

Review

Advancing sustainable energy solutions: AI hybrid renewable energy systems with hybrid optimization algorithms and multi-objective optimization in Portugal

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ABSTRACT

The effects of global warming are becoming increasingly evident in our daily lives, making it essential to develop sustainable, carbon-neutral solutions. The energy sector is a major contributor to global warming due to its reliance on coal, oil, and natural gas. Therefore, transitioning to renewable energy is crucial. However, renewable sources face intermittency issues, as their availability depends on weather conditions. To address this, a hybrid energy system that integrates multiple renewable sources can enhance reliability.

This study optimized a hybrid renewable energy system for Portugal. It began with a systematic literature review on artificial intelligence and energy, identifying nine relevant studies that helped formulate problem. A hybrid system incorporating solar panels and wind turbines was designed and optimized using a novel algorithm that combined Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO). By leveraging the strengths of both methods, the algorithm improved convergence toward the global optimum. To further enhance efficiency, the algorithm was parallelized to reduce execution time and computational demands.

Three experiments were conducted to optimize the system. In the first experiment, the Average Best Fitness (ABF) started below 0.420, decreased to 0.390 by the third iteration, but later increased to approximately 0.400. To improve performance, hyperparameters were adjusted in a second experiment. However, results worsened, with ABF starting at 0.480 and only reaching 0.455 by iteration 14. The third experiment yielded the most promising results, with an initial ABF of 0.150, followed by a sharp drop at iteration 3 and a gradual decline with fluctuations.

Future research should explore a broader range of hyperparameter combinations to refine optimization results. Additionally, incorporating economic and social objectives alongside technical and environmental criteria will provide a more comprehensive assessment of hybrid energy systems.

Acronyms

AOA	Arithmetic Optimization Algorithm
AI	Artificial Intelligence
AD	Autonomous Days
BSS	Battery Storage Systems
COE	Cost of Energy
DPSP	Deficit of Power Supply Probability
DG	Diesel Generator
EIR	Energy Index Reliability
GA	Genetic Algorithm
GPUs	Graphic Processing Units
GSA	Gravitational Search Algorithm

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GWO	Grey Wolf Optimizer
H	Home
HHO	Harris Hawks Optimizer
hHHO-AOA	Harris Hawks Optimizer-Arithmetic Optimization Algorithm
HC	Hybrid Constant
HFAPSO	Hybrid Firefly Particle Swarm Optimization
PSOGSA	Hybrid Particle Swarm-Gravitational Search Algorithm
HRES	Hybrid Renewable Energy System
HRES-WS	Hybrid Renewable Energy System Without Storage
LCOE	Levelized Cost Of Energy
LRQ	Literature Research Question

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LPSP	Loss of Power Supply Probability
MFO	Moth-Flame-Optimizer
MOEA	Multi-objective Evolutionary Algorithm
MOPSO	Multi-objective Particle Swarm Optimization
NPC	Net Present Cost
NSGA II	Non-dominant Sorting Genetic Algorithm II
PSO	Particle Swarm Optimization
PV	Photovoltaic
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
R	Rural areas
REN	Redes Energéticas Nacionais
RES	Renewable Energy Sources
RQ	Research Question
SB	Storage Battery
SC	Smart Cities
SDGs	Sustainable Development Goals
SLR	Systematic Literature Review
TNPW	Total Net Present Worth
U	University
WCA	Water Cycle Algorithm
WMO-MILP	Weighted Multi-Objective Mixed-Integer Linear Programming
WOA	Whale Optimization Algorithm
WT	Wind Turbines

Nomenclature

a)	Hybrid Algorithm GA-PSO multi-objective
ACS	Annual cost of the system
AO	Time by which clocks are set ahead of the local time zone
A_s	Photovoltaic panel area
A_w	Wind turbine swept area
A_{WT}	Total swept area of a wind turbine
b)	Hybrid Algorithm PSO-GSA multi-objective
B	Direct irradiance falling on a surface perpendicular to the sun's rays
B₀	Solar constant (1367 W/m ²)
B(β, α)	Direct irradiance on an inclined surface
BS	Battery storage capacity
b_t	Type of battery
c)	Hybrid Algorithm WMO-MILP-Monte Carlo simulation multi-objective
C_{p-max}	Power coefficient of the wind turbine
cos θ_s	Angle of incidence between the sun's rays and the normal to the surface
cos θ_{zs}	Solar zenith angle
d)	Hybrid Algorithm MOEA-GA multi-objective
DPSP	Deficit of power supply probability
D(β, α)	Diffuse irradiance on an inclined surface
D^c(β, α)	Circumsolar component of diffuse irradiance on an inclined surface
Dⁱ(β, α)	Isotropic component of diffuse irradiance on an inclined surface
d_n	Day number counted from the beginning of the year
d_t	Type of diesel generator
e)	Hybrid Algorithm PSO-GWO multi-objective
E_{DE} (t)	Energy deficit (kWh)
E_{dumped}	Energy stored into the battery
E_{LOAD} (t)	Total annual energy demand of the load (kWh/year)
f)	Hybrid Algorithm hHHO-AOA multi-objective
FF	Fill factor
f_i(x_{DV})	ith objective function of the weight sum method
f_i^{max}(x_{DV})	upper bound of the ith objective function of the weight sum method
F_{ws}	Scalarized objective function of the weight sum method
g)	Hybrid Algorithm PSO-GWO multi-objective
G	Global solar irradiance on a PV module
G(β, α)	Global irradiance on an inclined surface
gb_t	Amount of energy to be bought from the grid at time t
gs_t	Amount of energy to be sold from the grid at time t
h)	Hybrid Algorithm NSGA-GWO multi-objective
h	Wind turbines installation height
h_{E70}	Possible heights of E70 wind turbine installation
h_{E82}	Possible heights of E82 wind turbine installation
h_r	Reference height of wind turbine
i)	Hybrid Algorithm HFA-PSO multi-objective
IMP	Maximum power current
Inverter	Inverter capacity
I_{sc}	Short circuit current of a PV module
I_{sc-STC}	Short circuit current of a PV module for standard test conditions
i_t	Type of inverter/charger
k₁	Anisotropy index

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K_I	Short circuit current temperature coefficient
K_V	Open circuit voltage temperature coefficient
LCOE	Levelized cost of energy
LH	Reference longitude of the local time zone
LL	Local longitude
LPSP	Loss of power supply probability
NOCT	Nominal operating cell temperature
NPC	Net present cost
N_{AD}	Number of autonomous days
n_{Batt}	Number of battery storage banks
n_{DG}	Number of diesel generators
N_{PV}	Number of PV modules
N_{PV}^{min}	Minimum number of PV modules
N_{PV}^{max}	Maximum number of PV modules
N_{WT}	Number of wind turbines
N_{WT}^{min}	Minimum number of wind turbines
N_{WT}^{max}	Maximum number of wind turbines
P_{1gen}	Crossing point of supplying energy cost by means of the AC generator and batteries
P_{criticalgen}	Power in which the diesel generator provides the insignificant power
P_{mingen}	Minimal diesel generator operations power
P_{PV}	Power produced by PV modules
P_{PV-array}	Total output power from a PV array
p_t	Type of PV panel
P_{WT}	Power output wind turbine
P_{WT,r}	Rated Power
R(β, α)	Albedo irradiance on an inclined surface
R_{PV}	Solar panel power
R_{WT}	Wind turbine power
SB_{cap}	Battery capacity
SOC_{min}	Minimum SOC of the battery bank
SOC_{stopgen}	SOC set point of the batteries
t	Particular hour
TO	Local standard time
T_A	Ambient temperature
VMP	Maximum power voltage
v	Wind speed at hub height
V	Wind speed
V_{cut-in}	Cut-in wind speed
V_{cut-out}	Cut-out wind speed
V_{OC}	Open circuit voltage of a PV module
V_{OC-STC}	Open circuit voltage of a PV module for standard test conditions
v_r	Wind speed at reference height
V_r	Rated wind speed
x_{DV}	Vector of the decision variables of the problem
w_i	ith weighting coefficient
w_t	Type of wind turbine
z_t	Binary variables for maximum and minimum limit of amount of energy to be bought from the grid
β	Tilt angle of the PV modules
η_{PV}	Efficiency of PV module
α	Power law coefficient
ρ_{air}	Air density (kg/m ³)
ρ_{ref}	Reflectivity of the ground
δ	Solar declination
φ	Geographic latitude
ω	True solar time
ε₀	Eccentricity correction factor
ε	CO ₂ emissions coefficient (kg CO ₂ /Wh)

1. Introduction

Bilgen (2014) defines energy as "the ability to do work" that can be defined by: the form in which can be found, how it is processed, and its source. Electricity, a crucial form of energy, plays a vital role in the modern economy, where its demand is projected to rise due to factors such as increasing household incomes, the electrification of transport and heating systems, the growing use of digital devices, and the expansion of air conditioning (Electricity – World Energy Outlook, 2019 – Analysis – IEA, 2019). Bilgen (2014) also observed that economic growth leads to higher energy consumption, highlighting a direct relationship between these two variables. The surge in electricity demand contributed to 2018 becoming a record year for global CO₂ emissions in the energy sector (Electricity – World Energy Outlook, 2019 – Analysis –

IEA, 2019). Even before this record, the energy sector accounted for two-thirds of global CO₂ emissions, underscoring the need to reduce emissions through energy system decarbonization to combat global warming (Energy Transitions and Societal Change | Research Institute for Sustainability, 2024). Decarbonizing electricity could also help reduce CO₂ emissions in other sectors, including construction, industry, and transport (Electricity – World Energy Outlook, 2019 – Analysis – IEA, 2019).

Several international agreements have been established with the goal of creating a more sustainable future. In 1997, the Kyoto Protocol was adopted by various countries to encourage the use of energy sources with low levels of harmful emissions, doing this by introducing a price for CO₂ and other greenhouse gases (Solomon and Krishna, 2011). In 2015, the Paris Agreement was adopted by 196 parties at the UN Climate Change Conference (COP21), with the aim of keeping the rise in global average temperature "well below 2 °C above pre-industrial levels" and to pursue efforts "to limit the temperature increase to 1.5 °C above pre-industrial levels" (The Paris Agreement | UNFCCC, 2023). That same year, the UN established the 17 Sustainable Development Goals (SDGs), agreed upon by multiple countries. The SDGs outline a vision of ending poverty and other deprivations while simultaneously improving health, education, reducing inequality and fostering economic growth — all while addressing climate change and preserving the planet's oceans and forests (THE 17 GOALS | Sustainable Development, 2023).

The development of these agreements generally aims to achieve an energy transition to combat climate change, which poses a serious threat to the planet. Throughout history, energy transitions have been closely linked to industrial revolutions (He, 2015). The first industrial revolution, in the late 18th century (Team, 2019), saw firewood replaced by coal, leading to industrialized production, increased workplace productivity, and the rise of railways (He, 2015). In the second industrial revolution, at the end of the 19th century (Team, 2019), oil replaced coal (Kabeyi and Olanrewaju, 2022), and electricity was introduced. These innovations fueled mass production, such as Ford automatic engine production lines, and revolutionized transportation and communication with the advent of cars and the telephone (He, 2015). The third industrial revolution, beginning in the mid-20th century (Team, 2019), was marked by the emergence of nuclear energy, electronics, telecommunications, and computers (Team, 2019). The current fourth industrial revolution, or Industry 4.0, started in the early 21st century with the rise of the Internet (Team, 2019). These industrial revolutions, spanning several centuries, gave birth to an industrial civilization that, according to He (2015), represents "an unsustainable form of human society" contributing to resource depletion and climate change.

Before the revolutions that took place, communities relied on natural resources for everyday tasks, like drying clothes under the sun. However, as previously mentioned, these practices have shifted towards the use of fossil fuels, which harm our planet (Kabeyi and Olanrewaju, 2022). To address this, a transition to renewable energy sources (RES) is essential (Kabeyi and Olanrewaju, 2022). Renewable energy is derived from natural resources, this being "hydropower, solar, wind, wave, geothermal power, waste energy such as gases from landfills, incineration, biomass, and liquid biofuels" (Bishoge et al., 2019). Renewable energy stands out as a key option due to its availability, abundance, minimal environmental impact (Ajiboye et al., 2023), while at the same time offers numerous economic and social benefits, including environmental sustainability, decentralized energy access, reduced emissions, and local socio-economic development (Kabeyi and Olanrewaju, 2022). However, relying solely on a single renewable energy source presents challenges due to its intermittency, as it is weather-dependent. To address this, the combination of two or more renewable sources to create a hybrid renewable energy system (HRES) becomes necessary (Ajiboye et al., 2023), in addition to this, the intermittency can also be addressed through optimization to "create stability and reliability in renewable energy supply and use" (Kabeyi and Olanrewaju, 2022).

A key area of focus in renewable energy research is Artificial

Intelligence (AI), due to its potential for modeling, forecasting, optimizing, and managing energy sources (Entezari et al., 2023). Constant research into AI applications for the energy sector is crucial for developing more sustainable solutions, this type of research has expanded rapidly in recent years, not only in renewable energy but also in areas like smart grids, energy consumption, and storage (Entezari et al., 2023).

To efficiently harness renewable energy, it is essential to design optimal HRES using AI algorithms, which enable better monitoring, operation, maintenance, and storage of renewable energy sources (Liu et al., 2022). AI-based techniques have shown great promise, being considered more acceptable than traditional methods due to their ability to search for global optima, high computational precision, and fast convergence rates (Sawle et al., 2023). However, as was pointed by these authors relying on a single optimization algorithm often prevents achieving truly optimal results. In fact, several researchers have recognized opportunities for improvement through the combination of two or more algorithms, which can "complement each other and produce better optimization efficiency" (Cai et al., 2022). They argue that such hybrid approaches "can provide more accurate results and have the ability to solve multi-objective optimization problems" (Sawle et al., 2023) and that could be especially beneficial since real-world problems usually involve conflicting objectives that cannot be easily reduced to a single objective function. However, this approach wasn't yet properly addressed in the Portuguese context by the scientific community.

This highlights the need for research on AI-based Hybrid Renewable Energy Systems, focusing on exploring new combinations of optimization algorithms that can efficiently handle multiple objective functions. As a result, the research question (RQ) placed in this investigation is: "What novel hybrid optimization algorithms can be developed to effectively address diverse objective functions in the context of AI-based Hybrid Renewable Energy Systems in Portugal?". As for the objectives to achieve in the research, the following ones were set:

- Make a systematic literature review on the field of AI and Energy;
- Proposal of a hybrid optimization approach, which allows the existence of a complementarity and synergy between them to handle a broader spectrum of objective functions;
- Development of experiments to evaluate the performance of the hybrid optimization algorithm, to optimization of Hybrid Renewable Energy System (HRES) in Portugal.

2. Related work

A Systematic Literature Review (SLR) was conducted following the PRISMA methodology (Preferred Reporting Items for Systematic Reviews and Meta-Analyses), with the purpose of exploring the current state of the art on the research topic and to gather relevant knowledge. To ensure a thorough review of the literature in the field of AI and Energy, the following literature research questions (LRQs) are formulated:

LRQ1: What are the optimization algorithms that were used to create hybrid optimization algorithms to optimize HRES?

LRQ2: How do optimization algorithms contribute to overcoming challenges associated with the intermittent nature of renewable energy sources?

LRQ3: How has multi-objective optimization been used in the design and operation of HRES?

To conduct the literature review, the steps outlined in the PRISMA methodology were followed. It was defined the eligibility criteria, establishing the inclusion and exclusion criteria for articles in the review. It was included only articles published after 2014, ensuring that the information gathered on Artificial Intelligence and Hybrid Renewable Energy Systems is only the most recent. Given that the objective of this SLR is to explore the state of the art on Hybrid Renewable Energy

Systems using Hybrid Optimization Algorithms with Multi-objective Optimization in Portugal, the inclusion criteria outlined in Table 1 were defined. Regarding the exclusion criteria, articles were excluded if they: do not align with the scope of this thesis, are unavailable in full text, are not written in English, or focus on optimization software rather than algorithms.

To conduct this SLR, several databases were used: Scopus, Web of Science, IEEE Xplore, and Taylor & Francis. These databases were accessed directly, without the use of aggregators.

In the initial literature review, multiple keywords were identified, and only those most relevant to the study were selected. This process led to the development of the following query for an efficient search across the various information sources:

"hybrid renewable energy systems" AND (ensemble OR "hybrid algorithm" OR "hybrid optimization") AND ("multiobjective optimization" OR "multi-objective optimization")*

This query was applied to the selected databases, where in the initial identification phase, 39 articles were found across the databases: 8 from Scopus, 6 from Web of Science, 1 from IEEE Xplore, and 24 from Taylor & Francis. Additionally, 5 more relevant articles were identified through other methods, bringing the total to 44 articles. After removing duplicates, 38 articles remained. In the second phase, the screening phase, these 38 articles were reviewed based on their titles and abstracts, resulting in the exclusion of 27 articles that did not align with the scope of this systematic literature review. The remaining 11 articles were then retrieved, with all being successfully obtained, so none were excluded for reason 2. During the eligibility phase, the full texts of these 11 studies were evaluated against the inclusion and exclusion criteria, ultimately leading to the inclusion of 9 articles in the final review. Subsequently, the LRQ outlined before are answered for each of the 9 articles.

To determine the optimal size of a HRES, Amereh et al. (2014) employed a hybrid algorithm, that results from the combination of genetic algorithm (GA) and particle swarm optimization (PSO). The GA is used in the initial optimization phase and after a set number of iterations, defined as the Hybrid Constant (HC), PSO is applied to enhance optimization speed and local tuning ability (Amereh et al., 2014). The hybrid GA-PSO algorithm is designed to address a multi-objective optimization problem, aiming to minimize the Total Net Present Worth (TNPW) and maximize the Energy Index Reliability (EIR), achieving this by employing an ϵ -constraint method, where TNPW serves as the primary optimization function and EIR acts as a constraint, through this approach, the optimization makes it possible to obtain key system parameters (wind turbine (WT) swept area, photovoltaic (PV) panel area, and storage battery (SB) capacity) (Amereh et al., 2014). The HRES in the study consists of wind turbines, photovoltaic panels, and a storage battery, which is included to address the intermittency of renewable energy sources (Amereh et al., 2014).

Diab et al. (2019) conducted a study focused on optimizing the size of a HRES, where various algorithms have been applied: Whale Optimization Algorithm (WOA), Water Cycle Algorithm (WCA), Moth-Flame Optimizer (MFO), and the Hybrid Particle Swarm-Gravitational Search Algorithm (PSOGSA). The hybrid PSOGSA algorithm combines PSO with

the Gravitational Search Algorithm (GSA), leveraging the exploitation capability of PSO and the exploration efficiency of GSA (Diab et al., 2019). The optimization task was multi-objective, since its aim was to minimize the Loss of Power Supply Probability (LPSP), Cost of Energy (COE), and dummy load. To address the multiple objective functions, weights for each were determined through trial and error, to achieve the best results (Diab et al., 2019). Since the HRES in the study relies on intermittent renewable energy sources, the authors incorporated an energy storage system, specifically a battery bank, and a diesel generator, the latter being only used when renewable sources and the battery bank could not meet energy demands (Diab et al., 2019).

The study developed by Capraz et al. (2020) aimed to optimize the sizing of a hybrid renewable energy system without storage (HRES-WS), by combining a weighted multi-objective mixed-integer linear programming (WMO-MILP) model with Monte Carlo simulation. The WMO-MILP model enables an analysis of how different objective functions influence system sizing, with the weights assigned to each function reflecting the decision-maker's priorities, whether cost-based, environmental-based, or a mix of both (Capraz et al., 2020). Monte Carlo simulation is used to account for the stochastic nature of the modeling environment, allowing for the prediction of weather data and load demand based on historical data (Capraz et al., 2020). The model handles a multi-objective optimization problem, where the goals are to minimize the gap between total cost and revenue, and to reduce the total annual CO₂ emissions. Capraz et al. (2020) found that increasing the weight of the CO₂ minimization objective leads to higher system costs.

Rathish et al. (2021) conducted a study to optimize the design of a HRES for Tamil Nadu, India, using a hybrid algorithm that combines the Multi-objective Evolutionary Algorithm (MOEA) and GA. This optimization approach considered three key objectives: minimizing Net Present Cost (NPC), unmet load, and the CO₂ emissions from the system (Rathish et al., 2021). The MOEA evaluates these objectives in a vector, with each objective linked to the problem's decision variables, enabling the identification of a Pareto set of non-dominated solutions (Rathish et al., 2021). The GA then selects the solution that minimizes NPC from the component combinations generated by the MOEA (Rathish et al., 2021). The proposed HRES consists of PV, wind, diesel, and battery systems, though the study demonstrated that energy demand could be met without relying on the diesel generator, highlighting the feasibility of using renewable energy sources in the region (Rathish et al., 2021).

To determine the optimal size of a microgrid in Bihar, India, Suman et al. (2021) used a hybrid PSO-GWO algorithm, which combines PSO and Grey Wolf Optimization (GWO). While PSO is effective at exploitation, it has limited exploration capability, often converging to local optima rather than the global solution, to address this, GWO was integrated in order to "minimize the probability of falling into a local minimum" (Suman et al., 2021). The optimization problem is multi-objective, since it aims to minimize both the COE and the Deficit of Power Supply Probability (DPSP), to address this they were transformed into a single-objective problem using linear scalarization, where "the objectives are either combined to form a linear function or are taken as constraint for optimization" (Suman et al., 2021). Each objective function was assigned a weight to reflect its importance, along with a fraction between the value of the objective function and its maximum limit (Suman et al., 2021). The study's energy system is a HRES, relying primarily on RES, which are inherently intermittent, to address this, the system includes a battery storage unit and a diesel generator. When the energy produced by RES exceeds demand, the excess is stored in the battery. If the combined energy from the RES and the battery is insufficient to meet demand, the diesel generator is used as a backup (Suman et al., 2021).

The study conducted by Çetinbaş et al. (2022) focused on the "sizing optimization and design of autonomous microgrids" (Çetinbaş et al., 2022) using the hybrid algorithm Harris Hawks Optimizer-Arithmetic Optimization Algorithm (hHHO-AOA), that allows to improve the solution accuracy and computational speed by improving search

Table 1
Inclusion and exclusion criteria definition.

Inclusion criteria	Meet the scope of this thesis	Considers a Hybrid Renewable Energy System (HRES) Hybrid optimization algorithm in the context of HRES Multi-objective optimization algorithm in the context of HRES
Exclusion criteria	Reason 1	Does not meet the scope
	Reason 2	Not available as full text
	Reason 3	Not in English language
	Reason 4	Uses software for optimization instead of an algorithm

efficiency. The optimization problem addressed in the study is multi-objective, with the goal of minimizing the LPSP and the COE, to address this, the authors made the problem into a single-objective optimization using the weighted sum method, where it is assigned specific weights to each objective function (Çetinbaş et al., 2022). In response to the challenges associated with renewable energy sources, the study incorporated a battery storage system (BSS) and a diesel generator (DG) to ensure uninterrupted operation (Çetinbaş et al., 2022).

The study conducted by Fendzi Mbasso et al. (2023) aimed to "assess and improve the reliability and autonomy of the HRES" (Fendzi Mbasso et al., 2023), through the application of a hybrid algorithm that combines PSO with GWO, the latter has the exploration capability, making it possible to avoid local optima (Fendzi Mbasso et al., 2023). The optimization problem is multi-objective, aiming to minimize the DPSP, maximizing Autonomous Days (AD), and maximizing the energy stored in the Battery Storage System (BSS), the authors achieved this optimization using two parameters obtained through trial and error (Fendzi Mbasso et al., 2023). A component of the system is the battery storage system (BSS), which ensures a "reliable, suitable, and sustainable system" (Fendzi Mbasso et al., 2023) by addressing the intermittency of renewable energy sources in the HRES.

The study of Hossain et al. (2023) aimed to determine the optimal sizing of a HRES using a hybrid algorithm that combines the Non-dominant Sorting Genetic Algorithm II (NSGA II) and the GWO. NSGA II offers fast and efficient convergence but comes with high computational complexity, while GWO has slower convergence, lower complexity, and greater exploration ability (Hossain et al., 2023). By merging these two algorithms, the NSGA-GWO "preserves the ingenuity of both algorithms and combines them to generate a much more reliable outcome" (Hossain et al., 2023). The problem was framed as a multi-objective optimization with two main goals of minimizing the total cost and the LPSP, addressing these as a single objective function that simultaneously minimizes these two factors (Hossain et al., 2023). To manage the intermittent nature of renewable energy, the study incorporated an energy storage device within the HRES (Hossain et al., 2023).

To tackle the problem of optimal sizing for a HRES, Güven et al. (2023) employed the Hybrid Firefly Particle Swarm Optimization (HFAPSO) algorithm. This method was chosen for its ability to navigate complex optimization landscapes, find global optimal solutions, and handle intricate constraints, demonstrating its robustness (Güven et al., 2023). The optimization task is multi-objective, since it aims to minimize the annual system cost (ASC), the levelized cost of energy (LCOE), and the net present cost (NPC). To ensure system reliability, the HRES integrates a battery and a diesel generator (Güven et al., 2023).

As a result of the systematic literature, it was possible to draw conclusions regarding the decision variables and objective functions used by context area, the most used objective functions and their respective best results, and to identify the associated hybrid algorithms.

Analyzing the decision variables and hybrid algorithms, used in the nine articles identified in the SLR, in the various context areas verified (rural, university, smart cities, or home), it was possible to construct Table 2. This table highlights that the decision variables, such as the number of PV modules, wind turbines, and battery storage banks, are present across all four context areas. The number of PV modules, wind turbines and diesel generators hold particular significance in rural and university settings. The number of autonomous days, while less frequently used, appears in both rural and university areas. The remaining decision variables are distributed sporadically across the different context areas.

It was also essential to create Table 3 to assess the objective functions applied across different context areas. According to the table, in rural areas, the most used objective functions are minimizing the COE and minimizing the DPSP, while in other areas of context, the objective functions appear more varied. Overall, across all four context areas, the

Table 2

Hybrid algorithm, context area and respective decision variables.

		Context areas			
		R	U	SC	H
Decision variables	A_W				
	A_S				
	SB_{cap}				
	N_{PV}	b), e)	c), f), i)	d)	h)
	N_{WT}	b), e)	c), f), i)	d)	h)
	n_{Batt}	b)	i)	d)	h)
	n_{DG}	b), e)	f), i)		
	gb_t		c)		
	gs_t		c)		
	z_t		c)		
	p_t			d)	
	w_t			d)	
	b_t			d)	
	d_t			d)	
	i_t			d)	
	P_{mingen}			d)	
	P_{1gen}			d)	
	$P_{criticalgen}$			d)	
	$SOC_{stopgen}$			d)	
	SOC_{min}			d)	
	N_{AD}	g)	f)		
	$DPSP$	g)			
	E_{dumped}	g)			
	β				h)
	h				h)
	ACS		i)		
	$LCOE$		i)		
	NPC		i)		
	BS		i)		
	$Inverter$		i)		
	R_{WT}		i)		
	R_{PV}		i)		

most frequently used objective functions are minimizing the COE, LPSP, total annual CO₂ emissions, TNPC, and DPSP.

Table 4 presents the most used objective functions mentioned earlier, while also highlighting the best results obtained for each function, leading to the identification of three hybrid algorithms: MOEA-GA, PSO-GWO, and NSGA-GWO.

This systematic literature review (SLR) offers a novel contribution to the field of Hybrid Renewable Energy Systems (HRES) optimization through two key aspects: the inclusion of recent studies and a comprehensive analysis of hybrid optimization algorithms. By applying the PRISMA methodology, this review ensures a rigorous and up-to-date perspective on the state of the art, focusing on studies published after 2014. This timeframe captures the latest advancements in hybrid algorithms and multi-objective optimization techniques applied to HRES, particularly those incorporating AI. By prioritizing recent studies, this review presents a timely reflection of current trends and breakthroughs in the field, ensuring that the findings remain relevant to ongoing research and practical applications. The focus on recent developments allows for a deeper understanding of emerging methodologies and their impact on optimizing hybrid renewable energy systems. Additionally, this review introduces a structured analysis of hybrid optimization algorithms based on three key research questions: (i) identifying the optimization algorithms used to develop hybrid approaches for HRES, (ii) assessing how these algorithms address the challenges posed by the intermittent nature of renewable energy sources, and (iii) examining the role of multi-objective optimization in the design and operation of HRES. Through this analysis, the review explores the decision variables and optimization techniques applied in different context areas (rural areas, universities, smart cities, and residential applications). It also examines the objective functions commonly used in these environments and highlights the best-performing approaches. This comparison provides new insights into how hybrid optimization algorithms can effectively balance multiple objectives. Furthermore, it identifies key hybrid

Table 3
Hybrid algorithm, context area and respective objective function.

		Hybrid algorithm						
		b)	c)	d)	e)	f)	g)	h)
Objective functions	Minimize COE (\$/kWh)	0.185			0.169	0.209		
	Minimize LPSP (%)	9.073×10^{-7}				6.506		0
	Minimize total annual amount of CO ₂ produced (kg CO ₂ /year)		1469	806				
	Minimize TNPC			61,027.9 €				35,693.77\$
	Minimize DPSP (%)				6		1.375	

Table 4
Systems performance, objective functions more used and respective best values obtained.

		Context areas			
		R	U	SC	H
Objective functions	Minimize TNPW (\$)				
	Maximize EIR (%)				
	Minimize COE (\$/kWh)	b),	f)		
		e)			
	Minimize LPSP (%)	b)	f)		h)
	Minimize P_{dummy} (kWh)	b)			
	Minimize difference in total cost and total revenue (USD)		c)		
	Minimize total annual amount of CO ₂ produced (kg CO ₂ /year)		c)	d)	
	Minimize TNPC (\$)			d)	h)
	Minimize UL (%)			d)	
	Minimize DPSP (%)	e),			
		g)			
	Maximize AD	g)			
	Maximize E_{dumped} (Kw)	g)			
	Minimize ASC (\$)		i)		
	Minimize LCOE (\$/kWh)		i)		
	Minimize NPC (\$)		i)		

optimization strategies that have demonstrated superior performance across various scenarios, contributing to a clearer understanding of the most effective methodologies for optimizing HRES.

Based on the analysis carried out previously, it is possible to recommend as decision variables to use in the context of rural areas and universities: number of solar panels, wind turbines, and diesel generators. Regarding objective functions to use in the context of rural areas it is recommended: minimizing COE and minimizing DPSP. For the other considered contexts that aren't mentioned in the recommendations of decision variables and objective functions, the observations are too scattered to make scientifically supported recommendations. Regarding the choice of algorithms for developing a hybrid model, while several algorithms, such as the WMO-MILP algorithm, are commonly employed for optimizing hybrid renewable energy systems, based on Tables 4 and it is recommended to use PSO, GWO, and NSGA. With this we opted to proceed with the PSO-GWO algorithm.

3. Problem formulation

Following the analysis of related work, in this section it is applied the information gathered so far to optimize a Hybrid Renewable Energy System using a hybrid algorithm with multi-objective functions, within the context of Portugal. This section is structured into three main points: data, problem formulation, and algorithms. Point 3.1 presents the data that was used, specific to Portugal: (1) characteristics of the most used photovoltaic panels and wind turbines; (2) weather conditions; and (3) load demand. Point 3.2 outlines the problem formulation, describing the decision variables considered in the optimization process, the equations used to calculate the power output of the photovoltaic panels and wind turbines, and the objective functions. Finally, Section 3.3 introduces the HPPSGWO hybrid algorithm.

3.1. Data collection

This point outlines the data used in terms of components, weather conditions, and load demand.

Regarding the components, the idealized hybrid renewable energy system consists of photovoltaic panels and wind turbines, therefore, data on those that are most used in Portugal were gathered from manufacturers (Tables 5 and 6).

A renewable energy system depends on weather conditions for energy production, with this, it was necessary the collection of weather data such as direct irradiance, diffuse irradiance, albedo irradiance, air temperature, and wind speed to estimate energy output. For this purpose, data from the Copernicus Atmosphere Monitoring Service (CAMS) and the Copernicus Climate Change Service (C3S) was used (Table 8).

To gather data from CAMS, the option "Both cloud-free and actual weather conditions" was chosen over "Cloud-free only" to ensure the most accurate representation of weather conditions. The data retrieved was specific to Portugal, with coordinates set to latitude 39.0000 and longitude -7.0000, covering the period from January 2008 to April 2024, with an hourly time step and universal time reference (Copernicus Atmosphere Monitoring Service, 2020) (Table 7). Additionally, data from C3S was used, specifically the "wind speed at 10m" and "2m air temperature" aggregated spatially at the country level and temporally at an hourly level (Table 8). This resulted in one file per variable for the entire time series (Copernicus Climate Change Service, 2020).

The data retrieved from CAMS and C3S was then preprocessed, resulting in an unique dataframe. Given that the project involves optimizing a hybrid renewable energy system for a single year, it can be chosen any year between.

2008 and 2023, consequently, depending on the chosen year, the preprocessed dataframe will cover from January of the selected year to December of the same year (Table 7).

To calculate the considered objective functions and assess whether the hybrid energy system generates enough energy to meet demand, data on load demand in Portugal was collected and analyzed. This involved using open-source data from REN (REN, 2024), which spans from January 2008 to April 2024, although data for 2010 is only available for January 1st (Table 9).

3.2. Problem formulation

The optimization of the HRES, that consists in photovoltaic panels and wind turbines, was performed hourly over the span of a year, equating to the optimization of 8760 h. The variables adjusted during this process were N_{PV} , β , N_{WT} and h . The optimization performed was multi-objective, as it simultaneously addresses the minimization of LPSP and the minimization of the amount of CO₂ emissions produced by the hybrid system.

3.2.1. Decision variables and constraints

To optimize the size of a hybrid energy system, four decision variables were used, as mentioned earlier: N_{PV} , β , N_{WT} and h . The constraints defining the lower and upper limits for each decision variables are outlined in equations (1)–(3), while equations (4) and (5) specify the potential heights for the E70 and E82 wind turbines, respectively.

Table 5

Characteristics of the solar panels considered.

#	Manufacturer	Power Output (W)	VMP (V)	IMP (A)	V _{OC} (V)	I _{SC} (A)	Temperature coefficient of V _{OC} (%/°C)	Temperature coefficient of I _{SC} (%/°C)	NOCT (°C)	η _{PV}
1	Tallmax	330	34.9	7.04	46.2	9.27	−0.29	0.05	44	17
2	Tallmax	335	35.1	7.12	46.3	9.36	−0.29	0.05	44	17.3
3	Tallmax	340	35.2	7.19	46.5	9.45	−0.29	0.05	44	17.5
4	Tallmax	345	35.5	7.25	46.7	9.50	−0.29	0.05	44	17.8
5	Tallmax	350	35.6	7.33	46.9	9.60	−0.29	0.05	44	18.0
6	Tallmax	355	35.8	7.40	47.0	9.69	−0.29	0.05	44	18.3
7	Canadian Solar	355	35.4	7.32	46.8	9.61	−0.30	0.053	45	17.85
8	Canadian Solar	360	35.6	7.36	47.0	9.69	−0.30	0.053	45	18.10
9	Canadian Solar	365	35.8	7.41	47.2	9.77	−0.30	0.053	45	18.35
10	Canadian Solar	370	36.0	7.45	47.4	9.85	−0.30	0.053	45	18.60
11	JA Solar	315	34.45	6.77	45.85	9.01	−0.33	0.058	45	16.22
12	JA Solar	320	34.64	6.84	46.12	9.09	−0.33	0.058	45	16.47
13	JA Solar	325	34.82	6.91	46.38	9.17	−0.33	0.058	45	16.73
14	JA Solar	330	35.03	6.97	46.40	9.28	−0.33	0.058	45	16.99
15	JA Solar	335	35.21	7.04	46.70	9.35	−0.33	0.058	45	17.25
16	JA Solar	340	35.06	7.09	46.86	9.46	−0.30	0.06	45	17.5
17	JA Solar	345	35.33	7.14	47.05	9.54	−0.30	0.06	45	17.76
18	JA Solar	350	35.59	7.19	47.24	9.61	−0.30	0.06	45	18.02
19	JA Solar	355	35.81	7.25	47.45	9.69	−0.30	0.06	45	18.28
20	JA Solar	360	36.03	7.31	47.66	9.78	−0.30	0.06	45	18.57

Table 6

Characteristics of the wind turbines considered.

#	Manufacturer	Name	V _r (m/s)	V _{cut-in} (m/s)	V _{cut-out} (m/s)	A _w (m ²)	h
1	Enercon	E70	14	2.5	34	3959	57
2	Enercon	E70	14	2.5	34	3959	64
3	Enercon	E70	14	2.5	34	3959	85
4	Enercon	E70	14	2.5	34	3959	98
5	Enercon	E70	14	2.5	34	3959	113
6	Enercon	E82	12	2.5	34	5281	78
7	Enercon	E82	12	2.5	34	5281	85
8	Enercon	E82	12	2.5	34	5281	98
9	Enercon	E82	12	2.5	34	5281	108
10	Enercon	E82	12	2.5	34	5281	138

Table 7

df_tmy_year and df_consume_year data description.

Data type	Latitude	Longitude	Temporal coverage	Temporal resolution
Time series	39.0000	−7.0000	January of the selected year to December of the selected year	1-hourly

Table 8

df_tmy_year variables description.

Name	Units	Description
GHI	Wh m ^{−2}	Global horizontal all sky irradiation
BHI	Wh m ^{−2}	Direct horizontal all sky irradiation
DHI	Wh m ^{−2}	Diffuse horizontal all sky irradiation
wind_speed	m s ^{−1}	“Magnitude of the two-dimensional horizontal air velocity at height of 10 m” (Copernicus Climate Change Service, 2020)
air_temperature	°C	“The ambient air temperature near to the surface, typically at height of 2m” (Copernicus Climate Change Service, 2020)

Table 9

df_consume_year variables description.

Name	Units	Description
Consumption	Wh	Amount of electricity that has been consumed by end users
Total sold	Wh	Amount of electricity sold by REN

$$N_{PV}^{min} \leq N_{PV} \leq N_{PV}^{max} \quad (1)$$

$$N_{WT}^{min} \leq N_{WT} \leq N_{WT}^{max} \quad (2)$$

$$0^\circ \leq \beta \leq 90^\circ \quad (3)$$

$$h_{E70} = [57, 64, 85, 113] \quad (4)$$

$$h_{E82} = [78, 85, 98, 108, 138] \quad (5)$$

3.2.2. Modeling of hybrid renewable energy system

The power generated by a PV panel is given by equation (6) (Hossain et al., 2023), the calculation of which depends on equations (7)–(25). This is influenced by environmental factors, such as global solar irradiance and ambient temperature, and on the manufacturer information that was gathered. Of the equations mentioned, we highlight the one relating to global irradiance, that is the sum of direct, diffuse, and albedo irradiance.

$$P_{PV}(t, \beta) = N_{PV} \cdot V_{OC}(t, \beta) \cdot I_{SC}(t, \beta) \cdot FF(t) \quad (6)$$

$$FF(t) = \frac{VMP \cdot IMP}{V_{OC}(t, \beta) \cdot I_{SC}(t, \beta)} \quad (7)$$

$$V_{OC}(t, \beta) = \{V_{OC_STC} - K_V T_C(t)\} \quad (8)$$

$$I_{SC}(t, \beta) = \{I_{SC_STC} + K_I [T_C(t) - 25^\circ C]\} \frac{G(\beta, \alpha)}{1000} \quad (9)$$

$$T_C(t) = T_A + (NCOT - 20^\circ C) \frac{G(\beta, \alpha)}{800} \quad (10)$$

$$P_{PV_array}(t, \beta) = \eta_{PV} \cdot N_{PV} \cdot P_{PV}(t, \beta) \quad (11)$$

$$G(\beta, \alpha) = B(\beta, \alpha) + D(\beta, \alpha) + R(\beta, \alpha) \quad (12)$$

$$B(\beta, \alpha) = B \max(0, \cos \theta_s) \quad (13)$$

$$B = \frac{B(0)}{\cos \theta_{zs}} \quad (14)$$

$$\cos \theta_s = [\text{sign}(\phi)] \sin \delta \sin(\text{abs}(\phi) - \beta) + \cos \delta \cos(\text{abs}(\phi) - \beta) \cos \omega \quad (15)$$

$$\delta = 23.45 \sin \left[\frac{360(d_n + 284)}{365} \right] \quad (16)$$

$$\omega = 15 \times (\text{TO} - \text{AO} - 12) - (\text{LL} - \text{LH}) \quad (17)$$

$$B_0 = 1367 \text{ W/m}^2 \quad (18)$$

$$\cos \theta_{zs} = \sin \delta \sin \phi + \cos \delta \cos \phi \cos \omega \quad (19)$$

$$D(\beta, \alpha) = D^I(\beta, \alpha) + D^C(\beta, \alpha) \quad (20)$$

$$D^I(\beta, \alpha) = D(0) (1 - k_1) \frac{1 + \cos \beta}{2} \quad (21)$$

$$k_1 = \frac{B}{B_0 \varepsilon_0} \quad (22)$$

$$\varepsilon_0 = 1 + 0.033 \cos \left(\frac{360 d_n}{365} \right) \quad (23)$$

$$D^C(\beta, \alpha) = \frac{D(0)k_1}{\cos \theta_{zs}} \max(0, \cos \theta_s) \quad (24)$$

$$R(\beta, \alpha) = \rho_{ref} G(0) \frac{1 - \cos \beta}{2} \quad (25)$$

The power generated by a wind turbine is described by equations (26) and (27) or (28) (Çetinbaş et al., 2022; Hossain et al., 2023), this being dependent on the wind speed, the turbine's rated power, and manufacturer-supplied parameters. The wind speed at a specific height can be determined using equation (29), which considers the wind speed at the reference height, the reference height, and the installation height of the turbine - a decision variable of the optimization problem (Hossain et al., 2023). The rated power is calculated using equation (30), incorporating the maximum power coefficient, a value provided by manufacturers and dependent on wind speed. The power curves provided by each manufacturer on a wind turbine help to determine the maximum power coefficient.

If $V < V_{cut-in}$ or $V > V_{cut-out}$:

$$P_{WT} = 0 \quad (26)$$

If $V_{cut-in} \leq V \leq V_r$:

$$P_{WT} = V^3 \left(\frac{P_{WT_r}}{V_r^3 - V_{cut-in}^3} \right) - P_{WT_r} \cdot \left(\frac{V_{cut-in}^3}{V_r^3 - V_{cut-in}^3} \right) \quad (27)$$

If $V > V_{cut-out}$:

$$P_{WT} = P_{WT_r} \quad (28)$$

$$V_r \left(\frac{h}{h_r} \right)^a \quad (29)$$

$$P_{WT_r} = C_{p,max} \frac{1}{2} \rho_{air} A_{WT} V_r^3 \quad (30)$$

3.2.3. Objective functions

One of the objective functions evaluated in this project is LPSP, which serves as an indicator of the reliability of the hybrid renewable

energy system. The LPSP is defined as the ratio of unmet energy demand, as expressed in equation (31), where its value ranges from 0 to 1, where 0 indicates that the energy demand is fully satisfied, representing maximum system reliability, while a value of 1 signifies a complete failure to supply energy to the load, indicating an unreliable system (Çetinbaş et al., 2022).

$$LPSP = \frac{\sum_{t=1}^{t=8760} E_{DE}(t)}{\sum_{t=1}^{t=8760} E_{LOAD}(t)} \quad (31)$$

The second objective function serves as an environmental indicator, as it seeks to minimize the annual CO₂ emissions generated by the hybrid energy system. CO₂ emissions are calculated based on the amount of electricity purchased from the grid, multiplied by the CO₂ emission coefficient per watt-hour (Wh), which is 0.000866 kg CO₂/Wh (Capraz et al., 2020). This objective function is represented by equation (32).

$$CO_2 = \varepsilon \sum_{t \in T} g b_t \quad (32)$$

To perform the multi-objective optimization, the two objective functions outlined earlier were both evaluated on an annual basis. This multi-objective problem was approached as a single-objective optimization, using the weighted sum method, which is represented by equations (33) and (34) (Çetinbaş et al., 2022; Suman et al., 2021), being this later adapt to the optimization problem of this paper, resulting in equation (35). Equation (33) normalizes the objective functions by dividing the value of each objective function by its maximum, ensuring the functions are scaled between 0 and 1 (Capraz et al., 2020). Since the objective function related to the minimization of LPSP, already has values between 0 and 1, only the objective function that seeks the minimization of the annual CO₂ emissions generated by the system, was normalized as indicated in equation (35). As the minimization of the CO₂ emissions depends on the amount of electricity purchased from the grid, it is assumed that its maximum value is achieved when all electricity consumption is met by the grid, meaning the hybrid energy system generates no energy to meet demand.

$$F_{WS}(x_{DV}) = \sum_{i=1}^k w_i \cdot \frac{f_i(x_{DV})}{f_i^{max}(x_{DV})} \quad (33)$$

$$\sum_{i=1}^k w_i = 1, 0 < w_i \leq 1, i = 1, \dots, n \quad (34)$$

$$F_{WS}(N_{PV}, N_{WT}, \beta, hh) = \min \left[w_1 \cdot LPSP(N_{PV}, N_{WT}, \beta, hh) + w_2 \cdot \frac{CO_2(N_{PV}, N_{WT}, \beta, hh)}{CO_2^{max}(N_{PV}, N_{WT}, \beta, hh)} \right] \quad (35)$$

3.2.4. Hybrid parallel PSO-GWO (HPPSGWO)

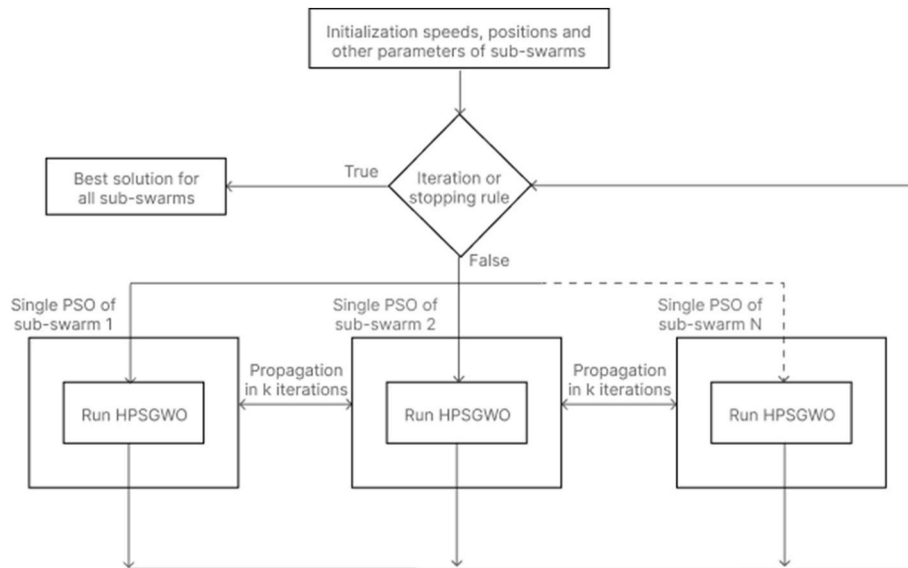
To leverage the strengths of both PSO and GWO, Şenel et al. (2019) developed a hybrid PSO-GWO algorithm. However, its extended runtime remained a key limitation due to the additional computational overhead of incorporating GWO (Şenel et al., 2019). To overcome this, the algorithm was parallelized using the PPSO approach introduced by Charillogis et al. (2023) and implemented on GPUs with CuPy and cuDF libraries. This Hybrid Parallel PSO-GWO (HPPSGWO) aimed to reduce the likelihood of getting stuck in local minima, shorten execution time, and optimize computational resource utilization. By integrating PSO's exploitation capability, GWO's global search efficiency, and the speedup of PPSO-based parallelization, HPPSGWO achieves superior performance. The pseudocode for HPPSGWO is shown in Algorithm 1, and its graphical representation is provided in Fig. 1.

Algorithm 1. Pseudocode for Hybrid Parallel PSO-GWO.

Algorithm 1: Pseudocode for Hybrid Parallel PSO-GWO.

N_I : the total number of parallel processing units
 N_R : the number of iterations, after which each processing unit will send its best particles to the remaining units
 N_P : the number of migrated particles between the parallel processing units
 PS : the number of population sizes set by the user
 $prob$: small possibility rate set by the user
Initialize particles
 $k = 0$ the iteration number
for $j = 1, \dots, N$ do in parallel

Execute an iteration of the HPSGWO algorithm on processing unit j
for $j = 1$ to PS do
Run PSO
Update the velocity and the position of current particle
if $\text{rand}(0,1) < prob$ then
Set a, A, C values
for $k = 1$ to 10 do
for $m = 1$ to 10 do
Run GWO
Update the position of α, β, δ wolves
Update a, A, C values
end for
end for
position of current particle
= mean of the positions of three best wolves
end if
end for
if $k \bmod N_R = 0$ then
Get the best N_P particles from algorithm j
Propagate these N_P particles to the rest of processing units
end
end
Update $k = k + 1$
Check the proposed termination rule. If the termination rule is valid, continue else go to for loop
Terminate and report the best value from all processing units

**Fig. 1.** Flowchart of the HPPSGWO.

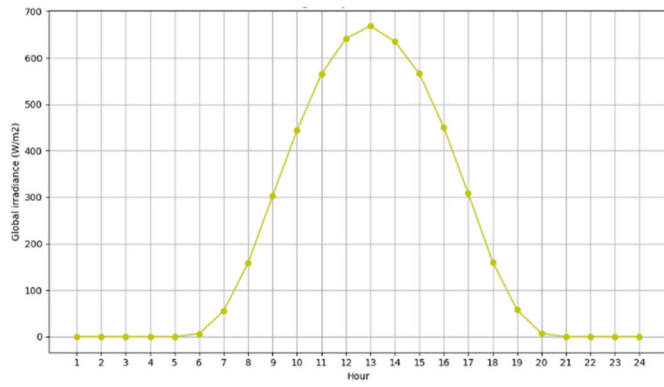


Fig. 2. Average daily global irradiance in 2022.

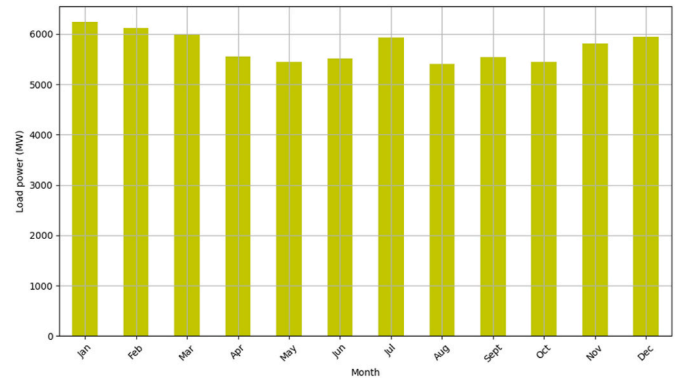


Fig. 5. Average monthly load power in 2022.

4. Results

4.1. Exploration of data

An analysis of global irradiance, load power, and wind speed in Portugal in the year of 2022 was conducted, having revealed significant patterns relevant to energy production and consumption.

Global irradiance data shows a clear daily and seasonal cycle. Daily, irradiance peaks at 1 p.m. with values exceeding 600 W/m^2 , while it stays in 0 W/m^2 between 1 a.m. and 5 a.m. and from 9 p.m. to midnight. This pattern reflects the hours of sunlight, with a gradual increase in irradiance from just after 6 a.m. to the peak and a subsequent decline after 1 p.m. (Fig. 2). Monthly data indicates that irradiance is highest in July, approaching 350 W/m^2 , and lowest in December, ranging between 50 and 100 W/m^2 . The seasonal trend shows higher irradiance from

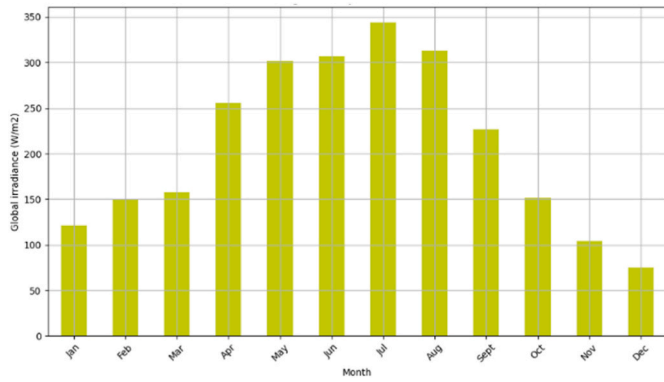


Fig. 3. Average monthly global irradiance in 2022.

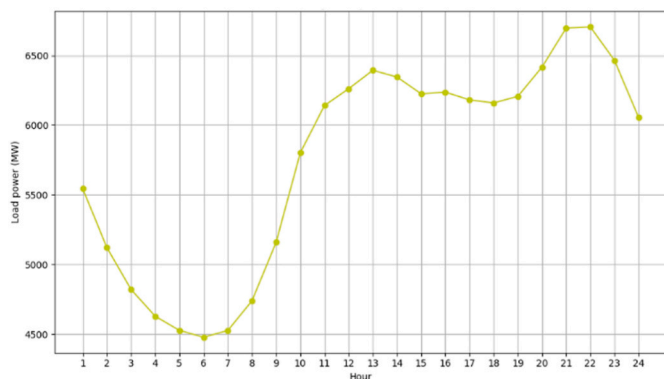


Fig. 4. Average daily load power in 2022.

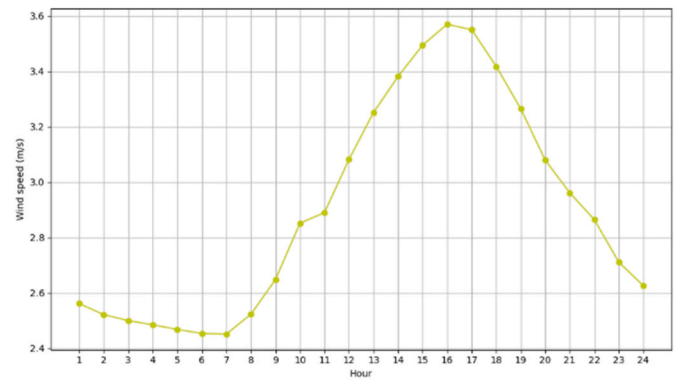


Fig. 6. Average daily wind speed in 2022.

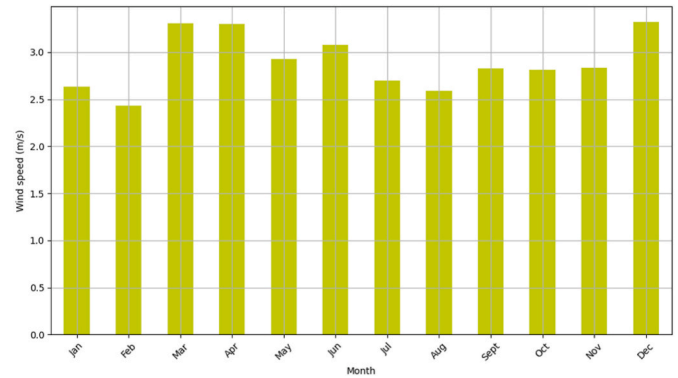


Fig. 7. Average monthly wind speed in 2022.

spring to summer and lower values in winter, making April to August the optimal period for solar energy production, with July being particularly favorable (Fig. 3).

Load power data reveals that power consumption has distinct daily and monthly trends. Daily, load power peaks at around 1 p.m. and again between 9 p.m. and 10 p.m., reaching values over 6500 MW, while the lowest consumption occurs around 6 a.m. This trend reflects increased energy use during daytime and evening hours (Fig. 4). Monthly data

Table 10

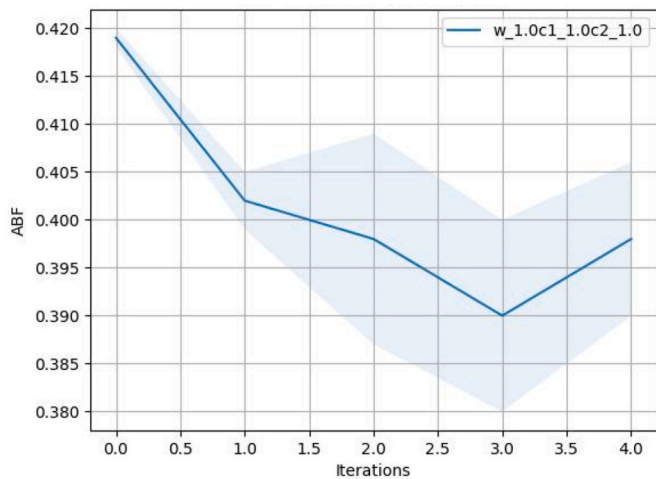
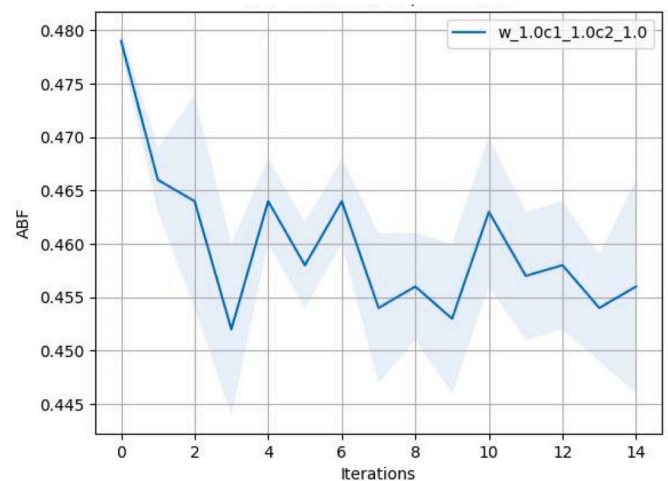
Upper and lower bounds of decision variables for experiment 1 and 2.

	N_{PV}	N_{WT}	β	h
Upper bound	1500	1001	90	(check 3.2.1.)
Lower bound	1000	500	0	(check 3.2.1.)

Table 11

Values for the parameters of HPPSGWO for experiment 1, 2 and 3.

	Parameter	Meaning	Experiment		
			1	2	3
PSO	$size_{swarm}$	Size of swarm, number of particles to generate	100	100	200
	$iter_{max}$	Maximum number of generations to perform	5	15	20
	$runs_{max}$	Maximum number of runs to perform	10	10	10
	w	Inertia weight	1.0	1.0	1.0
	c_1	Cognitive component	1.0	1.0	2.0
GWO	c_2	Social component	1.0	1.0	2.0
	$prob$	Small possibility rate	0.4	0.4	0.4
	$iter_{small}$	Small number of iterations that the GWO will run	10	10	10
	$small_{swarm}$	Small number of swarm size that the GWO will run	10	10	10
	w_1	Weight for objective function 1	0.5	0.5	0.5
MOO	w_2	Weight for objective function 2	0.5	0.5	0.5
	N_I	Total number of parallel processing units	4	4	8
Parallel execution	N_R	Number of iterations, after which a processing unit sends its best particles to the remaining units	15	15	15
	N_P	Number of migrated particles between the parallel processing units	5	5	5
	ϵ	Small value (used in the termination rule)	10^{-6}	10^{-6}	10^{-6}
	N_M	Number of continuous repetitions (used in the termination rule)	15	15	15

**Fig. 8.** ABF results for experiment 1.**Fig. 9.** ABF results for experiment 2.

shows that load power is highest in January, exceeding 6000 MW, and lowest in August, just above 5000 MW. The increased load in winter is likely due to heating needs, while high consumption in summer is attributed to cooling demands (Fig. 5).

Wind speed data displays both daily and monthly variations. Daily wind speed peaks at 4 p.m. at approximately 3.6 m/s, with the lowest speeds around 7 a.m. at about 2.4 m/s. Wind speeds are generally higher in the afternoon and lower in the early morning (Fig. 6). Monthly data shows that wind speed is highest in December, surpassing 3.0 m/s, and lowest in February, dropping below 2.5 m/s. Seasonal patterns indicate a moderate decrease in wind speed from winter to summer, with relatively consistent speeds during the rest of the year (Fig. 7).

These figures depict the optimization process of key system parameters - number of photovoltaic panels, tilt angle, number of wind turbines, and height of wind turbines—focusing on their impact on power supply reliability and environmental benefits over a one-year period. Overall, these observations provide valuable insights into the potential for solar and wind energy production in Portugal and highlight patterns in energy consumption, guiding future energy planning and use.

4.2. Experiments

Three experiments were conducted using the PSO-GWO parallel hybrid algorithm.

The upper and lower bounds for the decision variables in

experiments 1 and 2 are listed in Table 10. These bounds were selected based on values used in the previous studies reviewed in the SLR that employed the same decision variables.

The first experiment, lasted approximately 13 h to run, the HPPSGWO algorithm was tested with the parameters present in Table 11, with the upper and lower limits of the decision variables specified in Table 10. The optimization process is shown in Fig. 8. Regarding the convergence trend, the average best fitness (ABF) decreases over iterations, demonstrating the HPPSGWO algorithm's ability to improve solution fitness. Initially, the ABF is slightly below 0.420 and decreases to 0.390, showing improvement, but then slightly increased to around 0.400, indicating a minor deterioration. The shaded area around the convergence line represents the variability in the ABF values. A narrower shaded area indicates less variability, while a wider area signifies more. Observing Fig. 8, it is evident that variability increased over the iterations, with a brief narrowing from iteration 3 to 4, which might suggest potential stabilization if more iterations were performed. The slight rise in ABF from iteration 3 to 4, indicates that the hybrid

Table 12

Upper and lower bounds of decision variables for experiment 3.

	N_{PV}	N_{WT}	β	h
Upper bound	2500	2500	90	(check 3.2.1.)
Lower bound	0	0	0	(check 3.2.1.)

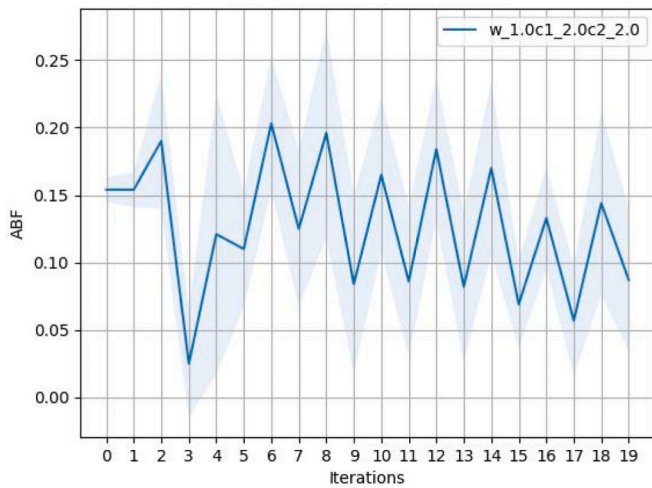


Fig. 10. ABF results for experiment 3.

algorithm encountered a local minimum. To address this, additional iterations or parameter adjustments might be necessary. Overall, the algorithm is optimizing effectively, though some parameter tuning could enhance its performance.

In the second experiment, the focus was on increasing the number of iterations to see if it helps escaping local minima and finding better solutions. This experiment took about 30 h, used the parameters specified in Table 11 and the upper and lower limits of the decision variables were set as it is indicated in Table 10. From the convergence curve (Fig. 9), it can be observed that the optimization algorithm continues to improve fitness as the.

Number of iterations increase. The ABF value starts at around 0.480 and, by iteration 14, reaches a value above 0.455, indicating a deterioration over the first experiment. There was still high variability in the ABF values, though less pronounced between iterations 4 and 6. The results displayed similar behavior to the first experiment, particularly between iterations 0 and 4. From iteration 4 to iteration 14, peaks and troughs in the ABF values, suggest that the algorithm encounters local minima, but manages to escape them, as evidenced by the convergence line decreasing after each peak. Despite these fluctuations between iterations 4 and 14, the overall ABF trend shows a gradual decline, from 0.465 in iteration 4 to approximately 0.455 by the final iteration. The reported behavior suggests that further experimentation with different parameter values might be beneficial.

In the third experiment, various parameters of the HPPSGWO algorithm were adjusted to improve optimization outcomes. These changes are detailed in Table 11 and are explained next. The number of iterations was increased to assess whether further improvements in ABF could be achieved or if fitness would stabilize. For the PSO-specific parameters, both cognitive and social components were set to 2, as this value “has been shown to be appropriate for several applications” (Vanneschi and Silva, 2023). Additionally, the swarm size in the Particle Swarm Optimization was doubled to improve solution quality, as larger swarms allow for the exploration of more regions within the solution space, thus enhancing convergence towards the global optimum. To further explore the search space, the upper and lower bounds for the decision variables – number of solar panels and number of wind turbines – were increased (as shown in Table 12). This adjustment expanded the search space, allowing the algorithm to investigate solutions that were previously inaccessible due to the earlier limits. Lastly, the number of parallel processing units was increased to 8, as prior studies have shown that this increase “significantly improves the efficiency of the technique in finding the global minimum” (Charilogis et al., 2023). The convergence line of this experiment is presented in Fig. 10, having lasted about 60 h. The convergence curve shows that the hybrid algorithm begins with an

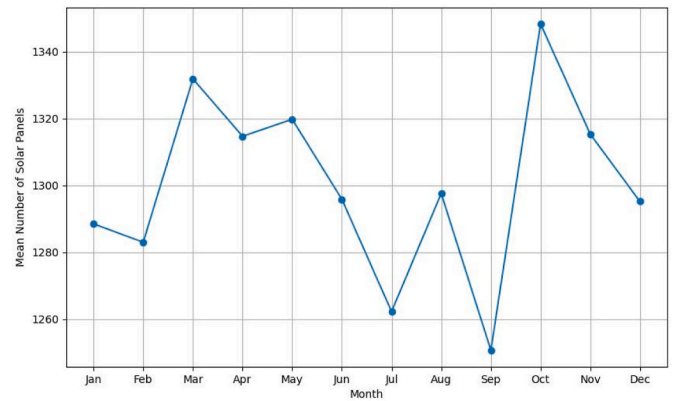


Fig. 11. Experiment 3 best solution, mean number of solar panels per month.

initial ABF value of 0.150, which is significantly lower than the starting values in experiment 1 and experiment 2. Between iterations 0 and 1, the ABF value remains constant, followed by a slight increase from iteration 1 to 2. However, a sharp decrease occurs up to iteration 3, where the lowest ABF value is reached. This rapid improvement in the early iterations indicates that the algorithm is effective at enhancing solution quality in its initial stages. After iteration 3, the algorithm’s performance exhibits oscillations, with a gradual downward trend between iterations 6 (with an ABF value of 0.20) and 19 (where the ABF value falls below 0.10). This suggests that the algorithm is making incremental improvements over time. Observing Fig. 10 it is also possible to see a significant variability across different runs, likely due to the stochastic nature of the hybrid algorithm. While the fluctuations and variability may indicate a strong exploration capability, further parameter tuning is required to reduce variability and stabilize convergence.

For a potential experiment 4, it would be necessary to fine-tune the parameters of the hybrid algorithm, to stabilize convergence and reduce variability.

When comparing the convergence line of experiment 2 and experiment 3, experiment 2 begins with an ABF value close to 0.480, which is higher than the initial value of approximately 0.150 in experiment 3, meaning that the initial solution of experiment 3 is of higher quality than in experiment 2. Experiment 2 shows a general downward trend, with minor fluctuations in the last few iterations, indicating that the solution is stabilizing. In contrast, experiment 3 exhibits more oscillations and lacks a clear downward trend, suggesting less stability and a stronger emphasis on exploration of the search space, even during the final iterations. Analyzing the impact of parameter changes between the two experiments, the larger swarm size in experiment 3, compared to experiment 2, contributes to greater variability and more oscillations, as larger swarm explores a wider area of the search space. The cognitive

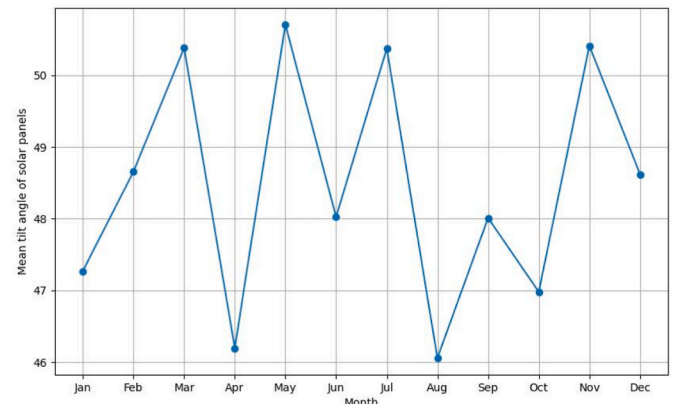


Fig. 12. Experiment 3 best solution, mean tilt angle of solar panels per month.

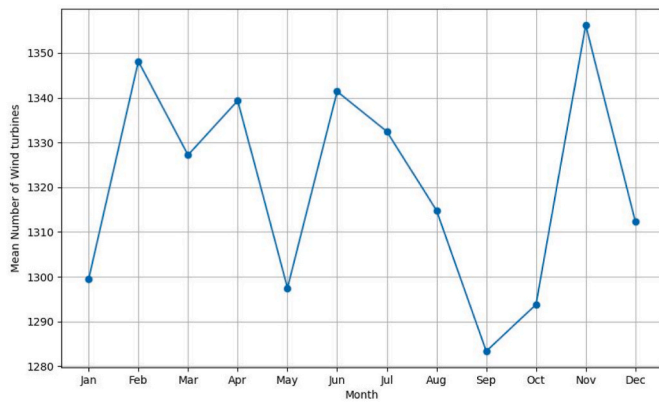


Fig. 13. Experiment 3 best solution, mean number of wind turbines per month.

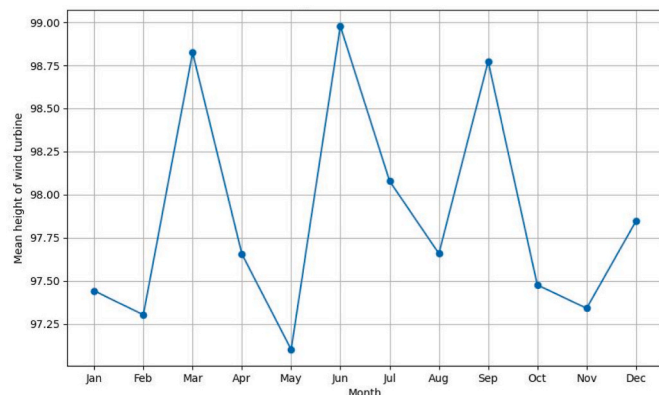


Fig. 14. Experiment 3 best solution, mean height of wind turbines per month.

and social components were also increased from 1.0 in experiment 2 to 2.0 in experiment 3, amplifying the influence of individual and social learning, this results in more exploration, leading to increased fluctuations. Additionally, experiment 3 used broader decision variable limits compared to experiment 2, expanding the search space and further contributing to increased variability.

The experiments revealed that the lowest ABF value of 0.025 was achieved in experiment 3, iteration 3. The run with the lowest fitness value in iteration 3 was run 5, with a value of 0.000506, which was also the lowest across all 20 iterations, thus, this configuration was analyzed regarding the decision variables.

Fig. 11 shows the average number of solar panels per month, where seasonal variations are observed. In winter months it is possible to see a slight decline, reaching its lowest in February (above 1280 panels), while summer shows a more pronounced decrease, bottoming out in July (~1260 panels). The number rises in the fall, peaking in October (~1340 panels).

Fig. 12 illustrates the mean angle of the solar panels throughout the year, showing a seasonal pattern of a decrease followed by an increase each season. The angle remains between 46° and just over 50°.

Fig. 13 presents the average number of wind turbines, with fluctuations throughout the year. Winter shows a slight decrease, followed by a rise, while spring and summer exhibit a downward trend. Fall shows an increasing trend, peaking in November (~1350 turbines).

Fig. 14 highlights the average height of wind turbines, showing a consistent decrease across seasons, with the highest values seen at the start of each season and ending with lower values.

5. Conclusions and future work

This study addresses the urgent need for a sustainable and carbon-neutral energy transition to mitigate global warming, emphasizing the need to use natural resources for energy production. To address the intermittent nature of renewable sources, the concept of Hybrid Renewable Energy Systems is introduced. In the introduction it is discussed the growing research on applying artificial intelligence to optimize HRES, particularly through combining algorithms to improve outcomes. The research developed focused on framing a hybrid optimization algorithm for HRES in Portugal, aimed at minimizing the loss of power supply probability and the amount of CO₂ produced.

A systematic literature review on AI and HRES optimization was performed using the PRISMA methodology, having made it possible to identify and analyze nine articles to understand the state of the art and support the development of an informed proposal. The analysis carried out allowed to identify key elements: decision variables, hybrid algorithms used, system types, context, activity area, and objective functions. This data was cross-referenced to gain insights and provide recommendations on suitable decision variables, objective functions based on the activity area, and algorithms for creating hybrid algorithms in the context of Hybrid Renewable Energy Systems.

The empirical study began by selecting renewable energy sources for creating a HRES, having chosen photovoltaic panels and wind turbines. After defining the components, the models that are commonly used in Portugal were identified, and their specifications were gathered. Additionally, data on Portugal's weather conditions and load demand were obtained. The problem was then formulated, defining decision variables, constraints, objective functions, and equations for calculating the output power of photovoltaic panels and wind turbines. Next, the development of a hybrid parallel PSO-GWO optimization algorithm was explained. Three experiments were conducted with varying parameters to find the global optimum. In the third experiment, a local optimum close to the global minimum was achieved early, but limited computational resources and execution time constrained the number of experiments.

The development of a hybrid multi-objective algorithm for HRES in Portugal faced several limitations during the empirical study. First, identifying the components (photovoltaic panels and wind turbines) commonly used in Portugal was challenging due to limited available information, which was only obtained through expert input. For weather data collection, incomplete datasets were an issue, and only a full dataset containing essential variables (irradiance, temperature, wind speed) was found via Copernicus.

Executing the hybrid PSO-GWO algorithm was hindered by limited computational resources, requiring the use of a Cloud GPU platform and the high execution time also restricted the ability to carrying out more experiments regarding hyperparameters and restricted the number of iterations and runs carried out.

Despite these constraints, the study made contributions to both Data Science and the energy industry, setting a foundation for future research aimed at solving energy challenges in Portugal and working towards a more sustainable, carbon-neutral future.

The development of the proposed hybrid parallel PSO-GWO algorithm for optimizing hybrid renewable energy systems (HRES) in Portugal offers substantial potential across multiple applications. A key area of impact is smart grid optimization, where the algorithm can efficiently balance energy generation from diverse sources—such as wind, solar, and hydro—ensuring a stable, reliable, and sustainable energy supply. It also supports load balancing and real-time demand-side management, reducing grid congestion and enhancing energy distribution. In rural and remote areas, integrating HRES with the algorithm can drive regional development by improving access to clean electricity, promoting energy equity, and fostering socioeconomic growth. For businesses, the algorithm provides an opportunity to reduce electricity costs, enhance power reliability, and support sustainability objectives, making it a valuable tool for optimizing energy use and

operations. Additionally, the algorithm improves energy dispatch by optimizing the scheduling of renewable resources, reducing reliance on fossil fuels, and strengthening the national grid. It enhances grid stability by ensuring the seamless integration and operation of hybrid energy systems, further reinforcing Portugal's energy infrastructure. In coastal regions, the algorithm can facilitate the integration of wave and offshore wind energy with solar power, enabling efficient hybridization and maximizing the potential of these renewable resources. Importantly, the algorithm's optimization capabilities can significantly contribute to reducing Portugal's carbon footprint, aligning with the country's ambitious carbon neutrality goals. By addressing these diverse applications, the hybrid parallel PSO-GWO algorithm demonstrates its transformative potential to advance renewable energy adoption and sustainability in Portugal.

For future research, it is recommended to use more powerful computing resources to reduce computation time, allowing for more extensive testing and increasing the likelihood of achieving the global minimum. We aim to explore the application of the HMEO algorithm, as Wang et al. (2024) demonstrated that this hybrid approach surpasses the individual algorithms that constitute the HPSOGWO method proposed in this study. The HMEO algorithm combines swarm intelligence and physics-based mechanisms: swarm intelligence fosters diversity for robust global exploration, while the physics-based component enhances intensification for precise local optimization. Notably, Wang et al. achieved highly promising results when applying the HMEO algorithm to a mobile robot path planning (MRPP) problem. Building on these findings, future research should investigate the potential of HMEO in optimizing hybrid energy systems. This approach could yield even more favorable outcomes than those achieved in this study with HPSOGWO. Additionally, exploring a broader range of hyperparameter combinations for parameter tuning could enhance optimization results. The study could also be expanded by incorporating two additional objective functions in the economic and social categories, alongside the technical and environmental aspects already addressed, to optimize the HRES design comprehensively. Finally, obtaining feedback from AI and Energy experts in Portugal through interviews is suggested to refine the project through an iterative improvement process.

CRedit authorship contribution statement

Maria Mendonça: Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Vítor Santos:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

References

- Ajiboye, O.K., Ochiogbu, C.V., Ofosu, E.A., Gyamfi, S., 2023. A review of hybrid renewable energies optimisation: design, methodologies, and criteria. *Int. J. Sustain. Energy* 42 (1), 648–684. <https://doi.org/10.1080/14786451.2023.2227294>.
- Amereh, M., Khozani, Z.S., Kazemi, A., 2014. Multi objective design of stand-alone PV/wind energy system by using hybrid GA and PSO. In: 2014 22nd Iranian Conference on Electrical Engineering (ICEE), pp. 695–699. <https://doi.org/10.1109/IranianCEE.2014.6999628>.
- Bilgen, S., 2014. Structure and environmental impact of global energy consumption. *Renew. Sustain. Energy Rev.* 38, 890–902. <https://doi.org/10.1016/j.rser.2014.07.004>.
- Bishoge, O.K., Zhang, L., Mushi, W.G., 2019. The potential renewable energy for sustainable development in Tanzania: a review. *Cleanroom Technol.* 1 (1), 70–88. <https://doi.org/10.3390/cleantechnol1010006>.
- Cai, W., Li, C., Agbossou, K., Bénard, P., Xiao, J., 2022. A review of hydrogen-based hybrid renewable energy systems: simulation and optimization with artificial intelligence. *J. Phys. Conf. Ser.* 2208 (1), 012012. <https://doi.org/10.1088/1742-6596/2208/1/012012>.
- Capraz, O., Gungor, A., Mutlu, O., Sagbas, A., 2020. Optimal sizing of grid-connected hybrid renewable energy systems without storage: a generalized optimization model. *Energy Sources, Part A Recovery, Util. Environ. Eff.* 0 (0), 1–34. <https://doi.org/10.1080/15567036.2020.1803454>.
- Çetinbaş, İ., Tamyurek, B., Demirtaş, M., 2022. The hybrid harris hawks optimizer-arithmetic optimization algorithm: a new hybrid algorithm for sizing optimization and design of microgrids. *IEEE Access* 10. <https://doi.org/10.1109/ACCESS.2022.3151119>, 1–1.
- Charilolis, V., Tsoulos, I.G., Tzallas, A., 2023. An improved parallel particle swarm optimization. *SN Computer Science* 4 (6), 766. <https://doi.org/10.1007/s42979-023-02227-9>.
- Copernicus Atmosphere Monitoring Service, 2020. CAMS solar radiation time-series. <https://ads.atmosphere.copernicus.eu/cdsapp#!/dataset/cams-solar-radiation-timeseries?tab=overview>.
- Copernicus Climate Change Service, 2020. Climate and energy indicators for Europe from 1979 to present derived from reanalysis [object Object]. <https://doi.org/10.24381/CDS.4BD77450>.
- Diab, A., Sultan, H., Mohamed, I.S., Kuznetsov, O., Do, T., 2019. Application of different optimization algorithms for optimal sizing of PV/Wind/Diesel/Battery storage stand-alone hybrid microgrid. *IEEE Access*. <https://doi.org/10.1109/ACCESS.2019.2936656>, 1–1.
- Electricity – World Energy Outlook 2019 – Analysis – IEA, 2019. IEA. <https://www.iea.org/reports/world-energy-outlook-2019/electricity>.
- Energy Transitions and Societal Change, 2024. Research Institute for Sustainability. <https://www.rifs-potsdam.de/en/research-area/energy-systems-and-societal-change>.
- Entezari, A., Aslani, A., Zahedi, R., Noorollahi, Y., 2023. Artificial intelligence and machine learning in energy systems: a bibliographic perspective. *Energy Strategy Rev.* 45, 101017. <https://doi.org/10.1016/j.esr.2022.101017>.
- Fendzi Mbasso, W., Dzonde Naoussi, S., Molu, R.J.J., Tsozbe, S., 2023. Contribution into robust optimization of renewable energy sources: case study of a standalone hybrid renewable system in Cameroon. *Int. J. Renew. Energy Resour.* 12, 1094. https://www.researchgate.net/publication/374472514_Contribution_into_Robust_Optimization_of_Renewable_Energy_Sources_Case_Study_of_a_Standalone_Hybrid_Renewable_System_in_Cameroon.
- Güven, A., Yörükeren, N., Tageldin, E., Samy, M., 2023. Multi-objective optimization of an islanded green energy system utilizing sophisticated hybrid metaheuristic approach. *IEEE Access* 11. <https://doi.org/10.1109/ACCESS.2023.3296589>.
- He, J.-K., 2015. Objectives and strategies for energy revolution in the context of tackling climate change. *Adv. Clim. Change Res.* 6 (2), 101–107. <https://doi.org/10.1016/j.accre.2015.08.005>.
- Hossain, M.A., Ahmed, A., Tito, S.R., Ahshan, R., Sakib, T.H., Nengroo, S.H., 2023. Multi-objective hybrid optimization for optimal sizing of a hybrid renewable power system for home applications. *Energies* 16 (1), 96. <https://doi.org/10.3390/en16010096>.
- Kabeyi, M., Olanrewaju, O., 2022. Sustainable energy transition for renewable and low carbon grid electricity generation and supply. *Front. Energy Res.* 9, 45. <https://doi.org/10.3389/fenrg.2021.743114>.
- Liu, Z., Sun, Y., Xing, C., Liu, J., He, Y., Zhou, Y., Zhang, G., 2022. Artificial intelligence powered large-scale renewable integrations in multi-energy systems for carbon neutrality transition: challenges and future perspectives. *Energy and AI* 10, 100195. <https://doi.org/10.1016/j.egyai.2022.100195>.
- Rathish, R.J., Mahadevan, K., Selvaraj, S.K., Booma, J., 2021. Multi-objective evolutionary optimization with genetic algorithm for the design of off-grid PV-wind-battery-diesel system. *Soft Comput.* 25 (4), 3175–3194. <https://doi.org/10.1007/s00500-020-05372-y>.
- REN, 2024. Sistema de informação de MERCADOS de energia. <https://mercado.ren.pt/PT/Electr/Explora%C3%A7%C3%A3o3odosistema/Consumo/Paginas/Verif.aspx>.
- Sawle, Y., M. T., Lala, H., 2023. A comprehensive review on optimization of hybrid renewable energy systems using various optimization techniques. *Renew. Sustain. Energy Rev.* 176, 113192. <https://doi.org/10.1016/j.rser.2023.113192>.
- Şenel, F.A., Gökçe, F., Yüksel, A.S., Yiğit, T., 2019. A novel hybrid PSO-GWO algorithm for optimization problems. *Eng. Comput.* 35 (4), 1359–1373. <https://doi.org/10.1007/s00366-018-0668-5>.
- Solomon, B.D., Krishna, K., 2011. The coming sustainable energy transition: history, strategies, and outlook. *Energy Policy* 39 (11), 7422–7431. <https://doi.org/10.1016/j.enpol.2011.09.009>.

- Suman, G.K., Guerrero, J.M., Roy, O.P., 2021. Optimisation of solar/wind/bio-generator/diesel/battery based microgrids for rural areas: a PSO-GWO approach. *Sustain. Cities Soc.* 67, 102723. <https://doi.org/10.1016/j.scs.2021.102723>.
- Team, iED., 2019. A Brief History of the 4 Industrial Revolutions that Shaped the World. Institute of Entrepreneurship Development. <https://ied.eu/project-updates/the-4-industrial-revolutions/>.
- THE 17 GOALS | sustainable development. <https://sdgs.un.org/goals>, 2023.
- The paris agreement | UNFCCC. In: <https://unfccc.int/process-and-meetings/the-paris-agreement>, 2023.
- Vanneschi, L., Silva, S., 2023. Particle swarm optimization. In: Vanneschi, L., Silva, S. (Eds.), *Lectures on Intelligent Systems*. Springer International Publishing, pp. 105–111. https://doi.org/10.1007/978-3-031-17922-8_4.
- Wang, Z., Ala, A., Liu, Z., Cui, W., Ding, H., Jin, G., Lu, X., 2024. A hybrid equilibrium optimizer based on moth flame optimization algorithm to solve global optimization problems. *J. Artif. Intell. Soft Comput. Res.* 14 (3), 207–235. <https://doi.org/10.2478/jaiscr-2024-0012>.