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Optimal Wind Farm Siting Using a Fuzzy Analytic Hierarchy Process: Evaluating the Island of Andros, Greece

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Abstract: In recent decades, fuzzy logic and fuzzy multi-criteria decision-making systems have been applied in several fields. This paper aims to determine the optimal wind farm siting solution in a fuzzy environment. Therefore, the main research question of the present paper is whether and to what extent the uncertainty in the researcher's judgments affects the ranking of wind farm siting solutions. The fuzzy analytical hierarchy method is applied to an existing case study of wind farm siting on the island of Andros, examining the stability of the final priorities of the alternatives under a regime of gradual increases in ambiguity, as well as whether the introduced ambiguity in the model corresponds to any uncertainty the researcher has during the process of scoring the criteria and alternatives. Five assessment criteria (wind potential, ground slope, distance from road network, distance from high-voltage network, and social acceptance of local population) and eight eligible suitable alternatives (A1–A8) for wind farm siting are considered in the computations. The methodology includes the fuzzification of initial decision-maker judgments, the calculation of fuzzy intermediate priorities (weights), the defuzzification of fuzzy intermediate priorities (weights), and the synthesis of intermediate priorities into final priorities of alternatives, according to the procedures of the crisp AHP (CAHP). Under the assumptions of the initial case study, the results show that the final priorities are quite robust when faced with increased ambiguity. In almost all the examined cases, the alternative initially chosen as the best, A1, is dominant, followed by A3. In addition, in all cases, social acceptance favors alternative A1, and wind velocity favors alternative A8. Therefore, fuzzy multi-criteria methods can be applied to determine an optimal wind farm siting solution when criteria with qualitative characteristics are used and the manifestation of preferences involves strong elements of subjectivity.

Keywords: onshore wind farm; fuzzy analytic hierarchy process (FAHP); triangular fuzzy numbers; Andros Island

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1. Introduction

In recent decades, the energy market has turned to renewable energy sources (RESs) as an efficient, economical, but, above all, clean and environmentally friendly solution. Renewable energy sources such as wind, hydropower, and oceanic energy sources should be introduced to promote energy conservation [1]. Regarding the policy of reducing greenhouse gas emissions, RESs have emerged as a dominant pillar in the production of electricity, which is constantly growing. In addition, target 7 (SDG 7) of the Sustainable Development Goals (SDGs) proposes an increase in the global percentage of renewable energy [2]. Therefore, RESs can significantly contribute to sustainability.

According to the European Environment Agency, the share of energy consumed in the EU during 2021 and 2022 generated from renewable sources was 21.9% and 23%, respectively [3]. Solid biomass represented 40% of the total renewable energy supply in

Europe in 2022, followed by wind (15%), hydropower (10%), and liquid biofuels (7%), whereas other significant contributions include heat pumps (7%) and solar photovoltaics (7%), as well as biogases, renewable waste, geothermal, and solar thermal [3]. Meeting the new target of 42.5% for 2030 will demand more than double the rates of renewables deployment seen over the past decade [3]. Wind energy, both onshore and offshore, appears as one of the most basic sources, with an ever-increasing percentage of total energy production, as it emerges as a particularly environmentally friendly but also economically competitive source. Globally, wind energy production exceeded 900 GW in 2022 [4], while the installed capacity in Greece, in particular, reached 4681.4 MW [5].

Simultaneously with the deployment of the sector, the interest of national and international organizations, investors, academia, and researchers in finding the optimal wind farm siting solutions is continuously increasing. Researchers begin with the identification and delineation of exclusion zones, i.e., areas deemed unsuitable for the deployment of wind farms. Exclusion areas include protected areas, national parks, areas with very low wind potential, areas that do not meet the minimum distance from residential areas, archaeological sites, road networks, airports, areas that are migratory paths for birds, and military areas. Omitting these helps identify suitable areas for wind farm siting, from which optimal areas can be defined based on several environmental, technical, economic, and social criteria. These criteria often include the wind potential of the area, distances from the electricity and road network, slope, land uses, and visual nuisance. In addition, the acceptance of wind farm projects by the local population is of particular interest. The peculiarity of the visual nuisance criterion is that the degree of acceptance is not "easily" measurable, but it also can change over time. Public acceptance is influenced by various factors not necessarily scientifically documented and, moreover, is prone to sensationalist rhetoric. A well-organized and effective information campaign can change an initially formed attitude.

A geographical information system (GIS) is a basic tool for data analysis. GISs have been recently used extensively as a decision support system to identify potential areas for wind farm installations [6–8]. However, finding the optimal solutions requires the assessment and combination of a series of criteria that are not directly related to each other. This assessment, to a certain extent and depending on the criterion, depends on the experience and subjectivity of the researcher or the decision maker. Multi-criteria decision-making (MCDM) methods are often applied in the assessment phase. They combine criteria and alternatives, use mathematical equations to derive results, and prioritize the alternatives based on the selected criteria, offering the decision maker a series of optimal solutions. The most frequently used MCDM methods in the literature regarding wind farm siting solutions are the analytical hierarchy process (AHP) (e.g., [6,9–12]), a technique for order of preference by similarity to ideal solution (TOPSIS) (e.g., [13–17]), VIKOR (e.g., [18–20]), elimination et choix traduisant la realité (ELECTRE) (e.g., [16,21,22]), and the preference ranking optimization method for enrichment evaluation (PROMETHEE) (e.g., [23,24]). In a recent study in which wind energy and MCDM methods were discussed, Eroglu et al. [25] concluded that the AHP method is the most frequently used method.

A special category of MCDM methods comprises those that use "fuzzy inference" or "fuzzy logic" in their mathematical computations, with fuzzy AHP and fuzzy TOPSIS being the most widespread. These methods are particularly used for the expression of subjectivity, as well as in cases where the criteria describe vague concepts, e.g., when one has a positive, very positive, negative, or very negative attitude toward a project or activity.

Although there are numerous case studies in the international literature that use AHP for criteria weighting (e.g., [6,9–12]) in wind farm siting processes, there are really a handful of studies that use the fuzzy analytic hierarchy process (FAHP).

More specifically, Sánchez-Lozano et al. [26] employed FAHP approaches of various MCDM strategies to select appropriate sites for wind farms on the coast of the Murcia Region (southeastern Spain). The criteria were converted into a fuzzy decision matrix using triangular fuzzy numbers (TFNs), and the authors used a GIS to construct a database of the options. The results indicated that the best alternative obtained by the FTOPSIS method is the same as that obtained by the other fuzzy MCDM methods (fuzzy WSM, fuzzy AHP, fuzzy revised AHP), and the positions of the next best options are likewise very comparable.

In similar research, Ayodele et al. [27] proposed a GIS-based model for the interval type-2 FAHP to identify the best locations for wind farm deployment in Nigeria. The approach aimed to overcome the problems of ambiguity, vagueness, and inconsistency in the selection of appropriate areas for wind farm siting by focusing on the usage of fuzzy sets to express experts' linguistic assessments. The model assessed the suitable sites using two sets (weighted and constraint) of social, environmental, or economic criteria. The results showed that the country is estimated to have a suitable area of 125,728.6 km^2, 2650.1 km^2 of which is considered extremely appropriate for wind farm locations.

Tercan et al. [28] developed an integrated methodology for assessing the wind farm siting of offshore bottom-fixed structures in two areas (Cyclades and the İzmir region) in two countries (Greece and Turkey, respectively). The combined use of MCDM methods and a GIS was implemented, and a group of experts used fuzzy sets and linguistic terms to achieve more consistent and independent rankings and results. The results indicated that 289 km^2 (3.22%) of the study area in the Greek region was deemed to be appropriate for offshore wind farms compared to 519 km^2 (10.23%) in the Turkish region.

In another study, Rehman et al. [29] provided a preliminary investigation on a rule-based wind farm turbine selection methodology based on fuzzy logic ideas. In conjunction with the turbine selection model, they examined several scenarios, and two test scenarios were used to illustrate the applicability of the methodology. A total of 17 turbines from various manufacturers with rated capacities ranging from 1.5 to 3 MW were assessed using data from a real potential location in Saudi Arabia.

Meanwhile, Eroğlu [30] used a GIS and the FAHP to identify the most appropriate areas for wind farm siting in the mountainous province of Gümüşhane in the Black Sea Region of Turkey and create a model with 81 sub-criteria and 17 primary criteria pertinent to wind power plants. A suitability map with restricted areas, very suitable areas, and less suitable areas for the study area was created. The results indicated several crucial wind farm installation areas in the southwest, middle, and northwest regions of the study area.

Dhingra et al. [31] developed a framework for identifying and prioritizing the barriers to the growth of offshore wind energy in India using an MCDM approach and applying the FAHP. Their findings showed that the most significant obstacles to the expansion of offshore wind energy in India are financial and technical, while the least significant obstacles are supply chain and regulatory and political barriers.

In addition, it should be noted that regarding the insular environment in Greece, there have been previous efforts regarding wind farm siting (e.g., [32–36]), and all of them use the AHP method in their calculations to provide the most suitable sites for wind farm deployment.

The selection of optimal wind farm siting solutions is a process that requires the combined analysis of several criteria, some of which can be measured and quantified, while others cannot. Although even quantitative criteria may contain a degree of uncertainty, criteria such as public opinion rely on assessments based on qualitative judgments that include the natural ambiguity that governs human intelligence and behavior.

This study aims to investigate whether the researcher's uncertainty is introduced into the FAHP and how the outcome of the final weights and priorities are affected during the pairwise comparison process of assessment criteria and alternatives in an effort to identify the optimal wind farm siting solutions. The island of Andros (South Aegean Region, Greece) is the study area for this evaluation, resulting in nine eligible siting alternatives based on the exclusion siting criteria in one of the authors' earlier publications [32]. The FAHP method with gradually increasing ambiguity rates is applied, and results are compared in order to investigate the changes.

The main contributions of the paper can be summarized by the following.

(i) A fuzzy logic-based method is applied that allows the decision maker to create flexible decision rules for the wind farm siting challenge. The proposed methodology is scalable and reliable, and it may be expanded to any number of assessment criteria in the decision-making process. (ii) To the authors' knowledge, this is the first study in Greece that investigates the resilience of the results and the final ranking of alternative wind farm siting locations to a gradually increasing ambiguity in judgments and examines whether the ambiguity of the researcher during the pairwise comparison is introduced into the model and calculations during the triangular fuzzy number (TFN) construction. (iii) The present work also contributes to the body of research where the assessment criteria are determined by sharp values rather than by linguistic labels or fuzzy triangular numbers. (iv) This study offers crucial background information for the decision-making processes regarding the deployment of WFs' siting decisions.

The remainder of this paper is organized as follows. Section 2 explains the FAHP methodology. Section 3 presents the study area, provides evidence for the assessment criteria and alternatives, and outlines the proposed research methodology. The analytical findings are shown in Section 4, and Section 5 discusses the results and concludes with useful remarks.

2. Fuzzy Analytical Hierarchy Process Methodology

Fuzzy logic (FL), an extension of binary logic to multi-faceted logic, was first introduced in 1965 by Lotfi Zadeh [37]. The truth of each statement is a matter of degree, as determined by a membership function $\mu A(x)$ that maps the input value x to an appropriate participation value in the closed set [0, 1]. The non-fuzzy numbers "clear, specific" are called "crisp" and have a participation grade of 1. This paper uses TFNs (Figure 1). The numbers are denoted as $A = (l, m, u)$ (i.e., lower, middle, upper), while the membership function $\mu A(x)$ of the TFN is provided in Equation (1).

$$\mu A(x) = \begin{cases} \frac{x-l}{m-l}, & l \leq x \leq m \\ \frac{x-u}{m-u}, & m \leq x \leq u \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

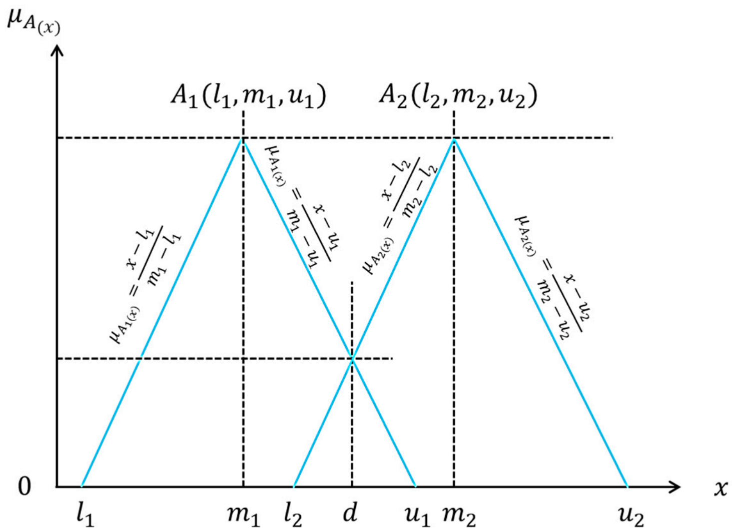

Figure 1. TFNs $A_1 = (l_1, m_1, u_1,)$, $A_2 = (l_2, m_2, u_2)$.

In an MCDM method, when judgments and priorities are real numbers, calculating and comparing the final priorities of alternatives are straightforward. However, if fuzzy numbers represent judgments or priorities, then applying algebraic operations between them can be complex. Due to the nature of fuzzy numbers and the existence of membership functions, the methods of calculating algebraic operations are complex. Moreover, the more complex the membership function is, the more difficult the algebraic operations are. These operations are based on the basic properties of the fuzzy sets of Zadesh [37]. In the international literature, there are many methods used for calculating arithmetic operations of fuzzy numbers [38–44]. This paper employs the results of papers that used the a-cut method, in which fuzzy numbers contain the concept of intervals. A fuzzy number can consider a generalization of the concept of interval since; instead of considering one interval, more intervals are considered at various levels $\alpha \in [0, 1]$. If the intervals at the different levels are calculated, then operations between fuzzy numbers are reduced to operations between intervals, while fuzzy arithmetic is transformed into interval arithmetic.

When operations are performed between TFNs $A(l, m, u)$, basic algebraic operations are further simplified (becoming approximate in terms of multiplication and division operations). Equations (2)–(7) are the most widespread and most used in the numerous variants of FAHPs [45,46] and, ultimately, the equations this paper uses. Of note, this paper employs the results of the work of Palash et al. [47] to define the algebraic operations.

If we let $A(l_1, m_1, u_1)$ and $B(l_2, m_2, u_2)$ be two TFNs and $l_1, m_1, u_1, l_2, m_2, u_2 \in \mathbb{R}^+$, then the following holds:

$$\text{Addition}: A \oplus B = (l_1, m_1, u_1) + (l_2, m_2, u_2) = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \tag{2}$$

$$\text{Subtraction}: A \ominus B = (l_1, m_1, u_1) - (l_2, m_2, u_2) = (l_1 - u_2, m_1 - m_2, u_1 - l_2) \tag{3}$$

$$\text{Multiplication with } k \in \mathbb{R}: k * (l_1, m_1, u_1) = \begin{cases} (k * l_1, k * m_1, k * u_1) \; if \; k > 0 \\ (k * u_1, k * m_1, k * l_1) \; if \; k < 0 \end{cases} \tag{4}$$

$$\text{Multiplication}: A \otimes B = (l_1, m_1, u_1) * (l_2, m_2, u_2) = (l_1 * l_2, m_1 * m_2, u_1 * u_2) \tag{5}$$

$$\text{Inverse}: A^{-1} = (l_1, m_1, u_1)^{-1} = \left(\frac{1}{u_1}, \frac{1}{m_1}, \frac{1}{l_1}, \right), \; l_1, m_1, u_1 \neq 0 \tag{6}$$

$$n^{th}\text{root}: A^{\frac{1}{n}} = (l_1, m_1, u_1)^{\frac{1}{n}} = \left(l_1{}^{\frac{1}{n}}, \; m_1{}^{\frac{1}{n}}, \; u_1{}^{\frac{1}{n}}\right) \tag{7}$$

Our methodology was selected with the application of geometric mean and centroid defuzzification based on Buckley's model [48], which has been characterized by Liu et al. [46] as being "...a simple but practical tool". The methodology can be broken down into four steps as follows:

1. Fuzzification of initial decision-maker judgments (pairwise comparison judgments);
2. Calculation of fuzzy intermediate priorities (weights);
3. Defuzzification of fuzzy intermediate priorities (weights);
4. Synthesis of intermediate priorities into final priorities of alternatives according to the procedures of the crisp AHP (CAHP).

2.1. Fuzzification of Initial Decision-Maker Judgments

The fuzzification of the initial judgments of the decision maker (Step 1) captures the uncertainty the researcher has in the process of evaluating criteria and alternatives using fuzzy numbers to change from ambiguity to the realm of mathematics. According to Deng [49], the comparison process can be quite complex and may produce unreliable results. Srdjevic and Medeiros [50] also noted that the application of FAHP can produce questionable results if an unbalanced nine-point Saaty scale is used or if this fuzzy scale is not entirely justified. The most common fuzzy scales use five- or nine-point scales [46].

In these cases, the concept of fuzzy distance δ is introduced, and each evaluation is converted to the symmetric TFN $A(l = m - \delta, m, u = m + \delta)$ with the fuzzy distance usually ranging from 0.5 to 2. For example, a judgment of strong importance "5" with a fuzzy distance $\delta = 1$ is converted to the TFN $A(4,5,6)$. The most common value for δ is 1, as shown in Figure 2.

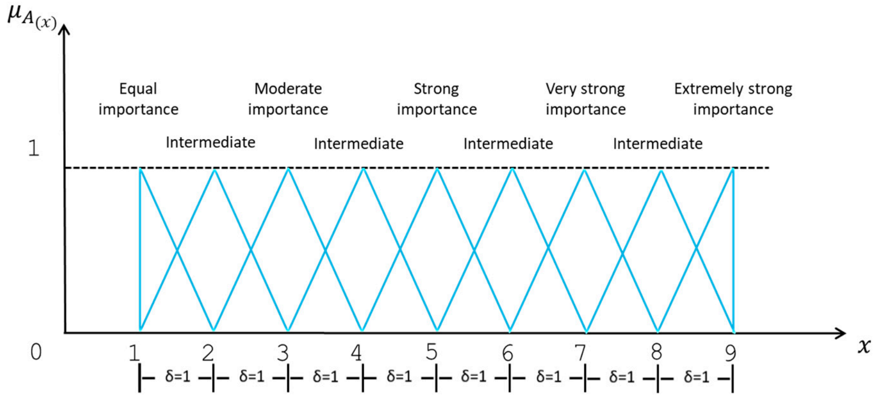

Figure 2. Fuzzy scale of nine points. Source: [40].

This paper aims to investigate the extent to which uncertainty in the researcher's judgments affects the ranking of wind farm siting solutions. The scale shown in Figure 2 is used, and the fuzzy distance δ is gradually increased. However, the fuzzification of the initial judgments is a process in which the researcher should capture their own ambiguity. The use of a standard fuzzy scale of Saaty, in any form, inevitably introduces the ambiguity of the scale maker rather than the researcher carrying out the work. Even if the researcher chooses or constructs their own scale, the assessment is inevitably carried out under the assumption of an even distribution of ambiguity in all judgments. In this case, fuzzy numbers do not capture any doubt or uncertainty that the researcher has during the evaluation phase of the criteria and alternatives but enable an internal process of the method that ignores the researcher's personal attitude to any judgments, which risks unreliable results.

In this paper, the ambiguity for each judgment is initially estimated as a percentage, yielding a scale that is easy, simple, and relatively understandable to the human mind. Then, assuming that 0% ambiguity corresponds to a crisp number and 100% ambiguity corresponds to the maximum space that a TFN can occupy on the Saaty scale, the fuzzy distance δ is calculated in a linear way, staying within the boundaries where 1 denotes equal importance and 9 equals extremely strong importance. Thus, the maximum fuzzy distance is $2 \times \delta = 9 - 1 = 8$. For a TFN $A(l, m, u)$, the fuzzy distance $2 \times \delta$ is defined as follows:

$$A(l, m, u) : 2 \times \delta = l - u \tag{8}$$

For example, the fuzzy number $A(4, 5, 6)$ expresses strong importance and uncertainty: $(6 - 4)/8 = 25\%$. In this way, the expression of ambiguity as a percentage is matched with the fuzzy distance $2 \times \delta$. Because we assume that the limits of the scale [1, 9] are inviolable, the fuzzy numbers close to the scale borders will not be symmetric, and the researcher's uncertainty will be distributed asymmetrically. For example, if the researcher expresses a judgment of extremely strong importance (9) and an uncertainty of 10%, all of the uncertainty is distributed toward strong–very strong importance. In any case, the values l, u of the fuzzy number $A(l, m, u)$ can be derived by the following:

$$\text{IF } m + \delta \le 9 \text{ AND } m - \delta \ge 1 \text{ THEN } \begin{cases} u = m + \delta \\ \quad \text{AND} \\ l = m - \delta \end{cases} \tag{9}$$

$$\text{IF } m + \delta \ge 9 \text{ THEN } \begin{cases} \quad u = 9 \\ \quad \text{AND} \\ l = 9 - 2\delta \end{cases} \tag{10}$$

$$\text{IF } m - \delta \le 1 \text{ THEN } \begin{cases} u = 1 + 2\delta \\ \quad \text{AND} \\ \quad l = 1 \end{cases} \tag{11}$$

The numbers u and l can take values in the closed subset of $\mathbb{R}$ [1, 9] and m in the closed subset of $\mathbb{N}$ [1, 9], while, in any case, $u - l = 2 \times \delta$.

In all the above cases, the barrier imposed at the borders of the scale (1 and 9) pushes the ambiguity to be increasingly spread toward central values. In the case of extremely strong importance, this fact makes practical sense. Since no evaluation can be greater than extremely strong importance (9), inevitably, the whole ambiguity is allocated to values of lesser importance. However, in the case of equal importance, the ambiguity should also be distributed to areas where a reversal of preference is present. Thus, in the next step, the scale is extended to values less than 1 (inverse numbers), which indicate a corresponding weakness instead of importance in judgments (e.g., 1/5, indicating strong weakness).

Finally, ideally, the researcher defines l as the lower limit on its uncertainty and u as the maximum limit, based on Saaty's scale. For example, a judgment for very strong importance, which can also be moderate importance or extremely strong importance, can be captured by the TFN $A(3, 7, 9)$. In this way, the researcher defines the limits of ambiguity as perceived in each case. For the examination of the above, a case study is examined in this paper where the construction of the TFNs considers the variation in the judgment values after the completion of a questionnaire survey by experts.

2.2. Consistency Check

A consistency check helps minimize inconsistencies in the matrixes resulting from pairwise comparison. According to Liou et al. [46], there are two ways of measuring the consistency of the fuzzy pairwise comparison matrix: "crisp consistency" is computed by translating the fuzzy matrix to a representative crisp one and "fuzzy consistency" calculates a consistency index directly from a fuzzy matrix. "Fuzzy consistency" methods are either very complicated (fuzzy programming method), or little research has been performed in the field (geometric consistency index). "Crisp consistency", on the other hand, is the most used and suitable for all types of fuzzy sets [46]. Moreover, according to Mahmoudzadeh and Bafandeh [51], checking "crisp consistency" can express the consistency of a fuzzy matrix. By applying α-cuts, they proved that if the matrix obtained from the α-cuts of the fuzzy numbers for $\alpha = 1$ is consistent, then the fuzzy matrix resulting from the pairwise comparison is also consistent. Thus, in the case of a TFN $A(l, m, u)$, the α-cut for $\alpha = 1$ coincides with the crisp number m, and the matrix with the α-cuts coincides with a crisp matrix where its elements are the values of m. For those reasons, this paper adopts the results of Mahmoudzadeh and Bafandeh [51]; thus, for the consistency check, crisp matrixes are used where each element a_{ij} equals the middle m_{ij} of each fuzzy number $A(l, m, u)$. In the case study examined in this paper [32], the authors have already performed the consistency check of these matrixes.

2.3. Calculation of Fuzzy Intermediate Priorities (Weights)

Various methods have been proposed for aggregating judgments and, ultimately, calculating the priorities (weights) of criteria and alternatives. The most common are those that make use of arithmetic, logarithmic, or geometric means. Of these, the geometric mean is considered quite valid for composition, and according to Barzilai [52], it avoids problems arising from reversal operations and the order in which the operations are performed. This paper uses the geometric mean method based on Buckley's model [48]. Thus, given a fuzzy matrix A_{ij} of magnitude n and using Equations (2)–(7) for the algebraic operations, the geometric mean for each line is first calculated according to Equation (12).

$$\overline{r_i} = \left(\prod_{i=1}^{n} a_{ij} \right)^{\frac{1}{n}} \tag{12}$$

The fuzzy intermediate priorities (weights) are then calculated using Equation (13).

$$\overline{w_i} = \overline{r_i} \otimes (\overline{r_1} \oplus \overline{r_2} \oplus \ldots \oplus \overline{r_n})^{-1} \tag{13}$$

2.4. Defuzzification of Fuzzy Intermediate Priorities (Weights)

The centroid method, or the center of area (COA) or center of gravity (COG), is the most prevalent defuzzification method [46,53]. Its principle is Equation (14), where x^* is the defuzzified value, x indicates the element, and $\mu(x)$ is its associated membership function.

$$x^* = \frac{\int \mu_{(x)} x dx}{\int \mu_{(x)}} \tag{14}$$

For a TFN with integration limits from l to u, the result is as follows:

$$x^* = \frac{l + m + h}{3} \tag{15}$$

Apart from the above equations, several other variations have been used. For instance, Büyüközkan [54] defuzzified a TFN using an a-cut set, and the result is Equation (16), which also corresponds to Yager's approach [55], which analyzes the mean of the elements within an interval. Furthermore, Facchinetti, Ricci, and Muzzioli [56] showed that this method takes into consideration the worst and best results arising from a fuzzy number. As a result, this paper uses Equation (16) to defuzzify TFN.

$$x^* = \frac{l + 2m + h}{4} \tag{16}$$

2.5. Synthesis of Intermediate Priorities into Final Priorities of Alternatives

The synthesis of intermediate priorities into the final priorities of the alternatives follows the procedures of Saaty's crisp AHP (CAHP) [57]. Equation (17) is used for the reduction to the unity of the crisp priorities in Equation (16).

$$w_i = \frac{w_i^*}{\sum_{i=1}^{n} w_i^*} \tag{17}$$

Finally, if a is the criterion, b is the alternative, w_a is the defuzzified priority of criterion a, and w_{ab} is the defuzzified intermediate priority of alternative b with regards to criterion a. Equation (18) yields the final priority of alternative b.

$$w_b = \sum_{a=1}^{w} w_a \times w_{ab} \tag{18}$$

The optimal solution is the alternative that gathers the higher score for w_b, while the ranking of the remainder is carried out in descending order of the w_b index.

3. Materials and Methods

Andros is the northernmost island of the Cyclades region in Greece and second in size after the island of Naxos, with an area of 379.21 km^2 and a total coastline length of 176 km. Andros is located between the islands of Evia and Tinos and is 6 and 1 nautical miles from them, respectively. It extends from the northwest to the southeast and has an elongated shape with a maximum length of 40 km and a width of 17 km. The island has a permanent population of 8826 inhabitants [58]. The wind potential of Andros is very high, and in most parts of the island, a wind velocity of 8–10 m/s and even higher prevails. However, in the northern and central parts of the island, there are some areas where the wind velocity ranges from 7 to 8 m/s, while there are also very few places where the wind velocity does not exceed 5 m/s. The ground slope on the island of Andros is low and, in many areas, does not exceed 20%. Large slopes (45–70%) are only observed along the coastline of the island and in close proximity to it. The road network on Andros has a total length of approximately 510 km, of which 145 km belongs to the provincial network and 365 km to the municipal network. The high-voltage power grid runs along the western part of the island.

3.1. Assessment Criteria and Alternatives

The assessment criteria selected for the process of identifying suitable areas for the siting of wind farms, according to the study by Bili and Vagiona [32], aim at the economic efficiency of the project, the minimization of its construction costs, and the easiest possible acceptance of the construction of the project by the society of Andros, and they are as follows: wind potential (K1), ground slope (K2), distance from the road network (K3), distance from the high-voltage network (K4), and social acceptance of the local population (K5).

3.1.1. Wind Velocity (K1)

One crucial economic factor that influences the site of a wind farm anywhere is the wind potential. A site's potential for producing wind energy is dependent on the wind velocity at that specific location. The wind potential criterion has been incorporated into almost every wind farm siting case study (e.g., [9,27,59,60]). The study of an area's wind data is critical for assessing its site suitability and selecting a suitable wind turbine. Areas with higher wind speeds are considered more suitable for wind farm siting.

3.1.2. Ground Slope (K2)

The morphology of the soil determines an area's suitability for wind farm siting. In the case of high slopes, special works and foundations are needed. All these processes result in increased project costs and a more substantial impact of the wind farm project on the natural landscape of the site. Therefore, in many case studies, to avoid the negative impacts due to unsuitable ground, a slope limit is defined (e.g., [11,61–63]). Areas with slight or even flat slopes are considered more suitable for wind farm siting.

3.1.3. Distance from the Road Network (K3)

The exploitation of existing road networks is essential in wind farm siting studies. Creating new roads needed to access the wind farm projects has negative effects on the environment, especially during the construction phase. Furthermore, the distance from the road network is considered an important criterion [21,64,65], as construction far away from roads increases the installation and repair costs.

3.1.4. Distance from the High-Voltage Network (K4)

The distance from the medium- or high-voltage power grid affects the technical–economic viability of a project and has been used in several studies in the wind farm siting literature (e.g., [21,66,67]). The siting of wind turbines should be carried out near the electrical network to minimize the cost of electricity delivered to the consumer and avoid the need for new electricity lines, which would result in increased project costs. The distance from the high-voltage electricity grid has been used in this study.

3.1.5. Social Acceptance (K5)

Community acceptance reflects the extent to which people affect and are affected by the deployment and use of wind farm projects. Although local community opinion and other factors that influence community acceptance regarding wind farm projects have been investigated in the literature [68], only a handful of studies (e.g., [27,69–71]) used participatory planning and incorporate public opinion in the wind farm siting process.

After applying several exclusion criteria, a study by Billi and Vagiona [32] identified eight potentially suitable areas for onshore wind farm siting, as depicted in Figure 3. They applied the AHP to rank the potential areas, and according to their final priorities, the results were as follows: A1 (0.24), A3 (0.18), A2 (0.16), A8 (0.11), A4 (0.09), A5 (0.09), A6 (0.07), and A7 (0.06). The most suitable area is site 1, followed by A3, while the least suitable is A7.

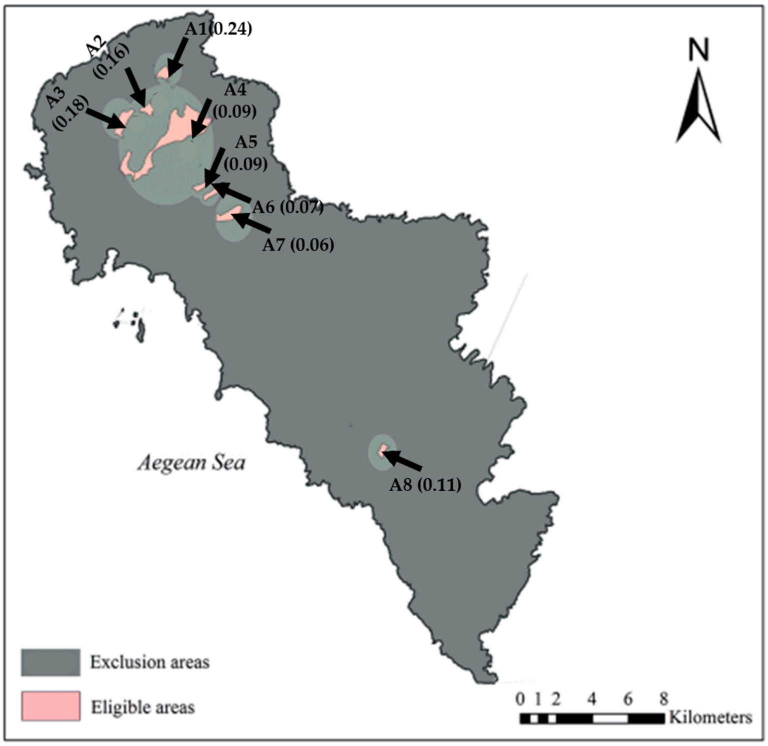

Figure 3. Potential areas for wind farm siting on Andros and AHP ranking [30].

3.2. Methodology Diagram

The present research used the results of [32], applied an FAHP, gradually increased the degree of ambiguity, and compared the results to investigate the changes. In addition, we investigated whether any uncertainty of the researcher during the process of pairwise comparison of assessment criteria and alternatives was introduced into the method and how the final priorities were affected.

The principal four steps of the research methodology applied in this study, as mentioned in Section 2, include (i) the fuzzification of initial decision-maker judgments; (ii) the calculation of fuzzy intermediate priorities; (iii) the defuzzification of fuzzy intermediate priorities; and (iv) the synthesis of intermediate priorities into final priorities of alternatives, according to the procedures of the crisp AHP (CAHP). The methodology used for the fuzzification of the judgments is presented in Figure 4.

The questionnaire survey aimed to record experts' preferences on the significance of the five assessment criteria (K1–K5); thus, it included a comparative assessment of the five assessment criteria. A total of 15 experts participated in the survey, all of whom were graduates of the postgraduate study program "Environmental Protection and Sustainable Development" and attended courses related to renewable energy resources. The processing of the experts' responses provided the quantification of the relative weights of the assessment criteria.

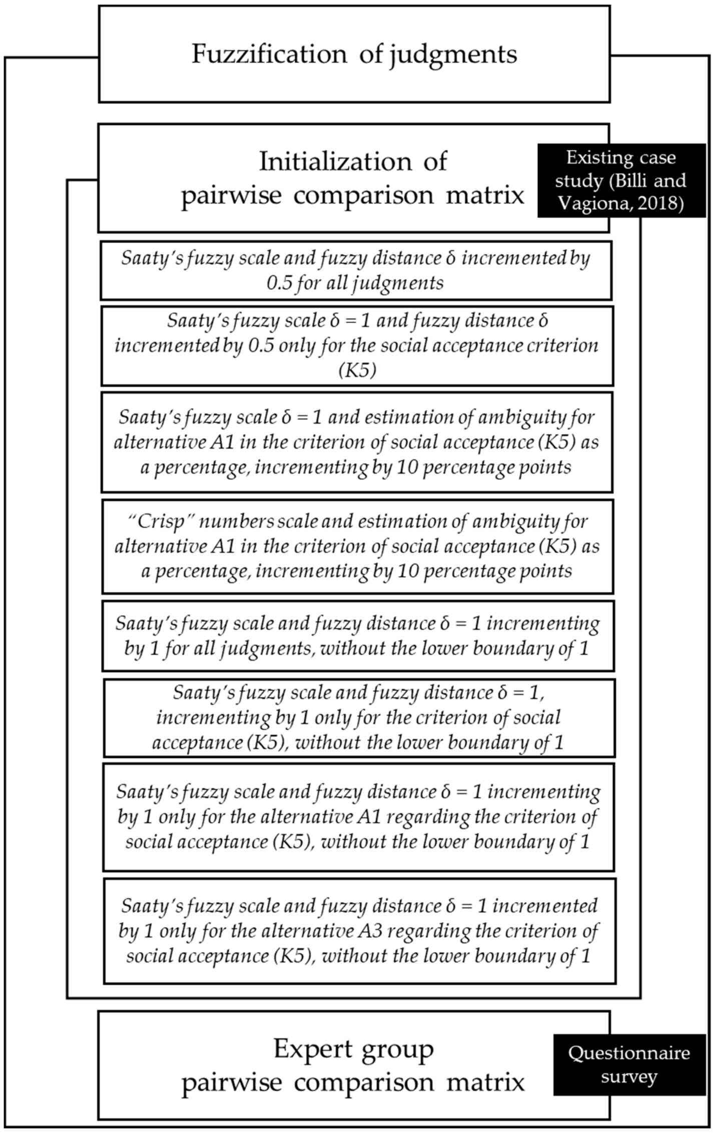

Figure 4. Fuzzification of the judgments in research methodology [32].

4. Results

The final priorities of the alternatives were parametrically investigated and calculated, applying the methodology described above. The parameter that changed was the uncertainty manifested in the initial judgments expressed, in most cases, by a fuzzy distance δ, as described earlier. In each subsection, different assumptions are made, priorities are calculated, and results are compared with the use of diagrams.

4.1. Using Saaty's Fuzzy Scale and Fuzzy Distance δ Incremented by 0.5 for All Judgments

The final priorities are first calculated for a fuzzy distance δ of 0.5, and then, δ is increased each iteration by a step of 0.5 to δ = 3. The scale is bounded between 1 and 9, which means that no initial judgments can be outside these limits. For every fuzzy distance "δ", a different fuzzy scale results, and the outcome is different final priorities for the alternatives. Figure 5 depicts the fuzzy scales that were used to fuzzify the initial "crisp" judgments when δ = 1 and δ = 2. Tables 1 and 2 depict the initial judgments and priorities of the criteria for δ = 0.5, respectively, and Figure 6 depicts the final priorities of the best alternatives vs. the fuzzy distance δ. The uncertainty that enters the model, with the use of the fuzzy distance "δ", affects the final priorities of the alternatives. This dependence on the best alternatives, A1 and A3, is depicted in Figure 6, in which the trend can also be observed.

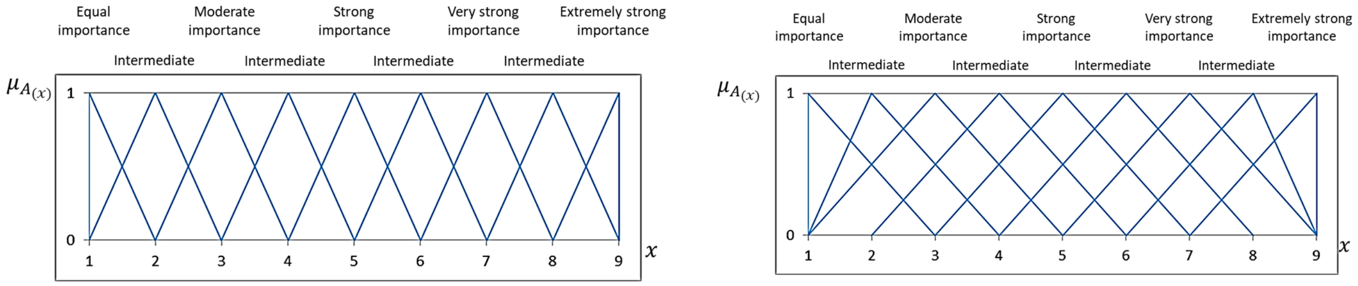

Figure 5. Fuzzy scale for $\delta = 1$ (**left**) and $\delta = 2$ (**right**).

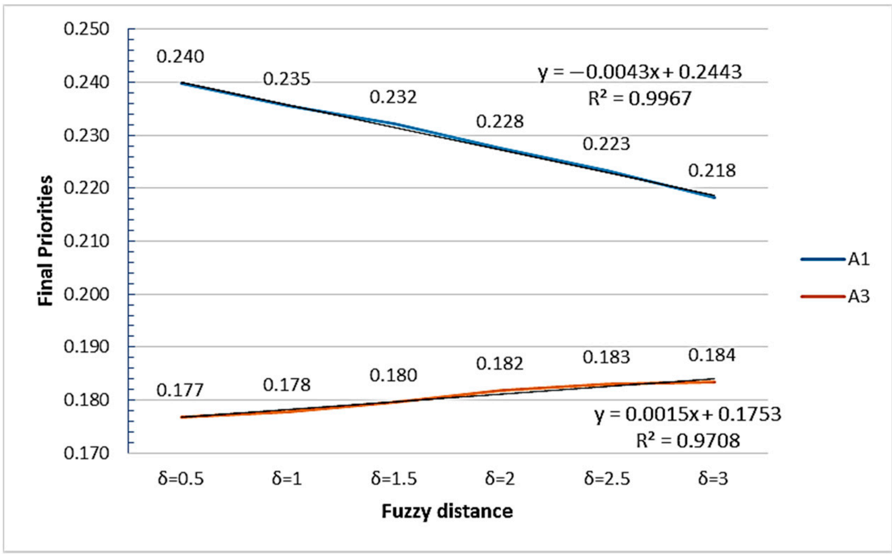

Figure 6. Final priorities for best alternatives vs. fuzzy distance δ.

The results show that the final priorities are quite stable and resistant to ambiguity. No change occurs in the final priorities, with area A1 dominating in all cases. However, the increase in ambiguity seems to favor the alternative A3, second in the ranking, which converges with A1 and theoretically intersects at a fuzzy distance δ of 11.89, which, however, exceeds the boundaries of the scale and has no practical meaning. Of note, the application of the scale imposes symmetry on fuzzy numbers, except for the boundaries, and the same assessment of ambiguity for all judgments, which may deviate from the actual doubts or uncertainty that a researcher may have. Moreover, while, as mentioned, the upper boundary of 9 makes practical sense, the lower boundary of 1, which indicates a judgment of equal importance, does not, and it would be more correct if a reversal of preference occurs for the lower (l) number of the TFNs.

Table 1. Initial judgments for criteria. TFN with fuzzy distance δ = 0.5.

	Wind Potential (K1)			**Slope (K2)**			**Distance from Road Network (K3)**			**Distance from High-Voltage Network (K4)**			**Social Acceptance (K5)**		
	l	***m***	***u***	***l***	***m***	***u***	***l***	***m***	***u***	***l***	***m***	***u***	***l***	***m***	***u***
Wind potential (K1)	1.0000	1.0000	1.0000	2.5000	3.0000	3.5000	2.5000	3.0000	3.5000	2.5000	3.0000	3.5000	0.1818	0.2000	0.2222
Slope (K2)	0.2857	0.3333	0.4000	1.0000	1.0000	1.0000	1.0000	1.0000	1.5000	1.0000	1.0000	1.5000	0.1333	0.1429	0.1538
Distance from road network (K3)	0.2857	0.3333	0.4000	0.6667	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.5000	0.1333	0.1429	0.1538
Distance from high-voltage network (K4)	0.2857	0.3333	0.4000	0.6667	1.0000	1.0000	0.6667	1.0000	1.0000	1.0000	1.0000	1.0000	0.1333	0.1429	0.1538
Social acceptance (K5)	4.5000	5.0000	5.5000	6.5000	7.0000	7.5000	6.5000	7.0000	7.5000	6.5000	7.0000	7.5000	1.0000	1.0000	1.0000

Table 2. Criteria priorities w_a. TFN with fuzzy distance δ = 0.5.

	Fuzzy Geometric Mean $\check{r}_i$			$\bar{r}_1 \oplus \bar{r}_2 \oplus \ldots \oplus \bar{r}_n$			$\bar{w}_i = \bar{r}_i \otimes \left(\bar{r}_1 \oplus \bar{r}_2 \oplus \ldots \oplus \bar{r}_n\right)^{-1}$				$w_i^* = \frac{l+2m+u}{4}$			**Crisp AHP W (Normalized)**
	l	***m***	***u***	***l***	***m***	***u***		***l***	***m***	***u***			**Normalized**	
Wind potential (K1)	1.2322	1.4011	1.5696	6.8277	7.4676	8.1475	$\hat{w}_1$=	0.1512	0.1876	0.2299	w_1=	0.1891	0.1876	0.1916
Slope (K2)	0.5202	0.5439	0.6734	$(\bar{r}_1 \oplus \bar{r}_2 \oplus \ldots \oplus \bar{r}_n)^{-1}$			$\hat{w}_2$=	0.0638	0.0728	0.0986	w_2=	0.0770	0.0764	0.0732
Distance from road network (K3)	0.4797	0.5439	0.6209	*l*	*m*	*u*	$\hat{w}_3$=	0.0589	0.0728	0.0909	w_3=	0.0739	0.0733	0.0732
Distance from high-voltage network (K4)	0.4423	0.5439	0.5726	0.1227	0.1339	0.14646	$\hat{w}_4$=	0.0543	0.0728	0.0839	w_4=	0.0710	0.0704	0.0732
Social acceptance (K5)	4.1533	4.4346	4.7110				$\hat{w}_5$=	0.5098	0.5938	0.6900	w_5=	0.5969	0.5922	0.5887
											tot=	1.0078	1.0000	1.0000

4.2. Using Saaty's Fuzzy Scale δ = 1 and Fuzzy Distance δ Incremented by 0.5 Only for the Social Acceptance Criterion (K5)

The four assessment criteria (K1–K4) used by Bili and Vagiona [32] were evaluated based on measurable data, while the criterion of social acceptance (K5) was assessed through experts' judgments. When measurable data are used, the uncertainty inherent in the initial judgments is expected to be relatively small and dependent on measurement errors, model assumptions, or other systemic or non-systemic errors. However, in the case of K5, where the initial judgment is estimated based on the "feelings" experts have about the subject, the uncertainty behaves differently. This phenomenon makes the K5 criterion interesting to investigate specifically in relation to the uncertainty introduced in the initial judgments. Thus, in this subsection, the classic fuzzy scale of Saaty is used, i.e., with a fuzzy distance $\delta = 1$ for all judgments, except for K5, in which δ is increased by 0.5. As in Section 4.1, the scale is bounded above and below [1, 9]. Figure 7 depicts the final priorities of the best alternatives vs. the fuzzy distance δ.

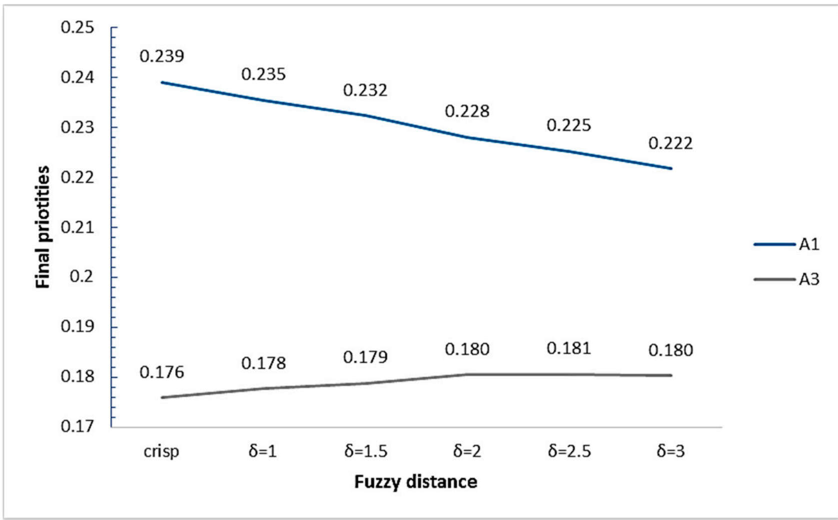

Figure 7. Final priorities for best alternatives vs. fuzzy distance δ.

As in Section 4.1, the final priorities seem to be quite stable and resistant to ambiguity. No change occurs in the final priorities, with area A1 dominating in all cases. Again, with the increase in ambiguity, a trend toward convergence occurs between the first (A1) and second (A3) alternative, while what has been stated about the symmetry of triangular numbers and the lower boundary of the scale also applies.

4.3. Using Saaty's Fuzzy Scale δ = 1 and Estimation of Ambiguity for Alternative A1 in the Criterion of Social Acceptance (K5) as a Percentage, Incrementing by 10 Percentage Points

In this case, all judgments have a fixed estimate of uncertainty, which is approximated using the fuzzy scale of Saaty with fuzzy distance $\delta = 1$, except for alternative A1, to the criterion of social acceptance. In this case, the uncertainty is estimated as a percentage, as described in Section 2.1, which increases from 10% to 100% in steps of 10 percentage points. The criterion of social acceptance (K5) as qualitative is considered to contain the element of ambiguity to a greater extent and is of greater interest in terms of its influence. For this criterion, the behavior of the most dominant alternative, A1, is investigated to evaluate how changes in ambiguity affect the final priorities of the alternatives. As in the previous cases, the scale is bounded above and below [1, 9]. Figure 8 depicts the final priorities for the best alternatives vs. uncertainty.

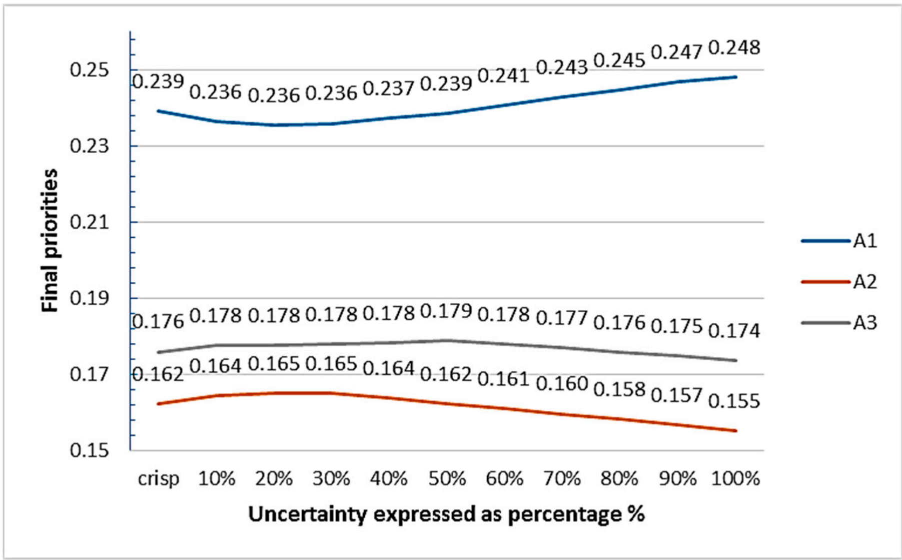

Figure 8. Final priorities for alternatives vs. uncertainty expressed as percentage %.

The results show that the first (A1), second (A3), and third (A2) alternatives initially start to converge with the increase in ambiguity and then diverge. This characteristic is attributed to a flaw in the scale, which is bounded above and below; thus, as ambiguity increases, it is distributed toward the central values of the scale (Figure 9), creating, in this case, this divergence between the best, the second-best, and the third-best alternatives. As mentioned before, in the case of the upper boundary of 9, shifting the ambiguity toward the central values of the scale is appropriate—no judgment can be greater than "extremely strong importance"—but in the case of the lower boundary of 1, the scale cannot include values of ambiguity (i.e., <1) for which the preference in the alternative should change. Of course, the same remark also applies in cases where the most common fuzzy scale of Saaty $\delta = 1$ is used, though to a much lesser extent. In the case of a fuzzy scale with $\delta = 1$, the ambiguity of the judgment "equal importance" is distributed only to the right of the scale, i.e., to "moderate importance". However, in this case, the effect is more intense and better visualized with the diagrams.

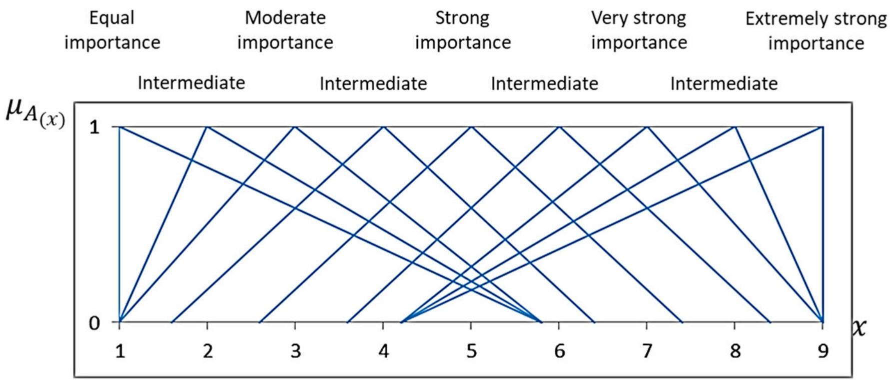

Figure 9. Fuzzy scale expressed as a percentage equal to 60%.

4.4. Using a "Crisp" Numbers Scale and Estimation of Ambiguity for Alternative A1 in the Criterion of Social Acceptance (K5) as a Percentage, Incrementing by 10 Percentage Points

Following Section 4.3, this case uses "crisp" numbers for all judgments, apart from the alternative A1 to the criterion of social acceptance (K5), whose uncertainty is estimated as a percentage, as in Section 4.3. The remaining assumptions are the same. The aim is to check how much the use of the fuzzy scale, with $\delta = 1$ for the remainder of the initial judgments, influences the observed divergence in the diagrams in Section 4.3. Figure 10 depicts the final priorities of the best alternatives vs. uncertainty.

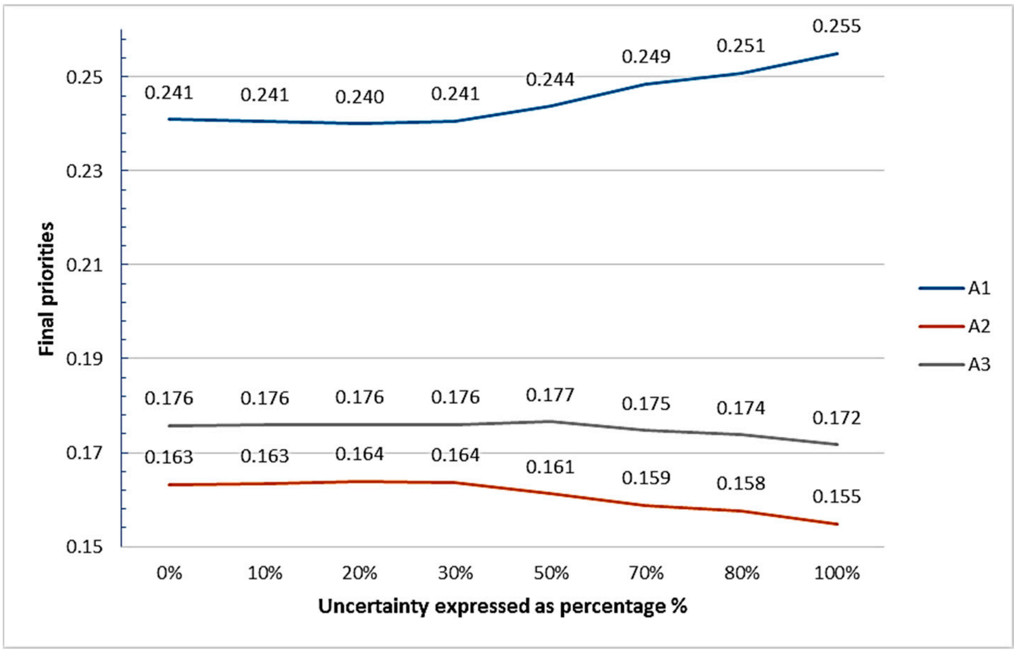

Figure 10. Final priorities for alternatives vs. uncertainty expressed as a percentage.

Figures 9 and 10 are very similar, which enhances the attribution of the observed divergence between the best and the second- and third-best alternatives to the fuzzy scale used and enhances its weakness regarding the lower boundary of 1. Moreover, the use of crisp numbers instead of the fuzzy scale $\delta = 1$ does not seem to affect the results. One reason for this behavior may be the symmetry imposed by the scale on all TFNs, which, at least for small values of the fuzzy distance δ, favors the central values (m) of the TFN that coincide with the corresponding crisp numbers.

4.5. Using Saaty's Fuzzy Scale and Fuzzy Distance $\delta = 1$ Incrementing by 1 for All Judgments, without the Lower Boundary of 1

To deal with the weakness of the fuzzy scale regarding the lower boundary of 1, as described above, in the following cases, the lower number l of the TFNs of the initial judgments can use values below 1, reversing the preference. This is carried out using the reverse numbers of Saaty's scale, i.e., 1/3 for "moderate weakness". For example, for a judgment of "moderate importance", when the fuzzy distance is $\delta = 2$, the TFN is 1, 3, and 5; when $\delta = 3$, the TFN becomes 1/2, 3, and 6; and when $\delta = 4$, the TFN becomes 1/3, 3, and 7. The rest of the TFNs are formed accordingly. Apart from that, this case is similar to the case presented in Section 4.1. Starting with a fuzzy distance $\delta = 1$ and increasing δ by a step of 1 to $\delta = 4$ for all judgments of criteria and alternatives, the final priorities are calculated. Figure 11 depicts the final priorities of the best alternatives vs. fuzzy distance δ.

The results now show a greater convergence of the final priorities of the prevailing alternatives (A1 and A3). A1 is still the prevailing alternative in most cases until the fuzzy distance δ reaches 3.265, with A3 becoming dominant. However, the fuzzy distance for which the trend lines intersect is quite high, and A1 is still considered to be the best option.

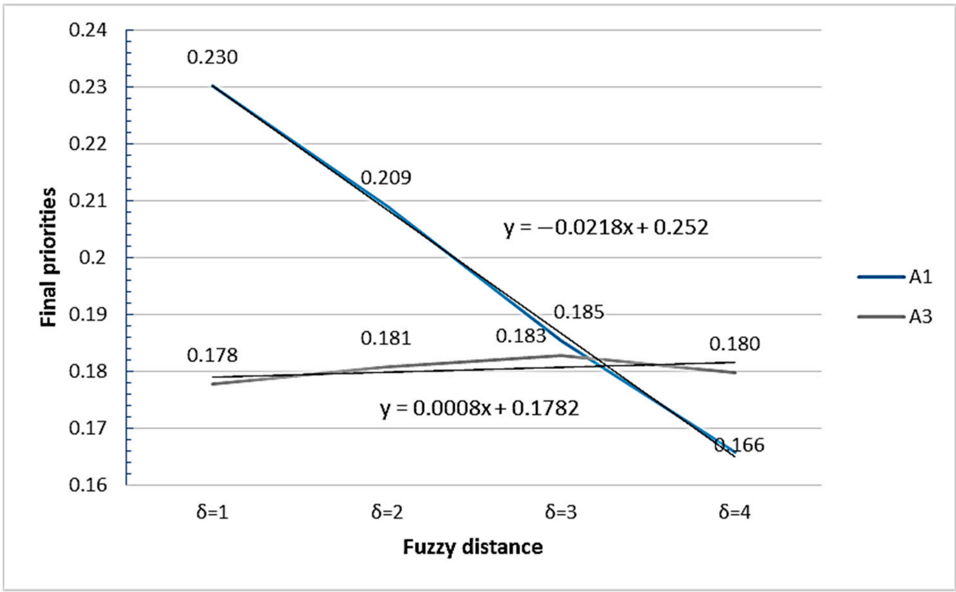

Figure 11. Final priorities for best alternatives vs. fuzzy distance δ.

4.6. Using Saaty's Fuzzy Scale and Fuzzy Distance δ = 1 Incrementing by 1 Only for the Criterion of Social Acceptance (K5), without the Lower Boundary of 1

This case is similar to the case presented in Section 4.2. Considering that the criterion K5 has a special interest, increases in the fuzzy distance δ are being applied only to the judgments of this criterion. As in Section 4.5, no lower boundary of 1 (one) for the TFNs is used. Figure 12 depicts the final priorities of the best alternatives vs. fuzzy distance δ.

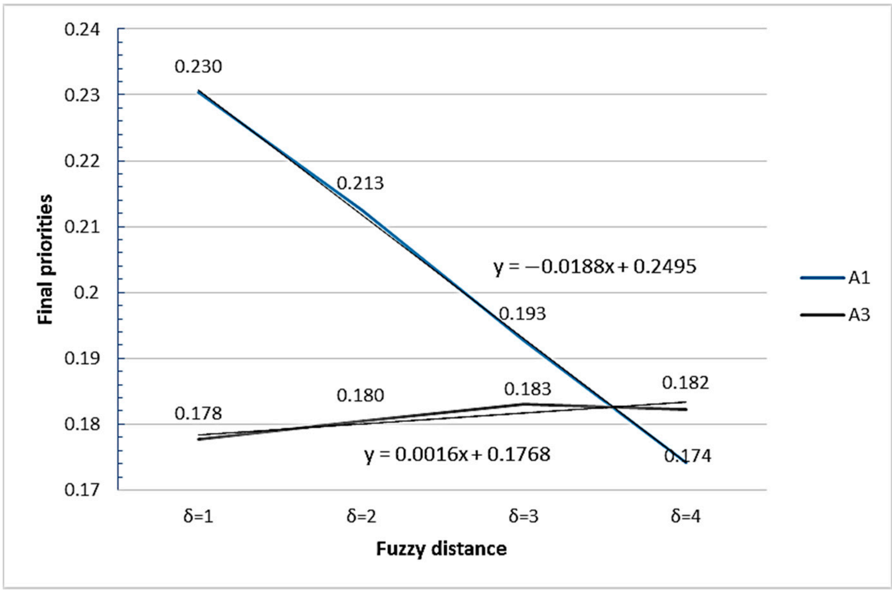

Figure 12. Final priorities for best alternatives vs. fuzzy distance δ.

Similar to the previous case (Section 4.5), the results show a convergence trend of the final priorities of the prevailing alternatives (A1 and A3). A1 is still the prevailing alternative in most cases until the fuzzy distance δ reaches 3.56, with A3 becoming dominant. As in Section 4.5, this value for fuzzy distance is also considered quite high, and A1 is still estimated to be the best option.

4.7. Using Saaty's Fuzzy Scale and Fuzzy Distance $\delta = 1$ Incrementing by 1 Only for the Alternative A1 Regarding the Criterion of Social Acceptance (K5), without the Lower Boundary of 1

This section makes the same assumptions as Section 4.3, except it uses the fuzzy distance δ for the estimation of ambiguity instead of a percentage. In addition, like in previous sections, no lower boundary of 1 for the TFNs is used. Figure 13 depicts the final priorities of the best alternatives vs. fuzzy distance δ.

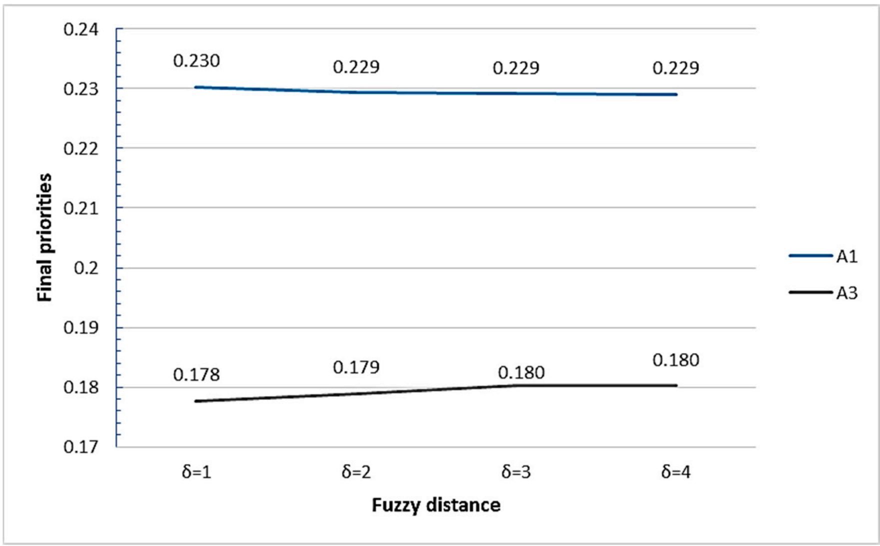

Figure 13. Final priorities for alternatives vs. fuzzy distance "δ".

The results show that the final priorities are not affected by the increase in ambiguity. Alternative A1 is dominant in all cases, while the difference with the second option is almost the same in all cases.

4.8. Using Saaty's Fuzzy Scale and Fuzzy Distance $\delta = 1$ Incremented by 1 Only for the Alternative A3 Regarding the Criterion of Social Acceptance (K5), without the Lower Boundary of 1

This section's case resembles that presented in Section 4.7, except the investigation is performed for the second predominant alternative (A3). For this alternative, and only regarding the criterion K5, the fuzzy distance is incremented by 1, starting with $\delta = 1$. The remaining assumptions are the same as the assumptions considered in Section 4.7. Figure 14 depicts the final priorities of the best alternatives vs. fuzzy distance δ.

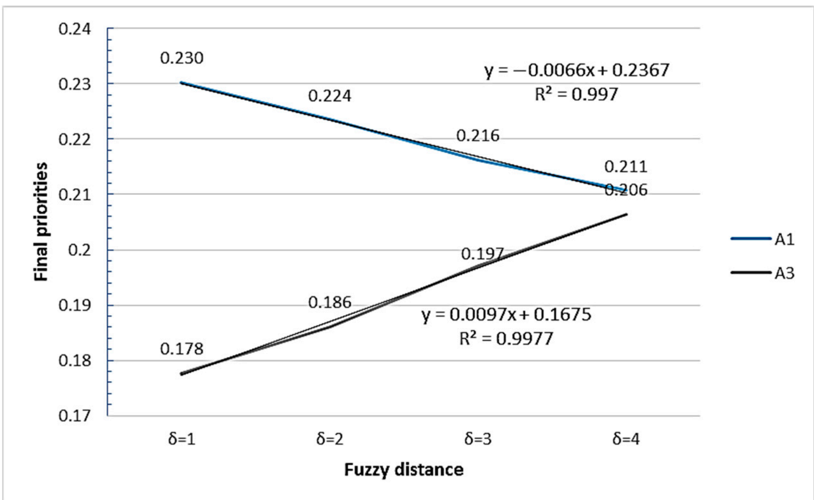

Figure 14. Final priorities for alternatives vs. fuzzy distance δ.

The results, contrary to the previous case, show an almost convergence between the two prevailing alternatives. A1 is still the prevailing alternative, with A3 approaching it as the fuzzy distance δ increases. The trend lines intersect at a fuzzy distance of $\delta = 4.245$, with A3 becoming dominant. However, this fuzzy distance value is also considered quite high, and A1 is still estimated to be the best option. Finally, a comparison of the results of paragraphs in Sections 4.7 and 4.8 (Figures 13 and 14) shows that alternative A3 is more affected by ambiguity in judgments in a positive way compared to alternative A1, which is almost indifferent to ambiguity.

4.9. Using a Questionnaire for the Judgments of the Criteria and Saaty's Fuzzy Scale with Fuzzy Distance $\delta = 1$ for the Remainder

In this last case examined, we assess the ambiguity in pairwise comparisons of criteria using the judgments of postgraduate students with an environmental background. This paper claims that the use of standard fuzzy scales, in any form, inevitably introduces the ambiguity of the scale maker instead of the researcher, and that the best way to introduce ambiguity into the method is for the researchers to construct the TFNs individually every time.

To carry out such an approach, a questionnaire for the judgments of the criteria was completed by the postgraduate students. Thus, for the TFN construction, the median (MEDIAN), minimum (MIN), and maximum (MAX) of the judgments from the questionnaires are used to define the middle value m, the low value l, and the high value u, respectively. Moreover, aiming to exclude extreme values in judgments, a second approach was followed using quadrants P_{25}, P_{50}, and P_{75}, where values for l, m, and u of the TFNs include 25%, 50%, and 75% of the judgments, respectively. Regarding the judgments in the alternatives, no modification is made, as the judgments are assumed to have been derived either from measurements or from estimates of local experts; these experts are familiar with the peculiarities of the alternative locations on the island of Andros. Thus, the classic fuzzy Saaty scale with a fuzzy distance $\delta = 1$ is used for all judgments. Consequently, we assume that the ambiguity is symmetrical and has the same value for all judgments in pairwise comparisons of all alternatives. However, the students who completed the questionnaire had no special knowledge of the peculiarities of the island of Andros (i.e., the series of protests against the installation of the wind farms, which led to an increased sensitivity regarding the social acceptance criterion), so any comparison with the results of the previous subsections should be performed carefully. The main goal of examining this case was to detect the extent of the ambiguity in the judgments of the criteria and estimate how this ambiguity affects the final priorities.

After the completion of the pairwise matrix for the criteria and the construction of the TFNs, a "crisp" consistency check was performed, yielding a consistency index CR of 0.009 (<0.1); therefore, the matrix of the criteria was consistent. Tables 3 and 4 depict the TFNs of the criteria matrix, while Tables 5 and 6 depict the final priorities of the alternatives.

The first conclusion from the results is that the variance transformed into ambiguity is quite large; thus, methodologies that use fuzzy calculus can be useful when including this variance in the calculations. In the case where MIN and MAX are used to determine the boundaries of triangular numbers, the fuzzy distance is between $\delta = 4$ and $\delta = 5$, and when quadrants P_{25}, P_{50}, and P_{75} are used to exclude extreme judgments, the fuzzy distance is between $\delta = 2$ and $\delta = 3$. Moreover, this variation appears even though the questionnaires were completed by a relatively homogeneous group.

Regarding the priorities of criteria K1 and K2, K1 prevails over K2 in the case of the use of quadrants P_{25}, P_{50}, and P_{75}, which is consistent with most relevant research in the field [72]. However, the criterion of social acceptance is rarely used directly, as the most common approach of the researchers is to indirectly express social acceptance through other relevant criteria, such as visual disturbance or distance from residential areas.

Table 3. Judgment criteria matrix with TFNs, where l = MIN, m = MEDIAN, and u = MAX.

	Wind Potential (K1)			Slope (K2)			Distance from Road Network (K3)			Distance from High-Voltage Network (K4)			Social Acceptance (K5)		
	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u
Wind potential (K1)	1.0000	1.0000	1.0000	0.2000	5.0000	9.0000	0.2000	5.0000	9.0000	0.2000	5.0000	7.0000	0.1111	3.0000	7.0000
Slope (K2)	0.1111	0.2000	5.0000	1.0000	1.0000	1.0000	0.2000	1.0000	9.0000	0.2000	1.0000	9.0000	0.1111	0.3333	5.0000
Distance from road network (K3)	0.1111	0.2000	5.0000	0.1111	1.0000	5.0000	1.0000	1.0000	1.0000	0.2000	1.0000	5.0000	0.1111	0.3333	5.0000
Distance from high-voltage network (K4)	0.1429	0.2000	5.0000	0.1111	1.0000	5.0000	0.2000	1.0000	5.0000	1.0000	1.0000	1.0000	0.1111	0.3333	9.0000
Social acceptance (K5)	0.1429	0.3333	9.0000	0.2000	3.0000	9.0000	0.2000	3.0000	9.0000	0.1111	3.0000	9.0000	1.0000	1.0000	1.0000

Table 4. Judgment criteria matrix with TFNs, where $l = P_{25}$, m = MEDIAN, and $u = P_{75}$.

	Wind Potential (K1)			Slope (K2)			Distance from Road Network (K3)			Distance from High-Voltage Network (K4)			Social Acceptance (K5)		
	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u
Wind potential (K1)	1.0000	1.0000	1.0000	3.0000	5.0000	7.0000	2.0000	5.0000	6.5000	0.6667	5.0000	6.0000	0.2000	3.0000	5.0000
Slope (K2)	0.1429	0.2000	0.3333	1.0000	1.0000	1.0000	0.3333	1.0000	4.0000	0.3333	1.0000	3.0000	0.1714	0.3333	1.5000
Distance from road network (K3)	0.1538	0.2000	0.5000	0.2500	1.0000	3.0000	1.0000	1.0000	1.0000	0.6667	1.0000	2.5000	0.2000	0.3333	0.4167
Distance from high-voltage network (K4)	0.1667	0.2000	1.5000	0.3333	1.0000	3.0000	0.4000	1.0000	1.5000	1.0000	1.0000	1.0000	0.2000	0.3333	2.0000
Social acceptance (K5)	0.2000	0.3333	5.0000	0.6667	3.0000	5.8333	2.4000	3.0000	5.0000	0.5000	3.0000	5.0000	1.0000	1.0000	1.0000

Table 5. Final priorities of alternatives for TFNs, where l = MIN, m = MEDIAN, and u = MAX.

Final Priorities of Alternatives			Rank	
	Fuzzy	**Crisp**	**Fuzzy**	**Crisp**
A1	0.1483	0.1473	3rd	4th
A2	0.1367	0.1277	5th	5th
A3	0.2058	0.1907	1st	2nd
A4	0.1633	0.1536	2nd	3rd
A5	0.0690	0.0623	7th	6th
A6	0.0636	0.0504	8th	7th
A7	0.0697	0.0556	6th	8th
A8	0.1436	0.2123	4th	1st
Total	1.0000	1.0000		

Table 6. Final priorities of alternatives for TFNs, where $l = P_{25}$, m = MEDIAN, and $u = P_{75}$.

Final Priorities of Alternatives			Rank	
	Fuzzy	**Crisp**	**Fuzzy**	**Crisp**
A1	0.1557	0.1473	3rd	4th
A2	0.1313	0.1277	5th	5th
A3	0.1922	0.1907	1st	2nd
A4	0.1554	0.1536	4th	3rd
A5	0.0673	0.0623	6th	6th
A6	0.0553	0.0504	8th	7th
A7	0.0602	0.0556	7th	8th
A8	0.1826	0.2123	2nd	1st
Total	1.0000	1.0000		

Regarding the final priorities, five out of eight alternatives (A1, A2, A3, A4, A8) are the most prevalent in all cases of crisp and fuzzy calculus. When using crisp calculus, the best choice is A8. With the introduction of ambiguity, however, the optimal choice changes from A8 to A3, regardless of whether MIN, MEDIAN, and MAX or P_{25}, P_{50}, and P_{75} are used. In addition, the ranking of the other prevalent alternatives changes significantly.

In the case where ambiguity was not introduced by an internal mechanism of the method and TFNs were not required to be symmetric but instead were constructed by the variation in the judgment values, ambiguity plays an important role in the final ranking of the alternatives. This effect of ambiguity is estimated to be even greater if something similar were performed on the judgments of the alternatives, for which symmetric TFNs with a distance δ of 1 were used.

5. Discussion and Conclusions

The need to prioritize possible sites for wind farms has led to MCDM methods being the focus of research. Of these methods, especially for the AHP, where criteria and alternatives are evaluated through pairwise comparisons based on data and estimates of experts, an element of uncertainty and doubt is almost always present. This issue, which can be resolved through fuzzy calculus and fuzzy MCDM methods, is addressed in the present paper.

This paper applies an FAHP based on the Buckley model [48] that uses geometric mean and centroid defuzzification. This model was applied in a case study of wind farm siting on the island of Andros, Greece [32]. The aim was to investigate the resilience of the results and the final ranking of alternative locations to a gradually increasing ambiguity in judgments and whether any ambiguity that the researcher has during the pairwise comparison is introduced into the model and calculations during the TFN construction. A major reason for choosing this case study was because it uses the criterion of social acceptance (K5) as an independent criterion, using expert assessment for the evaluation of alternatives to this criterion. The choice of an independent criterion, the scoring of alternatives based on estimates, and the subjectivity involved in such estimates made this case study interesting from the point of view of the existence of ambiguity in the judgments.

Regarding the methodology used, the application showed that standard fuzzy scales cannot capture ambiguity when exceeding certain values that cause a reversal in preference. To be more precise, fuzzy scales that are bounded below do not allocate ambiguity properly since they cannot include values below the unity (i.e., <1) for which the preference in the alternative should change. In some cases (Sections 4.3 and 4.4) that appear to be problematic, we observed that for small values of ambiguity, a trend toward convergence between the prevailing alternatives occurs, and for large values, there is divergence, which was assumed to be a defect of the scale. This inability seems irrelevant for small values of ambiguity, but for large values, it seems to have a significant effect. To overcome this weakness, fuzzy scales that use values of less than 1 were tested to express ambiguity when a reversal in preference (values less than 1) occurs. In any case, however, more research and investigation are necessary in order to reach safe conclusions.

Based on the results and under the assumptions of this study [32], the final priorities are quite resistant to increasing ambiguity. In almost all cases, the alternative initially chosen as the best, A1, is dominant, followed by A3. In the cases discussed in Sections 4.6–4.8, which are considered more accurate, A3 eventually becomes the best option. However, this is the case for large ambiguity values ranging from $\delta = 3.56$ to $\delta = 4.25$. In addition, the increase in ambiguity seems to affect the alternative A3 more and in a positive way (Section 4.8).

In the last case, where the criteria assessment was performed by postgraduate students, the first observation is the existence of large variations in judgments despite coming from a relatively homogeneous group. This supports the view that apart from the use of central values (i.e., average or median), the use of fuzzy calculus can be useful when including this variance in the calculations. In this case, we observed the ambiguity in judgments playing a crucial role, producing different results and ranking the final priorities of the alternatives. When applying crisp calculus, K1 is judged to be the most important, followed by K5. The prevailing alternative is A8, followed by A3, while five alternatives (A1, A2, A3, A4, and A8) receive high scores. When we apply FL, the variation in judgments causes a significant effect on the final priorities. The criterion K1 continues to prevail in the case of quadrants P_{25}, P_{50}, and P_{75} but with a lower percentage, while, in the case of MIN, MEDIAN, and MAX, it almost equals that of K5. Regarding the final priorities, alternative A3 was first, followed by A4.

As a general comment on all cases, K5 favors the alternative A1, and K1 favors the alternative A8, while the alternative A3 gathers high scores in all cases. In addition, the alternative A3 seems to be favored more than all other alternatives by the existence of ambiguity in judgments, and, in some cases, it is considered the optimal choice.

The method faces limitations when using scales for the fuzzification of the judgments. The application of the scales imposes symmetry on fuzzy numbers, except for the boundaries, and the same assessment of ambiguity for all judgments, which may deviate from the actual uncertainty of the researcher. On the other hand, when the TFNs are constructed considering the variation in the judgment values after the completion of a questionnaire (Section 4.8), in case the consistency check fails, it is very difficult to construct a consistent matrix and at the same time respect the values given by the questionnaire.

Finally, regarding the procedure as a whole, this paper agrees with Deng [49] and Srdjevic and Medeiros [50] that a risk of producing unreliable results is present, and special care is needed during the fuzzification step. The use of standard scales with a fixed fuzzy distance is not always the best way to capture ambiguity. Moreover, the existence of a lower boundary of 1, used by many standard scales, seems to be a weak point. In any case, the optimal approach to producing reliable TFNs is to define the lower and maximum limits of every judgment separately.

Future studies may test the use of trapezoidal or Gaussian distribution in computations and compare the results. In addition, a combination of fuzzy approaches of different multi-criteria methods (e.g., FAHP and FTOPSIS) could be applied to onshore wind farm site selection decision problems in future research. The proposed methodology may also be replicated in other case studies regarding wind farm siting in order to enhance the conclusions drawn from this study.

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