation. Sizing of the components of these systems is a critical design element that has a significant impact on the performance, reliability and economic viability of the systems. The present paper provides a detailed review of the prominent sizing methods used in HRES, such as traditional optimization methods, AI-based methods, hybrid optimization methods, and software-assisted design methods. The study reviews the literature and commonly adopted modeling platforms in depth and analyzes the operational principles, advantages, disadvantages and suitability of the methods for solving the highly non-linear, uncertain and multi-objective nature of HRES design problems. Intelligent and hybrid optimization methods are usually superior when dealing with complex search spaces, uncertainty and conflicting design goals, software-based tools are usually more practical and user friendly when analyzing systems, given some modelling limitations. The results also reveal that there is no universally best sizing technique, as it is dependent upon system requirements, resources characteristics, optimization goals and user expertise. The study offers a new comparative review of the existing sizing approaches, which can serve as useful guidance for energy planners, engineers and researchers aiming to increase system reliability, reduce lifecycle costs and pursue the deployment of sustainable energy in remote and underserved regions. Further, the review highlights new research areas and gaps that can be used to augment the creation of more comprehensive and efficient HRES sizing frameworks.

Keywords: Hybrid renewable energy systems, Metaheuristic algorithm, multi-objective optimization, performance metrics, software-based modelling.

I.Introduction

Rapid population growth, expanding economies, and rising standards of living continue to intensify global energy demand [8]. In response to the environmental and sustainability challenges associated with conventional power generation, renewable energy technologies have become increasingly attractive alternatives for meeting this demand [4], [21]. Yet, these resources, particularly solar and wind, are inherently intermittent and fluctuate with weather and climatic conditions, limiting their reliability in standalone applications [22]. To address these limitations, hybrid renewable energy systems (HRES), which combine complementary energy sources and storage options, have gained prominence as a technically and economically viable solution [16]. The HRES have surfaced as a viable remedy to address the growing energy demand while mitigating environmental issues related to traditional power generation using fossil fuels [35]. These systems integrate multiple renewable energy sources (RES), such as wind, solar, and hydro, together with energy storage technologies and, in some cases, conventional generators. Optimal sizing and design of HRES components play a crucial

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role in ensuring the cost-effectiveness, reliability, and sustainability of the power system [48]. Over the years, various sizing methodologies have been developed and employed for HRES design, ranging from traditional analytical and numerical methods to advanced artificial intelligence (AI) techniques and combined (hybrid) algorithms. The traditional approaches, such as probabilistic, numerical, graphic construction, iterative, and analytical approaches, have been widely used owing to their simplicity and ease of usage [27], [33], [51]. However, these methods often face limitations in handling the complexity, nonlinearity, and dynamic nature of HRES, as well as the need for extensive data and computational resources [16].

AI-based techniques such as Cuckoo Search (CS), Ant Colony Optimization (ACO), Artificial Bee Colony (ABC), Particle Swarm Optimization (PSO), Simulated Annealing (SA), Genetic Algorithms (GA), and Harmony Search (HS), have gained significant attention in addressing these challenges [20], [47]. These methods can effectively tackle nonlinear and complex problems, handle incomplete data, and account for intermittency issues associated with renewable energy sources [3]. Moreover, hybrid techniques that integrate the strengths of different algorithms have been explored to leverage their advantages and obtain better sizing results [7].

Several software tools, including hybrid optimization genetic algorithm (HOGA), transient system simulation tool (TRNSYS), hybrid optimization model for electric renewables (HOMER), general algebraic modelling system (GAMS), hybrid power simulation model (HYBRID2), and (HYBRIDS), have been created in addition to sizing approaches to maximize the component capacities of HRES [23], [46]. The tools offer different approaches, optimization objectives, and user flexibility. Still, they have limitations in terms of calculation time, visibility of algorithms, consideration of probabilistic analysis, and integration of advanced optimization techniques [42].

Evaluating the performance and sustainability of HRES requires a comprehensive set of indicators spanning economic, environmental, social, and technical aspects [19]. Economic indicators, such as net present value (NPV), cost of energy (COE), total annualized cost (TAC), the annualized cost of the system (ACS), life cycle cost (LCC), and levelized cost of energy (LCOE) assess the financial feasibility of the system [28]. Environmental indicators, like embodied energy (EE), carbon emission (CE), carbon footprint of energy (CFOE), and life cycle assessment (LCA) quantify the system's impact on the environment [29]. Social indicators, including social cost of carbon (SCC), portfolio risk (PR), job creation (JC), human development index (HDI), and social acceptance (SA), measure the system's contribution to sustainable development [31], [32]. Additionally, technical indicators, such as loss of load probability (LOLP), loss of power supply probability (LPSP), expected energy not supplied (EENS), loss of load expected (LOLE), and loss of energy expected (LOEE) evaluate the system's reliability and performance [4], [25].

This study contributes to HRES optimization by providing a comprehensive analysis of optimization techniques, proposing a framework for method selection, and identifying research gaps. These contributions aim to enhance HRES design efficiency and guide future research in this field. This Section (introduction) establishes the research context, highlighting the critical role of renewable energy systems and the need for advanced optimization techniques. Section 2 (objectives) delineates the study's purpose in systematically evaluating sizing methodologies. Section 3 gives the literature underpinning the study and elaborates on the research approach, detailing decision variables, objective functions, and constraint frameworks. Section 4 (research methodology) gives the methodological framework adopted in this study which centers on identifying and analyzing the key performance indicators commonly applied in the optimal HRES. Section 5 (results) presents a critical analysis of optimization techniques, encompassing traditional methods, AI-driven approaches, hybrid algorithms, and software tools. Section 6 (discussion) rigorously interprets findings, contextualizing performance metrics and identifying research gaps. Section 7 (conclusion) synthesizes key insights, providing strategic recommendations for future HRES design and optimization research. By integrating diverse methodological perspectives, this review offers a comprehensive assessment of current HRES

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optimization strategies and their potential for sustainable energy solutions.

II.**Objective**

This review paper aims to provide a comprehensive and critical examination of Hybrid Renewable Energy System (HRES) optimization methodologies. The primary objectives are to systematically evaluate sizing techniques across traditional, AI-driven, hybrid approaches, and software tools, critically analyzing their capabilities in addressing HRES complexity and nonlinear optimization challenges. By rigorously analyzing performance metrics, the study seeks to identify methodological limitations, assess multi-dimensional optimization strategies, and illuminate potential research directions for developing advanced, reliable, and sustainable HRES design techniques.

III.**Theories/Literature Underpinning the Study**

A wide range of theoretical and methodological foundations supports research on HRES. Understanding these foundations is essential because HRES design involves combining multiple energy sources, storage technologies, and power management strategies under varying environmental and load conditions. Recent literature highlights the diversity of system configurations, the complexity of optimization requirements, and the evolution of analytical and computational techniques used in HRES modelling.

This section provides an overview of the principal classifications of HRES, the optimization theories that guide their design, and the methodological approaches widely adopted in contemporary studies. It outlines how traditional analytical techniques, artificial intelligence algorithms, hybrid metaheuristic models, and software-based tools have been applied to address multi-objective, nonlinear, and constraint-driven challenges associated with HRES sizing and performance evaluation. By synthesizing these theoretical perspectives, the section establishes the foundation upon which modern HRES research is built and sets the stage for the detailed methodological discussions that follow.

The HRES can be classified based on the combination of renewable energy sources (RES) and energy storage (ES) systems employed, as well as the presence of non-renewable energy sources [37], [45]. Figure 1 shows the criteria for classification are:

i.Inclusion of one RES and ES

ii. Combination of two or more RESs (with or without ES)

iii. Integration of one or more RESs and one or more non-renewable energy sources (with or without ES)

Based on the available literature, hydropower/pumped hydro storage (PHS), solar/photovoltaic (PV), and wind are the main RES used in HRES. The power generation from these sources is affected by factors like runoff, solar irradiation, wind speed, and ambient temperature.

HRES without hydropower or pumped hydro storage [26]. This category primarily includes combinations such as PV-wind, PV-ES, wind-ES, PV-wind-ES, and PV-wind-diesel-ES systems [26]. More than 90% of these systems are off-grid, and energy storage is commonly employed to improve the power supply reliability due to the intermittent nature of wind and solar energy sources [4].

HRES with hydropower and/or pumped hydro storage: Hydropower/PHS is advantageous compared to energy storage batteries in terms of capacity, flexibility, reliability, and economic costs [4], [42]. Therefore, this system is being studied as a crucial topic, and many countries with feasible conditions, such as Brazil, the United States, and China, are producing designs and applications for large-scale grid-connected hydro-PV-wind multi-energy complementary bases to promote rapid development of renewable energy and build a clean, low-carbon, safe, and efficient energy system [4], [6].

The classification of HRES based on the integration of different renewable and non-renewable sources, as well as energy storage systems, is essential for understanding the system configurations and their potential applications.

A.Optimization of HRES

The optimization of HRES is a multi-objective, non-linear, non-convex problem with discrete and integer variables and non-linear and linear constraints [11]. The multimodal nature of the HRES sizing issue necessitates investigating the global optimum solution. The primary objective in designing an HRES is to continuously supply the

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required load while minimizing costs and satisfying all imposed constraints [11], [14]. Optimization is identifying the most cost-effective outcomes within
specified constraints, aiming to maximize desired factors and minimize undesired ones. This involves achieving maximum yields with minimal effort. In recent years, the utilization of metaheuristic techniques in real-world problems has witnessed a notable increase in finding applications across diverse research domains [16].

To design an HRES, four primary viewpoints must be identified: optimization techniques, decision variables, objective function, and cost. The general mathematical formulation of an optimization problem is as follows:

$$\text{Min } F(k_1, k_2, \ldots, k_n)$$
$$\text{limits } G(k_1, k_2, \ldots, k_n) \geq 0$$
(1)
$$k_i \in S_i$$

Here, F is the objective function, k_i is the variable vector, G is the constraint function, and S_i is the solution set for variable ranges or types [11].

Optimization problems can be categorized across multiple dimensions, including constrained or unconstrained formulations, discrete or continuous variables, single or multiple objectives, and deterministic or stochastic methodologies. Multi-objective optimization problems involve optimizing

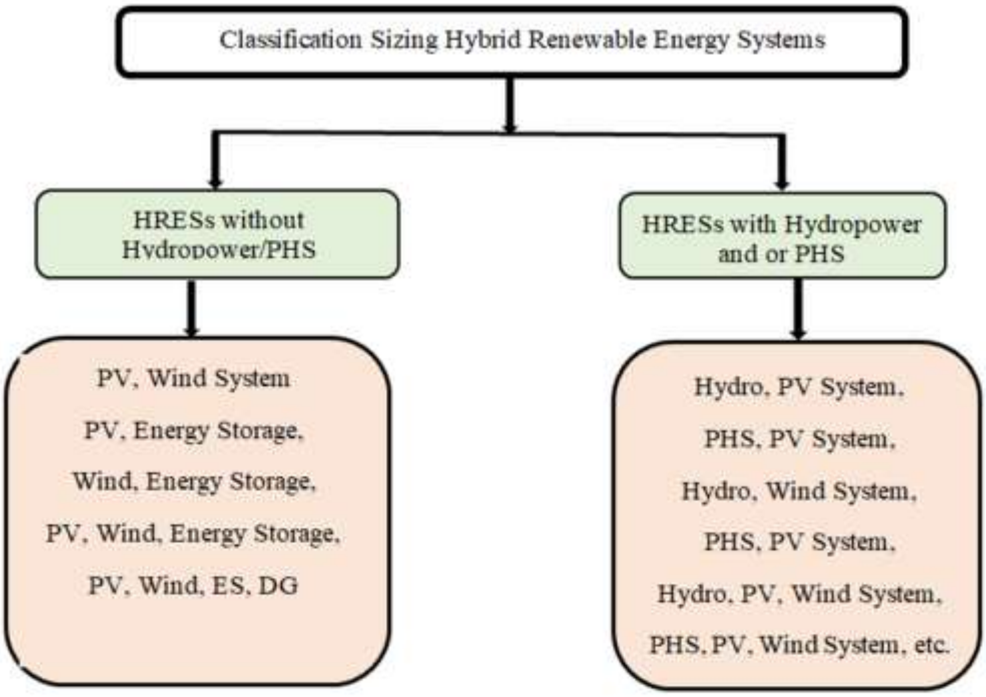

Figure 1. Classification Criteria of Sizing HRES

multiple objectives concurrently, and the concept of Pareto optimality is crucial in solving such problems. Pareto-optimal solutions are non-dominated solutions where no objective can be enhanced without deteriorating at least one other objective, forming the Pareto front [11]. The general mathematical formulation of multi-objective optimization problems is given as in Equation 2 [11].

$$\begin{cases} \text{minimize } F(k) = \left(f_1(k), \ldots, f_f(k)\right)^T \\ h_i(k) = 0, i = 1, \ldots, m, \\ g_i(k) \leq 0, j = 1, \ldots, n, \\ \text{Limits } k_L \leq k \leq k_U \end{cases}$$
(2)

with $k \in \mathbb{R}^d$ is the vector of decision variables, $\{f_1, \ldots, f_l\}$ is the ensemble of objective functions [11]. The optimization of HRES falls under the category of multi-objective optimization problems, where numerous objectives, such as minimizing

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costs, maximizing reliability, and minimizing environmental impact, need to be optimized simultaneously while considering various constraints and decision variables [44]. However, multi-objective problems pose a unique challenge due to the absence of a universally optimal solution. Researchers and practitioners have developed methods to either transform the problem into a single-objective form or generate a set of solutions with Pareto-optimality, providing decision support to aid in the selection of the most appropriate solution based on the specific requirements and constraints of the problem [11].

1).Decision variables

Decision variables are the quantities that need to be determined, such as the number, types, and capacities of various system components, including distributed energy generators (e.g., photovoltaic (PV), wind turbines, biomass, diesel generators), energy storage systems (e.g., batteries, fuel cells), and energy conversion devices (e.g., converters, inverters). Defining these decision variables is one of the most challenging steps in formulating the problem [11].

2).Objective function

The objective function defines the optimization goal, which is used to find the optimal sizes of HRES components to reduce costs while ensuring a stable and environmentally adequate power supply. Numerous indicators reported in the literature, including reliability, economic, and environmental factors, are used to assess the HRES and determine the appropriate system capacity. In addition to these indicators, some studies have considered social assessments, such as social acceptance, portfolio risk, job creation, human development index, and social cost of carbon [11] as presented in subsequent sections.

3).Constraints

Constraints are logical relationships or properties that the variables must satisfy, limiting the search space for the optimization algorithm. These constraints can take the form of equalities or inequalities, either linear or non-linear. In HRES optimization, constraints may include the number, capacity, installation area, or other specifications of the system components [11].

A. Sizing Optimization Methodologies for HRES

Accurate sizing of components is crucial for the effective design and operation of HRES. Due to the intermittent nature of RES, as well as the significant variation in electricity consumption patterns based on time of day and season, the problem of sizing HRES is critical [11]. Various methodologies have been developed and employed for optimal sizing of HRES, each with its strengths and limitations. These methodologies can be broadly categorized into traditional approaches, artificial intelligence (AI)-based approaches, hybrid algorithms approaches, and software methods, each having strengths and limitations [7]. Accurate sizing of HRES components is essential to ensure reliable and cost-effective operation while meeting energy demands and adhering to environmental constraints. The flowchart in Figure 2 illustrates the various sizing methodologies employed for HRES.

1).Traditional Sizing Methods

Traditional methods for sizing HRES have been widely employed and extensively studied in the literature. These methods aim to determine the optimal configuration and sizing of the system components, such as RES, ESS, and conventional generators, to meet specific design objectives and constraints. The primary traditional methods can be categorized as follows [27], [33], [50], [51];

i.Graphic construction method
ii.Probabilistic method
iii.Iterative method
iv.Numerical method
v.Analytical method

Generally, these traditional methods often face limitations in handling the complexity, nonlinearity, and dynamic nature of HRES, as well as the need for extensive data and computational resources. Table 1 presents the reviewed traditional methods along with their limitation.

2).Artificial intelligence methods

Artificial Intelligence (AI) methods or algorithms are computational techniques and models designed to exhibit intelligent behavior and solve complex problems by imitating certain aspects of human intelligence [13], [50], [51]. Compared to traditional approaches, AI algorithms can effectively tackle nonlinear and intricate problems, as well as handle inconsistent data records and intermittent issues associated with solar and wind power generation [42]. Therefore, by performing intricate calculations, an

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appropriate global optimal scheme based on AI algorithms can efficiently identify the maximum economic feasibility and reliability of the system [47]. A range of studies have explored the optimal sizing and design of HRES using various Artificial Intelligence (AI) algorithms. These algorithms include CS, ACO, ABC, RKO, PSO, SA, GA, and HS. Table 2 gives the review summary.

3.Hybrid methods

The goal is to efficiently leverage the strengths of individual techniques and obtain better capacity results [42]. Therefore, hybrid approaches are more effective than single techniques in addressing the complex and multifaceted optimization problems associated with the optimal sizing of HRES. Although hybrid approaches might lessen some of the drawbacks of single approaches, they may still

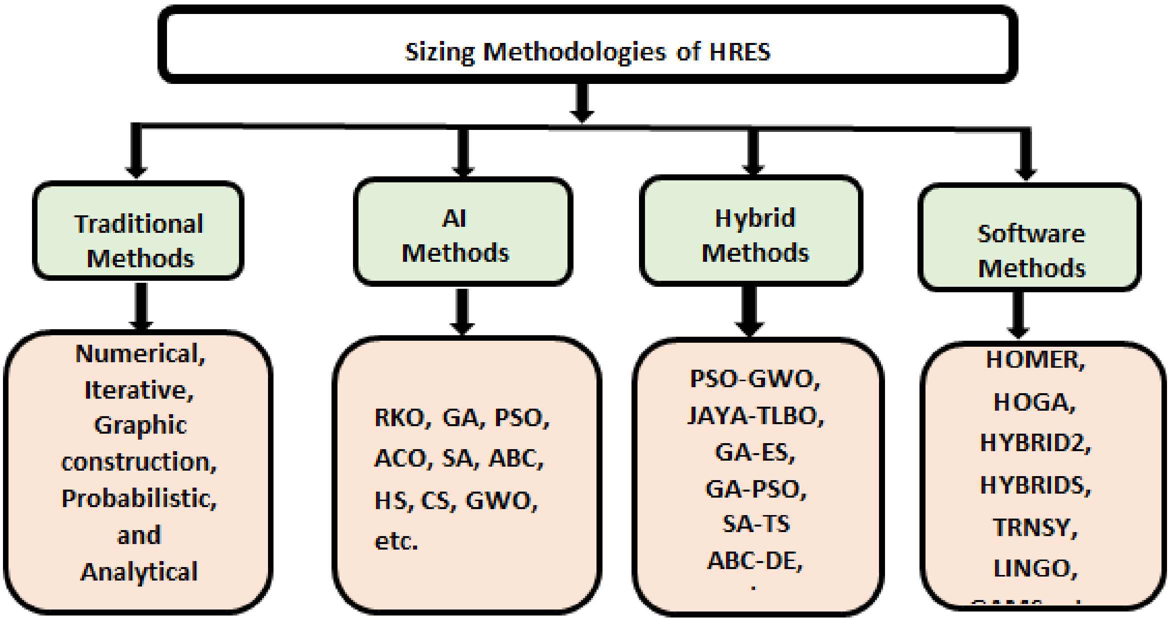

Figure 2: Sizing Methodologies of HRES

Table 1 Review summary of traditional methods

Author(s)	Method/Technique	Limitations
[27]	Graphic Construction Method	Lacks flexibility, involves various approximations, and risk of system component over/under-sizing
[51]	Probabilistic Method	May fail to provide optimal results, cannot accurately represent system dynamic performance, and results may not be suitable as optimal scheme
[33]	Iterative Method	Cannot optimize crucial parameters such as solar PV panel solar PV inclination angle, Solar PV panel area, WT swept area, WT installation height
[36], [51]	Numerical Method	Requires long-term meteorological data, demands extensive calculations, and computationally intensive particularly for stochastic approaches
[27]	Analytical Method	Difficulty in estimating position-related mathematical equation coefficients, may affect sizing results accuracy, and limited by mathematical complexity

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when handling extremely difficult, multi-modal optimization problems with a large number of constraints [18]. Additionally, the computational complexity and parameter-tuning requirements of hybrid methods can be higher than single methods, potentially increasing the computational burden and the need for domain-specific expertise [49]

4.Software tools method

Numerous software programs with various calculation modules are used to maximize the HRES component capacity [23] These software tools offer different approaches and capabilities for HRES capacity optimization, with varying levels of accuracy, data requirements, optimization objectives, and user flexibility. However, limitations exist in terms of calculation time, visibility of algorithms, consideration of probability analysis, and integration of advanced optimization techniques. Some commonly used software tools include [23]:

i.HOMER
ii.HOGA
iii.HYBRID2
iv.HYBRIDS etc.

While these software tools offer various methods and capabilities for sizing HRES, they also have certain limitations. One significant limitation is the calculation time, which can become excessively long as the number of variables and system complexity increases, particularly for tools that use hourly or shorter time steps [49]. Additionally, some tools treat their algorithms and calculation processes as black boxes, making it difficult for users to understand and modify the underlying methodologies [33].

IV.Performance Metrics For Hres

In the process of sizing optimization for HRES, various performance metrics are employed to assess the suitability and effectiveness of the proposed system configurations. These metrics, also known as evaluation indicators serve as criteria to evaluate the system's reliability, economic viability, environmental impact, and other relevant factors. The choice of suitable performance metrics is crucial as they guide the optimization algorithms toward identifying the optimal sizing of HRES components that meet the desired objectives [11].

Common performance metrics used in HRES sizing optimization include reliability indicators, economic indicators, and environmental [11]. Additionally, some studies may incorporate social metrics, SA, JC, HDI, and PFR to holistically evaluate the system's sustainability and impact [33].

By defining and considering these performance metrics during the sizing optimization process, researchers and practitioners aim to design HRES configurations that strike the right balance between reliable energy supply, cost-effectiveness, environmental sustainability, and societal considerations.

Table 2: Review summary of AI-based methods

Authors	AI Algorithm	Strengths and Applications
[17]	HS	Superior performance in HRES component optimization, and effective for comprehensive system component sizing
[47]	PSO	Demonstrated effectiveness in HRES sizing
[8], [10]	CS	Achieves global minimum cost conditions, prevents local minima problems, and superior accuracy and computational time compared to GA and PSO
[8], [34]	HS	Provides most techno-economically optimal unit sizing, superior performance compared to Jaya and PSO, and effective for comprehensive system optimization
[15], [43]	GWO	Achieves lower total annual costs, faster convergence rates, potential benchmark algorithm for HRES optimization and effective for hybrid wind and solar systems

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A. Reliability Indicators

Reliability indicators play a crucial role in evaluating the ability of HRES to meet load demands, considering how weather and climate change can have an unpredictable impact on power generation [17]. These indicators are essential for evaluating the reliability and adequacy of proposed HRES configurations in meeting the energy demand. The following subsections present the reliability indicators which often quantify the extent of energy deficits, supply failures, or unmet load over a defined time horizon.

1).Loss of Power Supply Probability (LPSP)

LPSP expresses the proportion of the total demand that could not be served throughout the simulation period [17]. The generalized form of LPSP is espressed in Equation 3.

$$\mathrm{LPSP} = \frac{\sum_{\tau=1}^{T} D_{def}(\tau)}{\sum_{\tau=1}^{T} P_{load}(\tau)\Delta\tau} = \frac{\sum_{\tau=1}^{T} F(\tau)}{T} \quad (3)$$

Where:

$D_{def}(\tau)$ = power deficit at time τ

$P_{load}(\tau)$ = demanded power

$\Delta\tau$ = simulation time step

T = total number of time steps considered

2).Loss of Load Probability (LOLP)

The Loss of Load Probability quantifies the fraction of the annual demand that the hybrid system fails to supply due to insufficient generation or storage. It provides a probabilistic measure of supply inadequacy over a typical year [25], [50], [51]. A generalized mathematical form of this indicator is given as in Equation 4 which characterizes the overall likelihood of experiencing unmet demand by comparing cumulative energy deficits to the total annual load requirement

$$\mathrm{LOLP} = \frac{\sum_{t=1}^{N} E_{short}(t)}{\sum_{t=1}^{N} L_{d}(t)} \quad (4)$$

Where:

$E_{short}(t)$ = energy not supplied at hour t

$L_d(t)$ = hourly load demand

N = number of hours in a year

3)Expected Energy Not Supplied (EENS)

The Expected Energy Not Supplied represents the cumulative amount of electrical demand that remains unmet over a full evaluation period. Unlike probability-based measures, EENS directly quantifies the magnitude of energy deficits, making it an important indicator for assessing reliability and adequacy in HRES planning [37]. The mathematical representation of this metric is given in Equation 5.

$$\mathrm{EENS} = \sum_{t=1}^{N} E_{unsup}(t) \quad (5)$$

Where:

$E_{unsup}(t)$ = energy shortfall at time t

4.Deficiency of Power Supply Probability (DPSP)

DPSP expresses the proportion of total demand that remains unmet during the evaluation period, serving as a key indicator of supply inadequacy [6], [52]. The mathematical formulation is expressed in Equation 6 and it quantifies how frequently the system fails to satisfy demand and is widely used to assess HRES reliability

$$\mathrm{DPSP} = \frac{\sum_{t=1}^{T} D_{unsup}(t)}{\sum_{t=1}^{T} L(t)} \quad (6)$$

Where:

$D_{unsup}(t)$ = unmet load

$L(t)$ = load demand at time step t

B.Economic Indicators

The economic status is reflected in phases of the system's design, installation, refinement, and operational stages. The HRES optimization aims to develop a system capable of meeting and handling the load demand at an acceptable cost [34], [49]. Consequently, to evaluate the viability of HRES, economic metrics that account for startup costs, operating expenses, maintenance costs, and other expenditures are now essential. The following summarizes the major indicators applied in recent optimization studies.

1).Total Annualized Cost (TAC)

The TAC estimates the yearly cost required to install, operate, and maintain the system. It is expressed as the sum of annualized capital expenditure and annual maintenance cost [49]. Equation 7 gives the mathematical representation of TAC.

$$\mathrm{TAC} = C_{cap,ann} + C_{main,ann} \quad (7)$$

Where:

$C_{cap,ann}$ = annnualized capital cost

$C_{main,ann}$ = annual operation and maint cost

The annualization is typically performed using a capital recovery factor (CRF), computed as in equation 8. The CRF is used to convert the total capital investment into annualized equivalent.

$$\mathrm{CRF} = \frac{r\,(1+r)^{d}}{(1+r)^{d}-1} \quad (8)$$

Where:

r = discount rate (fraction/year)

d = syestem lifetime(year)

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2).Annualized cost of the System (ACS)

The ACS expands the TAC formulation by including the annual replacement cost components as expressed in Equation 9 [39].

$$ACS = C_{cap,ann} + C_{main,ann} + C_{rep,ann} \quad (9)$$

Where:

$C_{rep,ann}$ = annnualized replacement cost

3).Cost of Energy (COE)

The COE denotes the average unit cost of electricity delivered by the system [5]. First, the total annual energy production (T_{AEP}) is obtained and expressed as in equation 10.

$$T_{AEP} = \sum_{i=1}^{Y_d} E_{gen}(i) \quad (10)$$

Where:

Y_d = total number of days in a year (365)

$E_{gen}(i)$ = genererated energy on day

The mathematical expression of COE is given in Equation 11.

$$COE = \frac{\sum_{i=1}^{n} A_{CSi}}{\sum_{i=1}^{n} T_{AEPi}} \quad (11)$$

Where:

A_{CSi} = annualized cost for each component i

n = number of components or time steps

4).Life Cycle Cost (LCC)

The LCC accounts for all expenditures over the entire project lifetime, including initial investment, discounted operating costs, replacement expenses, and salvage value [2]. Equation 12 gives the mathematical expression of this indicator which supports long-term financial evaluation.

$$LCC = C_{initial} + C_{OM,npv} + R_{npv} - S_{npv} \quad (12)$$

Where:

$C_{initial}$ = initial capital investment

$C_{OM,npv}$ =net present value over operation and maintenance

R_{npv} = NPV of replacements over system life

S_{npv} = salvage value at the end of life

5).Levelized Cost of Energy (LCOE)

The LCOE expresses the lifetime cost per unit of electricity delivered. It is derived by dividing the total annualized cost by the total energy supplied [41]. The LCOE is characterized by the mathematical formulation in Equation 13.

$$LCOE = \frac{TAC}{E_{tot}} \quad (13)$$

Where:

E_{tot} = total energy produced by the HRES

6).Net Present Value (NPV)

The NPV evaluates the profitability of an HRES by discounting future incomes and costs to present value and is mathematical expressed in Equation 14 *(Meenakumari, 2021)*.

$$NPV = \Sigma NPV_i + \Sigma NPV_e - C_i - \Sigma NPV_{OM} - \Sigma NPV_r \quad (14)$$

Where:

NPV_i = present value of income from energy sales

NPV_e = end of life value of the system

C_i = initial investement cost

NPV_{OM} = present value of operation and maintenance costs

NPV_R = presesent value of replacement cost

B. Environmental Indicators

The Fossil sources of energy contribute to numerous pollution problems, such as the significant release of sulfur dioxide and carbon dioxide. The notable reasons for developing RES are to lessen the energy access challenges,minimize environmental contamination, and attain sustainable environmental growth. These indicators quantify greenhouse gas emissions, material and manufacturing impacts, and overall lifecycle burdens associated with system deployment. These indicators should therefore be given enough consideration in the HRES optimization design to keep up with the current trend in energy development [12], [29]. The following summarizes the principal environmental indicators adopted in recent HRES sizing studies.

1).Carbon Emissions (CE)

The CE estimate the amount of greenhouse gases produced during system operation [30]. The generalized representation is given in Equation 15.

$$E_{tce} = \sum_{t\epsilon T} \sum_{n\epsilon N} E_{fgn} g_{on,t} \quad (15)$$

Where:

E_{tce} = total carbon emissions over period T ($kg\ CO_2$)

E_{fgn} = emission factor of generator n ($kg\ CO_2/kWh$)

$g_{on,t}$ = electrical output of generator n at time t (kWh)

T = total time horizon

N = number of emmiting components

2).Embodied Energy (EE)

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The EE accounts for the total energy consumed during the manufacturing, transport, and installation of HRES components [38]. The Typical expressions for HRES components are presented in equations 16. The EE highlights the upfront environmental cost of system construction.

$$\begin{cases} EE_{WT} = 28.342A_{wt}^2 + 2361.3A_{wt} \\ EE_{PV} = 3379A_{PV} \\ EE_{Bat} = 60 \times C_n \end{cases} \quad (16)$$

Where:

EE_{PV} = embodied energy of PV array (MJ)
A_{PV} = PV area (m^2)
EE_{WT} = embodied energy of wind turbine (MJ)
A_{wt} = swept area of wind turbine (m^2)
EE_{Bat} = embodied energy of battery bank (MJ)
C_n = norminal storage capacity (Ah or kWh, depeending on the model)

3).Carbon Footprint of Energy

The carbon footprint of energy (CFOE) reflects the ratio of lifecycle emissions to the energy delivered by the system. It supports environmental comparison among competing designs [39]. A generalized mathematical representation of CFOE is given in Equation 17.

$$CFOE = \frac{Y_{PV}(P_r)+Y_{strc}(P_r)+Y_{Bt}(K_{Bt})}{d_{sl}.E_L} + \frac{Y_{inv}(P_r)+Y_{binv}(P_{binv})+Y_{Wt}(P_r)+Y_C(P_r,K_{Bt})}{d_{sl}.E_{dL}} \quad (17)$$

Where:

Y_{PV} = carbon emissions associated with PV modules
Y_{strc} = carbon emissions with structural components
Y_{Bt} = carbon emissions associated with the battery system
Y_{inv} = emissions related to inverter
Y_{binv} = emissions related to bidirectional inverter
Y_{Wt} = emissions related to wind subsystem
Y_C = emissions related to controller
P_r = rated power
d_{sl} = system lifetime
E_{dL} = energy delivery over lifetime

4).Life Cycle Assessment (LCA)

The LCA provides an aggregate measure of environmental burden across all system stages, including operation and component replacement [39]. A generalized yearly LCA formulation is given in Equation 18. This indicator evaluates cumulative environmental impacts and is widely used for sustainability benchmarking.

$$LCA = \left(EM_w \sum_{t=1}^{24} P_w^t.N_W.\Delta t + EM_{PV} \sum_{t=1}^{24} P_{PV}^t.N_{PV}.\Delta t + EM_{bt}.S_{bt}.N_b + EM_d \sum_{t=1}^{24} E_d^t\right) D_y d \quad (18)$$

Where:

$EM_W, EM_{PV}, EM_{Batt}, EM_d$ = emission multipliers for wind, PV, battery, and diesel components
N_W, N_{PV} = numberof wind and PV units
S_{bt} = size of battery storage system
N_b = number of batteries
E_d^t = diesel generator output at hour
Δt = time step (1 hour)
d = project duration (years)
D_y = 365 days in a yea

C. Social Indicators

Social Indicators: The goals of sustainable social development, which include decreasing air pollution and fostering the growth of associated sectors, are what drive the development of RES [33]. These indicators are essential for evaluating how energy interventions influence community well-being, the potential social impacts, benefits, and public acceptance of HRES configurations within the local and broader community context making them indispensable for sustainable energy planning [39].

1).Human Development Index (HDI)

The HDI is used to approximate the improvement in living standards attributable to increased access to electricity. Several authors [1], [26] correlate household energy availability with social well-being using an empirical expression in Equation 19.

$$HDI = 0.0978\ln\left(E_{l\_an\_per\_capita}\right) - 0.0319 \quad (19)$$

Where:

$E_{l_{an_{per_{capita}}}}$ = annual electricity consumption per person (kWh).

A higher HDI score reflects improved health, education, and living standards driven by reliable energy access.

2).Job Creation (JC)

Employment generation is another crucial social dimension, reflecting how renewable energy investments stimulate local economies. The job creation potential of HRES components has been modelled by previous

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studies [1], [24], [31] using an additive relation expressed in Equation 20.

$$JC = \beta_{PV}P_{PV} + \beta_{WT}P_{WT} + \beta_{DG}E_{DG} + \beta_{BAT}E_{BAT} + \beta_{HYD}E_{HYD} \quad (20)$$

Where:

$\beta =$ job coefficients (job per unit capacity or energy),

$P_{PV}, P_{WT}, P_{WT} =$ installed capacitors of PV, wind, and hydro systems,

$E_{DG}, E_{BAT} =$ annual diesel and battery energy throughput

3. Portfolio Risk (PR)

Portfolio risk measures the vulnerability of the energy mix to uncertainties in resource availability and generation costs. It has been widely applied in multi-resource HRES studies [11]. A general formulation is expressed in equation 21.

$$PR = \sum_{t\epsilon T}\left(\sum_{j\epsilon F}\alpha_{j,t}\sum_{n\epsilon N_j} gn_{nt}\right) \quad (21)$$

Where:

$\alpha_{j,t} =$ the variability or uncertainty level of source j at time t,

$gn_{n,t} =$ output of generator n at time t

$F =$ set of energy sources,

$N =$ evaluation period

Lower portfolio risk indicates a more robust and resilient energy system.

4.Social Cost of Carbon (SCC)

The SCC reflects the monetized environmental damage associated with carbon emissions from diesel-based generation or other carbon-emitting components. A common representation is given in Equation 22. This indicator emphasizes the long-term climate burden associated with fossil-fuel backup [11].

$$SCC = \begin{cases} \sum_{i=1}^{d} \frac{O'_{DG'}C_E}{(1+r)^i}, & \text{if diesel generation is present} \\ 0, & \text{otherwise} \end{cases}$$

Where:

$O'_{DG'} =$ operation of diesel genertors

$C_E =$ unit external costs of emissions

$r =$ the discount rate

$d =$ is the analysis horizon

5).Social Acceptance (SA)

The SA refers to the extent to which communities, regulators, and other stakeholders support an HRES project. It reflects perceived benefits, socio-economic impacts, cultural alignment, and trust in the technology [1]. Although often measured qualitatively, social acceptance plays a decisive role in determining the feasibility and long-term success of HRES deployment. It typically considers:

- **i.** perceptions of system reliability and benefits,
- **ii.** environmental and social impacts,
- **iii.** cultural alignment and local norms,
- **iv.** policy and regulatory openness.

V.Results

The review highlights the need for further research and development in advanced optimization methods, to address the challenges associated with HRES sizing, incorporating multiple objectives, handling uncertainty, and ensuring system reliability and power quality. These findings emphasize the importance of employing suitable sizing methodologies and performance metrics to design optimal HRES configurations that meet the desired objectives while addressing the complexities and challenges associated with renewable energy integration, economic viability, environmental sustainability, and social acceptance.

A.Findings on HRES Sizing Methodologies

Traditional sizing methods for HRES, face limitations in handling complexity, nonlinearity, dynamic nature, and extensive data and computational requirements.

- **i.** AI techniques, including CS, ACO, ABC, PSO, SA, GA, and HS, have demonstrated promising capabilities in tackling nonlinear and complex HRES sizing problems, handling incomplete data, and accounting for intermittency issues associated with renewable energy sources.
- **ii.** Hybrid techniques that integrate the strengths of individual algorithms have emerged as effective solutions for multifaceted and complex optimization problems associated with HRES sizing, mitigating limitations of single techniques and potentially obtaining better capacity results.
- **iii.** Software tools like HOMER, TRNSYS, HOGA, GAMS, HYBRID2, and HYBRIDS offer various approaches and capabilities for HRES sizing optimization. Still, they may have limitations in terms of calculation time, visibility of algorithms, consideration of probabilistic analysis, and integration of advanced optimization techniques.

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B. Performance Metrics for HRES Evaluation

A comprehensive set of performance metrics spanning reliability indicators, economic indicators,environmental, and social indicators are crucial for assessing the suitability and efficacy of proposed HRES configurations. The appropriate sizing method and performance metrics are crucial for designing HRES configurations that strike a balance between reliable energy supply, cost-effectiveness, environmental sustainability, and societal considerations.

VI.Conclusion

The comprehensive review HRES sizing methodologies reveals significant insights into the current state of optimization techniques and performance evaluation metrics.

A.Methodological Comparative Analysis

Traditional sizing methods demonstrate inherent limitations in addressing the complex, dynamic nature of RES. Researchers has consistently highlighted the challenges of managing nonlinear characteristics and the high computational demands in hybrid renewable energy system optimization [9], [22], [40]. In contrast, AI techniques have emerged as promising alternatives, offering more adaptable and sophisticated optimization approaches.

B.AI and Hybrid Method Advancements

The reviewed literature indicates that AI methods, including GA and PSO, have successfully addressed key challenges in HRES sizing. These techniques excel in managing incomplete data and accounting for the intermittent nature and variability of RES. Hybrid methods further enhance optimization capabilities by combining individual algorithm strengths, potentially overcoming limitations of single-approach techniques.

C.Software Tool Implications

While tools like HOMER and HOGA provide valuable optimization capabilities, their limitations in algorithmic transparency and advanced technique integration suggest a critical area for future research. The need for more sophisticated, user-friendly software tools that can incorporate complex optimization techniques is evident.

D.Performance Metrics Significance

The multifaceted performance evaluation approach demonstrates the complexity of HRES design. By integrating reliability, economic, environmental, and social indicators, researchers can develop more comprehensive and holistic system designs. This approach addresses the critical need to balance technical efficiency with broader sustainability considerations.

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