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Evaluating the feasibility of a photovoltaic-wind-diesel-battery hybrid microgrid for sustainable off-grid electrification in Dakhla, Morocco

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ABSTRACT

Hybrid renewable energy systems (HRES) present a promising solution for improving energy reliability and reducing costs in remote, off-grid areas. This study explores the feasibility of implementing an HRES in Dakhla, Morocco, where conventional electrical infrastructure is lacking. By integrating photovoltaic (PV) panels, wind turbines, diesel generators, and battery storage, this study aims to optimize energy resource management while balancing technical performance and economic viability. Using real-world data on energy consumption, climatic conditions, and installation constraints, advanced simulation tools such as HOMER were employed to evaluate both technical and economic parameters. The objective was to minimize the cost of energy (COE) while ensuring reliability, availability, and a high renewable fraction. The results, compared with optimization algorithms like genetic algorithm (GA), particle swarm optimization (PSO), and simulated annealing (SA), revealed the PV-wind-diesel-battery configuration as the most cost-effective solution. This configuration resulted in a net present cost (NPC) of $829,380, a COE of $0.160/kWh, and minimal CO2 emissions of 54.9 kg/year. The findings highlight the viability of this hybrid microgrid as a sustainable off-grid electrification solution and emphasize the role of renewable energy in addressing global energy challenges.

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ABBREVIATIONS AND NOMENCLATURE

RES	Renewable energy system	$v_{cut\text{-}in}$	Cut-in speed of the wind turbine
FC	Fuel cell	$v_{cut\text{-}out}$	Cut-out of the wind turbine
DG	Diesel generator	v_r	Rated speed of the wind turbine
Batt	Battery	v	Wind speed
WT	Wind turbine	$P_{DG,\ out}$	Diesel output power
DEGS	Diesel electric generating system	P_{DG}	Diesel rated power
COE	Cost of energy	A_G, B_G	Fuel consumption curve coefficient
NPC	Net present cost	E_{Load}	Daily load
CFR	Capital recovery factor	AD	Autonomy days number
CO_2	Carbon dioxide	DOD	Discharge depth (80%)

O&M	Operation and maintenance	η_{inv}	Inverter efficiency
HOMER	Hybrid optimization of multiple energy resources	η_B	Battery efficiency
PSO	Particle swarm optimization	C_I	Capital cost
SA	Simulated annealing	C_R	Replacement cost
GA	Genetic algorithm	$C_{O\&M}$	Operating and maintenance costs
A	PV area	i	The annual interest
I	Solar radiation	n	Project lifetime
η_r	Reference efficiency	n_{Diesel}	Lifetime of diesel generator
η_t	Efficiency of the MPPT	n_{Batt}	Lifetime of battery
T_a	Ambiant temperature	P_{Load}	The hourly consumed power by the load
P_r	Rated power of the wind turbine		

1. INTRODUCTION

Access to electricity is a critical driver of economic growth and social progress, inherently linked to development [1]. As industrialization expands and global populations increase, energy demand continues to surge. However, traditional energy sources like fossil fuels are increasingly inadequate due to their finite nature, high operational costs, significant contribution to greenhouse gas emissions, and worsening climate change. RES, including PV, WT, and hydropower, present a sustainable alternative [2]. These sources are abundant, inexhaustible, and environmentally friendly, making them essential for meeting global energy demands while mitigating climate change impacts. The global transition toward clean energy is gaining momentum, driven by international commitments to reduce carbon footprints and enhance energy efficiency [3]. Bridging the electricity access gap is critical to achieving global development goals and ensuring equitable access to sustainable energy.

Standalone RES, such as WT and PV panels, face reliability challenges due to natural resources' sporadic nature [4]. Solar energy availability is limited to daylight hours, while wind speeds fluctuate unpredictably. These variabilities make it difficult for standalone systems to ensure a consistent energy supply. To overcome these challenges, HRES has been introduced as an effective solution. By integrating multiple renewable sources, such systems can compensate for the weaknesses of individual sources. For instance, wind energy can complement solar energy during periods of low irradiance and vice versa, enhancing overall system reliability. In addition to improving reliability, hybrid systems optimize resource use, reduce dependency on backup fossil fuels, and minimize environmental impacts. They contribute to a cleaner environment by ensuring stable and continuous renewable energy production, supporting energy security and sustainable development goals [5].

Energy storage is a crucial component of renewable energy systems, particularly for standalone applications, as it mitigates the intermittency of resources like solar and wind. Storage systems allow for the retention of excess energy generated during times of abundant resources, ensuring availability during periods of lower production or higher demand. Batteries are common among storage technologies because of their adaptability, scalability, and quick reaction times, which make them perfect for short-term storage.

Proper sizing and optimization are fundamental to ensuring the efficiency, reliability, and cost-effectiveness of autonomous HRES. Sizing involves determining the appropriate capacity of components, such as PV panels, wind turbines, and batteries, to meet energy demands. Undersized systems can lead to frequent shortages, while oversized systems result in unnecessary capital costs and inefficiencies [6]. Optimization focuses on fine-tuning system configurations to balance energy generation, storage, and consumption effectively. This involves minimizing costs, reducing environmental impacts, and enhancing reliability. Advanced optimization algorithms, such as GA and PSO, are employed to analyze different scenarios and operating conditions, enabling the optimal design of HRES.

Microgrids are locally controlled energy systems that can operate both separately and in tandem with the national electrical grid [7]. They integrate a variety of RES, including hydropower, WT, and PV panels, along with traditional generators and advanced energy storage solutions. Microgrids cater to diverse energy demands across residential, commercial, and industrial sectors. Advanced control equipment ensures efficient energy flow, stability, and reliability, reducing dependence on external power sources and supporting sustainable energy practices [8].

Several studies have focused on optimizing the sizing of microgrids (MG), acknowledging the inherent complexity in selecting the optimal configuration that balances technical performance, cost-effectiveness, and environmental sustainability [9]. The process of determining the ideal size for a microgrid can be broadly categorized into three main approaches: software tools, deterministic methods, and metaheuristic algorithms. Each approach has its own set of advantages and limitations.

The first section comprises software tools, such as HOMER Pro, PVSYST, HOGA, RAPSIM, and IHOGA. These tools are widely used due to their user-friendly interfaces and their ability to model and simulate various microgrid configurations [10]. However, despite their ease of use, they have notable limitations, including a lack of flexibility in selecting the most suitable components for the system and limited transparency in the underlying algorithms and calculations. Users often struggle to fully understand the decision-making process or make customized adjustments, as these tools typically do not allow direct access to the optimization algorithms or the detailed computations driving the system design [11].

The second section involves deterministic approaches, including iterative, analytical, numerical, and graphical methods. While these approaches offer more control and precision over the design process, they are computationally demanding. These methods require exhaustive evaluation of all system components, making simulations time-consuming. Although effective, they are limited in their ability to efficiently handle the complex dynamics of hybrid microgrids, often resulting in high computational costs [12], [13].

In response to these challenges, metaheuristic or bioinspired algorithms have emerged as a promising solution for microgrid optimization [14]. These algorithms are especially well-suited for resolving non-deterministic polynomial time-hard (NP-hard) problems that cannot be solved by precise mathematical optimization techniques. They draw inspiration from natural phenomena such as swarm behavior and evolution. Metaheuristic approaches, including GA [15], PSO, and grasshopper optimization algorithms (GOA), search for global optimal solutions by simulating natural phenomena. Among these, the GA has been used extensively to optimize hybrid microgrid designs, but its implementation is challenging due to its complexity [16]. In contrast, PSO has gained considerable popularity due to its faster convergence to optimal solutions, making it especially effective for hybrid microgrids that integrate multiple components such as PV systems, WT, Batt, and DG [17]. Numerous studies have demonstrated PSO's ability to optimize the design and operation of various hybrid microgrid configurations, such as PV, WT, and Batt [18]. Utilized GOA to determine the optimal configuration for a hybrid microgrid in Yobe State, Nigeria, composed of PV, WT, Battery, and DG, with the COE as the objective function [19]. Similar to this, [20] used the FA to determine the ideal dimension for an autonomous microgrid, taking into account the LDR and COE as crucial metrics for assessing the cost and dependability of the power supply.

These studies highlight the increasing significance of metaheuristic algorithms in optimizing the design, sizing, and operation of hybrid microgrids. By leveraging these advanced optimization techniques, researchers can enhance the efficiency, economic feasibility, and reliability of microgrids, positioning them as a more viable and sustainable solution for future energy systems. Table 1 presents a thorough literature review, summarizing and analyzing previous studies on the design and operation of microgrids.

Table 1. Comprehensive overview of optimization techniques and methods for HRES

Ref.	Location	year	HES	Algorithm/tool	Objective function	Weakness
[21]	Ouenska, Morocco	2024	PV/WT/ Batteries	HOMER	COE, NPC	The analysis has not fully accounted for more variable wind conditions or higher wind speeds.
[22]	Dakhla, Morocoo	2023	WT /FC/DG	TRNSYS	COE	The limitations of the simulation model using TRNSYS are evident, as the outcomes are not contrasted with those of other algorithms.
[23]	Tunisia	2023	PV/WT/BESU/ Hudraulic	NSGA-II	LPSP, COST	The limitations of the simulation model using NSGA-II are evident, as the outcomes are not contrasted with those of other algorithms.
[24]	2023	Sudan	PV/WT/DG/ Battery	MILP	LPSP, NPC	The outcomes are not contrasted with those of other algorithms.
[25]	2023	Sonderborg, Denmark	PV/WT/DG/ Battery	MOMFO, NSGA-II, MOPSO, and MOSEO	LPSP, LCOE	The proposed scenarios recommend incorporating areas with diverse topography to improve the accuracy of the decision-maker's analysis, particularly in conditions of low solar radiation and wind speed.
[26]	2022	Turkey	PV/WT/DG/ Battery	HS/JAYA/ACO/ HOMER	ACS	The analysis of sensitivity has not been included.
[27]	2021	Tunisia	PV/WT/DG/ Battery	RG	TNPC/EC	The outcomes are not contrasted with those of other algorithms.

This study explores the optimization of hybrid renewable energy systems (HRES) to assess their techno-economic feasibility for electricity generation in Dakhla, Morocco. Employing HOMER Pro software alongside advanced optimization methods such as GA, SA, and PSO, the research evaluates and compares four HRES configurations based mainly on solar and wind resources. The outcomes derived from HOMER will be systematically compared to those obtained through these algorithms. Furthermore, the study analyzes key economic indicators, including NPC and COE, while benchmarking Morocco's COE against other developing countries to provide deeper insights into the costs associated with renewable energy deployment in the area.

2. METHOD

This approach aims to: i) Minimize electricity costs by optimizing system parameters, including production, storage, and energy consumption capacities. And ii) Compare the performance of various optimization techniques to identify the most efficient and sustainable energy system configuration.

The methodological framework follows these key steps:

a. Data collection: Gather data specific to Dakhla's local conditions, including solar irradiance, wind potential, and energy load profiles.
b. Simulation: Use tools such as HOMER to model and evaluate potential system configurations.
c. Optimization: Apply meta-heuristic algorithms to refine solutions in terms of economic viability, reliability, and sustainability.
d. Comparative analysis: To identify the ideal configuration, assess the results of various optimization strategies.
e. Validation and result illustration: Discuss and validate the results.

By employing this approach, which combines advanced simulation tools with proven optimization techniques, this research seeks to provide a tailored and feasible energy solution that aligns with the specific characteristics and requirements of the Dakhla region.

2.1. Study location

The study is conducted in Dakhla, a city in Morocco, located at a latitude of 23.7° N and a longitude of 15.9° W. Dakhla is known for its abundant solar and wind energy resources, making it an ideal area for renewable energy projects. Table 2 presents monthly data on wind speed, solar irradiance, and clearness index for Dakhla city, sourced from NASA via HOMER software. Solar irradiance varies significantly throughout the year, peaking at 7.12 kWh/m²/day in April and dropping to 4.02 kWh/m²/day in December, with an annual average of 5.76 kWh/m²/day. This suggests significant seasonal variability, with higher irradiance in the spring and summer, and lower values in the fall and winter. The clearness index, ranging from 0.572 in July to 0.68 in April, reflects the proportion of direct sunlight reaching the surface, with clearer skies in the spring. Wind speed follows a similar seasonal pattern, with the highest average of 7.13 m/s in July and the lowest of 5.59 m/s in November, resulting in an annual average wind speed of 6.48 m/s. These patterns suggest that both solar and wind resources are variable but generally favorable, supporting the feasibility of a HES at this location.

Table 2. Monthly average solar irradiance, clearness index and wind speed

Months	Solar irradiance (kwh/m²/day)	Clearness index	Wind speed (m/s)
1	4.46	0.644	6.610
2	5.26	0.655	6.57
3	6.34	0.675	6.76
4	7.12	0.68	6.93
5	7.1	0.644	6.73
6	6.8	0.609	7.08
7	6.43	0.572	7.13
8	6.18	0.584	6.65
9	5.7	0.591	6.31
10	5.18	0.622	5.64
11	4.57	0.643	5.59
12	4.02	0.613	5.79
Annual	5.76	0.628	6.48

2.2. Load profile

The hybrid model configurations developed in this study are specifically designed to satisfy the energy requirements of a community that includes 20 LED streetlights, 80 households, a small commercial shop, a school, and a health center as detailed in Table 3. The total average daily electricity consumption for the 80 households is estimated at 996 kWh, with each household consuming approximately 12.45 kWh. The 20 LED streetlights collectively consume 24 kWh/day, while the small commercial shop and the school each require 28 kWh/day. The health center's daily energy consumption is 24.48 kWh. Consequently, the microgrid serving this community is predicted to have an average power load of 1,097.62 kWh, with a peak demand of 400 kW, plus an additional 5% variability to accommodate fluctuations in load demand throughout the year. Figure 1 illustrates the average energy consumption of the community.

Table 3. Quantity and rating of power-consuming appliances for various sectors

Sector	Quantity	Appliance	Rating (W)	Utilizing time (h)	Daily electricity demand (kWh/day)
Residential comminuty	80	Air conditioners	500	8	4
		Fridge	200	24	4.8
		Television	100	4	0.8
		Washing machine	400	0.75	0.3
		Phone charger	5	2	0.03
		Computers	30	2	0.12
		Light bulbs	60	8	2.4
Small commercial shops	1	Air conditioners	500	8	4
		Small refrigerators	200	24	4.8
		Big refrigerators	500	24	12
		Lighting	120	12	7.2
Health center	1	Air conditioners	500	8	4
		Refrigerators	500	24	12
		Desktop computer	30	8	0.48
		Lighting	100	8	8
School	1	Ceiling Fan	30	7	4.2
		Lighting	20	4	3.6
		Television	80	8	0.64
		Fridge	200	6	1.2
		Printer	250	2	0.5
		Desktop computer	200	5	3
		Air conditioners	500	8	12
Stree-lights	20	Lighting	100	12	24

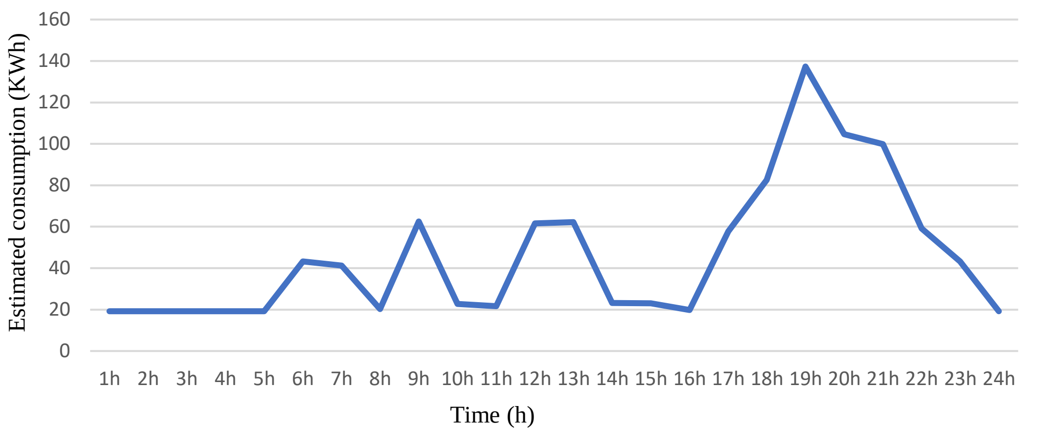

Figure 1. Hourly electrical load demand profile

2.3. Hybrid energy system modeling

2.3.1. PV modeling

The PV system's output power (PPV) at time t can be calculated using (1).

$$P_{PV}(t) = N_{PV} \times I(t) \times A \times \eta_r \times \eta_t \times [1 - \beta \times (T_a(t) - T_r) - \beta \times I(t) \times (\frac{T_{NOCT}-20}{800})(1 - \eta_r \eta_t)] \quad (1)$$

2.3.2. Wind turbine modeling

The wind turbine (PWT) system's generated power at time t is determined as (2).

$$P_{WT} = N_{WT} \times \begin{cases} 0 \; v(t) \leq v_{cut-in} \quad or \quad v(t) \geq v_{cut-out} \\ p_r \frac{v(t)-v_{cut-in}}{v_r - v_{cut-out}} \; v_{cut-in} < v(t) < \; v_r \\ \quad p_r \; v_r < v(t) < \; v_{cut-out} \end{cases} \quad (2)$$

2.3.3. Diesel generator modeling

The following formula represents the diesel generator's fuel consumption:

$$F_{DG}(t) = B_G P_{DG} + A_G P_{DG-out} \tag{3}$$

2.3.4. Battery modeling

The battery system is a crucial element in isolated microgrids, serving as a power source when solar radiation or wind speed is unavailable. The daily load energy and the amount of time needed to supply this load from the battery bank are used to determine the battery capacity.

$$C_{Batt} = \frac{E_{Load} \times AD}{DOD \times \eta_{inv} \times \eta_B} \tag{4}$$

2.4. Objective function

The primary objective of the optimization problem presented in this study is to minimize the COE while achieving an optimal system configuration in terms of cost. The COE, defined as an objective function, is directly influenced by the NPC, which encompasses investment, O&M, and replacement costs. The net present cost of the system is calculated as (5)

$$NPC = C_{PV} + C_{WT} + C_{Batt} + C_{DG} + C_{INV} \tag{5}$$

These costs can be determined using the following calculations:

$$C_{PV} = N_{PV}\left(C_I^{PV} + C_{O\&M}^{PV} \times \left(\frac{(1+i)^n - 1}{i(1+i)^n}\right)\right) \tag{6}$$

$$C_{WT} = N_{WT}\left(C_I^{WT} + C_{O\&M}^{WT} \times \left(\frac{(1+i)^n - 1}{i(1+i)^n}\right)\right) \tag{7}$$

$$C_{Batt} = C_I^{Batt} + C_{O\&M}^{Batt} \times \left(\frac{(1+i)^n - 1}{i(1+i)^n}\right) + C_R^{Batt} \times \sum_{j=1}^{\frac{n}{n_{Batt}}-1} \left(1 + \frac{1}{(1+i)^{jn_{Batt}}}\right) \tag{8}$$

$$C_{DG} = C_I^{DG} + C_{O\&M}^{DG} \times \left(\frac{(1+i)^n - 1}{i(1+i)^n}\right) + C_R^{DG} \times \sum_{j=1}^{\frac{n}{n_{DG}}-1} \left(1 + \frac{1}{(1+i)^{jn_{DG}}}\right) \tag{9}$$

The cost of energy (COE) is the average cost of producing each kWh of electricity, it can be determined using the (10)

$$COE = \frac{NPC}{\sum_{h=1}^{8760} P_{Load}} \times CRF \tag{10}$$

The annual present value of equal cash flows is determined using CRF. The CRF is given by [28]:

$$CRF = \frac{i(1+i)^n}{(1+i)^n - 1} \tag{11}$$

2.5. Optimization algorithms and tool

Optimization algorithms are crucial for designing reliable and cost-efficient systems by identifying the best configuration from a set of feasible options. They minimize costs, such as capital, operation, and maintenance expenses, while meeting reliability constraints like uninterrupted power supply. Using methods like heuristic or deterministic approaches, these algorithms balance cost and performance, ensuring robust and sustainable system designs. Table 4 provides an overview of several optimization methods and tools. Figure 2 outlines the methodology for designing and optimizing a HRES. The process involves defining the study area, collecting climatic data (e.g., solar radiation, wind speed), establishing the load profile, simulating system configurations, optimizing for technical and economic feasibility, and selecting the optimal configuration. Table 5 outlines the economic data used in this study for Dakhla city in Morocco. The HOMER simulation results provide detailed economic outputs, including system costs derived from capital investment, component replacement costs, and annual operation and maintenance expenses. Tables 6-8 provide the pseudocode for the algorithms discussed.

Table 4. optimization methods and tools

Ref.	Algorithmes/Tool	Definition	Advantages
[29]	PSO	An optimization method inspired by the social behavior of birds and fish, where each "particle" explores the search space and shares information.	- Simple to implement and understand. - Rapid convergence towards an optimal solution. - Adaptable to a variety of optimization problems.
[4]	GA	An algorithm inspired by the process of natural selection, where populations of individuals (potential solutions) evolve through selection, crossover, and mutation processes.	- Strong ability to explore large search spaces. - Effective for complex problems with multiple local optima. - Flexible and robust.
[30]	SA	An optimization algorithm based on the physical process of heating and cooling materials to reach a stable state, thereby seeking an optimal solution.	- Effective at avoiding local minima. - Well-suited for nonlinear and large-scale problems. - Simple to implement and understand.
[31]	HOMER	A software tool designed for optimizing the design of microgrids, particularly in the context of renewable energy systems. It evaluates various configurations and energy generation technologies.	-Tailored for renewable energy system optimization. - Delivers precise economic and technical analyses. -Renowne for efficient microgrid modeling.

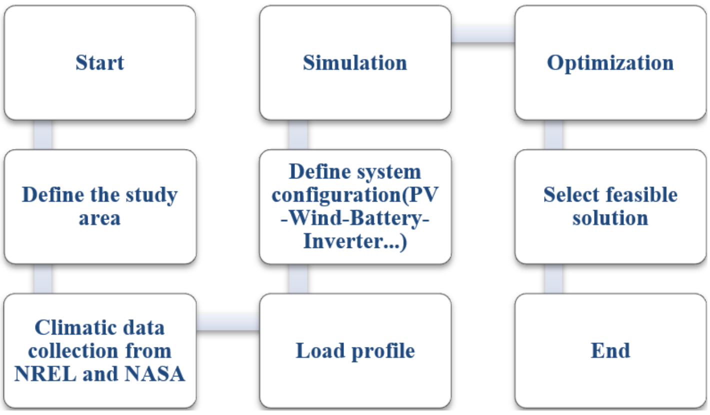

Figure 2. Flowchart of the HOMER software process

Table 5. Economic input data

Variable	Value
Discount rate	8%
Inflation	2%
Project lifetime	25 years

Table 6. The pseudo-code of PSO algorithm

Pseudo-code of PSO algorithm
1: Initialization:
2: Randomly initialize the positions and velocities of all particles.
3: Evaluate the objective function for each particlr $f(x_i)$.
4: Set each particle's personal best $p_{best,\, i}=x_i$.
5: Set the global best $g_{best}=min(f(x_i))$.
6: Repeat until the stopping condition is satisfied:
7: (a) For each particle i:
8: Update the velocity v_i using the formula:
$v_i = w.v_i+c_1.r_1.(p_{best,\, i} - x_i)+c_2.r_2.(g_{best} - x_i)$
9: Update the position $x_i = x_i + v_i$
10: Evaluate $f(x_i)$.
11: If $f(xi) < f(p_{best,\, i})$:
12 Update $p_{best,\, i}=x_i$
13: If $f(xi) < f(g_{best,\, i})$:
14: Update $g_{best,\, i}=x_i$
15: End for
16: End Repeat.
17: Return the global best solution g_{best} .

Table 7. The pseudo-code of GA algorithm

Pseudo-code of GA algorithm
1: Initialization:
2: Generate an initial population of size N.
3: Evaluate the fitness of each individual in the population.
4: Repeat until the stopping condition is satisfied:
5: (a) Selection:
6: Select parents based on their fitness
$v_i = w.v_i + c_1.r_1.(p_{best,\,i} - x_i) + c_2.r_2.(g_{best} - x_i)$
7: (b) Crossover:
8: Combine genes of the selected parents to produce off spring.
Apply crossover with a probability P_c.
9: (c) Mutation:
10: Mutate genes of the off spring with a probability P_m.
11: (d) Replacement:
12: Replace the worst individuals in the population with the new off spring.
13: (e) Evaluate the fitness of the update population.
14: End Repeat.
15: Return the global best solution g_{best} .

Table 8. The pseudo-code of SA algorithm

Pseudo-code of SA algorithm
1: Initialization:
2: Evaluate the cost of S, ie, cost(S).
3: Set the initial temperature T.
5: Set the cooling rate α.
6: Repeat until the stopping condition is satisfied:
7: (a) Generate a new solution S_{new} by perturbing S:
8: (b) Evaluate cost(S_{new}).
9: (c) If cost(S_{new})<cost(S):
10: Set $S=S_{new}$
11: (d) Else:
12 Accept Snew with probability P=exp(-Δcost/T)
Where Δcost= cost(S_{new})-cost(S)
14: (e) Update temperature T= T. α
16: End Repeat.
17: Return the global best solution found.

2.6. The system components specifications

Figure 3 shows a hybrid energy system combining alternating current (AC) and direct current (DC) power sources to meet the community's energy needs. It includes a generator and wind turbine on the AC side, connected to an inverter (XTH 8000-48) that manages energy flow. On the DC side, a solar photovoltaic system (Fron20) and a battery storage unit (H3000) store and supply power. The system handles an average daily consumption of 1,097.62 kWh and a peak load of 226.91 kW, ensuring reliable energy supply from renewable sources and conventional generation. Table 9 highlights the cost and lifespan differences among the various system components.

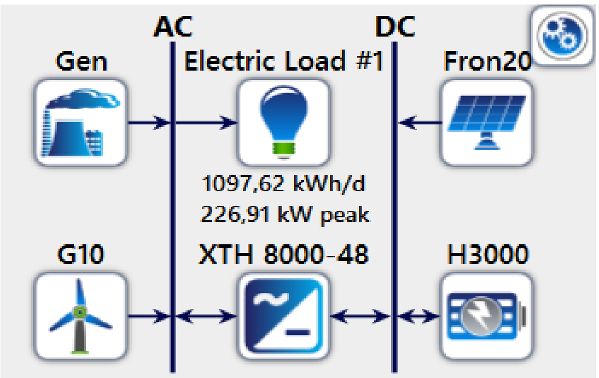

Figure 3. Hybrid system

Table 9. Economic specifications for each element of the HES

Parameters	PV	Wind Turbine	Generator diesel	Battery	Converter
Rated capacity (kW)	20	10	10	7.15	8
Capital cost ($)	3000	15000	5000	1200	300
Replacement ($)	3000	15000	5000	840	300
O&M ($/year)	10	75	0.3	12	70
Lifetime (years)	25	25	15000	20	10

3. RESULTS AND DISCUSSION

Table 10 summarizes the most feasible HRES configurations that meet the design constraints set by the system designer. The configurations are ranked in ascending order based on their cost of energy (COE), with the top four options being the most cost-effective and recommended for implementation. These configurations differ in their technological combinations, which include wind, PV, diesel, and battery components. The sizes of the PV systems range from 0 to 20 kW, while wind turbine capacities vary from 29 to 36 kW. Two of the configurations incorporate diesel generators, while the other two rely entirely on renewable energy sources, with battery capacities ranging from 11,025 to 16,170 units. The net present cost (NPC) of these systems ranges from $820,656 to $890,890, with COEs between $0.158 and $0.172 per kWh. The table also includes initial and operating costs, the renewable fraction (100% for all configurations), and total fuel consumption, which is zero in systems without a diesel generator.

Table 11 details the annual electricity production in the hybrid system, totaling 399,564 kWh. Wind turbines (generic 10 kW) dominate with 353,416 kWh (88.5%), making wind the primary energy source. PV panels (Fronius Symo 20.0-3-M) add 46,003 kWh (11.5%), while the diesel generator, used only as a backup, contributes a negligible 145 kWh (0.036%). This highlights the system's heavy reliance on wind energy, with solar as a secondary source and minimal diesel backup.

Table 10. The most feasible HRES configurations

	Wind/Diesel/Battery	PV/Wind/Diesel/Battery	Wind/Battery	PV/Wind/Battery
PV (kW)	-	20	-	20
Wind turbine (kW)	33	29	34	36
Generator (kW)	10	10	-	-
Battery	16170	13440	13545	11025
Converter (kW)	188	189	198	199
NPC ($)	820656	829380	842940	890890
COE ($)	0.158	0.160	0.163	0.172
Initial cost ($)	571787	580659	582314	627298
Operating cost ($)	19251	19240	20161	20390
Ren Frac (%)	100	100	100	100
Total Fuel (L/year)	56.1	54.9	-	-

Table 11. The energy production from each component of the hybrid system and its percentages

Production	kWh/year	%
Fronius symo 20.0-3-M with generic PV	46003	11.5
Generic 10 kW fixed capacity genset	145	0.036
Generic 10 kW	353416	88.5
Total	13 084	100

Figure 4 provides a detailed breakdown of the renewable energy system's cost structure. It highlights the system's high initial capital investment, primarily due to the procurement and installation of renewable energy components. The replacement costs, though moderate, are necessary over the system's lifespan to maintain efficiency and reliability. Operating and maintenance expenses remain minimal, reflecting the low upkeep requirements of renewable technologies. Additionally, fuel costs are negligible, reinforcing the system's complete dependence on renewable sources. A small salvage value is anticipated at the end of the system's operational life, further supporting its long-term economic viability and sustainability

Figure 5 illustrates the monthly average electricity production from the HES, showing contributions from three sources: wind turbines (G10), PV solar panels (Fron20), and a diesel generator (Gen). The wind turbines (represented by the orange bars) consistently provide the majority of electricity throughout the year, reflecting their dominant role in the system. Production is fairly stable, with a slight peak in the summer months, particularly in July, when wind energy reaches its highest level. Solar PV panels (shown in green) contribute a smaller but steady amount each month, aligning with their 11.5% share of total annual production. Finally, the diesel generator (indicated by the small brown segments at the bottom of the bars) plays a minimal role, producing only a negligible amount of electricity, likely reserved for emergency backup use. Overall, the system relies heavily on wind energy, with solar playing a secondary role and the generator used sparingly.

The implementation and execution of the heuristic algorithms are carried out using MATLAB software, which provides a robust computational environment for optimization tasks. The algorithms are coded and executed within MATLAB's dedicated optimization toolbox and custom script files, ensuring efficient computation and result analysis. Table 12 presents the key parameter settings for the three heuristic algorithms PSO, GA, and SA. These parameters, including population size, mutation rate, cooling schedule, and inertia weight, are carefully selected to balance convergence speed and solution accuracy, thereby optimizing the performance of each algorithm

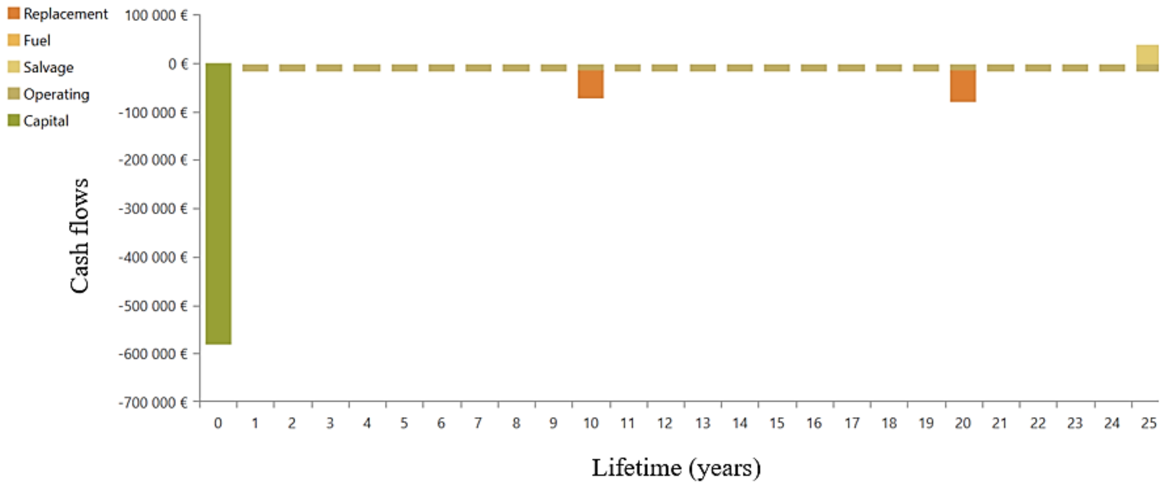

Figure 4. Cash flow for the chosen solution

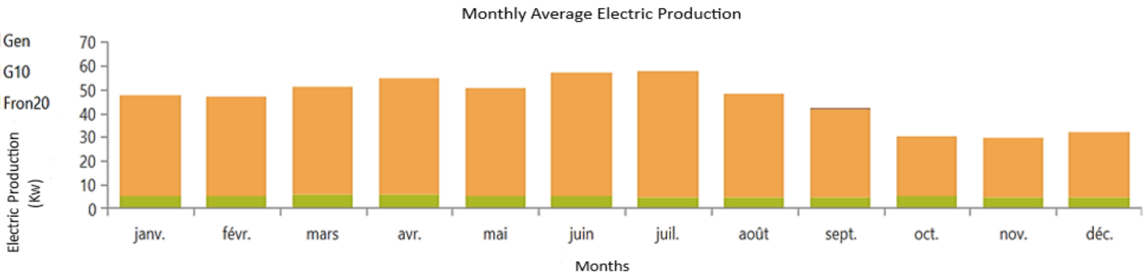

Figure 5. Average monthly electrical output from the optimal configuration system

Table 12. The three algorithms' parameter values

Parameter values	PSO	GA	SA
Population size	25	10	10
Personal learning coefficient	2.01	-	-
Inertia weight damping ratio	0.9	-	-
Global learning coefficient	1.92	-	-
Inertia weight	0.95	-	-
Total number of itarations	100	100	1000
Generations	-	20	-
Generation gap	-	0.9	-
Probability of Muation	-	0.0477	-
Crossover points	-	2	-
Crossover probability	-	0.7	-
Number of neighbors per individual	-	-	5
Initial temperature	-	-	100
Cooling parameters	-	-	0.97

Using HOMER software, the results identify the PV-wind-diesel-battery configuration as the most cost-effective solution, with a COE of $0.160/kWh. To validate the optimality of the system, alternative algorithms such as PSO, GA, and SA were employed. Table 13 presents a comparative analysis of the economic outcomes achieved using HOMER and these alternative algorithms across all configurations.

Table 13. Comparison of economic results with alternative algorithms

Algorithms/tool	Microgrid system	COE ($)
PSO	PV/WT/DG/Batt	0.163
	PV/WT/Batt	0.176
	WT/DG/Batt	0.160
	WT/Batt	0.168
GA	PV/WT/DG/Batt	0.161
	PV/WT/Batt	0.174
	WT/DG/Batt	0.155
	WT/Batt	0.166
SA	PV/WT/DG/Batt	0.159
	PV/WT/Batt	0.170
	WT/DG/Batt	0.156
	WT/Batt	0.160
HOMER	PV/WT/DG/Batt	0.160
	PV/WT/Batt	0.172
	WT/DG/Batt	0.158
	WT/Batt	0.163

4. CONCLUSION

In conclusion, this research significantly advances the field of HRES, particularly in remote and off-grid areas like Dakhla, Morocco, where conventional energy infrastructure is inadequate. The research presents a practical and cost-effective solution to provide sustainable, reliable, and environmentally friendly power to regions facing energy access challenges. By integrating PV panels, WT, DG, and Battery storage, an optimized HRES configuration is developed that balances both technical and economic considerations. The novelty of this work lies in its tailored approach to HRES design and optimization for Dakhla's specific context, utilizing real-world data on local energy consumption, climatic conditions, and installation constraints. This distinguishes it from previous studies, which often focus on generalized or theoretical models. Additionally, the study compares the proposed system with recent metaheuristic optimization algorithms: GA, PSO and SA, demonstrating the system's optimal performance. A key contribution of this research is the identification and validation of the PV-WT-DG-Batt configuration as the most reliable and cost-effective solution for off-grid electrification in Dakhla. The system achieves a NPC of $829,380, a COE of $0.160/kWh, and minimal CO_2 emissions of 54.9 kg/year. These quantified results illustrate the scalability and practical applicability of the proposed HES, which can be replicated in other regions with similar energy access challenges. Compared to prior studies, the advantage of this work lies in the integration of advanced simulation techniques, real-world data, and a comprehensive approach that ensures both technical feasibility and economic viability. While many earlier studies have concentrated on individual energy technologies or theoretical models, this study provides a clear pathway for developing cost-effective, sustainable, and reliable off-grid energy systems. The results offer valuable insights for addressing global energy access challenges, providing a scalable solution for implementation in off-grid regions worldwide.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The dataset supporting this study's findings is publicly accessible at https://power.larc.nasa.gov/data-access-viewer/. It provides comprehensive meteorological parameters for Dakhla City, Morocco.

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