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Wind Energy Development Site Selection Using an Integrated Fuzzy ANP-TOPSIS Decision Model

Mahmood Shafiee

Mechanical Engineering Group, School of Engineering, University of Kent, Canterbury CT2 7NT, UK; m.shafiee@kent.ac.uk

Abstract: The identification of appropriate locations for wind energy development is a complex problem that involves several factors, ranging from technical to socio-economic and environmental aspects. Wind energy site selection is generally associated with high degrees of uncertainty due to the long planning, design, construction, and operational timescales. Thus, there is a crucial need to develop efficient methods that are capable of capturing uncertainties in subjective assessments provided by different stakeholders with diverse views. This paper proposes a novel multi-criteria decision model integrating the fuzzy analytic network process (FANP) and the fuzzy technique for order performance by similarity to ideal solution (TOPSIS) to evaluate and prioritize the potential sites for wind power development. Four major criteria, namely economic, social, technical, and geographical, with nine sub-criteria are identified based on consultation with wind farm investors, regulatory bodies, landowners and residents, developers and operators, component suppliers, ecologists, and GIS analysts. The stakeholders' preferences regarding the relative importance of criteria are measured using a logarithmic least squares method, and then the alternative sites are prioritized based on their relative closeness to the positive ideal solution. The proposed model is applied to determine the most appropriate site for constructing an onshore wind power plant consisting of 10 wind turbines of 2.5 MW. Finally, the results are discussed and compared with those obtained using the traditional AHP, ANP and ANP-TOPSIS decision-making approaches.

Keywords: wind energy; site selection; uncertainty; multi-criteria decision making (MCDM); analytic hierarchy process (AHP); analytic network process (ANP); technique for order of preference by similarity to ideal solution (TOPSIS)

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1. Introduction

Many industrialized nations have recently paid more attention to using renewable energy sources as the most effective means of reducing energy-related greenhouse gas (GHG) emissions. Among the renewable energy sources, wind energy is considered as the fastest-growing energy source, currently supplying over 3% of global electricity consumption. The cumulative installed capacity of wind power in the world has increased from 24 gigawatts (GW) in the year 2001 to 837 GW at the end of 2021, which represents compound annual growth rate (CAGR) of about 20 percent [1]. Numerous wind power plants are planned to be built over the next decade in different countries around the world. Presently, China, with a total capacity of 281,993 MW, is the world leading wind energy producer, followed by the US, with a cumulative installed capacity of 117,744 MW. The United Kingdom (UK), with 2594 onshore and 40 offshore operational wind projects (consisting of 11,092 wind turbines), is ranked as the world's sixth-largest producer of wind power [2].

One of the most important decisions in the development of future wind energy projects, from both a technical and financial perspective, is to select an appropriate location for the siting of wind turbines and related infrastructure. Site selection plays a critical role in the lifecycle performance of wind power plants in terms of energy yield, financial profitability, installation cost and time, maintenance and repair accessibility, and decommissioning and removal costs. The site selected for wind energy projects cannot easily be further modified when the project is approved and the installation process begins. Therefore, it is crucial for wind energy developers to adopt a whole lifecycle approach to assess the potential wind energy development sites, so as to minimize changes after the acceptance and approval of the project and during the construction phase.

The selection of a suitable site for wind energy development is a complex decision-making problem that involves many technical, economic, social, environmental, and regulatory factors such as wind speed, road access, population density, electrical grid infrastructure, industrial support for construction, tourism infrastructure, etc. [3,4]. Tegou et al. [5] identified some social and environmental factors affecting the decisions concerning wind turbine siting, such as visual pollution, topographic and geographic constraints, public opposition, and local, state, and federal regulatory barriers. In addition to this, the site selection process for wind energy projects is generally associated with high degrees of uncertainty due to the long investment cycle (usually between 25 and 30 years) and complex environmental changes. The selection process may become further complicated when project stakeholders, including investors, government authorities, landowners, technology suppliers and residents who live near the site have different interests, and these interests may be in conflict.

The above-mentioned complexities in the selection of wind farm locations have caused the existing Geographic Information System (GIS) tools to be less practical in multi-stakeholder multi-criteria environments. Advancements in multi-criteria decision-making (MCDM) and fuzzy systems have prompted the development of new data-driven approaches that can capture uncertainties in subjective assessments provided by different stakeholders with diverse views. These approaches can take qualitative data in the form of linguistic variables and then transform such information into equivalent crisp queries.

MCDM approaches have become very popular in recent years for evaluating and prioritizing the potential sites for renewable energy development, including solar, onshore and offshore wind, wave, tidal, hydro, hydrogen and biomass [6]. In this approach, each candidate site is evaluated with respect to some attributes (i.e., decision criteria) using some suitable measures. Then, the evaluation ratings are aggregated to obtain a global evaluation for each site. Finally, the sites are prioritized according to their ratings and the best option is selected. Based on their methodological concepts, the MCDM approaches can also be classified into: (i) *weighting* methods such as simple addictive weighting (SAW), the analytic hierarchy process (AHP) and the analytic network process (ANP); (ii) *compromising* methods such as the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and Višekriterijumsko Kompromisno Rangiranje (VIKOR); (iii) *outranking* methods such as Elimination Et Choix Traduisant la Realité (Elimination and Choice Expressing Reality) (ELECTRE) and the Preference Ranking Organization Method for Enrichment of Evaluations (PROMETHEE); and (iv) *structural* methods such as Decision Making Trial and Evaluation Laboratory (DEMATEL). There are also a new generation of MCDM methods, such as: multi-objective optimization on the basis of ratio analysis (MOORA), weighted aggregated sum product assessment (WASPAS), combinative distance-based assessment (CODAS), evaluation based on distance from average solution (EDAS), simultaneous evaluation of criteria and alternatives (SECA), mixed aggregation by comprehensive normalization technique (MACONT), additive ratio assessment (ARAS), pivot pairwise relative criteria importance assessment (PIPRECIA), stepwise weight assessment ratio analysis (SWARA), and so on. Some of these methods are used for weight determination, whereas some are applied to rank the alternatives. The readers can refer to [7,8] for additional information and more specific details. In what follows, we provide a brief overview of the previous studies exploring the use of MCDM methods to solve the wind farm site selection problem.

Aras et al. [9] proposed an AHP method to identify the most suitable location for building a wind observation station on the campus of a university in Turkey. Lee et al. [10]

proposed an MCDM model based on the AHP-associated benefits, opportunities, costs and risks (BOCR) approach to select the most suitable sites for wind farm projects. Hwang et al. [11] utilized the AHP, fuzzy AHP, and the TOPSIS method to choose the best site among two locations for wind power development in Malaysia. Talinli et al. [12] applied the fuzzy AHP technique to determine technical, economic, environmental, and socio-political aspects of wind farm site selection. Georgiou et al. [13] developed a hybrid SAW-AHP decision analysis method for wind farm site selection in the Larnaca District area in the island of Cyprus. Chatterjee and Bose [14] developed a fuzzy MCDM approach based on the complex proportional assessment (COPRAS) methodology to solve the wind farm site selection. Kang et al. [15] proposed a combined fuzzy ANP and BOCR approach to solve the wind farm site selection decision-making problem. Azizi et al. [16] presented an integrated ANP-DEMATEL method to assess the feasibility of establishing a wind farm in Ardabil province in the northwest of Iran. The DEMATEL technique was used to determine the relationships among criteria, and then, the ANP technique was applied to obtain the importance weights of evaluation criteria. Fetanat and Khorasaninejad [17] proposed an integrated fuzzy ANP-DEMATEL-ELECTRE methodology to identify the best site among four sites in Bandar Deylam in the southwest of Iran for offshore wind farm development. The sites were evaluated with respect to six criteria, namely depths and heights, environmental conditions, proximity to facilities, economic performance, availability of technical resources, and culture. Rezaian and Jozi [18] applied the AHP technique to determine suitable areas for the construction of a wind farm in Qazvin Province in the north of Iran. Wu et al. [19] proposed a fuzzy ELECTRE-III model to determine potential sites for offshore wind energy development in China. Asadi and Karami [20] used the AHP technique to find the most suitable locations for the construction of a wind farm in Sistan and Baluchistan province in the southeast of Iran. The alternative locations were evaluated based on five criteria, namely climate, geography, socio-economy, environment, and geology. Chaouachi et al. [21] used the AHP technique to identify suitable offshore wind sites in the Baltic States based on some criteria such as power network security, economic performance, operational costs, and capacity factors. Gigović et al. [22] developed a hybrid ANP-DEMATEL model to identify the most suitable locations for the construction of wind farms in the province of Vojvodina in Serbia. Vasileiou et al. [23] used the AHP technique to identify the most appropriate offshore sites for the development of a hybrid offshore wind and wave energy system in Greece. Vagiona and Kamilakis [24] proposed an integrated methodology of GIS, AHP and TOPSIS for the evaluation of alternative sites for the development of offshore wind energy in the South Aegean in Greece. The methodological framework included several technical, spatial, economic, social, and environmental criteria. Rehman et al. [25] proposed an integrated quantitative and qualitative MCDM framework based on PROMETHEE for selecting wind power plant locations in Saudi Arabia. The model was applied to determine the most suitable site among five possible locations based on 17 evaluation criteria. Moradi et al. [26] used the AHP technique to identify suitable sites for wind energy development in Alborz province in Iran. Their methodology considered the slope of the terrain, wind speed, proximity to electricity grid and substations, distance from urban areas, and access to highways and roads as performance criteria. Xu et al. [27] proposed a novel method integrating GIS with AHP and VIKOR techniques to solve wind energy site selection problem in the Wafangdian region in China. Two factors, namely biodiversity conservation and production safety, were considered to determine alternative locations. Then, the AHP method was applied to determine the weights of evaluation criteria, including the social-economical impacts and environment protection. Finally, the suitability indexes of various alternatives were calculated by the VIKOR method. Elgabiri et al. [28] employed the AHP and pairwise comparison methods in a GIS environment to identify the optimal sites for wind energy development in Bahrain. The land information as well as infrastructure and transport data were used to exclude those areas with physical and safety hazards. Feng [29] proposed a fuzzy AHP method integrated with a satisfaction degree-based fuzzy axiomatic design approach to determine the optimal onshore wind farm site based on geographic, technical, economic, social, and environmental criteria. Caceoğlu et al. [30] presented a quantitative methodology for offshore wind power plant site selection in Northwest Turkey using GIS and AHP. Five alternative suitable sites were evaluated with respect to 17 selection criteria, including the power grid connection, average wind speed, environmental concerns, etc. Wang et al. [31] developed a hybrid MCDM framework, combining the fuzzy AHP and an extended version of SAW, to choose the best location for an offshore wind power station construction in Vietnam.

Table 1 summarizes the past studies that have used the MCDM methods to solve the wind farm site selection problem.

Table 1. A review of the MCDM methods applied to solve the wind farm site selection problem.

Ref	Year	Type of Model		MCDM Technique									
		Fuzzy	Classical	SAW	AHP	ANP	TOPSIS	DEMATEL	COPRAS	ELECTRE	PROMETHEE	VIKOR	BOCR
[9]	2004		√		√								
[10]	2009		√		√								√
[11]	2011	√			√		√						
[12]	2011	√			√								
[13]	2012		√	√	√								
[14]	2013	√							√				
[15]	2013	√				√							√
[16]	2014		√			√		√					
[17]	2015	√				√		√		√			
[18]	2016		√		√								
[19]	2016	√								√			
[20]	2017		√		√								
[21]	2017		√		√								
[22]	2017		√			√		√					
[23]	2017		√		√								
[24]	2018		√		√		√						
[25]	2019		√								√		
[26]	2020		√		√								
[27]	2020		√		√							√	
[28]	2021		√		√								
[29]	2021	√			√								
[30]	2022		√		√								
[31]	2022	√		√	√								

The integrated approach of Fuzzy-ANP-TOPSIS is a novel and a highly effective methodology to capture uncertain information in group decision-making process and solve complicated interrelationships between multiple factors and variables. The technique has been highlighted in several past studies in the context of the optimal marketing strategy [32], technology selection [33], assessing the integrity of medical devices [34], etc. However, to the best our knowledge, there has been no research developing a Fuzzy-ANP-TOPSIS methodology to evaluate and optimize the placement of wind turbines and other supporting infrastructure. In an attempt to fill this research gap, we propose a Fuzzy-ANP-TOPSIS framework to solve the wind farm site selection decision-making problem in complex, multi-stakeholder, and uncertain environments. The performance of this method is compared with other MCDM methods reported in the literature and its advantages and limitations are discussed. The site evaluations are conducted based on four major criteria, namely economic, social, technical, and geographical, and nine sub-criteria identified by consultation with wind farm investors, regulatory bodies, landowners and residents, developers and operators, component suppliers, ecologists, and GIS analysts. Furthermore, the dependences between criteria and alternatives are investigated and represented by a network structure in the ANP model. The stakeholders' preferences regarding the relative importance of criteria are obtained in the form of linguistic terms and represented by fuzzy triangular numbers. The fuzzy weights of criteria and sub-criteria with respect to the overall goal are derived by a logarithmic least square method, and finally, the alternatives are prioritized based on their distance from the ideal or anti-ideal solutions. To evaluate and compare the efficacy of the proposed model, we provide a real-life application of an onshore wind farm consisting of 10 wind turbines of 2.5 MW in Iran. Three potential locations in the country are studied for wind energy development, including Ardabil, Zabol and Takestan, and the most suitable location for the construction of the wind farm is determined based on the Fuzzy-ANP-TOPSIS approach. The results of the analysis are then compared with those obtained from the traditional AHP, ANP and ANP-TOPSIS decision-making approaches.

The rest of the paper is organized as follows. In Section 2, we provide some background information on the fuzzy theory and the ANP and TOPSIS approaches. Section 3 presents the Fuzzy-ANP-TOPSIS decision model to select the most suitable location for wind turbine installation. In Section 4, we provide a real-life application to illustrate the applicability of the proposed method. Finally, Section 5 concludes the paper and indicates future directions for research.

2. Research Background

2.1. Fuzzy Theory

In cases when there is no clear idea or a lack of information about an event, the public and experts will be more likely to express their opinions in subjective ways using verbal language variables such as 'much better', 'better', 'equal', etc. These subjective terms are not as good as numbers in terms of information representation accuracy. The fuzzy theory, introduced by Zadeh in 1965 [35], is a powerful tool to handle the uncertainty and vagueness associated with humans' subjective perceptions and experience in decision-making processes. In this paper, the fuzzy linguistics approach is used to obtain the stakeholders' judgments or preferences based on words such as "equally", "moderately", "strongly", "very strongly", "extremely" or "significantly". In this approach, the linguistic terms are represented by fuzzy numbers such as triangular and trapezoidal fuzzy numbers. A triangular fuzzy number (TFN) is a special type of fuzzy number whose membership is defined as a triple $\tilde{O}$ = (l, m, u), where l is the smallest possible value, m is the most promising value, and u is the largest possible value. The mathematical expression of the membership function for $\tilde{O}$ = (l, m, u) is defined by Equation (1) as follows:

$$\mu_{\tilde{O}}(x) = \begin{cases} \frac{x-l}{m-l}; & l \leq x \leq m \\ \frac{u-x}{u-m}; & m \leq x \leq u \\ 0; & \text{otherwise} \end{cases}. \tag{1}$$

The membership function, $\mu_{\tilde{O}}(x)$ is depicted in Figure 1.

Assume $\tilde{O}_1$ and $\tilde{O}_2$ are two TFNs represented by (l_1, m_1, u_1) and (l_2, m_2, u_2), respectively. The main algebraic operations of these two TFNs are defined as follows:

Addition of two TFNs

$$\widetilde{O}_1(+)\widetilde{O}_2 = (l_1 + l_2\,,\, m_1 + m_2\,,\, u_1 + u_2);\ l_1, l_2\ \geq 0. \tag{2}$$

Subtraction of two TFNs

$$\widetilde{O}_1(-)\widetilde{O}_2 = (l_1 - l_2\,,\, m_1 - m_2\,,\, u_1 - u_2);\ l_1, l_2\ \geq 0. \tag{3}$$

Multiplication of two TFNs

$$\widetilde{O}_1(\times)\widetilde{O}_2 = (l_1 l_2\,,\, m_1 m_2\,,\, u_1 u_2);\ l_1, l_2\ \geq 0. \tag{4}$$

Division of two TFNs

$$\widetilde{O}_1(\div)\widetilde{O}_2 = (l_1/l_2\,,\, m_1/m_2\,,\, u_1/u_2);\; l_1, l_2\, \geq 0. \tag{5}$$

Multiplication of a TFN by a constant

$$k \times \widetilde{O}_1 = (kl_1\,,\, km_1\,,\, ku_1);\; k\,,\, l_1\, \geq 0. \tag{6}$$

Inverse of a TFN

$$\widetilde{O}_2{}^{-1} = (1/u_2\,,\, 1/m_2\,,\, 1/l_2);\; l_2, m_2, u_2 > 0. \tag{7}$$

Distance between two TFNs according to the vertex method

$$d\left(\widetilde{O}_1, \widetilde{O}_2\right) = \sqrt{\frac{1}{3}[(l_1 - l_2)^2 + (m_1 - m_2)^2 + (u_1 - u_2)^2]}. \tag{8}$$

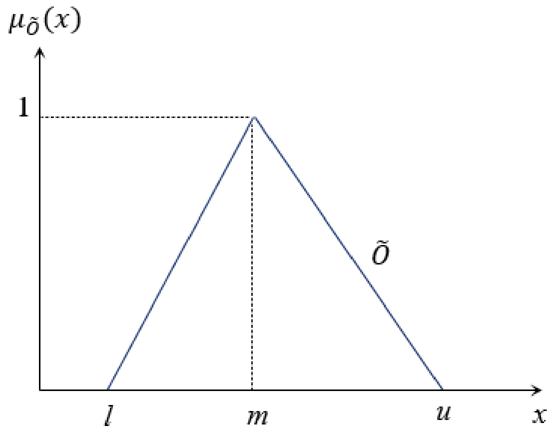

Figure 1. The membership function of a triangular fuzzy number $\tilde{O}$ = (l, m, u).

2.2. Analytic Network Process (ANP)

The analytic hierarchy process (AHP) is a decision analysis method proposed by Saaty [36] in the 1970s to deal with complex decision-making problems with multiple attributes, multiple decision-makers, and high uncertainty. The AHP method comprises various steps including the collection of data for pairwise comparisons, the estimation of criteria weights, and the calculation of consistency of the comparison matrix. The relative importance of each factor with respect to others is determined based on a 1 to 9 scale, where a score of 1 represents equal importance between the two factors and a score of 9 indicates the extreme importance of one factor compared to another one. AHP also allows the decision markers to evaluate the consistency of the pairwise comparisons by calculating a consistency ratio (CR). If the value of CR is smaller than or equal to 10%, the inconsistency is acceptable. However, if the CR value is greater than 10%, then the matrix is inconsistent, and it needs to be revised.

In the AHP method, the problem is modelled in a hierarchical structure where the goal, decision criteria, and alternatives are arranged in multi-level. Each element in the hierarchy is independent of all the other elements, and hence, the interactions and feedback between the elements are ignored. To overcome this limitation, the analytic network process (ANP) method was introduced by Saaty [37]. The ANP is a generalization of the AHP by considering the dependence between the clusters and elements within a cluster (see Figure 2). In other words, the ANP provides a general framework to deal with complicated decisions without making assumptions about the independence of higher-level elements from lower-level elements and about the independence of the elements within a level. The ANP is a coupling of two parts: (i) a control hierarchy or a network of criteria and sub-criteria that control the interactions in the system; and (ii) a network of influences among the elements and clusters [38].

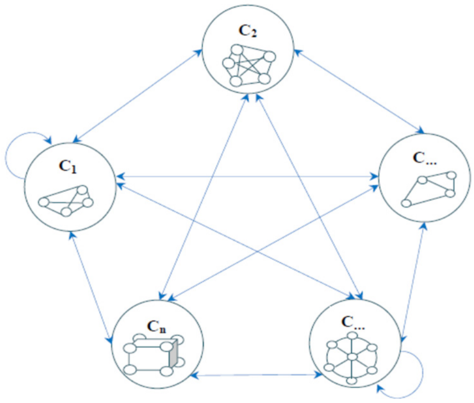

Figure 2. An ANP model structure.

2.3. Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)

TOPSIS is a practical and useful MCDM methodology which was developed for the first time by Hwang and Yoon in 1981 [39]. The technique is based on the concept that the selected alternative should have the shortest geometric distance from the positive ideal solution (PIS) and the farthest distance from the negative ideal solution (NIS). The relative closeness of each alternative to the PIS can be calculated by dividing the distance from the NIS with the summation of the distance from PIS and distance from NIS. Finally, the alternatives are ranked based on their relative closeness index. The TOPSIS procedure consists of the following steps: the calculation of the normalized decision matrix, the determination of the PIS and NIS, the calculation of the separation measures using the n dimensional Euclidean distance, the evaluation of the relative closeness to the PIS, and ranking the preference order.

In both the ANP and TOPSIS methods, there is a need to integrate mathematical models with human experiences. To obtain the relative importance of decision elements, a pairwise comparison should be carried out between all pairs of criteria. Moreover, to construct the decision matrix, the performance rating of each alternative with respect to criteria needs to be determined. Such information is often obtained from experts with knowledge and experience in relevant areas. However, there still may exist some inherent uncertainties associated with the mapping of the decision-makers' perception onto crisp values. These uncertainties in the initial stages of the decision-making process may limit the chances of obtained satisfactory results. For this reason, an integrated Fuzzy-ANP–TOPSIS approach is developed in the next section, wherein fuzzy numbers are used instead of crisp values.

3. The Proposed Methodology

Our proposed methodology to determine the most favorable location for wind farm development is shown in Figure 3. The steps of the methodology are described in detail in the following sections:

Step 1: Form a group of wind energy project stakeholders

The selection of a suitable site for the development of a wind energy project is a multi-stakeholder, multi-agency, and multi-stage activity. For this reason, a group of decision makers and experts including investors, local authorities and public sector bodies, landowners and residents, developers and operators, component suppliers and service providers, environmentalists, geologists, and financial analysts must be involved in the process. Each stakeholder has their own interests and reasons to either support or reject the project. The stakeholders' opinions and assessments are often gathered by conducting surveys or brief interviews. In such a process, the experts are asked separately about their views on different elements considered. After collecting the opinions of stakeholders, some feedback will be provided to individuals about the other stakeholders' opinions. The stakeholders will have the opportunity to change their opinions after getting this feedback, if desired.

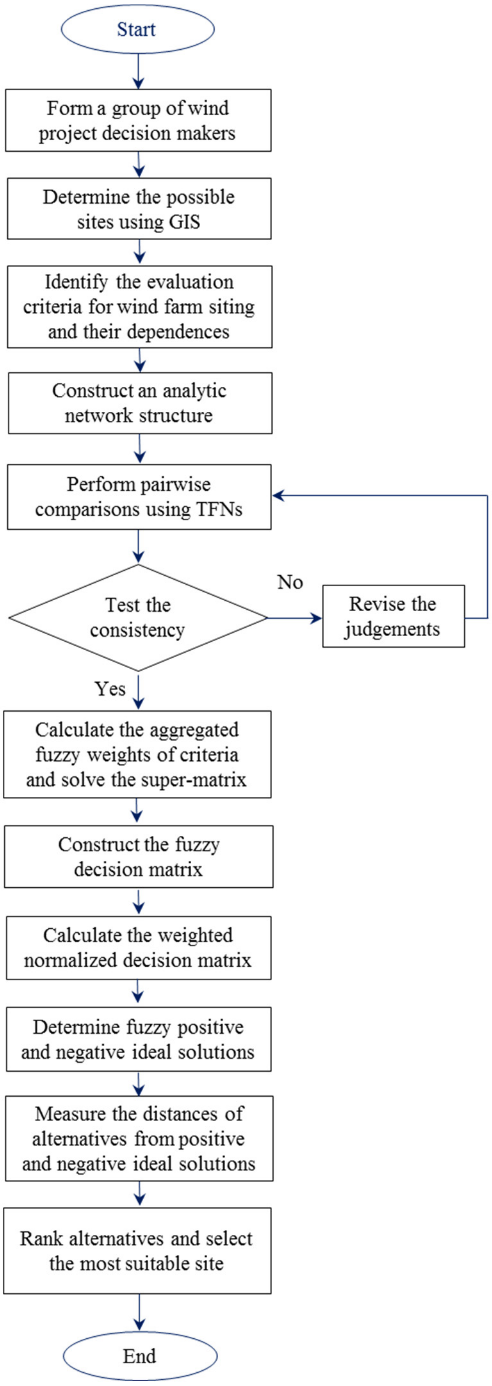

Figure 3. The proposed Fuzzy-ANP–TOPSIS methodology for wind farm site selection.

Step 2: Identify some possible locations for wind farm placement using GIS tools

Many countries have regulatory limitations on the installation of wind turbines in residential districts. These regulations may be local (town, city), state, or federal. GIS is a computer software tool that stores geographic information or spatial data for the purpose of manipulation and analysis to find some possible locations for the construction of wind power plants in a particular region. GIS tools can help to build a spatial database with geographical features, such as topography, land use, road networks, locations of public interest, etc.

Step 3: Identify the site selection criteria and their dependences

In this step, we identify the most significant criteria and determine the corresponding factors that are considered to be important for selecting a suitable wind farm site. Different stakeholders may have different interests and priorities. For this study, we first prepared an extensive list of criteria that are important for the site selection of wind energy projects by reviewing the relevant literature. Then, we classified the identified criteria into different groups based on their similar and dissimilar characteristics. Next, we gathered the stakeholders' opinions on the list of criteria by means of a Delphi questionnaire survey. The questionnaire used a Likert scale between 1 to 5, where a score of 1 expresses 'very unimportant', 2 expresses 'unimportant', 3 expresses 'general', 4 expresses 'important', and 5 expresses 'very important'. After analyzing the stakeholders' feedback, the criteria with low importance scores were deleted from the list. Eventually, four groups of criteria, namely economic, social, technical, and geographical, with nine sub-criteria, were agreed as the most influencing factors in wind farm siting. All of these criteria and sub-criteria are further described in the following sections:

C_1. *Economic criteria*

To determine the most suitable location for a wind farm, all economic costs and benefits throughout the lifetime of the project must be evaluated by the stakeholders. The factors contributing to the economic criteria are:

$C_{1.1}$ *Energy security*

The regions with scarce fossil fuel resources will have a higher priority for establishing the desired wind power plant. Siting wind farms in such areas will have positive impact on the region's energy security and economic well-being.

$C_{1.2}$ *Job creation*

The development, construction, operation, and maintenance of renewable wind energy projects will create many job opportunities, some of which will be filled by local residents.

$C_{1.3}$ *Overall economic profit*

Constructing a new wind farm requires some new infrastructure to be built or the existing infrastructure to be rehabilitated. A proportion of the project's profit should be spent on the region's economic development to support constructing new roads, schools, libraries, hospitals, and other infrastructure. The overall economic profit represents the difference between revenues of the wind energy project (from selling power to the national grid) and its expenses (including pre-development, installation, operation, and maintenance) during the lifecycle. The local communities benefit from these infrastructure facilities, as they provide an improved business environment for local inhabitants to perform their activities and quality of life.

C_2. *Social criteria*

Public perception and attitude towards wind power play an important role in the placement decision-making. Social criteria include the following sub-criteria:

$C_{2.1}$ *Social acceptance*

Many people find wind farms to be an interesting feature of the landscape. However, the residents living near wind farms usually have a negative perception and attitude towards noise disturbance and visual pollution from wind turbines. These perceptions must be addressed to maximize social acceptability.

$C_{2.2}$ *Regional reputation*

This criterion represents the human and social benefits of the wind energy project development in a region. Establishing a wind farm in a deprived region can help improve morale among locals.

C_3. *Technical criteria*

Technical issues are among the most important considerations in determining the location of a wind power plant. These issues are extensive but can be grouped into wind conditions and the technology situation of the alternative regions.

$C_{3.1}$ Wind efficiency

Wind efficiency (intensity, direction, consistency, and uniformity) plays a key role in wind farm placement. The wind project investors are more likely to invest in regions with better wind conditions.

$C_{3.2}$ Readiness of domestic technologies

To establish a wind power plant in a particular region, the readiness of domestic technologies (e.g., materials' supply, energy storage, grid connection, power transfer, recycling facility, etc.) must be considered.

C_4. Geographic criteria

The geographical suitability of the potential locations for establishing a wind energy project should be examined. The geographic criteria include the following sub-criteria:

$C_{4.1}$ Land suitability

Land suitability plays an important role in the wind farm development planning. This factor includes the land use, land ownership, access to the land, distance from cities or the coast, distance from power lines, distance from substations, distance from urban areas, distance from highways and roads, proximity to natural resources, distance from the epicenters of earthquakes, etc.

$C_{4.2}$ Environmental friendliness

Environmental pollution (e.g., visual and noise pollution, bird mortality, and interference with radar) is an important issue in the process of wind farm site selection. The locations in which the construction and operation of wind turbines cause less pollution will have higher priority for selection.

The evaluation criteria for wind farm site selection might be dependent on each other; for instance, the dependence between two criteria of "job creation" and "social acceptance" is such that a wind energy project with higher job-creation potential will generally have more acceptance from residents of the region. The dependences among decision criteria and sub-criteria are identified and shown in Tables 2 and 3, respectively.

Table 2. Dependences among decision criteria for wind farm site selection.

Criteria	**C_1**	**C_2**	**C_3**	**C_4**
C_1		√	√	√
C_2	√		√	√
C_3	√	√		√
C_4	√	√	√	

Table 3. Dependences among decision sub-criteria for wind farm site selection.

Sub-Criteria	**C_{11}**	**C_{12}**	**C_{13}**	**C_{21}**	**C_{22}**	**C_{31}**	**C_{32}**	**C_{41}**	**C_{42}**
C_{11}	√		√			√	√	√	
C_{12}			√	√			√		
C_{13}	√	√		√	√	√	√	√	√
C_{21}		√	√		√				√
C_{22}			√	√					
C_{31}	√		√					√	
C_{32}	√	√	√						
C_{41}	√		√			√			√
C_{42}			√	√				√	

Step 4: Construct a network structure

In this step, a network structure is built to show all the decision-making criteria, sub-criteria and alternatives and their interactions. Figure 4 illustrates a network model for the decision problem of selecting a suitable wind farm placement.

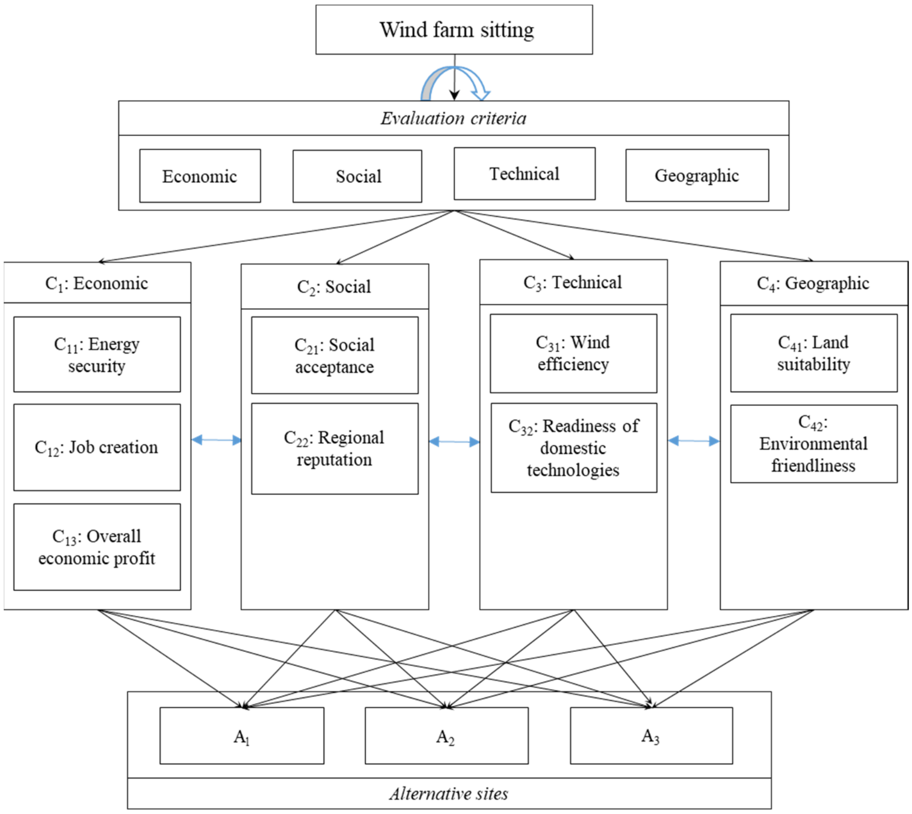

Figure 4. A network model for wind farm site selection.

Step 5: Perform pairwise comparisons using a TFN linguistic scale

After constructing the network model, the stakeholders will be asked to express their opinions about the preference/importance of criteria/sub-criteria with respect to the overall goal. One of the most common methods for weighing the criteria/sub-criteria is the pairwise comparison technique. In this technique, the stakeholders are asked to compare the importance of decision elements with respect to one another. In this study, a triangular fuzzy scale $\widetilde{1} - \widetilde{9}$ as presented in Table 4 was used. The results of the pairwise comparisons are presented in the form of a matrix, called fuzzy pairwise comparison matrix. This is a square matrix of size $n \times n$ that is represented by $\widetilde{A}_k = \left[\widetilde{a}_{ijk}\right]$, where $\widetilde{a}_{ijk}$ denotes the comparative importance of criterion i with respect to criterion j from the point of view of expert k. Thus, $\widetilde{a}_{ijk}$ can be defined by a TFN as follows:

$$\widetilde{a}_{ijk} = \begin{cases} \left(l_{ijk}, m_{ijk}, u_{ijk}\right) & i \neq j \\ (1, 1, 1) & i = j \end{cases}, \ i, j = 1, 2, \ldots, n, \text{ and } k = 1, 2, \ldots, K, \tag{9}$$

where K is the number of stakeholders. The preference of element j over element i for expert k is represented by $\widetilde{a}_{jik}$, which is the inverse of fuzzy number $\widetilde{a}_{ijk}$ and is defined by Equation (7).

Table 4. Triangular fuzzy scale used for pairwise comparisons [40].

TFN	Linguistic Scale for Importance	Triangular Fuzzy Scale
1	Equally preferred	(1, 1, 1)
2	Equally to moderately preferred	(1, 1.5, 1.5)
3	Moderately preferred	(1, 2, 2)
4	Moderately to strongly preferred	(3, 3.5, 4)
5	Strongly preferred	(3, 4, 4.5)
6	Strongly to very strongly preferred	(3, 4.5, 5)
7	Very strongly preferred	(5, 5.5, 6)
8	Very strongly to extremely preferred	(5, 6, 7)
9	Extremely preferred	(5, 7, 9)

Step 6: Test the consistency of fuzzy pairwise comparisons

The consistency test aims to make sure that the fuzzy pairwise comparison results are accurate and reliable. According to Buckley [41], a fuzzy comparison matrix is consistent if:

$$\widetilde{a}_{ijk} \approx \widetilde{a}_{ipk}(\times)\widetilde{a}_{pjk}\ ;\ i\ ,\ j\ ,\ p = 1, 2\ , \ldots,\ n, \text{ and } k = 1, 2\ , \ldots,\ K, \tag{10}$$

where $\approx$ denotes fuzzy equal to, and $(\times)$ represents the multiplication operation on fuzzy numbers and is defined by Equation (4). For a comparison matrix which fails the consistency test, the stakeholders will be asked to revise their pairwise comparisons.

Step 7: Calculate the aggregated fuzzy weights of criteria and solve the super-matrix

When all fuzzy comparison matrices pass the consistency test, an aggregated fuzzy comparison matrix is established. The aggregated fuzzy comparison matrix for a group of stakeholders is represented by $\widetilde{A} = [\widetilde{a}_{ij}]_{n\times n}$, where $\widetilde{a}_{ij} = \left(a^l_{ij}, a^m_{ij}, a^u_{ij}\right)$ denotes the aggregation of responses from all experts and can be obtained by the following equation:

$$\widetilde{a}_{ij} = \frac{1}{K} \times [\widetilde{a}_{ij1}(\times)\widetilde{a}_{ij2}(\times)\ldots(\times)\widetilde{a}_{ijK}],\ i\ ,\ j = 1, 2\ , \ldots,\ n. \tag{11}$$

where $\times$ represents the multiplication by a constant and is defined as in Equation (6).

After establishing the aggregated fuzzy pairwise comparison matrix, the logarithmic least squares method is used to estimate the fuzzy weights of criteria. The aggregated fuzzy weights of the criteria i can be obtained using the following equations [42]:

$$\widetilde{w}_i = \left(w^l_i\ ,\ w^m_i\ ,\ w^u_i\right)\ ,\ i = 1, 2\ , \ldots,\ n, \tag{12}$$

$$\widetilde{w}^s_i = \frac{\left(\prod_{j=1}^{n} a^s_{ij}\right)^{\frac{1}{n}}}{\sum_{p=1}^{n}\left(\prod_{j=1}^{n} a^m_{pj}\right)^{\frac{1}{n}}}\ ,\ s \in \{l, m, u\}. \tag{13}$$

where a^l_{ij}, a^m_{ij} and a^u_{ij} represent the lower limit value, the most promising value, and the upper limit value of TFN $\widetilde{a}_{ij}$.

The way that decision elements impact one another in a network is presented by a matrix, termed the unweighted super-matrix. The unweighted super-matrix is a partitioned matrix where each sub-matrix consists of the fuzzy weights obtained from the pair-wise comparisons. The columns of the super-matrix represent the relationships between two clusters and the corresponding values in the columns reflect the influence that the elements of the clusters on the left-hand side of the matrix exert on those in the header of the matrix. If there exists no relationship between two clusters, the corresponding entry in the super-matrix will be (0, 0, 0). The unweighted super-matrix elements are multiplied by the corresponding weights of criteria with respect to the goal and the weighted super-matrix is obtained. Eventually, the final weights are obtained by raising the weighted super-matrix by large powers, usually $2k$ + 1 (where k is a large arbitrarily number), until the matrix converges into a stable super-matrix. All the columns of the limit super-matrix are the same, so the final weights of the elements can be derived from any column in the matrix.

Step 8: Construct the decision matrix based on the criteria weights obtained from the fuzzy ANP

After obtaining the weights of criteria from the fuzzy ANP model, the next step is to apply the fuzzy TOPSIS method to rank the alternative wind farm sites. The fuzzy TOPSIS method uses linguistic variables with different semantic word sets to rate the alternatives, including 'very poor', 'poor', 'medium poor', 'medium', 'medium good', 'good' and 'very good'. The linguistic terms with their corresponding TFNs used for rating the alternative wind farm sites are given in Table 5.

Table 5. Linguistic terms used for rating the alternative wind farm sites [43].

Linguistic Terms	Very Poor	Poor	Medium Poor	Medium	Medium Good	Good	Very Good
TFN	(0, 0, 1)	(0, 1, 3)	(1, 3, 5)	(3, 5, 7)	(5, 7, 9)	(7, 9, 10)	(9, 10, 10)

The performance ratings of the alternative wind farm sites with respect to criteria are expressed in a decision matrix format $\widetilde{D}$, as shown in Equation (14). This matrix has a size of $m \times n$, where m and n are the number of alternatives and the number of evaluation criteria (sub-criteria), respectively.

$$\begin{array}{cc} & \begin{array}{cccc} \boldsymbol{C_1} & \boldsymbol{C_2} & \cdots & \boldsymbol{C_n} \\ \tilde{w}_1 & \tilde{w}_2 & \cdots & \tilde{w}_n \end{array} \\ \begin{array}{c} \mathbf{A_1} \\ \boldsymbol{A_2} \\ \cdots \\ \boldsymbol{A_m} \end{array} & \begin{pmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{pmatrix} \end{array} \tag{14}$$

Step 9: Normalize the decision matrix and compute the weighted normalized matrix

Denote by $\widetilde{R}$ the normalized fuzzy decision matrix which is a matrix of size $m \times n$. We use a linear normalization method to normalize each element $\widetilde{x}_{ij}$ in the decision matrix $\widetilde{D}$ into a corresponding element $\widetilde{r}_{ij}$ in the normalized decision matrix $\widetilde{R}$. In this method, each element $\widetilde{r}_{ij}$, $i = 1, 2, \ldots, m$; $j = 1, 2, \ldots, n$, is obtained by the following equations [44]:

$$\widetilde{r}_{ij} = \left(\frac{x_{ij}^l}{x_j^u}, \frac{x_{ij}^m}{x_j^u}, \frac{x_{ij}^u}{x_j^u} \right), \text{ for } j \in P;\ x_j^u = \max_j \left\{ x_{ij}^u \right\}, \tag{15}$$

$$\widetilde{r}_{ij} = \left(\frac{x_j^l}{x_{ij}^u}, \frac{x_j^l}{x_{ij}^m}, \frac{x_j^l}{x_{ij}^l} \right), \text{ for } j \in N;\ x_j^l = \min_j \left\{ x_{ij}^l \right\}, \tag{16}$$

where x_{ij}^l, x_{ij}^m and x_{ij}^u represent the lower limit value, the most promising value, and the upper limit value of the TFN of $\widetilde{x}_{ij}$, respectively, and P and N represent the sets of positive criteria and negative criteria, respectively. After normalizing the decision matrix, the weighted normalized decision matrix, $v = [v_{ij}]$, should be calculated. To achieve this aim, each element of the normalized decision matrix is multiplied by the fuzzy weights for criteria/sub-criteria that were obtained using the fuzzy ANP model in Step 7. Thus,

$$\widetilde{v}_{ij} = \widetilde{r}_{ij}(\times)\widetilde{w}_j, \text{ for } i = 1,\ 2, \ldots,\ m;\ j = 1,\ 2, \ldots,\ n. \tag{17}$$

Step 10: Determine the fuzzy positive and negative ideal solutions

After calculating the weighted normalized decision matrix, the fuzzy positive ideal solution (FPIS, $\widetilde{A}^{+}$) and the fuzzy negative ideal solution (FNIS, $\widetilde{A}^{-}$) are determined according to Equations (18) and (19), respectively [45]:

$$\widetilde{A}^{+} = \left[\widetilde{v}_1^{+}, \widetilde{v}_2^{+}, \ldots, \widetilde{v}_n^{+}\right], \text{ where } \widetilde{v}_j^{+} = (1,1,1)(\times)\widetilde{w}_j = \widetilde{w}_j, \tag{18}$$

$$\widetilde{A}^{-} = \left[\widetilde{v}_1^{-}, \widetilde{v}_2^{-}, \ldots, \widetilde{v}_n^{-}\right], \text{ where } v_j^{-} = (0,0,0). \tag{19}$$

Step 11: Measure the distances of each alternative from FPIS and FNIS

The distances of alternative i ($i = 1, 2, \ldots, m$) from fuzzy positive and negative ideal solutions (d_i^{+} and d_i^{-}, respectively) are calculated by Equation (20):

$$d_i^{+} = \sum_{j=1}^{n} d\left(\widetilde{v}_{ij}, \widetilde{v}_j^{+}\right) \text{ and } d_i^{-} = \sum_{j=1}^{n} d\left(\widetilde{v}_{ij}, \widetilde{v}_j^{-}\right), \tag{20}$$

where d represents the distance between two TFNs according to the vertex method given in Equation (8).

Step 12: Rank the alternatives and select the most suitable wind farm site

The alternative wind farm sites are ranked by preference according to their closeness to the FPIS. The closeness coefficient (CL) of alternative i with respect to the FPIS is defined as follows:

$$L_i^{+} = \frac{d_i^{-}}{d_i^{-} + d_i^{+}}, \text{ for } i = 1,\ 2,\ \ldots,\ m. \tag{21}$$

A larger CL means a more favorable wind farm site. The alternative with the largest CL will be chosen as the most suitable site for wind energy development.

4. Application

In this section, a case study is provided to illustrate the applicability of the proposed integrated fuzzy ANP and fuzzy TOPSIS decision model to select the most suitable location for constructing a 10 × 2.5 MW wind power plant in Iran. Three potential locations in the country were considered for wind energy development:

- Ardabil (A_1) is a city located in the northwest of Iran. The city stands about 70 km from the Caspian Sea and has an average altitude of 1350 m and total area of 11,081 km^2. The city's temperature ranges from −8 °C in winter to 23 °C in summer. The highest wind power potential occurs during months of September and October.
- Zabol (A_2) is a city in and the capital of Zabol County, Sistan and Baluchestan Province, in the southeast of Iran. The city is located in a region subject to seasonal winds from different directions. The "120-day winds" locally known as Levar are a distinguishing feature of the region, showing its great potential for energy production.
- Takestan (A_3) is a city in and the capital of Takestan County in Qazvin, a province in the north-central region of Iran. This region has favorable wind resources for producing energy. At 70 m height, the wind speed is in the range of 6.69–12.45 m/s. The highest wind power potential occurs during the months of January and December.

The information required for the analysis included social, economic, financial, natural resources, and environmental indicators. This information was gathered from a literature review, interviews with key stakeholders involved in the project, and GIS databases, as well as wind energy resource atlases. The criteria and sub-criteria presented in Section 3 were agreed upon by all stakeholders. The dependences between four main criteria and nine sub-criteria were also considered as presented in Tables 2 and 3, respectively.

The fuzzy pairwise comparison matrix of all criteria with respect to each other was formed and presented in Table 6. The linguistic terms and corresponding TFNs given in Table 4 are used for pairwise comparisons in this study. Using the data of pairwise comparison matrix and applying Equation (13), the fuzzy weights of all criteria are calculated. For instance, the fuzzy weights of economic criteria are obtained as below:

$$\sum_{p=1}^{n}\left(\prod_{j=1}^{n} a_{pj}^{m}\right) = (1 \times 1.5 \times 4 \times 2)^{\frac{1}{4}} + (0.667 \times 1 \times 2 \times 1.5)^{\frac{1}{4}}$$
$$+(0.25 \times 0.5 \times 1 \times 0.667)^{\frac{1}{4}} + (0.5 \times 0.667 \times 1.5 \times 1)^{\frac{1}{4}} = 4.428$$
$$\widetilde{w}_1^{l} = (1 \times 1 \times 3 \times 1)^{\frac{1}{4}}/4.428 = 0.297;$$
$$\widetilde{w}_1^{m} = (1 \times 1.5 \times 4 \times 2)^{\frac{1}{4}}/4.428 = 0.42;$$
$$\widetilde{w}_1^{u} = (1 \times 1.5 \times 4.5 \times 2)^{\frac{1}{4}}/4.428 = 0.433$$

Table 6. Pairwise comparison matrix of four criteria with respect to each other.

Criteria	C_1	C_2	C_3	C_4	Fuzzy Weights
C_1	(1, 1, 1)	(1, 1.5, 1.5)	(3, 4, 4.5)	(1, 2, 2)	(0.297, 0.42, 0.433)
C_2	(0.667, 0.667, 1)	(1, 1, 1)	(1, 2, 2)	(1, 1.5, 1.5)	(0.204, 0.269, 0.297)
C_3	(0.222, 0.25, 0.333)	(0.5, 0.5, 1)	(1, 1, 1)	(0.667, 0.667, 1)	(0.118, 0.121, 0.172)
C_4	(0.5, 0.5, 1)	(0.667, 0.667, 1)	(1, 1.5, 1.5)	(1, 1, 1)	(0.172, 0.19, 0.25)

After performing pairwise comparisons with respect to every criterion, the priority weights of criteria with respect the overall goal are obtained. The results are presented in Table 7.

Table 7. Fuzzy weights of criteria with respect to the overall goal.

Criteria	C_1	C_2	C_3	C_4
C_1	(0.5, 0.5, 0.5)	(0.206, 0.248, 0.26)	(0.272, 0.328, 0.356)	(0.197, 0.258, 0.268)
C_2	(0.067, 0.07, 0.091)	(0.5, 0.5, 0.5)	(0.061,0.063,0.091)	(0.048, 0.052, 0.066)
C_3	(0.274, 0.331, 0.358)	(0.18, 0.19, 0.227)	(0.5, 0.5, 0.5)	(0.172, 0.19, 0.226)
C_4	(0.083, 0.099, 0.105)	(0.057, 0.062, 0.069)	(0.083, 0.109, 0.114)	(0.5, 0.5, 0.5)

After computing the fuzzy weights of all criteria with respect to the overall goal, the pairwise comparison matrices of sub-criteria with respect to each other and their corresponding criterion are formed, and their fuzzy weights are calculated. Table 8 gives the fuzzy weights of sub-criteria with respect to the economic criterion.

Table 8. Pairwise comparison matrix of sub-criteria with respect to the economic criterion.

	C_1	C_2	C_3	C_4
C_{11}	(0.558, 0.647, 0.703)	(0, 0, 0)	(0, 0, 0)	(0, 0, 0)
C_{12}	(0.134, 0.14, 0.186)	(0, 0, 0)	(0, 0, 0)	(0, 0, 0)
C_{13}	(0.163, 0.213, 0.234)	(0, 0, 0)	(0, 0, 0)	(0, 0, 0)
C_{21}	(0, 0, 0)	(0.471, 0.667, 0.667)	(0, 0, 0)	(0, 0, 0)
C_{22}	(0, 0, 0)	(0.333, 0.333, 0.471)	(0, 0, 0)	(0, 0, 0)
C_{31}	(0, 0, 0)	(0, 0, 0)	(0.72, 0.778, 0.831)	(0, 0, 0)
C_{32}	(0, 0, 0)	(0, 0, 0)	(0.208, 0.222, 0.24)	(0, 0, 0)
C_{41}	(0, 0, 0)	(0, 0, 0)	(0, 0, 0)	(0.807, 0.846, 0.884)
C_{42}	(0, 0, 0)	(0, 0, 0)	(0, 0, 0)	(0.147, 0.154, 0.161)

Next, the logarithmic least squares method is applied to determine the fuzzy priority weights of criteria/sub-criteria with respect to each other. These weights will be used in an unweighted super-matrix. To find the final weights of the criteria with respect to the overall goal, the weighted super-matrix is calculated. The fuzzy weights of sub-criteria with respect to the overall goal are presented in Table 9.

Table 9. Fuzzy weights of sub-criteria with respect to the overall goal.

Sub-Criteria	Fuzzy Weights
C_{11}	$\widetilde{w}_{11}$ = (0.117, 0.193, 0.267)
C_{12}	$\widetilde{w}_{12}$ = (0.036, 0.068, 0.095)
C_{13}	$\widetilde{w}_{13}$ = (0.092, 0.161, 0.244)
C_{21}	$\widetilde{w}_{21}$ = (0.045, 0.082, 0.112)
C_{22}	$\widetilde{w}_{22}$ = (0.030, 0.044, 0.076)
C_{31}	$\widetilde{w}_{31}$ = (0.102, 0.166, 0.229)
C_{32}	$\widetilde{w}_{32}$ = (0.043, 0.073, 0.107)
C_{41}	$\widetilde{w}_{41}$ = (0.105, 0.169, 0.232)
C_{42}	$\widetilde{w}_{42}$ = (0.027, 0.044, 0.061)

After computing the weights of criteria and sub-criteria by means of the fuzzy ANP method, the normalized decision matrix is calculated. Then, it is multiplied by the weights of sub-criteria determined by the fuzzy ANP method to obtain the weighted normalized decision matrix. Table 10 gives the weighted normalized decision matrix.

Table 10. Weighted normalized decision matrix.

	C_{11}	C_{12}	C_{13}
A_1	(0.07, 0.15, 0.27)	(0.01, 0.03, 0.07)	(0.01, 0.04, 0.08)
A_2	(0.04, 0.11, 0.21)	(0, 0.02, 0.05)	(0, 0.02, 0.06)
A_3	(0.04, 0.11, 0.21)	(0.03, 0.06, 0.1)	(0.03, 0.07, 0.11)

	C_{21}	C_{22}
A_1	(0, 0.02, 0.06)	(0, 0.01, 0.04)
A_2	(0.01, 0.04, 0.08)	(0.01, 0.02, 0.05)
A_3	(0.04, 0.07, 0.11)	(0.02, 0.04, 0.08)

	C_{31}	C_{32}
A_1	(0.09, 0.15, 0.22)	(0.02, 0.06, 0.11)
A_2	(0.05, 0.12, 0.21)	(0.02, 0.06, 0.11)
A_3	(0.03, 0.08, 0.16)	(0.01, 0.04, 0.08)

	C_{41}	C_{42}
A_1	(0.01, 0.05, 0.12)	(0.02, 0.03, 0.06)
A_2	(0.05, 0.12, 0.21)	(0.01, 0.02, 0.05)
A_3	(0.07, 0.15, 0.23)	(0, 0, 0.02)

The best and the worst attribute values for each sub-criterion are then calculated and the FPIS and FNIS are obtained. The distances of each alternative from the FPIS and FNIS are measured using Equation (20). After computing the distances from the best and the worst attribute values, the closeness coefficients of the three alternative locations are determined and then the superior alternative is chosen. The distances and the relative closeness of alternatives with respect to the FPIS are given in Table 11. As shown, the third alternative (Takestan city) with a relative closeness of 0.4801 is chosen to be the most favorable location for the installation of the wind turbines, followed by the first alternative (Ardabil city) with a closeness coefficient of 0.4352 and the second alternative (Zabol city) with a closeness coefficient of 0.4244.

Table 11. The distances and relative closeness of three alternatives with respect to the positive idea solution (Note: superscript numbers represent the rank of the alternatives).

Alternatives	d_i^+	d_i^-	CL
A_1	0.77	0.59	0.4352 $^{(2)}$
A_2	0.79	0.58	0.4244 $^{(3)}$
A_3	0.73	0.66	0.4801 $^{(1)}$

To evaluate the efficacy of the proposed hybrid Fuzzy-ANP-TOPSIS model, the results of this study were compared with those obtained from the classical techniques of AHP and ANP as well as with an integrated ANP and TOPSIS approach. We implemented these techniques by the software packages of 'Expert Choice' (http://Expertchoice.com), 'Super Decisions' (http://www.superdecisions.com), and 'Fuzzy Topsis Solver' (https://fuzzy-topsis-solver-2013.software.informer.com/), respectively. The final priorities obtained from these techniques and the ranking of the alternatives are presented in Table 12. While comparing the results, it is found that the results from the proposed model are in good agreement with those obtained from AHP and ANP-TOPSIS. All three of these techniques ranked Takestan as the first, Ardabil as the second, and Zabol as the third most favorable location for wind farm development in the country. However, in the proposed approach, the stakeholders were more comfortable with expressing their preferences in the form of linguistic terms rather than mathematical expressions. According to the ANP method, Ardabil was chosen to be the most suitable location for establishing the planned wind farm, closely followed by Takestan.

Table 12. The score of alternatives obtained from traditional AHP, ANP and hybrid ANP-TOPSIS models. (Note: superscript numbers represent the rank of the alternatives).

Alternatives	AHP	ANP	ANP-TOPSIS
A_1	$0.118840^{(2)}$	$0.238306^{(1)}$	$0.496078^{(2)}$
A_2	$0.088101^{(3)}$	$0.190649^{(2)}$	$0.392679^{(3)}$
A_3	$0.126393^{(1)}$	$0.237711^{(3)}$	$0.543322^{(1)}$

5. Conclusions

Selection of the most suitable location or site for the placement of wind turbines is a key decision in the future development of both onshore and offshore wind power. Improper siting of wind turbines can have adverse effects on energy yield, financial profitability, installation cost and time, maintenance and repair accessibility, and decommissioning and removal costs of wind farms. The site selection process for wind turbines is a complex decision-making problem that involves high degrees of uncertainty due to the long investment cycle and complex environmental changes, different or conflicting interests of the stakeholders, and several technical, economic, social, environmental, and regulatory factors that need to be considered in the analysis.

In this paper, a novel multi-criteria decision-making (MCDM) approach was proposed for the evaluation, prioritization, and selection of suitable sites for wind farm development by involving all key stakeholders and state and non-state actors. To address uncertainties associated with all aspects of the wind farm site selection decision-making process, an integrated fuzzy analytic network process (FANP) and fuzzy technique for order performance by similarity to ideal solution (FTOPSIS) decision model was developed. Several evaluation criteria were identified through consultation with wind energy investors, local authorities and public sector bodies, landowners and residents, developers and operators, component suppliers and service providers, environmentalists, geologists, and financial analysts. These criteria were then categorized into four main groups, namely economic, social, technical, and geographic factors. The fuzzy weights of criteria with respect to the overall goal were derived by a logarithmic least square method and the alternatives were prioritized based on their relative closeness to the positive ideal solution.

To illustrate the applicability of the proposed Fuzzy-ANP-TOPSIS decision model, it was applied to determine the most favorable location for constructing an onshore wind farm with a power capacity of 25 MW in Iran. Three potential locations, namely Adrabil (in the northwest of the country), Zabol (in the southeast of the country) and Takestan (in the north-center of the country) were considered. The required information was collected from a literature review, Delphi and on-site interviews with key stakeholders involved in the renewable energy sector of the country, GIS platforms, and the country's wind energy resource atlas. Finally, the results were compared with those obtained using the traditional AHP, ANP and hybrid ANP-TOPSIS models. The results obtained from the proposed model show good agreement with those obtained from AHP and ANP-TOPSIS analyses. Based on these results, Takestan was chosen as the most suitable location for establishing the planned wind farm, followed by Ardabil and Zabol. However, Ardabil is ranked first, Takestan is ranked second, and Zabol is ranked third according to the ANP technique.

There is substantial scope for future research in the area of optimal site selection for renewable energy systems. The following are some possible extensions:

(a) The proposed decision model can be extended to determine suitable sites for the development of hybrid renewable energy systems (e.g., wind-solar or wind-wave);
(b) Although the proposed methodology was shown to be efficient from an accuracy point of view, it was found to be computationally intensive. In order to address this issue, some other new MCDM models can be developed. For instance, the weights of criteria can be determined using methods such as Fuzzy FUCOM and Fuzzy BWM. The ranking of alternatives can be obtained through methods such as Fuzzy MABAC, Fuzzy MARCOS, Fuzzy EDAS, Fuzzy ARAS, Fuzzy CODAS, etc.
(c) A sensitivity analysis can be carried out to support the decision-making process. This will help decision-makers find out how robust the results are.
(d) Designing an *interactive* and *web-based dashboard* to use for site selection of renewable energy projects could be very beneficial to industries.

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Nomenclature

K	Number of decision-makers
n	Number of criteria/sub-criteria
$\tilde{O} = (l, m, u)$	A fuzzy triangular number
$\widetilde{A}_k = \left[\widetilde{a}_{ijk}\right]$	Fuzzy pairwise comparison matrix for expert k; $k = 1, 2, \ldots K$
$\widetilde{a}_{ijk}$	Comparative importance of criterion i with respect to criterion j from the point of view of expert k; $i, j = 1, 2, \ldots, n$
$\widetilde{w}_i$	Aggregated fuzzy weights of criteria i
$\widetilde{A}^+$	Fuzzy positive ideal solution (FPIS)
$\widetilde{A}^-$	Fuzzy negative ideal solution (FNIS)
d_i^+	Distance of alternative i from fuzzy positive ideal solution
d_i^-	Distance of alternative i from fuzzy negative ideal solution
CL	Closeness coefficient
$\widetilde{D}$	Fuzzy decision matrix
$\widetilde{R}$	Normalized fuzzy decision matrix
$\widetilde{v}$	Weighted normalized decision matrix

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