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Research Paper

An innovative approach to assessing and optimizing floating solar panels

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ABSTRACT

Floating photovoltaic energy is an emerging solution to the need for decarbonization of the current society. It is currently in the early stages of implementation, so there are not many previous experiences to standardize decision-making and the most relevant operating parameters such as, the tilt angle of a fast as in conventional photovoltaics. In addition, the lack of specific design tools and production calculations for floating solar is a barrier to the correct understanding of the real advantages of floating solar versus conventional solar. From the point of view of the investment, the stakeholders do not have a complete analysis of the profitability of their investment. From a technical, environmental and legislative point of view, there is not enough information available to establish standards and criteria for the design and selection of the most suitable water bodies at local, regional or state level. This research aims to fill this gap by proposing a specific framework based on geographic information systems (GIS), multi-criteria analysis (MCDA) and intelligent optimization (Genetic Algorithm). The objective is to select within a set of water bodies those where the investment is most beneficial from a holistic perspective considering technical, economic, social, environmental, and legislative criteria. Once the optimal location is obtained, the framework obtains the tilt angles that minimize the Levelized Cost of Energy (LCOE) by means of intelligent optimization techniques that evaluate the characteristics of each water body, such as location or available surface. The tilt angle obtained in this research achieves LCOE improvements of between 2.1% and 8.4% with respect to the tilt angle obtained by conventional methods applied to ground photovoltaics. Spain has been chosen as a case study as it is a region with a high solar potential and an even distribution of water bodies in which there is still no legislative framework in force.

1. Introduction

The current European energy landscape is at the beginning of a profound restructuring. On the one hand, it has to cope with a decarbonization of the sector to mitigate the effects of climate change [1] and the end of fossil fuel reserves [2], so that conventional energy sources increasingly have to be replaced by renewable energy sources. On the other hand, the Russia-Ukraine war has brought to light a problem that has been latent since the end of the Cold War, namely the division of the planet into two great social masses, the West and the East [3]. In this context, it is imperative to transform the electricity system towards a more independent, resilient and cleaner system than the current one, in order to reduce dependence on third parties [4]. With this goal in mind, solar photovoltaics (PV) is one of the most promising technologies in the renewable energy market [5]. Different applications with different characteristics can be distinguished: rooftop mounting [6] or ground-PV [7], and with different scales: standalone application [8], energy communities (EC) [9] or solar farm [10]. Due to multiple applications and cost reductions in recent years, PV installed capacity has grown exponentially [11]. It can be stated that PV is a mature technology in which there is a great experience of years in this field and, although it is still being researched and developed, the technology is more than tested and proven to know that it is a competitive alternative in different applications. Nevertheless, it has a series of limitations that may hinder the development of the technology: i) it occupies large areas of land and conflicts with other sectors that are also critical for sustainable development, such as agriculture or livestock farming [12]; ii) it presents considerable efficiency losses due to high cell operating temperature and fouling of the modules, forcing the introduction of cooling [13] and

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Nomenclature

AI	Artificial Intelligence
CFD	Computational Fluid Dynamics
EC	Energy Communities
FPV	Floating Photovoltaic
GA	Genetic Algorithm
GIS	Geographic Information System
MPPT	Maximum Power Point Tracking
MADA	Multi-Attribute Decision Analysis
MAUT	Multi-Attribute Utility Theory
MCDA	Multi-Criteria Decision Analysis
MOO	Multiple-Objective Optimization
PV	Photovoltaic
STC	Standard Temperature Condition
TRL	Technological Readiness Level
UTM	Universal Transverse Mercator

Formulae

T_{amb}	Ambient temperature, °C
E_{year}	Annual energy, kWh
OM	Annual operating and maintenance cost, €/kW/year
K	Boltzmann constant, J/k
CF	Capacity Factor, %
α	Cell short circuit current temperature coefficient of I_{SC}, %/°C
δ_i	Declination angle, °
DR	Degradation rate, %/year
d	Discount rate, %
d_2	Distance between module end point and next module initial point, mm
d_1	Distance between module initial and next module initial point, mm
q	Elementary charge of the electron, C
E_g	Forbidden band width, eV
H	Height, mm
A	Ideality factor of diode, –
I_{PH}	Illumination current, A
I_0	Initial investment, €/kW
G_i	Irradiance of the cell at time $t = i$, W/m^2
ϕ	Latitude, °
L	Length, mm
$LCOE$	Levelized Cost of Energy, €/MWh
T	Lifetime, year
$S_{allowed}$	Maximum allowable surface area, ha
P_{mp}	Maximum power at STC, W
I_{mp}	Maximum power current, A
V_{mp}	Maximum power voltage, V
N	Number of solar panels, unit
V_{OC}	Open circuit voltage at STC, V
V	Output voltage of the module, V
S	Panel Surface, m^2
M	Panel Weight, kg
nd	Position in relation to a calendar year., –
P_{STC}	Power at STC, W
G_{STC}	Reference irradiance, W/m^2
T_{STC}	Reference temperature, °C
I_S	Saturation current, A
I_{rs}	Saturation current of the diode, A
I_{SC}	Short-circuit current at STC, A
h	Solar height, °
T_i	Temperature of the cell at time $t = i$, °C
β	Tilt angle, °
N_p	Total parallel cells, unit
N_s	Total series cells, unit
V_W	Wind velocity, m/s
W	With, mm
t	Year considered, –

cleaning systems, which increase operating costs [14].

For these reasons, the use of water bodies to install Floating Solar Panels (FPV) has recently been considered. In this way, no land would be occupied, so this could continue to be used, for example, in the primary sector. The use of water bodies has other advantages, such as improved energy production compared to solar systems on land, due to the evaporative cooling effect of the water [15] and to the increase in production due to higher water reflectivity [16]. Not only does it have advantages for production, but also for the environment as it reduces deforestation, bird deaths and others [17]. On the other hand, it could have a negative impact on the region's ecosystems [18].

FPV-related projects can be found at different Technology Readiness Levels (TRL) and to a lesser extent in commercial applications [19]. Most of these studies are framed in mainland waters such as reservoirs, hydroelectric, dams, small lakes man-made and others, but few applications are exploring the sea as it is a very aggressive environment [20]. Despite the growth of the sector in recent years, it is still necessary to solve many barriers that allow to know the real potential of the technology, highlighting the advantages and disadvantages that allow the Decision Maker to make the right decision and governments to establish the standards in an appropriate way. On the other hand, for FPV to develop commercially, profitability must be competitive with other production technologies. From an economic point of view, it is not yet fully competitive. Levelized Cost of Energy (LCOE) of FPV varies in the range of 35–65 €/MWh [21], 33–97 €/MWh [19], or 100–120 €/MWh [22], according to the reference consulted. This is considered to be due to the low maturity and low implementation of the technology. The LCOE of PV is around 34 €/MWh, wind power is around 38 €/MWh, and conventional technologies such as coal are around 71 €/MWh or nuclear 76 €/MWh [23]. Therefore, it can be deduced that it is competitive with conventional production technologies, but not yet competitive with mature renewable technologies such as PV or wind. Therefore, much more research on the cost-effectiveness of FPV is needed to provide more evidence at different locations and with different parameters to confirm this trend. One of the barriers detected in the commercial application of this technology is the absence of FPV specific software tools to obtain production or profitability [19]. The state of the art reviewed shows that the tendency is to introduce manual variations in some parameters in specific software for PV such as PVSyst [19].

The main objective of this paper is to fill this gap. For this purpose, a holistic framework capable of detecting in a specific territory defined by the user, those water bodies with the highest potential for FPV application, considering different criteria, is proposed. The result of this multi-criteria analysis is very useful for Decision Makers and for the process of generating government standards. Once the ordered list of water bodies is obtained from highest to lowest potential, the user can select the desired number of water bodies. The selected water bodies will be subjected to an optimization process based on Artificial Intelligence (AI) in which the optimal tilt angle that maximizes the profitability of the FPV installed in each water body will be obtained. In this way, a completely new, specific framework is created, which is very useful for designers, companies, and governments.

The paper is organized as follows. Section 2 provides a critical analysis of the current state of the art regarding the main techniques evaluated in the research and establishes the main contributions of the article. Section 3 presents the definition of the problem, explaining the data used, the methodology followed in the research, as well as the mathematical model employed. Section 4 compiles the results of the different simulations performed and their implications. Finally, section 5 summarizes the main conclusion of the research.

2. Current developments and contributions

The section provides a literature review related to the technology under investigation. A systematic review from the most general to the most specific concept has been approached in order to highlight the novelty of the research. The last five years (2019–2023) of the three main fields have been considered: Geographic System Information (GIS), Multi Criteria Decision Analysis (MCDA) and optimization standards. The database used was SCOPUS, using TITLE+ABS+KEY as search fields. The search criteria used are shown in Fig. 1. The searches obtained 1123 hits (avoiding duplicity screening). Only research indexes as “Article”, “Conference Paper”, “Review” and “Book Chapter” and English language have been considered as relevant. It can be note that there is a relatively little research to FPV (around 2 %, 24 publications) on the topic considered in current research. It can be noted the increasing evolution in the number of publications in the fields within the scope of the current research. This reinforces the novelty and the interest of the scientific community in these fields.

Fig. 1 shows a small number of studies applying MCDA techniques in floating solar. This can be justified by the fact that FPV is in its early stages of development. There is an increasing trend in the number of publications in this field, not only in FPV but also in PV. This is considered to be due to the need of decarbonization of the economy and the increasing competition between projects and technologies, which forces to be much more accurate in the selection of the location to ensure the profitability of the investment [24]. On the other hand, FPV systems are still not very cost competitive compared to conventional systems and to other generation technologies [25]. Therefore, it is necessary to evaluate each investment from different points of view, such as environmental [26] or social [27] in order to assess the benefits of a project from a holistic perspective. In this sense, the application of MCDA can be very useful in FPV for new project developers and authorities, as it allows them to identify those water bodies from which they will obtain the best return on their investment, taking into account their target market. For example, if the installation is focused on the sale of energy in wholesale markets, criteria such as distance to transmission networks must be taken into account [28]. If a local impact is to be generated with FPV, criteria such as employability or social acceptance must be considered [29]. On the other hand, the trend observed in the state of the art is to apply the same techniques and tools that have been applied in PV [30]. Nevertheless, it is not as commonly considered as cooling effect of the water itself [31] or the higher production due to less dust presence [32]. However, much more research is needed in this field that includes criteria related to new business models such as EC and that will help authorities and project developers to maximize the efficiency of their decisions by taking into account as much information as possible in an automated way.

In this sense, the development in recent years of artificial intelligence (AI) can help in some respects. AI requires increasing data acquisition and integration from different sources and at different resolutions. Fig. 1 shows an increasing trend in the use of GIS in PV and very few publications applying GIS to FPV. GIS offers great potential for data integration in a structured way to enable accurate decision making by applying MCDA [33]. The availability of a large set of geolocated structured data enables solutions to be obtained for specific parameters,

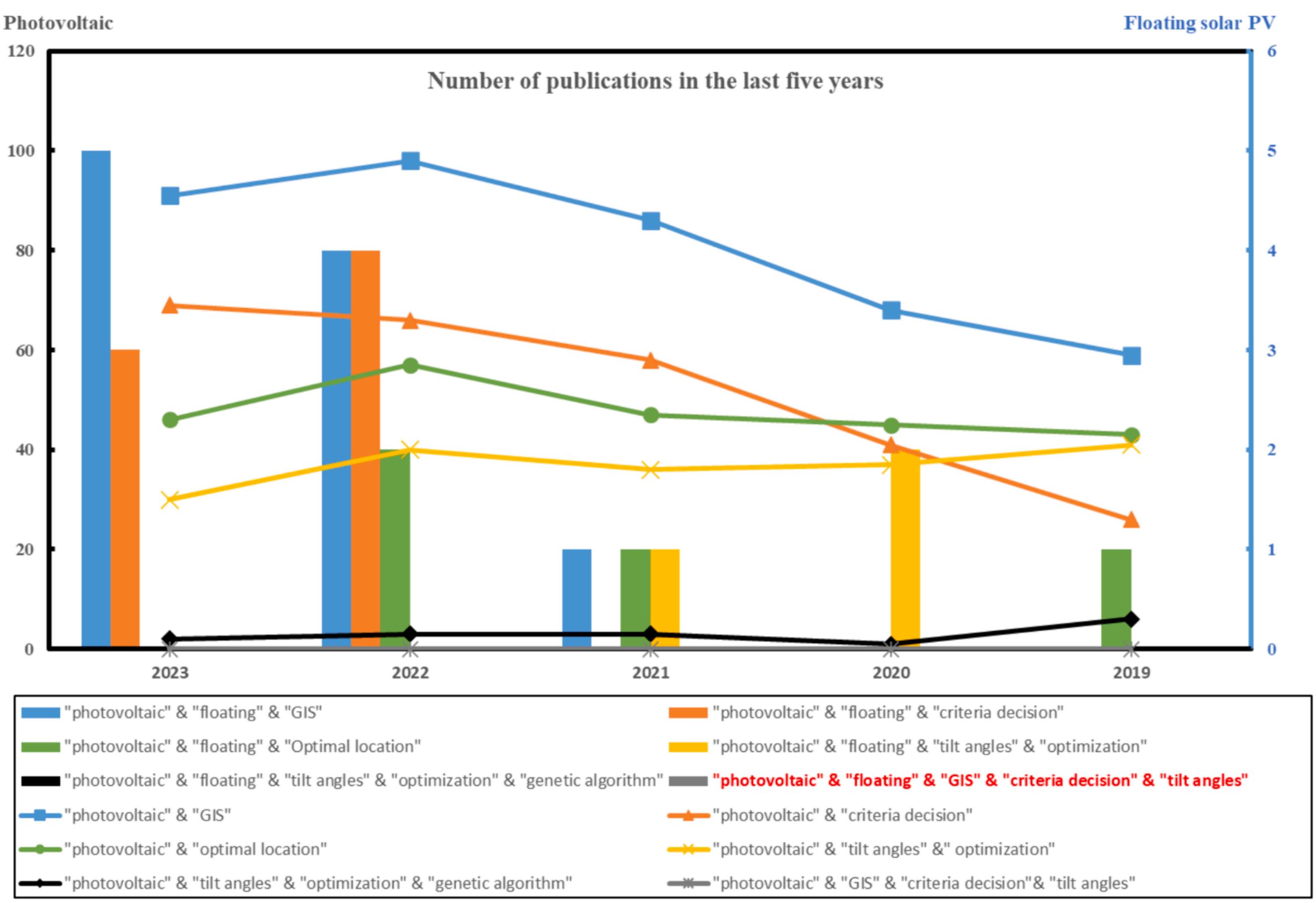

Fig. 1. Number of publications in the last five years per search terms.

such as the optimal tilt that maximizes the annual PV profitability. by applying AI-based techniques as intelligent optimization algorithms. Fig. 1. shows the absence of previous research combining these AI-based techniques and GIS and MCDA in both FPV and PV. In PV, there is research in which AI is applied to obtain concrete sizing parameters for a specific plant, such as plant layout [34] or tilt angles [35]. Recent studies show the great impact of climate zone [36] and tilt angle on the Levelized Cost of Energy (LCOE) of the FPV [25]. Nevertheless, there is no previous research exploring the capabilities of the joint application of these new developments, let alone establishing a methodology with the ability to do so semi-automatically in a case study in which there is a distribution of potential locations (water bodies) scattered with different environmental parameters (climatic, social, economic, and legislative).

2.1. Literature review

2.1.1. Multicriteria decision methods application photovoltaic panel based on GIS

MCDA began to be applied in the energy sector in the 1980 s. Until that time, the only criterion considered was economic, but with the new advances in renewable energies, the environmental benefits of the different alternatives considered could not be fully evaluated. MCDAs are very useful for examining different attributes that conflict with each other. MCDA can be classified according to Seppälä, J. et al. [37] into Multi-Attribute Decision Analysis (MADA) and Multiple-Objective Optimization (MOO). Both differ in the number of alternatives considered. In the MADA case the alternatives evaluated are a finite number and, whereas MOO, an infinite number of alternatives are evaluated. MOOs are outside the scope of this research and therefore the literature review will be conducted on MADAs. MADAs can be classified into different methods: Elementary methods, Multi-attribute Utility theory methods (MAUT), Outranking methods and others methods [37].

The elementary methods do not perform a relative evaluation between criteria to obtain the final solution. This means that it is not necessary to weigh the relative importance between the criteria, since the selection rule is an absolute method. They are based on the concept of evaluating the most restrictive criterion and using it as the solution to the problem. It is considered that since there is no comparison between the different criteria, no references have been found in the state of the art.

MAUTs are the most common methods in the PV, FPV, and renewable energy literature. They are based on the assumption that the Decision Maker has sufficient experience and knowledge to define different preferences among the attributes. In this case, a normalization of the different attributes is performed to have a single scale for comparison. How the standardization is performed and how the comparison is made is what distinguishes the different methods. The final result is the assignment of a value to each alternative, which allows us to order them and obtain the best solution. Among the different methods, the following stand out: the Technique for Order Preferences by Similarity to Ideal Solution (TOPSIS) [38], Weighted Sum Model (WSM) [39], The COmplex PRoportional ASsessment (COPRAS) [40], VIekriterijumsko KOmpromisno Rangiranje (VIKOR) [41], and Stepwise Weight Assessment Ratio Analysis (SWARA) [42]. Di Grazia, S. and Tina, G. M [33] applied the TOPSIS method for optimal FPV selection establishing Croatia as a case study. Cao, Q. et al. [43] applied SWARA together with Full Consistency Method (FUCOM) [44] for FPV application in China. Furtado, P. A and Herrero Sola, A. V [45] employed the COPRAS method for the location of new PV plants in southern Brazil. Chiarini, E et al. [46] conducted a study on Concentrated Solar Power (CSP) in Brazil in which they applied the Vikor method to determine the areas with the highest potential.

On the other hand, the Outranking method relies on the Decision Maker having sufficient experience and knowledge to define a strict hierarchy, indifference, or weak preference. The comparison between alternatives is done in pairs, establishing a dominance relationship between pairs of alternatives. This allows for determining which alternative is better through various methods. Within this group, the following stand out: Elimination et Choix Traduisant la REalite (ELECTRE) [47], and Preference Ranking Organization METhod for Enrichement of Evaluations (PROMETEE) [48]. The studies carried out by Ridha, H, M. et al. [49], in which they use the modified PROMETHEE-II method to find the optimal configuration of hybrid renewable systems, can be highlighted. Rehman, A. U [50] uses PROMETHEE visuals for the selection of cooling systems in photovoltaic panels. Some studies using the ELECTRE can also be highlighted. Mokarram, M. et al. [51] use ELECTRE to optimally locate solar farms. Cavallaro, F. [52] applies ELECTRE-III for a comparison between thin-film photovoltaic production processes.

Finally, within the Other methods category, one can find popular methods such as Analytical Hierarchy Process (AHP) [53], which has hybrid characteristics between MAUT and Outranking methods. There are also combinations of methods in the literature seeking to explore the advantages of different types to obtain a more accurate solution. This is the case of AHP-TOPSIS [54], Fuzzy-Z-AHP [55], and SAW-TOPSIS-GRA [56]. Nevertheless, it can be deduced from the state of the art that the amount of research referred to FPV is scarce, and it has been carried out recently, so more research is required to develop the technology.

In terms of GIS, different platforms are used. Pouran, H. et al. [57] use open source software such as Quantum GIS (QGIS) [58] to carry out an analysis of the different water bodies in Vietnam for agricultural application. Silalahi, D.F. and Blakers, A. [59] employ QGIS to work with wave height in an offshore floating solar application. In contrast, other studies such as those conducted by Lee and Lee [60] or Nebey, A. H. et al. [61] use fee-software such as ArcGIS [62]. A comparison of GIS applied to PV and FPV has not been found in the state-of-the-art. Nevertheless, it is considered that the GIS software used is relevant, due to the different tools they have implemented. A Javascript-based Web-GIS platform can provide many customization advantages by adjusting to the different types of potential users. The Web platforms offered by most of the specific software have a series of previously established tools and may not be able to fully adapt to the needs of floating solar. For this reason, the multi-source and multi-resolution data integration research has been carried out in a Web-GIS.

2.1.2. Optimization intelligent techniques photovoltaic panel potential evaluation

Optimization is an important part of the design and evaluation process of a new PV. It is more important when the technology is in the early stages of implementation, such as the case of FPV, for which no previous experience is available to help in making decisions on different design parameters, such as tilt angle. Tilt angle is one of the most important parameters to increase the amount of energy produced by the solar installation [63]. Accurately obtaining the optimum tilt angle for each location is crucial to maximize the energy captured and to increase the profitability of the system [64]. In PV many authors have established analytical correlations based on experimentation to determine the tilt angle. Some correlations are very simple, involving only latitude [65], and others are more complex, involving a larger number of parameters, such as latitude, month, or day of the year. [66]. After years of experience in PV there are web tools that directly provide the optimal tilt angle that optimizes not only the maximum energy captured, but also the profitability of the plant in an accurate way such as PVGIS [67]. Nevertheless, these types of correlations are not considered to be applicable to FPV as the environment is very different. For example, water cools the panels, increasing productivity [68]. This is why other optimization methods are required to obtain this angle. To the authors' knowledge, there is no tool dedicated exclusively to FPV modelling [69]. The trend in the state of the art is to use software for ground PV modelling, such as PVSyst [70] or Hybrid Optimization Model for Multiple Energy Resources (HOMER) [71], and introduce some modifications manually to obtain the plant performance [19]. For this reason, the need for further research in this field is considered fundamental to understand the feasibility of FPV in a comprehensive manner.

Most of the publications related to FPV performance found in the state of the art are focused on techno-economic studies that include certain environmental aspects. They establish the optimal tilt angles based on economic criteria, such as LCOE discrete intervals. Lopez, M. et al. [31] compared the LCOE in three different water bodies in Spain, for an occupied FPV surface of 10 %. They performed the calculations for a tilt angle between 0 and 40° in discrete 10° intervals. The result they obtained was that the minimum LCOE was around 10°. Nevertheless, with the established methodology, they did not obtain a solution with a higher resolution. The final tilt angle result could be affected by the percentage of water surface covered or by the climatology and it could be different depending on the location and climatology of the selected water bodies. The methodology established by the authors has a low degree of automation and therefore requires more human–computer interaction when applied to a larger number of reservoirs. Redón Santafé, M et al. [72] applied a similar methodology in which they obtained that the optimum angle was also around 10°. Nevertheless, they went a step further by validating the results with a pilot plant of about 20 kWp.

Once the state of the art has been analyzed, it is observed that there is no application of optimization techniques that allow to obtain in a semi-automatic, robust, and simultaneous way the optimal tilt angle in different water bodies taking into account the climatology and the maximum available surface for its use for FPV. In this sense, the state of the art of PV has been reviewed [73], finding that intelligent optimization techniques could be very useful to establish standards to help designers and governments in the tilt angle decision making process. Yang, J. and Yang, J [74] define it as *"Intelligence optimization algorithms are a large class of probabilistic optimization algorithms, which solve varieties of complex optimization problems by mimicking the physical or biological phenomena, including Simulated Annealing, Genetic Algorithms, Ant Colony Optimization, and Particle Swarm Optimization and so on"*. Based on this definition, the systematic review shown in Fig. 1 was carried out, but no results were found that applied these techniques in FPV, highlighting the novelty of the research proposed. Most of the studies consulted employ this technique to obtain the optimal production technology mix in hybrid sustainable generation applications [75] where one of the technologies considered is PV. Nevertheless, there are a few publications that apply this type of algorithms in the design and sizing of the solar collection system itself. Khan, A, Y et al. [34] employed Genetic Algorithms (GA) in conjunction with Computational Fluid Dynamics (CFD) to obtain tilt angle based layouts to reduce the effect of wind on the panels. Jain, D. and Lalwani, M. [76] used GA to obtain the optimal tilt angle by varying the time periods over a year. Ismail, M.S. et al. [77] employed GA to model and design hybrid renewable energy system. In this case study, one of the decision variables was the tilt angle. Yassir, A. et al. [78] employ genetic algorithms for tilt-angle optimization using an Indonesian region as a case study.

From the state of the art, it can be concluded that intelligent optimization techniques have the potential to be applied to FPV. Nevertheless, more research is needed to do it in an integrated way with a semi-automatic and robust tool, combining the advantages provided by GIS.

2.2. Research gap and contributions

After review of the state of the art has been reviewed, no previous research that combine FPV, GIS MCDA and intelligent optimization has been found. Thus, the research proposed here contributes to the current state of the art by holistically investigating the potential for FPV production, optimal site selection, and tilt angle optimization using GIS techniques reinforced with MCDA for a double purpose: (1) automate the determination of the optimal FPV installation design, especially regarding the determination of the optimal tilt-angle; (2) automate the selection of optimal locations for FPV installations, considering both regulations in force and social-economic criteria. In addition, the following specific contributions are made:

- Semi-automatic selection based on MCDA-GIS of water bodies with the highest potential for FPV application. Spain has been selected as a case study, but the methodology can be applicable in any other region, including energy communities for industrial, residential, or agricultural use.
- Inclusion of energy communities (EC) as possible recipients of the energy, either for industrial or agricultural use. The potential of EC for the use of FPV relies on the possibility of sharing the initial investment, consequently reducing the rate of return.
- A novel distance criterion has been included to assess the possibility of applying FPV in the regulatory framework for ECs.
- Analysis of the proposed Spanish standards regarding the water bodies included in the legislation, and whether the selection made is the most optimal.
- Novel automatic determination of the tilt angle by means of an intelligent optimization based on GA taking into account the water-cooling effect, applying GIS.

3. Material and methods

The proposed methodology aims to obtain a framework (Fig. 2) to evaluate the optimal allocation and evaluation standards for FPV based on GIS, MCDA, and intelligent optimization. The methodology is presented through its application in Spain, selected as case study, and is organized according to the following steps:

I. **Multi-source and multi-resolution data integration** (Section 3.1). Problem definition, consisting of the GIS integration of the different water bodies, power lines, and solar potential and the selection of a photovoltaic panel as a basis for study.
II. **FPV potential evaluation** (Section 3.2). Evaluation of the generation potential of floating solar energy, including in the model the cooling effect of water and the distance needed between panels to avoid shading.
III. **Multicriteria Decision Analysis** (Section 3.3) Identification of the water bodies with the highest potential to be optimized. Two MCDAs, such as COPRAS and WASPAS have been compared.
IV. **Tilt angle intelligent optimization** based in metaheuristic algorithms, such as genetic algorithm, applied to selected water bodies (Section 3.4).
V. **Results and discussion** (Section 4). Comparative analysis between the potential established by the Draft Royal Decree in Spain [79] and all the water bodies considered, and comparative analysis of the optimized production potential.

The following sections describe in detail the methodology followed in this research.

3.1. Problem definition

3.1.1. Case study description

The objective of the proposed research is to carry out an energy, economic, and environmental analysis of the implementation of an FPV in a specific territory, such as Spain. The Iberian Peninsula is located in the southwest Europe, and it consists of Spain, Portugal, Andorra, and Gibraltar. Spain is composed of 17 administrative regions, 15 of which are located in the Iberian Peninsula, and two archipelagos, one located in the southwest in the Atlantic Ocean (Canary Islands) and the other in the east, in the Mediterranean Sea (Balearic Islands). Fig. 3 shows the geographical distribution of the peninsular water bodies in Spain, the distribution of the power grid and the climatic zones. A distinction has been made between the water bodies contemplated in the draft Spanish

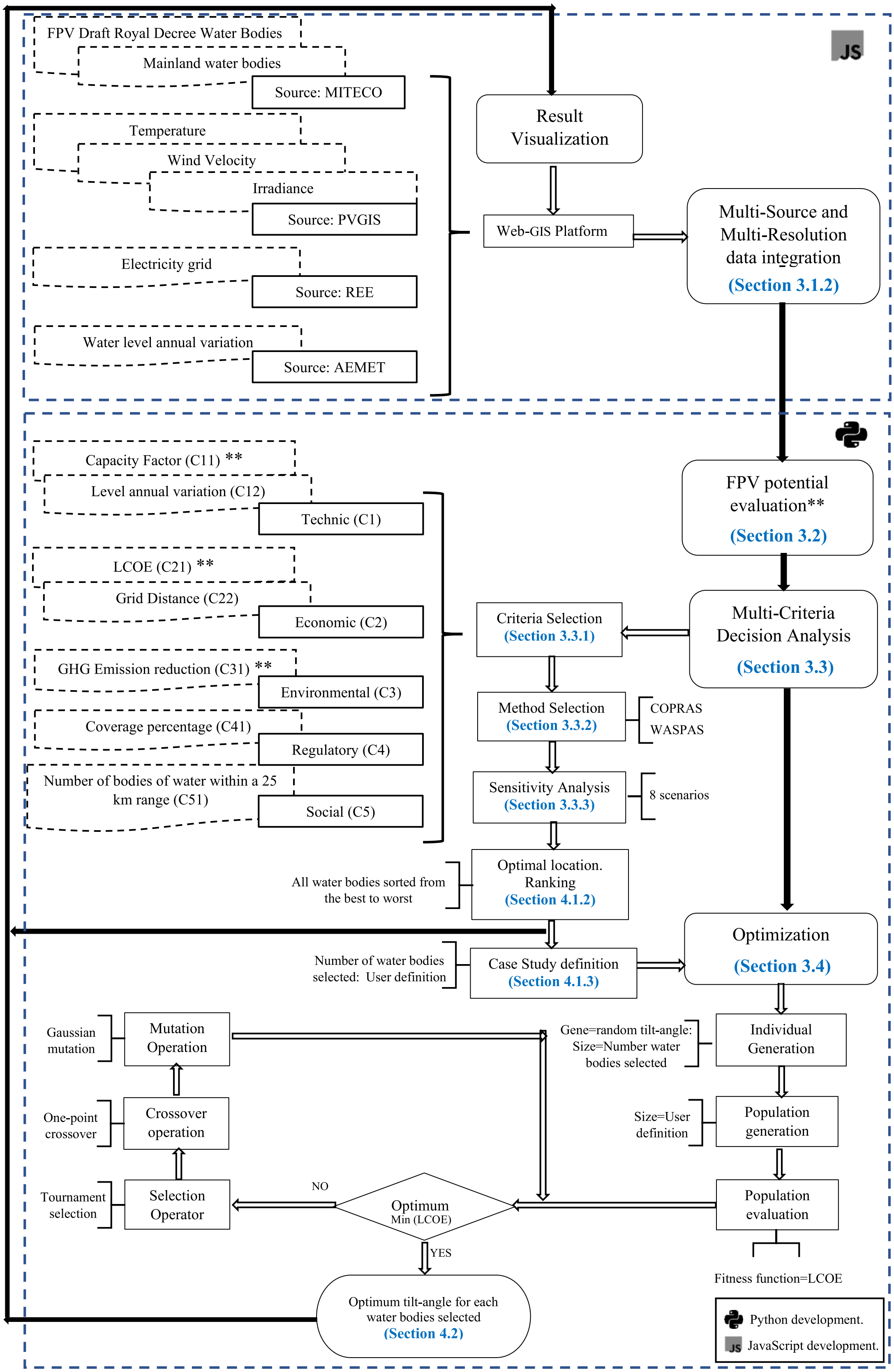

Fig. 2. Framework flowchart.

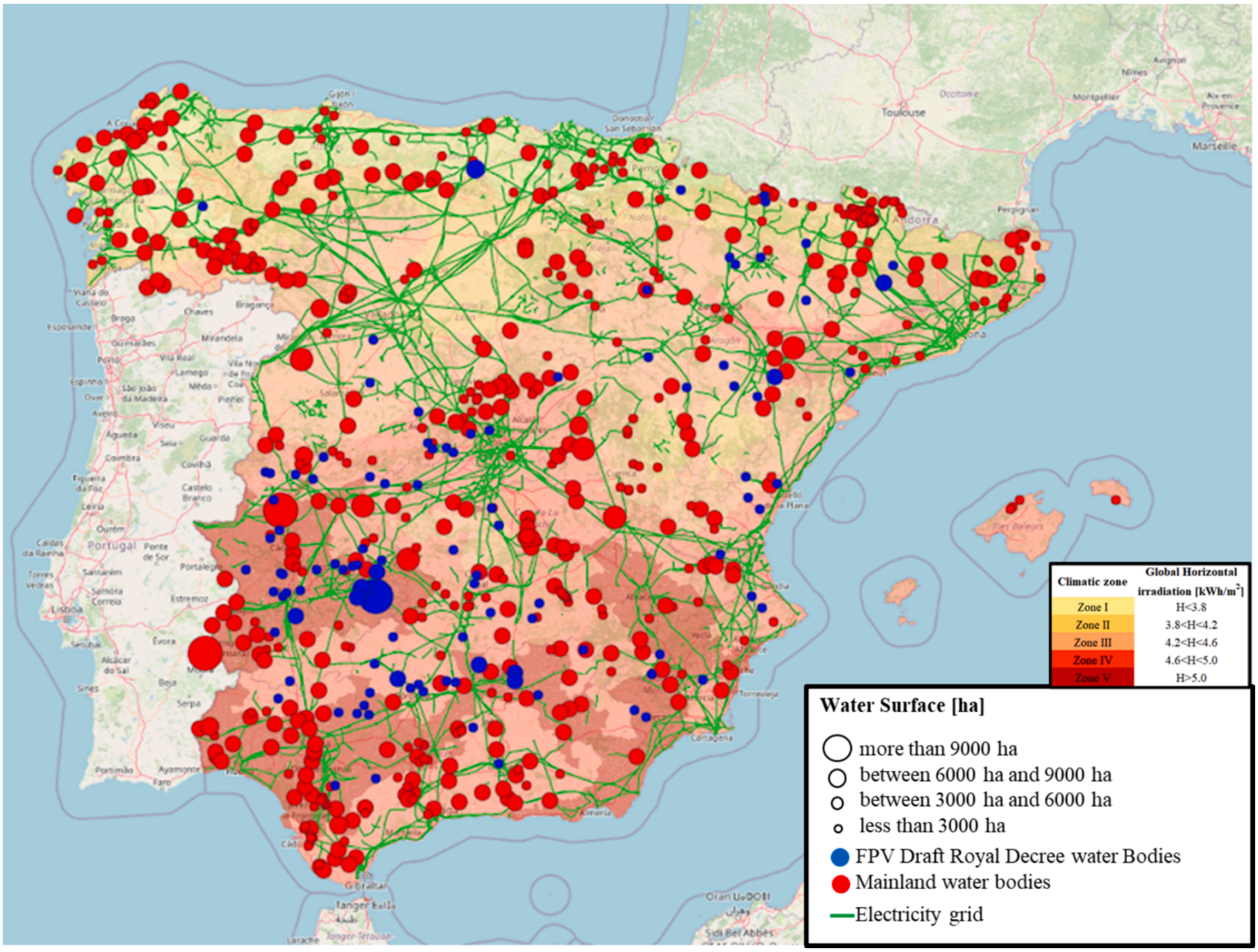

Fig. 3. Surface of mainland water bodies, electricity grid and climate zones in Spain.
Adapted from [79–81]

legislation (blue color) [79] and the total existing water bodies (red color) [80]. The first visual conclusion that can be drawn is that the Draft Royal Decree is very conservative with respect to the use of water bodies. In addition to the number of reservoirs, the distribution is uneven, since in the northern zone the Draft barely contemplates any water bodies to be used for FPV. The criteria for selecting the water bodies included in the Draft are unknown. In this research, whether the selection of the water bodies included in the draft is optimal, according to the MCDA, will be evaluated.

On the other hand, Fig. 3 shows that Spain has a large solar energy potential and an extensive distribution network that establishes Spain as a good candidate as a pilot region for the implementation of FPV, which would allow the extraction of conclusions to its application in other regions. In turn, considering all the water bodies, a uniform distribution is observed throughout the territory. This fact invites us to think about the possibility of integrating FPV in EC in rural environments. The objective would be double. On the one hand, agriculture is a major water consumer and is usually distributed in regions close to water bodies, so it would be a great opportunity to consider the FPV and thus share the investment among more users, reducing the impact on each of them. On the other hand, when introduced within an EC, the use of the electricity grid would be lower, reducing the investment needed to increase the transmission capacity, which in Spain in particular is saturated [82]. This would also increase the resilience and efficiency of the system.

Table 1 shows the energy consumption, installed capacity of solar PV, and installed capacity of wind power by administrative regions in Spain. The administrative regions in Spain are very different in size, consumption and installed renewable capacity, as well as in the distribution of water bodies. Thus, the impact of the introduction of FPV in each administrative region is very different. For example, the "Comunidad de Madrid" is one of the administrative regions with the highest consumption, around 10 % of the total. Nevertheless, the PV installed capacity is less than 0.3 % and it has no wind power installed capacity. On the other hand, Extremadura has one of the lowest consumption in the country, around 2 %, and already has a solar installed capacity of almost 25 % of the country's total, due to its climate.

3.1.2. Multi-source and multi-resolution data integration

The integration of multi-source and multi-resolution data is performed in a Web-GIS platform designed through the combination of Javascript and Python. The objective is to take advantage of the ease of interaction, visualization and dissemination of results offered by a Web platform, and the of computational power offered by Python, especially in intelligent optimization algorithms, such as GA. Priority has been given to the use of geo-referenced public databases to ensure data accessibility and open libraries to guarantee the universality of methods and results. The databases used to compile the data are shown in Table 2.

The multi-source and multi-resolution architecture allows for a scalable and easily adaptable structure to different territories. In order to adapt the framework to other territories, it is only necessary to replace the water bodies layer. In the specific case of Spain, FPV has not been legislated yet. The only regulation that exists is a draft of a Royal Decree

Table 1
Energy consumption, installed capacity of on-ground photovoltaic, installed capacity of wind power, surface area, water bodies density and number of water bodies by administrative region in Spain. .

	Energy consumption [TWh]	Installed Capacity on-ground photovoltaic [GW]	Installed capacity wind power [GW]	Surface area [10^3 km^2]	Water bodies density [%] **		Number of water bodies [-] **	
					●	●	●	●
Andalucía	38.77	4.21	3.61	87.60	0.142	0.636	23	117
Aragón	10.21	1.90	5.04	47.73	0.118	0.366	14	44
Principado de Asturias	8.83	0.00	0.70	10.61	0	0.138	0	12
Cantabria	3.62	0.00	0.04	5.326	0.807	0.066	1	4
Castilla- La Mancha	11.71	4.11	4.78	79.41	0.079	0.488	14	5
Castilla y León	13.38	1.45	6.62	94.22	0.013	0.382	5	67
Cataluña	44.89	0.30	1.38	32.21	0.050	0.204	3	98
Comunidad de Madrid	27.52	0.06	0.00	8.025	0.105	0.546	4	95
Comunidad Valenciana	27.06	0.43	1.24	23.27	0.067	0.332	7	17
Extremadura	4.85	5.35	0.04	41.68	0.615	0.833	29	39
Galicia	13.76	0.02	3.89	29.69	0.003	0.538	1	52
Islas Baleares	6.04	0.23	0.00	5.018	0	0.024	0	14
La Rioja	1.60	0.10	0.45	5.041	0	0.106	0	5
Región de Murcia	9.05	1.41	0.26	11.31	0.046	0.076	4	10
Navarra	5.04	0.17	1.36	10.39	0.072	0.097	1	20
País Vasco	15.21	0.05	0.16	7.23	0	0.384	0	7
Total	250.47	19.99	30.15	498.77	2.12	5.22	106	606

** FPV Royal Decree Water Bodies and Mainland water bodies.
Adapted from [79,80,83]

Table 2
Multi-source and multi-resolution data characteristics.

	Dataset format	Source	Resolution
Mainland water bodies	Geojson	[80]	Multi-Polygon
FPV Draft Royal Decree water bodies	DataFrame	[75,79]	Numeric Value (converted to Multi-Polygon)
Temperature	DataFrame	[84]	Numeric Value
Solar Irradiance	DataFrame	[84]	Numeric Value
Wind velocity	DataFrame	[84]	Numeric Value
Electricity grid	Geojson	[85]	Line string
Water level variation	Array	[86]	Numeric Value

[79] which establishes the public water bodies that can be used for FPV (106 water bodies) and the percentage of their total surface that can be covered depending on the trophic degree of each water body (Mesotrophic (5 %), Eutrophic (15 %), Hypereutrophic (20 %)). In this research, due to the absence of regulatory restrictions, it has been decided to consider all the public reservoirs recognized by the Ministry of Ecological Transition and the Demographic Challenge (MITECO) [80] (712 water bodies). Therefore, an integration of both databases has been carried out. The draft Royal Decree database has been manually created by georeferencing each water body using Google Earth software [75]. In the case of water bodies that are not mentioned in the Draft Royal Decree, it has been decided to assign a maximum surface cover with panels of 10 % selected because is a recurrent value in the literature [31]. The data structure is a multi-polygon defined by the contour of each water body discretized into segments of different lengths defined by the Universal Transverse Mercator (UTM) coordinates of their ends. Regarding environmental and solar irradiance data, the Python library PVLIB [87] is used, which allows the extraction of annual irradiance ("G(h)"), temperature ("T2m") and wind ("W10s") data with a temporal discretization of one hour. The coordinates for obtaining the environmental and solar irradiance data correspond to the centroid of the water body. The power transmission grid has been obtained from the system operator "Red Eléctrica de España" (REE-Spanish Electricity Network), defined by multi-lines, where each line is referenced by its UTM coordinates at the ends [85]. Lastly, the average variation of the water reservoir of the water bodies has been obtained from the meteorological services agency Spanish Meteorological Agency (AEMET) [86]. The variation value of the average level of the last 10 years assigned to each water body corresponds to the average value of the region in which it is located.

The Web-GIS platform has been generated through Javascript using open access libraries: Openlayers [88] has been used for the processing and integration of multi-source data through an interactive map generated by OpenStreetmap [89]. The visualization of results is done through canvasjs [90]. As for the calculations performed with Python, only mathematical and data structure libraries, such as numpy [91], pandas [92] and DEAP framework tools [93] have been used to program the genetic algorithm.

3.2. FPV potential evaluation

3.2.1. Photovoltaic panel specification

The FPV potential evaluated in this research corresponds to large water bodies, such as lakes, swamps, reservoirs, and some large river mouths. In these types of water bodies, the most common FPV structure is the rigid one, in which rigid panels are installed on rigid floats generally made of plastic material [94]. This is because the level fluctuations are not as pronounced as they could be in water bodies with more fluctuating levels, such as irrigation ponds. Therefore, these small fluctuations and possible surges due to the magnitude of the water masses are absorbed by the anchorages between floats [95]. Among photovoltaic technologies, the most widespread is monocrystalline silicon [96]. The model selected as the basis of calculation for this study is the JAM78S10 455MR model, whose technical specifications are shown in Table 3.

3.2.2. Photovoltaic panel mathematical model

The single diode equivalent circuit model [98] has been used to obtain the power generated by each PV system. This model allows the I-V and P-V curves of the panel to be obtained accurately, introducing the effect of cell reduction with the cooling of the reservoir water and the

Table 3
Technical specifications for PV module JAM78S10 455MR [97].

Parameter	Variable	Value
Manufacturer	–	JA Solar
Model	–	JAM78S10 455MR
Type	–	Si Monocrystalline
Dimensions [mm]	$LxWxH$	2180 x 996 x 40
Surface [m^2]	S	2.17
Weight [kg]	M	24.6
Maximum power at STC [W]	P_{mp}	455
Maximum power voltage [V]	V_{mp}	45.83
Maximum power current [A]	I_{mp}	9.93
Open circuit voltage at STC [V]	V_{OC}	53.87
Short-circuit current at STC [A]	I_{SC}	10.56
Total series cells	N_s	156
Total parallel cells	N_p	1
Ideality factor of diode	A	1.3
Cell short circuit current temperature coefficient of Isc [%/°C]	α	0.044
Reference temperature [°C]	T_{STC}	25
Reference Irradiance [W/m^2]	G_{STC}	1000

variation of the irradiance in hourly time intervals. The mathematical model of the I-V curve is compiled in Eq (1).

$$I = N_P \bullet I_{PH} - N_P \bullet I_S \bullet \left[\exp\left(\frac{q \bullet V}{N_s \bullet K \bullet A \bullet T_i}\right) - 1\right] (1).$$

Where N_P is the number of cells in parallel of the module, I_{PH} is the illumination current calculated according to Eq. (2), I_S is the saturation current calculated according to Eq. (3), q is the elementary charge of the electron ($q = 1.602 \bullet 10^{-19} C$) [99], V is the output voltage of the module, N_s is the number of cells in series, K is the Boltzmann constant ($K = 1.3805 \bullet 10^{-23} \frac{J}{K}$) [100], A is the ideality factor of the diode and T_i is the temperature of the cell at time $t = i$ considered.

$$I_{PH} = [I_{SC} + \alpha(T_i - T_{STC})] \frac{G_i}{G_{STC}} (2).$$

Where I_{SC} is the short-circuit current of the panel, α is cell short circuit current temperature coefficient of I_{SC}, T_{STC} and G_{STC} are reference temperature and solar irradiance and G_i is the irradiance on the panel at the instant $t = i$ for a given inclination and orientation

$$I_S = I_{rs} \bullet \left[\frac{T_i}{T_{STC}}\right]^3 \bullet exp\left(\left[\frac{q \bullet E_g}{A \bullet K}\right] \bullet \left[\frac{1}{T_{STC}} - \frac{1}{T_i}\right]\right) (3).$$

Where I_{rs} is the saturation current of the diode at temperature is obtained according to Eq. (4), T_i is obtained according to Eq. (5) y E_g is the forbidden band width that depends on the material ($E_{g(Si)} = 1.1eV$) [101].

$$I_{rs} = \frac{I_{sc}}{\exp\left(\frac{q \bullet V_{oc}}{N_s \bullet K \bullet A \bullet T_i}\right) - 1} (4).$$

Where V_{oc} is open-circuit voltage.

Finally, the power is calculated as the product of the voltage and the current according to Eq. (5).

$$P = I \bullet V = \left(N_P \bullet I_{PH} - N_P \bullet I_S \bullet \left[\exp\left(\frac{q \bullet V}{N_s \bullet K \bullet A \bullet T_i}\right) - 1\right]\right) \bullet V (5).$$

The cell operating temperature T_i has to be corrected taking into consideration the cooling effect of the water. A model proposed by Kamayu et al. [102] has been used which relates empirically, through Eq. (6) ambient temperature (T_{amb}), solar irradiance (G_i) and wind velocity (V_W) of the specific location.

$$T_i = 2.048 + 0.9458 \bullet T_{amb} + 0.0215 \bullet G_i - 1.2376 \bullet V_W (6).$$

The number of panels to install is directly determined by the allowed percentage of water surface. Nevertheless, the shading between panels, which is influenced by the slope and location of the water body, must be taken into account. Fig. 4 shows the shadow model used to calculate the number of total panels. The criterion established is to ensure that no shading occurs at any time of the year (Eq. (7) and Eq. (8)).

$$d_2 = \frac{L \bullet \sin\beta}{\tan h} (7).$$

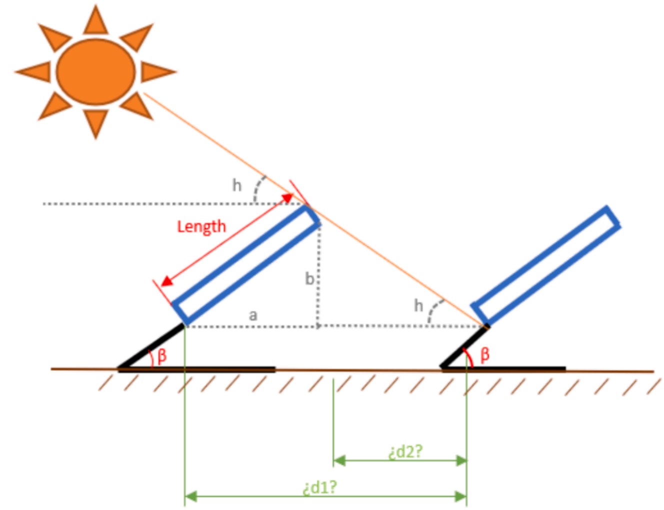

Fig. 4. Shading angle diagram.

$$d_1 = d_2 + (L \bullet \cos\beta) (8).$$

Where L is the length of the panel, β is the tilt angle, h is the minimum solar altitude over the whole year, d_2 and d_1 are the objective distance.

The hourly solar height h_i depends on the day and time of the year. The calculation of shadows is done at solar midday for which Eq. (9) is used.

$$h_i = (90 - arcos(sen\delta_i \bullet sen\phi + \cos\delta_i \bullet \cos\phi)) (9).$$

where δ_i is the declination angle calculated according to Eq. (10), which is a function of the day of the year and ϕ is the latitude of the considered water body.

$$\delta_i = 23.45 \bullet sin\left(360 \bullet \frac{284 + nd}{365}\right) (10).$$

Therefore, h will be the minimum height of all the days of a complete year according to Eq. (11) and nd position in relation to a calendar year.

$$h = \min(h_i) (11).$$

Therefore, knowing the surface occupied by each panel and having the maximum coverable surface allowed, the maximum number of panels can be obtained so that no shadows are produced between them according to Eq. (12).

$$N = \frac{S_{allowed}}{d_1 \bullet W} (12).$$

Where $S_{allowed}$ is the maximum allowable surface area which is a function of the legislation for each water body, d_1 is the distance between panels calculated according to Eq. (8) and W is the width of the panel. Finally, the annual energy is obtained from the aggregation of the maximum powers in each period of time considered according to Eq. (13).

$$E_{year} = \sum_{t=1}^{T} P_{mppt}(G_i, T_i) \bullet \Delta t (13)$$

Where $P_{mppt}(G_i, T_i)$ The maximum power at each time instant is a function of solar irradiance and temperature T_i, which vary the I-V and P-V curves, so the Newton-Raphson method is applied to obtain the voltage V that maximizes the power in Eq. (5) by modeling an inverter with Maximum Power Point Tracking (MPPT) [103].

3.3. Selection of water bodies. Multicriteria decision

This section compiles the methodology followed to carry out the MCDA. Section 3.3.1 justifies the selected criteria. Section 3.3.2 justifies the two multi-criteria methods used. Finally, in Section 3.3.3, a sensitivity analysis is performed to establish the relative weights of each criterion.

3.3.1. Criteria selection

Seven criteria have been considered to evaluate each alternative from different points of view: technical (C1), economic (C2), environmental (C3), legal (C5), and social (C6). It distinguishes between two types of criteria, the positive criteria ("+") which greater value is more desirable and is associated with a higher suitability score, and the negative criteria ("-") which lower value is more desirable and is associated with a higher suitability score. Table 4 shows a brief description of the selected criteria as well as the hierarchy and typology of the sub-criteria used in the multi-criteria analysis.

3.3.1.1. Technical criteria (C1). The Capacity Factor (CF) (C11) is the ratio of total annual generation and installed capacity. It is calculated according to Eq. (14).

$$CF = \frac{E_{year}}{\sum_{i=1}^{n} P_{STC} \bullet N \bullet \Delta t} \bullet 100 \quad (14)$$

where E_{year} is the annual year (Eq. (10), P_{STC} is the panel power referred to STC (Table 3), N is the total number of panels installing over each water body and Δt is the increment of time considered, in this case a full year has been considered with an hourly discretization. Level annual variation (C12) is the average variation of the water level in the reservoir over the last 10 years.

3.3.1.2. Economic criteria (C2). The LCOE (C21) quantifies the average current cost of power generation of a production technology during its entire life cycle. The analysis performed is restrictive as it does not consider subsidies that may reduce the initial investment. The LCOE is calculated by dividing the total costs (investment + operation and maintenance) during the lifetime and the energy produced according to Eq. 15.

$$LCOE = \frac{I_0 + \sum_{t=1}^{T} \frac{OM}{(1+d)^t}}{\sum_{t=1}^{T} \frac{E_{year} \bullet (1-DR)^t}{(1+d)^t}} \quad (15)$$

Where I_0 is the initial investment set at 750 €/kW [25], OM is the annual operating and maintenance cost set at 15.2 €/kW/year [25], E_{year} is the annual energy, DR is the annual degradation rate set at 1.18 %/year [104], d is the discount rate set at 5.1 % [25], t is the year considered and T is the lifetime set at 25 year [19].

Grid Distance (C22): This distance is evaluated between the water body and the nearest point of the electricity grid. First, the nearest point of the grid is selected by projecting a point on a straight line. In this case, the projection of each water body is made on all the segments in which the line string of the electricity grid is defined. Once located, the orthodromic distance between both points is calculated. The distance to the grid has a significant impact on the plant's investment and on the environmental impact associated with the construction of the connection section.

Table 4
Selection, description, and structure of criteria.

Criteria	Subcriteria	Type	Description	Reference
Technical (C1)	Capacity factor (C11)	+	The ratio of annual total generation and power install capacity	[31]
	Level annual variation (C12)	–	Average annual seasonal variation of water level over the last 10 years	[61]
Economic (C2)	LCOE (C21)	–	Quantifies the average cost to sell the electricity generated during the plant life cycle	[31,33]
	Grid Distance (C22)	–	Distance to the nearest transmission electricity grid	[33]
Environmental (C3)	GHG Emission reduction (C31)	+	GHG emission can be avoided	[31,33]
Legal (C4)	Coverage percentage (C41)	+	Percentage of area covered allowed	[31,61]
Social (C5)	Number of water bodies within a 25 km range (C51)	+	Number of water bodies within the allowable range for energy communities	–

3.3.1.3. Environmental (C3). GHG Emission reduction (C31). Measure of the quantity of emissions avoided by producing energy through FPV. The magnitude depends on the occupied surface of each water body and the climatology, which determine the production potential. It is obtained by comparing the emissions associated with the system without FPV and with FPV. Emissions associated with the energy mix of 0.160 tCO_2/MWh in 2022 have been considered [105].

3.3.1.4. Regulatory (C4). The Coverage percentage criterion (C41) takes into account the maximum surface allowed for the installation of FPV. This parameter is subject to the regulations of each region, which will establish the maximum allowed surface in order not to affect the ecosystem environmentally. In the case study considered, the regulations are under development, allowing coverage percentages between 5 and 20 % depending on the trophic degree of each water body [79].

3.3.1.5. Social (C5). The social criteria included in the study is based on the number of water bodies within a 25 km range from the point of consumption (C51). This distance can be configured for each case study, or according to the needs of the study. In this proposed research and the case study of Spain, the distance of 25 km is selected because this is the maximum radius established for the creation of Energy Communities (EC), which are considered in this study as potential beneficiaries of FPV, and due to the highest social acceptance of small installations [106]. For this reason, it was decided to incorporate this criterion to take into account sets of water bodies susceptible to be jointly exploited within a EC by being located within a radius of 25 km [107].

3.3.2. Method selection

A comparison between different methods for the selection of criteria in the specific application of FPV has not been found in the state of the art. Nevertheless, by reviewing other applications, such as [41,108–111] there is no consensus in which one method is more valid than another, the general conclusion is that it must be studied case by case and that the choice of method is closely linked to the objectives pursued. Within the two main groups established in the literature review, MAUTs have been considered, since there is no previous evidence with which to rank the criteria to guarantee a correct solution. The objective of the MCDA carried out is to obtain a set of solutions ordered from most to least suitable. Therefore, according to the state of the art, the most suitable are the MAUTs [112]. Two methods have been selected from those used in the state of the art that were analyzed in Section 2.1.1: COPRAS and the Weighted Aggregates Sum Product Assessment (WASPAS) [113] method. WASPAS introduces an improvement over WSM, as it includes not only a weighting using the sum, but also the product Conclusions drawn from different studies have been evaluated in the selection process. The robustness of COPRAS [114] and the publication date of WASPAS [113], which is more recent than other methods considered in the literature such as VIKOR [115] or TOPSIS [116], were evaluated.

The COPRAS method was introduced by Zavadskas and Kaklauskas [117]. This method can be applied to maximize or minimize criteria in an assessment where more than one criterion should be considered. The COPRAS method ranks and evaluates alternative for their importance and utility degree [118]. The WASPAS method was introduced by Zavadskas, Turskis, Antucheviciene, and Zakarevicius in 2012 [119]. It is now being widely accepted as an efficient decision-making tool due to the mathematical simplicity and capability to provide more accurate results as compared to WSM and WPM methods [120]. For more specific details on the methods considered, please refer to Appendix A.

3.3.3. Sensitivity analysis

The results obtained by an MCDA are subject to the input values [109]. The selection of certain parameters of the analysis is based on a review of the literature and the Decision Makers' own experience. To mitigate the variability of results depending on the input parameters, it is common in the literature to perform sensitivity analyses [121]. In this research only the weights relative to each criterion are the input parameters. Therefore, different scenarios have been established. Within the terminology of a sensitivity analysis of an MCDA, the term scenario is used as a combination of different weights. Eight different scenarios have been considered following the methodology established by Hsing-Chen Lee and Ching-Ter Chang [108]. The first of them establishes an equal distribution of weights and the remaining seven are assigned a weight double that of the rest of the criteria. Table 5 shows the scenarios considered. The objective of this analysis is twofold: On the one hand, it aims to evaluate which is the more robust method of the two chosen; that is, the one which winning alternatives have low variability. On the other hand, it is intended to establish the most optimal set of solutions as those that have undergone the least variation.

3.4. Optimization problem definition

The MCDA analysis allows to select among all the water bodies those that are the most suitable for the incorporation of FPV within an energy community. This research proposes a methodology that goes one step further and once the optimal water bodies are selected, the optimal tilt angles that minimize the LCOE of the water bodies selected by the Decision Maker are calculated. Therefore, the objective function of the optimization problem is the average LCOE (Eq.15). The decision variable is the tilt angle, which can vary in a range of 0–90°. The constituted problem is a nonlinear problem, which is dependent on the number of selected water bodies. For an automation of this optimization process it has been decided that the GA are the most suitable due to the modeling of the decision variables in individuals and the robustness in the convergence. The genes of the individual will be the tilt angle of FPV in a water body and therefore the individual will vary in length as a function of the number of water bodies selected.

GA are algorithms widely used to solve optimization problems. GA are metaheuristic methods based on Darwin's theory of evolution. Metaheuristic methods, unlike exact methods, do not guarantee the optimal solution, but have an advantage over exact methods. In cases where for example the calculation of derivatives is very complex or even impossible, it is more useful to use GA [122]. The Mupluslambda algorithm [123] is used in this research. This algorithm consists in that the individuals λ, are created from the ancestors μ, through the genetic operators of the descendants λ.

Table 6 collects the aspects that define the GA used. There are no global hyper-parameters valid for all problems, but they have to be established for each specific problem. The parameters have been initially selected on the basis of a literature review [136] and from these, by means of a sensitivity analysis and the authors' own experience, they have been adjusted iteratively until the values shown in Table 6. Further details of the genetic algorithm and the convergence analysis that allows the selection of the hyper-parameters that define the GA (Table 6) are collected in the Appendix B.

Table 6
Parameters of the Muspluslambda genetic algorithm used.

Mupluslambda parameters		
Initial population of the algorithm	*NPOP*	1000
Number of selected individuals	*MU*	1000
Number of children in each generation	λ	1000
Crossover probability	*CXPB*	0.5
Mutation probability	*MUTPB*	0.5
Number of generations of the algorithm	*NGEN*	150
Selection		
Individuals selected for the tournament	*Toursize*	3
Crossover		
Crossover probability	*indpb*	0.3
Mutation		
Mean of normal distribution	*mu*	0
Standard deviation of normal distribution	*sigma*	5
Mutation probability	*indpb*	0.2

4. Results and discussion

4.1. Selection of water bodies. Multicriteria decision

4.1.1. Sensitivity analysis result. Validation results.

To establish the robustness of the results, many researchers perform sensitivity and validation analyses. Sensitivity analysis examines the impact of weighting each criterion by exploring a hypothetical scenario in which all criteria are assigned the same weighting and then comparing the results. Comparative validation, on the other hand, is performed by applying other MCDM methods in the process of weighting criteria or evaluating alternatives. Table 7 shows the results of the sensitivity and comparative analysis performed for the eight scenarios considered in Section 3.3.3 (Table 5), with the two MCDA selected: COPRAS and WASPAS. Table 7 shows that COPRAS presents more stable ranking than WASPAS. This trend is consistent with results from other research studies [110]. For this reason, provided the results in Table 7, COPRAS method are selected as more accurate than the WASPAS method.

4.1.2. Evaluating standards

Fig. 5 shows the complete geolocalized ranking according to the results provided by COPRAS. There is no area with a higher concentration of reservoirs with a higher degree of suitability, but rather they are evenly distributed throughout the area under study. This aspect is considered positive since it allows a greater distribution of resources and a better use of the existing electric power transmission grid. Nevertheless, the water bodies with the greatest potential are distributed in the southern half of the country. They are characterized by a higher solar potential and lower water level variation in spite of their higher degree of drought, since reservoir levels remain more stable seasonally. This is so for two main reasons. The first reason is due to capacity. In general, the reservoirs in the south have greater capacity and are framed in a climate with less rainfall, while those in the north, being smaller and with greater rainfall, suffer greater fluctuation. The other reason is due

Table 5
Criteria weights under different scenarios.

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Scenario 8
C11	0.143	0.250	0.125	0.125	0.125	0.125	0.125	0.125
C12	0.143	0.125	0.250	0.125	0.125	0.125	0.125	0.125
C21	0.143	0.125	0.125	0.250	0.125	0.125	0.125	0.125
C22	0.143	0.125	0.125	0.125	0.250	0.125	0.125	0.125
C31	0.143	0.125	0.125	0.125	0.125	0.250	0.125	0.125
C41	0.143	0.125	0.125	0.125	0.125	0.125	0.250	0.125
C51	0.143	0.125	0.125	0.125	0.125	0.125	0.125	0.250

Table 7
Sensitivity and comparative analysis results.

Ranking	1		2		3		4		5	
Scenario 1										
	Water Body	**Value**	**Water Body**	**Value**	**Water Body**	**Value**	**Water Body**	**Value**	**Water Body**	**Value**
COPRAS	Alqueva	0.0082	Alcántara II	0.0063	La Serena	0.0060	Buendía	0.0054	Alarcón	0.0050
WASPAS	La Serena	0.2502	Alqueva	0.2421	El Grado	0.2303	Santa Ana	0.2224	Nuestra Señora del Agavanzal	0.2221
Scenario 2										
	Water Body	**Value**	**Water Body**	**Value**	**Water Body**	**Value**	**Water Body**	**Value**	**Water Body**	**Value**
COPRAS	Alqueva	0.0073	Alcántara II	0.0057	La Serena	0.0054	Buendía	0.0049	Alarcón	0.0046
WASPAS	La Serena	0.2760	Alqueva	0.2692	Alcántara II	0.2519	Villar del Rey	0.2489	Vega del Jabalón	0.2482
Scenario 3										
	Water Body	**Value**	**Water Body**	**Value**	**Water Body**	**Value**	**Water Body**	**Value**	**Water Body**	**Value**
COPRAS	Alqueva	0.0136	Alcántara II	0.0099	La Serena	0.0094	Buendía	0.0083	Alarcón	0.0078
WASPAS	Alqueva	0.2743	La Serena	0.2600	Alcántara II	0.2373	Buendía	0.2210	Alarcón	0.2076
Scenario 4										
	Water Body	**Value**	**Water Body**	**Value**	**Water Body**	**Value**	**Water Body**	**Value**	**Water Body**	**Value**
COPRAS	Alqueva	0.0074	Alcántara II	0.0057	La Serena	0.0055	Buendía	0.0049	Alarcón	0.0046
WASPAS	La Serena	0.2761	Alqueva	0.2692	Alcántara II	0.2519	Villar del Rey	0.2489	Vega del Jabalón	0.2482
Scenario 5										
	Water Body	**Value**	**Water Body**	**Value**	**Water Body**	**Value**	**Water Body**	**Value**	**Water Body**	**Value**
COPRAS	Alqueva	0.0072	Alcántara II	0.0058	La Serena	0.0053	Buendía	0.0048	Alarcón	0.0046
WASPAS	El Grado	0.2640	Santa Ana	0.2515	Nuestra Señora del Agavanzal	0.2472	La Serena	0.2190	Frieira	0.2143
Scenario 6										
	Water Body	**Value**	**Water Body**	**Value**	**Water Body**	**Value**	**Water Body**	**Value**	**Water Body**	**Value**
COPRAS	Alqueva	0.0073	Alcántara II	0.0057	La Serena	0.0056	Buendía	0.0049	Alarcón	0.0046
WASPAS	La Serena	0.2813	Villar del Rey	0.2520	Vega del Jabalón	0.2518	Casar de Caceres	0.2486	Montijo	0.2481
Scenario 7										
	Water Body	**Value**	**Water Body**	**Value**	**Water Body**	**Value**	**Water Body**	**Value**	**Water Body**	**Value**
COPRAS	Alqueva	0.0073	Alcántara II	0.0056	La Serena	0.0054	Buendía	0.0050	Alarcón	0.0047
WASPAS	La Serena	0.2190	Alqueva	0.2118	El Grado	0.2015	Santa Ana	0.1946	Nuestra Señora del Agavanzal	0.1944
Scenario 8										
	Water Body	**Value**	**Water Body**	**Value**	**Water Body**	**Value**	**Water Body**	**Value**	**Water Body**	**Value**
COPRAS	Alqueva	0.0072	Alcántara II	0.0056	La Serena	0.0053	Buendía	0.0048	Alarcón	0.0044
WASPAS	d'Airoto	0.2419	Superior de Rosari	0.2386	Cuenca del Peguera	0.2365	Tort de Peguera-Trulló	0.2356	Lac de Ríus	0.2342

to the orography. In the northern zone the water bodies are deeper and less extensive. This means that small variations in volume translate into large variations in level. On the contrary, in the south they are much more extensive, so the level variations are much smaller, and that is why they are more suitable for use in FPV. The total generation potential of all the masses consulted is 55.8 TWh, which represents 22.3 % of the country's annual demand in 2022, which was 250.42 TWh [83]. It can be deduced that FPV can be a very relevant technology in a territory like Spain.

Table 8 shows the main energy parameters grouped according to the MCDA results. It can be seen that installing FPV in eleven water bodies would represent about 32 % of the total installed power. This shows that, with the methodology followed, those water bodies where the impact of the investment is greater are obtained, making it very interesting in the early stages of implementation of the technology in a new region.

Fig. 6 shows the average LCOE by administrative regions in Spain for different tilt angles and for the water bodies that are included and not in the Draft Royal Decree. It can be seen that not all administrative regions in Spain have water bodies included in the draft Royal Decree. This is the case of "Principado de Asturias", "Pais Vasco", "La Rioja" and "Islas Baleares". These administrative regions have a LCOE above the average, so they are not regions with a high priority for the implementation of FPV compared to other regions, such as "Andalucia", "Extremadura", "Castilla La-Mancha" or "Region de Murcia", which have LCOE below the country's average. The region of Madrid stands out, as it does not have installed renewable energy power, and with the implementation of FPV it could increase its independence and the overall efficiency of transport, since it would take advantage of the resources of the area, reducing transport losses. As a general rule, the water bodies included in the FPV Draft Royal Decree offer lower average LCOE than those not included, so that in the first phase of implementation of the technology the results indicate that it is best to adhere to the proposed legislation.

Fig. 7 shows the LCOE for each climate zone defined in Spain. This analysis is relevant since the Spanish legislation on solar energy is based on these climate zones. In addition, the consumption habits vary from one to another to adapt to the climatic difference. In this case, it is observed that climate zone III does not include any water body in the FPV Draft Royal Decree. Comparing between climate zones, it is observed that considering only the water bodies that are included in the FPV Draft Royal Decree, the LCOE remains practically constant, which indicates that the selection of water bodies has been done in a correct way. On the other hand, considering the water bodies not included in climatic zone I, a very high LCOE above the whole country is observed, which suggests that it is not a good investment from a purely economic point of view to consider these water bodies in the first stages of the

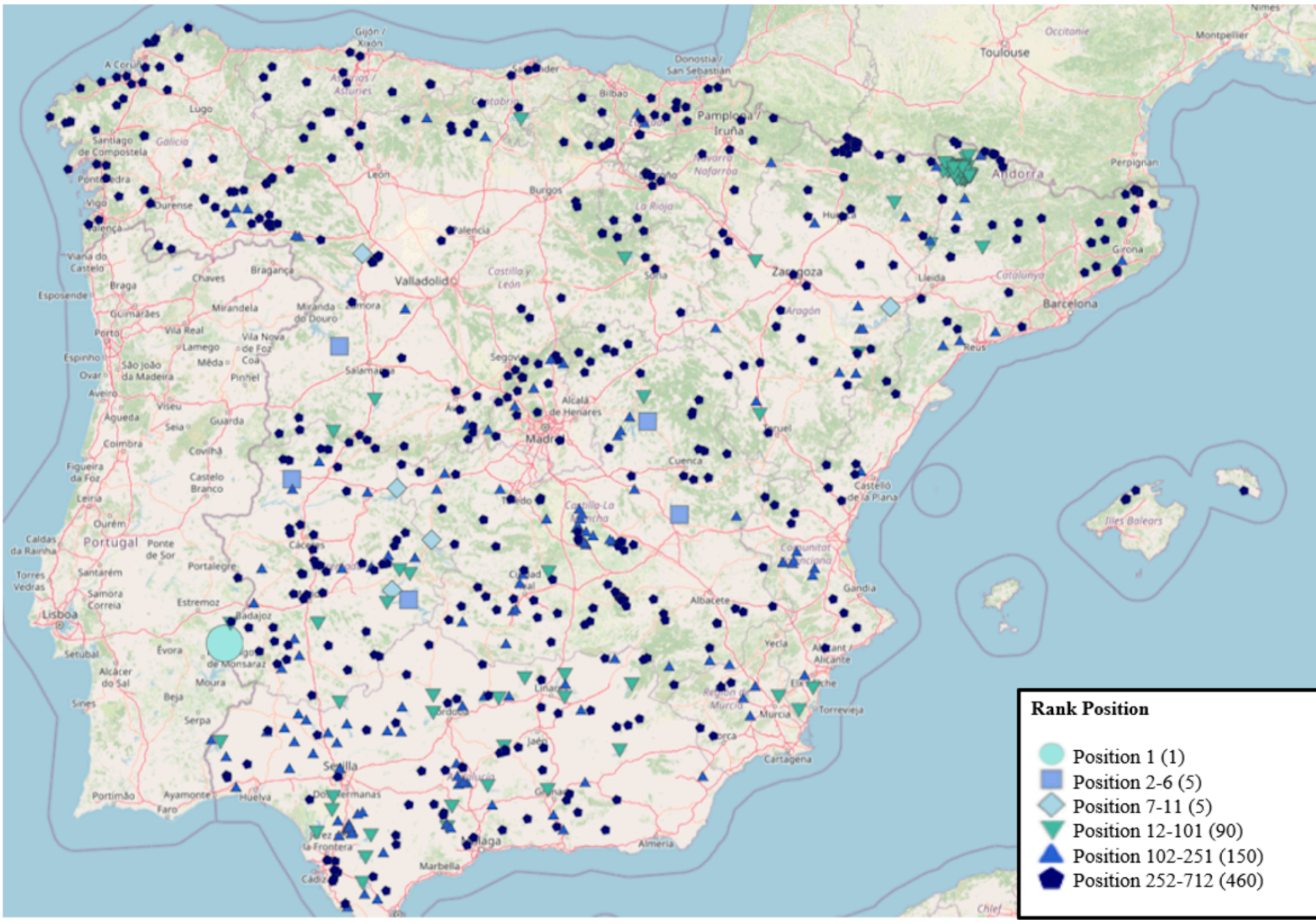

Fig. 5. MCDA results. Water Bodies Rank Position.

Table 8
Water Bodies MCDA results. Energy parameters.

	Legend	Installed Capacity [GW]	Energy Potential [TWh]	Average LCOE [€/MWh]	Average CF [%]
Position 1		1.68	2.12	45.33	14.41
Position 2–6 (5)		6.10	7.87	44.77	14.60
Position 7–11 (5)		3.78	4.65	46.64	14.03
Position 12–101 (90)		8.89	11.00	57.86	11.89
Position 102–251 (150)		8.58	10.62	46.13	14.34
Position 252–712 (460)		7.54	8.32	54.57	12.56
Overall	–	35.71	43.53	53.07	12.88

implementation of the technology. There is also a difference between the angles: it is observed as a general trend that in climate zones IV and V, where solar radiation is higher, the angles that optimize the LCOE are slightly lower than those of climate zones I and II.

4.1.3. Optimal location result. Water bodies selected

Finally, it was decided to select the Top 5 water bodies to undergo the optimization process to obtain the tilt angle that minimizes the LCOE of the set. Although only the five most suitable water bodies have been selected to show these results and to highlight the value of the established methodology, it can be applied to all water bodies. Thus, the methodology is applicable locally or regionally, depending on the data available and the objective of the analysis. Table 9 shows the water bodies selected as further case study.

The location of the Top-5 water bodies is in the regions of "Extremadura" and "Castilla-La Mancha", belonging to climate zones IV and V with the highest generation potential. These regions have the lowest energy consumption in Spain (4.85 TWh and 11.71 TWh, respectively) [124] and therefore, with the use of the mentioned water bodies, they could increase renewable energy generation and practically cover their total energy consumption with this technology. It should be noted that only "La Serena" is mentioned in the draft Royal Decree. The Alqueva reservoir stands out, which despite the result obtained, is not included in the draft of the Royal Decree. It is considered that this is due to the fact that only 10 % of its surface area belongs to Spanish territory and it shares ownership with Portugal. For this reason, it is considered that it has not been included in the draft of the current Royal Decree. The research carried out shows the importance of this body of water, which must be considered in future developments of the regulations. It is considered that the location is not a barrier, since the electricity market in Spain and Portugal is the same, and the Alqueva reservoir is included in the Spanish databases. The selection shown in Table 9 is an indication that the water bodies included in the Draft Royal Decree have not been evaluated from a multi-criteria perspective. Therefore the inclusion of these water bodies would introduce a substantial improvement to the generation potential of these regions in particular and of the country in general.

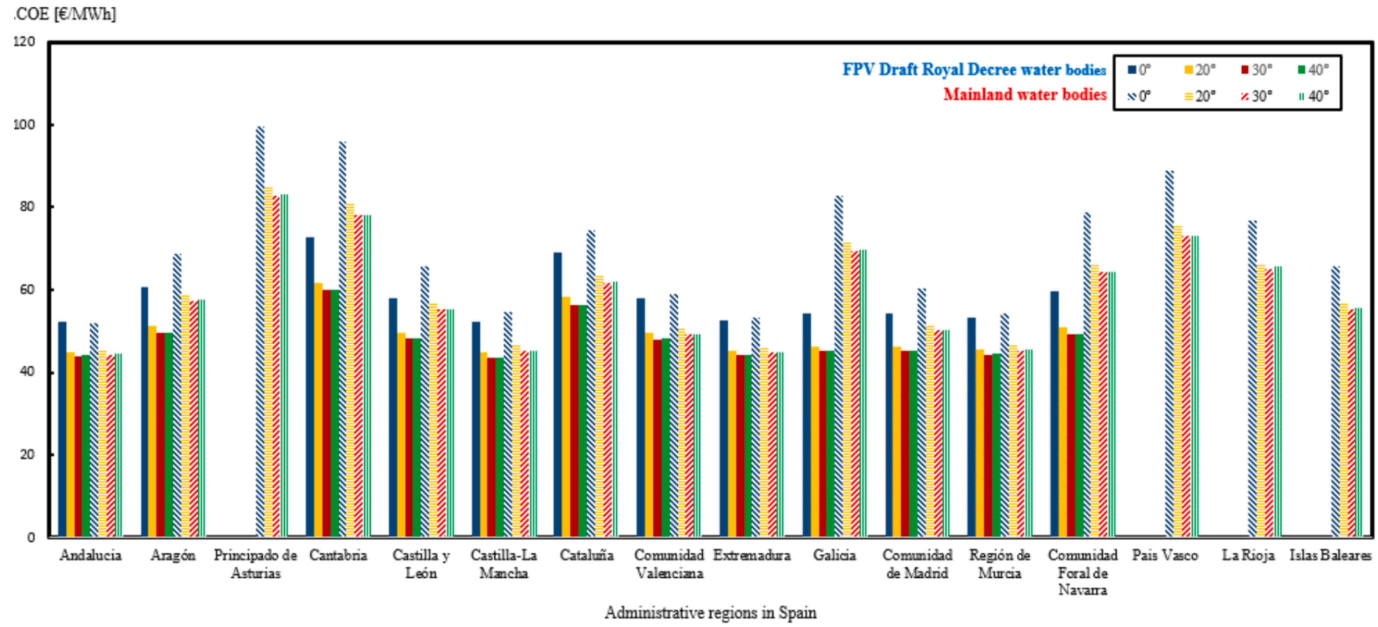

Fig. 6. Water bodies LCOE by administrative regions in Spain.

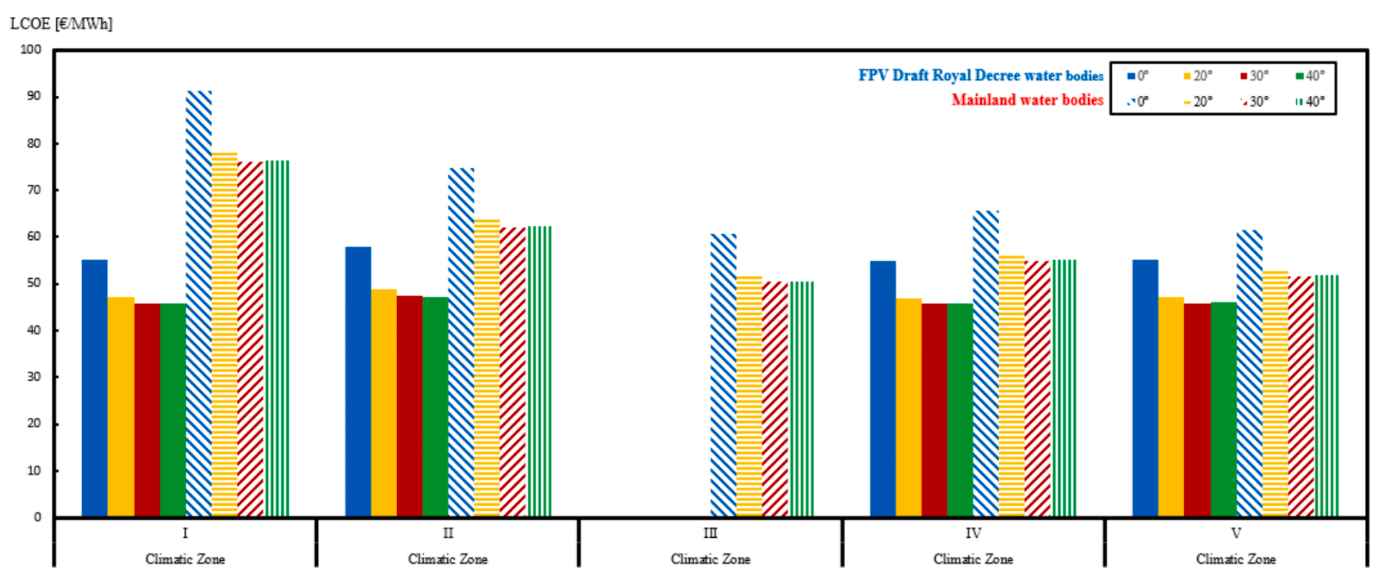

Fig. 7. Water bodies LCOE by climate zones in Spain.

Table 9
Water Bodies Selected.

Water Body	Latitude [°]	Longitude [°]	Total Superface [ha]	Coverage Porcentaje [%]	Climatic Zone	Region	Position Ranking	Draft Royal Decrete Included
Alqueva	38.7410	−7.2252	14,478	10	V	Extremadura	1	No
Alcántara II	39.9711	−6.5445	10,091	10	V	Extremadura	2	No
La Serena	38.9280	−5.2330	9595	20	V	Estremadura	3	Yes
Buendía	40.4667	−2.5548	8432	10	IV	Castilla-La Mancha	4	No
Alarcón	39.6668	−2.2002	7968	10	IV	Castilla- La Mancha	5	No

4.2. Tilt angle optimization result

Table 10 shows the optimal tilt angle for each of the five selected case study water bodies, obtained by the present investigation and the most common methods found in the ground-PV literature [81]:

- Method 1 (M1):.$\beta_{opt} = |\phi|$
- Method 2 (M2):.$\beta_{opt} = |\phi| - 10$

Table 10
Optimal tilt angle obtained by different methods.

Water Body	Current research [°]	M1 [°]	M2 [°]	M3 [°]	M4 [°]	M5 [°]	M6 [°]
Alqueva	30.00	38.55	28.55	30.30	37.19	34.00	33.00
Alcántara II	30.00	39.97	29.97	31.28	38.18	34.00	33.00
La Serena	30.00	38.92	28.92	30.56	37.46	34.00	33.00
Buendía	34.99	40.47	30.47	31.62	38.52	34.00	35.00
Alarcón	35.00	39.67	29.67	31.07	37.97	34.00	35.00

- Method 3 (M3):.$\beta_{opt} = 3.7 + 0.69 \bullet |\phi|$
- Method 4 (M4):.$\beta_{opt} = 3.7 + 0.69 \bullet |\phi + 10|$
- Method 5 (M5):.$\beta_{opt} = 34$
- Method 6 (M6):.$\beta_{opt} = \beta_{opt,PVGIS}$

The result obtained in the current research are obtained through the application of the last step of the methodology defined in Fig. 2 to the water bodies shown in Table 9. Traditional methods offer a series of rapid design methodologies pursuing only energy criteria and based on a single parameter, such as the latitude of the location. The tilt-angle selection process did not take into account possible effects on energy production, such as temperature. The proposed optimization method takes into account different climatic variables, such as temperature, wind and the cooling effect of the reservoir water within the optimization process itself, so that the obtained tilt-angle maximizes profitability. Fig. 8 shows that the tilt-angle obtained by the present investigation improves in the different key performance indicators compared to traditional methodologies.

Fig. 8a) shows the average LCOE for the set of water bodies with the tilt angles shown in Table 10. The LCOE improvements obtained by the presented framework are in the range of 2.1 and 8.4 %. Fig. 8b) shows the total annual energy produced and the improvements obtained range from 0.65 % to 9.98 %. Fig. 8c) shows the CF with improvements between 3.53 % and 8.33 %. Finally, Fig. 8d) shows the GHG emissions avoided within a range of 0.66 % and 10.3 %. It is shown that the decision methods employed in ground-PV are not accurate enough for FPV. This is because they do not incorporate the differentiating features of FPV, such as the cooling effect of water. It is therefore demonstrated that the correlations used in on ground-PV are not directly applicable to FPV and further research, such as the one carried out, is required to establish new standards. On the other hand, it should be noted that M2 is the method that obtains the best results and that for a quick pre-dimensioning it can be used to obtain, for example, how many panels fit on a given surface.

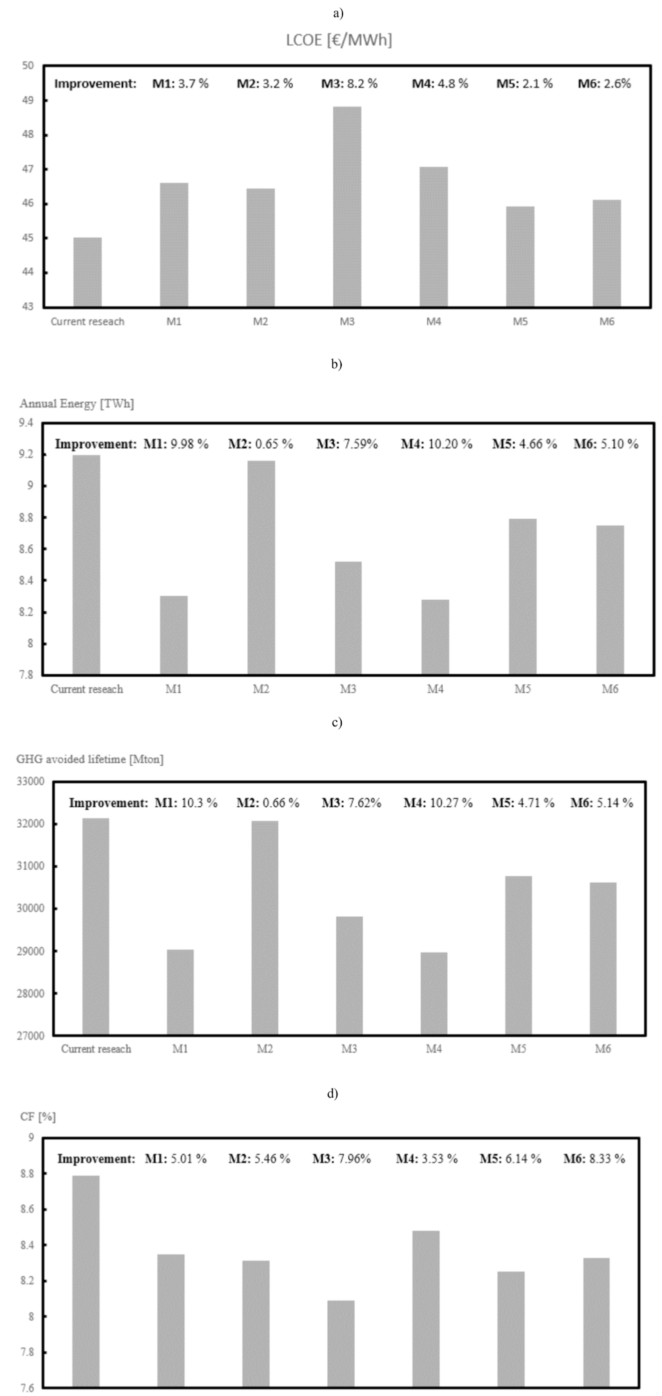

Fig. 8. Key performance indicators for different methods. (a) Average LCOE [€/MWh], (b) Total annual energy [TWh], (c) Average CF [%], (d) GHG avoided lifetime [ton].

5. Conclusions

FPV is recently generating interest due to the advantages it has over on-ground PV. On the one hand, it offers better performance and higher production due to the cooling effect of the reservoir water. On the other hand, it does not compete in land use with other applications, such as agriculture, so socially it can be very well accepted. Nevertheless, due to the lack of many previous experiences, it faces a series of challenges in order to be implemented on a commercial scale. One of these challenges is the selection of the most suitable water bodies and the selection of design parameters, such as the tilt angle. The literature has shown that there is no specific software capable of integrating the differentiating characteristics of FPV. This research proposes a framework capable of filling this gap.

The presented framework has three differentiating features. The first one is that the integration of multi-source and multi-resolution geo-localized data is performed in a javascript and python-based Web-GIS environment. This differential aspect allows a great diffusion and adaptability to different environments and data sources, as well as a wider scope of the results. The second is the use of integrated geolocated data for the selection of the most suitable water bodies from a multi-criteria perspective: technical, economic, environmental, legislative, and social. The MCDA used was COPRAS, which has proved to be the one that offers the most stable results. To demonstrate the applicability of the framework, Spain was used as a case study, as it is a region with a homogeneous distribution of water and high solar potential, making it an ideal place to exploit the full potential of FPV. The case of Spain, as in many other regions, does not have specific regulations for FPV, so the conclusions drawn from the analysis are very useful for designers, project developers and governments. It has been observed that the FPV Draft Royal Decree is very conservative since it includes a reduced number of water bodies with respect to the total public use. Also, the distribution of water bodies is not uniform in all the administrative regions of Spain, since there are certain regions that do not have water bodies included in the Draft Royal Decree. Nevertheless, it is observed that the water bodies included in the proposal offer better economic results, with an average LCOE of about 45 €/MWh, while those that are not included offer an LCOE higher than 60 €/MWh. For this reason, it is considered that the proposed standard is a good starting point, but that as the technology is implemented it is necessary to review and expand it from a multi-criteria perspective as proposed in this research.

Finally, it is observed that there is no parameter selection criterion, such as the tilt angle that, helps designers to make decisions that maximize the profitability of the installation as it occurs in PV. Therefore, the third part of the framework includes an intelligent optimization based on GA, in which the tilt angle that minimizes the LCOE of different selected water bodies is obtained. The five water bodies with the highest-ranking scores have been used as a case study, but it is applicable to any other number of water bodies. The result obtained has been compared with six of the widely accepted criteria in on-ground PV to establish the tilt angle. The results obtained with the methodology proposed in this research offer significant improvements in all the key parameters evaluated. For example, in the case of LCOE the improvements are between 2.1 % and 8.4 %, or in the case of GHG avoided the improvements are between 0.66 % and 10.3 %.

In short, this research proposes a novel framework applied to FPV based on MCDA and intelligent optimization techniques, capable of integrating geolocated data from different sources and resolutions in a Web-GIS environment. The applicability and potential of the framework has been demonstrated and validated through the application of a case study such as Spain. The framework has allowed an analysis of the potential application of FPV in the region, as well as a critical analysis of the current standards and their comparison with on-ground PV standards. The extrapolation of PV standards to FPV has been deepened, showing that it is not enough and that FPV requires specific analysis, methodologies, and calculation software. The advantage of the proposed framework is that it easily adapts to new requirements and evaluation criteria, so that as the technology is implemented and developed. One of the limitations of the framework is that it does not consider the loss of energy production due to soiling. The effect of soiling production loss in FPV is not adequately addressed in the literature, so future work should aim to include this effect when going deeper into the literature. Another limitation is that the optimization has only one objective, which is to minimize the LCOE, which is the most common strategy when applying metaheuristic algorithms in PV. In future research, it is intended to perform a multi-objective optimization with multi-objective algorithms such as NSGA-II, to take into account two conflicting parameters, such as minimizing LCEO and maximizing GHG emission avoided.

CRediT authorship contribution statement

Néstor Velaz-Acera: Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Gustavo Hernández-Herráez:** Software, Data curation. **Jorge López-Rebollo:** Writing – review & editing, Funding acquisition, Conceptualization. **Julián Gónzalez-Ayala:** Conceptualization. **David J. Yáñez- Villareal:** Project administration, Funding acquisition, Conceptualization. **Susana Lagüela:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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Appendix A. Multicriteria decision method

This appendix is included to facilitate the reader’s mathematical understanding of the two Multicriteria Decision methods used in this research. The methods used here have been programmed in Python directly by the authors, avoiding the use of open repositories, such as [125] and [126], to ensure a correct understanding and validity of the results obtained.

Both methods have the same input information: The matrix of alternatives and attributes X which is defined by Eq. (A1) and the matrix of weights for each attribute (ω) as defined in Eq. (A2).

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix} \rightarrow i = 1, 2, \cdots, m; j = 1, 2, \cdots, n \tag{A1}$$

$$\omega = [\omega_1, \omega_2, \cdots, \omega_n] \tag{A2}$$

Where n is the number of attribute/criteria and m is the number of alternatives. In this research, n is equal to seven criteria and m is equal to 712 water bodies.

A.1. COPRAS method

The COPRAS procedure consist of [127]:

- Calculating the normalized decision matrix:

Eq. (A3) is used to normalize matrix X. The COPRAS method normalizes the decision matrix with the sum total of each criterion. This is one of the differences with respect to the WASPAS method.

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \rightarrow j = 1,\ 2,\ \cdots,\ n \tag{A3}$$

- Calculating the weighted normalized decision matrix:

Eq. (A4) is used to obtain the weighted normalized decision matrix.

$$\widehat{r}_{ij} = r_{ij} \bullet \omega_j \rightarrow i = 1, 2, \cdots, m; j = 1, 2, \cdots, n \tag{A4}$$

- Calculating maximizing, S^{+i}, and minimizing, S^{-i}, indexes:

Eq. (A5) and Eq. (A6) are used to obtain the maximizing and minimizing indexes.

$$S^{+i} = \sum_{j=1}^{g} \widehat{r}_{ij} \rightarrow i = 1, 2, \cdots, m \tag{A5}$$

$$S^{-i} = \sum_{j=g+1}^{n} \widehat{r}_{ij} \rightarrow i = 1, 2, \cdots, m \tag{A6}$$

Where g is the number of positive attributes and n-g is the number of negative attributes.

- Calculating the relative significance value:

Eq. (A7) represent the relative significance value of each alternative.

$$Q_i = S^{+i} + \frac{\sum_{i=1}^{m} S^{-i}}{S^{-i} \sum_{i=1}^{m} \frac{1}{S^{-i}}} \tag{A7}$$

- Final Ranking alternatives:

Eq. (A8) ranks in descending order from the highest to the least relative significance value of the solution alternative.

$$A^* = \left[A_i | \max_i Q_i \right] \tag{A8}$$

A.2. WASPAS method

The WASPAS procedure consist of [119]:

- Calculating the normalized decision matrix:

Eq. (A9) is used to normalize the positives criteria with the maximum value of each attribute of the matrix X, while Eq. (A10) is used to normalize the negative criteria using the minimum value of each attribute of the X matrix. In this way, the R normalized matrix is obtained.

$$r_{ij} = \frac{x_{ij}}{\max x_{ij}} \rightarrow i = 1, 2, \cdots, m; j = 1, 2, \cdots, n \tag{A9}$$

$$r_{ij} = \frac{\min x_{ij}}{x_{ij}} \rightarrow i = 1,\ 2,\ \cdots,\ m\ ; j = 1,\ 2,\ \cdots,\ n \tag{A10}$$

- Calculating the additive relative importance:

Eq. (A11) is used to calculate the additive relative importance in the weighted normalized matrix of each alternative.

$$Q_i^{(1)} = \sum_{j=1}^{n} r_{ij} \bullet \omega_j \rightarrow j = 1, 2, \cdots, n \tag{A11}$$

- Calculating the multiplicative relative importance:

Eq. (A12) is used to calculate the multiplicative relative importance in the weighted normalized matrix of each alternative.

$$Q_i^{(2)} = \prod_{j=1}^{n} r_{ij}^{\omega_j} \rightarrow j = 1, 2, \cdots, n \tag{A12}$$

- Calculating the joint generalized criterion:

Eq. (A13) is used to integrate additive and multiplicative methods:

$$Q_i = \lambda \bullet Q_i^{(1)} + (1-\lambda) \bullet Q_i^{(2)} \rightarrow i = 1, 2, \cdots, m;\ \lambda \in [0,1] \tag{A13}$$

Where λ is a user defined parameter to increase the ranking accuracy.

- Final Ranking alternatives:

Eq. (A14) ranks in descending order to from the highest to the least relative significance value of the solution alternatives.

$$A^* = \left[A_i \,|\, \max_i Q_i \right] \tag{A14}$$

Appendix B. . Genetic algorithm. Convergence analysis

Genetic Algorithms (GA) are meta-heuristic intelligence optimization algorithms that have been widely used for solving complex engineering problems. GAs are based on the Darwinian theory of biological evolution. The basic idea is to have a set of potential solutions, that is called the population, which evolves over a number of generations by using genetic operators, such as selection, crossover, and mutation. The potential solutions encode in a chromosome-like structure the design variables. This structure is called an individual, and each design variable represents a gene. This research is an optimization of different tilt angle panel in different water body's locations. Therefore, the coding of the problem will depend on the number of water bodies selected by the Decision Maker, which can be from one gen, up to the maximum number of water bodies collected in the dataset.

In this situation, the search for hyper-parameters valid for all the cases considered is pursued. With this objective in mind, in order to ensure correct convergence and obtain an optimal result, two sensitivity analyses have been carried out. On the one hand, a sensitivity analysis of the crossover and mutation hyper-parameters, which are the basis of the operation of the GA. On the other hand, a sensitivity analysis of the population size and the number of generations to ensure sufficient exploitation and exploration. With both analyses, it is considered that the solution obtained is the optimal for the problem.

B.1. Adjusting hyper-parameters: Genetic operators

Genetic operators are of three types: crossover, mutation, and selection. The crossover operation is a probabilistic operation that allows two randomly selected individuals to exchange their genetic information to create new individuals. There are different types of crossover operators; in this case, due to the nature of the problem, the "one-point crossover" has been used, which consists of exchanging the genetic information of the parents [128]. For the mutation operation, the "Gaussian mutation" has been used. This mutation operator consists of mutating with a probability each of the genes that make up the individual, adding a certain random amount to each gene [129]. This random quantity is defined with a Gaussian probability function of fixed mean and standard deviation. Finally, the selection mechanism used is the tournament. The tournament consists of choosing a certain number of individuals from the last generation of the algorithm and comparing their fitness values, in order to choose, in a minimization problem, the one with the lowest fitness value [130]. In the research carried out, the tournament size is three. Fig. B1 shows a generic application of these genetic operators.

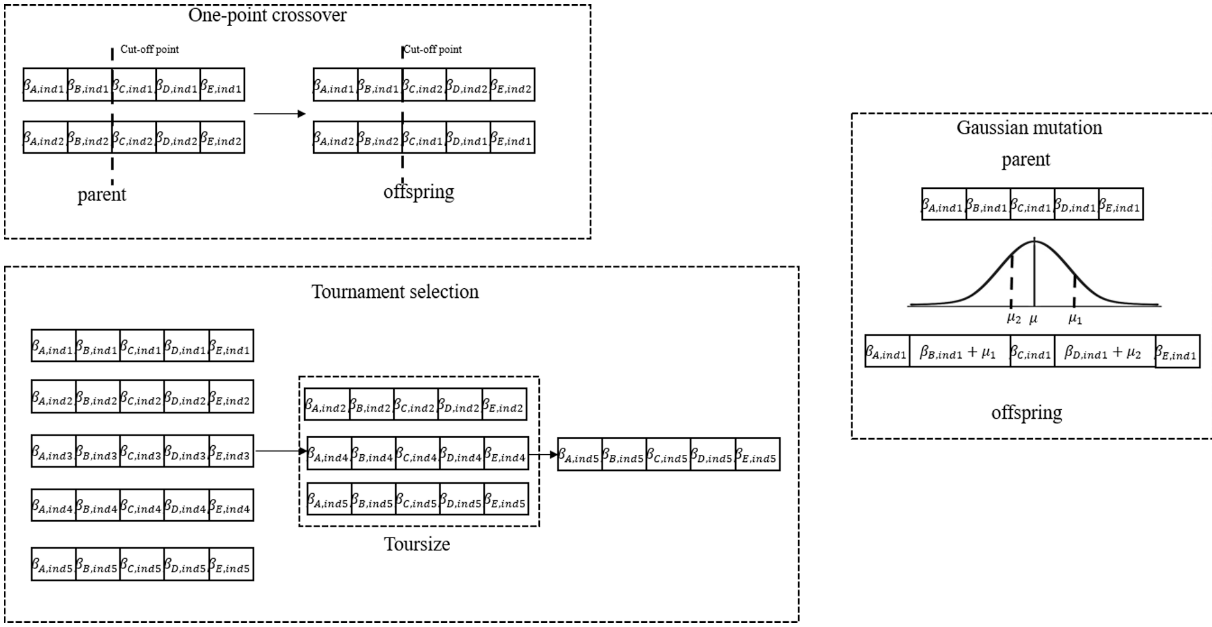

Fig. B1. Diagram of the crossover, mutation and selection models used.

There are not global parameters valid for all problems, but they must be established for each specific problem. The parameters have been initially selected on the basis of a literature review [131] and from these, by means of a sensitivity analysis and the experimental experience, they have been adjusted iteratively until the values shown in Table 6 have been reached. With these parameters set, a sensitivity analysis was performed to determine the probabilities of crossover and mutation occurring. This was done by varying the coefficients CXPB (Crossover Probability) and MUTB (Mutation Probability). The sum of these coefficients must always be 1 (Eq (B1)).

$$CXPB + MUTPB = 1 \tag{B1}$$

The algorithm has been run five times, among which the average of the five simulations has been considered as the final value. In order to be able to analyze the evolution in the variation of the absolute error, the absolute error has been calculated.

Fig. B2 compiles the absolute errors for each CXPB and MUTB combination. As can be seen, the absolute error in general terms decreases until it reaches 0.3 and 0.7 (CXPB and MUTB respectively), and then increases. Therefore, these values have been selected for all simulations. Despite this, the influence of these coefficients in this case is minimal since the values of population and number of generations were high (1000 and 150 respectively) and the algorithm has already converged.

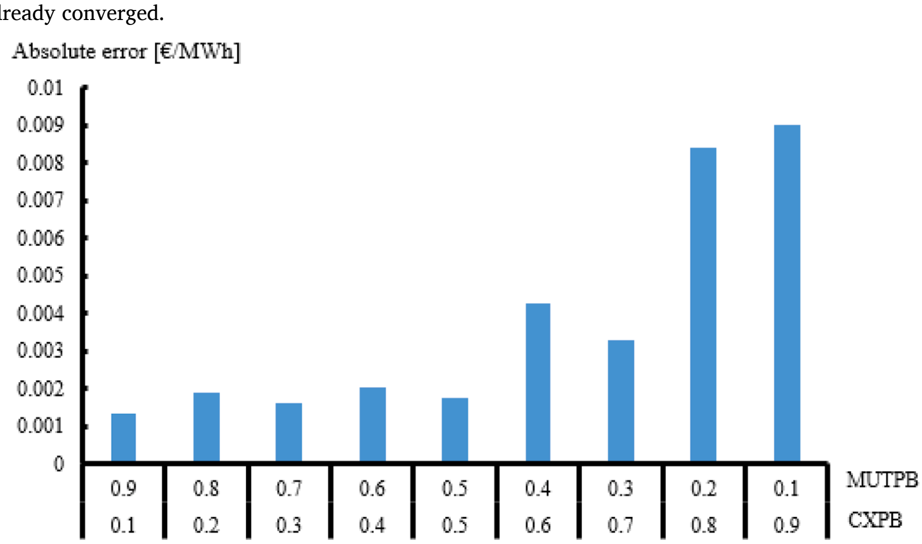

Fig. B2. Absolute error.

B.2. Adjusting of population size and number of generations

The next step, to ensure convergence, is to verify that population values (NPOP, MU and λ) and the number of generations (NGEN) (shown in Table 6) are sufficiently large to ensure correct convergence and not to obtain a local minimum. For this purpose, another sensitivity study has been carried out, where these two values are varied and the absolute error is analyzed, in a similar way to the previous analysis.

Fig. B3 shows the evolution of the fitness value for different population sizes and number of generations. As can be seen from 150 and 400 (NGEN, NPOP, respectively), the convergence is clear. Nevertheless, as the calculation time was limited (around 20 min), it was decided to set the values at 150 and 1000 (NGEN and NPOP, respectively) with an approximate calculation time of 30–35 min to better ensure convergence. The values for the number of offspring in each generation (λ) and the number of individuals selected in the offspring (MU) were kept equal to the number of individuals in each generation, so that the population size remained constant.

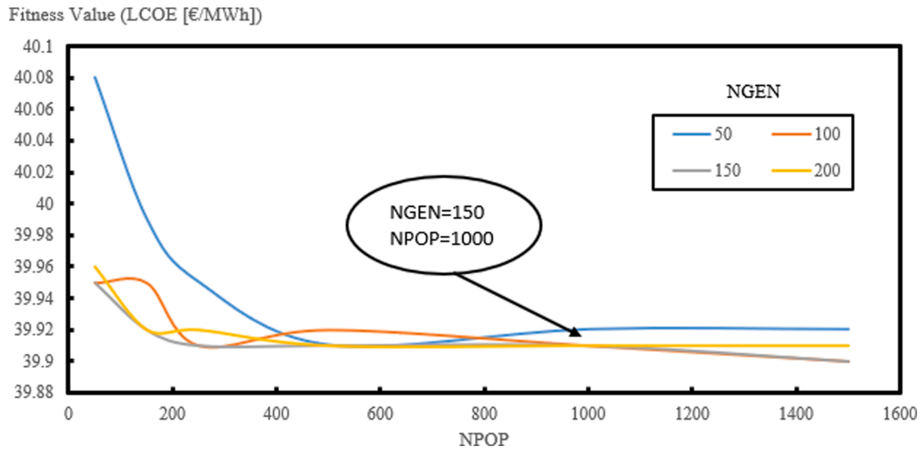

Fig. B3. Convergence analysis.

References

[1] Papadis E, Tsatsaronis G. Challenges in the decarbonization of the energy sector. Energy Aug. 2020;205:118025. https://doi.org/10.1016/j.energy.2020.118025.

[2] Lenferna GA. Can we equitably manage the end of the fossil fuel era? Energy Res Soc Sci Jan. 2018;35:217–23. https://doi.org/10.1016/j.erss.2017.11.007.

[3] Laes E, Bombaerts G. Energy Communities and the Tensions Between Neoliberalism and Communitarianism. Sci Eng Ethics Jan. 2022;28(1):3. https://doi.org/10.1007/s11948-021-00359-w.

[4] Pedersen TT, Gøtske EK, Dvorak A, Andresen GB, Victoria M. Long-term implications of reduced gas imports on the decarbonization of the European energy system. Joule Jul. 2022;6(7):1566–80. https://doi.org/10.1016/j.joule.2022.06.023.

[5] Bórawski P, Holden L, Bełdycka-Bórawska A. Perspectives of photovoltaic energy market development in the european union. Energy May 2023;270:126804. https://doi.org/10.1016/j.energy.2023.126804.

[6] O'Shaughnessy E. Rooftop solar deployment, what's next? Energy Mar. 2023;1(1):100002. https://doi.org/10.1016/j.nxener.2023.100002.

[7] Pourasl HH, Barenji RV, Khojastehnezhad VM. Solar energy status in the world: A comprehensive review. Energy Rep Nov. 2023;10:3474–93. https://doi.org/10.1016/j.egyr.2023.10.022.

[8] Qazi S. Chapter 2 - Fundamentals of Standalone Photovoltaic Systems. In: Qazi S, editor. Standalone Photovoltaic (PV) Systems for Disaster Relief and Remote Areas. Elsevier; 2017. p. 31–82. https://doi.org/10.1016/B978-0-12-803022-6.00002-2.

[9] Neves D, Baptista P, Rosa P. Solar Energy Communities: An open data and georeferenced based modelling framework to pre-assess deployment potential at urban level. Energy Nov. 2023;282:128838. https://doi.org/10.1016/j.energy.2023.128838.

[10] Scovell M, McCrea R, Walton A, Poruschi L. Local acceptance of solar farms: The impact of energy narratives. Renew Sustain Energy Rev Jan. 2024;189:114029. https://doi.org/10.1016/j.rser.2023.114029.

[11] Madsen DN, Hansen JP. Outlook of solar energy in Europe based on economic growth characteristics. Renew Sustain Energy Rev Oct. 2019;114:109306. https://doi.org/10.1016/j.rser.2019.109306.

[12] Hermoso V, Bota G, Brotons L, Morán-Ordóñez A. Addressing the challenge of photovoltaic growth: Integrating multiple objectives towards sustainable green energy development. Land Use Policy May 2023;128:106592. https://doi.org/10.1016/j.landusepol.2023.106592.

[13] Verma S, Mohapatra S, Chowdhury S, Dwivedi G. Cooling techniques of the PV module: A review. Mater Today Proc Jan. 2021;38:253–8. https://doi.org/10.1016/j.matpr.2020.07.130.

[14] Hachicha AA, Al-Sawafta I, Said Z. Impact of dust on the performance of solar photovoltaic (PV) systems under United Arab Emirates weather conditions. Renew Energy Oct. 2019;141:287–97. https://doi.org/10.1016/j.renene.2019.04.004.

[15] Nisar H, Kashif Janjua A, Hafeez H, Shakir S, Shahzad N, Waqas A. Thermal and electrical performance of solar floating PV system compared to on-ground PV system-an experimental investigation. Sol Energy Jul. 2022;241:231–47. https://doi.org/10.1016/j.solener.2022.05.062.

[16] Golroodbari S, van Sark W. On the effect of dynamic albedo on performance modelling of offshore floating photovoltaic systems. Sol Energy Adv Jan. 2022;2:100016. https://doi.org/10.1016/j.seja.2022.100016.

[17] Manolache AI, Andrei G, Rusu L. An evaluation of the efficiency of the floating solar panels in the western black sea and the Razim-Sinoe Lagunar system. J Mar Sci Eng 2023;11(1). https://doi.org/10.3390/jmse11010203.

[18] Li W, Wang Y, Wang G, Liang Y, Li C, Svenning J-C. How do rotifer communities respond to floating photovoltaic systems in the subsidence wetlands created by underground coal mining in China? J Environ Manage Aug. 2023;339:117816. https://doi.org/10.1016/j.jenvman.2023.117816.

[19] Oliveira-Pinto S, Stokkermans J. Assessment of the potential of different floating solar technologies – Overview and analysis of different case studies. Energy Convers Manag May 2020;211:112747. https://doi.org/10.1016/j.enconman.2020.112747.

[20] Ikhennicheu M, Danglade B, Pascal R, Arramounet V, Trébaol Q, Gorintin F. Analytical method for loads determination on floating solar farms in three typical environments. Sol Energy May 2021;219:34–41. https://doi.org/10.1016/j.solener.2020.11.078.

[21] Rosa-Clot M, Tina GM. In: Chapter 10 - Levelized Cost of Energy (LCOE) Analysis. Academic Press; 2020. p. 119–27. https://doi.org/10.1016/B978-0-12-817061-8.00010-5.

[22] Martinez A, Iglesias G. Site selection of floating offshore wind through the levelised cost of energy: A case study in Ireland. Energy Convers Manag Aug. 2022;266:115802. https://doi.org/10.1016/j.enconman.2022.115802.

[23] Idel R. Levelized full system costs of electricity. Energy Nov. 2022;259:124905. https://doi.org/10.1016/j.energy.2022.124905.

[24] Jain A, Yamujala S, Gaur A, Das P, Bhakar R, Mathur J. Power sector decarbonization planning considering renewable resource variability and system operational constraints. Appl Energy Feb. 2023;331:120404. https://doi.org/10.1016/j.apenergy.2022.120404.

[25] Micheli L, Talavera DL. Economic feasibility of floating photovoltaic power plants: Profitability and competitiveness. Renew Energy Jul. 2023;211:607–16. https://doi.org/10.1016/j.renene.2023.05.011.

[26] Cromratie Clemons SK, Salloum CR, Herdegen KG, Kamens RM, Gheewala SH. Life cycle assessment of a floating photovoltaic system and feasibility for application in Thailand. Renew Energy May 2021;168:448–62. https://doi.org/10.1016/j.renene.2020.12.082.

[27] Bax V, van de Lageweg WI, van den Berg B, Hoosemans R, Terpstra T. Will it float? Exploring the social feasibility of floating solar energy infrastructure in the Netherlands. Energy Res Soc Sci Jul. 2022;89:102569. https://doi.org/10.1016/j.erss.2022.102569.

[28] Díaz H, Soares CG. A multi-criteria approach to evaluate floating offshore wind farms siting in the canary Islands (Spain). Energies 2021;14(4). https://doi.org/10.3390/en14040865.

[29] Codemo A, Barbini A, Mantouza A, Bitziadis A, Albatici R. Integration of public perception in the assessment of licensed solar farms: a case study in Greece. Sustainability 2023;15(13). https://doi.org/10.3390/su15139899.

[30] Kozlov V, Sałabun W. Challenges in reliable solar panel selection using MCDA methods. Procedia Comput Sci Jan. 2021;192:4913–23. https://doi.org/10.1016/j.procs.2021.09.269.

[31] López M, Soto F, Hernández ZA. Assessment of the potential of floating solar photovoltaic panels in bodies of water in mainland Spain. J Clean Prod Mar. 2022;340:130752. https://doi.org/10.1016/j.jclepro.2022.130752.

[32] Essak L, Ghosh A. Floating photovoltaics: a review. Clean Technol 2022;4(3). https://doi.org/10.3390/cleantechnol4030046.

[33] Di Grazia S, Tina GM. Optimal site selection for floating photovoltaic systems based on Geographic Information Systems (GIS) and Multi-Criteria Decision Analysis (MCDA): a case study. Int J Sustain Energy 2023:1–23. https://doi.org/10.1080/14786451.2023.2167999.

[34] Khan AY, Ahmad Z, Sultan T, Alshahrani S, Hayat K, Imran M. Optimization of photovoltaic panel array configurations to reduce lift force using Genetic Algorithm and CFD. Energies 2022;15(24). https://doi.org/10.3390/en15249580.

[35] Osmani K, Ramadan M, Lemenand T, Castanier B, Haddad A. Optimization of PV array tilt angle for minimum levelized cost of energy. Comput Electr Eng Dec. 2021;96:107474. https://doi.org/10.1016/j.compeleceng.2021.107474.

[36] Maraj A, Kërtusha X, Lushnjari A. Energy performance evaluation for a floating photovoltaic system located on the reservoir of a hydro power plant under the mediterranean climate conditions during a sunny day and a cloudy-one. Energy Convers Manag X Dec. 2022;16:100275. https://doi.org/10.1016/j.ecmx.2022.100275.

[37] Seppälä J, Basson L, Norris GA. Decision Analysis Frameworks for Life-Cycle Impact Assessment. J Ind Ecol 2001;5(4):45–68. https://doi.org/10.1162/10881980160084033.

[38] Hwang C-L, Yoon K. "Methods for Multiple Attribute Decision Making", in Multiple Attribute Decision Making: Methods and Applications A State-of-the-Art Survey. In: Hwang C–L, Yoon K, editors. Lecture Notes in Economics and Mathematical Systems. Berlin, Heidelberg: Springer; 1981. p. 58–191. https://doi.org/10.1007/978-3-642-48318-9_3.

[39] Harsanyi JC. Cardinal Welfare, Individualistic Ethics, and Interpersonal Comparisons of Utility. J Polit Econ Aug. 1955;63(4):309–21. https://doi.org/10.1086/257678.

[40] Zagorskas J, Burinskienė M, Zavadskas E, Turskis Z. Urbanistic assessment of city compactness on the basis of GIS applying the COPRAS method. vol. 53, pp. 55–63; Feb. 2007.

[41] Opricovic S, Tzeng G-H. Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. Eur J Oper Res Jul. 2004;156(2):445–55. https://doi.org/10.1016/S0377-2217(03)00020-1.

[42] Keršuliene V, Zavadskas EK, Turskis Z. Selection of rational dispute resolution method by applying new step-wise weight assessment ratio analysis (Swara). J Bus Econ Manag Jan. 2010;11(2):243–58. https://doi.org/10.3846/jbem.2010.12.

[43] Cao Q, Esangbedo MO, Bai S, Esangbedo CO. Grey SWARA-FUCOM weighting method for contractor selection MCDM problem: a case study of floating solar panel energy system installation. Energies 2019;12(13). https://doi.org/10.3390/en12132481.

[44] Puška A, Stević Ž, Pamučar D. Evaluation and selection of healthcare waste incinerators using extended sustainability criteria and multi-criteria analysis methods. Environ Dev Sustain 2022;24(9):11195–225. https://doi.org/10.1007/s10668-021-01902-2.

[45] Furtado PAX, Sola AVH. Fuzzy complex proportional assessment applied in location selection for installation of photovoltaic plants. Energies 2020;13(23). https://doi.org/10.3390/en13236260.

[46] Chiarani E, Antunes AFB, Drago D, Oening AP, Paschoalotto LAC. Optimal Site Selection using Geographical Information System (GIS) Based Multicriteria Decision Analysis (MCDA): A case study to Concentrated Solar Power Plants (CSP) in Brazil. Accessed: Dec. 01, 2023. [Online]. Available: Anuário Inst Geociências 2023;46. https://www.redalyc.org/journal/6953/695375062001/html/.

[47] Govindan K, Jepsen MB. ELECTRE: A comprehensive literature review on methodologies and applications. Eur J Oper Res Apr. 2016;250(1):1–29. https://doi.org/10.1016/j.ejor.2015.07.019.

[48] Morfoulaki M, Papathanasiou J. Use of PROMETHEE MCDA method for ranking alternative measures of sustainable urban mobility planning. Mathematics Jan. 2021;vol. 9, no. 6, Art. no. 6. https://doi.org/10.3390/math9060602.

[49] Ridha HM, Hizam H, Mirjalili S, Othman ML, Ya'acob ME, Ahmadipour M. Innovative hybridization of the two-archive and PROMETHEE-II triple-objective and multi-criterion decision making for optimum configuration of the hybrid renewable energy system. Appl Energy Jul. 2023;341:121117. https://doi.org/10.1016/j.apenergy.2023.121117.

[50] Rehman AU. Solar panel cooling system evaluation: visual PROMETHEE multi-criteria decision-making approach. Sustainability 2023;15(17). https://doi.org/10.3390/su151712947.

[51] Mokarram M, Mokarram MJ, Gitizadeh M, Niknam T, Aghaei J. A novel optimal placing of solar farms utilizing multi-criteria decision-making (MCDA) and feature selection. J Clean Prod Jul. 2020;261:121098. https://doi.org/10.1016/j.jclepro.2020.121098.

[52] Cavallaro F. A comparative assessment of thin-film photovoltaic production processes using the ELECTRE III method. Energy Policy Jan. 2010;38(1):463–74. https://doi.org/10.1016/j.enpol.2009.09.037.

[53] Saranya T, Saravanan S, Jennifer JJ, Singh L. Chapter 7 - Assessment of groundwater vulnerability in highly industrialized Noyyal basin using AHP-DRASTIC and Geographic Information System. In: Pal I, Shaw R, Djalante R, Shrestha S. (editors)., Disaster Resilience and Sustainability, Elsevier, 2021, pp. 151–170. doi: 10.1016/B978-0-323-85195-4.00009-3.

[54] Ahmad S, Parvez M, Khan TA, Khan O. A hybrid approach using AHP–TOPSIS methods for ranking of soft computing techniques based on their attributes for prediction of solar radiation. Environ Chall Dec. 2022;9:100634. https://doi.org/10.1016/j.envc.2022.100634.

[55] Tüysüz N, Kahraman C. An integrated picture fuzzy Z-AHP & TOPSIS methodology: Application to solar panel selection. Appl Soft Comput Dec. 2023;149:110951. https://doi.org/10.1016/j.asoc.2023.110951.

[56] Wang P, Zhu Z, Wang Y. A novel hybrid MCDM model combining the SAW, TOPSIS and GRA methods based on experimental design. Inf Sci Jun. 2016;345:27–45. https://doi.org/10.1016/j.ins.2016.01.076.

[57] Pouran H, Padilha Campos Lopes M, Ziar H, Alves Castelo Branco D, Sheng Y. Evaluating floating photovoltaics (FPVs) potential in providing clean energy and supporting agricultural growth in Vietnam. Renew. Sustain. Energy Rev. 2022;169. https://doi.org/10.1016/j.rser.2022.112925.

[58] "Bienvenido al proyecto QGIS!" Accessed: Dec. 01, 2023. [Online]. Available: https://www.qgis.org/es/site/.

[59] Silalahi DF, Blakers A. Global Atlas of Marine Floating Solar PV Potential, Solar, vol. 3, no. 3, Art. no. 3, Sep. 2023, doi: 10.3390/solar3030023.

[60] Lee K, Lee W. Floating Photovoltaic Plant Location Analysis using GIS. J Korean Soc Geospatial Inf Syst Mar. 2016;24:51–9. https://doi.org/10.7319/kogsis.2016.24.1.051.

[61] Nebey AH, Taye BZ, Workineh TG. GIS-Based Irrigation Dams Potential Assessment of Floating Solar PV System. J Energy May 2020;2020:e1268493.

[62] "Inicio de sesión de cuenta - ArcGIS Online." Accessed: Dec. 01, 2023. [Online]. Available: https://www.arcgis.com/index.html.

[63] Mamun MAA, Islam MM, Hasanuzzaman M, Selvaraj J. Effect of tilt angle on the performance and electrical parameters of a PV module: Comparative indoor and outdoor experimental investigation. Energy Built Environ Jul. 2022;3(3):278–90. https://doi.org/10.1016/j.enbenv.2021.02.001.

[64] Prunier Y, Chuet D, Nicolay S, Hamon G, Darnon M. Optimization of photovoltaic panel tilt angle for short periods of time or multiple reorientations. Energy Convers Manag X Oct. 2023;20:100417. https://doi.org/10.1016/j.ecmx.2023.100417.

[65] Barbón A, Bayón-Cueli C, Bayón L, Rodríguez-Suanzes C. Analysis of the tilt and azimuth angles of photovoltaic systems in non-ideal positions for urban applications. Appl Energy Jan. 2022;305:117802. https://doi.org/10.1016/j.apenergy.2021.117802.

[66] Abdelaal AK, El-Fergany A. Estimation of optimal tilt angles for photovoltaic panels in Egypt with experimental verifications. Sci. Rep. 2023;13(1). https://doi.org/10.1038/s41598-023-30375-8.

[67] Huld T, Müller R, Gambardella A. A new solar radiation database for estimating PV performance in Europe and Africa. Sol Energy Jun. 2012;86(6):1803–15. https://doi.org/10.1016/j.solener.2012.03.006.

[68] Bajc T, Kostadinović D. Potential of usage of the floating photovoltaic systems on natural and artificial lakes in the Republic of Serbia. J Clean Prod Oct. 2023;422:138598. https://doi.org/10.1016/j.jclepro.2023.138598.

[69] Manoj Kumar N, Chakraborty S, Kumar Yadav S, Singh J, Chopra SS. Advancing simulation tools specific to floating solar photovoltaic systems – Comparative analysis of field-measured and simulated energy performance. Sustain Energy Technol Assess 2022;52:102168. https://doi.org/10.1016/j.seta.2022.102168.

[70] "PVsyst – Photovoltaic software." Accessed: Dec. 07, 2023. [Online]. Available: https://www.pvsyst.com/.

[71] "HOMER - Hybrid Renewable and Distributed Generation System Design Software." Accessed: Dec. 07, 2023. [Online]. Available: https://www.homerenergy.com/.

[72] Redón Santafé M, Torregrosa Soler JB, Sánchez Romero FJ, Ferrer Gisbert PS, Ferrán Gozálvez JJ, Ferrer Gisbert CM. Theoretical and experimental analysis of a floating photovoltaic cover for water irrigation reservoirs. Energy 2014;67:246–55. https://doi.org/10.1016/j.energy.2014.01.083.

[73] Yadav AK, Chandel SS. Tilt angle optimization to maximize incident solar radiation: A review. Renew Sustain Energy Rev Jul. 2013;23:503–13. https://doi.org/10.1016/j.rser.2013.02.027.

[74] Yang J, Yang J. Intelligence Optimization Algorithms: A Survey. Int J Adv Comput Technol May 2011;3:144–52. https://doi.org/10.4156/ijact.vol3.issue4.16.

[75] "Introducción – Google Earth," Google Earth. Accessed: Nov. 27, 2023. [Online]. Available: https://www.google.com/intl/es/earth/.

[76] Jain D, Lalwani M. Multi-objective optimization of solar irradiance and variance at pertinent inclination angles. J Inst Eng India Ser C Oct. 2019;100(5):811–31. https://doi.org/10.1007/s40032-018-0464-4.

[77] Ismail MS, Moghavvemi M, Mahlia TMI. Genetic algorithm based optimization on modeling and design of hybrid renewable energy systems. Energy Convers Manag Sep. 2014;85:120–30. https://doi.org/10.1016/j.enconman.2014.05.064.

[78] Yassir A, Zamzami U, Fauzan K, Hasannuddin T, Subhan. Optimization of tilt angle for photovoltaic: case study Sabang-Indonesia. IOP Conf Ser Mater Sci. Eng 2019;536(1):012055. https://doi.org/10.1088/1757-899X/536/1/012055.

[79] "Real Decreto XXX/200X, de XX de XX, por el que se establece el régimen de instalación de plantas fotovoltaicas flotantes en el dominio público hidráulico y se modifica el Reglamento del Dominio Público Hidráulico que desarrolla los títulos preliminar, I, IV, V, VI, VII y VIII del texto refundido de la Ley de Aguas, aprobado por el Real Decreto Legislativo 1/2001, de 20 de julio." Accessed: Nov. 27, 2023. [Online]. Available: https://www.miteco.gob.es/es/agua/participacion-publica/pp-rd-instalacion-plantas-fotovoltaicas-flotantes-dph.html.

[80] "Masas de agua PHC (2015-2021)." Accessed: Nov. 27, 2023. [Online]. Available: https://www.miteco.gob.es/es/cartografia-y-sig/ide/descargas/agua/masas-de-agua-phc-2015-2021.html.

[81] González-González E, Martín-Jiménez J, Sánchez-Aparicio M, Del Pozo S, Lagüela S. Evaluating the standards for solar PV installations in the Iberian Peninsula: Analysis of tilt angles and determination of solar climate zones. Sustain Energy Technol Assess Feb. 2022;49:101684. https://doi.org/10.1016/j.seta.2021.101684.
[82] Bonilla-Campos I, Sorbet Fco J, Astrain D, Radical change in the Spanish grid: Renewable energy generation profile and electric energy excess. Sustain. Energy Grids Netw., vol. 32, p. 100941; Dec. 2022, doi: 10.1016/j.segan.2022.100941.
[83] Eléctrica R. REData - Generación," Red Eléctrica. Accessed: Dec. 19, 2023. [Online]. Available: https://www.ree.es/es/datos/generacion.
[84] JRC Photovoltaic Geographical Information System (PVGIS) - European Commission. Accessed: Nov. 27, 2023. [Online]. Available: https://re.jrc.ec.europa.eu/pvg_tools/en/tools.html.
[85] Eléctrica R. Gestor de la red y transportista. Red Eléctrica. Accessed: Nov. 27, 2023. [Online]. Available: https://www.ree.es/es/actividades/gestor-de-la-red-y-transportista.
[86] Embalses S5. Accessed: Nov. 27, 2023. [Online]. Available: http://embalses.aemet.es/embalses/sclimwareS5.html.
[87] Holmgren WF, Hansen CW, Mikofski MA. pvlib python: a python package for modeling solar energy systems. J Open Source Softw Sep. 2018;3(29):884. https://doi.org/10.21105/joss.00884.
[88] OpenLayers - Welcome. Accessed: Nov. 27, 2023. [Online]. Available: https://openlayers.org/.
[89] OpenStreetMap. OpenStreetMap. Accessed: Nov. 27, 2023. [Online]. Available: https://www.openstreetmap.org/.
[90] Beautiful HTML5 Charts & Graphs | 10x Fast | Simple API. CanvasJS. Accessed: Nov. 27, 2023. [Online]. Available: https://canvasjs.com/.
[91] NumPy reference — NumPy v1.26 Manual. Accessed: Nov. 27, 2023. [Online]. Available: https://numpy.org/doc/stable/reference/index.html#reference.
[92] pandas - Python Data Analysis Library. Accessed: Nov. 27, 2023. [Online]. Available: https://pandas.pydata.org/.
[93] DEAP. (Nov. 27, 2023). Python. Distributed Evolutionary Algorithms in Python. Accessed: Nov. 27, 2023. [Online]. Available: https://github.com/DEAP/deap.
[94] Kim SH, Won YS, Seo SH, Park JK, Yoon SJ. Fabrication and Construction of Floating Photovoltaic Energy Generation Structures Using Fiber Reinforced Polymer Plastic (FRP) Members. Key Eng Mater 2017;730:613–9. https://doi.org/10.4028/www.scientific.net/KEM.730.613.
[95] Cazzaniga R, Cicu M, Rosa-Clot M, Rosa-Clot P, Tina GM, Ventura C. Floating photovoltaic plants: Performance analysis and design solutions. Renew Sustain Energy Rev Jan. 2018;81:1730–41. https://doi.org/10.1016/j.rser.2017.05.269.
[96] Huang G, Tang Y, Chen X, Chen M, Jiang Y. A comprehensive review of floating solar plants and potentials for offshore applications. J Mar Sci Eng 2023;11(11). https://doi.org/10.3390/jmse11112064.
[97] JA Solar. 455 W MBB Half-Cell PERC Module JAM78S10 435-455/MR datasheet. [Online]. Available: https://www.jasolar.com/uploadfile/2020/0508/20200508101149946.pdf.
[98] Vinod, Kumar R, Singh SK. Solar photovoltaic modeling and simulation: As a renewable energy solution. Energy Rep., vol. 4, pp. 701–712; Nov. 2018, doi: 10.1016/j.egyr.2018.09.008.
[99] López-Martínez SD, Juárez-Ramírez I, Sánchez-Martínez D. Photocatalytic activity of non-oxides materials TiB2, TiC, and TiN. J Phys Chem Solids Jan. 2024;184:111701. https://doi.org/10.1016/j.jpcs.2023.111701.
[100] Pitre L, Plimmer MD, Sparasci F, Himbert ME. Determinations of the Boltzmann constant. Comptes Rendus Phys Jan. 2019;20(1):129–39. https://doi.org/10.1016/j.crhy.2018.11.007.
[101] Zhang L, Zhu C, Yu S, Zhou Z, Ge D. Band gap of silicon photonic crystal with square-lattice and windmill-shaped defects. Results Phys Dec. 2021;31:105054. https://doi.org/10.1016/j.rinp.2021.105054.
[102] Charles Lawrence Kamuyu W, Lim JR, Won CS, Ahn HK. Prediction model of photovoltaic module temperature for power performance of floating PVs. Energies 2018;11(2). https://doi.org/10.3390/en11020447.
[103] Yetayew TT, Jyothsna TR. Parameter extraction of photovoltaic modules using Newton Raphson and simulated annealing techniques. In: 2015 IEEE Power, Communication and Information Technology Conference (PCITC); 2015. p. 229–34. https://doi.org/10.1109/PCITC.2015.7438166.
[104] Goswami A, Sadhu PK. Degradation analysis and the impacts on feasibility study of floating solar photovoltaic systems. Sustain Energy Grids Netw Jun. 2021;26:100425. https://doi.org/10.1016/j.segan.2020.100425.
[105] R. Eléctrica. REData - No renovables detalle emisiones CO2. Red Eléctrica. Accessed: Dec. 18, 2023. [Online]. Available: https://www.ree.es/es/datos/generacion/no-renovables-detalle-emisiones-CO2.
[106] Rodríguez-Segura FJ, Osorio-Aravena JC, Frolova M, Terrados-Cepeda J, Muñoz-Cerón E. Social acceptance of renewable energy development in southern Spain: Exploring tendencies, locations, criteria and situations. Energy Policy Feb. 2023;173:113356. https://doi.org/10.1016/j.enpol.2022.113356.
[107] Directive (EU) 2018/2001 of the European Parliament and of the Council of 11 December 2018 on the promotion of the use of energy from renewable sources (recast) (Text with EEA relevance)Text with EEA relevance. 2022. Accessed: Sep. 12, 2023. [Online]. Available: http://data.europa.eu/eli/dir/2018/2001/2022-06-07/eng.
[108] Lee H-C, Chang C-T. Comparative analysis of MCDM methods for ranking renewable energy sources in Taiwan. Renew Sustain Energy Rev Sep. 2018;92:883–96. https://doi.org/10.1016/j.rser.2018.05.007.
[109] Cinelli M, Kadziński M, Gonzalez M, Słowiński R. How to support the application of multiple criteria decision analysis? Let us start with a comprehensive taxonomy. Omega Oct. 2020;96:102261. https://doi.org/10.1016/j.omega.2020.102261.
[110] Więckowski J, Szyjewski Z. Practical Study of Selected Multi-Criteria Methods Comparison. Procedia Comput Sci Jan. 2022;207:4565–73. https://doi.org/10.1016/j.procs.2022.09.520.
[111] Wątróbski J, Jankowski J, Ziemba P, Karczmarczyk A, Zioło M. Generalised framework for multi-criteria method selection. Omega Jul. 2019;86:107–24. https://doi.org/10.1016/j.omega.2018.07.004.
[112] Taufik I, Alam CN, Mustofa Z, Rusdiana A, Uriawan W. Implementation of Multi-Attribute Utility Theory (MAUT) method for selecting diplomats. IOP Conf Ser Mater Sci Eng Mar. 2021;1098(3):032055. https://doi.org/10.1088/1757-899X/1098/3/032055.
[113] Zavadskas EK, Turskis Z, Antucheviciene J, Zakarevicius A. Optimization of weighted aggregated sum product assessment. Elektron Ir Elektrotechnika 2012;122(6). https://doi.org/10.5755/j01.eee.122.6.1810.
[114] Sahabuddin Md, Khan I. Multi-criteria decision analysis methods for energy sector's sustainability assessment: Robustness analysis through criteria weight change. Sustain Energy Technol Assess Oct. 2021;47:101380. https://doi.org/10.1016/j.seta.2021.101380.
[115] Alinezhad A, Khalili J. "VIKOR Method" in New Methods and Applications in Multiple Attribute Decision Making (MADM). In: Alinezhad A, Khalili J. (Eds.), in International Series in Operations Research & Management Science. , Cham: Springer International Publishing, 2019, pp. 23–27. doi: 10.1007/978-3-030-15009-9_4.
[116] Paradowski B, Więckowski J, Dobryakova L. Why TOPSIS does not always give correct results? Procedia Comput Sci Jan. 2020;176:3591–600. https://doi.org/10.1016/j.procs.2020.09.027.
[117] Zavadskas EK, Kaklauskas A, Vilutienė T. Multicriteria evaluation of apartment blocks maintenance contractors: Lithuanian case study. Int J Strateg Prop Manag 2009;13(4). https://doi.org/10.3846/1648-715X.2009.13.319-338.
[118] Hezer S, Gelmez E, Özceylan E. Comparative analysis of TOPSIS, VIKOR and COPRAS methods for the COVID-19 Regional Safety Assessment. J Infect Public Health Jun. 2021;14(6):775–86. https://doi.org/10.1016/j.jiph.2021.03.003.
[119] Alinezhad A, Khalili J. "WASPAS Method," in New Methods and Applications in Multiple Attribute Decision Making (MADM). In: Alinezhad A, Khalili J. (Eds.) in International Series in Operations Research & Management Science. , Cham: Springer International Publishing, 2019, pp. 93–98. doi: 10.1007/978-3-030-15009-9_13.
[120] Chakraborty S, Zavadskas E, Antucheviciene J. Applications of waspas method as a multi-criteria decision-making tool. Econ Comput Econ Cybern Stud Res Acad Econ Stud Jan. 2015;49:5–22.
[121] Nabavi SR, Wang Z, Rangaiah GP. Sensitivity Analysis of multi-criteria decision-making methods for engineering applications. Ind Eng Chem Res May 2023;62(17):6707–22. https://doi.org/10.1021/acs.iecr.2c04270.
[122] Alvarado-Barrios L, Rodríguez del Nozal A, Tapia A, Martínez-Ramos JL, Reina DG. An evolutionary computational approach for the problem of unit commitment and economic dispatch in microgrids under several operation modes. Energies 2019;12(11). https://doi.org/10.3390/en12112143.
[123] Ter-Sarkisov A, Marsland S. Convergence Properties of Two ({\mu} + {\lambda}) Evolutionary Algorithms On OneMax and Royal Roads Test Functions. ArXiv11084080 Cs, Aug. 2011, Accessed: Jun. 27, 2021. [Online]. Available: http://arxiv.org/abs/1108.4080.
[124] Eléctrica R. REData - Demanda, Red Eléctrica. Accessed: Dec. 30, 2023. [Online]. Available: https://www.ree.es/es/datos/demanda.
[125] pyDecision: A MCDA Library Incorporating a Large Language Model to Enhance Decision Analysis. Accessed: Nov. 28, 2023. [Online]. Available: https://github.com/Valdecy/pyDecisions.
[126] Kizielewicz B, Shekhovtsov A, Sałabun W. pymcdm—The universal library for solving multi-criteria decision-making problems. SoftwareX May 2023;22:101368. https://doi.org/10.1016/j.softx.2023.101368.
[127] Alinezhad A, Khalili J. COPRAS Method," in New Methods and Applications in Multiple Attribute Decision Making (MADM). In: Alinezhad A, Khalili J. (Eds.), in International Series in Operations Research & Management Science, Cham: Springer International Publishing, 2019, pp. 87–91. doi: 10.1007/978-3-030-15009-9_12.
[128] Poli R, Langdon WB. Genetic Programming with One-Point Crossover. In: Chawdhry PK, Roy R, Pant RK, editors. Soft Computing in Engineering Design and Manufacturing. London: Springer; 1998. p. 180–9. https://doi.org/10.1007/978-1-4471-0427-8_20.
[129] Hinterding R. Gaussian mutation and self-adaption for numeric genetic algorithms. In: Proceedings of 1995 IEEE International Conference on Evolutionary Computation; Nov. 1995, pp. 384-. doi: 10.1109/ICEC.1995.489178.
[130] Fang Y, Li J. A review of tournament selection in genetic programming; Oct. 2010, pp. 181–192. doi: 10.1007/978-3-642-16493-4_19.
[131] Pereira J, Mendes J, Júnior JSS, Viegas C, Paulo JR. A review of genetic algorithm approaches for wildfire spread prediction calibration. Mathematics 2022;10(3). https://doi.org/10.3390/math10030300.