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Research paper

Evaluation of criteria for site selection of solar photovoltaic (PV) projects using fuzzy logarithmic additive estimation of weight coefficients

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ABSTRACT

The aim of this study is to determine the degree of importance of criteria affecting site selection of solar photovoltaic (PV) projects using a decision-making model. This study consists of four consecutive stages, as follows: criteria identification, questionnaire (survey), statistical analyses, and degree of importance of criteria. In the first stage, the criteria are determined by reviewing the scientific literature on solar PV projects. Secondly, we conduct a questionnaire to identify the importance of the criteria for solar PV project site selection. We received responses from 33 internationally renowned experts from 22 countries, including academia and industry, using an international evaluation method. Thirdly, statistical analysis is performed in SPSS regarding each criterion, comparing the averages between the groups who filled out the questionnaire. Finally, a novel logarithmic additive estimation of weight coefficients (LAAW) under fuzzy environment is proposed to determine the degree of importance of each criterion for solar PV site selection. The results show that the most important criteria for solar PV site selection are solar radiation, economic performance indicators (net present value (NPV), internal rate of return (IRR), and return on investment (ROI)), carbon emission savings, and policy support.

1. Introduction

Renewable energy sources such as wind, biomass, hydropower, geothermal, wave, tide, and solar (Al Garni and Awasthi, 2017; Ecer et al., 2021) have gained importance in light of the rapid increase in energy demand in the world, due to limited of fossil fuel reserves (Abdmouleh et al., 2015; Ecer, 2021; Deveci et al., 2021b; Krishankumar et al., 2021), uncertainty in fossil fuel price and global warming (Shukla et al., 2017). The renewable resources have the potential to provide clean, cheap energy (Breton and Moe, 2009; Mostafaeipour, 2010; Ecer, 2020) and to be more sustainable, secure, and with low-carbon emission (Al Garni and Awasthi, 2017; Ecer et al., 2019), while the traditional fossil fuels, such as coal, natural gas, and oil result in air pollution and produce CO_2, which is the primary cause of climate change (Kempton et al., 2005). Hence, many countries have been developing policies to support the growth of renewable energy resources and have continued to increase their installed capacities.

Renewable energy used in electricity generation rose by roughly 15.2% to an almost equal rise in global electricity production. The share of renewable energy in global electricity production also reached 6.7% from 2.0% a decade earlier (BP, 2016). Electricity demand is increasing day by day, and by 2035 half of the expected increase in demand is predicted to be covered by renewable energy sources (IEA, 2013a, b). According to a BP report, renewable energy sources are expected to grow fourfold in the next 20 years due to global energy demand. More than half of the growth recorded in renewable energies came from wind energy, which increased by 16% in 2016. Solar energy, mainly photovoltaic (PV), has grown by 30%. Although solar energy accounts for only 18% of renewable energy production, solar energy growth accounts for about one-third of the overall growth in renewable energy (BP, 2017). Solar energy, among other renewable energy sources, has become an important resource in universal electricity generation (Merrouni et al., 2016).

Site selection of solar PV projects is a critical issue for utility-sized projects due to the importance of weather factors, distance to residential areas and network connection, impact of local residential life, and environmental risk (Al Garni and Awasthi, 2017). Site selection is an important decision and must be analysed in

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terms of many factors. The aim of this study is to develop a set of comprehensive solar PV siting criteria which includes technical, economic, environmental, and social/political considerations under various sub-criteria. We investigate the degree of importance of criteria affecting the site selection of solar PV projects using a decision-making model.

In this study, a new model for determining the weight coefficients of the site selection criteria of solar PV projects based on the logarithmic additive assessment of the weight coefficients (LAAW) is proposed. The LAAW model is based on a logarithmic assessment of the relationship between expert criterion assessments and absolute anti-ideal assessments. By applying fuzzy logic, the LAAW model was extended, which enabled the processing of uncertain expert estimates and a rational evaluation of the criteria's significance. The advantages of applying the LAAW model are multiple, including simple mathematical formulation, elimination of inconsistencies in expert estimates, and reliable, rational, and consistent values of weighting coefficients.

The rest of this paper is organized as follows. In Section 2, we introduce an overview of solar PV studies on site selection. The main criteria and sub-criteria are defined in Section 3. In Section 4, we introduce the proposed methodology used in the study. The survey results are given in Section 5. In Section 6, we present the result obtained from the proposed methodology, as well as results and discussion. Finally, Section 7 concludes the study.

2. Literature review

2.1. Decision-making approaches for solar PV projects

In order to achieve high efficiency in electricity generation, it is very important to identify the most suitable sites to install solar PV power plants (Merrouni et al., 2016). In fact, many interesting studies have been published in the literature concerning the identification of the most suitable solar PV power plant location.

The solar PV site selection problem is often addressed using a multi-criteria decision-making (MCDM) approach together with geographic information system (GIS) software to determine the most suitable area or alternative. A summary of studies using a hybrid MCDM and GIS approach to find the best site for solar PV projects is presented in Table 1. The following studies can be given as examples: Geographic Information System (GIS)-based Analytical Hierarchy Process (AHP) (Uyan, 2013; Effat, 2013; Georgiou and Skarlatos, 2016; Aly et al., 2017; Doljak and Stanojević, 2017; Suuronen et al., 2017; Yushchenko et al., 2018; Doorga et al., 2019; Giamalaki and Tsoutsos, 2019), AHP and TOPSIS (Sánchez-Lozano et al., 2013), ELECTRE (Sánchez-Lozano et al., 2014), AHP, TOPSIS, and ELECTRE TRI (Sánchez-Lozano et al., 2016). Fuzzy sets are based on AHP and GIS (Asakereh et al., 2014; Noorollahi et al., 2016; Suh and Brownson, 2016), AHP and TOPSIS (Sindhu et al., 2017), AHP and VIKOR (Solangi et al., 2019), AHP, DEA, and TOPSIS (Wang et al., 2018), Fuzzy ANP and VIKOR (Lee et al., 2015).

The majority of the works are devoted to solar PV power plants, but demand for Concentrated Solar Power (CSP) plants is increasing (Haddad et al., 2021). Studies based on PV and CSP are shown in Fig. 1. Studies on CSP include Haddad et al. (2021) and Wu et al. (2019) and studies on solar PV-CSP include Alami Merrouni et al. (2016), Aly et al. (2017), Yushchenko et al. (2018), and Giamalaki and Tsoutsos (2019).

Number of published studies in terms of journals are presented in Table 2. According to the distribution of the journals, "Renewable Energy", "Renewable and Sustainable Energy Reviews", and "Energies" are the most popular journals.

The geographical distribution of case studies in the publications is shown in Fig. 2. It can be seen that 13.7% and 11.8% of the case studies in the literature are in China and Spain, respectively.

It can be seen from the results in Table 1 that the number of alternatives and criteria in published studies vary. Aragonés-Beltrán et al. (2010) evaluated four alternatives regarding 12 main and 50 sub-criteria for solar PV site selection using the Analytic Network Process (ANP). Jun et al. (2014) analysed solar PV-wind site selection in terms of seven alternatives under five criteria and 13 sub-criteria. Vafaeipour et al. (2014) assessed the suitability of 25 solar projects in Iran with the help of four criteria and 14 sub-criteria. Suh and Brownson (2016) evaluated the potential of solar farms in Korea using Fuzzy AHP and GIS. They considered three alternatives regarding six main and eight sub-criteria.

Many studies have been published on solar PV site selection, taking into account various main and sub-criteria (see Table 1). In these studies, solar PV site alternatives are evaluated under criteria such as technical, economic, ecological, social, environmental, natural resources, orographic, political and so on. On the other hand, it can be seen that some criteria are taken into account in site selection throughout the studies. In addition to these, it is understood that fuzzy MCDM models are frequently preferred in the energy literature in solar PV site selection. The contribution of our study is to evaluate the criteria used for Solar PV site selection and to develop a decision support system. It is known that there is no study in the literature evaluating and discussing 44 criteria that can be considered in the selection of Solar PV site. Due to this lack of literature, the main motivation of our study is to determine the importance of the criteria affecting the site selection of solar photovoltaic (PV) projects using the delphi-based decision making method.

3. Criteria definition

The topic-related criteria definitions are discussed under four main groups: (1) technical, (2) economic, (3) environmental, and (4) social/political.

1. Technical

Technical criteria describe the technical factors, parameters, and attributes related to the solar PV power plant's (SPV PP) design, construction, and operation phases. The following technical sub-criteria are covered within the scope of this study:

1.1. *Solar Radiation:*

Solar radiation refers to the radiant energy in the form of electromagnetic radiation emitted from the sun as sunlight (Carrión et al., 2008). The solar irradiance is the amount of solar radiation received on virtual space and is expressed in per unit area by a given surface (W/m^2). This factor is the most impactful parameter to determine the energy generation potential of the SPV PP.

1.2 *Temperature*

Ambient temperature also has an impact on the performance of the solar PV panels (Sánchez-Lozano et al., 2013). Solar PV panels are designed to work under certain temperature conditions. Regular commercial PV solar panels are tested and certified for 25 °C. Depending on the project location, PV panels are usually operated between 15 °C and 35 °C, during which solar cells harvest maximum or close to maximum efficiency. However, most types of PV solar panels can be operated up to 65 °C, where the efficiency of the system reduces.

1.3. *Sunshine hours*

Sunshine hours is a meteorological metrics (Jun et al., 2014) that is used for quantifying duration of sunshine for a specific period (e.g., a year or a day) for a specific location.

1.4. *Distance to network connection*

Approximation to the nearest power grid is another critical parameter in terms of identifying the technical challenges (Watson and Hudson, 2015). The amount of power system loss is proportional to the length and type of the transmission or distribution line. Projects where the planned SPV PP is located far away from the nearest transmission or distribution grids inevitably cause higher electrical power losses while connecting the SPV

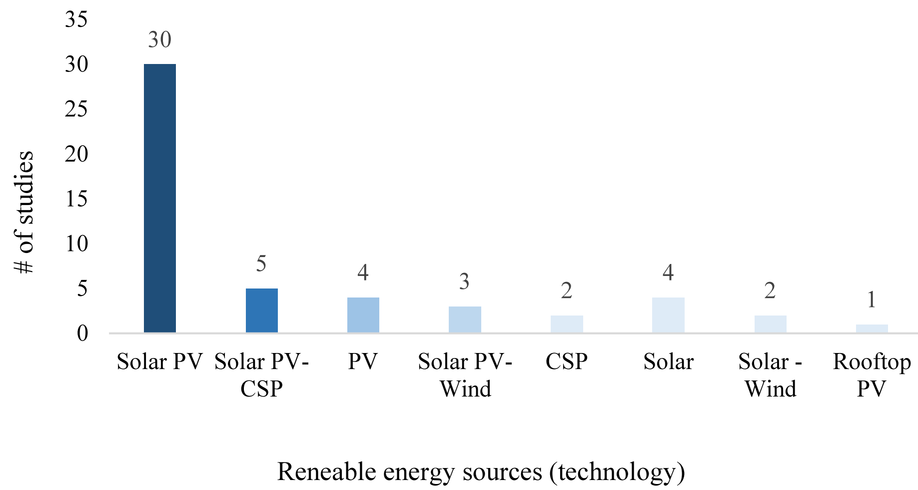


Fig. 1. Renewable energy sources publications.

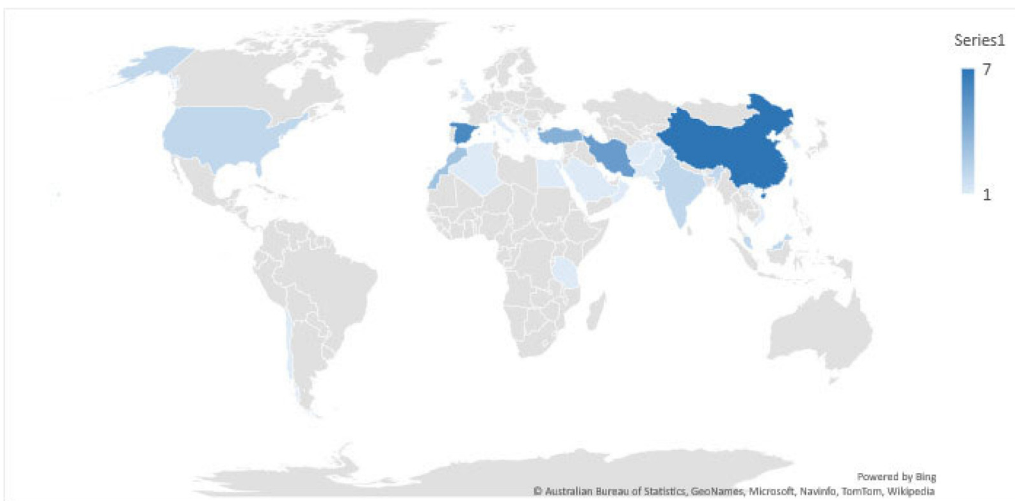


Fig. 2. Distribution of case studies.

PP to the power grid's substation. Beside technical impacts, this factor heavily impacts the economic metrics of the project in two manners: (1) losses in the annual energy yield and revenue of the project due to additional electrical power losses and (2) additional cost of capital expenditures (CAPEX) or investment costs associated with longer cabling costs.

1.5. *Land use*

The current, permanent, and future plans regarding the land use is one of the key components of PV solar energy project development activities (Uyan, 2013). SPV PP investment decisions determining land use are vital, including land scarcity, the need for preserving the ecological balance, and the availability of land for agricultural purposes. This parameter also has an impact on the economic criteria since the permanent or temporary use of the project land or site should be legally secured against additional investment or reoccurring cost elements.

1.6. *Distance to residential areas*

This factor has various aspects. Utility-scale SPV PPs are usually not located in very close proximity to residual areas, in order to minimize the security issues of the investment and public health related concerns of the local citizens, which may occur due to unauthorized visits to the project sites. Contrary, such a project should also not be located far away from residential areas and their electrical load potential, so that energy supply and resources can be located in an optimal location, if possible.

1.7. *Distance to roads and logistic works*

Especially during the construction of the utility-scale energy investments, logistics might be a challenging task for the project developers. The project location should be easily accessible to transfer the needed project components such as construction elements, PV panels and other needed power systems-related equipment to the project area. The project location should still be accessible during the operation phase of the project so that the technical crew can reach the project site in the case of planned and unplanned technical problems.

1.8. *Meteorological parameters (wind speed and average rainfall)*

Even though solar radiation and temperature are the most dominant meteorological parameters, it is essential to take the other meteorological parameters such as wind speed and average rainfall into account, to ensure safer design and operation of the SPV PP.

1.9. *Slope (% or degree)*

The slope of the surface where the PV solar panels will be located has an impact on the annual energy yield of the SPV

Table 1
Studies using combined GIS and decision making for solar PV site selection.

Authors	Year	RE source	Main-criteria	Sub-criteria	Alternatives	Case study	Fuzzy sets	Proposed methodologies
Carrión et al.	2008	Solar PV	4	18	–	Spain		GIS
Aragonés-Beltrán et al.	2010	Solar PV	12	50	4	Spain		AHP and ANP
Janke	2010	Solar PV-Wind	–	8	–	USA		Multi-criteria GIS modelling
Charabi and Gastli	2011	Solar PV-CSP	3	9	–	Oman	x	GIS-based spatial fuzzy multi-criteria evaluation
Uyan	2013	Solar	2	5	–	Turkey		GIS and AHP
Sánchez-Lozano et al.	2013	Solar PV	4	10	–	Spain		GIS, AHP, and TOPSIS
Effat	2013	Solar PV	–	5	8	Egypt		GIS and AHP
Sun et al.	2013	Solar PV	–	5	–	China		GIS
Sánchez-Lozano et al.	2014	Solar PV	4	10	–	Spain		GIS and ELECTRE
Asakereh et al.	2014	Solar PV	–	–	–	Iran	x	Fuzzy AHP and GIS
Jun et al.	2014	Solar PV-Wind	5	13	7	China		ELECTRE-II
Wu and Gang	2014	Solar PV-Wind	5	23	5	China		AHP
Vafaeipour et al.	2014	Solar	4	14	25	Iran		SWARA, WASPAS, and Delphi
Watson and Hudson	2015	Solar PV-Wind	4	7	–	UK		GIS and AHP
Borgogno Mondino et al.	2015	Solar PV	–	8	20	Italy		GIS and Artificial Neural Network (ANN)
Tahri et al.	2015	Solar PV	4	7	–	Morocco		AHP and GIS
Lee et al.	2015	Solar PV	3	12	15	Taiwan	x	Fuzzy AHP and DEA
Fernandez-Jimenez et al.	2015	PV	–	–	–	Spain		GIS
Sánchez-Lozano et al.	2016	Solar PV	–	10	–	Spain		GIS, AHP, TOPSIS, and ELECTRE TRI
Merrouni et al.	2016	Solar PV-CSP	–	13	–	Morocco		GIS
Noorollahi et al.	2016	Solar PV	4	11	31	Iran	x	Fuzzy AHP and GIS
Sabo et al.	2016	Solar PV	5	8	–	Malaysia		GIS
Suh and Brownson	2016	Solar PV	6	8	3	Korea	x	Fuzzy AHP and GIS
Kareemuddin and Rusthum	2016	Solar PV	–	–	–	India		GIS and Image Processing
Georgiou and Skarlatos	2016	Solar PV	4	10	–	Cyprus		GIS and AHP
Al Garni and Awasthi	2017	Solar PV	2	7	–	Saudi Arabia		GIS and AHP
Aly et al.	2017	Solar PV-CSP	4	7	–	Tanzania		GIS and AHP
Anwarzai and Nagasaka	2017	Solar PV-Wind	–	9	–	Afghanistan		GIS
Liu et al.	2017	Solar PV	3	8	4	China		Grey cumulative prospect theory
Sindhu et al.	2017	Solar PV	5	18	5	India	x	AHP and Fuzzy TOPSIS
Doljak and Stanojević	2017	Solar PV	3	7	–	Serbia		GIS and AHP
Zoghi et al.	2017	Solar	4	15	–	Iran	x	GIS and AHP
Lee et al.	2017	Solar PV	4	10	5	Taiwan	x	Fuzzy ANP and VIKOR
Suuronen et al.	2017	Solar PV	3	12	–	Chile		GIS and AHP
Yushchenko et al.	2018	Solar PV-CSP	–	19	–	West Africa		GIS and AHP
Wu et al.	2018	Rooftop PV	5	16	5	China		ANP and VIKOR
Wang et al.	2018	Solar	5	15	7	Vietnam	x	Fuzzy AHP, DEA, and TOPSIS
Merrouni et al.	2018	PV	4	8	–	Morocco		GIS and AHP
Ozdemir and Sahin	2018	Solar PV	–	5	3	Turkey		GIS and AHP
Fang et al.	2018	PV	4	10	4	China		Rough PT-based TOPSIS
Yousefi et al.	2018	Solar PV	3	9	–	Iran	x	GIS and Boolean-Fuzzy Logic Model
Majumdar and Pasqualetti	2019	Solar PV	4	9	–	USA		GIS and Multi-Criteria Analysis
Solangi et al.	2019	Solar PV	6	20	14	Pakistan	x	AHP and Fuzzy VIKOR
Wu et al.	2019	CSP	5	13	5	China	x	PROMETHEE
Giamalaki and Tsoutsos	2019	Solar PV-CSP	–	10	–	Greece		GIS and AHP
Doorga et al.	2019	Solar PV	3	9	–	Mauritius		GIS and AHP
Colak et al.	2020	Solar PV	–	10	–	Turkey		GIS and AHP
Sreenath et al.	2020	Solar PV	–	6	11	Malaysia		ForgeSolar software
Haddad et al.	2021	CSP	4	7	–	Algeria		GIS and AHP
Lindberg et al.	2021	PV	–	–	–	Sweden		GIS
Soydan	2021	Solar PV	–	11	–	Turkey		GIS and AHP

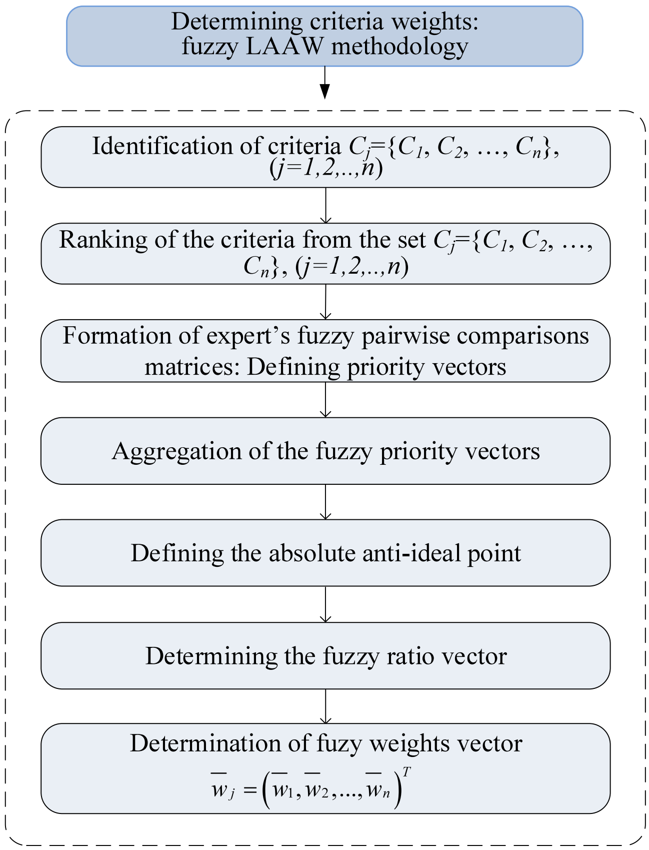


Fig. 3. Fuzzy LAAW model.

Table 2
Journals of published studies.

Journals	# of studies
Renewable Energy	14
Renewable and Sustainable Energy Reviews	10
Energies	4
Energy Conversion and Management	3
Applied Energy	2
Journal of Cleaner Production	2
Sustainability	2
Energy	1
Energy Policy	1
Environmental Earth Sciences volume	1
Environmental Science and Pollution R.	1
Geosci. Instrum. Method. Data Syst.	1
IJITR	1
International Journal of Advanced Remote Sensing and GIS	1
International Journal of Advanced Science and Technology	1
International Journal of Green Energy	1
Landscape and Urban Planning	1
Measurement	1
SN Applied Sciences	1
Sustainable Cities and Society	1
Sustainable Energy Technologies and Assessments	1

PP investments. The tilt angle of the slope of the PV panels must be determined depending on the location of the project site, geographic topography, and the type of elements under construction.

1.10. *Humidity*
Ambient humidity has some impact on performance in terms of annual energy yield of the project and the degradation rate of the PV panels in the long run.

1.11. *Topography*
A project site's topological characteristics have an impact on the planning and construction activities of the investment. Topographic surveys are used to determine the requirements of the soil relief during the planning phase of the construction of solar PV panels.

1.12. *Service life*
Service life of project components such as PV panels, construction elements, and electrical equipment influences the technical and economic viability of the investment.

1.13. *Elevation (m)*
Project locations' elevation has a very limited impact on the performance of the SPV PPs (Elkhatib et al., 2015).

1.14. *Hydrographic areas and lines*
The impact of the hydrographic areas and lines on the project performance are very limited, if the PV project is not a floating PV solar type of project.

1.15. *Land cover*
Land cover categories have the potential for creating interrelationships between SPV PP development efforts and ecosystem preservation. The impact is similar to the land cover sub-criteria.

1.16. *Urban planning*
Urban planning activities for cities and counties are challenging undertakings, since such analysis and surveys require well trained interdisciplinary teams of engineers, urban planners, and environmental experts to analyse the contribution of solar energy in their urban plans (Kanters and Horvat, 2012).

1.17. *Strength of the existing grid*
Power grids are designed and operated to satisfy some set of technical requirements in terms of voltage stability and quality. The fluctuating behaviour of renewable energy generation often poses additional challenges to the power grids in terms of satisfying the required quality metrics. It is therefore vital to perform detailed power systems integration analyses, especially if the project scale of SPV PP is large.

1.18. *Solar PV material technology and efficiency*
The efficiency of standard PV solar panels depends on the quality of the material of the solar cells on them. The regular solar PV panels usually have an efficiency between 15% and 20%.

2. *Economic*
Economic perspectives of SPV PP investments are investigated using this main criterion.

2.1. *Initial investment cost*
This is the cost category that is related to the cost incurred during the initial stage of the investment, such as the cost of solar panels, construction, and electrical and civil works pertaining to the project. Capital expenditures (CAPEX) is a synonym of initial investment costs.

2.2. *Annual income*
The annual energy yield and consequently the annual capital income (revenue) which can be generated from the SPV PP investment primarily depends on the solar radiation value parameter.

2.3. *Operation and maintenance cost*
This is the cost category that is related to the cost incurred during the operational life of the project, such as the cost of the services related to maintenance, overhead costs of the company which operates the project, insurance premiums, and similar recurring costs elements. Operational expenditures (OPEX) is a synonym of operation and maintenance costs.

2.4. *Construction/infrastructure cost*

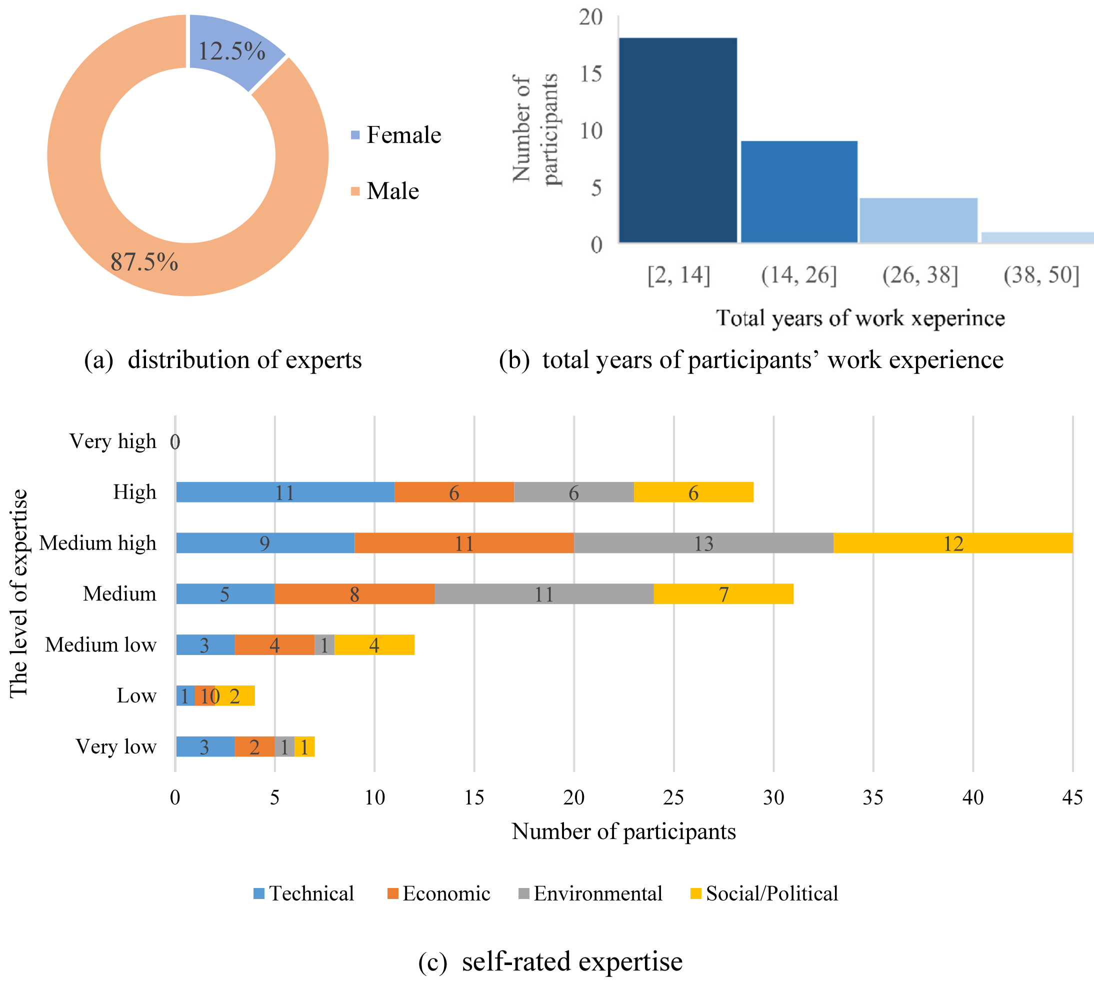


Fig. 4. The main characteristics of participants in Round 1.

This is sub-category of the *Initial investment cost (sub-criteria 2.2)* that only contains the civil and electrical works pertaining to the project.

2.5. *Land cost*

Depending on the agreement, type of land use, and land cover characteristics of the project location, the land where the SPV PP will be built can be bought or leased. If the land is bought, then this type of land cost can be counted as CAPEX. Otherwise, it can be considered a recurring cost.

2.6. *Levelized cost of energy evolution*

Levelized cost of energy (LCOE) is one of the most effective metrics in energy economics, which uses the per unit cost of the electrical energy harvested from the given SPV PP.

2.7. *Economic performance indicators (NPV, IRR, RoI)*

Other economic indicators such as net present value (NPV), internal rate of return (IRR), and return on investment (ROI) are general economic metrics for any type of investment as well as SPV PP.

2.8. *Local government subsidies*

Local or national governments may prefer to utilize some push policy instruments which are used to help to promote selected renewable energy resources with additional subsidies. Such support can be given directly during the investment phase or can be associated with the produced electricity in terms of MWh (e.g., Feed-In-Tariff), or can be applied as tax credit depending on the country, state, and region.

2.9. *Impact on regional development and local economies*

Particularly utility-scale renewable energy investments usually have a positive impact on the regional development and local economies where they are built. Such investments can create additional jobs during construction and operational phases of the project. Further, some of the project equipment and construction material can also be obtained from local producers or suppliers, to impact local economies positively.

2.10. *Impact on agriculture*

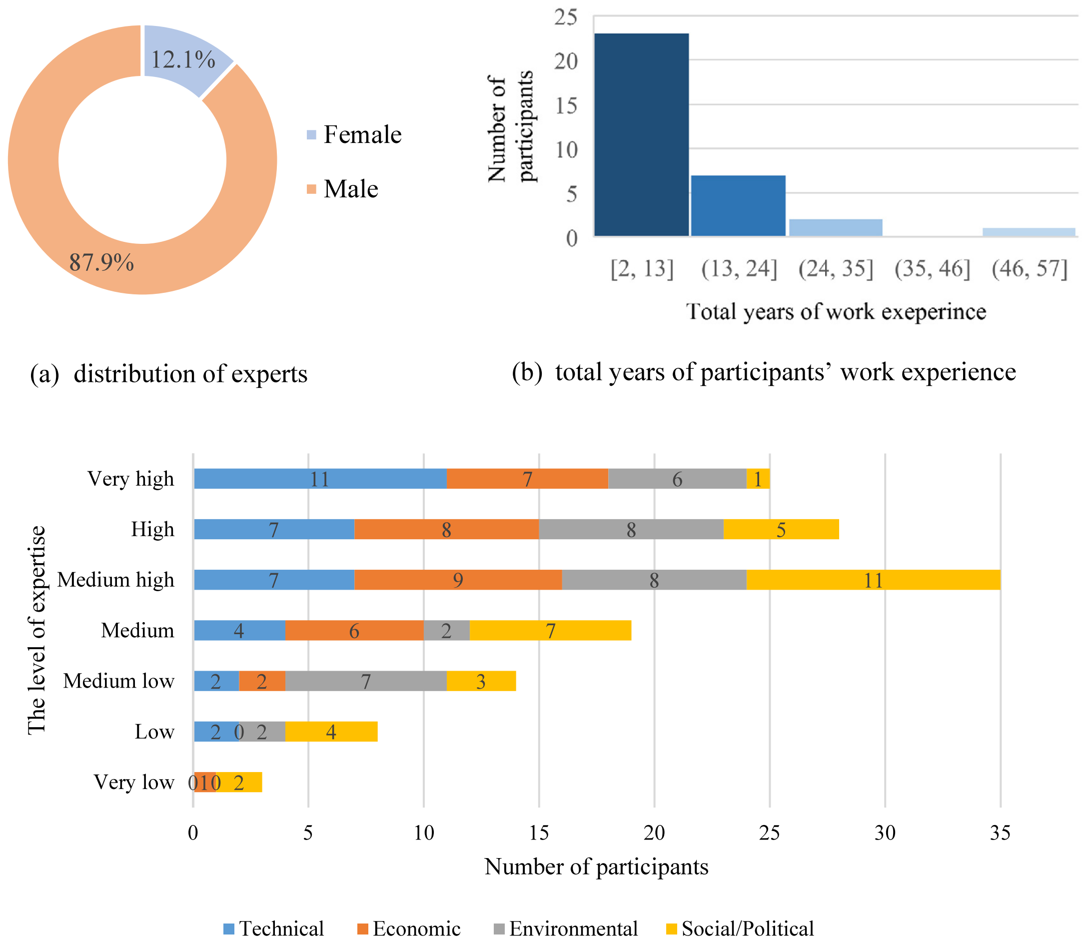
Since large-scale SPV PP investments can potentially occupy large amounts of land, the land use and related issues must be investigated very carefully. One such investigation should focus on the impact on the local agricultural economies for the considered project locations.

2.11. *Utility fee of electrical energy (electricity price for consumers)*

Utility fees are usually very good indicators, which can be compared with LCOE to ascertain the competitiveness of the SPV PP investment in comparison to the regular electricity prices from the utility. Ideally, the LCOE of the project will be lower than the utility fee if the project is built in a cost-effective manner.

3. *Environmental*

Renewable energy projects as a sustainable type of energy resource will ideally be designed in such a manner that the



(a) distribution of experts

(b) total years of participants' work experience

(c) self-rated expertise

Fig. 5. The main characteristics of participants in Round 2.

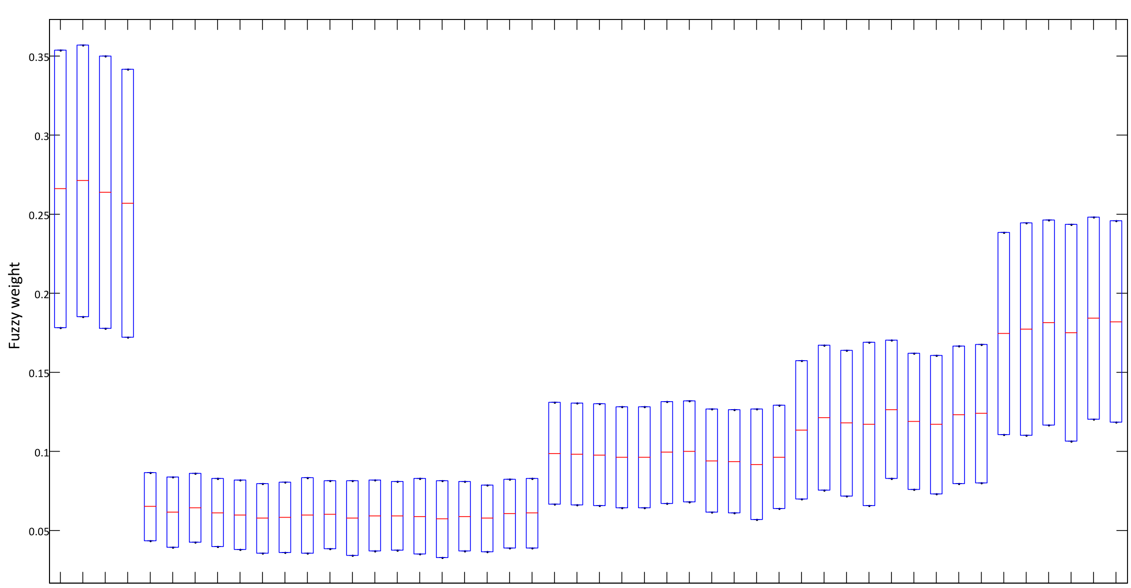


Fig. 6. Fuzzy local criteria weights.

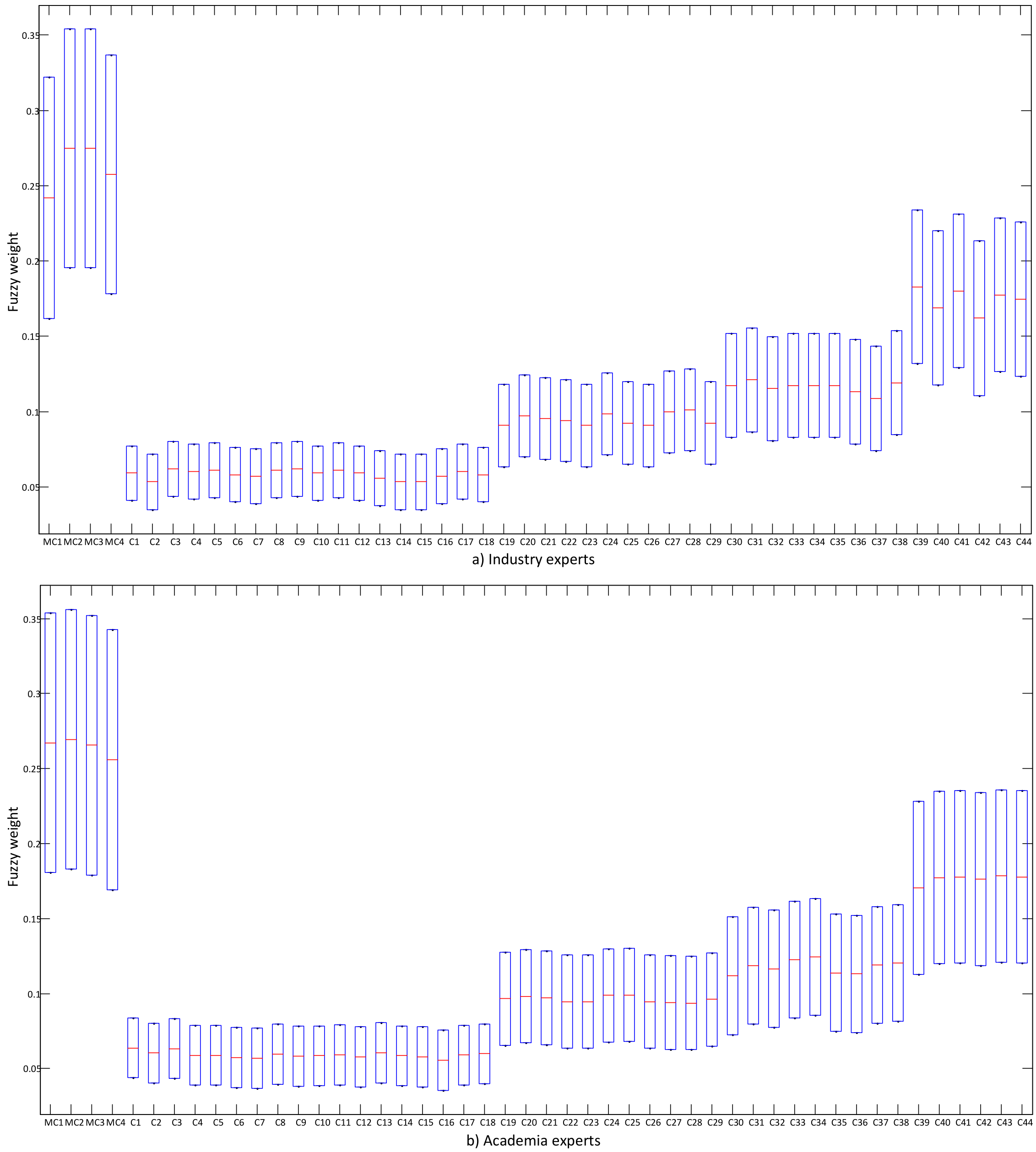


Fig. 7. The comparison of industry experts and academia.

project-related activities will result in minimum damage to the environment and humans.

3.1. *Soil structure and geology*

Soil structure and geological surveys are essential to investigate before the project construction phase. The outcomes of such surveys will help to make better decisions when identifying the best available type of construction whereon the PV panels will be installed. Geological surveys are also used within the scope of other civil works, such as road construction to the project site.

3.2. *Impact on the surrounding environment*

Depending on the country and state where the SPV PP project is planned, the project developers are obliged to familiarize themselves with the regulations related to environmental issues. Utility-scale SPV PP constructions legally require environmental surveys in many countries where there is potential damage to and impact on the ecological system and natural habitat from such projects.

3.3. *Visual impact*

The visibility of an SPV PP that is installed in a specific location is dependent on the altitude difference between the solar panels and the observer. The visual impact of the solar panels should be minimized during the planning process.

3.4. *Light pollution*

Polarization characteristics of the light reflected from an object may have a negative impact on some species, such as insects and waterbirds, which are critical elements of the ecosystem. Particularly, glass-coated PV modules may generate light pollution and can harm certain insect species – particularly water-seeking

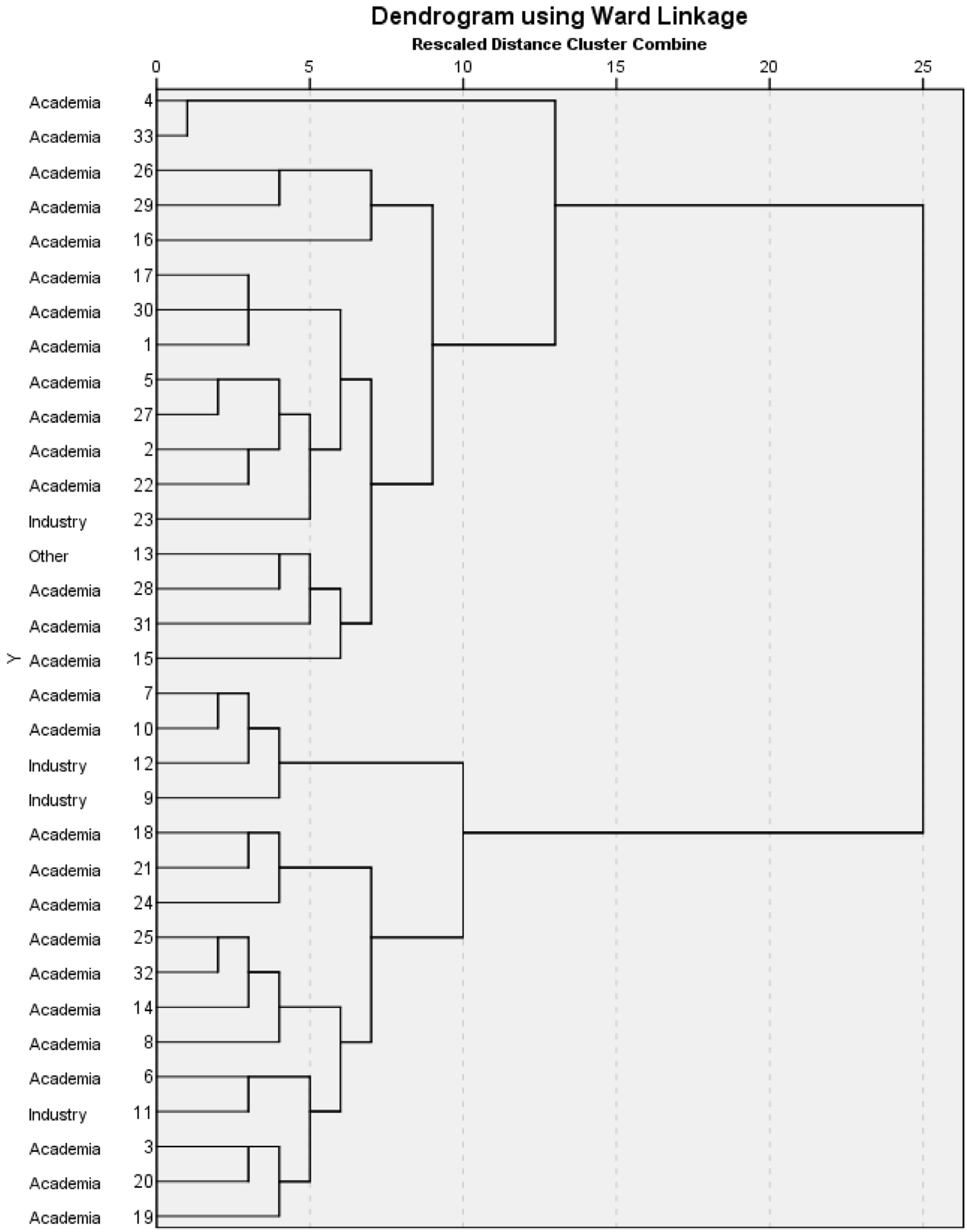


Fig. 8. The hierarchical relationship of participants' responses in Round 2.

aquatic insects – and waterbirds, as they are trapped by the light signals and thus lose their orientation (Fritz et al., 2020).[1]

3.5. *Carbon emission savings*

Energy resources' carbon emission levels vary depending on the technology employed. Fossil fuel-based power plants can generate 504 g/kWh carbon emissions, while solar PV projects generate 99 g/kWh. The positive impact of solar energy projects can be quantified by performing detailed carbon emission analyses to estimate the total annual carbon emissions savings (Pehnt, 2006).

3.6. *Impact on wildlife*

The concerns related to the impact of utility-scale SPV PP projects on wildlife are much more sophisticated than is commonly thought. For this reason, a detailed wildlife impact analysis

[1] https://www.bv.com/perspectives/impact-solar-energy-wildlife-emerging-environmental-issue

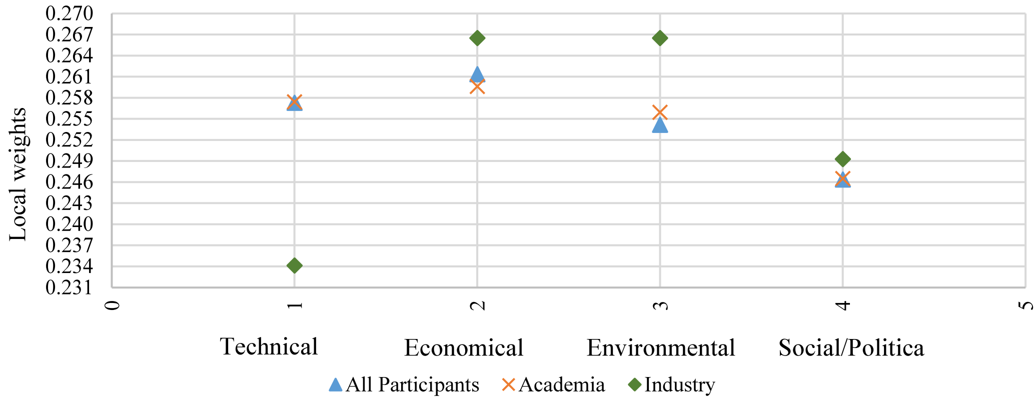


Fig. 9. The overlapping chart of cluster for three groups.

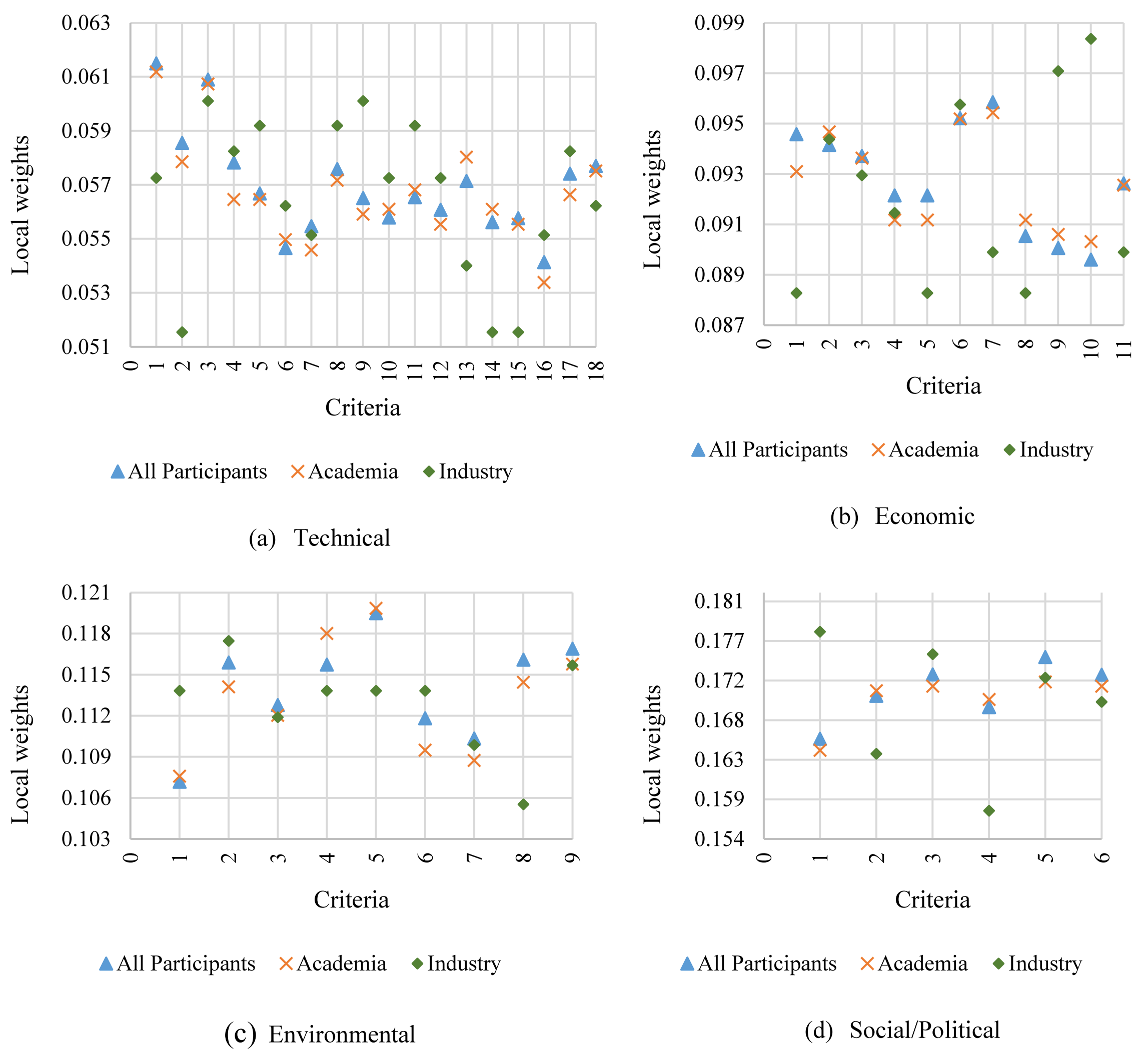


Fig. 10. The overlapping charts for three groups in terms of four clusters.

is highly recommended for such kinds of projects before the investment decision is made.

3.7. *Sand/dust risk*

Extreme weather conditions such as sandstorms and dust accumulation on the surface of the solar PV panels impact the energy production performance of the SPV PPs negatively. Moreover, the same factors reduces the degradation rates of the PV panels, which thus yields lower service lives.

3.8. *Ecology (ecological damage)*

More general surveys addressing the overall impact of SPV PP projects on ecosystems can also be used to investigate the ecological damage.

3.9. *Protected areas*

The project developers must be aware of protected areas before they start their first project development activities, in order not to make faulty decisions, as various historical and environmental protected areas are closed to any type of construction, including SPV PPs.

4. *Social/political*

Beside the technical, economic, and environmental aspects, it is important to analyse the social and political aspects of the investments.

4.1. *Skilled manpower availability*

Training of the manpower on different levels is usually a national or regional task undertaken by universities, vocational schools, and companies which have internal learning-by-doing processes. If there is a scarcity in terms of sufficient manpower to develop and operate SPV PPs, this can jeopardize the entire projects' viability. Hence, it is vital to have resilient HR planning activities.

4.2. *Regulatory boundaries*

National and local regulatory frameworks must be evaluated in order to identify the boundaries of the regulatory issues. For instance, if the country provides a subsidy to help renewable investments for a certain number of years and with certain conditions, this ought to be reflected in the advanced financial models of the project very precisely.

4.3. *Public acceptance/support*

Surveys, interviews, and meetings to understand and measure public acceptance and support is a vital part of the project preparations. Very strong opposition from local citizens can risk the entire investment. On the other hand, massive support from local citizens can help the project and contribute positively to local development.

4.4. *Policy support*

Local and national energy policy drivers and associated legislative documents must be processed to understand the rules of the game where the project is developed. Besides, it is vital to have policy support. Any political movement against such renewable investments has the potential to impact the project negatively.

4.5. *Legal constraint*

Regulatory, legislative, and contractual issues related to the land use, protection areas, land lease, engineering procurement construction (EPC) contracts, and similar domains should be carefully handled by a professional internal or outsourced legal team before making any investment decision. The legal services should ideally continue until the end of the project's life cycle.

Table 3
The main characteristic of participants for Round 1 and Round 2.

	Round 1	*Round 2*
	N	*N*
Number of participants	32	33
Countries		
Afghanistan	1	1
Belgium	0	1
Brazil	2	1
Canada	0	2
China	2	2
Cyprus	1	1
Czech Republic	0	1
Egypt	1	1
Finland	0	1
France	1	0
Germany	0	1
Greece	1	0
India	1	0
Indonesia	1	1
Italy	1	1
Lithuania	1	0
Malaysia	1	0
Mauritius	1	1
Morocco	2	1
Norway	2	2
Oman	1	1
Republic of Korea	0	1
Saudi Arabia	1	3
Spain	2	3
Sweden	2	0
Taiwan	3	3
Turkey	1	2
United Kingdom	1	0
USA	2	2
Occupation	***N*** (%)	***N*** (%)
Academia	29 (90.6%)	28 (84.9%)
Industry experts	1 (3.1%)	4 (12.1%)
Other	2 (6.3%)	1 (3%)

4. Preliminaries

4.1. Logarithmic additive estimation of weight coefficients

The weighting coefficients of the criteria were defined by applying the method for logarithmic additive assessment of the weighting coefficients (LAAW) as shown in Fig. 3. This is a new methodology based on a logarithmic assessment of the relationship between the criterion priority vector and the absolute anti-ideal point (Pamucar et al., 2021). Since this is a new method for determining the weights of the criteria, it is necessary to emphasize the advantages of the LAAW model: *(i)* the calculation of weights is done with a small number of comparisons of criteria; *(ii)* the mathematical formulation of the LAAW model is not complicated by an increase in the number of criteria, which is also shown in this study which considers 48 criteria. This feature makes it suitable for application in complex multi-criteria models that require the application of many criteria; *(iii)* the application of the LAAW model eliminates inconsistencies in the processing of expert preferences since the results of the LAAW model are always consistent; *(iv)* by applying the LBWA model, we obtain reliable values of the weight coefficients of the criteria that contribute to rational reasoning; and *(v)* Flexibility of the model in terms of using all the values from the predefined scale, i.e., it is not limited to integer values from the defined interval.

Using the LAAW model, optimal values of weight coefficients are obtained with simple mathematical apparatus that eliminates inconsistencies in expert preferences, which are tolerated in certain subjective models like Best Worst Method (Rezaei, 2015), Analytic Hierarchy Process (Saaty, 1980) or Step-wise Weight Assessment Ratio Analysis (Valipour et al., 2017).

The weighting coefficients of the criteria were defined by applying the method for logarithmic additive assessment of the weighting coefficients (LAAW). This is a new methodology based on a logarithmic assessment of the relationship between the criterion priority vector and the absolute anti-ideal point. Since this is a new method for determining the weights of the criteria, it is necessary to emphasize the advantages of the LAAW model: *(i)* the calculation of weights is done with a small number of comparisons of criteria; *(ii)* the mathematical formulation of the LAAW model is not complicated by an increase in the number of criteria, which is also shown in this study which considers

Table 4
The hierarchy of the evaluation criteria.

MC_1: Technical	Criteria
C_1	Solar radiation
C_2	Temperature
C_3	Sunshine hours
C_4	Distance to network connection
C_5	Land use
C_6	Distance to residential areas
C_7	Distance to roads and logistic works
C_8	Meteorological parameters (wind speed and average rainfall)
C_9	Slope (% or degree)
C_{10}	Humidity
C_{11}	Topography
C_{12}	Service life
C_{13}	Elevation (m)
C_{14}	Hydrographic areas and lines
C_{15}	Land cover
C_{16}	Urban planning
C_{17}	Strength of the existing grid
C_{18}	Solar PV material technology and efficiency
MC_2: Economic	Criteria
C_{19}	Initial investment cost
C_{20}	Annual income
C_{21}	Operation and maintenance cost
C_{22}	Construction/infrastructural cost
C_{23}	Land cost
C_{24}	Levelized cost of energy evolution
C_{25}	Economic performance indicators (NPV, IRR, ROI)
C_{26}	Local government subsidies
C_{27}	Impact on regional development and local economies
C_{28}	Impact on agriculture
C_{29}	A utility fee of electrical energy (electricity price for consumers)
MC_3: Environmental	Criteria
C_{30}	Soil structure and geology
C_{31}	Impact on the surrounding environment
C_{32}	Visual impact
C_{33}	Light pollution
C_{34}	Carbon emission savings
C_{35}	Impact on wildlife
C_{36}	Sand/dust risk
C_{37}	Ecology (ecological damage)
C_{38}	Protected areas
MC_4: Social/Political	Criteria
C_{39}	Population density
C_{40}	Skilled manpower availability
C_{41}	Regulatory boundaries
C_{42}	Public acceptance/support
C_{43}	Policy support
C_{44}	Legal constraint

Table 5
Fuzzy linguistic scale for criteria evaluation.

Linguistic terms	Membership function
Very low (VL)	(1,2,3)
Low (L)	(2,3,4)
Medium low (ML)	(3,4,5)
Medium (M)	(4,5,6)
Medium high (MH)	(5,6,7)
High (H)	(6,7,8)
Very high (VH)	(7,8,9)

48 criteria. This feature makes it suitable for application in complex multi-criteria models that require the application of many criteria; *(iii)* the application of the LAAW model eliminates inconsistencies in the processing of expert preferences since the results of the LAAW model are always consistent; and *(iv)* by applying the LBWA model, we obtain reliable values of the weight coefficients of the criteria that contribute to rational reasoning.

In group, multi-criteria models there exist greater or lesser uncertainties (Zavadskas et al., 2012, 2020; Ramakrishnan and Chakraborty, 2020; Erdogan et al., 2021), and fuzzy sets or various generalizations of fuzzy sets are most often used to address uncertainties (Kushwaha et al., 2020; Bozanic et al., 2020; Riaz et al., 2020; Karamaşa et al., 2021). To represent uncertainty using fuzzy set theory (Zadeh, 1965), researchers most commonly use triangular fuzzy numbers (Gharib, 2020; Blagojevic et al., 2020; Chatterjee and Stevic, 2019; Deveci et al., 2021a). A fuzzy number Z on R is a triangular fuzzy number (TFN) if its membership function R→[0,1] is equal to the following expression (1) (Milosevic et al., 2021):

$$\mu_Z(\lambda) = \begin{cases} \dfrac{\lambda - l}{m - l} & l \le \lambda \le m \\ \dfrac{u - x}{u - m} & m \le \lambda \le u \\ 0 & otherwise \end{cases} \tag{1}$$

where l and u are the lower and upper bounds of the fuzzy number Z, respectively, and m is the modal value for Z. The operational laws of TFNs are shown in Bakır and Atalık (2021).

Since fuzzy sets (Zadeh, 1965) were used in this study to process experts' preferences, the following section presents a fuzzy LAAW model for determining the criteria's weighting coefficients.

Step 1. Determining the fuzzy priority vector. Suppose that k experts $\Omega = \{\Omega_1, \Omega_2, \ldots, \Omega_k\}$ who evaluate n criteria $C = \{C_1, C_2, \ldots, C_n\}$ participate in the research. Also, suppose that a fuzzy linguistic scale is defined on the basis of which experts evaluate criteria

After defining a set of n criteria, the experts prioritize the criteria by assigning a higher TFN from the fuzzy scale to the more important criterion while assigning a smaller TFN from the fuzzy scale to the less important criterion. We thus obtain the fuzzy priority vector $\Upsilon^t = \left(\widetilde{\theta}_1^t, \widetilde{\theta}_2^t, \ldots, \widetilde{\theta}_n^t\right)$, where $\widetilde{\theta}_j^t = \left(\theta_j^{(l)t}, \theta_j^{(m)t}, \theta_j^{(u)t}\right)$ represents the TFN from the fuzzy scale assigned by the expert t $(1 \le t \le k)$ to the criterion n.

Step 2. Defining the absolute anti-ideal point ($\widetilde{\xi}_{AIP}$). The absolute anti-ideal point is defined by applying the expression (2)

$$\widetilde{\xi}_{AIP} < \min\left(\widetilde{\theta}_j^t, \widetilde{\theta}_j^t, \ldots, \widetilde{\theta}_j^t\right) \tag{2}$$

Step 3. Defining aggregated fuzzy relationship vectors (A). By applying the Bonferroni function expression (3), we obtain an aggregated fuzzy priority vector $\Upsilon = \left(\tilde{\theta}_1, \tilde{\theta}_2, \ldots, \tilde{\theta}_n\right)$:

$$\widetilde{\theta}_j = \left(\theta_j^{(l)}, \theta_j^{(m)}, \theta_j^{(u)}\right) = \left(\begin{array}{c} \left(\dfrac{1}{k(k-1)} \displaystyle\sum_{x=1}^{k} \left(\theta_j^{(l)(x)}\right)^{\alpha_1} \sum_{\substack{y=1\\y\neq x}}^{k} \left(\theta_j^{(l)(y)}\right)^{\alpha_2}\right)^{\frac{1}{\alpha_1+\alpha_2}}, \\ \left(\dfrac{1}{k(k-1)} \displaystyle\sum_{x=1}^{k} \left(\theta_j^{(m)(x)}\right)^{\alpha_1} \sum_{\substack{y=1\\y\neq x}}^{k} \left(\theta_j^{(m)(y)}\right)^{\alpha_2}\right)^{\frac{1}{\alpha_1+\alpha_2}}, \\ \left(\dfrac{1}{k(k-1)} \displaystyle\sum_{x=1}^{k} \left(\theta_j^{(u)(x)}\right)^{\alpha_1} \sum_{\substack{y=1\\y\neq x}}^{k} \left(\theta_j^{(u)(y)}\right)^{\alpha_2}\right)^{\frac{1}{\alpha_1+\alpha_2}} \end{array}\right) \tag{3}$$

where $\widetilde{\theta}_j = \left(\theta_j^{(l)}, \theta_j^{(m)}, \theta_j^{(u)}\right)$ represents the mean values of the priority vector; $\alpha_1, \alpha_2 \ge 0$ represents the stabilization parameters of the Bonferroni function; and k represents the total number of experts who participated in the research.

Using expression (4) determines the relationship between the fuzzy priority vector elements and the absolute anti-ideal point ($\widetilde{\xi}_{AIP}$):

$$\widetilde{\gamma}_j = \frac{\widetilde{\theta}_j}{\widetilde{\xi}_{AIP}} = \left(\frac{\theta_j^{(l)}}{\widetilde{\xi}_{AIP}^{(u)}}, \frac{\theta_j^{(m)}}{\widetilde{\xi}_{AIP}^{(m)}}, \frac{\theta_j^{(u)}}{\widetilde{\xi}_{AIP}^{(l)}}\right) \tag{4}$$

where $\widetilde{\theta}_j = \left(\theta_j^{(l)}, \theta_j^{(m)}, \theta_j^{(u)}\right)$ represents the elements of the priority vector Υ.

We thus obtain the fuzzy vector of the relation $A = \left(\widetilde{\gamma}_j, \widetilde{\gamma}_j, \ldots, \widetilde{\gamma}_j\right)$, t $(1 \le t \le k)$, where $\widetilde{\gamma}_j$ represents the element of the fuzzy vector of the relation obtained by applying expression (4).

Step 4. Determination of vectors of weight coefficients $\widetilde{w}_j = (\widetilde{w}_1, \widetilde{w}_2, \ldots, \widetilde{w}_n)^T$. By applying expression (5), we obtain the values of the weighting coefficients of the criteria:

$$\widetilde{w}_j = \frac{\ln\left(\widetilde{\gamma}_j\right)}{\ln\left(\widetilde{b}\right)} = \left(\frac{\ln\left(\gamma_j^{(l)}\right)}{\ln\left(b^{(u)}\right)}, \frac{\ln\left(\gamma_j^{(m)}\right)}{\ln\left(b^{(m)}\right)}, \frac{\ln\left(\gamma_j^{(u)}\right)}{\ln\left(b^{(l)}\right)}\right) \tag{5}$$

where $\widetilde{\gamma}_j = \left(\gamma_j^{(l)}, \gamma_j^{(m)}, \gamma_j^{(u)}\right)$ represents the elements of the fuzzy relation vector A, while $\widetilde{b} = \prod_{j=1}^{n} \widetilde{\gamma}_j = \left(\prod_{j=1}^{n} \gamma_j^{(l)}, \prod_{j=1}^{n} \gamma_j^{(m)}, \prod_{j=1}^{n} \gamma_j^{(u)}\right)$. The values of weight coefficients thus obtained satisfy the condition that $\sum_{j=1}^{n} w_j = 1$. When ranking the criteria, it is recommended to phase shift the fuzzy value $\widetilde{w}_j = \left(w_j^{(l)}, w_j^{(m)}, w_j^{(u)}\right)$ using the expression $def(w_j) = (w_j^{(l)} + 4 \cdot w_j^{(m)} + w_j^{(u)})/6$.

5. Survey

An online questionnaire was prepared to determine the importance of criteria for the site selection of solar PV projects. A total of 121 international experts from both industry and academia were invited to participate in two separate rounds. E-mail invitations were sent for the online questionnaire, which was completed using Google Drive. The website address link of our questionnaires for *Round 1* and *Round 2* are https://forms.gle/nyWofEGZGp6JViFn7 and https://forms.gle/8MhFFVtPBxWH2vpZ9, respectively. The main characteristics of participants in *Round 1* and *Round 2* are provided in Table 3. Participants' departments for *Round 1* and *Round 2* are presented in Table A.1 in Appendix.

In Round 1 there was a total of 32 participants, 29 of whom are from academia while only 1 are from industry. Similarly, in Round 2 there was a total of 33 participants, 28 of whom are from academia while only four are industrial experts. The distributions indicate that questionnaire evaluation results tend to be biased to academy rather than industry.

5.1. Round 1

There were two important goals in the first round of the solar PV questionnaire. First, to discuss potential criteria influencing the site selection of solar PV projects, and secondly to finally identify these criteria. The criteria that may affect the solar PV location selection were collected by reviewing the literature and were then discussed with experts. As a result, participants in the first round were able to remove any criteria or add a new one. In this round, participants were asked to evaluate 43 criteria under four clusters in terms of the following linguistic scale: "strongly disagree", "disagree", "neutral", "agree", and "strongly agree". A total of 121 international experts were invited to participate in the online survey in the first round, while 32 participants from 23 countries responded. Except for a few criteria, a consensus was reached in the expert group. Participants asked for some criteria to be removed and some new criteria to be added. As a result, two new criteria were suggested by the participants and added to the criteria list for Round 2.

Fig. 4 illustrates the distribution of the number of participants with respect to their gender, experience, and self-rated expertise. While 12.5% of the participants are female, 87.5% are male. Fig. 4(b) shows that eighteen participants have between two and 14 years of work experience, and one of the participants has more than 38. According to Fig. 4(c), the majority of participants in Round 1 have between medium and high levels of expertise.

5.2. Round 2

In this round, forty-four solar PV site selection criteria under four clusters were assessed by the participants. A total of 121 international experts were invited to participate in the online survey and 33 experts from 22 countries responded. While 84.9% of the participants are from academia, 12.1% are industry experts. The distribution of the number of participants with respect to their gender, experience, and self-rated expertise is shown in Fig. 5.

Table 6
Expert assessments of criteria.

MC_1: Technical	Criteria	VL	L	ML	M	MH	H	VH	Total
C_1	Solar radiation		1	2	1	11	8	10	33
C_2	Temperature			1	1	9	12	10	33
C_3	Sunshine hours			3	5	7	12	6	33
C_4	Distance to network connection	1		2	12	10	3	5	33
C_5	Land use				2	7	6	18	33
C_6	Distance to residential areas		2	2	5	9	7	8	33
C_7	Distance to roads and logistic works		1		1	9	7	15	33
C_8	Meteorological parameters			3	6	7	11	6	33
C_9	Slope (% or degree)		1	5	10	4	10	3	33
C_{10}	Humidity		1	8	6	7	7	4	33
C_{11}	Topography		2	4	9	10	7	1	33
C_{12}	Service life		6	5	8	5	5	4	33
C_{13}	Elevation (m)			4	6	8	12	3	33
C_{14}	Hydrographic areas and lines		5	6	12	5	4	1	33
C_{15}	Land cover		2	4	5	9	11	2	33
C_{16}	Urban planning	2	3	4	8	8	5	3	33
C_{17}	Strength of the existing grid		6	4	9	7	5	2	33
C_{18}	Solar PV material technology and efficiency		6	5	12	8	1	1	33
MC_2: Economic	Sub-criteria	2	3	3	10	9	5	1	33
C_{19}	Initial investment cost	2	1	4	7	14	1	4	33
C_{20}	Annual income		1	3	3	10	11	5	33
C_{21}	Operation and maintenance cost		1	3	1	11	10	7	33
C_{22}	Construction/infrastructural cost			1	5	9	7	11	33
C_{23}	Land cost			1	4	8	14	6	33
C_{24}	Levelized cost of energy evolution				11	7	10	5	33
C_{25}	Economic performance indicators				11	10	8	4	33
C_{26}	Local government subsidies			1	8	9	12	3	33
C_{27}	Impact on regional development and local economies			1	6	7	8	11	33
C_{28}	Impact on agriculture				5	8	9	11	33
C_{29}	A utility fee of electrical energy		1	2	5	12	11	2	33
MC_3: Environmental	Sub-criteria		1	4	5	10	9	4	33
C_{30}	Soil structure and geology		4	8	6	4	7	4	33
C_{31}	Impact on the surrounding environment		1	3	5	7	12	5	33
C_{32}	Visual impact	1	2	8	7	7	5	3	33
C_{33}	Light pollution		4	4	7	5	5	8	33
C_{34}	Carbon emission savings	3	7	6	5	3	7	2	33
C_{35}	Impact on wildlife	2	13	5	3	5	2	3	33
C_{36}	Sand/dust risk	2	3	2	2	3	11	10	33
C_{37}	Ecology (ecological damage)	1	1	3	7	10	6	5	33
C_{38}	Protected areas	1	2	5	5	9	8	3	33
MC_4: Social/ Political	Sub-criteria	1	2	3	7	4	9	7	33
C_{39}	Population density		1	4	4	5	7	12	33
C_{40}	Skilled manpower availability	2	3	3	7	10	6	2	33
C_{41}	Regulatory boundaries		4	2	8	9	7	3	33
C_{42}	Public acceptance/support	1	3	1	6	9	7	6	33
C_{43}	Policy support		5	4	6	8	7	3	33
C_{44}	Legal constraint	1	2		5	9	9	7	33

5.3. Experimental results

The following section presents the application of the fuzzy LAAW method to determine the significance of 44 criteria grouped within four clusters, as provided in Table 4.

Using fuzzy logarithmic additive methodology, the weight coefficients of the criteria were defined through the following steps.

Step 1: The study involved 33 experts who prioritized the criteria using the fuzzy scale presented in Table 5.

Based on the expert assessments given in Table 6, a priority vector was defined for each expert.

Step 2: The absolute anti-ideal point $\widetilde{\xi}_{AIP} = (0.4, 0.5, 0.6)$ is defined using expression (2).

Step 3: Using Bonferroni function (3), a fusion of expert preferences was performed. Based on the aggregated priority vectors and the anti-ideal point, the relationship vectors are defined by applying expression (4). The relationship vectors represent the relationships between the priority vector and the absolute anti-ideal point ($\widetilde{\xi}_{AIP} = (0.4, 0.5, 0.6)$), as given in Table 7.

The elements of the relationship vector for clusters (MC_1, MC_2, MC_3, and MC_4) are obtained by applying expression (4) as follows:

$$\tilde{\gamma}_{MC1} = \frac{(4.27, 5.42, 6.42)}{(0.4, 0.5, 0.6)} = (7.12, 10.85, 16.06)$$

$$\tilde{\gamma}_{MC2} = \frac{(4.61, 5.61, 6.61)}{(0.4, 0.5, 0.6)} = (7.68, 11.21, 16.52)$$

$$\tilde{\gamma}_{MC3} = \frac{(4.24, 5.24, 6.24)}{(0.4, 0.5, 0.6)} = (7.07, 10.48, 15.61)$$

$$\tilde{\gamma}_{MC4} = \frac{(4, 4.85, 5.85)}{(0.4, 0.5, 0.6)} = (6.67, 9.7, 14.62)\,,$$

Table 7
The relationship vectors.

Cluster	Criteria	Relation vector
MC_1: Technical		(7.12,10.85,16.06)
C_1	Solar radiation	(8.43,12.12,17.65)
C_2	Temperature	(6.87,10.85,16.06)
C_3	Sunshine hours	(7.98,11.88,17.35)
C_4	Distance to network connection	(7.02,10.42,15.53)
C_5	Land use	(6.41,10,15)
C_6	Distance to residential areas	(5.76,9.21,14.02)
C_7	Distance to roads and logistic works	(5.81,9.58,14.47)
C_8	Meteorological parameters	(5.71,10.67,15.83)
C_9	Slope (% or degree)	(6.57,9.88,14.85)
C_{10}	Humidity	(5.3,9.88,14.85)
C_{11}	Topography	(6.16,10,15)
C_{12}	Service life	(6.21,9.76,14.7)
C_{13}	Elevation (m)	(5.56,10.48,15.61)
C_{14}	Hydrographic areas and lines	(5.05,9.88,14.85)
C_{15}	Land cover	(6.11,9.64,14.55)
C_{16}	Urban planning	(6.01,8.91,13.64)
C_{17}	Strength of the existing grid	(6.67,10.3,15.38)
C_{18}	Solar PV material technology and efficiency	(6.77,10.42,15.53)
MC_2: Economic	Criteria	(7.68,11.21,16.52)
C_{19}	Initial investment cost	(7.53,11.03,16.29)
C_{20}	Annual income	(7.42,10.91,16.14)
C_{21}	Operation and maintenance cost	(7.32,10.79,15.98)
C_{22}	Construction/infrastructural cost	(6.97,10.36,15.45)
C_{23}	Land cost	(6.97,10.36,15.45)
C_{24}	Levelized cost of energy evolution	(7.68,11.21,16.52)
C_{25}	Economic performance indicators	(7.83,11.39,16.74)
C_{26}	Local government subsidies	(6.41,10,15)
C_{27}	Impact on regional development and local economies	(6.31,9.88,14.85)
C_{28}	Impact on agriculture	(5.61,9.94,14.92)
C_{29}	A utility fee of electrical energy	(6.87,10.55,15.68)
MC_3: Environmental	Criteria	(7.07,10.48,15.61)
C_{30}	Soil structure and geology	(5.61,9.03,13.79)
C_{31}	Impact on the surrounding environment	(6.46,10.97,16.21)
C_{32}	Visual impact	(5.91,10.3,15.38)
C_{33}	Light pollution	(5.05,11.39,16.74)
C_{34}	Carbon emission savings	(7.78,11.64,17.05)
C_{35}	Impact on wildlife	(6.57,9.88,14.85)
C_{36}	Sand/dust risk	(6.11,9.64,14.55)
C_{37}	Ecology (ecological damage)	(7.12,10.85,16.06)
C_{38}	Protected areas	(7.27,11.03,16.29)
MC_4: Social/Political	Criteria	(6.67,9.7,14.62)
C_{39}	Population density	(6.21,9.76,14.7)
C_{40}	Skilled manpower availability	(6.16,10.61,15.76)
C_{41}	Regulatory boundaries	(6.87,10.85,16.06)
C_{42}	Public acceptance/support	(5.81,10.48,15.61)
C_{43}	Policy support	(7.32,11.09,16.36)
C_{44}	Legal constraint	(7.07,10.79,15.98)

The remaining vectors of the relationship between the criteria and the clusters in Table 8 were obtained similarly.

Step 4: By applying expression (5), we obtain global fuzzy weighting coefficients of the criteria, as given in Table 8.

Weight coefficients for clusters (MC_1, MC_2, MC_3, and MC_4) are obtained by applying expression (5) as follows:

$$\widetilde{w}_{MC1} = \frac{\ln(7.12,\,10.85,\,16.06)}{\ln(2576.94,\,12366.74,\,60523.1)} = \left(\frac{\ln(7.12)}{\ln(60523.099)}, \frac{\ln(10.85)}{\ln(12366.74)}, \frac{\ln(16.06)}{\ln(2576.937624)}\right) = (0.178,\,0.253,\,0.353)$$

$$\widetilde{w}_{MC2} = \frac{\ln(7.68,\,11.21,\,16.52)}{\ln(2576.94,\,12366.74,\,60523.1)} = \left(\frac{\ln(7.68)}{\ln(60523.099)}, \frac{\ln(11.21)}{\ln(12366.74)}, \frac{\ln(16.52)}{\ln(2576.937624)}\right) = (0.185,\,0.257,\,0.357)$$

$$\widetilde{w}_{MC3} = \frac{\ln(7.07,\,10.48,\,15.61)}{\ln(2576.94,\,12366.74,\,60523.1)} = \left(\frac{\ln(7.07)}{\ln(60523.099)}, \frac{\ln(10.48)}{\ln(12366.74)}, \frac{\ln(15.61)}{\ln(2576.937624)}\right) = (0.178,\,0.249,\,0.350)$$

$$\widetilde{w}_{MC4} = \frac{\ln(6.67,\,9.7,\,14.62)}{\ln(2576.94,\,12366.74,\,60523.1)} = \left(\frac{\ln(6.67)}{\ln(60523.099)}, \frac{\ln(9.7)}{\ln(12366.74)}, \frac{\ln(14.62)}{\ln(2576.937624)}\right) = (0.172,\,0.241,\,0.342)$$

Table 8
Weight coefficients of criteria.

Cluster/Criteria	Local		
	Fuzzy w_j	Crisp w_j	Rank
MC_1	(0.178,0.253,0.353)	0.2573	2
C_1	(0.043,0.06,0.087)	0.0615	1
C_2	(0.039,0.057,0.084)	0.0586	3
C_3	(0.042,0.059,0.086)	0.0609	2
C_4	(0.04,0.056,0.083)	0.0578	4
C_5	(0.038,0.055,0.082)	0.0567	9
C_6	(0.036,0.053,0.08)	0.0547	17
C_7	(0.036,0.054,0.081)	0.0555	16
C_8	(0.036,0.057,0.083)	0.0576	6
C_9	(0.038,0.055,0.081)	0.0565	11
C_{10}	(0.034,0.055,0.081)	0.0558	13
C_{11}	(0.037,0.055,0.082)	0.0565	10
C_{12}	(0.037,0.055,0.081)	0.0561	12
C_{13}	(0.035,0.056,0.083)	0.0571	8
C_{14}	(0.033,0.055,0.081)	0.0556	15
C_{15}	(0.037,0.054,0.081)	0.0558	14
C_{16}	(0.037,0.052,0.079)	0.0541	18
C_{17}	(0.039,0.056,0.082)	0.0574	7
C_{18}	(0.039,0.056,0.083)	0.0577	5
MC_2	(0.185,0.257,0.357)	0.2614	1
C_{19}	(0.067,0.093,0.131)	0.0946	3
C_{20}	(0.066,0.092,0.13)	0.0942	4
C_{21}	(0.066,0.092,0.13)	0.0937	5
C_{22}	(0.064,0.09,0.128)	0.0922	7
C_{23}	(0.064,0.09,0.128)	0.0922	7
C_{24}	(0.067,0.093,0.131)	0.0952	2
C_{25}	(0.068,0.094,0.132)	0.0959	1
C_{26}	(0.061,0.089,0.127)	0.0905	9
C_{27}	(0.061,0.088,0.126)	0.0901	10
C_{28}	(0.057,0.089,0.127)	0.0896	11
C_{29}	(0.064,0.091,0.129)	0.0926	6
MC_3	(0.178,0.249,0.35)	0.2542	3
C_{30}	(0.07,0.104,0.157)	0.1072	9
C_{31}	(0.075,0.113,0.167)	0.1159	4
C_{32}	(0.072,0.11,0.164)	0.1128	6
C_{33}	(0.065,0.115,0.169)	0.1157	5
C_{34}	(0.083,0.116,0.17)	0.1195	1
C_{35}	(0.076,0.108,0.162)	0.1118	7
C_{36}	(0.073,0.107,0.161)	0.1103	8
C_{37}	(0.079,0.113,0.166)	0.1161	3
C_{38}	(0.08,0.113,0.167)	0.1169	2
MC_4	(0.172,0.241,0.342)	0.2464	4
C_{39}	(0.11,0.161,0.238)	0.1654	6
C_{40}	(0.11,0.167,0.244)	0.1703	4
C_{41}	(0.117,0.168,0.246)	0.1727	2
C_{42}	(0.106,0.166,0.244)	0.1690	5
C_{43}	(0.12,0.17,0.248)	0.1747	1
C_{44}	(0.118,0.168,0.246)	0.1727	3

The remaining weight vectors of the criteria in Table 8 were obtained similarly.

Local values of weight coefficients represent the significance of the cluster criteria, i.e., the group of criteria. Based on the obtained local values, we can see the impact of the considered criterion within the group. In the next step, local criteria weights were used to calculate the fuzzy global weighting values. A graphical representation of the local fuzzy weight coefficients is shown in Fig. 6.

Since two groups of experts participated in the research – a group of experts from industry and a group of experts from the academic community – we have defined weighting coefficients separately for each group to see the differences in expert preferences between these two considered groups. Fig. 7 presents the weighting coefficients of the criteria for both expert groups (industry and academia).

Hierarchical clustering is applied to find the similarity between the participants' responses. The hierarchical relationship between the responses is shown in Fig. 8, with the help of a dendrogram. It can be seen that the most similarity is present between participants {4 and 33}, {7 and 10}, {25 and 32}, and {5 and 27}, respectively.

6. Results and discussion

The comparison of grouping results by cluster – technical, economic, environmental, and social/political – is presented in Table 9 and Fig. 9. Survey participants are from both academia and industry, in order to reflect various points of view and thus minimizing the bias which may exist in any of the domains. Four main and forty-four sub-criteria have been investigated within the scope of this study.

According to the respondents of the survey, among the four clusters the most influential and important is MC_2 (economic), for participants from both academia and industry. The consensus on the importance of the economic main criteria is not a surprising outcome, since the main objective of the decision use-case of this study is a type of investment issue where the most influential impact is financial and economic. However, the least influential and important main criteria is MC_4 (social/political) and MC_1 (technical) for academia and industry, respectively. The reason that industry gave more weight to MC_4 is the fact that they are dealing with more real-life issues, such as the impact of political support or politics in general, in comparison to the academics who usually tend to oversee such matters. Similarly, industry participants ranked MC_3 (environmental) higher than purely technical criteria (MC_1). Depending on the location and its regulations, the environmental challenges have the potential to jeopardize the entire project in daily business conditions. The companies have to evaluate the entire investment opportunity and risks in an interdisciplinary and holistic manner. Therefore, within such an interdisciplinary structure, game stopper factors, such as any problem with environmental issues or any political resistance, are weighted accordingly. For academia, this real-life issue might easily be underestimated. On the other hand, industry players tend to slightly underestimate the importance of MC_1 (technical), or alternatively, they rely on their technical expertise levels as a controllable factor.

All participants – represented in the third category – merge both domains where the possible biases on separate expert domains (academy and industry) are normalized, so as to yield more realistic results. The comparison of grouping results is given in Table 10. The overlapping chart of data series for the three groups regarding the evaluation of the experts is shown in Fig. 10. The segmented analysis of the MC groups helps to identify the most influential sub-criteria and their comparative discussions. According to the results of MC_1, the sub-criteria solar radiation, sunshine hours, and temperature are the most important factors in this category, when all participants' responses are considered. The least important MC_1 sub-criteria are urban planning and distance to residential areas.

According to the results of MC_2, the sub-criteria economic performance indicators (NPV, IRR, RoI), levelized cost of energy evolution, and initial investment cost are the influential factors in this category. The least important MC_2 sub-criteria are impact on regional development and local economies and impact on agriculture.

According to the results of MC_3, the sub-criteria carbon emission savings, protected areas, and ecology (ecological damage) are the influential factors in this category. The least important MC_3 sub-criteria are soil structure and geology and sand/dust risk.

According to the results of MC_4, the sub-criteria policy support and regulatory boundaries and legal constraints are the influential factors in this category. The least important MC_4 sub-criteria are population density and public acceptance/support.

Table 9
Local weights of clusters for three groups.

Degree of importance	All participants		Academia		Industry	
	Cluster	Weights	Cluster	Weights	Cluster	Weights
Most important cluster	MC_2	0.2614	MC_2	0.2596	MC_2	0.2665
	MC_1	0.2573	MC_1	0.2574	MC_3	0.2665
	MC_3	0.2542	MC_3	0.2559	MC_4	0.2493
Least important cluster	MC_4	0.2464	MC_4	0.2465	MC_1	0.2341

MC_1: technical; MC_2: economic; MC_3: environmental; and MC_4: social/political.

Table 10
Local weights of criteria for three groups.

Degree of importance	All participants		Academia		Industry	
MC_1: Technical	Criteria	Local weights	Criteria	Local weights	Criteria	Local weights
Most important	C_1	0.0615	C_1	0.0612	C_3	0.0601
	C_3	0.0609	C_3	0.0607	C_9	0.0601
	C_2	0.0586	C_{13}	0.0580	C_5	0.0592
	C_4	0.0578	C_2	0.0579	C_8	0.0592
	C_{18}	0.0577	C_{18}	0.0575	C_{11}	0.0592
	C_8	0.0576	C_8	0.0572	C_4	0.0582
	C_{17}	0.0574	C_{11}	0.0568	C_{17}	0.0582
	C_{13}	0.0571	C_{17}	0.0566	C_1	0.0573
	C_5	0.0567	C_4	0.0565	C_{10}	0.0573
	C_{11}	0.0565	C_5	0.0565	C_{12}	0.0573
	C_9	0.0565	C_{10}	0.0561	C_6	0.0562
	C_{12}	0.0561	C_{14}	0.0561	C_{18}	0.0562
	C_{10}	0.0558	C_9	0.0559	C_7	0.0551
	C_{15}	0.0558	C_{12}	0.0555	C_{16}	0.0551
	C_{14}	0.0556	C_{15}	0.0555	C_{13}	0.0540
	C_7	0.0555	C_6	0.0550	C_2	0.0515
	C_6	0.0547	C_7	0.0546	C_{14}	0.0515
Least important	C_{16}	0.0541	C_{16}	0.0534	C_{15}	0.0515
MC_2: Economic	Criteria	Local weights	Criteria	Local weights	Criteria	Local weights
Most important	C_{25}	0.0959	C_{25}	0.0954	C_{28}	0.0984
	C_{24}	0.0952	C_{24}	0.0952	C_{27}	0.0971
	C_{19}	0.0946	C_{20}	0.0947	C_{24}	0.0958
	C_{20}	0.0942	C_{21}	0.0936	C_{20}	0.0944
	C_{21}	0.0937	C_{19}	0.0931	C_{21}	0.0929
	C_{29}	0.0926	C_{29}	0.0926	C_{22}	0.0915
	C_{22}	0.0922	C_{22}	0.0912	C_{25}	0.0899
	C_{23}	0.0922	C_{23}	0.0912	C_{29}	0.0899
	C_{26}	0.0905	C_{26}	0.0912	C_{19}	0.0883
	C_{27}	0.0901	C_{27}	0.0906	C_{23}	0.0883
Least important	C_{28}	0.0896	C_{28}	0.0903	C_{26}	0.0883
MC_3: Environmental	Criteria	Local weights	Criteria	Local weights	Criteria	Local weights
Most important	C_{34}	0.1195	C_{34}	0.1198	C_{31}	0.1175
	C_{38}	0.1169	C_{33}	0.1180	C_{38}	0.1157
	C_{37}	0.1161	C_{38}	0.1158	C_{30}	0.1138
	C_{31}	0.1159	C_{37}	0.1144	C_{33}	0.1138
	C_{33}	0.1157	C_{31}	0.1141	C_{34}	0.1138
	C_{32}	0.1128	C_{32}	0.1120	C_{35}	0.1138
	C_{35}	0.1118	C_{35}	0.1095	C_{32}	0.1119
	C_{36}	0.1103	C_{36}	0.1087	C_{36}	0.1099
Least important	C_{30}	0.1072	C_{30}	0.1076	C_{37}	0.1055
MC_4: Social/Political	Criteria	Local weights	Criteria	Local weights	Criteria	Local weights
Most important	C_{43}	0.1747	C_{43}	0.1718	C_{39}	0.1775
	C_{41}	0.1727	C_{41}	0.1713	C_{41}	0.1750
	C_{44}	0.1727	C_{44}	0.1713	C_{43}	0.1723
	C_{40}	0.1703	C_{40}	0.1709	C_{44}	0.1696
	C_{42}	0.1690	C_{42}	0.1699	C_{40}	0.1637
Least important	C_{39}	0.1654	C_{39}	0.1641	C_{42}	0.1572

7. Conclusion

Decarbonization of energy systems has been a very dominant trend, especially in the past two decades. International institutions such as United Nations and the European Union have announced their global targets in the fields of climate change, carbon emissions savings, and renewable energy resources in energy policy and at the strategic level. It is mostly up to industry to realize such ambitious targets in real life. Industrial players are commercial entities driven by pragmatic and realistic investment decisions. In this study we investigated forty-four different investment decision sub-criteria which are segmented under four main criteria groups. Importance ranking of forty-four sub-criteria is performed using two rounds of expert surveys which are then processed using the fuzzy LAAW model.

The proposed fuzzy LAAW model is a practical, rational, and robust tool for determining the criteria's weights. In addition to the advantages of the LAAW model listed in the previous sections of the paper, it is necessary to emphasize the proposed methodology's flexibility. The LAAW model's flexibility is based

Table A.1
Participants' departments for Round 1 and 2.

Participant	Round 1	Participant	Round 2
	Department		Department
1	Agriculture Engineering	1	Agriculture Engineering
2	Built Environment Energy Systems	2	Artificial Intelligence
3	Civil Engineering	3	Biodiversity/Building and Urbanization
4	Computer Science	4	Center for Environmental Studies and Research
5	Economics	5	Civil and Environmental Engineering
6	Electric Power Engineering	6	Economics
7	Electrical Engineering	7	Economics and Management
8	Electrical Engineering	8	Electric Power Engineering
9	Electrical Engineering	9	Electrical Engineering
10	Energy Engineering	10	Electrical Engineering
11	Energy Engineering	11	Electrical Engineering
12	Energy Systems	12	Electrical Engineering
13	Environmental Engineering	13	Electrical Engineering
14	Environmental Engineering	14	Energy Department
15	Environmental Management	15	Energy Engineering
16	Geographical Sciences	16	Environment and Energy
17	Geography Department	17	Environmental Change and Management
18	Human Geography	18	Geographical Sciences and Urban Planning
19	Industrial Engineering	19	Geomatics Engineering
20	Industrial Engineering and Management	20	Industrial Engineering
21	Management Science	21	Industrial Engineering and Management
22	Management Science	22	Information Systems Engineering
23	Mechanical Engineering	23	Laboratory of Decision Support Systems
24	Mechanical Engineering	24	Marketing/Sustainability
25	New Energies and Applications	25	Mechanical Engineering
26	Non-Governmental Research Organization	26	New Energies and Applications
27	Project Management	27	Non-Profit Research and Development Organization
28	Renewable Energy Division	28	Power Systems Engineering
29	Research and Innovation Centre of Excellence	29	Project Management
30	Science Department	30	Renewable Energy
31	Sustainable Energy Supply	31	Research and Innovation Centre of Excellence
32	Not Provided	32	Science Department
		33	Sustainable Energy Supply

on the ability to define anti-ideal point interval values, which allows for efficient sensitivity analysis. This creates the possibility of defining the limit values of the criteria's weight coefficients for a predefined anti-ideal point. Based on these results, it is possible to specify the influence of subjectively defined anti-ideal points on the final values of weight coefficients.

As this is a new methodology, it is necessary to direct future research towards an extension of the LAAW methodology, by applying other uncertainty theories such as rough sets, grey sets, etc. To exploit the effectiveness and rationality of the LAAW methodology, future research should be directed towards the formation of integrated models with traditional MCDM tools.

CRediT authorship contribution statement

Muhammet Deveci: Conceptualization, Data acquisition, Investigation, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Umit Cali:** Supervision, Conceptualization, Writing – review & editing. **Dragan Pamucar:** Methodology, Software, Validation, Visualization, Writing – review & editing.

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.

Appendix

Participants' departments for Round 1 and 2.
See Table A.1.

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