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Conference paper

Exploring Advanced Methodologies for Hybrid Energy System Sizing through Artificial Intelligence Techniques: a comprehensive review

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ABSTRACT

Hybrid energy systems (HES) provide an effective solution to the growing global energy demand while addressing the limitations of conventional sources and environmental challenges. By integrating renewable and conventional energy sources, these systems enhance reliability, reduce costs, and improve efficiency. However, the variability of renewable resources such as solar and wind makes HES design more complex. This paper explores various design and sizing methods for HES, focusing on combining clean sources, including wind and solar, with conventional energy options. Through advanced optimization techniques, including artificial intelligence (AI), the study demonstrates how AI can identify optimal configurations to ensure system reliability while minimizing costs. The paper also highlights the crucial role of HES in providing energy to remote and underserved areas with limited access. This work serves as a comprehensive introduction for researchers and engineers interested in HES sizing, offering insights into technical challenges and optimization strategies, and contributing to the advancement of sustainable energy systems.

1. INTRODUCTION

As cities expand and industries grow, the demand for energy increase, and this primarily relying on fossil fuels such as coal and oil. These traditional energy sources are finite and unevenly available across different regions of the world. In addition, they pose significant risks to the environment (Come Zebra

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et al., 2021). Conversely, renewable energy sources (RES) including wind and solar offer a cleaner, endless option. However, these green solutions come with their set of challenges, chiefly their dependence on variable weather conditions, which complicates consistent power supply (Hannan et al., 2020). In many regions, especially remote or rural areas far from urban centers, extending the main power grid is prohibitively expensive. Renewable energy steps in as a viable solution, providing localized power generation (Upadhyay & Sharma, 2014).

In light of the obstacles encountered by RESs, Hybrid Energy Systems (HES) appear as a crucial solution. These systems combine multiple forms of energy generation, such as solar and wind, often integrating traditional fossil fuels or newer, cleaner alternatives like bioenergy (Come Zebra et al., 2021). This integration supports a more stable and reliable energy supply, leveraging the strengths of each component to mitigate their individual weaknesses (Güven et al., 2024). For instance, when solar power is low due to cloudy weather, wind or photovoltaic (PV) components can compensate, ensuring a consistent energy flow. HESs offer numerous advantages, especially in improving energy security and dependability in areas where traditional power networks are inaccessible or not financially viable (Mishra et al., 2023). Moreover, they assume an essential role in minimizing emissions through the incorporation of a greater percentage of RESs, to make a significant contribution to the global effort to reduce climate change (Ali & Mohammed, 2024).

The utilization of renewable energy systems is not without complications. Determining the appropriate system size is challenging due to fluctuating local electricity demands and previously mentioned renewable energy challenges (Agajie et al., 2023). The design process must consider technological options, community needs, and resource availability (Luna-Rubio et al., 2012). This article aims to shed light on improving the reliability and efficiency of HES, particularly for specific applications. It delves into design considerations, control strategies, and the integration of different technologies to enhance system performance. Through this exploration, the goal is to advance renewable energy as a more feasible and reliable power source for a wider audience.

2. VARIATIONS IN HES DESIGNS

A HES is a combination of renewable and nonrenewable energy generators, alongside power conditioning units, storage, and loads, with the potential to connect to the grid. These systems come in different configurations, such as high frequency AC coupled, power frequency AC coupled, DC coupled and hybrid coupled systems, selected according to the specific requirements of the application (Upadhyay & Sharma, 2014). Their primary aim is to integrate multiple energy sources to meet electrical loads, primarily AC, while also capable of powering DC loads when needed (Ammari, 2022).

By combining alternative (renewable) and conventional (grid or diesel generator) energy sources, along with energy storage components like battery banks or fuel cells, HESs exploit the benefits of each energy source to counterbalance their limitations. For example, although sources like solar and wind may have unpredictable availability, their complementary patterns ensure a continuous energy supply when integrated into hybrid systems (Medghalchi, 2023).

These systems can function while connected to the grid, where they prioritize local demand and can return excess energy to the grid, or operate independently in isolated areas. Integration of solar or wind energy often requires auxiliary sources like battery banks or fuel cells to manage their intermittent availability (Güven et al., 2024). Additionally, a control unit is sometimes necessary to balance the availability of energy sources and decide which source should power the load. In recent years, numerous HES configurations have been extensively utilized, as outlined in Fig. 1 (Upadhyay & Sharma, 2014).

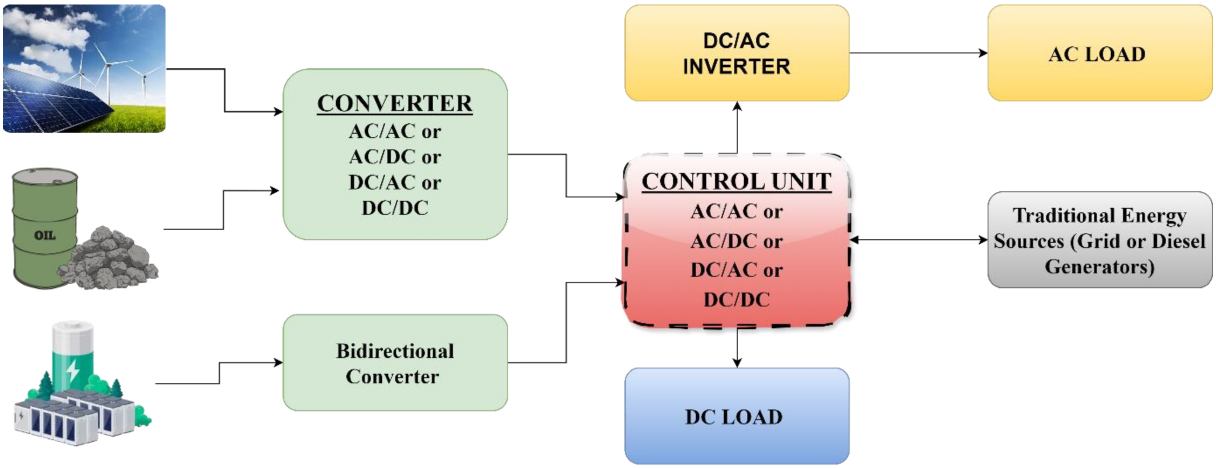

Fig. 1. Overview of basic components and architecture of hybrid energy systems.

3. HES EVALUATION METRICS

This section introduces the metrics utilized to evaluate the efficiency and economic feasibility of HESs. It serves as a foundation for assessing how effectively these systems operate and whether they are financially sustainable in the long run.

3.1 Performance metrics

Performance metrics are used to evaluate how well a HES functions in terms of reliability and effectiveness. They provide an understanding of the system's capability to reliably provide electricity and meet demand under various operating conditions.

3.1.1 Loss of power supply probability

In the field of wind and solar energy, where parameters fluctuate randomly, ensuring the reliability of a HES is paramount. The LPSP emerges as a critical metric. LPSP is essentially expresses the relationship between the energy shortfall and overall demand during the evaluation period. It can be calculated as (Agbehadji et al., 2021):

$$LPSP = \frac{\sum_{t=1}^{T} LPS(t)}{\sum_{t=1}^{T} E_L(t)} \tag{1}$$

Where: T is the total number of time periods, t is the time period $LPS(t)$ is the Loss of Power Supply for time period t and $E_L(t)$ is the Energy Load for time period t.

3.1.2 Loss of load expected

LOLE offers understanding into the expected deficit in energy when demand exceeds the system's ability to generate power. It requires evaluating various scenarios where load shedding could happen and estimating the probable duration of these scenarios based on their probabilities. The LOLE can be obtained using the following equation (Tezer et al., 2017):

$$LOLE = \sum_{t=1}^{T} \sum_{i \in S} P_i \times T_i \tag{2}$$

With: i is the counter for possible scenarios of load loss, S is the set of all possible scenarios that could result in load loss, P_i is the probability of each scenario "i" occurring during the year and T_i : is the time in hours during which scenario "i" results in load loss.

3.2 Economic metrics

Economic metrics focus on the financial aspects of HESs. They analyze the overall system cost throughout its lifetime, covering initial investment, maintenance costs, and operational expenses.

3.2.1 Annualized cost of system

The ACS is the total yearly expense of a system. It includes three main costs: the yearly capital cost (for buying and setting up the system), the yearly maintenance cost (for keeping it running), and the yearly replacement cost (for fixing or upgrading parts as needed) (Lian, 2019).

$$\text{ACS} = C_{cap} + C_{main} + C_{rep} \tag{3}$$

Where: C_{cap} : is th capital cost of the system, including initial investments, C_{main} is the main operational costs over the year and C_{rep} is the costs associated with system repairs or maintenance.

3.2.2 Levelized cost of energy

The LCOE simplifies the cost analysis of the HES by expressing the mean cost of generating electricity over its operational lifespan. The calculation involves dividing the yearly system cost by the overall energy demand over the year (Papaefthymiou & Papathanassiou, 2014). LCOE helps system designers to understand the economic feasibility of the system compared to other energy generation methods, aiding in investment decisions and long-term planning. It can be calculated using this formula (Gupta et al., 2021):

$$LCOE = \frac{\text{ACS}}{E_{tot}} \tag{4}$$

With: ACS is the annualized cost of the system and E_{tot} is the total load demand over the year.

4. SIZING METHODS OF HES

The process of determining the best size for HESs involves various methods. These methods aim to find the right mix of energy sources and components to make the system efficient. These approaches are present in Fig. 2 (Upadhyay & Sharma, 2014). Traditional methods use calculations and trials to figure this out. Newer methods, like artificial intelligence (AI), offer more advanced ways to optimize these systems, making them more effective. Together, these approaches help in designing energy systems that are both effective and sustainable, ensuring they meet our energy needs in the best possible way (Bhimaraju et al., 2022).

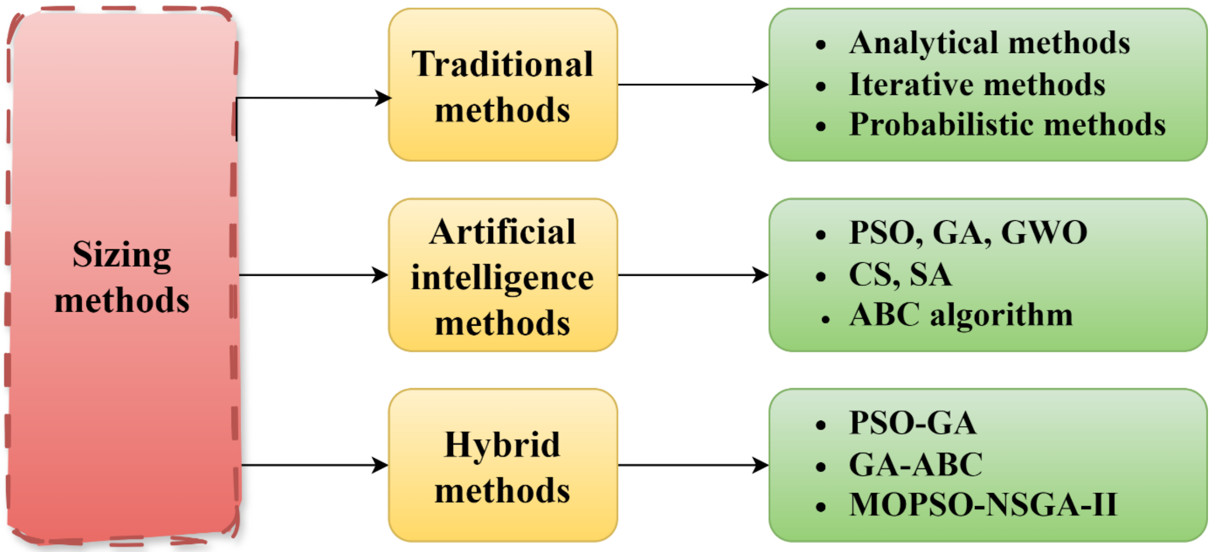

Fig. 2. Classification of Sizing Methods for HESs.

4.1 Traditional methods

The sizing of HESs involves several methodologies aimed to determine the optimal configuration for efficient operation. Traditional methods, including analytical, iterative, and probabilistic approaches, rely on mathematical models, trial-and-error techniques, and probabilistic methods to find the best solution while accounting for a range of potential challenges and variations (Ammari, 2022). Zhang et al. (Zhang et al., 2013) presented an optimization algorithm for sizing the components of HES composed of a PV-diesel-battery system utilizing an iterative method. The system was evaluated in Alaminos, Philippines. This algorithm aims to lower energy cost by considering initial costs of fuel, maintenance, and emission. Two sizing solutions for the HES are presented, with costs of energy (COE) at $0.3762 per kWh and $0.5639 per kWh, respectively. Yang et al. (Yang et al., 2003) introduced a probabilistic method to evaluate and study a hybrid PV-wind energy generation systems equipped with storage batteries, and additionally evaluates the systems' reliability. This research was performed on an island in Hong Kong. The results indicate that the HES of a 3-day energy storage capacity is suitable to ensure an LPSP less than 1%, while the HES of a 5-day energy storage capacity is suitable to ensure a LPSP equals to 0%.

4.2 AI methods

In the context of HESs, AI methods are essential for optimizing the configuration and operation of these systems. These methods enable the intelligent search for optimal or near-optimal solutions within a vast and complex solution space, taking into account the variability of RESs, the demand profiles, and system constraints (Khan et al., 2018).

4.2.1 Grey wolf optimization algorithm

The GWO algorithm takes inspiration from the social hierarchy and hunting techniques of grey wolves in nature. It mimics the way grey wolves organize themselves into a pack and how they hunt, encircle, and harass their prey until they find the opportune moment to attack (Srilakshmi et al., 2024). For sizing HESs, GWO is utilized to find the best possible system configuration by exploring the search space through the simulation of these behaviors. Agents in the algorithm represent potential solutions, and their movements through the search space are guided by the placements of the alpha (the best solution), delta and beta wolves (Srilakshmi et al., 2024). This algorithm is particularly valued for its simplicity, flexibility, and effectiveness in dealing with non-linear, multi-dimensional optimization problems. Abdulsamed et al. (Tabak et al., 2022) focused on meeting the energy demand of a facility using a HES comprising a wind turbine, PV panels, and a biomass (BM) system. The aim is to optimize power distribution, minimize costs and ensure reliability. An efficient optimization algorithm, known as the Grey Wolf Optimizer, has been developed to select power sources and enhancing system reliability. Common optimization methods, such as genetic algorithm (GA) and simulated annealing, are employed to compare their performance with the new algorithm. Comparative analysis reveals that GWO yields satisfactory results, outperforming GA and SA. The optimized PV/WT/BM HES effectively fulfills the facility's energy requirements while also mitigating CO2 emissions by 144.29 tons annually.

4.2.2 Improved grasshopper optimization algorithm

The GOA is developed based on the swarming actions of grasshoppers. This algorithm has been improved for HES applications by enhancing its exploration and exploitation capabilities (Wu et al., 2023). The improved version addresses the standard GOA's tendency to prematurely converge on local optima by introducing mechanisms that encourage diversity in the solutions and adapt the search intensity according to the phase of optimization. This makes it more suitable for finding the global optimum in the sizing and planning of HESs, where the solution space is vast and complex (Naderipour et al., 2022; Wu et al., 2023). Amirreza et al. (Naderipour et al., 2022) presented an optimized stand-alone HES comprising wind turbines, PV arrays, and battery storage. The optimization uses real data from a remote location, focusing on the optimal configuration of system components to minimize costs and ensure energy reliability. An innovative method, the improved GOA, is used for optimal system sizing, demonstrating superior performance in reliability and cost compared to traditional methods. The study also examines the effect of interest rate variations on system costs and reliability, finding significant impacts. Additionally, it notes that higher storage costs lead to increased overall costs and reduced reliability.

4.2.3 Improved search space reduction algorithm

This algorithm is a technique designed to efficiently narrow down the search space in optimization problems, making the search process more focused and faster. In (Bhimaraju et al., 2022) the authors focused on the best sizing of a HES that combines wind and solar power with pumped storage hydro-power (PSHS) for grid integration. The primary objective is to find the best mix of solar, wind, and PHS components to lower the overall energy cost, ensuring system reliability and maximizing the use of renewable sources to meet energy demands. This research introduces a novel approach by incorporating the variability of water inflow over the rainy season into the HRES sizing, a method not previously explored in optimal sizing studies. The paper presents a new algorithm, the search space reduction algorithm, and its improved version (ISSR) for determining the optimal system size. The ISSR algorithm's effectiveness is validated through performance comparison with other optimization methods, like the teaching-learning based optimization and GWO, demonstrating the ISSR's superior ability to minimize costs.

3.2.4 Non-dominated Sorting Genetic Algorithm II

The NSGA-II algorithm is a popular evolutionary method utilized for the resolution of multi-objective optimization issues. it starts with a population of random solutions and attempts to achieve the best solution to an optimization problem (Abdelkader et al., 2018). Abdelkader et al (Abdelkader et al., 2018) introduced a novel method for optimizing the design of a combined wind and solar photovoltaic HES, equipped with a hybrid storage system, for a location in Tunisia. The authors developed models for each element of the system to formulate the optimization algorithm they proposed. The optimization problem was redefined with the aim of simultaneously minimizing the LPSP for the load and the total cost. A multi-objective GA was utilized to determine the best size of the HES. Their findings indicated that the lowest LPSP could be achieved at a significantly reduced total electricity cost, highlighting the contribution of RESs to the enhancement of Tunisia's energy sector.

4.2.5 Particle swarm optimization

The PSO algorithm takes inspiration from the social nature of fish schooling or birds flocking. In PSO algorithm, particles, which represent possible solutions, move through the solution space by following the current best particles while also exploring the space based on their own and their neighbors' past experiences. This balance between exploration and exploitation allows PSO to be highly effective in finding optimal solutions for the sizing of HESs (El Boujdaini et al., 2022). In (El Boujdaini et al., 2022) authors focuses on simulating the electrical supply for isolated homes in Morocco, Spain, and Algeria. It is structured around two primary objectives: firstly, to optimize a hybrid system catering to various numbers of households, and secondly, to establish fixed values for chosen parameters. Utilizing the PSO technique, the research aims to optimize and evaluate a stand-alone hybrid system combining PV, wind, diesel, and battery technologies. The optimization goals were to adjust the sizes of system components to minimize the COE and also explores hydrogen generation from the electricity produced by the wind and PV systems.

4.2.6 Modified Orca Predation Algorithm

The mOPA is an enhancement of the original Orca Predation Algorithm, is developed based on the hunting patterns of orcas. It introduces two key improvements: Opposition-based learning and Levy flight. These techniques improve the algorithm's exploration and exploitation balance, enabling it to find optimal solutions while avoiding premature convergence to local optima. This makes mOPA highly suitable for addressing complicated global optimization challenges, including the sizing of HESs (Emam et al., 2023). In the driving phase of mOPA, Levy flights are used to enhance search diversity, helping orca agents to explore new areas of the search space. In contrast, the Opposition-based learning technique accelerates the convergence by comparing candidate solutions with their opposites, ensuring faster progress towards optimal solutions (Emam et al., 2023). In the study presented in (Emam et al., 2023), mOPA was applied to size an off-grid HES composed of PV panels, a BM gasifier, hydrogen tanks, and fuel cells in a remote region in Egypt. The algorithm optimized the system's components, minimizing the cost of energy while ensuring reliability. Compared to the original OPA, mOPA demonstrated superior performance, reducing both the COE and the system's total annual cost by a significant margin. The performance of mOPA in practical applications, proving its utility in optimizing HES configurations for remote locations.

4.2.7 Discrete Harmony Search Algorithm

The DHS algorithm is inspired by the musical process of harmony improvisation, where musicians continuously adjust pitches to improve harmony. In this algorithm, a set of potential solutions (harmonies) are iteratively adjusted based on predefined rules to search for optimal solutions (Mishra et al., 2023). The DHS algorithm, through pitch adjustment, random selection, and memory consideration, refines solutions over several iterations, allowing it to find near-optimal configurations for complex problems like HES sizing. In (Mishra et al., 2023), the DHS algorithm was used to optimally size a grid-connected HES consisting of solar PV, BM, and batteries. For a rural electrification project in Godinbuda Village, Madhya Pradesh, India, the DHS algorithm optimized the sizes of PV panels (83.50 kWp), biomass (30 kW), and batteries (38.40 kWh), minimizing the net present cost (NPC) to INR 13.07

million. The goal was to balance the intermittent renewable energy supply with the demand, ensuring power reliability while reducing the cost of energy (COE) to INR 4.66/kWh.

4.2.8 Multi-Objective Modified Firefly Algorithm

The MOMFA is an optimization method that mimics the social behavior of fireflies. In this algorithm, fireflies (representing potential solutions) are attracted to each other based on their brightness, which corresponds to the level of solution quality. A chaotic mapping mechanism is incorporated to enhance the exploration process, allowing the algorithm to efficiently search for the most favorable solutions. The multi-objective nature of MOMFA allows it to simultaneously optimize several goals, such as maximizing renewable energy reliability and minimizing costs (Le et al., 2023). Tay et al. (Le et al., 2023) applied MOMFA to optimize the energy storage system for a warehouse connected to the grid in a tropical climate using real electricity usage data. The goal was to size three different energy storage systems: battery-only, hydrogen-only, and a hybrid system. The optimization showed that battery systems provided the optimal results in terms of economic performance and reliability for short-term storage. However, for long-term storage needs, particularly in regions with high seasonal variations, the hydrogen storage system outperformed the battery system because of its capacity to store larger amounts of energy for longer durations. The hybrid system emerged as the most balanced solution, ensuring a reliable power supply year-round by leveraging the strengths of both technologies. This approach lowered component degradation and improved the overall economic feasibility of the system, delivering the highest self-sufficiency ratio and net present value.

4.2.9 Modified Dragonfly Algorithm

The MDA is an advanced metaheuristic optimization technique inspired by the static and dynamic swarming behaviors of dragonflies. In the MDA, individual solutions (dragonflies) explore the solution space by simulating movements like alignment, cohesion, separation, attraction, and distraction, mimicking the dragonfly's swarm behavior (Tittu George et al., 2023). The algorithm balances exploration and exploitation phases through these behaviors, ensuring global search capabilities while avoiding premature convergence to local optima. The authors in (Tittu George et al., 2023), used MDA to optimize the sizing of a hybrid solar-wind energy system for an educational institution. The model aimed to minimize the Net Present Value (NPV) of the system by balancing energy supply from solar and wind sources. This HRES was designed without battery storage, relying on grid interaction to maintain reliability and reduce costs. The optimization model considered real-time data on solar irradiation, wind speed, and load demand, offering a highly accurate configuration for the system. The best case identified was a grid-connected HRES, which significantly improved both reliability and cost-efficiency. The system included solar panels placed on underutilized rooftop spaces and wind turbines, maximizing the use of available space and renewable resources. By employing the MDA, the study demonstrated an optimal reduction in the NPV over the system's lifespan while providing a consistent power supply for the institution's needs. The model presented an efficient solution that promotes renewable energy adoption in institutional settings.

4.2.10 Differential Evolution (DE) Algorithm

The DE algorithm is a robust optimization technique inspired by natural evolution. It operates by initializing a population of potential solutions and iteratively improving them by combining existing solutions to explore the solution space. DE is particularly effective for optimizing complex, non-linear, and multi-modal problems, which makes it highly suitable for energy system sizing and cost optimization tasks (Thirunavukkarasu et al., 2023). In this study (Kamal et al., 2023), the DE algorithm was applied to optimize the sizing and cost of a standalone rural microgrid for electrification in

Uttarakhand, India. The microgrid incorporated renewable energy resources such as solar SPV, wind energy systems, BM, biogas, and micro-hydropower, all locally available. The DE algorithm was tasked with minimizing the NPC of the system while ensuring a continuous and reliable energy supply for the region. Through simulations, the DE algorithm outperformed other algorithms like PSO and Genetic Algorithm in both cost reduction and computational efficiency. The optimal configuration achieved a total NPC of $712,532 and a COE of $0.14/kWh. This makes the DE-optimized microgrid model a highly cost-effective solution for rural electrification. The study also conducted a sensitivity analysis, showing how the system performance responds to changes in input parameters such as fuel costs, load demand, and renewable energy availability.

There are also other algorithms that have been utilized in the literature for sizing HESs, such, the firefly algorithm (Yuan, n.d.), discrete GWO algorithm (Saha et al., 2023), the pattern search optimization algorithm (Ali & Mohammed, 2024).

4.2.11 Shared Strategies and Optimization Approaches in AI for Hybrid Energy Systems Design

Most of the AI algorithms used for designing HESs share the same fundamental principles. They necessitate the formulation of an objective function, usually aimed at minimizing energy costs or the NPC, along with setting constraints such as ensuring energy demand is met and adhering to system reliability and renewable energy targets. Additionally, these algorithms work with specific variables such as the number of solar panels, wind turbines, and batteries, which play a crucial role in determining the optimal system configuration. The diagram presented in Fig. 3 provides a comprehensive representation of how AI algorithms function in the process of sizing HES. It outlines the key steps and considerations necessary for optimizing the design of these systems, integrating various parameters such as resource availability, energy demand, cost factors, and system constraints. The process begins with data collection, where essential input data, including renewable energy resource potential, hourly or daily energy consumption, and capital and operational costs, is gathered. This information forms the basis for initializing the AI algorithm. Once the algorithm is initialized, two critical elements are addressed: the objective function definition and constraint setup. The objective function, which typically focuses on minimizing the COE or NPC, aims to meet the energy demand while optimizing other system performance metrics. The constraint setup, meanwhile, ensures that the solution adheres to the system's reliability, lifespan, and renewable energy targets. Adjusting the algorithm's parameters is a dynamic step in this process, allowing the AI algorithm to fine-tune its performance and adapt based on real-time feedback from the optimization process. The population initialization is a core component of the diagram, illustrating how AI techniques such as Genetic Algorithms, PSO, and DE begin with an initial random set of solutions. From here, the optimization process employs strategies like exploration and exploitation, where the algorithm searches for the most promising solutions while adjusting configurations in real-time. For example, PSO adjusts particle positions to find optimal solutions, and algorithms like Firefly or Dragonfly are inspired by natural behaviors to explore the solution space. Following the optimization process, fitness evaluation ensures that each solution is tested against the pre-set objective criteria, such as COE or NPC. The iterative nature of AI optimization is also highlighted in the diagram, showing how the system repeatedly refines its solutions through cycles of adjustment, validation, and comparison. The diagram emphasizes the importance of convergence, where the iteration process continues until an optimal or satisfactory solution is found. Finally, the flowchart addresses the stopping conditions, ensuring that the algorithm halts either when optimal conditions are met or when further improvements are not achievable. If the solution meets the necessary requirements, the algorithm concludes, delivering the best configuration for the HES. Otherwise, the system undergoes further iterations for refinement. This iterative cycle ensures that the AI sizing process produces reliable and economically feasible results for HESs, making it a powerful tool for modern energy system design.

4.3 Hybrid methods

Hybrid methods in the sizing of HESs combine the advantages of different optimization techniques to achieve more accurate, reliable, and efficient solutions. By combining the strengths of conventional methods, AI techniques, and heuristic methods, these approaches are able to address the complex problem of sizing HES (Victor O. & Nichodemus A., 2015).

Aykut et al. (Güven et al., 2024) focused on enhancing sustainability by minimizing carbon emissions at a university campus through the use of a HES that integrates wind turbines, PV panels, batteries and a diesel generator. The selection of system components was optimized using recorded data on wind speed, ambient temperature, solar radiation, and load demands to achieve cost-effectiveness and efficiency under varying environmental conditions. For the aim of optimization, gray wolf optimizer and cuckoo search algorithms were used within MATLAB/Simulink to determine the optimal size of the HES components. In the context of optimization tasks, the off-grid model demonstrates enhanced performance when the GWOCS algorithm is applied, providing quicker and more reliable outcomes to other methods.

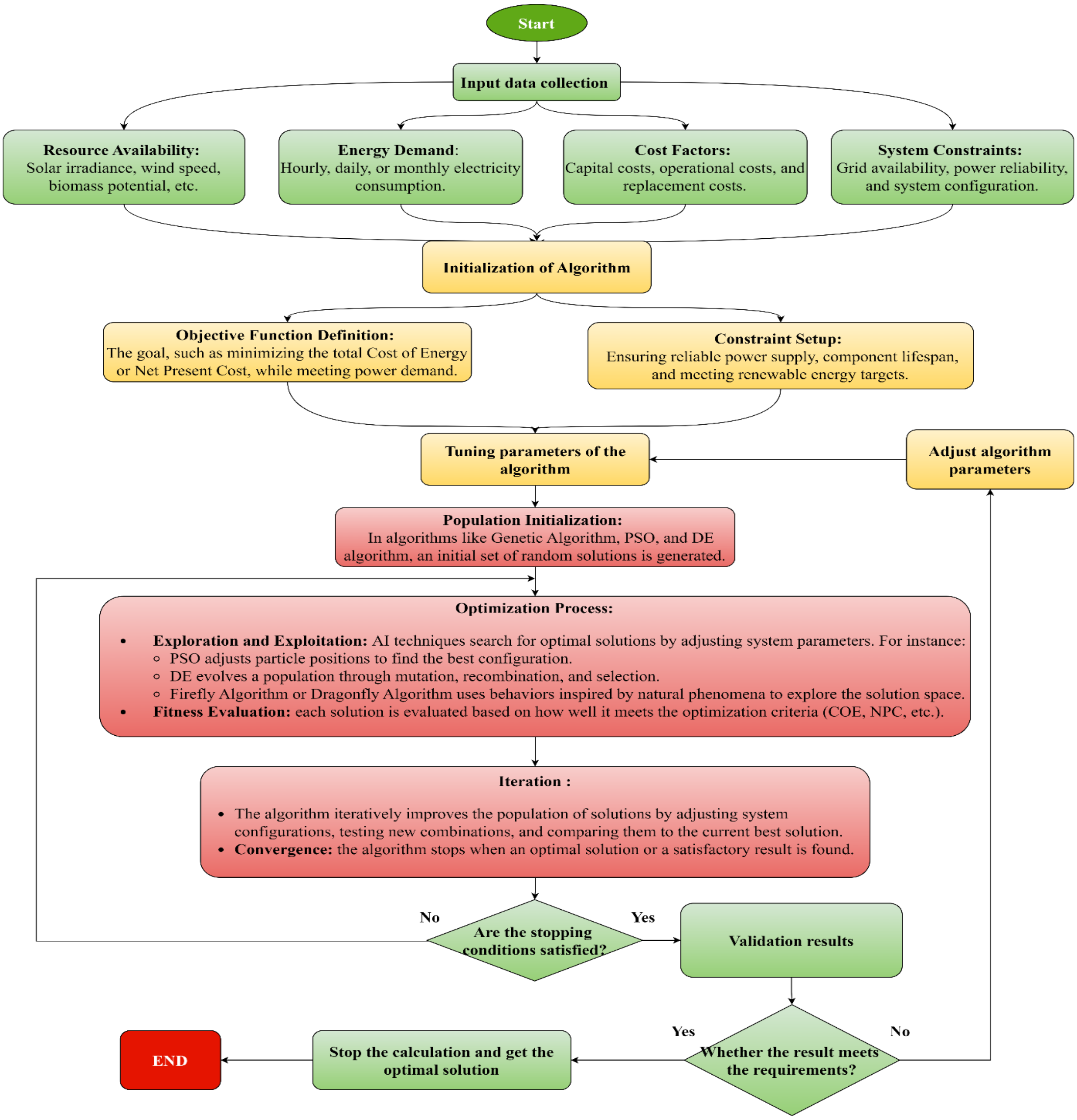

Fig. 3. Comprehensive diagram of AI algorithms for optimizing HESs sizing.

In (Medghalchi, 2023), the study presents an innovative approach for evaluating the integration of solar PV systems and wind turbines, and energy storage systems, including both Electrolyzer-Fuel Cell and Battery. The primary aim is to lower the overall cost of energy while ensuring a certain percentage of energy is sourced from renewables. To achieve this objective, the research proposes a combined optimization method that mixed PSO with GA. The study finds that a mix of wind and solar power with battery storage outperforms electrolyzer-fuel cell systems, reducing energy costs by 33-35% and enhancing supply reliability by 16-20%.

5. SUMMARY, CHALLENGES AND FUTURE SCOPE

The comprehensive review explores in detail the current methodologies used for sizing HES, combining renewable and non-RESs to offer efficient and reliable energy solutions. It covers the various configurations of HES, evaluation metrics for assessing performance and economic viability, and explores both traditional and AI-based optimization methods. These methodologies have significantly contributed to the design and sizing of HES, optimizing for cost-effectiveness, reliability, and environmental sustainability.

However, the field faces several challenges, including the complexity of integrating diverse energy sources, addressing the intermittency of renewables, high initial costs and economic analysis, and minimizing environmental impacts. The future scope involves tackling these challenges by innovating optimization techniques, enhancing energy storage solutions, and focusing on cost reduction. This effort aims to improve the feasibility and reliability of HES, making it an essential part in the shift towards more sustainable energy systems.

Table 1 shows a comparison of different sizing methods for HES without delving into technical specifics. It highlights the diversity of approaches used in this field, from traditional techniques to more advanced AI and hybrid methods. Each method brings a unique perspective to optimizing the design and operation of HES, illustrating the evolution of technology in this area. The table emphasizes how traditional methods, though simpler, may not be sufficient for addressing the complexity of modern energy systems, especially with the increasing integration of RESs. The diversity in methodologies also underscores the importance of selecting the right approach based on the specific objectives of a project, taking into account the complexity of the system, the available resources, and the desired outcomes. AI methods, with their ability to handle multi-objective optimization problems, represent a significant advancement over traditional approaches. These techniques allow for a more refined and efficient design process, improving the system's ability to balance cost, reliability, and sustainability. Meanwhile, hybrid methods emerge as a promising solution that combines the strengths of both traditional and AI techniques, offering a more adaptable and flexible approach to HES optimization. This comparative approach aids in understanding how the field has evolved and points toward future innovations that will further enhance HES performance.

This comprehensive review has explored various methods for sizing HES, focusing on traditional, AI, and hybrid methods. Each approach offers unique advantages and faces specific limitations, especially when applied to complex energy systems that aim to balance cost, reliability, and sustainability. The Table 2 summarizes the main advantages and disadvantages of the three methodologies discussed in this paper. This table serves to highlight the trade-offs between simplicity, computational efficiency, and optimization performance. As can be observed, while traditional methods are relatively easier to implement, they fall short in handling the complexities of modern HES. On the other hand, AI-based methods excel in optimization but require more computational power and expertise. Hybrid methods strike a balance, combining the strengths of both, but introduce complexity in implementation. These observations reinforce the need for careful selection of sizing techniques based on the specific requirements of each HES. The growing complexity of energy systems suggests a promising future for hybrid methods, which could offer better results by balancing the strengths of different AI algorithms.

Table 1 : Recent Advances in Optimization Methods for sizing HESs.

Methods	Sizing Techniques	System Elements	Optimization Objectives	Reference
Traditional methods	Iterative method	PV/diesel/Batt	COE	(Zhang et al., 2013)
	Probabilistic method	PV/WT/Batt	LPSP	(Yang et al., 2003)
AI Methods	GWO	PV/WT/BM	Total net present cost	(Tabak et al., 2022)
	IGOA	PV/WT/Batt	Total net present cost Loss of energy probability	(Naderipour et al., 2022)
	ISSR	PV/WT/PSHS	LCOE	(Bhimaraju et al., 2022)
	NSGA-II	PV/WT/HESS	Total cost of electricity LPSP	(Abdelkader et al., 2018)
	PSO	PV/WT/Batt	COE	(El Boujdaini et al., 2022)
	mOPA	PV/BM/Electro-lyzer/ hydrogen tank/fuel cell	COE LPSP Consumption of extra energy	(Emam et al., 2023)
	DHS	PV/BM/Batt	NPC	(Mishra et al., 2023)
	MOMFA	PV/Grid/Batt	NPV	(Le et al., 2023)
	MDA	PV/WT/Grid	NPV	(Tittu George et al., 2023)
	DE	PV/micro-hydropower/biogas/ Batt/BM/WT	Total net present cost	(Kamal et al., 2023)
	Firefly algorithm	PV/WT/Batt	Annual cost	(Yuan, n.d.)
	Discrete GWO	PV/BM/Batt	NPC	(Saha et al., 2023)
	derivative-free pattern search optimization	PV/WT/Fuel/Batt	Capital costs and dynamic operating expenses	(Ali & Mohammed, 2024)
Hybrid methods	GWOCS	PV/WT/diesel/Batt	ACS	(Güven et al., 2024)
	PSOGA	PV/WT/Batt	Weighted average cost of energy	(Medghalchi, 2023)

Table 2: Comparison of Advantages and Disadvantages of HES Sizing Methods *(He et al., 2023; Thirunavukkarasu et al., 2023)* .

Methods	Advantages	Disadvantages
Traditional Methods	- Straightforward and well-understood. - Suitable for simple HES configurations. - Often use deterministic models, which provide clear, predictable results.	- Limited flexibility and scalability for complex systems. - Requires more time due to trial-and-error approaches. - Often overlooks uncertainties.
AI Methods	- Highly effective for complex and non-linear problems. - Can optimize multiple objectives simultaneously (e.g., cost, reliability). - Faster convergence to solutions.	- Requires significant computational power. - Difficult to interpret or understand the underlying mechanics. - Susceptible to overfitting in certain cases.
Hybrid Methods	- Combines strengths of traditional and AI approaches, providing better optimization for complex HES. - Balances simplicity with computational efficiency.	- More complex to implement and manage due to the combination of techniques. - May require more advanced knowledge to fine-tune the system.

6. CONCLUSION

The article provides a comprehensive overview of the design, sizing, and control of integrated renewable energy and electrical power systems, considering a wide range of factors including technological, economic, and environmental influences. Highlighting the complexity of designing an efficient electrical power system, it underscores the need to select key influencing factors for system design. The use of computational tools and AI techniques such as particle swarm optimization and genetic algorithms for system sizing is discussed, as well as new AI methods that could potentially improve the design process. However, it is acknowledged that there are challenges in implementing these techniques due to the increasing number of variables. The article proposes integrating hybrid methodologies to overcome these limitations by optimizing the sizing of both renewable and non-renewable energy systems within electrical power systems. This literature review provides significant value in addressing the challenges and complexities associated with research on the sizing and optimization of electrical power systems that combine photovoltaic solar and wind sources.

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