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Master Degree Program in
Data Science and Advanced Analytics

ADVANCING SUSTAINABLE ENERGY SOLUTIONS: AI HYBRID RENEWABLE ENERGY SYSTEMS WITH HYBRID OPTIMIZATION ALGORITHMS AND MULTI-OBJECTIVE OPTIMIZATION IN PORTUGAL

Maria Mendes Mendonça

Master Thesis

presented as partial requirement for obtaining a Master's Degree in Data Science and Advanced Analytics

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Master Thesis presented as partial requirement for obtaining the Master's degree in Data Science and Advanced Analytics, with a specialization in Data Science

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

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ABSTRACT

The effects of global warming are increasingly evident in our daily lives, with climate change, due to the evolution of the economy and the population, therefore it is necessary to take an active role in the development of solutions aimed at achieving a sustainable and carbon neutral future.

The energy sector is one of the sectors of our society that contributes to global warming, with the use of coal, oil, natural gas, among others. This is therefore a sector that would benefit from the development of sustainable energy solutions, aimed at an energy transition focused on the use of natural resources. The use of renewable energy sources is, however, associated with the challenge of being intermittent, since it depends on the weather conditions, which is why it is necessary to combine two or more renewable energy sources to create a hybrid renewable energy system, to guarantee the system's reliability.

This is the purpose of this dissertation, the optimization of a hybrid renewable energy system in the context of Portugal. The research began with a literature review in the field of artificial intelligence and energy, and nine studies were identified from the systematic literature review, which enabled the problem to be formulated. With this a hybrid renewable energy system integrating solar panels and wind turbines was designed and optimized using a hybrid algorithm. The hybrid algorithm developed integrates the Particle Swarm Optimization and Grey Wolf Optimization algorithms, with the aim of combining the advantages of each and thus approaching the global optimum. This algorithm was also implemented in parallel, to overcome the difficulties experienced in terms of execution time and use of computing resources.

Three experiments were carried out on the hybrid algorithm developed to try to achieve the global minimum, however, it was only in the third experiment that it was possible to identify a local minimum with an ABF close to the global minimum. For this to be possible, experiment 3 integrated the changes mentioned in the two initial experiments as being necessary for a more efficient optimization.

KEYWORDS

Data Science; Artificial Intelligence; Hybrid Renewable Energy Systems; Multi-objective optimization

Sustainable Development Goals (SDG):

RESUMO

Os efeitos do aquecimento global são cada vez mais evidentes no nosso quotidiano, com as alterações climáticas, isto acontece devido à evolução da economia e da população, é por isso necessário ter um papel ativo no desenvolvimento de soluções que tenham como finalidade alcançar um futuro sustentável e neutro em carbono.

O setor da energia é um dos setores da nossa sociedade que contribui para o aquecimento global, com a utilização de carvão, petróleo, gás natural, entre outros. Este é assim um setor que beneficiaria do desenvolvimento de soluções energéticas sustentáveis, que visem a existência de uma transição energética focada na utilização de recursos naturais. A utilização de fontes de energia renovável tem, no entanto, associado o desafio de ser uma energia intermitente, uma vez que depende das condições meteorológicas, sendo por isso necessária a combinação de duas ou mais fontes de energia renovável para a criação de um sistema híbrido de energia renovável, por forma a garantir a fiabilidade do sistema.

É neste sentido que se apresenta esta dissertação, a otimização de um sistema híbrido de energia renovável no contexto de Portugal. Iniciou-se esta investigação com uma revisão de literatura na área de inteligência artificial e energia, tendo sido identificados nove estudos com a revisão sistemática da literatura realizada, que possibilitaram a formulação do problema. Desta forma, foi idealizado um sistema híbrido de energia renovável que integra painéis solares e turbinas eólicas, sendo este otimizado com o algoritmo híbrido desenvolvido. O algoritmo híbrido desenvolvido integra o algoritmo *Particle Swarm Optimization* e *Grey Wolf Optimization*, com o objetivo de articular as vantagens de cada um e assim aproximar-se do ótimo global. Este algoritmo foi ainda implementado de forma paralela, por forma a ultrapassar as dificuldades sentidas relativamente ao tempo de execução e utilização de recursos computacionais.

Foram realizadas três experiências ao algoritmo híbrido desenvolvido por forma a tentar atingir o mínimo global, no entanto, foi apenas na terceira experiência realizada que foi possível identificar um mínimo local com um ABF próximo do mínimo global. Para isto ser possível, a experiência 3 integrou as alterações mencionadas nas duas experiências iniciais, como sendo necessárias de concretizar para uma otimização mais eficiente.

PALAVRAS-CHAVE

Data Science; Inteligência Artificial; Sistemas híbridos de energia renovável; Otimização multiobjetivo

Sustainable Development Goals (SDG):

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LIST OF ABBREVIATIONS AND ACRONYMS

ACS	Annual System Cost
AOA	Arithmetic Optimization Algorithm
AI	Artificial Intelligence
AD	Autonomous Days
BSS	Battery Storage Systems
COE	Cost of Energy
DPSP	Deficit of Power Supply Probability
DSR	Design Science Research
DSRM	Design Science Research Methodology
DG	Diesel Generator
EIR	Energy Index Reliability
GA	Genetic Algorithm
GPUs	Graphic Processing Units
GSA	Gravitational Search Algorithm
GWO	Grey Wolf Optimizer
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
LR	Literature Review

LPSP Loss of Power Supply Probability

ML Machine Learning

MFO Moth-Flame-Optimizer

MOEA Multi-objective Evolutionary Algorithm

MOPSO Multi-objective Particle Swarm Optimization

NLP Natural Language Processing

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

QoL Quality of Life

REN Redes Energéticas Nacionais

RES Renewable Energy Sources

RQ Research Question

SB Storage Battery

SDGs Sustainable Development Goals

SES Sustainable Energy Systems

SLR Systematic Literature Review

TNPW Total Net Present Worth

WCA Water Cycle Algorithm

WMO-MILP Weighted Multi-Objective Mixed-Integer Linear Programming

WOA Whale Optimization Algorithm

WT Wind Turbines

NOMENCLATURE

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	Direct irradiance falling on a surface perpendicular to the sun's rays
B_0	Solar constant (1367 W/m^2)
$B(\beta,\alpha)$	Direct irradiance on an inclined surface
BS	Battery storage capacity
b_t	Type of battery
C_{p_max}	Power coefficient of the wind turbine
$cos\theta_S$	Angle of incidence between the sun's rays and the normal to the surface
$cos\theta_{ZS}$	Solar zenith angle
$DPSP$	Deficit of power supply probability
$D(\beta,\alpha)$	Diffuse irradiance on an inclined surface
$D^C(\beta,\alpha)$	Circumsolar component of diffuse irradiance on an inclined surface
$D^I(\beta,\alpha)$	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
$E_{DE}\ (t)$	Energy deficit (kWh)
E_{dumped}	Energy stored into the battery
$E_{LOAD}\ (t)$	Total annual energy demand of the load (kWh/year)
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	Global solar irradiance on a PV module
$G(\beta, \alpha)$	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	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
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
k_1	Anisotropy index
K_I	Short circuit current temperature coefficient
K_V	Open circuit voltage temperature coefficient
$LCOE$	Levelized cost of energy
LH	Reference longitude õf 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
$P_{1_{gen}}$	Crossing point of supplying energy cost by means of the AC generator and batteries
$P_{critical_{gen}}$	Power in which the diesel generator provides the insignificant power
$P_{min_{gen}}$	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
$R(\beta, \alpha)$	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
$SOC_{stop_{gen}}$	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	i^{th} 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
ε_0	Eccentricity correction factor
ε	CO_2 emissions coefficient (kg CO_2/Wh)

1. INTRODUCTION

1.1. BACKGROUND AND PROBLEM IDENTIFICATION

With the evolution of the economy and global population, the demand for more and more energy becomes inevitable, with examples of conventional sources being coal, oil, natural gas, among others. However, these contribute to global warming, which has been occurring through climate change for several decades (Sawle et al., 2023). Therefore, there is a need to coordinate efforts to find sustainable energy solutions so that the energy transition that takes place is fully sustainable and carbon neutral, to achieve this it is inevitable to turn to renewable energy due to its availability, abundance and minimal threat to the environment (Ajiboye et al., 2023). However, for the sole and exclusive use of renewable energy for power generation, it is necessary to resort to the combination of two or more of these resources for the formation of a hybrid renewable energy system (HRES), since the use of a single source of renewable energy, has the challenge of being intermittent, since it depends on weather conditions (Ajiboye et al., 2023).

A scientific area that has been explored in renewable energies with a lot of focus is Artificial Intelligence (AI), for its potential in modelling this type of energy source with the aim being the forecast and optimization and the management and supply of this type of energy (Entezari et al., 2023). AI presents itself as a technology with the potential to bring significant advances and improvements in society, being already applied in multiple fields such as healthcare, finance, transportation, entertainment, manufacturing and more. Thus, constant research in Artificial Intelligence and its applicability to the energy industry with the aim of achieving more sustainable solutions is extremely important, this type of research has been growing exponentially in recent years and in several areas besides the renewable energies such as smart power grids; energy consumption; energy storage; among others (Entezari et al., 2023).

To "efficiently utilize renewable energy sources, it turns out to be essential to perform an optimal design of HRES" (Liu et al., 2022) by using Artificial Intelligence algorithms, so that it is possible to "achieve a better monitoring, operation, maintenance and storage for RES" (Liu et al., 2022). According to Cai et al. (2022), the establishment of an optimization design of HRES is carried out through four aspects: design variables, objective functions and constraints (Figure 1.1). Characterizing each aspect:

- **Design variables,** the authors give as an example the "size (energy and/or power capacity) of each component of a system, a set of configurations of the system components, etc." (Cai et al., 2022);
- **Objective functions,** are divided into four categories those being:
    - **Technical,** when referring to indicators that allow to "evaluate the comprehensive ability of the systems to ensure the reliability and stability of the systems to satisfy the load demand" (Cai et al., 2022);

- **Economic,** when indicators related to costs associated with the system are applied, such as maintenance, replacement and others (Cai et al., 2022);
- **Environmental,** when indicators are used that assess emissions that damage the environment and that may eventually be produced by the system (Cai et al., 2022);
- **Social,** referring to indicators that "are applied to evaluate the capability of the systems to produce energy" and others (Cai et al., 2022);

- **Constraints,** as an example is given "number of units, renewable capacity, installation size" and others (Cai et al., 2022).
- **Optimization approach**

Regarding the optimization approach, AI-based techniques are found promising which are characterized "by being deemed more acceptable than conventional approaches due to their ability to look for global optimal, high calculation precision, and rapid convergence speeds" (Sawle et al., 2023). However, the use of a single optimization algorithm means that it is not possible to achieve optimal results, with that it was visible by researchers possibilities for their improvement through the combination of two or more algorithms, in order to "complement each other and produce better optimization efficiency" (Cai et al., 2022) these "can provide more accurate results and have the ability to solve multi-objective optimization problems effectively" (Sawle et al., 2023). The consideration of multiple optimization criteria has a great advantage since typically real-world problems involve conflicting objectives that cannot be easily combined into a single objective function.

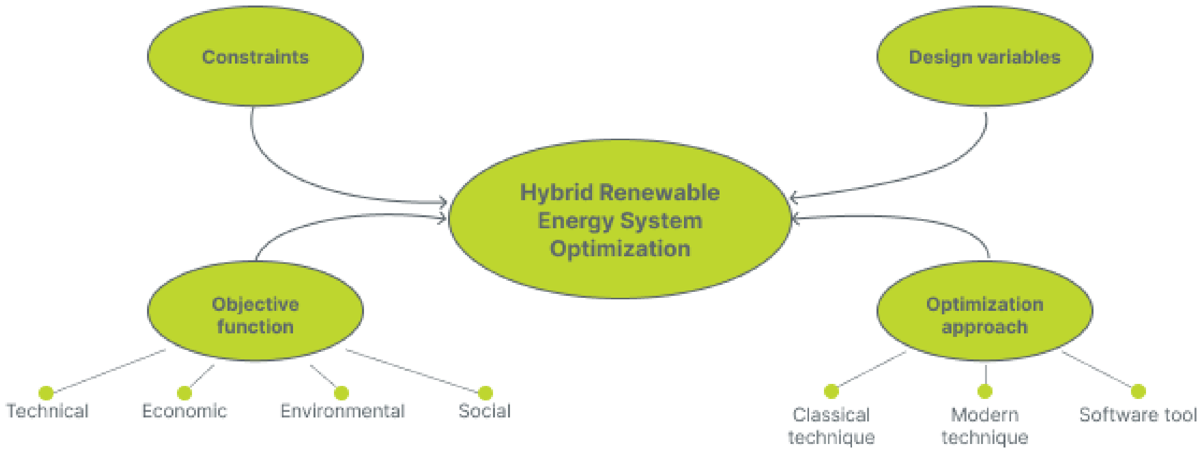

Figure 1.1 - Diagram of the optimization design of HRES

Source: Adapted from Cai et al. (2022)

With this, there is a need for research on AI Hybrid Renewable Energy Systems, looking to new combinations of optimization algorithms that may prove to be promising and still handle various objective functions effectively.

Therefore, the research question (RQ) that is placed is:

RQ: "What novel hybrid optimization algorithms can be developed to effectively address diverse objective functions in the context of AI Hybrid Renewable Energy Systems in Portugal?".

1.2. OBJECTIVES

To help answer the defined research question (RQ), the objective of the research is to propose a strategy for the optimization of HRES in Portugal, considering multiple criteria.

To achieve this objective, some intermediate objectives are also set:

- Make a 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.

1.3. IMPORTANCE AND RELEVANCE

It is very important to act quickly to implement renewable energy solutions to combat the climate change that is affecting our planet so much. Implementing this type of solution, we propose that would lead to positive changes in three pillars:

- **Environmental,** would make it possible for "no or little emission production of poisonous and exhaust gases" to occur (Hannan et al., 2021; Serban & Lytras, 2020); a reduction in pollution (Kumar, 2020) and an increase in energy security (Kumar, 2020);
- **Economic,** renewable energy sources are continuously regenerated by nature and can be found all over the world, so these resources produce cheaper electricity ("Greenvolt," n.d.), which would make its use possible to achieve low electricity costs (Hannan et al., 2021); the use of this type of energy solution would also lead to an increase in income (Kumar, 2020); given that renewable energy solutions end up using local resources (labor, materials, companies, etc.) there are therefore economic benefits, which result in increased regional development (Kumar, 2020);
- **Social,** the creation of these new sustainable solutions would result in the creation of new jobs due to their recent nature (Hannan et al., 2021; Serban & Lytras, 2020); there would be visible improvements in terms of community health, since there would be no or few emissions of gases harmful to the human system (Hannan et al., 2021; Serban & Lytras, 2020); taking into account that in order to be able to consume energy from renewable energy in a sustainable way, this type of energy must be obtained on the internal market, thus making it possible to reduce dependence on imports (Serban & Lytras, 2020), which results in the development of communities (Hannan et al., 2021) who will then be able to use "renewable sources that can be exploited recurrently, with no potential for exhaustion" (Serban & Lytras, 2020); it would also be possible to

see improvements in citizens' quality of life (QoL) (Kumar, 2020) and there would also be demographic implications with the adoption of this type of solution (Kumar, 2020).

2. LITERATURE REVIEW

2.1. ENERGY INDUSTRY

2.1.1. Characterization

According to Bilgen (2014), energy can be defined as "the ability to do work", existing three aspects that define it: the form in which it can be found, how it is processed and its source. Energy in the form of electricity plays a very important role in the modern economy, and its demand is expected to continue to increase due to rising household incomes, the electrification of transport and thermal energy solutions, the rise in demand for digital connected devices and air conditioning (Electricity – World Energy Outlook 2019 – Analysis – IEA, n.d.). It was verified by Bilgen (2014) that the increase in economic growth ends up having an impact on the increase in energy consumption, so it is possible to see a direct relationship between these two variables. The increase in demand for electricity turned out to be one of the reasons why 2018 was a record year for global CO2 emissions in the energy sector (Electricity – World Energy Outlook 2019 – Analysis – IEA, n.d.), although this record was broken in 2018, the energy sector already accounted for two thirds of global CO2 emissions, which must be reduced in order to combat global warming, by decarbonizing the energy system (Energy Transitions and Societal Change | Research Institute for Sustainability, n.d.). The decarbonization of electricity can also make it possible to reduce CO2 emissions in other sectors such as (Electricity – World Energy Outlook 2019 – Analysis – IEA, n.d.), construction, industry and transport.

Several agreements have been made with the overall aim of achieving a more sustainable future. In 1997, the Kyoto Protocol was adopted by several countries, with the aim of promoting the use of energy with low levels of polluting gases, thus establishing a price for CO_2 and other greenhouse gases (Solomon & Krishna, 2011). In 2015, the Paris Agreement was adopted by 196 Parties on the UN Climate Change Conference (COP21), with the aim that "the increase in the global average temperature to well below 2°C above pre-industrial levels" and look for "to limit the temperature increase to 1.5°C above pre-industrial levels" (The Paris Agreement | UNFCCC, n.d.). Also in 2015, the UN developed the 17 Sustainable Development Goals (SDGs), agreed to by several countries, his vision being the one that "ending poverty and other deprivations must go hand-in-hand with strategies that improve health and education, reduce inequality, and spur economic growth – all while tackling climate change and working to preserve our oceans and forests" (THE 17 GOALS | Sustainable Development, n.d.).

The development of all these agreements generally has the objective of achieving energy transition, to combat climate change that is threatening the planet. The energy transitions that have taken place over the centuries have ultimately led to industrial revolutions (He, 2015). In the first industrial revolution that took place, in the late 18th century (Team, 2019), firewood was replaced by coal, which led to industrialized production and increased productivity at work, as the railways came into being (He, 2015). In the second industrial revolution, in the end of the 19th century (Team, 2019), oil replaced coal (Kabeyi & Olanrewaju, 2022), electricity having also been invented, these changes resulted in mass industrial production, such as the Ford automatic engine production lines; the emergence of internal combustion engines and the effects of this revolution were also felt in the transportation and communication sectors, with cars and the telephone for example (He, 2015). The third industrial revolution began in the second half of the 20th century (Team, 2019), in which nuclear energy, electronics, telecommunications and computers emerged (Team, 2019). Lastly, the fourth industrial revolution or Industry 4.0, which is currently underway, began in the third millennium with the Internet (Team, 2019). With the industrial revolutions that took place over several centuries, an industrial civilization was born, that is according to He (2015), "an unsustainable form of human society", resulting in a scarcity of mineral resources and the existence of climate change.

Before the revolutions that took place, communities used natural resources to carry out their daily activities, such as drying clothes in the sun. However, as mentioned above, these behaviors have changed to the use of fossil fuels, which cause damage to our planet (Kabeyi & Olanrewaju, 2022), there needs to be an energy transition to renewable energy sources (RES) (Kabeyi & Olanrewaju, 2022). Renewable energy is a clean and inexhaustible form of energy, since its source is natural resources (Kabeyi & Olanrewaju, 2022), however, it should also be borne in mind that as an energy source related to weather conditions, it could be affected by climate change (Schaeffer et al., 2012). These types of green resources include energy from "hydropower, solar, wind, wave, geothermal power, waste energy such as gases from landfills, incineration, biomass, and liquid biofuels" (Bishoge et al., 2019). There are many advantages to using RES at an economic and social level, in terms of environmental energy sustainability, access to energy due to its decentralization, reduction in the emission of polluting gases and local socio-economic development (Kabeyi & Olanrewaju, 2022). However, the use of RES is accompanied by challenges such as low conversion efficiency and the variability and unpredictability of supply associated with this type of resource, which depends on natural conditions. Despite this, it is possible to combat these challenges through optimization to "create stability and reliability in renewable energy supply and use" (Kabeyi & Olanrewaju, 2022).

2.1.2. Sustainable Energy Systems

According to Bazmi & Zahedi (2011), the energy systems "are complex, often involving combinations of thermal, mechanical and electrical energy, which are used to achieve one or more of several possible goals, such as electricity generation, climate control of enclosed spaces, propulsion of transportation vehicles, and so on", which have five phases (Figure 2.1) (Wütscher, 2005). With the growing demand for energy due to industrial development and population growth, it is confirmed by Yoro et al. (2021) that the development of Sustainable Energy Systems (SES) is a priority. This type of energy system is defined as "a complete structure with energy supply and demand based on renewable energy as opposed to fossil and nuclear fuels" (Yoro et al., 2021), based on two essential pillars: the efficient use of energy and the increasing use of renewable resources (Wütscher, 2005).

Figure 2.1 - Phases of an energy system[1]

Source: Adapted from Wütscher (2005)

The view that current energy systems are unsustainable is gaining momentum due to global warming, poor air quality and dependence on fossil fuels, which is why attention is being paid to the necessary transition to more efficient systems that use renewable energy sources (Bazmi & Zahedi, 2011). The transition from the current energy system, which uses fossil fuels, to SES requires a "rethinking and a redesign of the energy system" (Lund et al., 2014) in order to be able to integrate renewable energy sources, as well as the appropriate technologies for the implementation of this type of energy system and also in this transition there must be an assessment of resources, since one of the characteristics of renewable energies is their specificity in each location (Østergaard et al., 2020).

The transition to a sustainable energy system has social, ecological and economic advantages, for example, by reducing the use of fossil resources and using a decentralized energy system, local economic development is possible (Wütscher, 2005). In the case of isolated areas, the development of SES is of greater importance, since in these places even fossil fuels are more expensive due to their transportation and storage, making renewable energies a more viable solution (Chu et al., 2020).

2.1.3. Hybrid Renewable Energy Systems

With the increase in carbon dioxide emissions, there is growing interest in using an alternative solution to fossil fuels to avoid the global warming that is the consequence of this increase in emissions, one solution being the use of renewable energy sources (RES) (Shivarama Krishna & Sathish Kumar, 2015). However, there are some challenges to renewable energies, such as their dependence on environmental conditions and their intermittent nature (Shivarama Krishna & Sathish Kumar, 2015), Therefore, in order to be able to make the transition to this green energy, it is necessary to use more than one energy source in order to form what is known as Hybrid Renewable Energy Systems (HRES), which according to Bajpai & Dash (2012), is defined by "one renewable and one conventional energy source or more than one renewable with or without conventional energy sources, that works in stand-alone or grid connected mode". The increase in demand for the transition to this energy system is due to "the potential techno-economic advantages of hybrid combinations and the rapid depletion

[1] In Sustainable Energy Systems (SES), in the first phase, energy is produced from natural resources, in the next phase it is converted to other energy carriers and then transported and distributed for use (Wütscher, 2005).

of conventional sources of energy" (Sawle et al., 2018). The classification of HRES is based on their operating mode and structure (Figure 2.2).

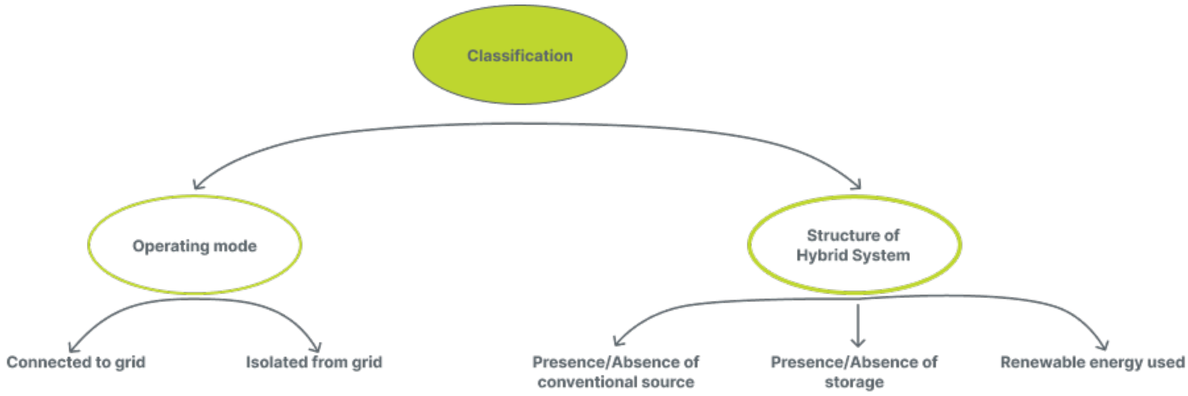

Figure 2.2 - Classification of Hybrid Renewable Energy Systems[2]

Source: Adapted from Kartite & Cherkaoui (2019)

The operating mode of a Hybrid Renewable Energy System (HRES) can be grid-parallel or stand-alone. The grid-parallel operating mode is typically used in urban areas, and when they don't have the necessary energy to meet their needs, it can be obtained from the grid and when more energy is generated than is used, the surplus is sold to the grid. As for the stand-alone operating mode, a form of storage is required (batteries, electrolyzer-fuel cell combinations, and conventional diesel generators) to ensure that there is always energy to supply when needed (Erdinc & Uzunoglu, 2012).

According to Olatomiwa et al. (2016), a hybrid system is then defined by "an energy system that uses more than one energy source", in which it converts multiple renewable energy resources into a single form, typically electrical, which can then be stored in a form (chemical, compressed air, mechanical, etc.) and then used to power a variety of loads (Nehrir et al., 2011). The components of a hybrid system are AC/DC energy source, AC/DC power electronic converters and loads (Figure 2.3), where is possible to have several configurations, DC coupled, AC coupled and Hybrid coupled system, differing according to the application of the system (Shivarama Krishna & Sathish Kumar, 2015).

[2] Operating mode as connected to the grid, also called grid-parallel, these operate in parallel to the grid. Operating mode as isolated, more often referred to as stand-alone, refers to autonomous hybrid systems. As far as structure is concerned, with the presence or absence of conventional source, there is a conventional power source (diesel generator, gas turbine, plant); presence or absence of storage capacity (rechargeable batteries, etc.); renewable energy source used (Kartite & Cherkaoui, 2019).

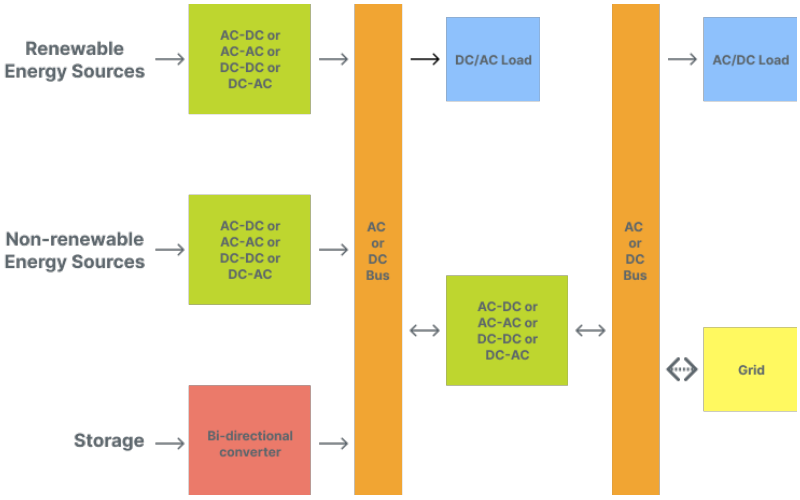

Figure 2.3 - Basic components of a Hybrid system

Source: Adapted from Shivarama Krishna & Sathish Kumar (2015)

The Hybrid Renewable Energy Systems (HRES) have a number of advantages, from the ability to integrate two or more renewable energy sources into them, so that local characteristics can be taken into account, in the case of small HRES they have lower costs than the systems we are used to today and the fact that the fuel for this type of energy system is "abundant, free and inexhaustible" (Bhandari et al., 2015).

2.2. Artificial Intelligence

2.2.1. Concepts & Main areas

The first appearance of the concept Artificial Intelligence (AI) emerged with the work of Alan Turing the "father of computer science", published in 1950 "Computing Machinery and Intelligence", this begins by asking the question "Can machines think?" which serves as a starting point for the "Turing Test", this test involves a human respondent trying to distinguish between a human response and that of a machine (What Is Artificial Intelligence (AI) ? | IBM, n.d.). According to McCarthy (2004), AI is defined by "the science and engineering of making intelligent machines, especially intelligent computer programs. It is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable", simplifying according to IBM, AI it is an area that encompasses computer science and robust datasets, with machine learning and deep learning as sub-domains, that have AI algorithms to make predictions or classifications based on input data, with the ultimate objective of solving problems (What Is Artificial Intelligence (AI) ? | IBM, n.d.).

Between 1950 and 1970 the emergence of AI was accompanied by a growing enthusiasm for "thinking machines", and the first neural networks were also developed at this time. Between 1980 and 2010, the subdomain of AI, Machine Learning (ML), began to gain more prominence so that nowadays, with advances in deep learning, there is a boost in AI (*Artificial Intelligence (AI) – What It Is and Why It Matters*, n.d.).

There are several areas in which the application of AI exists, from:

- **Speech recognition**, in which natural language processing (NLP) is used, which is "the ability to understand text and spoken words in much the same way human beings can" (What Is NLP (Natural Language Processing)? | IBM, n.d.);
- **Customer service**, where virtual agents are used to increasingly personalize a customer's passage through a website (What Is Artificial Intelligence (AI) ? | IBM, n.d.);
- **Computer vision**, that allows you to obtain information from visual data (What Is Artificial Intelligence (AI) ? | IBM, n.d.);
- **Recommendation engines**, in which information from each customer's previous consumption behaviors is used to make it possible, through AI algorithms, to discover trends and make recommendations (What Is Artificial Intelligence (AI) ? | IBM, n.d.);
- **Automated stock trading**, with the aim of optimizing stock portfolios (What Is Artificial Intelligence (AI) ? | IBM, n.d.).

With the increasing use of AI in multiple fields, it becomes increasingly necessary to also take into account aspects related to ethics in this area for conversation (What Is Artificial Intelligence (AI) ? | IBM, n.d.).

2.2.2. Artificial Intelligence applicability to the energy industry

The new advances that are being felt in the area of Artificial Intelligence (AI) have been revolutionizing the energy industry, this being the area that could allow cheap, clean and safe energy to be obtained, which will result in "reduce consumer electricity costs, reduce greenhouse gas emissions, and help grid operators and utilities maintain the power system's reliability" (Ahmad et al., 2021), there has even been interest on the part of several countries in the use of this technology for the integration of renewable energies in their energy systems, as well as in the search for improving their efficiency through "forecast supply and demand, manage the grid in real time, minimize downtime, optimize returns" (Ahmad et al., 2022). In Figure 2.4 it is possible to see how the integration of AI with energy systems is carried out.

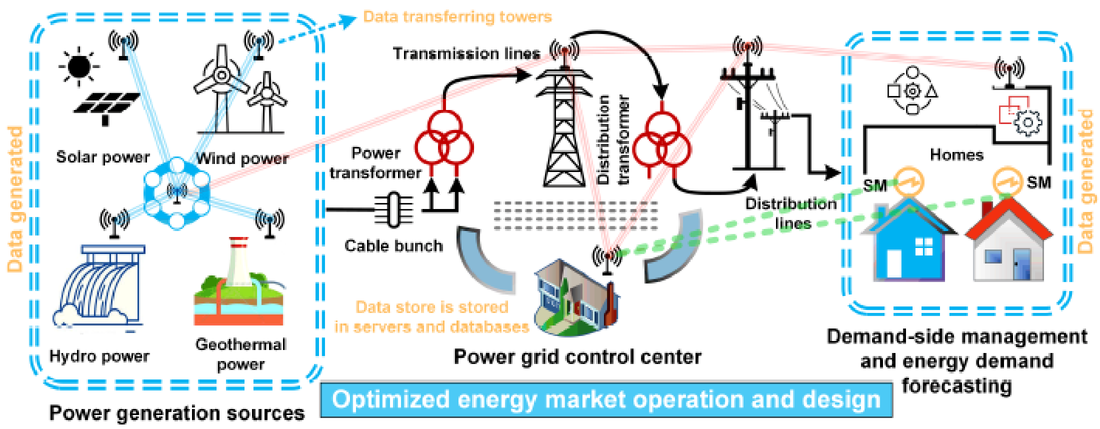

Figure 2.4 - AI and real-time applications in energy systems

Source: Ahmad et al. (2022)

With the integration of AI in the renewable energy sector, advances will be made in several areas:

- **Centralized and smart control centers**, in which with a large amount of data and the use of AI it will be possible through its processing to improve control operations, adapt supply taking into account demand, carry out weather and load forecasts (Ahmad et al., 2022);
- **Improve microgrid integration,** through the use of AI, it will be possible to seamlessly integrate units that generate renewable energy into the main grid (Ahmad et al., 2022);
- **Improved reliability and safety,** since with the use of this technology it is possible to understand patterns in the use of energy, of possible energy leakage as well as in the performance of the structures, which will thus allow to increase the stability, performance and reliability (Ahmad et al., 2022);
- **Expand the market,** with the participation of AI in the energy industry, new techniques may emerge (Ahmad et al., 2022);
- **Smart grid with AI-enabled storage,** that is, with the use of AI techniques together with forms of energy storage, it will enable the use of renewable energies in a safe and sustainable way (Ahmad et al., 2022).

2.3. Systematic Literature Review on Artificial Intelligence and HRES Optimization

In this chapter, a Systematic Literature Review (SLR) will be carried out using the PRISMA methodology (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) with the aim of understanding the state of the art in relation to the research topic and obtaining knowledge. To achieve the objective of making a comprehensive literature review on the field of AI and Energy, the following literature research questions (LRQ) are posed:

LRQ1: What are the optimization algorithms that were used to create hybrid optimization algorithms to optimize Hybrid Renewable Energy Systems (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 utilized in the design and operation of Hybrid Renewable Energy Systems?

2.3.1. Method

In order to carry out the literature review, the steps suggested by the PRISMA 2020 Checklist were followed: 1) Defined the eligibility criteria, i.e. the criteria for excluding and including articles in the review should be defined at this stage; 2) Specification of databases consulted; 3) Search strategy, the strategy adopted to carry out the search in all databases should be mentioned at this stage; 4) Selection process, specification of the process for selecting the final number of articles to be analyzed.

2.3.1.1. Eligibility criteria

The first stage in applying the PRISMA methodology is to define the criteria for including and excluding studies. The search only considered articles with a publication date after 2014, thus ensuring that the information obtained about Artificial Intelligence and Hybrid Renewable Energy Systems is only the most recent. Bearing in mind that the aim of this SLR is to find out the state of the art regarding Hybrid Renewable Energy Systems that use Hybrid Optimization Algorithms with Multi-objective Optimization in AI applications in Portugal, the inclusion criteria in Table 2.1 were defined. As far as the exclusion criteria are concerned, articles that: do not meet the scope of this thesis; are not available in full text; are not written in English and if it uses software for optimization instead of an algorithm, will be eliminated from analysis. The criteria presented can be seen in Table 2.1.

Table 2.1 - Inclusion and Exclusion criteria definition

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

2.3.1.2. Information sources

To carry out this SLR, several databases were used, including Scopus, Web of Science, IEEE xplore and Taylor & Francis. None of these databases were accessed through database aggregators.

2.3.1.3. Search strategy

Based on the literature review carried out earlier, several keywords were found, and only the most relevant to this study were selected, which led to the creation of the following query for an efficient search in the various sources of information:

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

2.3.1.4. Selection process

The query presented in the previous section was used to search the selected databases, as indicated in section 2.3.1.3, thus starting the selection process, which can be seen in Figure 2.5. In a first identification phase, 39 articles were identified through the databases, which corresponds to 8 articles from Scopus, 6 articles from Web of Science, 1 article from IEEE Xplore and 24 articles from Taylor and Francis, in addition to these, another 5 relevant articles were identified through other methods. Once a total of 44 articles had been identified, duplicates were eliminated. In a second phase, the screening phase, the remaining 38 articles were analyzed by their title and abstract, thus excluding 27 that did not meet the scope of this systematic literature review. Subsequently, the remaining 11 articles were sought for retrieval and it was possible to obtain all of them, so there were none that were excluded for reason 2. In the eligibility phase, the 11 studies were assessed using the full text, considering the inclusion and exclusion criteria defined above, which resulted in 9 articles to be included in the review.

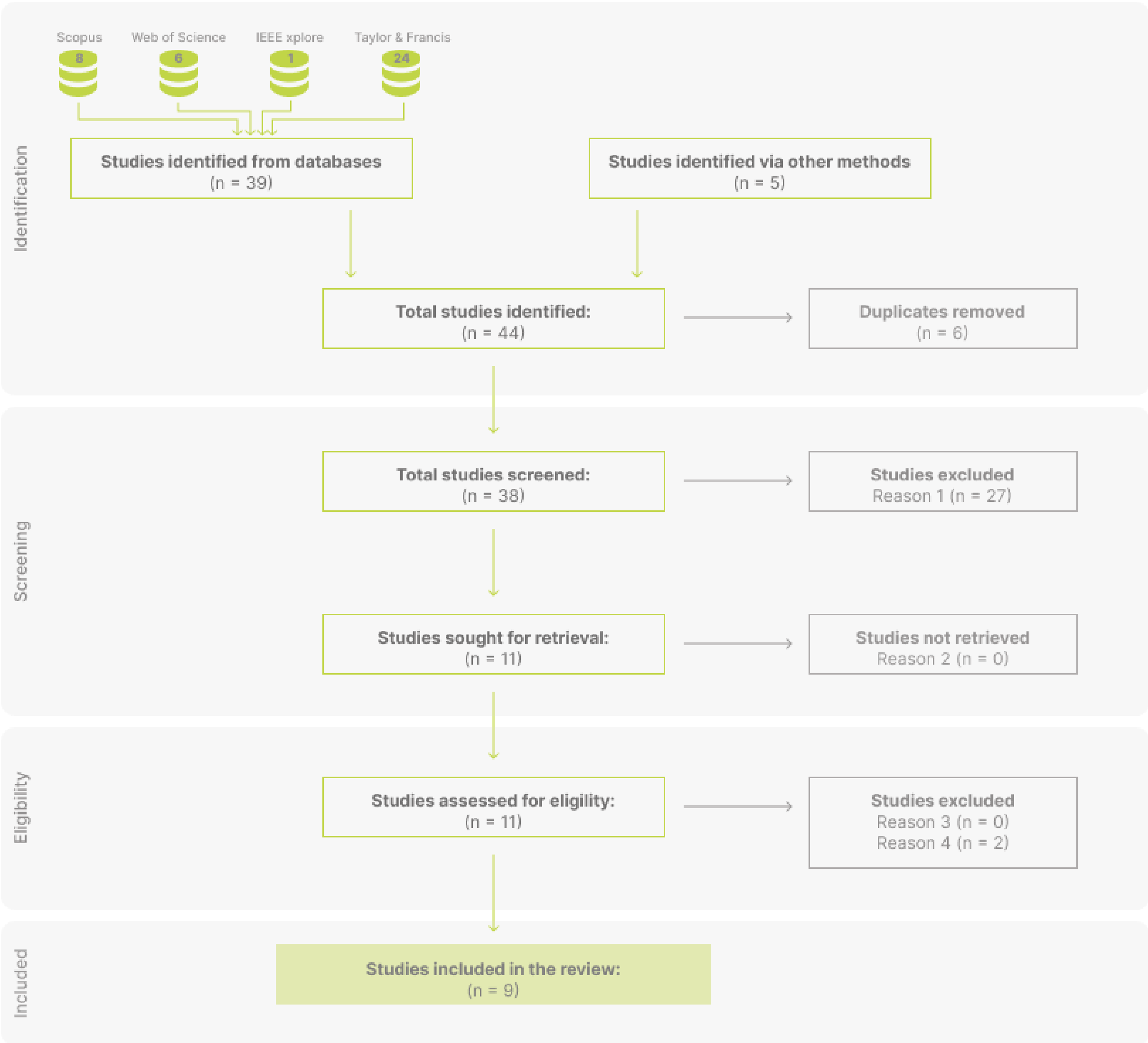

Figure 2.5 - SLR flow chart

Source: Adapted from Moher et al. (2009) and Page et al. (2021)

2.3.2. Results and discussion

The 9 articles identified for inclusion in the review were distinguished by their purpose: Optimal sizing and improvement of reliability. The studies used were published between 2014 and 2023, and all in scientific journals, which can be seen in Table 2.2.

Table 2.2 - Articles included using the PRISMA methodology

Ref. No.	Author(s)	Title	Type
[1]	Amereh et al., 2014	Multi objective design of stand-alone PV/wind energy system by using hybrid GA and PSO	Optimal sizing
[2]	Diab et al., 2019	Application of Different Optimization Algorithms for Optimal Sizing of PV/Wind/Diesel/Battery Storage Stand-Alone Hybrid Microgrid	Optimal sizing
[3]	Capraz et al., 2020	Optimal sizing of grid-connected hybrid renewable energy systems without storage: a generalized optimization model	Optimal sizing
[4]	Rathish et al., 2021	Multi-objective evolutionary optimization with genetic algorithm for the design of off-grid PV-wind-battery-diesel system	Optimal sizing
[5]	Suman et al., 2021	Optimisation of solar/wind/bio-generator/diesel/battery based microgrids for rural areas: A PSO-GWO approach	Optimal sizing
[6]	Çetinbaş et al., 2022	The Hybrid Harris Hawks Optimizer-Arithmetic Optimization Algorithm: A New Hybrid Algorithm for Sizing Optimization and Design of Microgrids	Improvement of reliability
[7]	Fendzi Mbasso et al., 2023	Contribution into Robust Optimization of Renewable Energy Sources: Case Study of a Standalone Hybrid Renewable System in Cameroon	Optimal sizing
[8]	Hossain et al., 2023	Multi-Objective Hybrid Optimization for Optimal Sizing of a Hybrid Renewable Power System for Home Applications	Optimal sizing
[9]	Güven et al., 2023	Multi-Objective Optimization of an Islanded Green Energy System Utilizing Sophisticated Hybrid Metaheuristic Approach	Optimal sizing

Thereafter, the LRQ set out at the section 2.3 are answered in relation to the information obtained from the articles included in Table 2.2.

[STUDY 1]

To obtain the optimal size for a HRES, the study by Amereh et al. uses a hybrid algorithm resulting from the combination of genetic algorithm (GA) and particle swarm optimization (PSO). The use of GA in the initial optimization phase makes it possible to find the global minimum, reducing the possibility of a local minimum, so that after a specific number of iterations, known as the Hybrid Constant (HC), PSO can be applied to improve optimization speed and local tuning ability (Amereh et al., 2014). The objective functions of the optimization carried out by the GA-PSO hybrid algorithm are to minimize Total Net Present Worth (TNPW) and maximize Energy Index Reliability (EIR), which is why it is a multi-objective optimization, with Amereh et al. (2014) using ε-constraint, i.e. "TNPW is the main optimization function and EIR is constraint" (Amereh et al., 2014). In this way, the optimization carried out will make it possible to obtain the system parameters (WT swept area, PV panel area and storage battery capacity) (Amereh et al., 2014). The HRES used in this study consists of wind turbines (WT), photovoltaic (PV) panels and, to overcome the challenges associated with using renewable energy sources, a storage battery (SB) was included as a backup (Amereh et al., 2014).

[STUDY 2]

The study by Diab et al. (2019) aimed to optimize the sizing of a HRES, having applied various algorithms to this optimization problem, such as Whale Optimization Algorithm (WOA), Water Cycle Algorithm (WCA), Moth-Flame-Optimizer (MFO), and Hybrid particle swarm-gravitational search algorithm (PSOGSA). One of the algorithms mentioned is the hybrid PSOGSA algorithm, which results from combining the particle swarm optimization (PSO) and gravitational search algorithm (GSA) algorithms, thus making it possible to combine the exploitation capacity of the PSO and the exploration efficiency of the GSA (Diab et al., 2019). The results obtained in the study concluded that the hybrid PSOGSA algorithm is faster than the others in reaching its optimal solution, however Diab et al. (2019) "concluded that WOA is the most promising among the proposed methods in solving the optimization problem" (Diab et al., 2019). This optimization problem is multi-objective, since its objective functions are to minimize the loss of power supply probability (LPSP), minimize the cost of energy (COE) and minimize the dummy load, using weights associated with each objective function, obtained through trial and error to obtain the best optimization results (Diab et al., 2019). As the system used in this study is an HRES, it is subject to the intermittent nature of renewable energy sources, to overcome this challenge, the authors opted to use an energy storage system, specifically a battery bank, as well as a diesel generator, which is only used when it is not possible to satisfy the demand for energy through renewable energy sources or a battery bank (Diab et al., 2019).

[STUDY 3]

The study by Capraz et al. (2020) seeks to achieve the optimal sizing of a hybrid renewable energy system without storage (HRES-WS), through the combination of a weighted multi-objective mixed-integer linear programming (WMO-MILP) model and Monte Carlo simulation. The use of WMO-MILP makes it possible to observe the impact that each objective function has on the sizing of the system, due to the possible weights associated with each function that reflect "the decision-maker's cost-based, environmental-based, or partially cost- and environmental-based priorities" (Capraz et al., 2020). Monte Carlo simulation, on the other hand, is inserted with the aim of addressing the stochastic nature of the modeling environment, thus making it possible to "predict weather data and load demand based on the historical data" (Capraz et al., 2020). The model developed address a multi-objective optimization problem, in which the objective functions are the minimization of the difference between the total cost and the total revenue and the minimization of the total annual amount of CO_2 produced by the system, Capraz et al. (2020) observed that increasing the weight associated with the objective function of minimizing the total annual amount of CO_2 results in an increase in the cost of the system (Capraz et al., 2020).

[STUDY 4]

Another approach to optimize the design of a HRES was carried out by Rathish et al. (2021) for the state of Tamil Nadu in India, in which the authors of the study used the Multi-objective evolutionary algorithm (MOEA) and Genetic Algorithm (GA) to create a hybrid algorithm. The multi-objective optimization carried out using MOEA-GA considers three objective functions, minimization of Net Present Cost (NPC), minimization of unmet load and minimization of CO_2 emissions from the system (Rathish et al., 2021). The MOEA considers the objective functions in a vector, in which each one has a vector composed of the problem's decisive variables, this algorithm thus makes it possible to obtain the Pareto set of the non-dominated solutions, while the GA returns the solution that minimizes the NPC of the combination of components obtained by the MOEA (Rathish et al., 2021). The HRES is composed of PV-Wind-Diesel-Battery, however it is possible to meet the energy demand without having to resort to the diesel generator, which is indicative of the capacity to use renewable energy sources in the study location (Rathish et al., 2021).

[STUDY 5]

To obtain the optimal size of a microgrid in the Indian state of Bihar, Suman et al. (2021) applied the hybrid PSO-GWO algorithm resulting from the combination of Particle Swarm Optimization (PSO) and Grey Wolf Optimizer (GWO). The PSO algorithm is capable of exploitation, although its ability to explore is not the same since it ends up converging on the local optima rather than the global optimum solution, GWO was therefore introduced into the hybrid algorithm with the aim of "minimise the probability of falling into a local minima" (Suman et al., 2021). The optimization problem addressed by Suman et al. (2021) is multi-objective, with the objective functions of minimizing the cost of energy (COE) and minimizing the Deficit of Power Supply Probability (DPSP), which are then transformed into a single objective problem through linear scalarization, that is characterized by "the objectives are either combined to form a linear function or are taken as constraint for optimization problem" (Suman et al., 2021). In this optimization problem, Suman et al. (2021) chose to associate each objective function with a weight that reflects its significance for the problem, as well as a fraction between the value of the objective function and its maximum limit (Suman et al., 2021). Bearing in mind that the energy system used in this study is a HRES, its main source of energy are renewable energy sources, which are characterized by their intermittent nature, for this reason, the battery storage unit and diesel generator are inserted as components of the system, so that if the energy produced by the RES is greater than the demand, the excess is stored in the storage unit and if both the energy produced by the RES and that stored in the battery storage unit is not enough to satisfy the demand, the diesel generation unit is used (Suman et al., 2021).

[STUDY 6]

The study by Çetinbaş et al. (2022) aimed to "sizing optimization and design of autonomous microgrids" (Çetinbaş et al., 2022) using a hybrid algorithm created by the authors called the Harris Hawks Optimizer-Arithmetic Optimization Algorithm (hHHO-AOA), since it results from the combination of the Harris Hawks Optimizer (HHO) and the Arithmetic Optimization Algorithm (AOA) (Çetinbaş et al., 2022). The use of this hybrid hHHO-AOA algorithm makes it possible to improve "solution accuracy and the computational speed by refining the search capability" (Çetinbaş et al., 2022). The optimization problem in this study is multi-objective since its objective functions are the minimization of the loss of power supply probability (LPSP) and the minimization of the cost of energy (COE) (Çetinbaş et al., 2022). The authors of the study approached the optimization problem by modifying it "into a single-objective optimization problem with the weighted sum method" (Çetinbaş et al., 2022), in which weights are assigned to each objective function. As a way of overcoming the challenges posed by the use of renewable energy sources, the authors of the study integrated a battery storage system (BSS) and a diesel generator (DG) into the system, thus allowing uninterrupted operation, since when the energy produced by the RES is greater than the load demand, the surplus is stored in the BSS, while when the energy produced by the RES is less than the load demand, the deficit is supplied by the BSS, or if this is not enough, in the second instance by the DG (Çetinbaş et al., 2022).

[STUDY 7]

The study carried out by Fendzi Mbasso et al. (2023) aimed to "assess and improve the reliability and the autonomy of the HRES" (Fendzi Mbasso et al., 2023), using the hybrid algorithm resulting from the combination of particle swarm optimization (PSO) and grey wolf optimizer (GWO), the latter having the capacity to explore, avoiding the local optima (Fendzi Mbasso et al., 2023). The optimization problem is multi-objective, in which the objective functions are minimizing the Deficit of Power Supply Probability (DPSP), maximizing the Autonomous Days (AD) and maximizing the energy kept into the BSS (Fendzi Mbasso et al., 2023). This optimization is possible by minimizing the DPSP and maximizing the two variables, the authors use two parameters obtained through trial-and-error (Fendzi Mbasso et al., 2023). It is also possible to respond to the objective functions mentioned above by sharing the information of the particles in the multi-objective particle swarm optimization (MOPSO), which allows them to approach the global optima as well as their best result, in addition, at the end of each iteration the non-dominated solutions obtained are stored temporarily (Fendzi Mbasso et al., 2023). An integral part of the system is the battery storage system (BSS) as a way of guaranteeing "a reliable, suitable, and sustainable system" (Fendzi Mbasso et al., 2023), since renewable energy sources are used in the HRES, which are sometimes intermittent. With the use of the BSS, it is therefore possible to store the energy produced that is not immediately used, so that it can later be applied to meet existing needs (Fendzi Mbasso et al., 2023).

[STUDY 8]

In the study by Hossain et al. (2023), the authors sought to achieve the optimal sizing of a hybrid renewable energy system (HRES) by optimizing with a hybrid algorithm originating from the combination of the Non-dominant Sorting Genetic Algorithm II (NSGA II) and the Grey Wolf Optimizer (GWO), since "hybrid algorithms provide the most precise optimum results for the sizing approach" (Hossain et al., 2023). NSGA II has a fast and efficient convergence, but a high computational complexity, while GWO has a slower convergence, lower complexity and a greater capacity for exploration, avoiding the optimum location, so the NSGA-GWO algorithm "preserves the ingenuity of both algorithms and combines them to generate a much more reliable outcome" (Hossain et al., 2023). The problem presented was approached as a multi-objective optimization, since it has two objective functions, minimizing the total cost and minimizing the loss of power supply probability (LPSP), so an objective function was formulated that minimizes them simultaneously (Hossain et al., 2023). As a way of addressing the intermittent nature of renewable energy sources, Hossain et al. (2023) resorted to using an energy storage device as part of the HRES, so that when the energy produced is greater than the demand for it, the surplus is stored and when the energy produced is less than that needed to be supplied, the deficit is replenished by the battery (Hossain et al., 2023).

[STUDY 9]

To address the problem of optimal sizing of a HRES, Güven et al. (2023) used the hybrid algorithm Hybrid Firefly Particle Swarm Optimization (HFAPSO), due to its ability to act in complex optimization landscapes, achieve the global optimum solution and also manage complex constraints, aspects which reflect its robustness (Güven et al., 2023). This optimization problem is multi-objective, since its objective functions are to minimize the annual system cost (ACS), minimize the levelized cost of energy (LCOE) and minimize the net present cost (NPC). As a way of guaranteeing system reliability, since renewable energy sources are used, a battery and diesel generator are an integral part of the HRES. When the energy generated by the renewable energy sources is greater than that required, it is stored in batteries, while when the load demand is greater than the energy generated, the deficit is supplied by the energy in the batteries (Güven et al., 2023). The diesel generator will "compensate for the absence of adequate power output by the resources such as PV or Wind and a battery bank" (Güven et al., 2023).

3. METHODOLOGY

Based on the research question in section 1.1, the goal of this study is to create a strategy, a hybrid optimization algorithm capable of considering various objective functions within the scope of Hybrid Renewable Energy Systems in Portugal. The expected result is therefore an artifact that represents the study of which optimization algorithms allow the system to achieve good results and its possible contribution to making changes in our daily lives, some of which are listed in section 1.3. With this, the methodology that is most suitable for carrying out this research is Design Science Research (DSR), since its main objective is to develop an artifact that presents itself as a possible solution to problems or needs in the real world (Hevner & Chatterjee, 2010).

3.1. DESIGN SCIENCE RESEARCH

The methodology used in this study is therefore Design Science Research (DSR), which is defined as "a research paradigm in which a designer answers questions relevant to human problems via the creation of innovative artifacts, thereby contributing new knowledge to the understanding that problem" (Hevner & Chatterjee, 2010). The most widely referenced process model of this methodology is the one developed by Peffers et al. (Figure 3.1) (Brocke et al., 2020) which consists of six steps: problem identification and motivation; definition of the solution's objectives; design and development; demonstration; evaluation and communication and four possible entry points: problem-centered initiation; objective-centered solution; design and development-centered solution and client/context initiated.

To better understand the DSR process, each step of the nominal process is presented in more detail below:

- **Activity 1 - identification of the problem and motivation,** in this first stage the research problem is defined, which will allow the development of the artifact that is presented as a solution to the problem (Peffers et al., 2007) and also the value that this solution would have, since it allows to motivate both the researcher and those who read the research in the search for a solution to the problem and also allows to understand how the researcher understands the problem (Brocke et al., 2020; Peffers et al., 2007). At this stage it is necessary to have an understanding of the state of the problem as well as the importance that a solution to it would represent (Brocke et al., 2020; Peffers et al., 2007);
- **Activity 2 - defining the objectives of the solution,** having defined the problem it is now possible to determine the objectives of the solution to be developed (Brocke et al., 2020; Peffers et al., 2007). To be able to carry out this phase, it is necessary to have knowledge of current solutions and their effectiveness, if they exist (Peffers et al., 2007);
- **Activity 3 - design and development,** once the functionality and architecture of the artifact have been defined, it can be created as constructs, models, methods,

instantiations or objects (Brocke et al., 2020; Peffers et al., 2007). In order to make the artifact a reality, it is necessary to have knowledge of the theory so that it can be integrated into the solution developed (Peffers et al., 2007);

- **Activity 4 - demonstration,** using the artifact in experimentation, simulation, case study, proof, or other to solve an instance of the problem initially identified (Brocke et al., 2020; Peffers et al., 2007), for this you need to know how to use the artifact to solve the instance presented (Peffers et al., 2007);
- **Activity 5 - evaluation,** it is by observing the use of the artifact in the defined context that it will be possible to verify whether it presents itself as the appropriate solution to the problem identified, this being possible by comparing the objectives defined in activity 2 with the results obtained in activity 4 (Brocke et al., 2020; Peffers et al., 2007). To carry out this activity, knowledge of metrics and analysis techniques is required (Peffers et al., 2007). At the end of this activity, researchers need to decide whether to move on to the communication activity or return to the design and development activity to improve the effectiveness of the artifact (Brocke et al., 2020; Peffers et al., 2007);
- **Activity 6 - communication,** in the last activity all the relevant aspects from the identification of the problem to the creation of the artifact are communicated to relevant stakeholders (Peffers et al., 2007).

Although the sequential process of the Design Science Research Methodology (DSRM) has been presented, it is to be expected that most researchers do not follow this process, but rather use the possible research entry points, which will be explained in more detail below:

- **Problem-centered initiation,** the basis of the nominal process sequence, therefore, begins in activity 1, where this sequence is followed when researchers observe the problem or it has been identified as future research in another investigation (Peffers et al., 2007);
- **Objective-centered solution,** a process that begins in activity 2, is appropriate when there is a need in industry or when there is a research need that can be solved by creating an artifact (Peffers et al., 2007);
- **Design and development-centered initiation,** begins in activity 3, since an artifact already exists, but it may have to be adapted because it is not suited to the existing problem (Peffers et al., 2007);
- **Client/Context initiated,** begins in activity 4 where observation has confirmed that the existing solution is suitable for the existing problem. However, to carry out the process, it is necessary for the researchers to intervene in the previous steps to apply rigor to the process (Peffers et al., 2007).

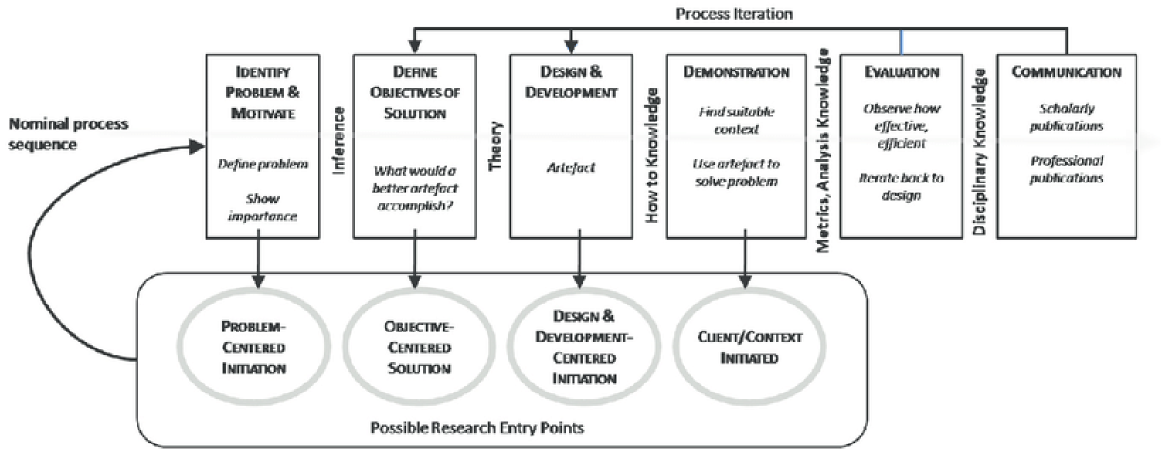

Figure 3.1 - Design Science Research Methodology Process Model

Source: Peffers et al. (2007)

3.2. Research implementation

To carry out this research, the DSRM was used, and each phase is presented in detail below:

- **Identification of the problem and motivation**, in section 1.1 the problem that this research will address was identified, the integration of AI algorithms in the optimization of Hybrid Renewable Energy Systems in Portugal, and the artifact that is sought to be developed to solve this problem is a strategy that presents the combination of the most appropriate algorithms for this optimization. The realization of this artifact would represent positive changes in several aspects, which were mentioned and explored in section 1.3;
- **Definition of the solution's objectives,** this stage defines the objectives that the artifact developed in the following phases must meet. In addition to the objective of proposing an optimization strategy for HRES in Portugal, other objectives that need to be met were identified: make a literature review on the field of AI and Energy, propose a hybrid optimization approach, which allows the existence of a complementarity and synergy between them to handle a broader spectrum of objective functions and the development of experiments to evaluate the performance of the hybrid optimization algorithm, to optimization of Hybrid Renewable Energy System (HRES) in Portugal;
- **Design and development,** to create an artifact at this stage, there needs to be a prior study of the theory, which is possible through three phases. In the first phase, a literature review is carried out in the areas of Artificial Intelligence and Energy, so that there is knowledge of concepts, challenges and opportunities, resulting in the definition of keywords, thus finding the answer to LRQ1 in this initial phase. In the second phase, a Systematic Literature Review (SLR) is carried out, using the PRISMA methodology with the keywords obtained in the previous phase. As a result of this phase, it is hoped to identify optimization algorithms that can be combined to create a hybrid optimization algorithm for optimizing HRES with various objective functions. With the conclusion of this phase, it is possible to answer LRQ2 and LRQ3. In the last

phase, a proposal is made for an artifact that takes into account all the information obtained from the previous phases;

- **Demonstration,** this phase seeks to prove the effectiveness of the developed artifact, the hybrid optimization algorithm in solving HRES optimization challenges in Portugal;
- **Evaluation,** the results obtained in the previous phase are analyzed. In addition, the objectives defined in phase 2 (Definition of the solution's objectives) are checked against the results of phase 4 (Demonstration) to confirm that the pre-defined objectives have been achieved with the proposed artifact.
- **Communication,** in the last phase it is hoped to present the research for evaluation, also making the process and results available through publication, with the aim of contributing to research in the area.

4. PROPOSAL

4.1. ASSUMPTIONS

Through the SLR (point 2.3), nine studies were identified, which are presented (point 2.3.2) by answering the LRQ in section 2.3. In this way, it was possible to identify for each of the studies mentioned, their system's decision variables and the hybrid algorithm used, these findings are summarized in Table 4. 1. In addition, it was also possible to recognize for each study identified in the SLR the type of system, context and respective area of activity of the four identified (rural area, university, smart cities and home), this information can be seen in Table 4.2.

Table 4.1 - Systems' decision variables

	Studies of SLR								
Decision variables	**Study 1**	**Study 2**	**Study 3**	**Study 4**	**Study 5**	**Study 6**	**Study 7**	**Study 8**	**Study 9**
A_W	a)								
A_S	a)								
SB_{cap}	a)								
N_{PV}		b)	c)	d)	e)	f)		h)	i)
N_{WT}		b)	c)	d)	e)	f)		h)	i)
n_{Batt}		b)		d)				h)	i)
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)					
$P_{min_{gen}}$				d)					
$P_{1_{gen}}$				d)					
$P_{critical_{gen}}$				d)					
$SOC_{stop_{gen}}$				d)					
SOC_{min}				d)					
N_{AD}						f)	g)		
$DPSP$							g)		
E_{dumped}							g)		
β								h)	
h								h)	
ACS									i)
$LCOE$									i)
NPC									i)
BS									i)
$Inverter$									i)
R_{WT}									i)
R_{PV}									i)

a) Hybrid algorithm GA-PSO with multi-objective optimization
b) Hybrid algorithm PSOGSA with multi-objective optimization
c) Hybrid algorithm WMO-MILP-Monte Carlo simulation with multi-objective optimization
d) Hybrid algorithm MOEA-GA with multi-objective optimization
e) Hybrid algorithm PSO-GWO with multi-objective optimization
f) Hybrid algorithm hHHO-AOA with multi-objective optimization
g) Hybrid algorithm PSO-GWO with multi-objective optimization
h) Hybrid algorithm NSGA-GWO with multi-objective optimization
i) Hybrid algorithm HFAPSO with multi-objective optimization

Table 4.2 - Studies type of system and context area

Study	System	Context	Area
1	Off-grid	-	-
2	Grid-independent	Abu-Monqar small village in south west egypt	Rural area
3	Grid-connected	Demand point in Denizli, Turkey	University
4	Off-grid	Future smart cities in the state of Tamil Nadu, India	Smart cities
5	Off-grid microgrid	3 locations in the Indian state of Bihar (rural areas)	Rural area
6	Off-grid microgrid	Technology Park building (hosting 128 companies) inside the Gazi University Campus, Ankara, Turkey	University
7	Off-grid microgrid	Rural communities in Cameroon	Rural area
8	Off-grid	Residential home in Auckland, New Zealand's	Home
9	Off-grid microgrid	University campus	University

After identifying the decision variables used in each study (shown in Table 4.1), the performance of the hybrid algorithms was checked in each of their objective functions (shown in Table 4.3).

Table 4.3 - Systems' performance

		Hybrid algorithm								
		GA-PSO	**PSO-GSA**	**WMO-MILP-Monte Carlo**	**MOEA-GA**	**PSO-GWO**	**hHHO-AOA**	**PSO-GWO**	**NSGA-GWO**	**HFA-PSO**
Objective functions	Minimize Total Net Present Worth (TNPW) ($)	22074896								
	Maximize Energy Index of reliability (EIR) (%)	95.01								
	Minimize Cost of Energy (COE) ($/kWh)		0.1850043			0.1693	0.2090			
	Minimize Loss of Power Supply Probability (LPSP) (%)		9.0726*10-7				6.5064		0	
	Minimize dummy load (P_{dummy}) (kWh)		15483.097892							
	Minimize difference between total cost and total revenue (USD)			14,685						
	Minimize total annual amount of CO2 produced by the system (kg CO2/year)			1,469	806					
	Minimize Total Net Present Cost (TNPC)				61,027.9 €				35,693.77$	
	Minimize unmet load (UL) (%)				0					
	Minimize deficit of power supply probability (DPSP) (%)					6		1.375		
	Maximize Autonomous Days (AD)							3		
	Maximize Energy kept into BSS (E_{dumped}) (Kw)							6.742		
	Minimize Annual System Cost (ASC) ($)									479340.57
	Minimize Levelized Cost of Energy (LCOE) ($/kWh)									0.2201
	Minimize Net Present Cost (NPC) ($)									7777668.32

4.2. AI HYBRID ALGORITHMS WITH MULTI-OBJECTIVE OPTIMIZATION FOR HRES

Analyzing the decision variables used in the different context areas identified (Table 4.1) made it possible to construct Table 4.4, in which it can be seen that the decision variables n_{PV} (number of PV modules), n_{WT} (number of wind turbines) and n_{Batt} (number of battery storage banks) are present in all four context areas, with greater significance for the use of n_{PV} (number of PV modules) and n_{WT} (number of wind turbines) in rural areas and university context. The constant use of the decision variable n_{DG} (number of diesel generators) is also visible in the contexts: rural areas and university. Less consistently used than the decision variables mentioned above is N_{AD} (number of autonomous days), which is used in both rural areas and universities. The use of the other decision variables is scattered throughout the context areas.

Table 4.4 - Hybrid algorithm, context area and respective decision variables

	Context areas			
Decision variables	**Rural areas**	**University**	**Smart cities**	**Home**
A_W				
A_S				
SB_{cap}				
N_{PV}	b) and e)	c), f) and i)	d)	h)
N_{WT}	b) and e)	c), f) and i)	d)	h)
n_{Batt}	b)	i)	d)	h)
n_{DG}	b) and e)	f) and 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)	
$P_{min_{gen}}$			d)	
$P_{1_{gen}}$			d)	
$P_{critical_{gen}}$			d)	
$SOC_{stop_{gen}}$			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)		

a) Hybrid algorithm GA-PSO with multi-objective optimization
b) Hybrid algorithm PSOGSA with multi-objective optimization
c) Hybrid algorithm WMO-MILP-Monte Carlo simulation with multi-objective optimization
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e) Hybrid algorithm PSO-GWO with multi-objective optimization
f) Hybrid algorithm hHHO-AOA with multi-objective optimization
g) Hybrid algorithm PSO-GWO with multi-objective optimization
h) Hybrid algorithm NSGA-GWO with multi-objective optimization
i) Hybrid algorithm HFAPSO with multi-objective optimization

It was also important for the researcher to construct Table 4.5 to evaluate the objective functions used in the different context areas. Looking at Table 4.5, in the rural areas, the most used objective functions are minimizing Cost of Energy (COE) and Minimize deficit of power supply probability (DPSP). In the other context areas, the objective functions used are scattered. From the perspective of the objective functions, the most used considering the four context areas, are minimize Cost of Energy (COE), minimize loss of power supply probability (LPSP), minimize total annual amount of CO_2 produced by the system, minimize total net present cost (TNPC) and minimize deficit of power supply probability (DPSP).

Table 4.5 - Hybrid algorithm, context area and respective objective function

		Context areas			
		Rural area	**University**	**Smart cities**	**Home**
Objective functions	Minimize Total Net Present Worth (TNPW) ($)				
	Maximize Energy Index of reliability (EIR) (%)				
	Minimize Cost of Energy (COE) ($/kWh)	b) and e)	f)		
	Minimize Loss of Power Supply Probability (LPSP) (%)	b)	f)		h)
	Minimize dummy load (P_{dummy}) (kWh)	b)			
	Minimize difference between total cost and total revenue (USD)		c)		
	Minimize total annual amount of CO2 produced by the system (kg CO2/year)		c)	d)	
	Minimize Total Net Present Cost (TNPC)			d)	h)
	Minimize unmet load (UL) (%)			d)	
	Minimize deficit of power supply probability (DPSP) (%)	e) and g)			
	Maximize Autonomous Days (AD)	g)			
	Maximize Energy kept into BSS (E_{dumped}) (Kw)	g)			
	Minimize Annual System Cost (ASC) ($)		i)		
	Minimize Levelized Cost of Energy (LCOE) ($/kWh)		i)		
	Minimize Net Present Cost (NPC) ($)		i)		

a) Hybrid algorithm GA-PSO with multi-objective optimization
b) Hybrid algorithm PSOGSA with multi-objective optimization
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h) Hybrid algorithm NSGA-GWO with multi-objective optimization
i) Hybrid algorithm HFAPSO with multi-objective optimization

As a result of the analyses carried out above, Table 4.6 was drawn up to summarize the information mentioned.

Table 4.6 - Decision variables, objective functions and respective context areas

	Context areas			
	Rural areas	University	Smart cities	Home
Decision variables	N_{PV}, N_{WT}, n_{DG}	N_{PV}, N_{WT}, n_{DG}	-	-
Objective functions	Minimize COE Minimize DPSP	-	-	-

Table 4.7 was also drawn up, similar to Table 4.3, with the aim of identifying the most used objective functions mentioned above and then highlighting the best values obtained for each of these, resulting in the identification of three hybrid algorithms: WMO-MILP-Monte Carlo (weighted multi-objective mixed-integer linear programming), PSO-GWO (Particle Swarm Optimization-Grey Wolf Optimizer) and NSGA-GWO (Non-dominant Sorting Genetic Algorithm II-Grey Wolf Optimizer).

Table 4.7 - Systems performance, objective functions more used and respective best values obtained

	Hybrid algorithm								
Objective functions	**GA-PSO**	**PSO-GSA**	**WMO-MILP-Monte Carlo**	**MOEA-GA**	**PSO-GWO**	**hHHO-AOA**	**PSO-GWO**	**NSGA-GWO**	**HFA-PSO**
Minimize Total Net Present Worth (TNPW) ($)	22074896								
Maximize Energy Index of reliability (EIR) (%)	95.01								
Minimize Cost of Energy (COE) ($/kWh)		0.1850043			**0.1693**	0.2090			
Minimize Loss of Power Supply Probability (LPSP) (%)		9.0726*10-7				6.5064		**0**	
Minimize dummy load (P_{dummy}) (kWh)		15483.097892							
Minimize difference between total cost and total revenue (USD)			14,685						
Minimize total annual amount of CO2 produced by the system (kg CO2/year)			**1,469**	806					
Minimize Total Net Present Cost (TNPC)				61,027.9 €				**35,693.77$**	
Minimize unmet load (UL) (%)				0					
Minimize deficit of power supply probability (DPSP) (%)					6		**1.375**		
Maximize Autonomous Days (AD)							3		
Maximize Energy kept into BSS (E_{dumped}) (Kw)							6.742		
Minimize Annual System Cost (ASC) ($)									479340.57
Minimize Levelized Cost of Energy (LCOE) ($/kWh)									0.2201
Minimize Net Present Cost (NPC) ($)									7777668.32

Considering all that was mentioned above, it is possible to recommend the use of the decision variables n_{PV}, n_{WT} and n_{DG} for rural areas and universities. As for the objective functions to be used, the following are recommended for rural areas: minimize cost of energy (COE) and minimize deficit of power supply probability (DPSP). Regarding the decision variables for context areas: smart cities and home and the objective functions for context areas: university, smart cities and home, the observations presented earlier in these cases are scattered, so it is not possible to make recommendations with sufficient scientific support (Table 4.6). Regarding the algorithms to be used to the development of a hybrid algorithm, considering Table 4.7, it is recommended the use of PSO, GWO and NSGA.

5. EMPIRICAL STUDY

After chapter 4, which allowed conclusions to be drawn regarding the studies identified in the SLR in point 2.3, this new chapter begins, where all the information gathered so far has been put into practice to optimize an HRES using a hybrid algorithm with multi-objective functions, in the context of Portugal.

This empirical study chapter is divided into three main points: data, problem formulation and algorithms, each of which is presented in more detail below. Point 5.1 presents the data for Portugal used in this dissertation: (1) characteristics of the photovoltaic panels and wind turbines most used in Portugal, which are part of the idealized HRES; (2) weather conditions and (3) load demand. In section 5.2, the problem is formulated in terms of the decision variables to be considered in the optimization; the equations that allow the output power produced by photovoltaic panels and wind turbines to be obtained are presented, as well as the objective functions to be considered in the optimization. Point 5.3 presents the algorithms that make up the HPPSGWO hybrid algorithm.

5.1. DATA

This section presents the data used in the development of this dissertation, which had to be collected in terms of components, weather conditions and load demand.

As far as the components are concerned, the idealized HRES would consist of photovoltaic panels and wind turbines. For this reason, information was collected from manufacturers on the characteristics of the most used in Portugal.

To calculate the energy produced by the selected components, it was necessary to collect weather condition data. The two datasets obtained with the desired data came from the Copernicus Atmosphere Monitoring Service and the Copernicus Climate Change Service.

To calculate the objective functions, it was also necessary to collect data on load demand in Portugal.

5.1.1. Components

The hybrid system considered for the development of the project consists of photovoltaic panels and wind turbines. The most used models of these components in Portugal were identified so that they could be considered in the project to be developed. The characteristics of the solar panels considered in the project can be seen in Table 5.1 and the characteristics of the wind turbines in Table 5.2.

Table 5.1 - Characteristics of the solar panels considered

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

Table 5.2 - Characteristics of the wind turbines considered

#	Ref.	Manufacturer	Name	V_r (m/s)	V_{cut-in} (m/s)	$V_{cut-out}$ (m/s)	A_W (m²)	h
1	Annex E & Annex F	Enercon	E70	14	2.5	34	3959	57
2	Annex E & Annex F	Enercon	E70	14	2.5	34	3959	64
3	Annex E & Annex F	Enercon	E70	14	2.5	34	3959	85
4	Annex E & Annex F	Enercon	E70	14	2.5	34	3959	98
5	Annex E & Annex F	Enercon	E70	14	2.5	34	3959	113
6	Annex G & Annex H	Enercon	E82	12	2.5	34	5281	78
7	Annex G & Annex H	Enercon	E82	12	2.5	34	5281	85
8	Annex G & Annex H	Enercon	E82	12	2.5	34	5281	98
9	Annex G & Annex H	Enercon	E82	12	2.5	34	5281	108
10	Annex G & Annex H	Enercon	E82	12	2.5	34	5281	138

5.1.2. Solar and wind

A renewable energy system relies on renewable sources that are dependent on weather conditions for energy production. Therefore, it is essential to collect weather data, specifically direct irradiance, diffuse irradiance, albedo irradiance, air temperature and wind speed, to calculate the energy output. The datasets provided by the Copernicus Atmosphere Monitoring Service and the Copernicus Climate Change Service were used to obtain these variables.

To collect the data from the Copernicus Atmosphere Monitoring Service (Copernicus Atmosphere Monitoring Service, 2020), the "Both cloud-free and actual weather conditions" option was selected as the sky type, rather than the "Cloud-free only" option, to obtain the most realistic data possible; the latitude (39. 0000) and longitude (-7.0000) of Portugal was indicated, since the project is being carried out in the context of Portugal; regarding the time range of the data, January 2008 to April 2024 was selected, with a time step of one hour and universal time reference.

Data was also obtained from the Copernicus Climate Change Service (Copernicus Climate Change Service, 2020) and only the variables "wind speed at 10m" and "2m air temperature" were selected, with a spatial aggregation at country level and a temporal aggregation at hourly level. By selecting spatial aggregation at country level, the data is stored in one file per variable and for the entire time-series.

The data was then preprocessed, resulting in the dataframe df_tmy_year, with the characteristics shown in Table 5.3 and Table 5.4. It should be noted that since the project developed optimizes the size of a hybrid renewable energy system for one year, it is possible to choose the year that the algorithm will optimize between 2008 and 2023, since the data from the Copernicus Atmosphere Monitoring Service has a temporal coverage from January 2008 to April 2024. Therefore, depending on the year selected, the temporal coverage of df_tmy_year will be from January of the chosen year until December of the same year.

Table 5.3 - df_tmy_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 5.4 - 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 metres" (Copernicus Climate Change Service, 2020)
air_temperature	ºC	"The ambient air temperature near to the surface, typically at height of 2m" (Copernicus Climate Change Service, 2020)

5.1.3. Load demand

To understand whether the hybrid energy system generates enough energy to meet demand, it is necessary to obtain data on the electricity consumed. To do this, it was used open-source data from REN (SISTEMA DE INFORMAÇÃO DE MERCADOS DE ENERGIA, n.d.), which is only available from January 2008 to April 2024, with 2010 only showing data from January 1, 2010. After pre-processing the data, it was possible to obtain the df_consume_year dataframe with the characteristics shown in Table 5.5 and Table 5.6.

Table 5.5 - 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 5.6 - 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

5.2. PROBLEM FORMULATION

The optimization of the HRES, that consists in photovoltaic panels and wind turbines, was carried out at the hourly level, over the course of a year, which corresponds to the optimization of 8760 hours, where the variables are manipulated: N_{PV}, β, N_{WT} and h, in order to minimize the multi-objective function that simultaneously considers the minimization of the loss of power supply probability and the minimization of the amount of CO_2 produced by the hybrid energy system.

5.2.1. Decision variables and constraints

Four decision variables were used to optimize the size of a hybrid energy system: N_{PV}, β, N_{WT} and h. The constraints that determine the lower and upper limits of these decision variables are shown in equations (1)-(3), while equations (4) and (5) show the possible heights that the E70 and E82 wind turbines can have, respectively.

$$N_{PV}^{min} \leq N_{PV} \leq N_{PV}^{max} \tag{1}$$

$$N_{WT}^{min} \leq N_{WT} \leq N_{WT}^{max} \tag{2}$$

$$0^{\circ} \leq \beta \leq 90^{\circ} \tag{3}$$

$$h_{E70} = [57, 64, 85, 113] \tag{4}$$

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

5.2.2. Modeling of the Hybrid Renewable Energy System

5.2.2.1. PV panels

The power obtained from a PV panel is given by equation (6) (Hossain et al., 2023), where the nomenclature of each variable can be found on page xii. The output power of a PV array depends on environmental conditions such as global solar irradiance and ambient temperature. The global irradiance on an inclined surface, G(β, α), shown in equation (12), results from the sum of the direct, diffuse and albedo components, G(β, α), D(β, α) and R(β, α), respectively (Pigueiras, 2005). Equation (12) is used to calculate the direct component, equation (20) for the diffuse component and equation (25) for the albedo component. The df_tmy_year dataframe was used to calculate these environmental variables. The ouptut power of a PV array also depends on the parameters supplied by the manufacturer, which are shown in Table 5.1.

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

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

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

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

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

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

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

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

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

$$\cos\theta_S = [sign(\phi)] \sin\delta \sin(abs(\phi) - \beta) + \cos\delta \cos(abs(\phi) - \beta) \cos\omega \quad (15)$$

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

$$\omega = 15 \, x \, (TO - AO - 12) - (LL - LH) \quad (17)$$

$$B_0 = 1367 \, W/m^2 \quad (18)$$

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

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

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

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

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

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

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

5.2.2.2. Wind turbines

The power obtained from a wind turbine is given by equation (28) (Çetinbaş et al., 2022; Hossain et al., 2023) where the nomenclature of each variable can be found on page xii. The output power of a wind turbine depends on the wind speed, its rated power and parameters supplied by the manufacturer. The wind speed at a given height can be calculated using equation (27), which considers the wind speed at the reference height of the df_tmy_year dataframe, the reference height and the height at which the turbine is to be installed (this being one of the decision variables of the problem) (Hossain et al., 2023). To calculate the rated power of a wind turbine (equation 26), the maximum power coefficient is considered, this is a value tabulated by the manufacturers and once again depends on the wind speed, Figure 5.1 shows the power curve of the E70 wind turbine and Figure 5.2 shows the power curve of the E82 wind turbine, allowing us to obtain the value of the maximum power coefficient. The output power of a wind turbine also depends on the parameters supplied by the manufacturer, which are shown in Table 5.2.

$$P_{WT} = \begin{cases} 0 & V < V_{cut-in} \\ V^3\left(\frac{P_{WT_r}}{V_r^3 - V_{cut-in}^3}\right) - P_{WT_r}\cdot\left(\frac{V_{cut-in}^3}{V_r^3 - V_{cut-in}^3}\right) & V_{cut-in} \le V \le V_r \\ P_{WT_r} & V_r \le V \le V_{cut-out} \\ 0 & V > V_{cut-out} \end{cases} \quad (26)$$

$$V = V_r\left(\frac{h}{h_r}\right)^{\alpha} \quad (27)$$

$$P_{WT_r} = C_{p\_max}\frac{1}{2}\rho_{air}A_{WT}V_r^3 \quad (28)$$

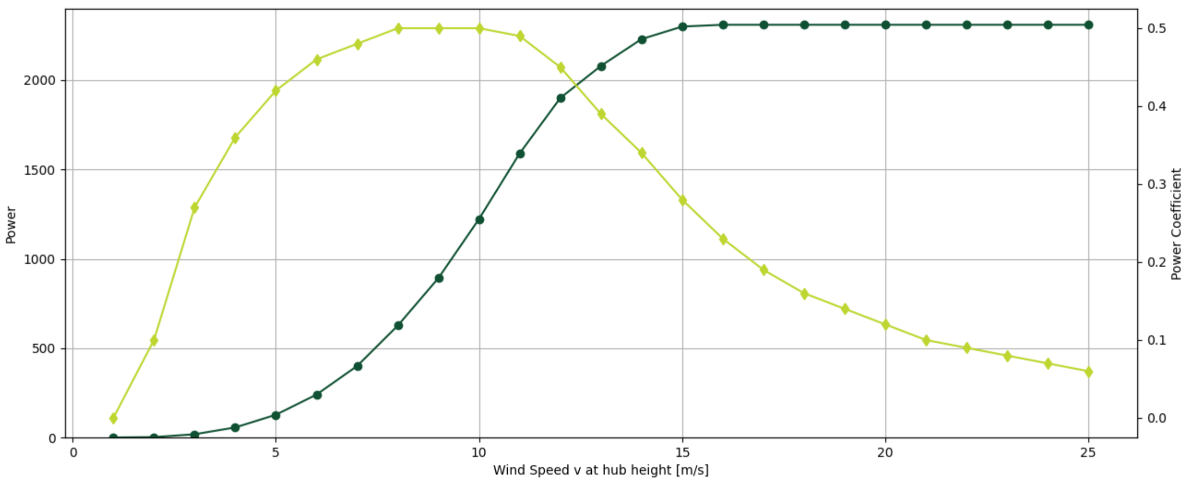


Figure 5.1 - Power curve of wind turbine E70

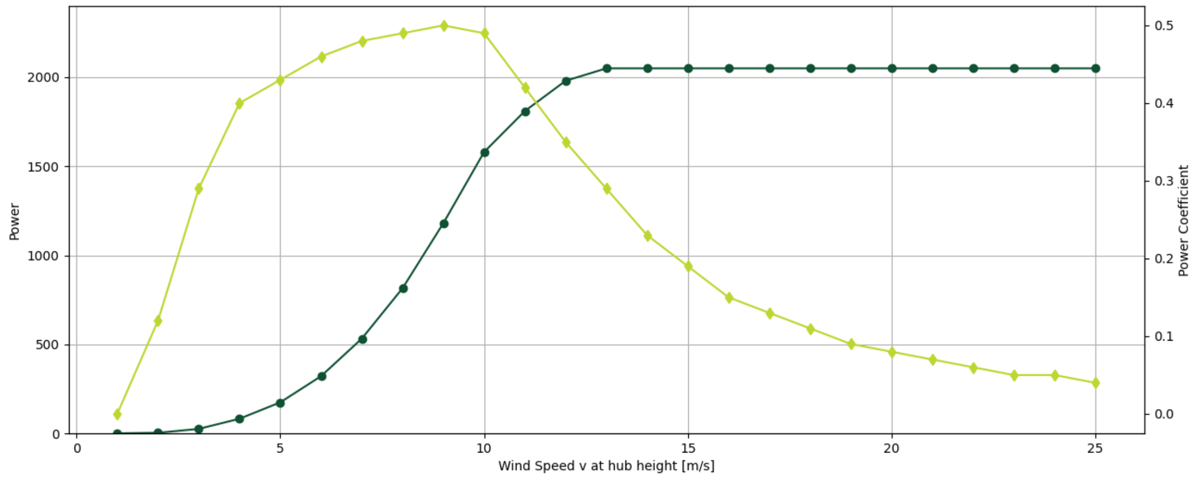


Figure 5.2 - Power curve of wind turbine E82

5.2.3. Objective Functions

5.2.3.1. Minimize Loss of Power Supply Probability (LPSP)

One of the objective functions considered is an indicator of the reliability of the hybrid renewable energy system developed in this project, specifically the Loss of Power Supply Probability (LPSP). The LPSP consists of the ratio of the energy that cannot be supplied, and it is given by equation (29). LPSP can take a value between 0 and 1, where 0 means that the energy demand is fully met, and therefore the system's reliability is at its maximum, while if the LPSP value is 1, it means that the system failed to energize the load and consequently the system is unreliable (Çetinbaş et al., 2022).

$$LPSP = \frac{\sum_{t=1}^{t=8760} E_{DE}\,(t)}{\sum_{t=1}^{t=8760} E_{LOAD}(t)} \tag{29}$$

5.2.3.2. Minimize amount of CO2 produced

The second objective function is an environmental indicator, since it aims to minimize the annual CO_2 emissions of the hybrid energy system developed. CO_2 emission results from the product between the amount of electricity bought from the grid and the CO_2 emission coefficient per Wh of buying electricity from the grid, which is 0.000866 kg CO_2 /Wh (Capraz et al., 2020), this is given by equation (30).

$$CO_2 = \varepsilon \sum_{t \in T} gb_t \tag{30}$$

5.2.3.3. Multi-objective optimization

To carry out the multi-objective optimization, the two objective functions mentioned in the previous points were considered: minimizing the Loss of Power Supply Probability (LPSP) and minimizing the amount of CO_2 produced, both of which were considered on an annual basis. This multi-objective optimization problem was converted into a single-objective optimization problem using the weighed sum method, which is represented in equation (31) and equation (33) (Çetinbaş et al., 2022; Suman et al., 2021). Equation (31) considers the normalization of the objective functions, by dividing the value obtained from the objective function by its maximum value, which is done to ensure that the objective functions have a value between 0 and 1 (Capraz et al., 2020). Since objective function 1 (point 5.2.3.1) already has values between 0 and 1, only the value of objective function 2 (point 5.2.3.2) was normalized, as shown in equation (33). Objective function 2, as mentioned in point 5.2.3.2, depends on the amount of electricity bought from the grid, so in equation (33), in the part relating to the maximum value of objective function 2, it was considered that the maximum value it could obtain would be in the case where the amount of electricity bought from the grid corresponds to the total value of consumption, i.e. the hybrid energy system would not produce any energy to satisfy demand.

$$F_{WS}\,(x_{DV}) = \sum_{i=1}^{k} w_i.\frac{f_i(x_{DV})}{f_i^{max}(x_{DV})} \tag{31}$$

$$\sum_{i=1}^{k} w_i = 1\,, 0 < w_i \ \leq 1, i = 1, \dots, n \tag{32}$$

$$F_{WS}\,(N_{PV}, N_{WT}, \beta, hh) = \\ = \min\left[w_1\,.LPSP(N_{PV}, N_{WT}, \beta, hh) + \ w_2\,.\frac{CO2(N_{PV}, N_{WT}, \beta, hh)}{CO2^{max}(N_{PV}, N_{WT}, \beta, hh)}\right] \tag{33}$$

5.3. ALGORITHMS

5.3.1. Particle Swarm Optimization

The Particle Swarm Optimization (PSO) algorithm was developed by Kennedy & Eberhart (1995), with the inspiration for its development being "the social behavior of bird flocking or fish schooling when searching for food" (Şenel et al., 2019), thus ending up belonging to the field of Swarm Intelligence (Vanneschi & Silva, 2023).

The pseudocode of PSO for the case of minimization problems is given in algorithm 1, where the maximum possible velocity parameter has been included, to ensure that "too-large "jumps" of the positions of the particles in the search space" are not given (Vanneschi & Silva, 2023).

The algorithm begins with the initialization of a population of random solutions, called particles, which "move" through the problem space in search of an optimal solution. Returning to the inspiration behind this algorithm, for a bird to reach a good landing point, it remembers "previous points they visited and tend to follow the lead of one of the flock's members" (Vanneschi & Silva, 2023), in other words, in the search for a solution it considers its individual and social knowledge (Vanneschi & Silva, 2023). In addition, the quality of a landing point for birds is assessed by estimating the probability of survival, which the PSO algorithm translates into the fitness function to be optimized, which assesses the quality of a solution (Vanneschi & Silva, 2023). The position of each particle in the search space is updated iteratively, guided by a speed that depends on the best position achieved so far and the best position achieved by the swarm (Vanneschi & Silva, 2023).

Algorithm 1: Pseudocode for Particle Swarm Optimization, in the case of a minimization problem (Adapted from (Vanneschi & Silva, 2023))

$\forall i = 1,2, \dots, n : initialize\ x_i\ and\ v_i$
$\forall i = 1,2, \dots, n : b_i \coloneqq x_i$

$g = argmin_{x_i} f(x_i), \forall i = 1,2, \dots, n$
$repeat\ until\ (termination\ condition)$
$\quad for\ each\ i = 1, 2, \dots, n\ do$
$\quad\quad for\ each\ j = 1, 2, \dots, m\ do$
$\quad\quad\quad x_{ij} \coloneqq x_{ij} + v_{ij}$
$\quad\quad\quad \max_{velocity} = \beta_j - \alpha_j$
$\quad\quad\quad if\ x_{ij} < \alpha_j\ then$
$\quad\quad\quad\quad x_{ij} \coloneqq \alpha_j$
$\quad\quad\quad\quad v_{ij} \coloneqq -v_{ij}$
$\quad\quad\quad else\ if\ x_{ij} > \beta_j\ then$
$\quad\quad\quad\quad x_{ij} \coloneqq \beta_j$
$\quad\quad\quad\quad v_{ij} \coloneqq -v_{ij}$
$\quad\quad\quad else$
$\quad\quad\quad\quad v_{ij} \coloneqq wv_{ij} + c_1 r_1 \left(b_{ij} - x_{ij}\right) + c_2 r_2 \left(g_j - x_{ij}\right)$
$\quad\quad\quad\quad if\ v_{ij} > \max_{velocity}\ then$
$\quad\quad\quad\quad\quad v_{ij} \coloneqq 0$
$\quad\quad\quad end$
$\quad\quad end$
$\quad\quad if\ \left(f(x_i) < f(b_i)\right)\ then$
$\quad\quad\quad for\ each\ j = 1, 2, \dots, m\ do\ b_{ij} \coloneqq x_{ij}$
$\quad\quad if\ \left(f(x_i) < f(g)\right)\ then$
$\quad\quad\quad for\ each\ j = 1, 2, \dots, m\ do\ g_j \coloneqq x_{ij}$
$\quad end$
$return\ g$

5.3.2. Parallel Particle Swarm Optimization (PPSO)

Algorithm 2 presented below (graphical representation in Figure 5.3) was included in this study with the aim of running the PSO algorithm faster and reducing the consumption of computing resources. The PPSO algorithm begins by dividing the initial particle swarm optimization population into sub-swarms, which will run on different parallel computing units.

The main components of PPSO are the particle propagation mechanism between parallel computing units and the termination rule. As far as the propagation mechanism is concerned, in this dissertation we opted for the 1 to N mechanism, which consists of a randomly selected processing unit sending its best particles to the other units, with the processing units that receive particles replacing their worst particles with the ones they receive. As far as the termination rule is concerned, it differs between units and is determined by calculating equation (34) in each iteration. If the value obtained from equation (34) is less than a predetermined limit ϵ for N_M continuous repetitions, the algorithm in that unit ends its execution and consequently the entire PPSO ends.

Algorithm 2: Pseudocode for Parallel Particle Swarm Optimization (Charilogis et al., 2023)

$Set\ N_I\ as\ the\ total\ number\ of\ parallel\ processing\ units$

$Set\ N_R\ as\ the\ number\ of\ iterations, after\ which\ each\ processing\ unit\ will$

$send\ its\ best\ barticles\ to\ the\ remianing\ units$

$Set\ N_P\ as\ the\ number\ of\ migrated\ particles\ between\ the\ parallel\ processing\ units$

$Set\ k = 0\ the\ iteration\ number$

$for\ j = 1, \ldots, N\ do\ in\ parallel$

  $Execute\ an\ iteration\ of\ the\ PSO\ algorithm\ on\ processing\ unit\ j$

  $if\ k\ mod\ N_R = 0\ then$

    $Get\ the\ best\ N_P\ particles\ from\ algorithm\ j$

    $Propagate\ these\ N_P\ particles\ to\ the\ rest\ of\ processing\ units$

  end

end

$Update\ k = k + 1$

$Check\ the\ proposed\ termination\ rule. If\ the\ termination\ rule\ is\ valid, continue\ else\ go\ to\ f$

  $Terminate\ and\ report\ the\ best\ value\ from\ all\ processing\ units$

$\delta_i^{(k)} = |f_{i,min}^{(k)} - f_{i,min}^{(k-1)}|$ (34)

$f_{i,min}^{(k)}$ is the best value in fitness function for unit i at iteration k;

In case $\delta_i^{(k)} < \epsilon$ for N_M continuous repetitions, the algorithm is terminated

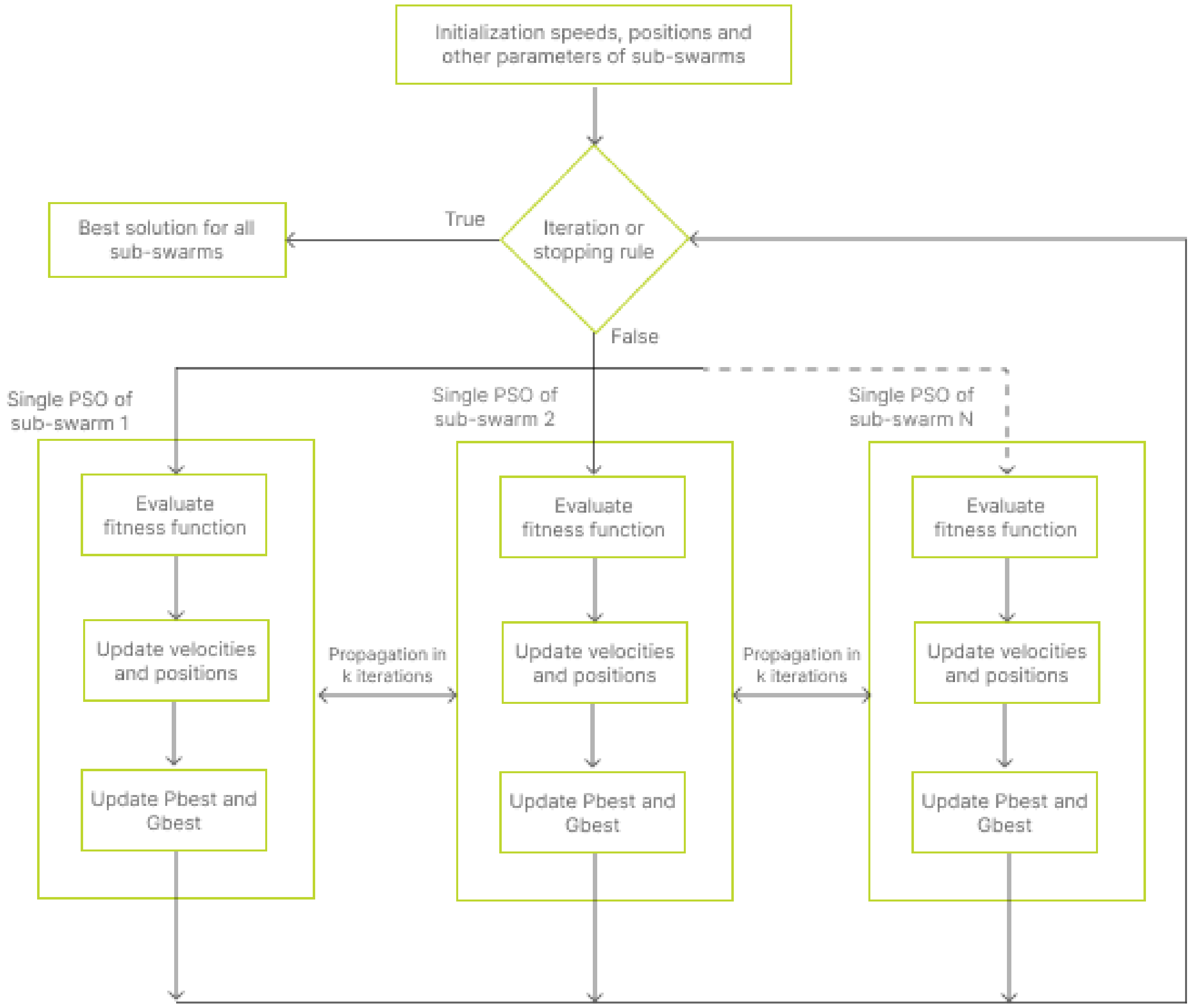


Figure 5.3 - Flowchart of the PPSO

5.3.3. Grey Wolf Optimization

The Grey Wolf Optimization (GWO) algorithm is inspired by the social hierarchy (visible in Figure 5.4) and group hunting of grey wolves, and its pseudocode can be seen in algorithm 3 (Mirjalili et al., 2014).

As far as the social hierarchy of grey wolves is concerned, at the top are the alpha wolves, immediately below them are their subordinates, the beta wolves, then next in the hierarchy are the delta wolves, also known as subordinates, who must submit to the alpha and beta wolves, but dominate the omega wolves, who submit to the dominant wolves (Mirjalili et al., 2014). The GWO algorithm thus considers the social hierarchy of grey wolves to define the fittest solutions, with the best solution being called alpha, the second best beta, the third best delta and the rest omega. The three best wolves, alpha, beta and delta, guide the optimization and the omega wolves just follow them.

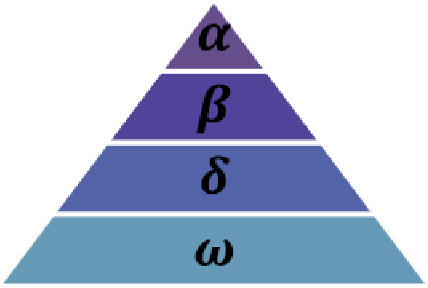


Figure 5.4 - Hierarchy of grey wolf (dominance decreases from top down)

Source: Mirjalili et al. (2014)

The grey wolf hunting phases are tracking, encircling and attack. Encircling the prey is mathematically modeled using the following equations:

$$\vec{D} = |\vec{C} \,.\overrightarrow{X_p}\,(t) - \vec{X}\,(t)| \quad (35)$$

$$\vec{X}\,(t+1) = \overrightarrow{X_p}\,(t) - \vec{A}\,.\vec{D} \quad (36)$$

t is the number of iterations; $\overrightarrow{X_p}$ is the position vector of the prey and $\vec{X}$ the position vector of the grey wolf (Mirjalili et al., 2014)

$$\vec{A} = 2\vec{a}.\overrightarrow{r_1} - \vec{a} \quad (37)$$

$$\vec{C} = 2\,.\overrightarrow{r_2} \quad (38)$$

$\vec{A}$ and $\vec{C}$ are coefficient vectors; $\vec{a}$ decreases linearly from 2 to 0 as the number of iterations decreases, to “emphasize exploration and exploitation” and $\overrightarrow{r_1}$ and $\overrightarrow{r_2}$ are uniformly selected random numbers between 0 and 1 (Mirjalili et al., 2014).

To mathematically model the tracking of a prey, meaning tracking the optimal solution, it is assumed that the three best wolves (alpha, beta and delta) are the ones with the best knowledge of its location, so these three best solutions (alpha, beta and delta) are saved and "oblige the other search agents (including the omegas) to update their positions according to the position of the best search agents" (Mirjalili et al., 2014), which is achieved through the equations (39) - (41), this position update is expressed graphically in Figure 5.5.

$$\overrightarrow{D_\alpha} = |\overrightarrow{C_1} . \overrightarrow{X_\alpha} - \vec{X}| \quad (39)$$
$$\overrightarrow{D_\beta} = |\overrightarrow{C_2} . \overrightarrow{X_\beta} - \vec{X}|$$
$$\overrightarrow{D_\delta} = |\overrightarrow{C_3} . \overrightarrow{X_\delta} - \vec{X}|$$

$$\vec{X}_1 = \overrightarrow{X_\alpha} - \vec{A}_1 . \overrightarrow{D_\alpha} \quad (40)$$

$$\vec{X}_2 = \overrightarrow{X_\beta} - \vec{A}_2 . \overrightarrow{D_\beta}$$

$$\vec{X}_3 = \overrightarrow{X_\delta} - \vec{A}_3 . \overrightarrow{D_\delta}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (41)$$

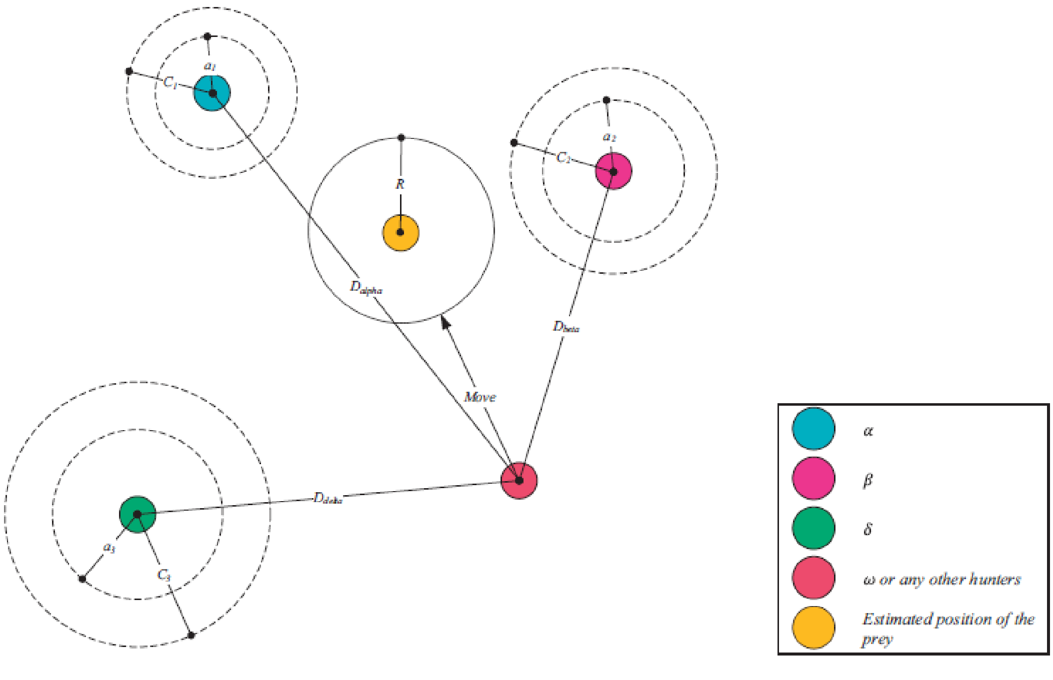


Figure 5.5 - Position update in GWO

Source: Mirjalili et al. (2014)

The attacking the prey phase is modeled using the variable a, which decreases over the course of the iterations, thus simulating the approach to the prey. This behavior of the variable a directly affects the behavior of the variable A, whereby when $| A | < 1$ the wolves are forced to converge on the prey and $| A | > 1$, to diverge from the prey (visible in Figure 5.6).

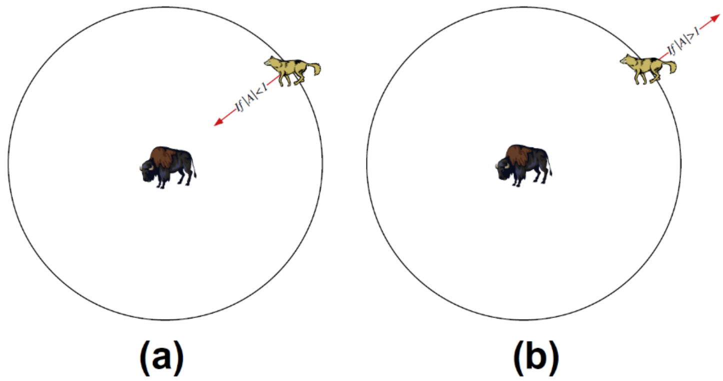


Figure 5.6 - Attacking prey (a) versus searching for prey (b)

Source: Mirjalili et al. (2014)

Algorithm 3: Pseudocode of the GWO algorithm (Mirjalili et al., 2014)

$Initialize\ the\ grey\ wolf\ population\ X_i\ (i = 1, 2, \dots, n)$

$Initialize\ a, A\ and\ C$

$Calculate\ the\ fitness\ of\ each\ search\ agent$

$X_a = the\ best\ search\ agent$

$X_\beta = the\ second\ best\ search\ agent$

$X_\delta = the\ third\ best\ search\ agent$

$while\ (t < \max number\ of\ iterations)$

    $for\ each\ search\ agent$

        $Update\ the\ position\ of\ the\ current\ search\ agent\ by\ equation\ (41)$

    $end\ for$

    $Update\ a, A\ and\ C$

    $Calculate\ the\ fitness\ of\ all\ search\ agents$

    $Update\ X_a, X_\beta\ and\ X_\delta$

    $t = t + 1$

$end\ while$

$return\ X_a$

5.3.4. Hybrid PSO-GWO

In the systematic literature review carried out in 2.3, it was possible to see that the PSO algorithm is used in the majority, and that it has been applied more than once in conjunction with the GWO algorithm. As a result, it was decided to apply a hybrid algorithm that integrates the PSO and GWO algorithms to optimize the sizing of a hybrid renewable energy system, more specifically, the hybrid PSO-GWO algorithm developed by Şenel et al. (2019) was implemented. The HPSGWO was proposed by Şenel et al. (2019), with the aim of "reduce the possibility of the PSO algorithm to trap into a local minimum", for which the authors used the GWO algorithm's exploitation capacity. In this way, particles are directed to positions in space that are improved by the GWO algorithm instead of random positions, which would happen if only the PSO algorithm was applied. The pseudocode of the hybrid algorithm is shown in algorithm 4 and is graphically represented in Figure 5.7.

Algorithm 4: Pseudocode of the HPSGWO algorithm (Şenel et al., 2019)

$maxitr$: $the\ number\ of\ maximum\ iterations\ set\ by\ the\ user$

PS: $the\ number\ of\ population\ sizes\ set\ by\ the\ user$

$prob$: $small\ possibility\ rate\ set\ by\ the\ user$

```
procedure HPSGWO
    Initialize particles
    for i = 1 to maxitr do
        for j = 1 to PS do
            Run PSO
            Update the velocity and the position of current particle
            if 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
    end for
end procedure
```

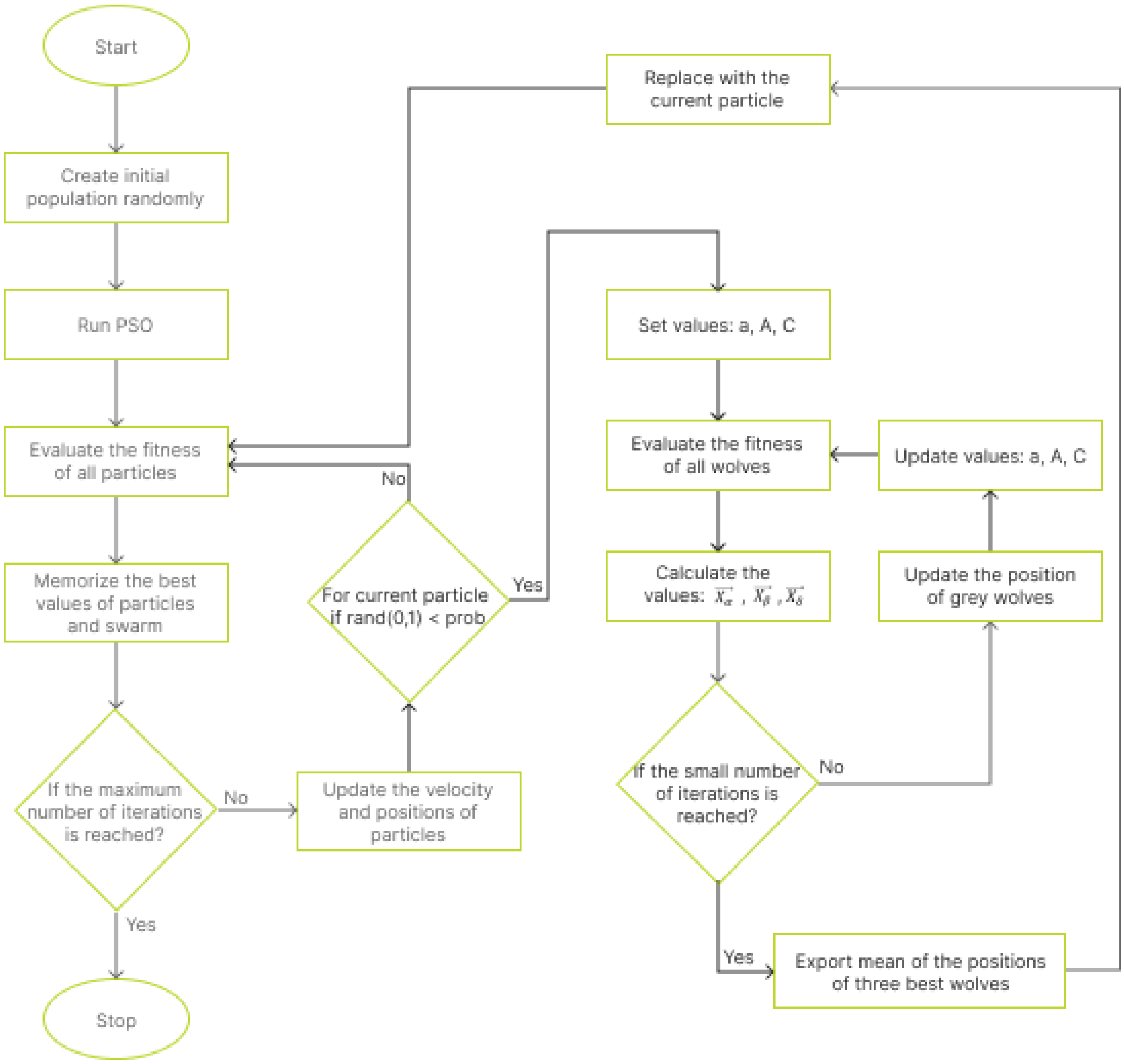


Figure 5.7 - Flowchart of the HPSGWO

Source: Şenel et al. (2019)

5.3.5. Hybrid Parallel PSO-GWO (HPPSGWO)

The hybrid PSO-GWO algorithm developed by Şenel et al. (2019) was implemented, which, despite its potential, is referred by the authors for its "running time is extended since the GWO algorithm is also employed in addition to the PSO algorithm" (Şenel et al., 2019), to overcome this, the code developed was successively optimized to reduce execution time and resource consumption. In this way, the PSO-GWO algorithm was parallelized according to the PPSO algorithm developed by Charilogis et al. (2023) presented in 5.3.2. Graphic Processing Units (GPUs) were also used to implement the parallelized hybrid algorithm, using the CuPy and cuDF libraries. The development of this Hybrid Parallel PSO-GWO (HPPSGWO) thus aimed to minimize the probability of the algorithm getting stuck in a minimal location, overcome the difficulties experienced regarding the amount of time to run the algorithm and make efficient use of the available computing resources. The HPPSGWO pseudocode is visible in algorithm 5 and is graphically outlined in Figure 5.8.

Algorithm 5: 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 barticles to the remianing 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, ..., 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 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 mod 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 f
        Terminate and report the best value from all processing units
```

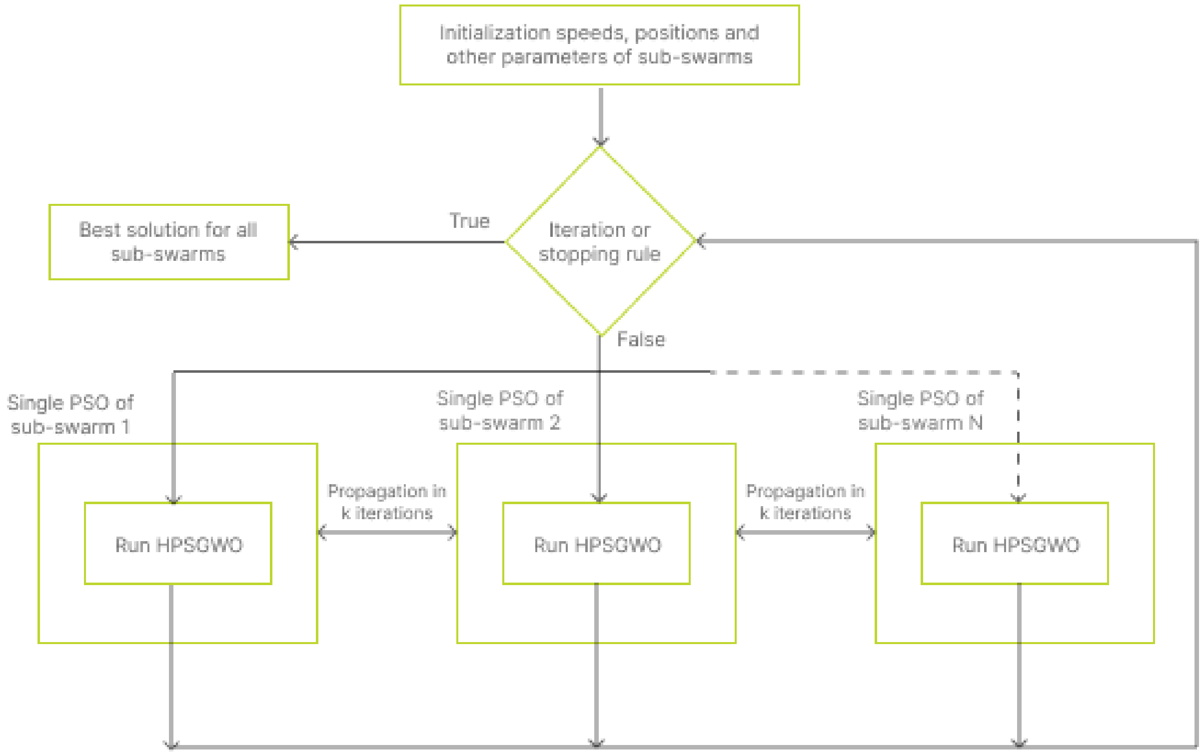


Figure 5.8 - Flowchart of the HPPSGWO

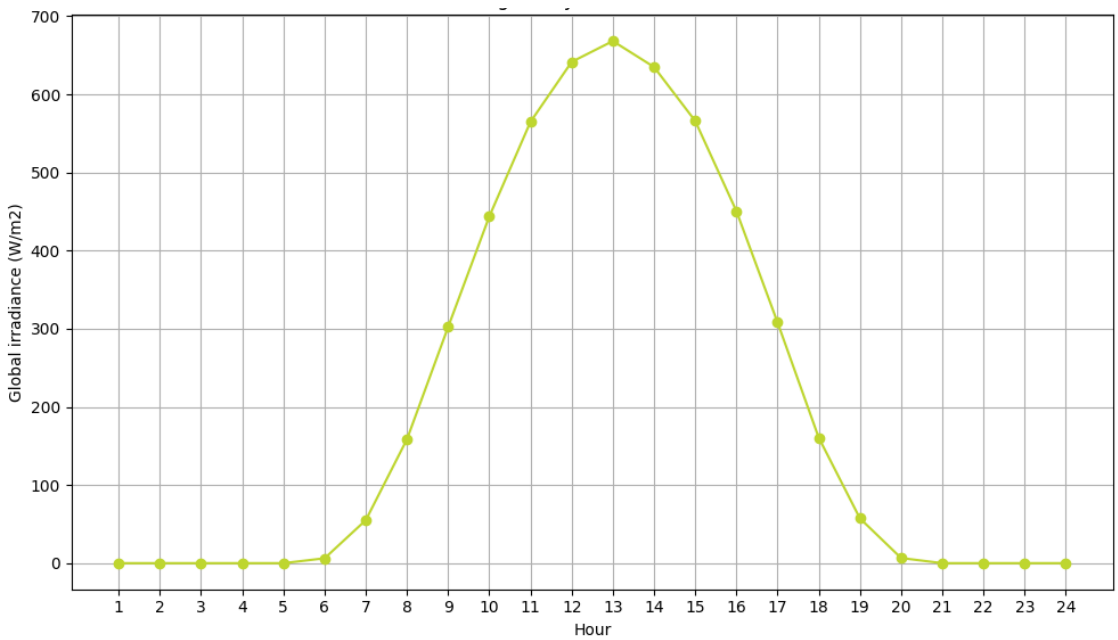
6. RESULTS AND DISCUSSION

6.1. Exploration of data

Before running the hybrid parallel PSO-GWO algorithm, the data was explored on global irradiance, load power and wind speed in Portugal in the year 2022.

Graphic 6.1 shows the average daily global irradiance over a 24-hour period in Portugal in 2022. The daily global irradiance peaks at 1 p.m. with a value of over 600 W/m^2, while the minimum of 0 W/m^2 occurs from 1 a.m. to 5 a.m. and from 9 p.m. to midnight, which is explained by the hours of sunlight throughout the day.

The general evolution of the average daily global irradiance can be described as constant at 0 W/m2 in the first hours of the day from 1am to 5am, with a value slightly above 0 W/m2 only visible at 6 a.m. From 6 a.m. until 1 p.m. there is a continuous increase from a value slightly above 0 W/m2 until it reaches its peak with a value above 600 W/m2. From 1 p. m. until 8 p.m., there is a decrease in irradiance from a value above 600 W/m2 to slightly above 0 W/m2. From 9 p.m. until midnight, global irradiance remains constant at 0 W/m2.

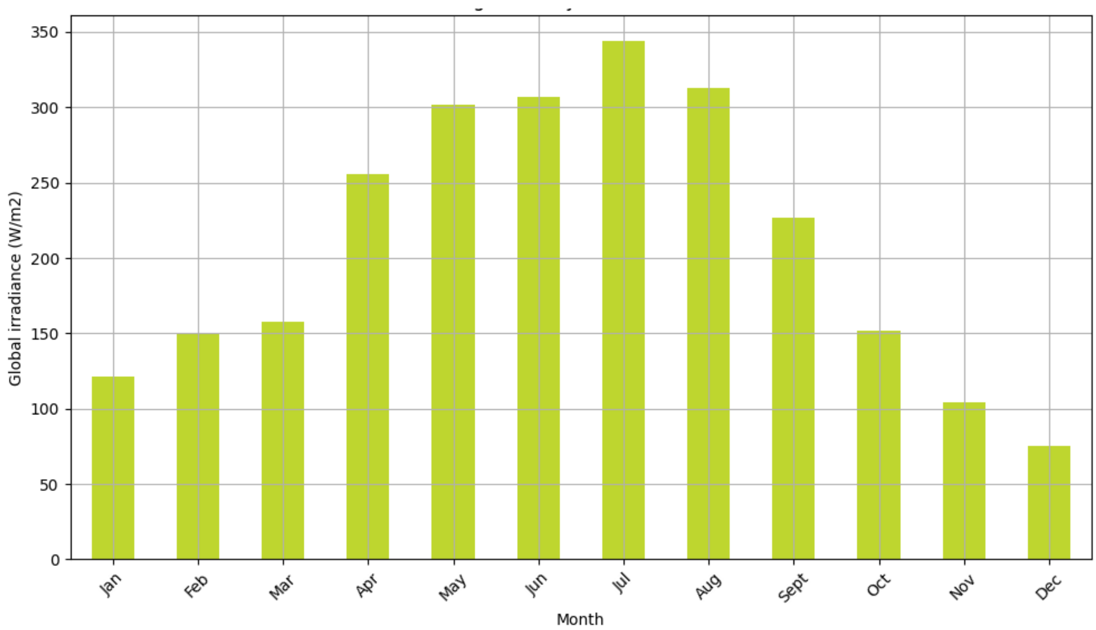


Graphic 6.1 - Average daily global irradiance in 2022

Graphic 6.2 shows the average monthly global irradiance in Portugal in the year 2022. The peak global irradiance is reached in July with a value close to 350 W/m^2, while the minimum global irradiance observed is in December, with a value between 50 W/m2 and 100 W/m^2.

With a more focused look, seasonal trends can be observed, with the winter months (December, January and February) having a global irradiance below 150 W/m^2. In the spring months (March, April and May) there is a visible increase from a value slightly above 150 W/m^2 in March, until a value of 300 W/m^2 is reached in May. In the summer months (June, July and August) there are the highest values of global irradiance, with June and August having values slightly below the value reached in the month when global irradiance peaked, July. In the fall months (September, October and November) there is a decline in global irradiance, starting in September with a value above 200 W/m^2 and ending with a value slightly above 100 W/m^2.

In conclusion, irradiance shows a typical seasonal pattern with an increase from winter to summer and a decrease from summer to winter. The information gathered by analyzing the Graphic 6.3 allows us to understand the potential of solar energy throughout the year. The best months for producing solar energy are from April to August, with July being the most beneficial.

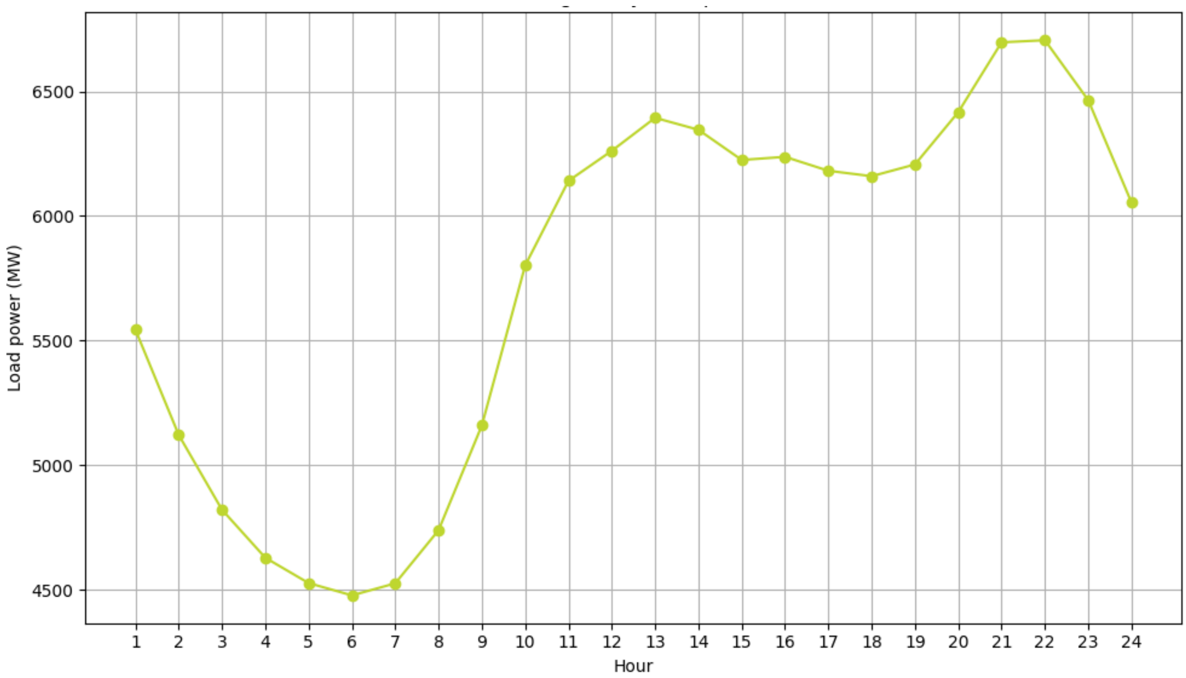


Graphic 6.2 - Average monthly global irradiance in 2022

Graphic 6.3 shows the average daily load power in the 24-hour period in Portugal in 2022. Looking at the graph, it is possible to see that at 1 p.m. there is a peak in load power, with a value close to 6500 MW, which is only exceeded by the peak that occurs between 9 p.m. and 10 p.m., with values above 6500 MW. The lowest load power occurs around 6 a.m., with a value slightly below 4500 MW.

Considering the general evolution, from 1 a.m. to 6 a.m. there is a visible decrease in load power, and only after 6 a.m. does it start to increase, reaching its first peak only at 1 p.m. From 1 p.m. onwards, this behavior changes so that load power typically remains constant with only a few oscillations. A significant increase can be seen from 7 p.m. onwards, with the second peak being reached between 9 p.m. and 10 p.m. After 10 p.m. there is a sharp decrease in load power until midnight.

The behavior of the average daily load power visible in Graphic 6.3 and described above, can be summarized as power consumption being lowest during early morning hours, eventually increasing throughout the day and peaking in the evening. This behavior can be described as common due to greater residential and commercial activity during the day and evening hours.

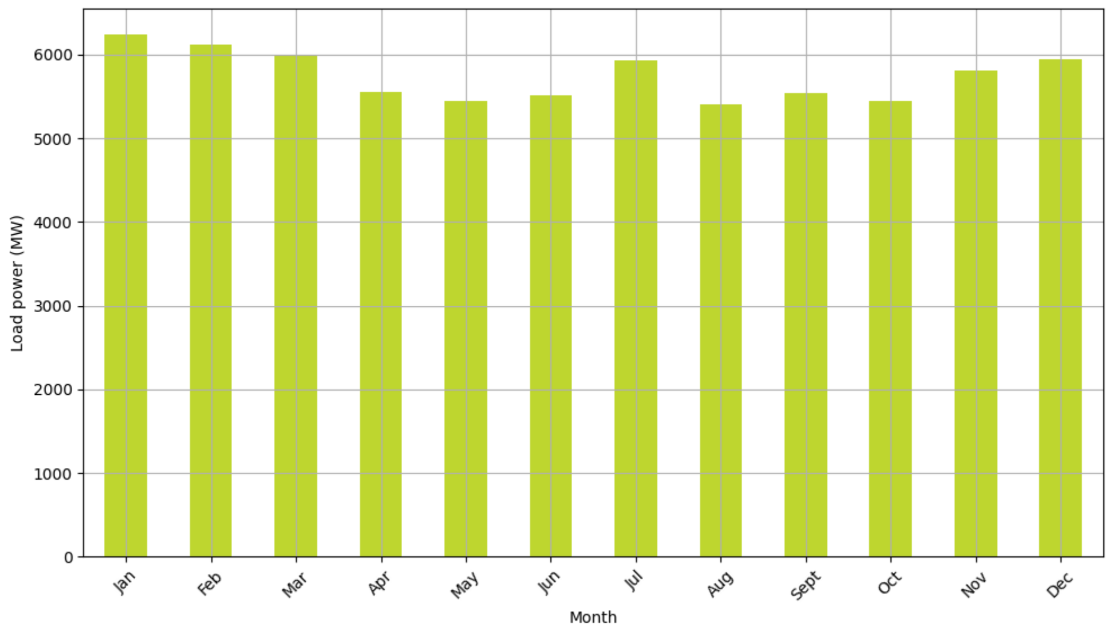


Graphic 6.3 - Average daily load power in 2022

Graphic 6.4 shows the evolution of the average monthly load power in Portugal in 2022. The highest load power is reached in January with a value of more than 6000 MW, while the lowest load power is observed in August by a minimum margin, with a value of more than 5000 MW.

The slight variation in average monthly load power shows seasonal trends. The winter months (December, January and February) see the highest load power values, with values above and close to 6000 MW, which may be due to a greater need for heating. The spring months (March, April and May) show a slight decrease in load power, from 6000 MW to just over 5000 MW. In the summer months (June, July and August) there are still high load power values, above 5000 MW and in July with a value slightly below 6000 MW, these values may remain high possibly due to air conditioning demand. In the fall months (September, October and November), load power starts to increase again, from above 5000 MW to slightly below 6000 MW.

It can be concluded from the analysis that, despite the slight variations in load power, the highest values are seen in the coldest months, but equally high values are seen in the hottest months. This trend can be explained by greater energy consumption for heating in the winter and cooling in the summer.

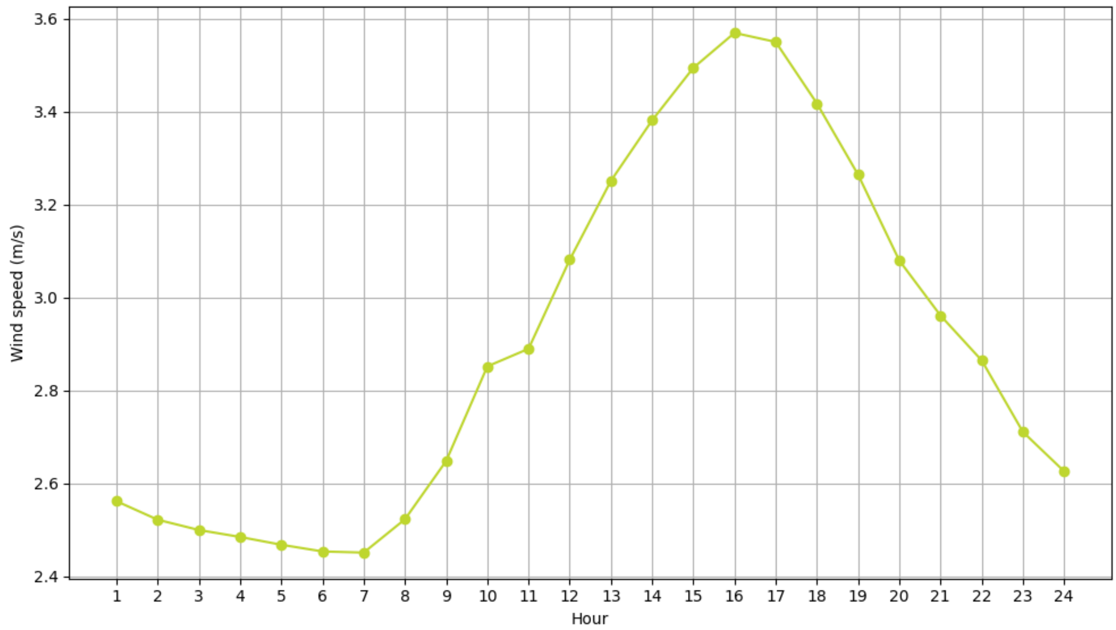


Graphic 6.4 - Average monthly load power in 2022

Graphic 6.5 shows the average daily wind speed in Portugal in 2022, peaking at 4 p.m. with a value close to 3.6 m/s, while the minimum value observed is close to 2.4 m/s at 7 a.m.

Considering the general evolution of the average daily wind speed, from 1 a.m. to 7 a.m. there is a slight decrease from a value close to 2.6 m/s to the minimum observed, a value close to 2.4 m/s. From 7 a.m. until 4 p.m. there was an increase in wind speed, from a value close to 2.4 m/s to one close to 3.6 m/s. Between 10 a.m. and 11 a.m. there was less growth than in the rest of the period. From 4 p.m. to midnight, the wind speed decreases from around 3.6 m/s to around 2.6 m/s.

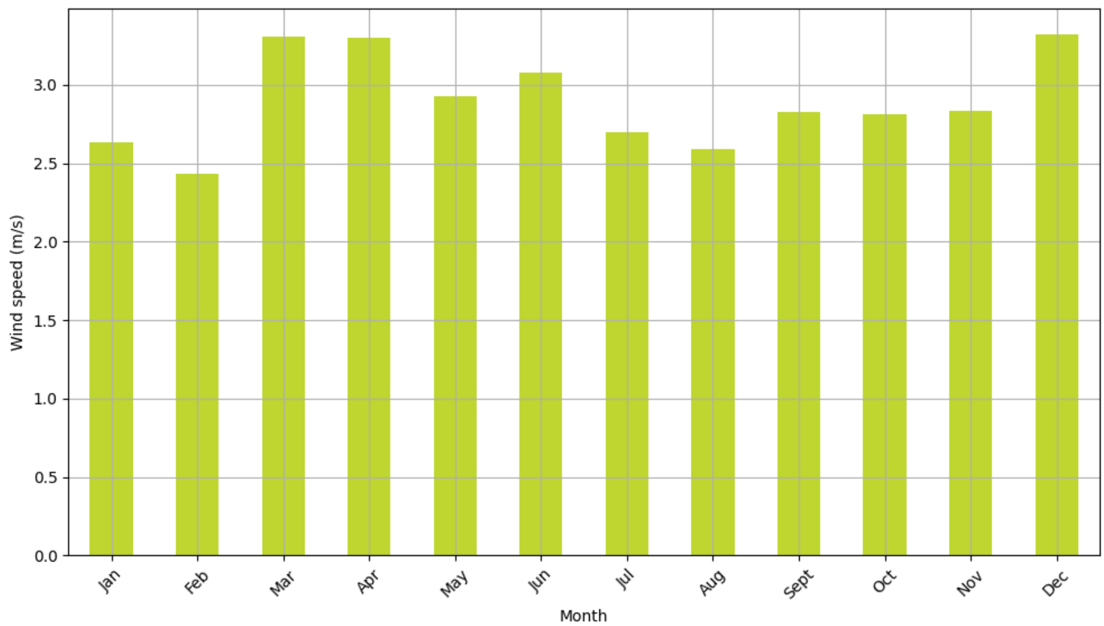
This shows that wind speed is higher in the afternoon, between 2 p.m. and 6 p.m., with values above 3.4 m/s or very close to it, while wind speed is lower, with values below 2.6 m/s, in the early hours of the day, between 1 a.m. and 7 a.m.



Graphic 6.5 - Average daily wind speed in 2022

Graphic 6.6 shows the average monthly wind speed in Portugal in the year 2022. The peak wind speed is in December, with a value of over 3.0 m/s, while the lowest wind speed is in February, with a value below 2.5 m/s.

The variation in the monthly wind speed shows seasonal trends, with the winter months (December, January and February) showing a decrease in wind speed, from above 3.0 m/s to below 2.5 m/s. In the spring months (March, April and May), the wind speed remains constant, despite a distinct value in May close to 3.0 m/s. In the summer months (June, July and August) there is a decrease in wind speed, from above 3.0 m/s to above 2.5 m/s. In the fall months (September, October and November), the wind speed remains constant at over 2.5 m/s.



Graphic 6.6 - Average monthly wind speed in 2022

Analyzing data on the average daily and monthly global irradiance and wind speed allows us to understand the potential for solar and wind energy production in Portugal, while analyzing data on the average daily and monthly load power allows us to understand energy consumption patterns in Portugal.

6.2. Results

Three experiments were carried out on the PSO-GWO parallel hybrid algorithm, using the values for its parameters shown in Table 6.2, Table 6.3 and Table 6.4, for experiment 1, experiment 2 and experiment 3 respectively. Regarding the upper and lower bounds of the decision variables, the values selected for the experiment 1 and experiment 2 are visible in Table 6.1, these were the chosen values because they were within the limits used by the studies identified in the SLR that used the same decision variables.

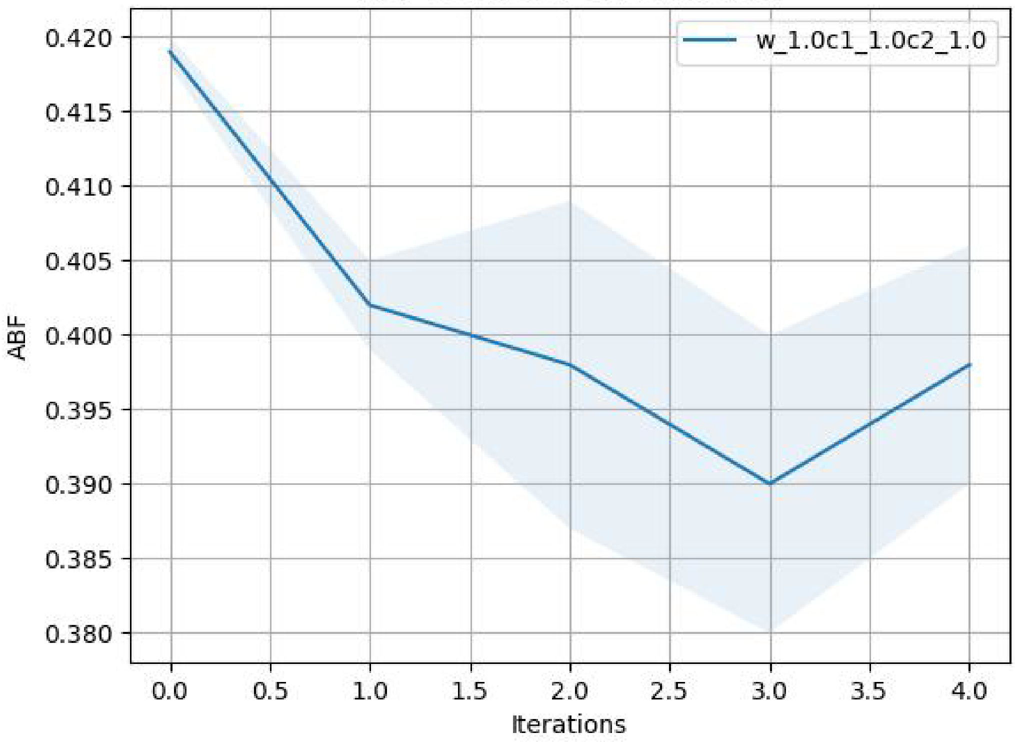
Table 6.1 - Upper and lower bounds of decision variables used in the experiment 1 and experiment 2

Study	N_{PV}	N_{WT}	β	h
Upper bound	1500	1001	90	(present in point 5.2.1)
Lower bound	1000	500	0	(present in point 5.2.1)

In the first experiment, the values for the HPPSGWO algorithm parameters shown in Table 6.2 were used, while the optimization performed is visible in Graphic 6.7. This experiment took approximately 13 hours to run.

Table 6.2 - Values for the parameters in experiment 1

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



Graphic 6.7 - ABF results for experiment 1

Regarding the convergence trend of this first experiment, the Average Best Fitness[3] (ABF) decreases over the iterations, which indicates that the developed HPPSGWO algorithm can successfully improve the fitness of the solutions. The ABF starts with a value slightly below 0.420, decreases to an ABF of 0.390, which is the sharpest decrease, and then increases slightly in iteration 4 with a value close to 0.400. This behavior shows an initial improvement in fitness, followed by a slight deterioration.

About the shaded area around the convergence line, this represents the variability in the ABF, so a narrower area indicates less variability, while a wider area indicates more variability. Bearing this in mind, looking at the Graphic 6.7 of experiment 1, it is possible to conclude that the variability increases as the interactions progress, with only a slight narrowing visible from iteration 3 to iteration 4, which could translate into a potential stabilization of the algorithm if more iterations were carried out. This increase in variability over the course of the iterations may also be due to the small number of runs carried out, since a greater number of runs would allow for a more robust measure of the HPPSGWO's performance and consequently a better understanding of the existing variability.

The slight increase in the ABF from iteration 3 to iteration 4 may suggest that the HPPSGWO algorithm has found a local minimum, which is why it is necessary to carry out more iterations or make changes to the algorithm's parameters to escape the local minimum and find a better solution.

3 “consists in computing the average of the best fitness obtained at a given generation, over all performed runs” (Vanneschi & Silva, 2023)

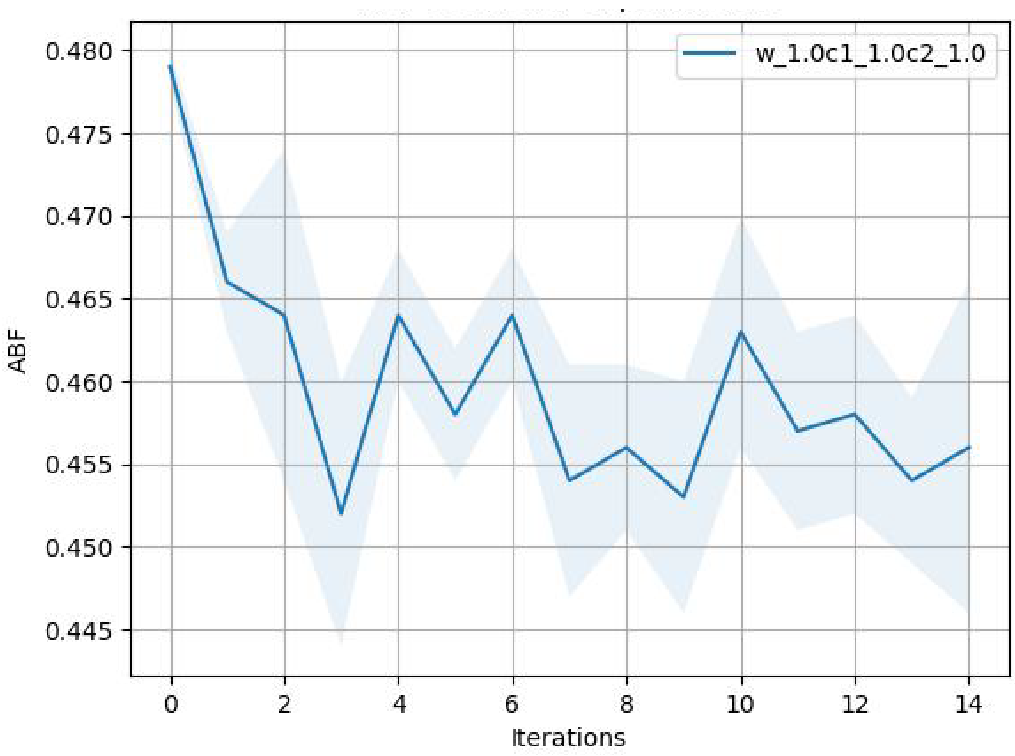
With this, it can be concluded that the algorithm is optimizing correctly, despite the slight increase in the ABF values from iteration 3 to iteration 4, which indicates the need for tuning the parameters used.

Considering the conclusions drawn from experiment 1, a second experiment was carried out, where only the number of iterations was changed to understand whether this modification contributes to escaping the local minimum and consequently finding the optimal solution.

The second experiment took approximately 30 hours to run. The values for the parameters of the parallel hybrid algorithm shown in Table 6.3 were used. Looking at the convergence line (visible in the Graphic 6.8), it can be said that the optimization algorithm continues to improve the fitness of the solutions as the iterations increase, with the ABF value starting at a value close to 0.480 and ending at iteration 14, with an ABF value slightly above 0.455, which is a slight improvement on the previous experiment.

Table 6.3 - Values for the parameters in experiment 2

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



Graphic 6.8 - ABF results for experiment 2

Regarding the variability in the ABF, this continues to be high, as in experiment 1, although there seems to be less variability compared to the other iterations, between iterations 4 and 6. Despite this, there is still high variability, which is to be expected since the number of runs has not been increased, only the number of iterations.

The ABF results obtained with experiment 2 (Graphic 6.8) show the same behavior as described in experiment 1, between iterations 0 and 4. After iteration 4 until the last iteration, iteration 14, therecanal peaks and troughs, which indicates that the algorithm encounters some local minima, although it is able to escape them, since a decrease in the convergence line is visible after a peak is reached. Despite all the peaks and troughs seen between iteration 4 and iteration 14, the ABF tended to decrease, since in iteration 4 it showed a value close to 0.465, ending with a value close to 0.455 in the last iteration. These variations indicate that it might be beneficial to carry out a third experiment with a greater number of changes in the values of the HPPSGWO algorithm parameters.

Considering the conclusions drawn from the analysis of experiment 2, a third experiment was carried out, in which various values were changed in the parameters of the HPPSGWO algorithm, these changes are visible in Table 6.4, each of which is explained below. The number of iterations was increased to understand whether there is still an improvement in ABF or whether there is a stabilization of fitness. Regarding the specific parameters of the PSO algorithm, the value of the cognitive component and social component was changed to 2, since this value "has been shown to be appropriate for several applications" (Vanneschi & Silva, 2023). The size of the swarm in the Particle Swarm Optimization was doubled, with the aim of finding better solutions, since each particle can explore different regions of the solution space, thus enabling better convergence towards the global optimum. In the same vein as exploring the search space, the upper limit of the decision variables number of solar panels and number of wind turbines was increased to widen the search space (Table 6.5), allowing for greater exploration of potential solutions that might previously have been inaccessible due to the limit previously set. Finally, the number of parallel processing units was increased to 8, since an increase in this parameter has previously been verified as "significantly improves the efficiency of the technique in finding the global minimum" (Charilogis et al., 2023).

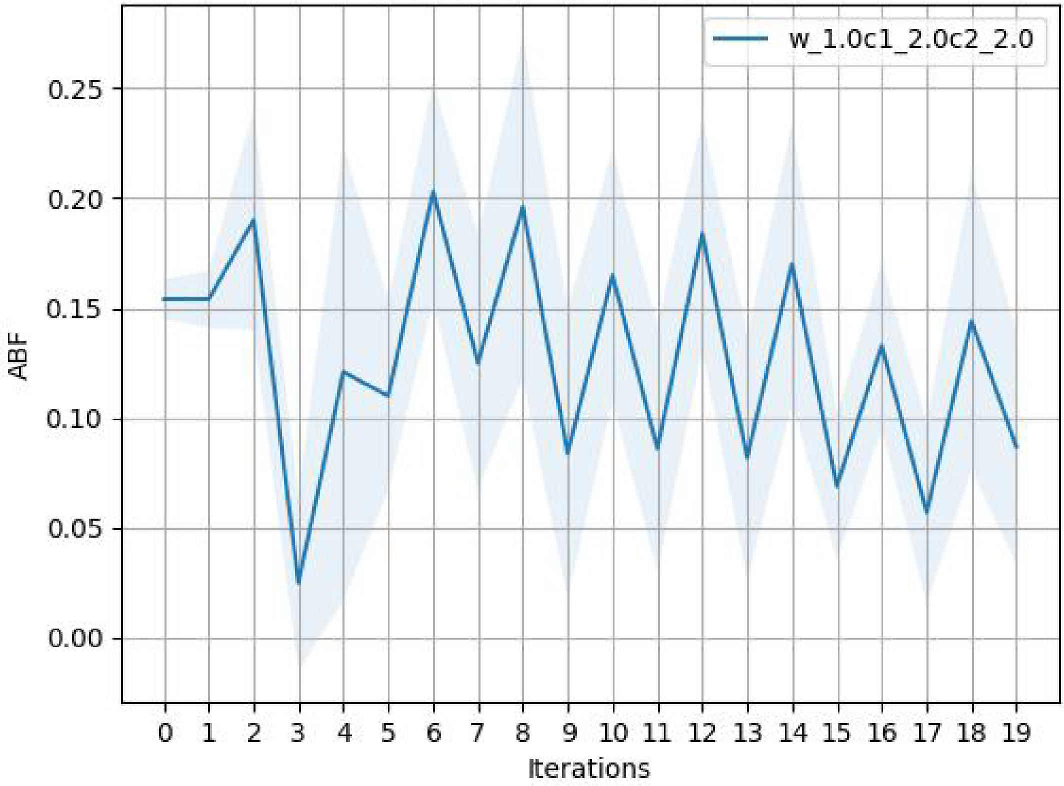
Table 6.4 - Values for the parameters in experiment 3

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

Table 6.5 - Upper and lower bounds of decision variables used in the experiment 1 and experiment 3

Study	N_{PV}	N_{WT}	β	h
Upper bound	2500	2500	90	(present in point 5.2.1)
Lower bound	0	0	0	(present in point 5.2.1)

The optimization performed in the third experiment is seen in Graphic 6.9, that took approximately 60 hours to run. Graphic 6.9 shows the convergence line for experiment 3, where the hybrid algorithm starts with an ABF value of 0.150, a much lower value than in experiments 1 and 2.



Graphic 6.9 - ABF results for experiment 3

Between iteration 0 and iteration 1, the ABF value remains constant, then there is a slight increase from iteration 1 to iteration 2, followed by a sharp decrease in the ABF value until iteration 3, where the lowest value is reached. The behavior described thus shows that the algorithm is capable of rapidly improving the quality of the solution in the initial iterations. After iteration 3, there are several oscillations in the hybrid algorithm's performance, with a slight downward trend between iteration 6 (ABF value of 0.20) and 19 (ABF value lower than 0.10), which suggests that it is making small improvements.

Regarding the variability of the results over the runs carried out, a significant variability can be seen in the Graphic 6.9, which may be due to the stochastic nature of the hybrid algorithm.

The variability and fluctuations visible in the Graphic 6.9 may indicate that the hybrid algorithm has a good exploration capacity. However, parameter tuning is necessary to reduce variability and make convergence more stable.

If an experiment 4 were to be carried out, it would be necessary to perform tuning of the algorithm PSO and GWO parameters, to try to stabilize convergence and reduce the variability of the algorithm. In a further attempt to achieve more stable convergence, the balance between the PSO and GWO algorithms should be adjusted using the $prob$ variable, which allows the two algorithms to be switched between.

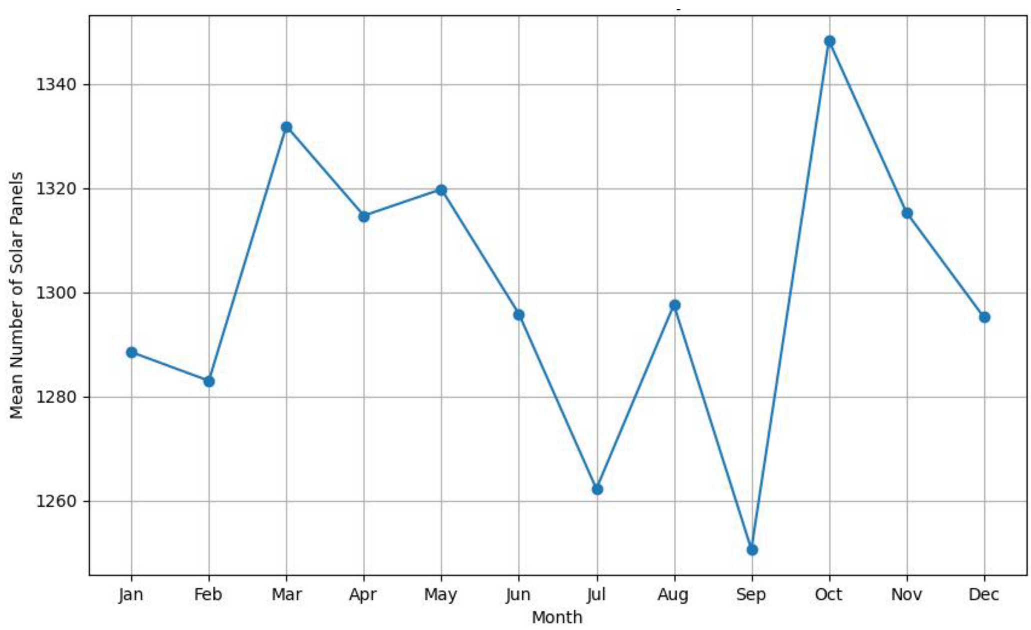
Comparing the execution of experiment 2 with experiment 3, experiment 2 starts with an ABF value close to 0.480, which is higher than that of experiment 3, which starts with a value close to 0.150, indicating that the initial solution of experiment 3 is of higher quality than that of experiment 2.

Experiment 2 shows a general downward trend with small fluctuations in the last few iterations, indicating that the solution is stabilizing. Experiment 3 ended up showing more oscillations without a clear downward trend, indicating less stability and greater exploration of the search space, even in the last iterations.

Evaluating the effect of changing the parameter values from experiment 2 to experiment 3, the larger swarm size of experiment 3 compared to experiment 2 contributes to greater variability and oscillations, since a larger swarm size explores more of the search space. Regarding the cognitive and social component, the value of these parameters was increased from 1.0 to 2.0, from experiment 2 to experiment 3 respectively, which means that there is a greater influence from individual and social learning, resulting in more exploration, which translates into more fluctuations. As far as the limits of the decision variables are concerned, experiment 3 had the widest limits compared to experiment 2, which means that the search space in experiment 3 is larger, which contributes to increased variability.

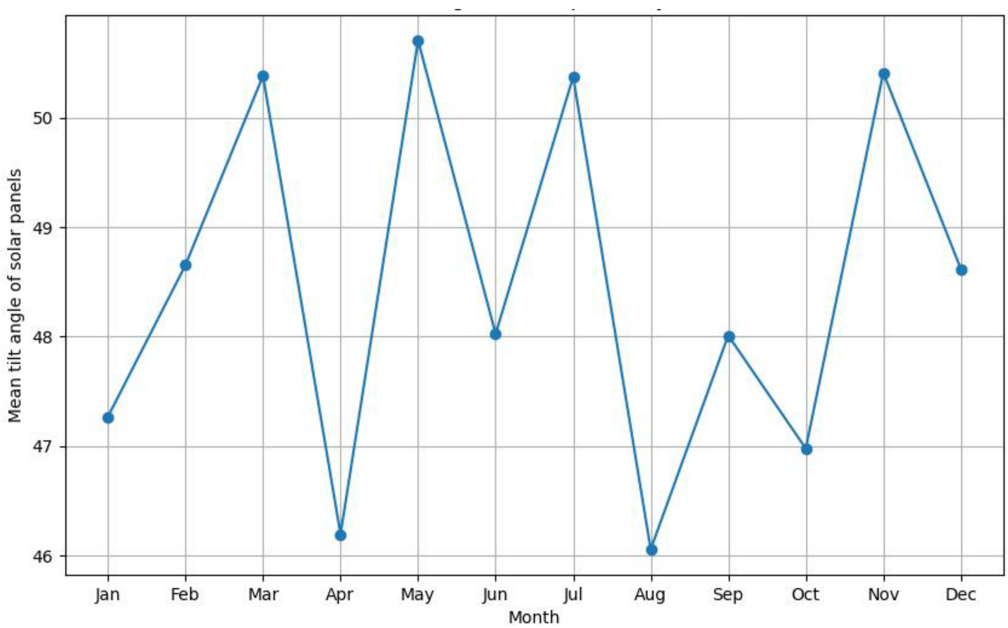
Considering the experiments carried out, the lowest ABF value obtained was in experiment 3, in iteration 3 with an ABF value of 0.025. In this way, it was observed in iteration 3 that the run with the lowest fitness value was run 5 with a value of 0.000506, and this value was also the lowest in run 5 over the 20 iterations. This configuration will be analyzed next through the Graphic 6.10, Graphic 6.11, Graphic 6.12 and Graphic 6.13.

Graphic 6.10 shows the mean number of solar panels per month over a year, with no pattern visible. In the winter months (December, January and February) there is a slight decrease from month to month, with the lowest point being reached in February, with a value above 1280 solar panels. In the spring months (March, April and May) there are small changes in the average number of solar panels, however, it is in March that one of the highest average number of solar panels is reached. In the summer months (June, July and August), the decrease in the average number of solar panels is more pronounced, with one of the lowest points being reached in July, with a mean of solar panels close to 1260. In the fall months (September, October and November) there is an increase in the mean number of solar panels, where this growth was more pronounced from September to October, reaching the lowest average number of solar panels in September, with approximately 1260 panels and the highest average number of solar panels is achieved in October, with approximately 1340 solar panels. After this abrupt growth, the mean number of solar panels fell to around 1320 in November.



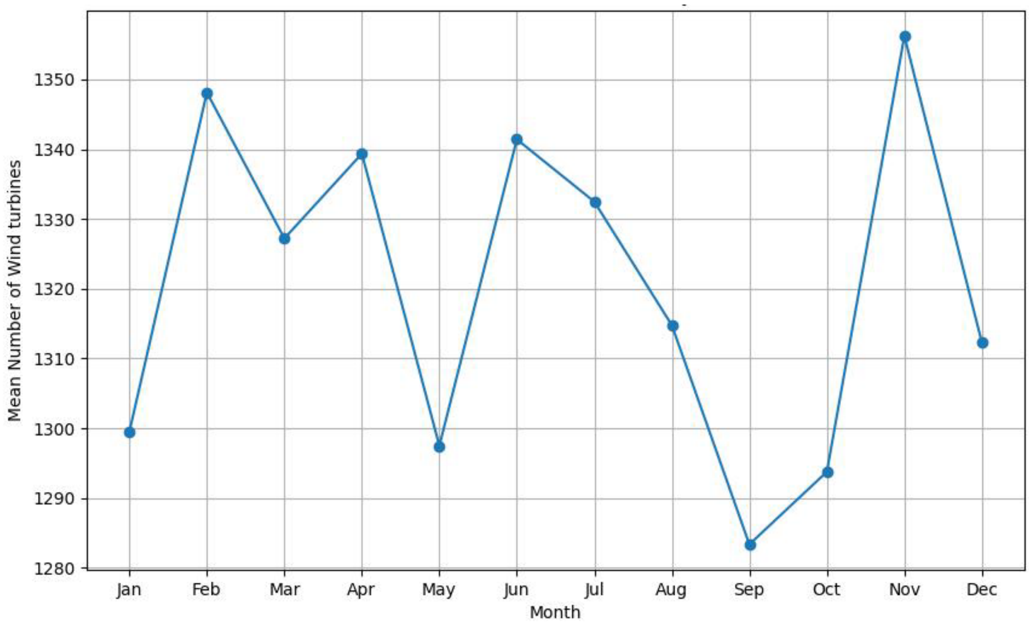
Graphic 6.10 - Experiment 3 - best solution, the mean number of solar panels per month

Graphic 6.11 shows the average angle of the solar panels throughout the year, with the values obtained with the optimization being very close, remaining between the range of 46 and a little above 50. A pattern is visible throughout each season, with a decrease in the mean tilt angle of solar panels from the first month of the season to the second and an increase in the mean tilt angle of solar panels from the second month to the third. In the winter months, the angle of the solar panels begins in December, with an angle close to 49 degrees, then decreases in January to an angle around 47 degrees, to then grow again to an average tilt angle of solar panels close to 49 degrees in February. In the spring months, the mean tilt angle of solar panels decreased from March to April, from a value above 50 degrees to one close to 46 degrees, and then increased again in May to a value above 50 degrees. In the summer months, the pattern seen in the other seasons is reversed, with a rise from June to July from a mean tilt angle of 48 degrees to over 50 degrees, and then a fall from July to August, where the lowest mean tilt angle of 46 degrees is seen. In the fall months, the pattern seen in the winter and spring is visible again, with a decrease from September to October from 48 degrees to 47 degrees, and then an increase from October to November, from 47 degrees to over 50 degrees.



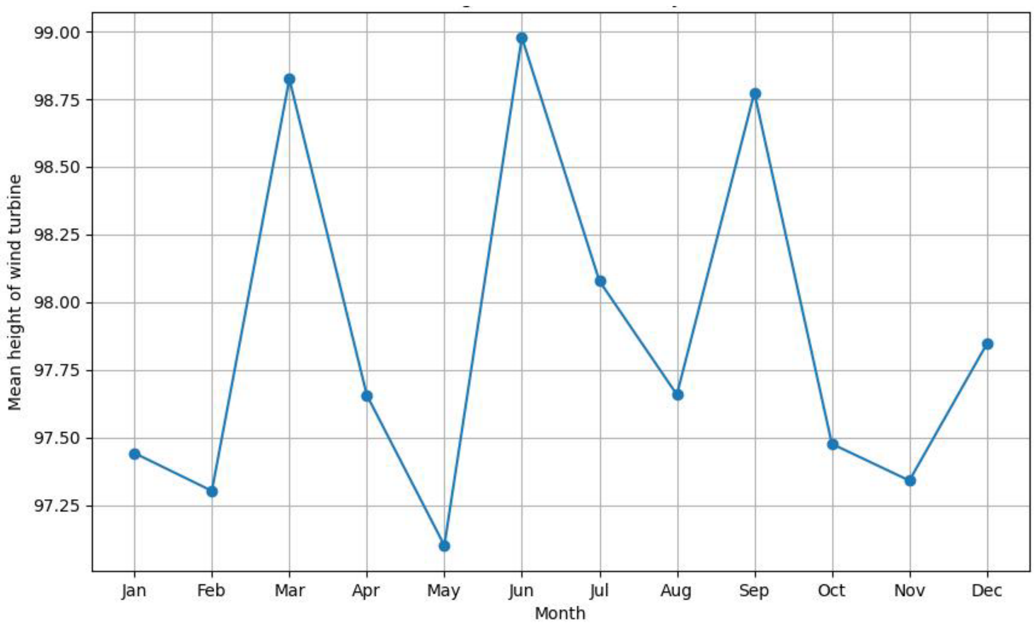
Graphic 6.11 - Experiment 3 - best solution, mean tilt angle of solar panels per month

Graphic 6.12 shows the average number of wind turbines per month, with a few fluctuations visible. Looking in more detail, in the winter months (December, January and February) there is a slight decrease from December to January, from a number of wind turbines close to 1310 to 1300, and then there was a more significant increase from January to February, from a mean number of wind turbines of 1300 to one close to 1350. In the spring months (March, April and May) one of the lowest points is reached in May, with a number of panels below 1300. In the summer months (June, July and August) there is a downward trend, starting in June with a mean number of wind turbines of over 1340 and ending in August with a value of over 1310. In the fall months (September, October and November) the trend is increasing, having reached the lowest mean number of wind turbines in September with a value close to 1280, and ending in November with the highest mean number of wind turbines with a value of over 1350.



Graphic 6.12 - Experiment 3 - best solution, mean number of wind turbines per month

Graphic 6.13 shows the average height of wind turbines per month, with a decreasing pattern visible throughout the seasons. In the winter months (December, January and February) the decrease begins in December with a value close to 97.75 m, and ends in February with the mean height of wind turbine close to 97.25 m. In the spring months, the pattern of decrease continues, with March showing a mean height close to 98.75 m, and May ending with the lowest mean height verified at 97.25 m. In the summer the pattern repeats itself, with June reaching the highest mean height of 99 m, and August ending with a value close to 97.75. In the fall months, the pattern repeats itself as in the other seasons.



Graphic 6.13 - Experiment 3 - best solution, mean height of wind turbines per month

7. CONCLUSIONS AND FUTURE WORKS

7.1. SYNTHESIS OF THE DEVELOPED WORK

In the first chapter of this dissertation, we began by identifying the current problem of the need for an energy transition that should be sustainable and carbon neutral, thus not contributing to global warming. To make this energy transition possible, the initial chapter mentioned the undeniable need to use natural resources to produce energy. However, considering that these renewable energy sources are characterized by being intermittent, it is necessary to combine various to build a system known as a hybrid renewable energy system (HRES), thus becoming the motto for the development of this dissertation. The potential of applying artificial intelligence (AI) techniques to the energy industry in the search for sustainable solutions was mentioned, where there has been an increase in research into the intersection of these two areas. With this, the possibility of obtaining an optimal result in the optimization of HRES was mentioned, through the combination of two or more algorithms that complement each other, but also the consideration of multi-objectives add value considering that the algorithm is intended to be applied in real-world problems. There was thus a need to develop research in the area of AI Hybrid Renewable Energy Systems, which considers diverse objective functions in the context of Portugal, with this the research question placed was: "What novel hybrid optimization algorithms can be developed to effectively address diverse objective functions in the context of AI Hybrid Renewable Energy Systems in Portugal?". Following the development of this dissertation, it is possible to mention the possibility of developing a Hybrid Parallel PSO-GWO algorithm, which considers two objective functions, a technical one that aims to minimize the loss of power supply probability and an environmental one, with the aim of minimizing the amount of CO_2 produced, considering the context of Portugal.

To formulate an answer to the RQ, intermediate objectives were set, that includes carrying out a literature review (LR) in the area of AI and Energy and proposing a hybrid algorithm.

Carrying out the LR in the area of energy made it possible to initially characterize it, mentioning the increase in demand for energy in the form of electricity that has been verified, which ultimately results in an increase in CO_2 emissions. Some of the existing agreements for achieving the energy transition were also mentioned, and a historical context was given regarding the energy transitions that have existed over several centuries and which have led to different industrial revolutions. The need for the next energy transition to use natural resources despite the associated challenges is mentioned, being possible to overcome them by optimizing systems to guarantee their reliability, in this sense, Sustainable Energy Systems and Hybrid Renewable Energy Systems were explored.

The LR developed on AI initially presented the concept, its main areas of activity and how it has been used in the energy industry. A systematic literature review on artificial intelligence and HRES optimization was also carried out to understand the state of the art and to obtain information on other research carried out in the area, to make an appropriate proposal. The SLR followed the PRISMA methodology and identified nine articles which were analyzed and synthesized to answer the literature research questions posed.

In the strategy development phase, the studies obtained through SLR were analyzed again to identify their decision variables, hybrid algorithm used, type of system, context, area of activity and their objective functions. The information gathered was then cross-referenced to obtain various insights and make recommendations regarding decision variables and objective functions, depending on the area of activity, as well as regarding the algorithms to be used to develop hybrid algorithms in the context of HRES.

In the empirical study phase, the first step was to establish which renewable energy sources would be used to create an HRES, having decided that this would include photovoltaic panels and wind turbines. Once the components to be used had been defined, an attempt was made to identify which models were most used in Portugal, to gather the characteristics provided by the manufacturer. In addition to the data on the components to be used in the HRES, data on weather conditions and load demand in Portugal was also obtained. Afterwards the problem was formulated, defining the decision variables, their constraints, the objective functions to be considered in the optimization and the equations needed to calculate the output power of photovoltaic panels and wind turbines. Subsequently, the algorithms used to develop the final hybrid parallel PSO-GWO algorithm were presented.

Three experiments were carried out, changing the values of the parameters from experiment to experiment to accommodate the analyzes carried out to find the global optimum. In the third experiment it was possible to reach a local optimum in the first iterations, with a value in ABF close to the global minimum. Despite this, the number of experiments carried out was restricted by the available computational resources, as well as the time required for execution.

7.2. LIMITATIONS

Although it was possible to develop a hybrid multi-objective algorithm for use in HRES in Portugal, there were some limitations throughout the empirical study process.

In the first phase of identifying the components (photovoltaic panels and wind turbines) most used in Portugal, with the aim of using them in the dissertation, little information was found on this aspect, and it was only obtained through information provided by an expert in the field.

Regarding the collection of data on weather conditions in Portugal, several datasets were found with missing variables or no data in some years, and it was only possible to obtain a complete dataset, i.e. with the variables direct irradiance, diffuse irradiance, albedo irradiance, air temperature and wind speed, through Copernicus.

In the execution phase of the hybrid parallel PSO-GWO algorithm, one of the main limitations was the computational resources available for its execution. It was necessary to use a Cloud GPU rental platform, using the researcher's own financial resources, which may have compromised performance, since it is usual for the PSO algorithm, one of the algorithms in the hybrid parallel PSO-GWO algorithm developed, to run for thousands or millions of iterations in the case of parallel and GPU-based solutions.

There were also limitations in terms of time, since, despite the use of the Cloud GPU rental platform, the algorithm's execution time was always very high, which restricted the ability to carry out more experiments with regard to hyperparameters, so a fixed number was established for them, while a low number of iterations and runs were used, so that it was possible to obtain results in a period that, although long, was practicable.

Despite the mentioned limitations, the dissertation contributed to the field of Data Science, as well as to its intersection with the energy industry, thus seeking to set the tone for further research aimed at finding solutions to existing problems in the energy industry in Portugal, with the aim of achieving a more sustainable and carbon neutral future.

7.3. RECOMMENDATIONS FOR FUTURE WORK

For future research, we recommend using computing resources with greater computing power, as this would allow results to be obtained in less time and consequently more tests to be carried out, which would increase the likelihood of achieving the global minimum. It is also recommended to explore the grid of hyperparameter combinations for parameter tuning, to verify the combination of parameters that allows the best results to be achieved in the minimization problem.

For future studies, we recommend considering two more objective functions in the economic and social categories, in addition to the two already implemented in this dissertation in the technical and environmental areas, to achieve the optimal design of the HRES in all these areas.

Regarding the evaluation of the project developed, it is recommended that feedback be obtained from experts in the field of AI & Energy in Portugal through interviews, which would consequently allow the improvements mentioned to be made, thus realizing an iterative process aimed at achieving a strategy that can be implemented.

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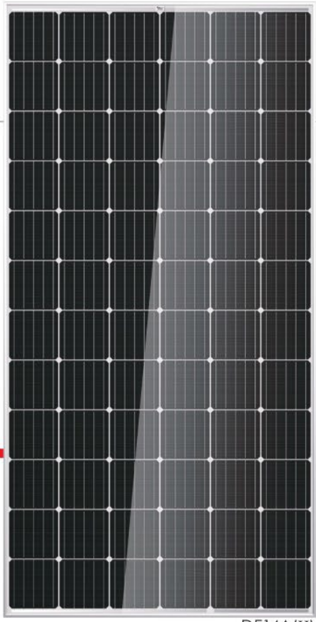
ANNEX A

Mono Multi Solutions



DE14A(II)

THE TALLMAX[M] PLUS+

1500V MODULE

72 CELL
MULTICRYSTALLINE MODULE

330-355W
POWER OUTPUT RANGE

18.3%
MAXIMUM EFFICIENCY

0~+5W
POSITIVE POWER TOLERANCE

As a leading global manufacturer of next generation photovoltaic products, we believe close cooperation with our partners is critical to success. With local presence around the globe, Trina is able to provide exceptional service to each customer in each market and supplement our innovative, reliable products with the backing of Trina as a strong, bankable partner. We are committed to building strategic, mutually beneficial collaboration with installers, developers, distributors and other partners as the backbone of our shared success in driving Smart Energy Together.

Trina Solar Limited
www.trinasolar.com

LINEAR PERFORMANCE WARRANTY

10 Year Product Warranty · 25 Year Linear Power Warranty

Trinasolar
Smart Energy Together

Ideal for large scale installations
- High powerful footprint reduces installation time and BOS costs
- UL1500V/IEC1500V certified

Maximize limited space with top-end efficiency
- Up to 183 W/m² power density
- Low thermal coefficients for greater energy production at high operating temperatures

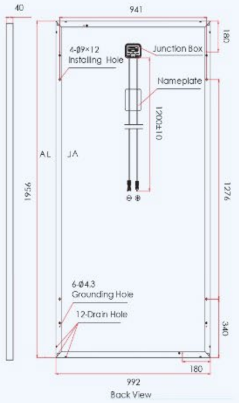
Highly reliable due to stringent quality control
- Over 30 in-house tests (UV, TC, HF, and many more)
- In-house testing goes well beyond certification requirements
- PID resistant
- 100% EL double inspection

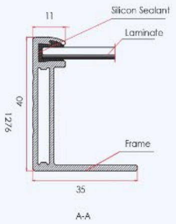
Certified to withstand challenging environmental conditions
- 2400 Pa wind load
- 5400 Pa snow load

Comprehensive products and system certificates

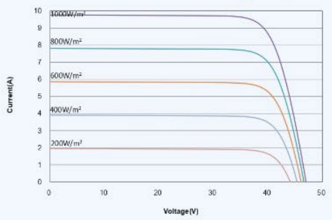
- IEC 61215/ IEC 61730/ UL 1703/ IEC 61701/IEC 62716
- ISO 9001: Quality Management System
- ISO 14001: Environmental Management System
- ISO 14064: Greenhouse Gases Emissions Verification
- OHSAS 18001: Occupation Health and Safety Management System

DIMENSIONS OF PV MODULE
unit:mm

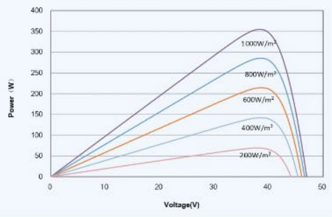




I-V CURVES OF PV MODULE(355W)



P-V CURVES OF PV MODULE(355W)



ELECTRICAL DATA (STC)

Peak Power Watts-P_{MAX} (Wp)	330	335	340	345	350	355
Power Output Tolerance-P_{MAX} (W)	0~+5					
Maximum Power Voltage-V_{MPP} (V)	37.8	37.9	38.2	38.4	38.5	38.7
Maximum Power Current-I_{MPP} (A)	8.73	8.84	8.90	9.00	9.09	9.17
Open Circuit Voltage-V_{OC} (V)	46.2	46.3	46.5	46.7	46.9	47.0
Short Circuit Current-I_{SC} (A)	9.27	9.36	9.45	9.50	9.60	9.69
Module Efficiency η_m (%)	17.0	17.3	17.5	17.8	18.0	18.3

STC: Irradiance 1000 W/m², Cell Temperature 25°C, Air Mass AM1.5.
*Test tolerance: ±3%.

ELECTRICAL DATA (NOCT)

Maximum Power-P_{MAX} (Wp)	246	250	253	257	261	264
Maximum Power Voltage-V_{MPP} (V)	34.9	35.1	35.2	35.5	35.6	35.8
Maximum Power Current-I_{MPP} (A)	7.04	7.12	7.19	7.25	7.33	7.40
Open Circuit Voltage-V_{OC} (V)	43.0	43.1	43.2	43.4	43.5	43.7
Short Circuit Current-I_{SC} (A)	7.49	7.56	7.63	7.67	7.75	7.82

NOCT: Irradiance at 800 W/m², Ambient Temperature 20°C, Wind Speed 1 m/s.

MECHANICAL DATA

Solar Cells	Monocrystalline 156 × 156 mm (6 inches)
Cell Orientation	72 cells (6 × 12)
Module Dimensions	1956 × 992 × 40 mm (77.0 × 39.1 × 1.57 inches)
Weight	26.0 kg (57.3 lb)
Glass	4.0 mm (0.15 inches), High Transmission, AR Coated Tempered Glass
Backsheet	White
Frame	Silver Anodized Aluminium Alloy
J-Box	IP 67 or IP 68 rated
Cables	Photovoltaic Technology Cable 4.0 mm² (0.006 inches²), 1200 mm (47.2 inches)
Connector	MC4 Compatible (1500V)

TEMPERATURE RATINGS

Nominal Operating Cell Temperature (NOCT)	44°C (±2°C)
Temperature Coefficient of P_{MAX}	- 0.39%/°C
Temperature Coefficient of V_{OC}	- 0.29%/°C
Temperature Coefficient of I_{SC}	0.05%/°C

MAXIMUM RATINGS

Operational Temperature	-40~+85°C
Maximum System Voltage	1500VDC (IEC) 1500VDC (UL)
Max Series Fuse Rating	15A

WARRANTY

10 year Product Workmanship Warranty

25 year Linear Power Warranty

(Please refer to product warranty for details)

PACKAGING CONFIGURATION

Modules per box: 26 pieces

Modules per 40' container: 572 pieces

TSM_EN_2016_A

Trinasolar
Smart Energy Together

CAUTION: READ SAFETY AND INSTALLATION INSTRUCTIONS BEFORE USING THE PRODUCT.

NEW

Preliminary Technical Information Sheet

CanadianSolar

KOOLPOWER (1500 V)
CS3U-355|360|365|370MS

Canadian Solar's new KoolPower 1500 V module is a product with innovative design which significantly improves product efficiency and reliability. High system voltage can increase the string length of solar systems by up to 50%, saving BOS costs while increasing the overall yield of the solar system.

KEY FEATURES

- More power output per unit area than conventional modules
- 1500 V — Designed for high voltage systems of up to 1500 V_{DC}, saving on BoS costs
- Lower hot spot temperature, for more reliable performance
- Lower temperature coefficient, for more power output
- Outstanding low irradiance performance of up to 96.0 %
- Heavy snow load up to 5400 Pa, wind load up to 2400 Pa

25 years linear power output warranty

10 years product warranty on materials and workmanship

MANAGEMENT SYSTEM CERTIFICATES*

ISO 9001:2008 / Quality management system
ISO 14001:2004 / Standards for environmental management system
OHSAS 18001:2007 / International standards for occupational health & safety

PRODUCT CERTIFICATES*

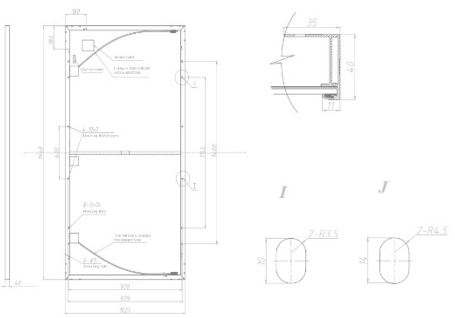
IEC 61215 / IEC 61730: VDE / CE (Expected in late Feb., 2017)
UL 1703: CSA (Expected in late Mar., 2017)
IEC 61701 ED2: VDE / IEC 62716: VDE (Expected in late Feb., 2017)

CANADIAN SOLAR INC. is committed to providing high quality solar products, solar system solutions and services to customers around the world. As a leading PV project developer and manufacturer of solar modules with over 17 GW deployed around the world since 2001, Canadian Solar Inc. (NASDAQ: CSIQ) is one of the most bankable solar companies worldwide.

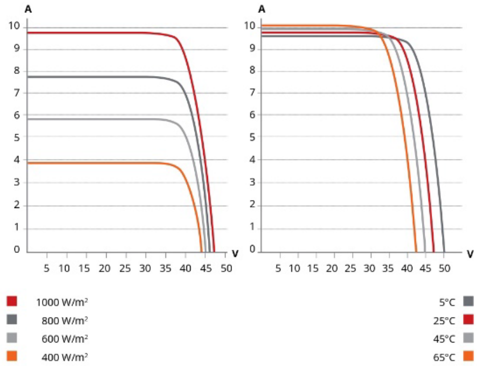
CANADIAN SOLAR INC.
545 Speedvale Avenue West, Guelph, Ontario N1K 1E6, Canada, www.canadiansolar.com, support@canadiansolar.com

ENGINEERING DRAWING (mm)

Rear View



CS3U-370MS / I-V CURVES



ELECTRICAL DATA | STC*

CS3U	355MS	360MS	365MS	370MS
Nominal Max. Power (Pmax)	355 W	360 W	365 W	370 W
Opt. Operating Voltage (Vmp)	39.0 V	39.2 V	39.4 V	39.6 V
Opt. Operating Current (Imp)	9.11 A	9.19 A	9.27 A	9.35 A
Open Circuit Voltage (Voc)	46.8 V	47.0 V	47.2 V	47.4 V
Short Circuit Current (Isc)	9.61 A	9.69 A	9.77 A	9.85 A
Module Efficiency	17.85%	18.10%	18.35%	18.60%
Operating Temperature	-40°C ~ +85°C			
Max. System Voltage	1500 V (IEC) or 1500 V (UL)			
Max. Series Fuse Rating	15 A			
Application Classification	Class A			
Power Tolerance	0 ~ + 5 W			

* Under Standard Test Conditions (STC) of irradiance of 1000 W/m², spectrum AM 1.5 and cell temperature of 25°C.

ELECTRICAL DATA | NOCT*

CS3U	355MS	360MS	365MS	370MS
Nominal Max. Power (Pmax)	259 W	262 W	265 W	268 W
Opt. Operating Voltage (Vmp)	35.4 V	35.6 V	35.8 V	36.0 V
Opt. Operating Current (Imp)	7.32 A	7.36 A	7.41 A	7.45 A
Open Circuit Voltage (Voc)	43.2 V	43.4 V	43.6 V	43.8 V
Short Circuit Current (Isc)	7.79 A	7.85 A	7.91 A	7.97 A

* Under Nominal Operating Cell Temperature (NOCT), irradiance of 800 W/m², spectrum AM 1.5, ambient temperature 20°C, wind speed 1 m/s.

MECHANICAL DATA

Specification	Data
Cell Type	Mono-crystalline, 6 inch
Cell Arrangement	144 (12 × 12 half-cells)
Dimensions	1948 × 1021 × 40 mm (76.7 × 40.2 × 1.57 in)
Weight	22.6 kg (49.8 lbs)
Front Cover	3.2 mm tempered glass
Frame Material	Anodized aluminium alloy
J-Box	IP68 (1500 V) / IP67 (1000 V), 3 diodes
Cable	PV1-1500&12AWG& 4.0mm² (IEC / UL1500 V), 1160 mm (45.7 in)
Connector	T4 series or MC4 series
Per Pallet	26 pieces
Per container (40' HQ)	624 pieces

TEMPERATURE CHARACTERISTICS

Specification	Data
Temperature Coefficient (Pmax)	-0.39 % / °C
Temperature Coefficient (Voc)	-0.30 % / °C
Temperature Coefficient (Isc)	0.053 % / °C
Nominal Operating Cell Temperature	45±2 °C

PERFORMANCE AT LOW IRRADIANCE

Outstanding performance at low irradiance, with an average relative efficiency of 96.0 % from irradiances, between 1000 W/m² and 200 W/m² (AM 1.5, 25°C).

The specification and key features described in this datasheet may deviate slightly and are not guaranteed. Due to on-going innovation, research and product enhancement, Canadian Solar Inc. reserves the right to make any adjustment to the information described herein at any time without notice. Please always obtain the most recent version of the datasheet which shall be duly incorporated into the binding contract made by the parties governing all transactions related to the purchase and sale of the products described herein.

Caution: For professional use only. The installation and handling of PV modules requires professional skills and should only be performed by qualified professionals. Please read the safety and installation instructions before using the modules.

PARTNER SECTION

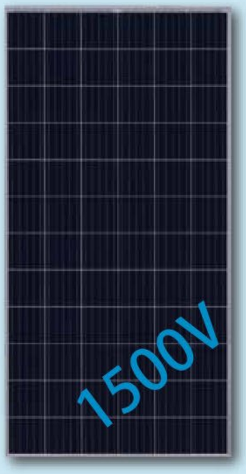
ANNEX C

JA SOLAR

JAP72S01

315-335 1500V Cypress Series

MULTICRYSTALLINE SILICON SOLAR MODULE



JA Solar Holdings Co., Ltd.

JA Solar Holdings Co.,Ltd is a world leading manufacturer of high-performance solar power products that convert sunlight into electricity for residential, commercial and utility-scale power generation. The company was founded in May 2005 and publicly listed on NASDAQ in February 2007. JA Solar has been the world's leading cell producer since 2010, and has firmly established itself as a tier 1 module supplier since 2012. Capitalizing on our strength in solar cell technology, we are committed to provide modules with unparalleled conversion efficiency, yield efficiency, and reliability to enable you to maximize your returns on PV projects. With its leading industry experience, continuous effort on R&D, customer-oriented service and solid financial status, JA Solar is your best choice of long-term trustworthy partner.

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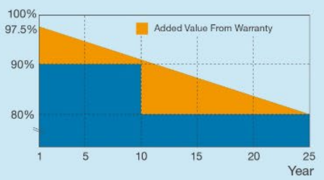
Superior Warranty

- 12-year product warranty
- 25-year linear power output warranty



Key Features

- 5BB design reduces cell series resistance and stress between cell interconnectors to improve module reliability and conversion efficiency
- High output, up to 17.25% module conversion efficiency
- Certified with 1500V DC IEC standard
  50% more strings and fewer components enable lower BOS costs
- Anti-soiling surface reduces power loss from dirt and dust
- Outstanding performance in low-light irradiance environments
- Excellent mechanical load resistance: Certified to withstand high wind loads (2400Pa) and heavy snow loads (5400Pa)
- Strong salt and ammonia resistance certified by TÜV NORD

Reliable Quality

- Positive power tolerance: 0~+5W
- Modules binned by current to improve system performance
- Potential Induced Degradation (PID) Resistant in accordance to IEC62804

Comprehensive Certificates

- IEC 61215, IEC 61730, UL1703, CEC Listed, MCS and CE
- ISO 9001: 2008: Quality management systems
- ISO 14001: 2004: Environmental management systems
- BS OHSAS 18001: 2007: Occupational health and safety management systems
- Environmental policy: The first solar company in China to complete Intertek's carbon footprint evaluation program and receive green leaf mark verification for our products

Specifications subject to technical changes and tests. JA Solar reserves the right of final interpretation.

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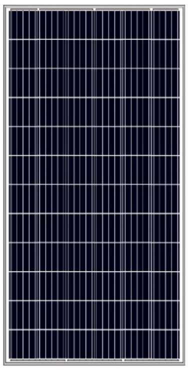
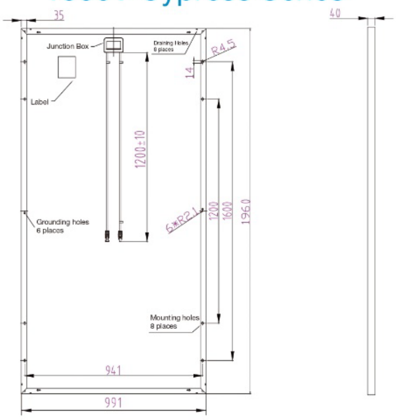
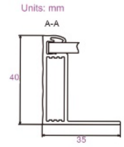
JAP72S01 315-335/SC

1500V Cypress Series

MECHANICAL DIAGRAMS







■ customized cable length available upon request

SPECIFICATIONS

Cell	Poly 156.75×156.75mm
Weight	22.5kg±3%
Dimensions	1960×991×40mm
Cable Cross Section Size	4mm²
No. of Cells	72 (6×12)
Junction Box	IP67, 3 diodes
Connector	PV-ZH202B
Packaging Configuration	27 Per Pallet

OPERATING CONDITIONS

Maximum System Voltage	1500V DC (IEC)
Operating Temperature	-40℃~+85℃
Maximum Series Fuse	20A
Maximum Static Load, Front Maximum Static Load, Back	5400Pa 2400Pa
NOCT	45±2℃
Application Class	Class A

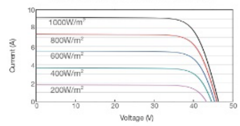
ELECTRICAL PARAMETERS AT STC

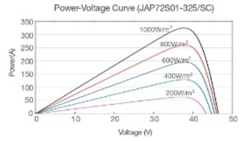
TYPE	JAP72S01 -315/SC	JAP72S01 -320/SC	JAP72S01 -325/SC	JAP72S01 -330/SC	JAP72S01 -335/SC
Rated Maximum Power (Pmax) [W]	315	320	325	330	335
Open Circuit Voltage (Voc) [V]	45.85	46.12	46.38	46.40	46.70
Maximum Power Voltage (Vmp) [V]	37.09	37.28	37.39	37.65	37.83
Short Circuit Current (Isc) [A]	9.01	9.09	9.17	9.28	9.35
Maximum Power Current (Imp) [A]	8.49	8.58	8.69	8.77	8.87
Module Efficiency [%]	16.22	16.47	16.73	16.99	17.25
Power Tolerance	-0~+5W				
Temperature Coefficient of Isc (α_Isc)	+0.058%/℃				
Temperature Coefficient of Voc (β_Voc)	-0.330%/℃				
Temperature Coefficient of Pmax (γ_Pmp)	-0.410%/℃				
STC	Irradiance 1000W/m², cell temperature 25℃, AM1.5G				

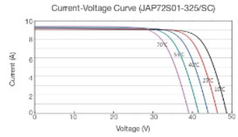
ELECTRICAL PARAMETERS AT NOCT

TYPE	JAP72S01 -315/SC	JAP72S01 -320/SC	JAP72S01 -325/SC	JAP72S01 -330/SC	JAP72S01 -335/SC
Max Power (Pmax) [W]	233	237	241	244	248
Open Circuit Voltage (Voc) [V]	42.84	43.04	43.24	43.41	43.63
Max Power Voltage (Vmp) [V]	34.45	34.64	34.82	35.03	35.21
Short Circuit Current (Isc) [A]	7.23	7.29	7.35	7.40	7.46
Max Power Current (Imp) [A]	6.77	6.84	6.91	6.97	7.04
NOCT	Irradiance 800W/m², ambient temperature 20℃, wind speed 1m/s, AM 1.5G				

CHARACTERISTICS







Electrical data in this catalog do not refer to a single module and they are not part of the offer. They only serve for comparison among different module types.

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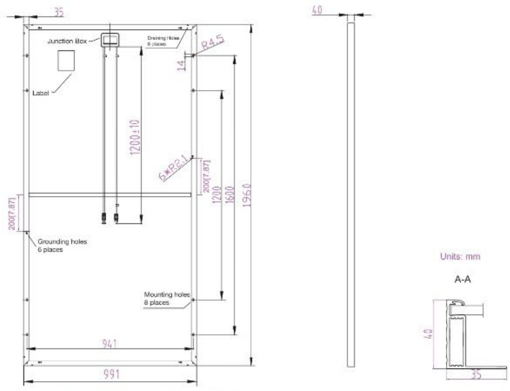
ANNEX D

JA SOLAR

JAM6(K)-72/340-360/PR/1500V
F 40-35

Engineering Drawings



■ customized cable length available upon request

MECHANICAL PARAMETERS

Cell (mm)	Almost Full Square Mono 156.75x156.75
Weight (kg)	23 (approx)
Dimensions (L×W×H) (mm)	1960×991×40
Cable Cross Section Size (mm^2)	4
No. of Cells and Connections	72 (6×12)
Junction Box	IP67, 3 diodes
Connector	Amphenol UTX
Packaging Configuration	27 Per Pallet

WORKING CONDITIONS

Maximum System Voltage	DC 1500V (IEC)
Operating Temperature	-40℃~+85℃
Maximum Series Fuse	15A
Maximum Static Load, Front Maximum Static Load, Back	5400Pa (112 lb/ft^2) 2400Pa (50 lb/ft^2)
NOCT	45±2℃
Application Class	Class A

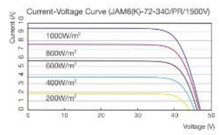
ELECTRICAL PARAMETERS

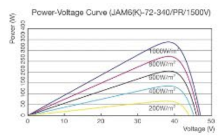
TYPE	JAM6(K)-72-340/PR/1500V	JAM6(K)-72-345/PR/1500V	JAM6(K)-72-350/PR/1500V	JAM6(K)-72-355/PR/1500V	JAM6(K)-72-360/PR/1500V
Rated Maximum Power at STC (W)	340	345	350	355	360
Open Circuit Voltage (Voc/V)	46.86	47.05	47.24	47.45	47.66
Maximum Power Voltage (Vmp/V)	38.18	38.39	38.58	38.76	38.96
Short Circuit Current (Isc/A)	9.46	9.54	9.61	9.69	9.78
Maximum Power Current (Imp/A)	8.91	8.99	9.07	9.16	9.24
Module Efficiency [%]	17.50	17.76	18.02	18.28	18.57
Power Tolerance (W)	-0~+5W				
Temperature Coefficient of Isc (αIsc)	+0.060%/℃				
Temperature Coefficient of Voc (βVoc)	-0.300%/℃				
Temperature Coefficient of Pmax (γPmp)	-0.390%/℃				
STC	Irradiance 1000W/m^2, Cell Temperature 25℃, Air Mass 1.5				

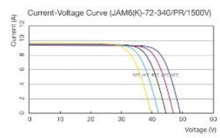
NOCT

TYPE	JAM6(K)-72-340/PR/1500V	JAM6(K)-72-345/PR/1500V	JAM6(K)-72-350/PR/1500V	JAM6(K)-72-355/PR/1500V	JAM6(K)-72-360/PR/1500V
Max Power (Pmax) [W]	248.57	252.23	255.89	259.55	263.20
Open Circuit Voltage (Voc) [V]	43.18	43.39	43.61	43.84	44.08
Max Power Voltage (Vmp) [V]	35.06	35.33	35.59	35.81	36.03
Short Circuit Current (Isc) [A]	7.68	7.74	7.81	7.88	7.95
Max Power Current (Imp) [A]	7.09	7.14	7.19	7.25	7.31
Condition	Under Normal Operating Cell Temperature, Irradiance of 800 W/m^2, spectrum AM 1.5, ambient temperature 20℃, wind speed 1 m/s				

I-V CURVE







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ANNEX E

E70
2,300 kW

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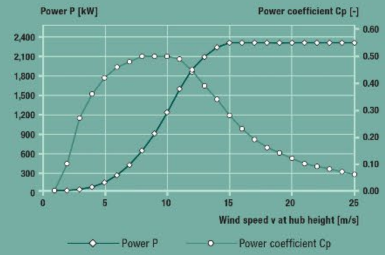
Calculated power curve



Wind [m/s]	Power P [kW]	Power coefficient Cp [-]
1	0.0	0.00
2	2.0	0.10
3	18.0	0.27
4	56.0	0.36
5	127.0	0.42
6	240.0	0.46
7	400.0	0.48
8	626.0	0.50
9	892.0	0.50
10	1,223.0	0.50
11	1,590.0	0.49
12	1,900.0	0.45
13	2,080.0	0.39
14	2,230.0	0.34
15	2,300.0	0.28
16	2,310.0	0.23
17	2,310.0	0.19
18	2,310.0	0.16
19	2,310.0	0.14
20	2,310.0	0.12
21	2,310.0	0.10
22	2,310.0	0.09
23	2,310.0	0.08
24	2,310.0	0.07
25	2,310.0	0.06

ρ = 1.225 kg/m³

For more information on the ENERCON power curve, please see the last page.

Technical specifications E-70 E4

Rated power: 2,300 kW
Rotor diameter: 71 m
Hub height: 57 m / 64 m / 85 m / 98 m / 113 m
Wind zone (DIBt): WZ III
Wind class (IEC): IEC/NVN IA and IEC/NVN IIA

WEC concept: Gearless, variable speed
Single blade adjustment

Rotor
Type: Upwind rotor with active pitch control
Rotational direction: Clockwise
No. of blades: 3
Swept area: 3,959 m²
Blade material: GRP (epoxy resin); Built-in lightning protection
Rotational speed: Variable, 6–21.5 rpm
Pitch control: ENERCON single blade pitch system; one independent pitch system per rotor blade with allocated emergency supply

Drive train with generator
Hub: Rigid
Main bearing: Double-row tapered/cylindrical roller bearings
Generator: ENERCON direct-drive annular generator

Grid feed: ENERCON inverter

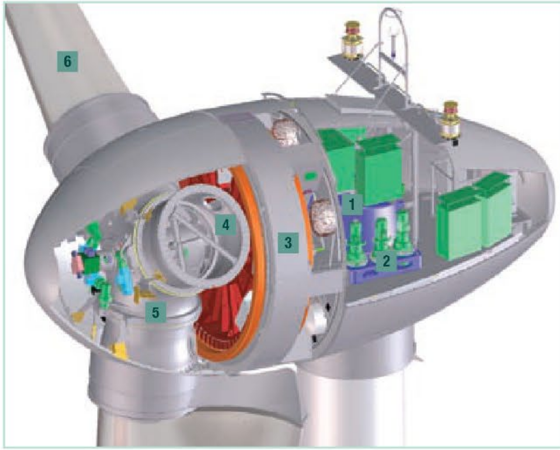
Brake systems:
– 3 independent pitch control systems with emergency power supply
– Rotor brake
– Rotor lock

Yaw system: Active via yaw gear, load-dependent damping

Cut-out wind speed: 28–34 m/s (with ENERCON storm control*)

Remote monitoring: ENERCON SCADA

*For more information on the ENERCON storm control feature, please see the last page.



1 Main carrier
2 Yaw drive
3 Annular generator
4 Blade adapter
5 Rotor hub
6 Rotor blade

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ANNEX F

3 TECHNICAL SPECIFICATIONS:

Turbine type:	**ENERCON E-70 E4**
Rated power:	2300 kW
Rotor diameter:	71 m
Hub height:	64 – 113 m (tower and foundation options)
Turbine concept:	Gearless, variable speed, single blade pitch control
Rotor	
Type:	Upwind rotor with active pitch control
Rotational Direction:	Clockwise
No. of blades:	3
Swept area:	3959 m²
Blade material:	Fibreglass (epoxy resin); integrated lightning protection
Speed:	Variable, 6 - 21 rpm
Tip speed:	22 - 80 m/s
Pitch control:	ENERCON blade pitch system, one independent pitching system per rotor blade with allocated emergency supply
Drive train with generator	
Hub:	Rigid
Main bearing:	Dual row tapered / cylindrical roller bearings
Generator:	ENERCON direct-drive synchronous annular generator
Grid power feed:	ENERCON inverter

Document Information:		**Translation Information**	
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Approved/date:	M.Kuhlmann / 04.11.05	Reference:	VI-Technical Description E-70 E4_rev002_ger-eng.doc
Revision	M.Heinemann/ 002/ 05.03.07		

Braking system	- 3 independent pitch systems with emergency power supply - Rotor brake - Rotor lock
Yaw control:	Active via adjustment gear, load-dependent damping
Cut-in wind speed:	2.5 m/s
Rated wind speed:	14 m/s
Cut-out wind speed:	28 - 34 m/s
Remote monitoring:	ENERCON SCADA

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Revision	M.Heinemann/ 002/ 05.03.07		

ANNEX G

E82

2,300 kW

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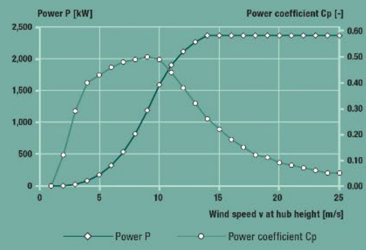
Calculated power curve



Wind [m/s]	Power P [kW]	Power coefficient Cp [-]
1	0.0	0.00
2	3.0	0.12
3	25.0	0.29
4	82.0	0.40
5	174.0	0.43
6	321.0	0.46
7	532.0	0.48
8	815.0	0.49
9	1,180.0	0.50
10	1,580.0	0.49
11	1,890.0	0.44
12	2,100.0	0.38
13	2,250.0	0.32
14	2,350.0	0.26
15	2,350.0	0.22
16	2,350.0	0.18
17	2,350.0	0.15
18	2,350.0	0.12
19	2,350.0	0.11
20	2,350.0	0.09
21	2,350.0	0.08
22	2,350.0	0.07
23	2,350.0	0.06
24	2,350.0	0.05
25	2,350.0	0.05

ρ = 1.225 kg/m³

For more information on the ENERCON power curve, please see the last page.

Technical specifications E-82 E2

Rated power:	2,300 kW
Rotor diameter:	82 m
Hub height:	78 m / 85 m / 98 m / 108 m / 138 m
Wind zone (DIBt):	WZ III
Wind class (IEC):	IEC/NVN IIA
WEC concept:	Gearless, variable speed Single blade adjustment
Rotor	
Type:	Upwind rotor with active pitch control
Rotational direction:	Clockwise
No. of blades:	3
Swept area:	5,281 m²
Blade material:	GRP (epoxy resin); Built-in lightning protection
Rotational speed:	Variable, 6 – 18 rpm
Pitch control:	ENERCON single blade pitch system; one independent pitch system per rotor blade with allocated emergency supply
Drive train with generator	
Hub:	Rigid
Main bearing:	Double-row tapered/cylindrical roller bearings
Generator:	ENERCON direct-drive annular generator
Grid feed:	ENERCON inverter
Brake systems:	– 3 independent pitch control systems with emergency power supply – Rotor brake – Rotor lock
Yaw system:	Active via yaw gear, load-dependent damping
Cut-out wind speed:	28 – 34 m/s (with ENERCON storm control*)
Remote monitoring:	ENERCON SCADA

*For more information on the ENERCON storm control feature, please see the last page.

1 Main carrier
2 Yaw drive
3 Annular generator
4 Blade adapter
5 Rotor hub
6 Rotor blade

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ANNEX H

3 TECHNICAL SPECIFICATIONS:

Turbine type:	**ENERCON E-82**
Rated power:	2000 kW
Rotor diameter:	82 m
Hub height:	78 – 108 m (tower and foundation options)
Turbine concept:	Gearless, variable speed, single blade pitch control
Rotor	
Type:	Upwind rotor with active pitch control
Rotational Direction:	Clockwise
No. of blades:	3
Swept area:	5281 m²
Blade material:	Fibreglass (epoxy resin); integrated lightning protection
Speed:	Variable, 6 – 19,5 rpm
Tip speed:	25 - 80 m/s
Pitch control:	ENERCON blade pitch system, one independent pitching system per rotor blade with allocated emergency supply
Drive train with generator	
Hub:	Rigid
Main bearing:	Dual row tapered / cylindrical roller bearings
Generator:	ENERCON direct-drive synchronous annular generator
Grid power feed:	ENERCON inverter

Braking system	- 3 independent pitch systems with emergency power supply - Rotor brake - Rotor lock
Yaw control:	Active via adjustment gear, load-dependent damping
Cut-in wind speed:	2.5 m/s
Rated wind speed:	12 m/s
Cut-out wind speed:	28 - 34 m/s
Remote monitoring:	ENERCON SCADA

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