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Selection of Wind Turbine Based on Fuzzy Analytic Network Process: A Case Study in China

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Abstract: Wind turbine selection is an evaluation problem involving many factors, such as technology, economy, society, etc., and there exist internal dependencies and circular relationships among these factors. This increases the complexity of the selection problem. At the same time, with the development of wind power technology, the types of wind turbines on the market are increasing. Therefore, it is necessary to establish a scientific and comprehensive evaluation system to guide the selection work. This paper extends the traditional indicator system, selecting a total of twelve evaluation indicators from three aspects: operation reliability, economy, and supplier cooperation. The selected indicators are defined in detail to clarify the relationship between them. Then the triangular fuzzy number is introduced to accurately reflect the preference information obtained from experts, and a fuzzy analytical network process (FANP) model for wind turbine unit selection is constructed by combining fuzzy preference programming (FPP) with analytic network process (ANP). In the end, a case study in China is carried out. Results show that the 2.5 W unit produced by Goldwind obtains the best comprehensive evaluation value, which is consistent with the expanding market share permanent magnet direct-drive wind turbines. This paper could provide references for future wind turbine selection questions.

Keywords: wind turbine; fuzzy analytic network process; unit selection; evaluation indicator system; supermatrix

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Citation: Pang, N.; Nan, M.; Meng, Q.; Zhao, S. Selection of Wind Turbine Based on Fuzzy Analytic Network Process: A Case Study in China. *Sustainability* **2021**, *13*, 1792. https://doi.org/10.3390/su13041792

Received: 10 January 2021
Accepted: 2 February 2021
Published: 7 February 2021

1. Introduction

Wind turbine selection is complex work that needs to take into consideration many factors not only matching with local wind energy resources but also ensuring good economic benefits and reliable energy quality of wind farms and so on during the operation period. At the same time, the prosperity of the wind power industry promotes the development of wind power generation technology. Nowadays, there are many types of wind power in the market, which makes the selection more difficult. In order to improve the efficiency and maximize the benefits of wind farms, it is necessary to select suitable units and make full use of wind energy resources. For a long time, the research on the selection of wind turbines mainly focused on the technical and economic aspects.

In the early stage, some scholars used some single indicators for evaluation, for example, capacity factor (CF), the cost of energy (COE), etc. Because the capacity factor can reflect the degree of matching between the wind resource and the wind turbine, many scholars took the capacity factor of the wind turbine as the indicator for wind turbine selection. Jangamshetti and Rau [1,2] use the Weibull distribution function combined with the mean wind speed and the power curve of the wind turbine to calculate the capacity factor, so as to select the best wind turbines. Hu and Cheng [3] put forward the calculation method of capacity factor. Albadi and El-Saadany [4] proposed a new method to calculate the capacity coefficient on the basis of Hu and Cheng [3]. Ritter and Deckert [5] presented a wind energy index, which is able to predict wind energy production based on reanalysis of

wind speed data from the modern-era retrospective analysis for research and applications (MERRA) and true production data. Some scholars also analyzed the cost of energy from the perspective of economy. Wang et al. [6] combined the Weibull distribution function and the existing economic benefit analysis method to select the best wind turbine and put forward the view that hub height cannot be pursued blindly. Harijan et al. [7] established a mathematical model of power generation costs. On the basis of fully considering the time value of money, using the net present value indicator to evaluate the economy of different wind turbines, Benatiallah et al. [8] defined the objective function of the total cost of wind turbine, used genetic algorithm and MATLAB tools to optimize the total cost, and selected the unit according to the minimum total cost. Chowdhury et al. [9] selected units based on energy production and introduced the particle swarm optimization algorithm for optimization calculation and unit selection. Andrés and Gilberto [10] used economic criteria to select wind turbines—through a systematic statistical analysis of the dataset of 176 turbines, they established a set of regression models to estimate energy cost. Because the selection of wind turbines is affected by many factors, the above methods, which are limited to a single index, cannot reflect the actual situation very well. Therefore, they cannot objectively, accurately, and comprehensively evaluate the advantages and disadvantages of wind turbines. The wind turbine selection problem has the following two typical characteristics: ① Complexity: technical evaluation indicator of wind turbines, numerous economics evaluation indicators, and a number of other indicators need to be taken into account. In addition, the wind turbine selection indicators have mutually influential relationships. ② Fuzziness: in practice, some qualitative indicators need to be transformed into quantitative indicators, which need to be quantified by using fuzzy math theory.

Wind turbine selection affects the energy quality and economic benefits of the wind farm; therefore, the issue of wind turbine selection is particularly important. The technical performance and economic performance of different turbine units vary greatly, which brings great difficulties to turbine selection. Our contributions are as follows:

(1) This paper extends the traditional unit selection indicator system, considering the supplier operating performance and service level, operation and maintenance costs, and other indicators; in the meanwhile, it clarifies the inter-relationship between them.
(2) Due to the large number and mutual influence of evaluation indexes, as well as the existence of qualitative indicators, the decision information is incomplete and imprecise. In order to accurately reflect the preference information obtained from experts, triangular fuzzy number and fuzzy comparison matrix are introduced, and a fuzzy analytical network process (FANP) model for unit selection is constructed by combining fuzzy preference programming (FPP) with analytic network process (ANP).

2. Literature Review

Some scholars consider using multiple indicators such as technology, economy, society, environment, and so on to evaluate the unit. Sarja and Halonen [11] conducted semi-structured interviews with experts and summarized five evaluation criteria, namely, product reliability, power generation, cost, availability, and maintenance organization. Perkin et al. [12] determined five selection indicators: rotor diameter, generator size, hub height, pitch angle range, and rotations per minute range (RPM) and embedded these indicators into the chromosome encoding of the genetic algorithm used for calculation and selection. Rehman and Khan [13] determined six evaluation indicators in the form of a questionnaire: hub height, wind speed, mean energy output, rotor diameter, cut in wind speed, and rated wind speed. The evaluation process is divided into two stages by using a fuzzy logic approach. In their latest research [14], fuzzy goal programming theory is applied to improve the original method. Ali and Jang [15] used a geographic information system (GIS) to help identify wind farm locations. Then, a detailed techno-economic assessment of turbines was presented, including parameters such as annual energy production (AEP), capacity factor (CF), levelized cost of electricity (LCOE), and net present value

(NPV). Shirgholami et al. [16] used an analytic hierarchy process (AHP) to make decisions. The decision indicators considered include the following: capacity coefficient, availability, rotor efficiency, initial capital costs, operation and maintenance costs, impact on wildlife, noise emission, visual impacts, supplier performance, and political stability.

There exist two research routes in the selection method: Some scholars use a multi-criteria decision-making method to make quantitative comparisons of wind turbines; while others gain results with the help of optimization theories such as genetic algorithms (GAs), back propagation neural networks (BPNNs), and so on. Kolios et al. [17] compared the performance of preference ranking organization method for enrichment of evaluations (PROMETHEE), technique for order preference by similarity to the ideal solution (TOPSIS) and ELimination Et Choix Traduisant la REalité (ELECTRE) in solving practical problems, and the results showed that PROMETHEE and TOPSIS are more suitable for complex environments. Bagočius et al. [18] used the weighted aggregates sum product assessment (WASPAS) method to make decisions. The decision-making process considered five criteria, namely, rated power of the wind turbine, actual maximum power, annual energy production (AEP), investment costs, and CO_2 emission. Using the interpretive structural modeling method (ISM), Lee et al. [19] took four aspects into consideration, namely: machine characteristics, economic indicators, technical level, and environmental issues, and used the ANP method to determine the impact relationship within various indicators. Supciller and Toprak [20] selected 21 criteria based on the interviews conducted with company experts, which covered four aspects: machine characteristics, economic impact, environmental impact, and technical specification. The linguistic variable-defined neutrosophic numbers were introduced, by using the Stepwise Weight Assessment Ratio Analysis (SWARA) method, thus, the criterion weights of alternatives could be generated. Anojkumar et al. [21] used FAHP to acquire the evaluation criteria weights, which were then given as the input for TOPSIS, VlšeKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), ELECTRE, and PROMTHEE for ranking the alternatives. Francisco et al. [22] found that the application of multi-objective evolutionary algorithms (MOEAs) to wind turbine selection is technically feasible, through the study of MOEAs and their variants. In order to improve the evaluation accuracy, Dong et al. [23] adopted particle swarm optimization (PSO), differential evolution (DE), and genetic algorithms (GAs) to select candidate wind turbines. Abdulrahman and Wood [24] implemented a cost model in their research, and the optimization was performed using the GA method. Three objective functions were considered: the output power, the capacity factor, and the cost per output power. Sun and Xu [25] established a comprehensive evaluation indicator system for wind turbines, including five top-grade indicators: wind turbine technical performance, wind farm adaption performance, economy, energy quality, and technical services. The BPNN model combined with particle swarm optimization algorithm was used to determine the indicator weights. Methods used in wind turbine selection in the last 5 years could be seen in Table 1.

Table 1. Methods used in wind turbine selection in the last 5 years.

Year	Method						
	Two-Stage Programming	**SWARA**	**GIS-MCDM**	**MERRA**	**Regression Model**	**BPNN**	**GA**
2015				Ritter and Deckert [5]			
2016	Rehman and Khan [13]						
2017						Sun and Xu [25]	Abdulrahman and Wood [24]
2018					Andrés and Gilberto [10]		
2019	Rehman and Khan [14]		Ali and Jang [15]				
2020		Supciller and Toprak [20]					

GA, genetic algorithm.

To sum up, there are two main problems in the existing wind turbine unit selection research: ① in the past, the selection method seldom considered the maximization of life time benefits of wind farms, ignoring the impact of operation reliability and operation and maintenance costs on the unit selection [26]; ② in the selection of wind turbine units, various evaluation indexes actually affect each other and most of the comprehensive evaluation methods do not consider the relationship between indicators.

3. Selection Criteria

With the continuous growth of the installed capacity of wind turbines, the operation status of wind turbines has more and more influence on power grid system. From the perspective of the safety of the power grid, the operation reliability of wind turbines should be an important evaluation index. In addition, in the previous evaluation of wind turbine unit selection, the supplier factor [27] is seldom considered, and the evaluation of supplier performance, supplier service level, and credibility is often ignored. In the perspective of life cycle, the supplier of wind turbines is also an important evaluation factor [28,29]. Based on the analysis of literature and the characteristics of wind turbine selection, this paper selects three kinds of evaluation indexes, i.e., operation reliability, economy, and supplier cooperation, to analyze the mutual influence relationships among the indexes. The meanings of three types of evaluation indexes and their sub indicators are as follows. The correlation between indicators can be expressed as shown in Table 2.

(1) Operational reliability

Availability: Availability refers to the percentage of the actual operation time of the wind turbine in the assessment time after the times of maintenance and failure are removed, which can reflect the failure level during the operation of the wind turbine. In addition to the quality of the turbine, the availability is mainly affected by the maintenance service level.

Technical route: The double-fed induction technology is the most mature, with low unit procurement cost but high failure rate and relatively increased maintenance cost [30]; direct-driven technology has the advantages of reducing the mechanical transmission loss, reducing the unit failure risk and maintenance cost, improving the power generation efficiency, etc. [31,32]; medium-speed permanent magnet and other emerging technologies have significant advantages in reducing cost.

Authentication: The wind turbine unit and its key parts need to undergo type authentication. This can ensure that the quality of the unit is consistent with the design. The operation of the same model also has an impact on the certification results. The authentication of the unit can reflect the manufacturing level of the supplier.

(2) Economic aspects

Initial investment: Since the costs of transformer substation, office area, and other conveyance engineering are not affected by the selection of the wind turbine, the initial capital cost considered in this study only includes equipment purchase and installation costs, land cost, and so on.

Operation and maintenance costs: These are directly related to the failure rate of wind turbines and the service level of suppliers, and the operation and maintenance costs will also have an impact on the reputation of suppliers in the industry.

Annual energy production (AEP): Annual energy production is the carrier of wind farm income, which directly affects the economic benefits of the project. After obtaining the wind source data of wind farms, Wind Farmer, Was P, and other professional software are generally used to obtain annual energy production estimates. This index is mainly affected by the operation reliability of the unit.

Unit generation cost: This is directly affected by the initial investment, operation and maintenance cost, and the operation status of the unit and is an important indicator to evaluate the unit economy.

Internal rate of return (IRR): It refers to the discount rate adopted when the project income and cost are equal. Internal rate of return is affected by cost index and power generation index.

(3) Supplier cooperation

Supplier service level: In the installation stage, the product supply should meet the installation progress requirements. In the operation and maintenance phase, the supplier shall have short fault response time, strong fault diagnosis ability, and timely supply of spare parts. High service level suppliers can effectively reduce the failure loss and improve the power generation quality.

Operation performance: The evaluation of operation performance mainly includes sales data and operation status. It can inspect the number of signing, lifting, and stable operations during 240 h of test and more than one year of trial operation of the fan, as well as the same capacity unit produced by the supplier. The operation performance is mainly affected by the economic performance of the unit and the service level of the supplier.

Credibility: Supplier acceptance degree, operational capability, and background are the important bases to evaluate supplier reputation. Good credibility of suppliers means the reduction of risks. At the same time, supplier credibility is affected by service level and operation performance.

Cooperation experience: The history of cooperation with suppliers can help both parties have a deeper understanding of each other's cooperation needs and internal operation of the company, help to provide more accurate services, and improve cooperation efficiency. The cooperation experience can also help reduce the purchase cost of unit equipment.

After detailed definition, the dependency and inter-relationship between indicators can be expressed in Table 2. In Table 2, $\surd$ indicates that the left indicator has an impact on the upper indicator. The FANP network of wind turbine selection indicator can be obtained as shown in Figure 1 below.

Table 2. Correlation between indicators.

	Availability Ratio	Technology Roadmap	Authentication Situation	One Investment	Operation and Maintenance Cost	Annual Energy Production	Unit Generation Cost	Internal Rate of Return	Service Level	Operation Performance	Supplier Reputation	Cooperation Experience
Availability ratio	√	√	√	√	√	√				√		
Technology roadmap	√	√	√	√	√	√				√		
Authentication situation	√	√	√	√	√	√				√		
One investment				√	√		√		√			
Operation and maintenance cost					√		√				√	
Annual energy production						√	√	√				
Unit generation cost				√			√	√				
Internal rate of return				√				√		√		√
Service level	√			√	√				√	√	√	
Operation performance			√							√	√	
Supplier reputation				√						√	√	
Cooperation experience				√					√			√

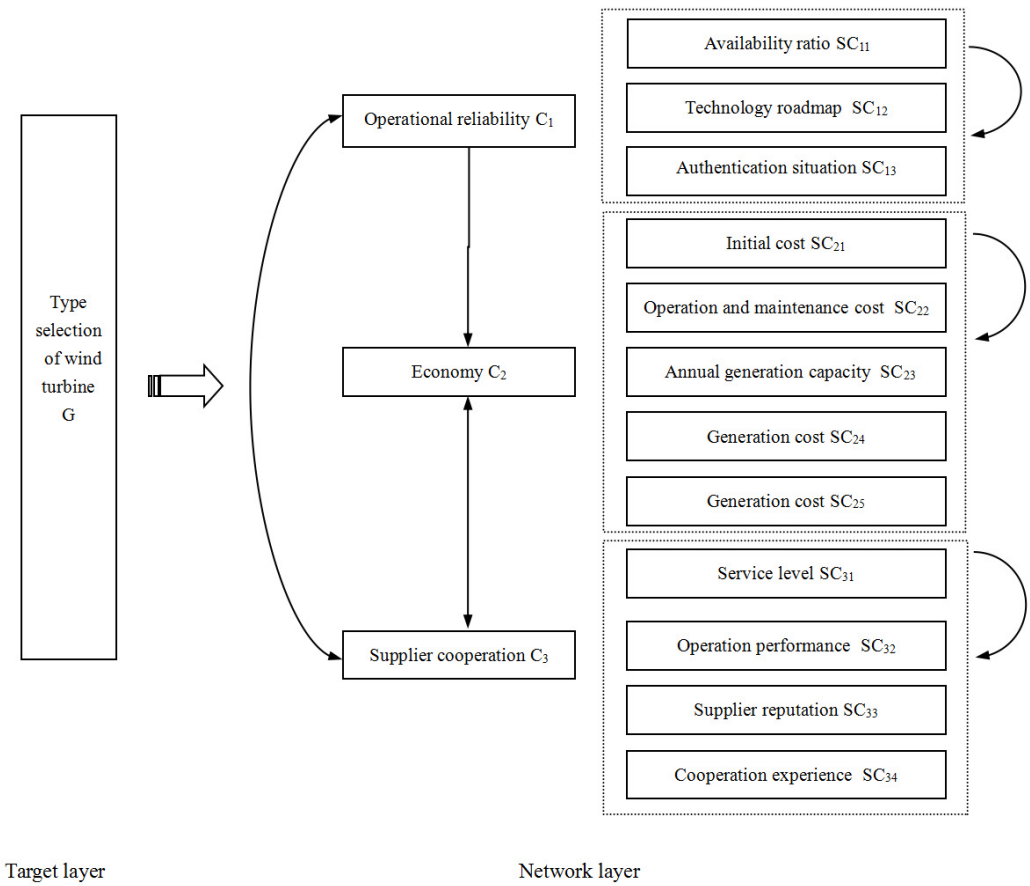

Figure 1. Fuzzy analytic network process (FANP) network of wind turbine selection indicator.

4. Methodology

The analytic network process (ANP) was proposed by Professor Saaty in 1996. By introducing the concepts of indirect priority and super matrix, ANP can analyze systems with influence and feedback [33–35]. An ANP network consists of a control layer and a network layer. The control layer contains goal and independent principles, or only one goal. The network layer consists of groups of elements that interact with each other.

The fuzzy analytical network process (FANP) proposed in this paper is an extension of the traditional method. The differences between FANP and ANP are mainly reflected in the construction and solution of the comparison matrix: the extended method constructs the fuzzy comparison matrix based on the linguistic variable–fuzzy number table; besides, the proposed FANP method uses fuzzy preference programming (FPP) [36,37] to calculate the weight vector. The steps using FANP method to evaluate the expected performance of variable types of wind turbine are as follows:

Step 1: Construct the fuzzy comparison matrix. Suppose there is only one target G in the control layer, and N element groups in the network layer: $C_1, C_2, \cdots, C_N$, k experts are invited to compare the influence of element $\left(SC_{i1}, SC_{i2}, \cdots, SC_{in_i}\right)$ in group $C_{\mathrm{i}}(\mathrm{i} = 1, 2, \cdots, \mathrm{N})$ on element SC_{jl} by taking target G as the criterion and element $SC_{jl}(l = 1, \cdots, n_j)$ in group $C_{\mathrm{j}}(\mathrm{j} = 1, 2, \cdots, \mathrm{N})$ as the secondary criterion. Opinions given by k experts construct a fuzzy judgment matrix, in which the elements are first represented by linguistic variable and then transformed to triangular fuzzy numbers according to Table 3 [38]. The fuzzy comparison matrix will be as follows:

SC_{jl}	SC_{i1}	SC_{i2}	$\cdots$	SC_{in_i}
SC_{i1}	e_{i11}	e_{i12}	$\cdots$	e_{i1n}
SC_{i2}	e_{i21}	e_{i22}		e_{i2n}
$\vdots$	$\vdots$		$\ddots$	$\vdots$
SC_{in_i}	e_{in1}	e_{in2}	$\cdots$	e_{inn}

Table 3. Linguistic variable–triangular fuzzy number.

Scale	Linguistic Variable	Triangle Fuzzy Number	Triangle Fuzzy Reciprocal
1	Equally important	(1,1,1)	(1,1,1)
2	Median	(1,2,3)	(1/3,1/2,1)
3	More important	(2,3,4)	(1/4,1/3,1/2)
4	Median	(3,4,5)	(1/5,1/4,1/3)
5	Important	(4,5,6)	(1/6,1/5,1/4)
6	Median	(5,6,7)	(1/7,1/6,1/5)
7	Very important	(6,7,8)	(1/8,1/7,1/6)
8	Median	(7,8,9)	(1/9,1/8,1/7)
9	Absolutely important	(9,9,9)	(1/9,1/9,1/9)

Step 2: Calculate synthetic comparison matrix. In order to eliminate the influence of aggregation on the consistency of the comparison matrix, this paper employs the geometric average approach to aggregate experts' responses. In this research, $((l_{iuv}, m_{iuv}, u_{iuv})$ represents the comparison result of element SC_{iu} to element SC_{iv} in $\mathrm{C_i}(\mathrm{i} = 1, 2, \cdots, \mathrm{N}))$. Taking the lower bound, l_{iuv}, of the fuzzy number as an example, the calculation formula is as follows:

$$l_{iuv} = \left(l_{iuv}^{(1)} \times l_{iuv}^{(2)} \times \cdots \times l_{iuv}^{(k)}\right)^{1/k} \tag{1}$$

Step 3: Calculate the weight vector using the FPP method. w_u, w_v represent the weight of element SC_{iu} and SC_{iv}, respectively. The membership degree of (w_u/w_v) is determined by Formula (2), and s_{iuv} represents the consistency between the solution weight and experts' judgment.

$$s_{iuv}\left(\frac{w_u}{w_v}\right) = \begin{cases} \frac{(w_u/w_v)-l_{iuv}}{m_{iuv}-l_{iuv}}, \frac{w_u}{w_v} \le m_{iuv} \\ \frac{u_{iuv}-(w_u/w_v)}{u_{iuv}-m_{iuv}}, \frac{w_u}{w_v} \ge m_{iuv} \end{cases} \tag{2}$$

The problem of solving the weight vector can be transformed into the following non-linear programming optimization model in Formula (3).

$$\begin{aligned} &\max \lambda \\ &s.t.\ \lambda w_v(m_{iuv} - l_{iuv}) - w_u + l_{iuv} w_v \le 0 \\ &\lambda w_v(u_{iuv} - m_{iuv}) + w_u - u_{iuv} w_v \le 0 \\ &\sum_{k=1}^{n_i} w_k = 1 \\ &w_k > 0,\ \ u = 1, 2, \cdots n_i - 1;\ v = 2, 3, \cdots n_i;\ v > u \end{aligned} \tag{3}$$

Step 4: Construct the unweighted super matrix. The weight vector $\left(w_{i1}^{(jl)}, w_{i2}^{(jl)}, \cdots, w_{in_i}^{(jl)}\right)^T$ of the judgment matrix is obtained. The column vector here represents the weight vector of the influences of element $SC_{i1}, SC_{i2}, \ldots, SC_{in_i}$ on element $SC_{jl}\left(l = 1, \cdots, n_j\right)$ in C_i. Note that sub-matrix W_{ij} is calculated.

$$W_{ij} = \begin{bmatrix} w_{i1}^{(j1)} & w_{i1}^{(j2)} & \cdots & w_{i1}^{(jn_j)} \\ w_{i2}^{(j1)} & w_{i2}^{(j2)} & & w_{i2}^{(jn_j)} \\ \vdots & & \ddots & \vdots \\ w_{in_i}^{(j1)} & w_{in_i}^{(j2)} & \cdots & w_{in_i}^{(jn_j)} \end{bmatrix}$$

If C_j is not affected by the elements in C_i, then $W_{ij} = 0$. The unweighted supermatrix, W, composed of the sub-matrix is as follows:

$$W = \begin{array}{c} \\ 1 \\ \vdots \\ n_1 \\ 1 \\ \vdots \\ n_2 \\ \vdots \\ 1 \\ \vdots \\ n_N \end{array} \begin{array}{c} \begin{array}{ccccccccc} 1 & \cdots & n_1 & 1 & \cdots & n_2 & \cdots & 1 & \cdots & n_N \end{array} \\ \begin{bmatrix} W_{11} & W_{12} & \cdots & W_{1N} \\ W_{21} & W_{22} & & W_{2N} \\ \vdots & & \ddots & \vdots \\ W_{N1} & W_{N2} & \cdots & W_{NN} \end{bmatrix} \end{array}$$

Step 5: Calculate the weighting matrix, A, and construct the weighted supermatrix $\overline{W}$. Sub-matrix W_{ij} is column normalized, but column normalization is still needed for W. Taking target G as criterion and element group $C_j (j = 1, 2, \ldots, N)$ as the sub-criterion, the influence degree of element group $C_i (i = 1, 2, \ldots, N)$ on element group $C_j (j = 1, 2, \ldots, N)$ is compared, and a fuzzy comparison matrix is constructed.

C_j	C_1	C_2	$\cdots$	C_N
C_1	e_{11}	e_{12}	$\cdots$	e_{1N}
C_2	e_{21}			e_{2N}
$\vdots$			$\ddots$	
C_N	e_{N1}		$\cdots$	e_{NN}

The weight vector $\left(a_1^{(j)}, a_2^{(j)}, \cdots, a_N^{j}\right)^T (j = 1, 2, \ldots, N)$ of the judgment matrix is obtained by using the FPP method. The column vector here represents the weight of the influence of element group $C_i (i = 1, 2, \ldots, N)$ on element group $C_j (j = 1, 2, \ldots, N)$. Note that the weighting matrix, A, is calculated.

$$A = \begin{array}{c} \\ C_1 \\ C_2 \\ \vdots \\ C_N \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_N \end{array} \\ \begin{bmatrix} a_1^{(1)} & a_1^{(2)} & \cdots & a_1^{(N)} \\ a_2^{(1)} & a_2^{(2)} & & a_2^{(N)} \\ \vdots & & \ddots & \vdots \\ a_N^{(1)} & a_N^{(2)} & \cdots & a_N^{(N)} \end{bmatrix} \end{array}$$

Step 6: Obtain the weighted super matrix, $\overline{W} = \left(a_i^{(j)} W_{ij}\right)$.

Step 7: Calculate the limit supermatrix. Suppose there are T indicators in the network layer, w_{pq} represents element in $\overline{W}$, indicating the influence degree of indicator $p (p = 1, 2, \cdots T)$ on indicator $q (q = 1, 2, \cdots T)$, also known as one-step priority. The influence degree of p on q can also be obtained through $\sum_{k=1}^{T} w_{pk} w_{kq}$, where the element in $\overline{W}^2$ calculated in this time is called two-step priority. When the $\overline{W}^{\infty} = \lim_{t \to \infty} \overline{W}^t$ limit matrix exists, the column vector in $\overline{W}^{\infty}$ is the weight vector of all indicators in the network layer to target G.

Step 8: Calculate the comprehensive evaluation value. Experts are invited to grade alternative units in T indicators, through multiplying the weight vector and the scores, the comprehensive evaluation value is compared, and the best unit scheme is obtained.

5. Case Study

In China, the total installed capacity of an onshore wind farm is 50 MW. According to the International Electrotechnical Commission (IEC) standard of the International Electrotechnical Association, the wind farm belongs to IIIB safety class. It is necessary to select wind turbines suitable for wind farms belonging to class IIIB and above. After preliminary screening, there are three alternative wind turbine units, namely: V110-2.0 MW unit of Vestas, G100-2.5 MW unit of Goldwind, and MySE135-2.5 MW unit of Mingyang Smart Energy. The technical performance of the three alternative units is shown in Table 4.

Table 4. Main technical performance indicators of alternative units.

Wind Turbine	V110-2.0MW	G100-2.5MW	MySE2.5-135MW
Unit capacity/MW	2.0	2.5	2.5
Number of units/set	24	20	20
Installed capacity/MW	48	50	50
Hub height/m	80	90	70
Swept area/m^2	9503	7854	12310
Annual generation capacity/GWh	4945	5237	5026
Power regulation mode	Variable speed constant frequency	Variable speed constant frequency	Variable speed constant frequency
Pitch control system	Hydraulic pressure	Hydraulic pressure	Electric
Generator type	Doubly fed induction generator	Permanent magnet direct-driven generator	Medium-speed permanent magnet generator
Design life/year	20	20	20

(1) Construct the unweighted supermatrix

Based on the criteria of the unit selection goal, G, an element in the element cluster is selected as the secondary criterion, and the group of elements that have influence on the element is found, and the degree of influence of elements in the group is compared.

Taking availability, SC_{11}, as an example, considering the impact of its own indicator group, C_1, and supplier cooperation indicator group, C_3, the comparison matrix showing operation indicators' influences on availability in C_1 given by expert $D_k(k = 1, 2, 3)$ are shown in Tables 5–7.

Table 5. Comparison matrix of expert D_1.

SC_{11}	SC_{11}	SC_{12}	SC_{13}
SC_{11}	(1,1,1)	(1,2,3)	(3,4,5)
SC_{12}	(1/3,1/2,1)	(1,1,1)	(1,2,3)
SC_{13}	(1/5,1/4,1/3)	(1/3,1/2,1)	(1,1,1)

Table 6. Comparison matrix of expert D_2.

SC_{11}	SC_{11}	SC_{12}	SC_{13}
SC_{11}	(1,1,1)	(2,3,4)	(2,3,4)
SC_{12}	(1/4,1/3,1/2)	(1,1,1)	(1,1,1)
SC_{13}	(1/4,1/3,1/2)	(1,1,1)	(1,1,1)

Table 7. Comparison matrix of expert D_3.

SC_{11}	SC_{11}	SC_{12}	SC_{13}
SC_{11}	(1,1,1)	(1,2,3)	(4,5,6)
SC_{12}	(1/3,1/2,1)	(1,1,1)	(2,3,4)
SC_{13}	(1/6,1/5,1/4)	(1/4,1/3,1/2)	(1,1,1)

By using the geometric average integration operator in Formula (3), the responses of the experts are aggregated. For example, the judgment matrix given by experts $D_k(k = 1, 2, 3)$ in the above example is shown in Tables 5–7, and the aggregated judgment matrix is shown in Table 8.

Table 8. The aggregated judgment matrix.

SC_{11}	SC_{11}	SC_{12}	SC_{13}
SC_{11}	(1,1,1)	(1.2599,2.2894,3.3019)	(2.8845,3.9149,4.9324)
SC_{12}	(0.3029,0.4368,0.7937)	(1,1,1)	(1.2599,1.8171,2.2894)
SC_{13}	(0.2027, 0.2554,0.3467)	(0.4368,0.5503,0.7937)	(1,1,1)

According to the aggregated judgment matrix, the nonlinear programming optimization model is constructed, and the weight vector of influence, $\left(w_{i1}^{(jl)}, w_{i2}^{(jl)}, \cdots, w_{in_i}^{(jl)}\right)^T$, and the consistency index (CI), λ, of each element group are obtained. For example, the aggregated judgment matrix of the above examples is shown in Table 8, and the construction model is as follows,

$$\begin{aligned}
&\max\lambda \\
s.t.\ &1.0295 \times \lambda w_2 - w_1 + 1.2599 \times w_2 \leq 0 \\
&1.0125 \times \lambda w_2 + w_1 - 3.3019 \times w_2 \leq 0 \\
&1.0304 \times \lambda w_3 - w_1 + 2.8845 \times w_3 \leq 0 \\
&1.0176 \times \lambda w_3 + w_1 - 4.9324 \times w_3 \leq 0 \\
&0.5572 \times \lambda w_3 - w_2 + 1.2599 \times w_3 \leq 0 \\
&0.4723 \times \lambda w_3 + w_2 - 2.2894 \times w_3 \leq 0 \\
&\sum_{k=1}^{3} w_k = 1 \\
&w_k > 0,\ k = 1, 2, 3
\end{aligned}$$

The influence weights, $w_k(k = 1, 2, 3)$, of availability, technical route, and authentication are 0.6339, 0.2147, and 0.1514, respectively. At the same time, $\lambda =$ 0.5524 is obtained, which shows that the fuzzy judgment matrix has good consistency. After calculation, the unweighted super matrix is obtained as shown in Table 9.

Table 9. The unweighted supermatrix.

	Availability Ratio	Technology Roadmap	Authentication Situation	One Investment	Operation and Maintenance Cost	Annual Generation Capacity	Unit Generation Cost	Internal Rate of Return	Service Level	Operation Performance	Supplier Reputation	Cooperation Experience
Availability ratio	0.6339	0.2631	0.4313	0.2857	0.2943	0.6322	0.0000	0.0000	0.0000	0.4348	0.0000	0.0000
Technology roadmap	0.2147	0.5435	0.1563	0.3779	0.3625	0.1756	0.0000	0.0000	0.0000	0.2174	0.0000	0.0000
Authentication situation	0.1514	0.1934	0.4125	0.3364	0.3432	0.1922	0.0000	0.0000	0.0000	0.3478	0.0000	0.0000
One investment	0.0000	0.0000	0.0000	0.4255	0.1754	0.0000	0.2373	0.0000	1.0000	0.0000	0.0000	0.0000
Operation and maintenance cost	0.0000	0.0000	0.0000	0.0000	0.8246	0.0000	0.1421	0.0000	0.0000	0.0000	1.0000	0.0000
Annual generation capacity	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.1612	0.2232	0.0000	0.0000	0.0000	0.0000
Unit generation cost	0.0000	0.0000	0.0000	0.3617	0.0000	0.0000	0.4594	0.3273	0.0000	0.0000	0.0000	0.0000
Internal rate of return	0.0000	0.0000	0.0000	0.2128	0.0000	0.0000	0.0000	0.4495	0.0000	1.0000	0.0000	1.0000
Service level	1.0000	0.0000	0.0000	0.4228	1.0000	0.0000	0.0000	0.0000	0.7647	0.1346	0.2825	0.0000
Operation performance	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.4808	0.4354	0.0000
Supplier reputation	0.0000	0.0000	0.0000	0.4155	0.0000	0.0000	0.0000	0.0000	0.0000	0.3846	0.2821	0.0000
Cooperation experience	0.0000	0.0000	0.0000	0.1617	0.0000	0.0000	0.0000	0.0000	0.2353	0.0000	0.0000	1.0000

(2) Calculate the limit supermatrix

The calculation of the weighting matrix is similar to the steps above. Fuzzy judgment matrices are constructed and solved to obtain the weighting matrix in Table 10.

Table 10. The weighting matrix.

	Operational Reliability	**Economy**	**Supplier Cooperation**
Operational reliability	0.6960	0.2765	0.3527
Economy	0	0.4849	0.2448
Supplier cooperation	0.3040	0.2386	0.4295

The multiplication of the matrices in Tables 9 and 10 gives the weighted supermatrix, in which the sum of each column is 1. MATLAB can be used to calculate the stable limit supermatrix, as shown in Table 11 below. In the limit super matrix, the column vector is the weight vector of the evaluation indicator.

(3) Calculate the comprehensive evaluation value of the wind turbine.

Then, by multiplying the weight vector obtained in Table 12 with the corresponding scores of 12 indicators, the comprehensive evaluation values of the wind turbines are obtained, which are 6.1008, 6.7417, and 5.6386, respectively.

Table 11. The limit supermatrix.

	Availability Ratio	Technology Roadmap	Authentication Situation	One Investment	Operation and Maintenance Cost	Annual Generation Capacity	Unit Generation Cost	Internal Rate of Return	Service Level	Operation Performance	Supplier Reputation	Cooperation Experience
Availability ratio	0.1649	0.1649	0.1649	0.1649	0.1649	0.1649	0.1649	0.1649	0.1649	0.1649	0.1649	0.1649
Technology roadmap	0.1199	0.1199	0.1199	0.1199	0.1199	0.1199	0.1199	0.1199	0.1199	0.1199	0.1199	0.1199
Authentication situation	0.0872	0.0872	0.0872	0.0872	0.0872	0.0872	0.0872	0.0872	0.0872	0.0872	0.0872	0.0872
One investment	0.0907	0.0907	0.0907	0.0907	0.0907	0.0907	0.0907	0.0907	0.0907	0.0907	0.0907	0.0907
Operation and maintenance cost	0.0299	0.0299	0.0299	0.0299	0.0299	0.0299	0.0299	0.0299	0.0299	0.0299	0.0299	0.0299
Annual generation capacity	0.0833	0.0833	0.0833	0.0833	0.0833	0.0833	0.0833	0.0833	0.0833	0.0833	0.0833	0.0833
Unit generation cost	0.0776	0.0776	0.0776	0.0776	0.0776	0.0776	0.0776	0.0776	0.0776	0.0776	0.0776	0.0776
Internal rate of return	0.0795	0.0795	0.0795	0.0795	0.0795	0.0795	0.0795	0.0795	0.0795	0.0795	0.0795	0.0795
Service level	0.1407	0.1407	0.1407	0.1407	0.1407	0.1407	0.1407	0.1407	0.1407	0.1407	0.1407	0.1407
Operation performance	0.0401	0.0401	0.0401	0.0401	0.0401	0.0401	0.0401	0.0401	0.0401	0.0401	0.0401	0.0401
Supplier reputation	0.0190	0.0190	0.0190	0.0190	0.0190	0.0190	0.0190	0.0190	0.0190	0.0190	0.0190	0.0190
Cooperation experience	0.0677	0.0677	0.0677	0.0677	0.0677	0.0677	0.0677	0.0677	0.0677	0.0677	0.0677	0.0677

Table 12. The expert scoring results of three alternative units.

	V110-2.0 MW				G100-2.5 MW				MySE135-2.5 MW			
	D_1	D_2	D_3	Average Scoring	D_1	D_2	D_3	Average Scoring	D_1	D_2	D_3	Average Scoring
Availability ratio	6	9	7	22/3	8	8	7	23/3	4	6	6	16/3
Technology roadmap	7	6	8	7	7	6	5	6	7	7	4	6
Authentication situation	5	6	6	17/3	6	9	8	23/3	5	4	7	16/3
One investment	4	3	5	4	5	4	5	14/3	3	6	5	14/3
Operation and maintenance cost	7	4	4	5	6	9	7	22/3	4	7	6	17/3
Annual generation capacity	5	6	7	6	8	7	6	7	4	5	3	4
Unit generation cost	4	7	5	16/3	9	6	7	22/3	7	4	8	19/3
Internal rate of return	2	3	4	3	8	7	9	8	6	5	4	5
Service level	6	7	8	7	5	4	6	5	7	9	7	23/3
Operation performance	8	7	9	8	7	6	8	7	6	7	6	19/3
Operation performance	7	6	5	6	6	8	7	7	5	4	5	14/3
Cooperation experience	6	8	7	7	7	9	8	8	4	6	5	5

The comprehensive evaluation values of three alternative units could be seen in Table 13, the second unit plan, G100-2.5 MW unit produced by Goldwind Company, was selected, and the decision's results are consistent with the actual unit model adopted by the wind farm. As a major manufacturer of direct-drive permanent magnet fans, Goldwind has grown to be the No. 1 wind turbine supplier in China and the No. 3 wind turbine supplier in the world. With the development of electronic technology, permanent magnet direct-drive technology is also evolving. Because of its excellent performance of power generation efficiency and low maintenance rate, the market recognition is also growing. In recent years, the market share of permanent magnet direct-drive wind turbines has been expanding among the newly installed units in the world, and it has been tested by time and the market.

Table 13. The comprehensive evaluation values of three alternative units.

	V110-2.0 MW	G100-2.5 MW	MySE135-2.5 MW
Comprehensive evaluation value	6.1008	6.7417	5.6386

6. Conclusions

Wind turbine selection is an important process in a wind farm construction project. With the rapid development of the wind power industry, different types of wind turbines are emerging in an endless stream. The technical performance, economic aspects, and supplier service of different turbines are quite different, so it is necessary to establish a scientific evaluation model to help the selection. In order to comprehensively evaluate alternative units, the selection indicator is expanded and improved in this study, including supplier operation performance and service level, unit operation and maintenance costs, and other indicators into the evaluation system. Considering that the evaluation indicator is not independent, this paper defines the evaluation indicators in detail, determines the impact relationship between the indicators, and constructs the evaluation index system of wind turbine. At the same time, a triangular fuzzy number is introduced to express expert's decision-making opinions. The FANP model proposed in this study can distribute the weight of the evaluation index more reasonably, so as to select the most suitable wind turbine. In the case study, the operational reliability indicators of wind turbines

are considered to be the most important, followed by the economic indicators; and the availability of wind turbines is considered to be the most important. The results are in line with the following facts: the operation of wind turbines has an increasing impact on the power grid system. From the perspective of power grid security, the operation of the unit should be the primary consideration; the main incentive means of governments for wind power construction is an economic subsidy policy, so it is very important to evaluate the economic level of the wind turbine. According to the statistical data of the Global Wind Energy Council, Bloomberg NEF, and other authorities over the years, the doubly fed induction technology is always the mainstream of the wind turbine industry. In recent years, newly installed capacity accounted for more than 60% of the global market share. Vestas, Siemens Gamesa, and GE Renewable are the main suppliers. As the main supplier of direct-driven permanent magnet synchronous generators, China's Goldwind company ranks first in terms of installed capacity in APAC. The global market share of hybrid-driven wind turbines produced by Mingyang Smart Energy, MHI Vestas, and Siemens Gamesa has risen to about 3%. In this study, the 2.5 MW turbine made by Goldwind technology was selected as the optimal scheme. As a local company, Goldwind benefits from China's subsidy policy, as well as providing more complete installation and faster maintenance services.

The FANP model proposed in this paper can also help evaluate other renewable energy equipment by changing indicators. There also exist shortcomings in the research: because of the introduction of the fuzzy number, the calculation becomes more complicated, and the workload of the evaluation process is increased. How to improve the evaluation model in this paper, making it easier to deal with the uncertainty and inaccuracy in the decision-making process and retain evaluation information at the same time, will be the direction of future research.

Author Contributions: Conceptualization, N.P. and M.N.; methodology, M.N.; software, M.N.; validation, M.N., Q.M. and S.Z.; formal analysis, M.N.; investigation, M.N.; resources, S.Z.; data curation, Q.M.; writing—original draft preparation, M.N.; writing—review and editing, Q.M.; visualization, S.Z.; supervision, N.P.; project administration, N.P.; funding acquisition, N.P. All authors have read and agreed to the published version of the manuscript. N.P., M.N., Q.M., S.Z.

Funding: This research was funded by The National Natural Science Foundation of China (General Program), grant number 71840004.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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