

Galih Pambudi; Narameth Nananukul

Article

A hierarchical fuzzy data envelopment analysis for wind turbine site selection in Indonesia

Energy Reports

Provided in Cooperation with:

Elsevier

Suggested Citation: Galih Pambudi; Narameth Nananukul (2019) : A hierarchical fuzzy data envelopment analysis for wind turbine site selection in Indonesia, Energy Reports, ISSN 2352-4847, Elsevier, Amsterdam, Vol. 5, pp. 1041-1047, <https://doi.org/10.1016/j.egy.2019.08.002>

This Version is available at:

<https://hdl.handle.net/10419/243650>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



<https://creativecommons.org/licenses/by-nc-nd/4.0/>



Research paper

A hierarchical fuzzy data envelopment analysis for wind turbine site selection in Indonesia

Galih Pambudi, Narameth Nanankul*

School of Management Technology, Sirindhorn International Institute of Technology, Thammasat University, Thailand

HIGHLIGHTS

- This research considers a case study with real data from Indonesia.
- The geographical and technicality data are integrated with opinions from experts.
- This research verifies the importance of factors by using the PCA method.

ARTICLE INFO

Article history:

Received 29 January 2019

Received in revised form 18 July 2019

Accepted 2 August 2019

Available online xxxx

Keywords:

Hierarchical fuzzy data envelopment analysis

Wind power plant site selection

Indonesia

Wind farm

Experts' opinion

Principal component analysis

ABSTRACT

The Indonesian archipelago has several suitable areas for building wind farms. In the site selection process, apart from wind intensity, there are other factors related to geographical and structural technicality that need to be considered. This research presents a hierarchical fuzzy data envelopment analysis model for identifying suitable locations for the construction of wind farms. The proposed hierarchy consists of two levels that are defined based on the 165 districts and 33 provinces in Indonesia based on data provided by different government organizations. Opinions from experts in different areas were collected and represented by the hesitant fuzzy linguistic term sets, which were converted to optimistic and pessimistic preferences by using linguistic aggregation and, later, integrated to the data envelopment analysis model. Principal component analysis by IBM SPSS was used to verify the importance of the factors that can reduce ineffective indicators from the analysis. The results show that the South Sumatra province has the highest potential for construction of wind farms, especially in the district of Palembang. The West Papua, Papua, and Maluku provinces have descending priority based on good infrastructure accessibility, high wind velocity, and lesser susceptibility to natural disasters.

© 2019 Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

1. Introduction

Natural energy resources such as wind energy is renewable and freely available, which could lead to sustainable energy usage. It can reduce greenhouse gas emissions with ecologically safe electricity generation. Selecting the most suitable sites that have the required optimal wind energy resource is a complicated decision-making process. Based on existing literatures, there are different approaches that have been used for wind power plant site selection. For instance, Haydar et al. (2004) used the analytical hierarchy process approach to define the suitable area for a station of wind observation in a university area. Bhatnagar and Sohal (2005) used the location factor as a criterion for the establishment of gas stations and power plants. Afshartous et al. (2009) developed an improved optimization model to determine the location of the coast guard air station. Gamboa and Munda

(2007) utilized the social framework as a multi-criterion method for determining wind plant site selection. Choudhary and Shankar (2012) determined thermal power plant site selection using a fuzzy data envelopment analysis.

At present, Indonesia has six main types of power plants that uses gas, steam turbines, combined cycle, geothermal, diesel engine, and hydro-power where fossil fuels are the major component for energy generation (Dutu, 2016). Within this decade, 96% of the electricity generation in Indonesia is based on fossil fuels and only 4% uses renewable energy. Hence, the government policy targets a portion of renewable energy resources to be increased up to 17% by 2025 (Hasan et al., 2012). The declining fossil fuel resources and growing environmental concerns are challenging the viewpoints in Indonesia's energy policy, which led to an attempt to increase the usage of renewable energy to increase energy efficiency (Mujiyanto and Tiess, 2013).

As is evident from the previous studies, the site selection is of prime concern for establishing a wind power plant. It requires the consideration of multiple factors, making the decision difficult

* Corresponding author.

E-mail address: narameth@siit.tu.ac.th (N. Nanankul).

and requiring complex modeling. Relevant data collection and observation are from the early of July 2017 up to the end of March 2018. Data sources are from Indonesian Statistics, Internal Ministry of Indonesia, Indonesian Agency for Meteorology, Climatology, and Geophysics, Ministry of Public Work and Public Housing Indonesia, and National Land Agency of Indonesia. In Indonesia there are 33 provinces where 5 suitable districts were selected in each province. This results in 165 districts. The majority of data collection are based on data provided by the government. The accessibility to each region was evaluated based on the available types of roads which were collected by using Arcgis maps of Indonesia, where the roads are divided into national road, provincial road, and district road. In this study, the method based on the hierarchical fuzzy data envelopment analysis (DEA) approach with multivariate factors is utilized for determining wind power plant sites in Indonesia. Opinions from experts in different areas were collected and represented by the hesitant fuzzy linguistic term sets (HFLTS), which were converted to optimistic and pessimistic preferences by using linguistic aggregation and, later, integrated to the DEA model. The advantages of this proposed study can, hopefully, be used as an alternative approach for site selection, especially for wind power plant. The validation of the significant criteria can be evaluated based on the principal component analysis (PCA).

The remainder of the paper is organized in five main sections. Section 2 presents the literature review related to various multi-criteria approaches. The criteria and the hierarchical fuzzy DEA are presented in Section 3. Section 4 provides the results and discussion. The conclusion is drawn in Section 5.

2. Literature review

DEA is a quantitative method for analyzing the performance efficiency of the comparable units called decision-making units (DMUs). Generally, every DMU performs the same function and the efficiency can be evaluated by computing the ratio between input and output criteria (Azadeh et al., 2011). The examples of studies that have applied DEA for site selection are described as follows: Ertek et al. (2012) determined the efficiency of on-shore wind turbines by using data-centric analysis. Sağlam (2016) applied a multi-criterion method based on the DEA to evaluate the quantitative efficiencies of wind power performance from 39 states. Wu et al. (2016) developed a two-stage DEA to assess the efficiency of wind power plants in China. The study identifies factors that can improve the performance of wind farms. Sueyoshi and Goto (2010) proposed an enhancement of the DEA called a Range Adjusted Measure (RAM). This approach provides a performance improvement over the traditional DEA. Seiford and Zhu (2002) proposed a multi-stage DEA where the importance of the input and output criteria is verified and validated by the PCA and numerical taxonomy. The result from this study shows that the efficiency of DMUs is based on land cost, road accessibility, infrastructure cost, population density, supply demand, natural vulnerability, wind velocity, and total area. DEA is a quantitative analysis method that has been applied to different cases related to site selection (Azadeh et al., 2014).

Considering the complexity of the decision-making process. The fuzzy logic approach on the multi-criteria decision-making for wind turbine selection in Saudi Arabia was proposed by Rehman and Khan (2016). Similar fuzzy logic approach was used for renewable energy plants location selection in Vietnam (Wang et al., 2018). A fuzzy multi-criteria based on supply chain operations reference (SCOR), fuzzy analytic network process (FANP), and technique for order of preference by similarity to ideal solution (TOPSIS) was used for wind power plant site selection in Vietnam (Wang et al., 2019). Due to the uncertainty of decision

Table 1

The summary of key related articles.

No	Author	Year	Methodology
1	Wang et al. (2019)	2019	A fuzzy multi-criteria decision making for selecting wind power plants in Vietnam
2	Wang et al. (2018)	2018	A multi-criteria decision making using fuzzy environment for renewable energy site selection in Vietnam
3	Chiciudean et al. (2018)	2018	A PCA for analyzing public perception regarding the alternative energy production in North-West Region of Romania
4	Sağlam (2016)	2017	A two-stage DEA for efficiency assessment of 39 states' wind power locations in the United States
5	Rehman and Khan (2016)	2016	A fuzzy logic based on multi-criteria decision making for wind turbine site selection in Qassim, Saudi Arabia
6	Aktak and Kabak (2016)	2016	A HFLTS algorithm for determining the importance of factors related to wind turbines locations

makers in criteria choices, the hesitant decision-making approach based on HFLTS can represent levels of certainty for the problem. The HFLTS algorithm was proposed by Yavuz et al. (2015). The statistical method PCA (Wu et al., 2016) can be used to reduce the number of variables under study and consequently rank and perform analysis of DMUs. The PCA was applied for analyzing public perception regarding the alternative energy production in North-West region of Romania (Chiciudean et al., 2018). The HFLTS algorithm was applied to determine the importance of factors related to locations of wind turbines (Aktak and Kabak, 2016). A summary of key related articles to this research is shown in Table 1.

3. Hierarchical fuzzy DEA

In this section, further information regarding the criteria and the methods used in this research are described.

3.1. Indicators of the model

The criteria based on geographical and technical structure that have influence on site selection of wind farm are considered in this research. Based on the availability of the data, the data were collected based on district and province levels of Indonesia. The factors are summarized in Table 2.

3.2. Hierarchical fuzzy DEA model

In the scope of the study, wind turbine site selection which is one of the most important problems related to sustainable energy development has many alternatives and requires multi-criteria decision-making. To be able to consider uncertainty from decision makers in criteria choices, the hesitant decision-making approach based on fuzzy logic was chosen for uncertainty representation.

The decision-making problem based on the HFLTS is preferred in this study. The objective of the HFLTS is to represent the flexibility and completeness of decision-making based on the fuzzy linguistic approach (Yavuz et al., 2015).

The steps of the algorithm are shown as follows:

Step 1. Setting the linguistic term set S .

$S = \{\text{no importance (n), very low importance (vl), low importance (l), medium importance (m), high importance (h), very high importance (vh), absolute importance (a)}\}$.

Step 2. Set the context-free grammar G_H .

Table 2

Factors for levels 1 and 2.

Level 1 (districts)	Level 2 (provinces)
<ul style="list-style-type: none"> • Land cost by districts in Indonesia Due to unprecedented increase in population density around the globe, land cost has become one of the important criterion which must be considered in the site selection process. • Transportation infrastructure Accessibility to the site chosen for wind farm construction is one of the most important factors that affect the reliability and the time required for transportation and distribution of construction materials to and from a site. • Infrastructure construction cost The construction of the infrastructure for wind farm requires a large amount of capital. At some sites, to transport construction materials to the sites incurs costs for building new roads in order to access the facility. This can increase the overhead costs of the wind farm construction. • Population A wind farm should be constructed in regions not too far from the demand points or a populated area. This is due to the fact that distributing electricity over a long distance incurs a loss of efficiency. • Land availability Regions that are densely populated and have small land availability may not be suitable for wind farm construction. The ratio of the number of people in each region divided by the total area is used to represent land availability in each region. 	<ul style="list-style-type: none"> • Wind velocity The wind velocity is the primary criterion which must be considered in the DDEA model for wind farm site selection. Every province has different average wind speed, based on the geography of the location. Areas with greater wind velocity are preferable for wind farm construction. • Electricity consumption Electricity consumption in each province is used as an output indicator of the DDEA model. The indicator is used to represent the electricity demand in each province. • Natural disaster The probability of the occurrence of natural disasters in the region has a significant impact on wind farm site selection. The damage caused by natural disasters can incur extra costs for maintenance, thus, increase the maintenance and operational overhead expenses of a wind farm. Four main parameters based on the chance of flood, volcanic eruption, earthquake, and land slide are included in the list of natural disasters that represents the indicators. • Population by province in Indonesia: In general, a province that has more population is preferred because it implies a greater demand for electricity. In order to avoid or minimize the cost of energy transmission to far-off places, areas with more people are given priority.

$G_H = \{\text{lower than, greater than, at least, at most, between, and}\}.$

Step 3. Collect the questionnaire from experts and summarize the preference relations.

Step 4. Transform the preference relations into linguistic terms.

Step 5. Determine the envelope containing pessimistic and optimistic preference relations.

Step 6. Computing the aggregated pessimistic L_{qr} (lower bound) and optimistic collective preferences U_{qr} (upper bound) for every pairwise criteria by applying the linguistic aggregation.

Based on the results from step 6, for every pair of criteria (q , r), the weight ratio v_q / u_r must be bounded by L_{qr} (lower bound) and U_{qr} (upper bound) as $L_{qr} \leq v_q / u_r \leq U_{qr}$. The bounded weight ratios can be integrated with the DEA (Lee et al., 2015). The primary data envelopment analysis can be expressed as follows:

$$\text{Max } \frac{\sum_{r=1}^R u_r Y_{rk'}}{\sum_{q=1}^Q v_q X_{qk'}} \quad (1)$$

Subject to

$$\frac{\sum_{r=1}^R u_r Y_{rk'}}{\sum_{q=1}^Q v_q X_{qk'}} \leq 1 \quad (2)$$

$$\frac{u_r}{\sum_{q=1}^Q v_q X_{qk'}} \geq \varepsilon, r = 1, \dots, R \quad (3)$$

$$\frac{v_q}{\sum_{q=1}^Q v_q X_{qk'}} \geq \varepsilon, q = 1, \dots, Q \quad (4)$$

$$L_{qr} \leq \frac{v_q}{u_r} \leq U_{qr}, r = 1, \dots, R; q = 1, \dots, Q \quad (5)$$

where v_q is the weight given to the q th input and u_r is the weight output to the r th output. $X_{qk'}$ is the amount of the q th input of the k' th DMU, $Y_{rk'}$ is the amount of the r th output. Q is the number of inputs and R is the number of outputs and K is the number of

DMUs. Data for levels 1 and 2 can be founded in the Mendeley data repository.

The efficiency scores from both levels, levels 1 and 2, of the hierarchical fuzzy DEA will be combined in order to generate the final scores. In level 1, all districts are considered in the analysis, where the districts in province k are represented by a set J_k using index j_k . In level 2, the provinces are considered; there are K provinces and each province is indexed by a subscript k . Combining results from both levels consists of three steps (Azadeh et al., 2011), which are explained as follows:

Step 1: Remove noise in level 1 by scaling each efficiency value by the average efficiency of group k .

$$f_{kj_k} = e_{kj_k} / \bar{e}_k, \bar{e}_k = \left(\sum_{j_k \in J_k} e_{kj_k} \right) / |J_k| \quad (6)$$

$|J_k|$ represents the number of members in set J_k .

Step 2: Calculate the net efficiency by multiplying the scaled value of f_{kj_k} with the efficiency of level 2 (e_k).

$$g_{kj_k} = f_{kj_k} \times e_k \quad (7)$$

Step 3: Scale the value of g_{kj_k} to $[0,1]$.

$$h_{kj_k} = g_{kj_k} \times R, R = \min_{k,j_k} \{1/g_{kj_k}\} \quad (8)$$

3.3. PCA

In this study, the PCA is used to verify the importance of the factors considered as the input and the output of the hierarchical fuzzy DEA. The objective of the PCA (Wu et al., 2016) is to verify the importance of the factors that can reduce ineffective indicators from the analysis. Functions from IBM SPSS software were used for evaluating the importance of different factors. Scree plot was used to determine the number of components to be

Table 3

Notation for input and output criteria considered in the questionnaire.

Level	Criteria	Notation
Level (district)	Land cost	LC
	Population in region	PinR
	Ratio of free usage land	RF
	Primary road	PR
	Secondary road	SR
	Tertiary road	TR
	Total required infrastructure cost	TCI
Level 2 (province)	Wind velocity	WV
	Population in province	PinP
	Total area	TA
	Electricity consumption	EC
	Landslide	LL
	Flood	LF
	Earthquake	LE
	Volcanic eruption	LVE

Table 4

Importance degree and context free grammar for HFLTS.

Number	Degree of importance	Context free grammar
0	No importance (n)	lower than
1	Very low importance (vl)	greater than
2	Low importance (l)	at least
3	Medium importance (m)	at most
4	High importance (h)	between
5	Very high importance (vh)	and
6	Absolute importance (a)	

extracted in the analysis. Direct Oblimin which is an approach to produce an oblique factor rotation where the factors solution can be actually correlated with each other was selected as a rotation method. After getting the Pattern Matrix for interpreting the results, the significance criteria were obtained by PCA to be used for measuring the efficiency of the locations both on district and province levels.

4. Results and discussion

In this section, the implementation of the hierarchical fuzzy DEA is presented. An example of how the responses from experts are processed is provided. Furthermore, the verification of the importance of factors based on the PCA is summarized.

4.1. Fuzzy hierarchical data envelopment analysis result

In this study, experts from different fields, including academic, Non-Governmental Organizations on renewable energy, integrated energy and environmental planning and policy of Indonesia, engineers in wind turbine projects in Indonesia, and the technical officers at the ASEAN Center for Energy were selected for their opinions related to the site selection of wind power plants. The notations for the input and output criteria are summarized in Table 3.

To process the responses from the experts, the fuzzy linguistic approach presented in Section 3.2 is used. The degree of importance and the context-free grammar built in the first and the second steps are shown in Table 4. In steps 3 and 4, the questionnaires from experts were collected and the preference relations were summarized. An example illustrates the implementation of the fuzzy linguistic approach for all steps. Table 5 depicts this example of the pairwise comparison of criteria from one of the experts based on the criteria used in level 1. After applying step 5, the envelope containing pessimistic and optimistic preference relations from an expert is shown in Table 6.

Table 6

Envelope containing pessimistic and optimistic preference relations from an expert.

E1	LC	PinR	RF	PR	SR	TR	TCI
LC	–	[l, a]	[l, m]	[m, m]	[l, m]	[l, m]	[l, l]
PinR	[n, h]	–	[vh, vh]	[h, vh]	[h, v h]	[n, vh]	[h, vh]
RF	[m, h]	[vl, vl]	–	[h, vh]	[h, vh]	[n, h]	[vl, l]
PR	[m, m]	[vl, l]	[vl, l]	–	[h, h]	[vh, vh]	[h, vh]
SR	[m, h]	[vl, l]	[vl, l]	[l, l]	–	[h, h]	[l, l]
TR	[m, h]	[vl, a]	[l, a]	[vl, vl]	[l, l]	–	[vl, vl]
TCI	[h, h]	[vl, l]	[h, vh]	[vl, l]	[h, h]	[vh, vh]	–

In step 6, the aggregation of the pessimistic and optimistic collective preferences from 10 experts based on a pairwise comparison of LC and PinR is shown as follows:

Pessimistic preference:

$$P_{L12}^- = \Delta \left(\frac{1}{10} \left(\Delta^{-1}(l, 2) + \Delta^{-1}(vl, 1) + \Delta^{-1}(m, 3) + \Delta^{-1}(vl, 1) + \Delta^{-1}(h, 4) + \Delta^{-1}(n, 0) + \Delta^{-1}(vh, 5) + \Delta^{-1}(h, 4) + \Delta^{-1}(a, 6) + \Delta^{-1}(h, 4) \right) \right)$$

$$P_{L12}^- = \Delta \left(\frac{1}{10} (2 + 1 + 3 + 1 + 4 + 0 + 5 + 4 + 6 + 4) \right)$$

$$P_{L12}^- = \Delta(3.00)$$

$$P_{L12}^- = \Delta(m, .00)$$

Optimistic preference:

$$P_{L12}^+ = \Delta \left(\frac{1}{10} \left(\Delta^{-1}(a, 6) + \Delta^{-1}(l, 2) + \Delta^{-1}(h, 4) + \Delta^{-1}(m, 3) + \Delta^{-1}(h, 4) + \Delta^{-1}(l, 2) + \Delta^{-1}(a, 6) + \Delta^{-1}(vh, 5) + \Delta^{-1}(a, 6) + \Delta^{-1}(h, 4) \right) \right)$$

$$P_{L12}^+ = \Delta \left(\frac{1}{10} (6 + 2 + 4 + 3 + 4 + 2 + 6 + 5 + 6 + 4) \right)$$

$$P_{L12}^+ = \Delta(4.20)$$

$$P_{L12}^+ = \Delta(h, .20)$$

The result after aggregating the pessimistic and optimistic collective preferences for district level from all experts is shown in Table 7. In step 7, the bounds of the weight ratios are summarized. An example of the bounds for a weight ratio is based on the weight ratio of land cost and population in region. Based on the results from Table 7, the lower bound of the ratio is 3.00 and the upper bound of the ratio is 4.20. The same procedure is carried out on all the pairwise criteria to calculate the pessimistic and optimistic collective preferences.

After including the constraints based on the bounds of weight ratios, the hierarchical fuzzy DEA is evaluated for both district and province levels. The efficiency scores from both levels can be combined by using Eqs. (6)–(8); the results for the top 5 provinces is shown in Table 8. The result shows that by considering the experts' opinions on the importance of significant criteria with regard to the input and output criteria, South Sumatra is the most appropriate location for establishing wind power plants.

4.2. PCA results

In this section, the PCA is used to evaluate the importance of the criteria for the hierarchical fuzzy DEA. Fig. 1 shows the pattern matrix of level 1 (district) criteria and Fig. 2 shows the pattern matrix of level 2 (province) criteria.

Table 5

An example of the pairwise comparison of criteria from one of the experts based on the criteria in level 1.

	LC	PinR	RF	PR	SR	TR	TCI
Expert 1's linguistic evaluations							
LC	–	at least l	between l and m	m	between l and m	between l and m	is l
PinR	at most h	–	is vh	between h and vh	between h and vh	at most vh	between h and vh
RF	between m and h	is vl	–	between h and vh	between h and vh	at most h	between vl and l
PR	is m	between vl and l	between vl and l	–	is h	is vh	between h and vh
SR	between m and h	between vl and l	between vl and l	is l	–	is h	is l
TR	between m and h	at least vl	at least l	is vl	is l	–	is vl
TCI	is h	between vl and l	between h and vh	between vl and l	is h	is vh	–

Table 7

Aggregated result of pessimistic and optimistic preference relations for district level (level 1).

Level 1	LC		PinR		RF		PR		SR		TR		TCI	
	P	O	P	O	P	O	P	O	P	O	P	O	P	O
LC	–	–	3.0	4.2	3.2	4.0	2.7	4.0	1.9	4.2	2.6	4.2	1.4	2.4
PinR	1.8	3.0	–	–	3.4	4.4	3.0	3.6	3.7	4.6	3.0	4.1	2.4	2.7
RF	2.0	2.8	1.6	2.6	–	–	2.1	3.2	2.0	4.3	1.6	3.5	1.0	1.4
PR	2.1	2.8	2.4	3.0	2.8	3.9	–	–	3.5	4.0	4.7	5.1	1.2	2.2
SR	1.8	4.1	1.5	2.3	1.7	4.0	2.0	2.5	–	–	3.0	4.0	1.3	2.0
TR	1.9	3.4	1.9	3.0	2.5	4.4	0.9	1.3	2.0	3.0	–	–	1.3	1.6
TCI	3.6	4.6	3.3	3.5	4.6	5.0	3.8	4.8	4.0	4.5	4.4	4.7	–	–

Based on the oblique rotated component solution, the pattern matrix can help identify the significant criteria of each component. For the first component, total cost of infrastructure is 92.2%, tertiary road is 92.2%, secondary road is 90.3%, and primary road is 87.8%. The first component represents the criteria related to the available infrastructure. The second component has two major loadings that are land cost (91.2%) and population (89.9%). The third component has one major loading that is the ratio of free space (99.8%). The result from the pattern matrix confirms the importance of the criteria in level 1.

From Fig. 2, the major positive loadings are population, electricity consumption, and wind velocity for the first component. The second component has 3 major loadings, which are volcanic eruptions, landslides and floods. The third component has total

area as the most important factor. Overall, we can conclude that each criterion has high positive loading in one of the components. Consequently, all criteria are statistically significant in level 2.

Based on the weights of district and province levels from the PCA, the hierarchical scores of all the provinces were calculated as shown in Table 9.

The ranking from the PCA is the same as the result from the hierarchical fuzzy DEA, where South Sumatra is the most appropriate location for establishing wind power plants.

4.3. Discussions

The top five provinces based on the hierarchical fuzzy DEA and the PCA are shown in Table 10. The ranks from both methods are the same although only the hierarchical fuzzy DEA considers the judgment from experts for the importance of the criteria. Expert judgment is beneficial for complex decision that involves factors from different categories. The top five suitable locations for establishing wind turbine power plant in Indonesia are South Sumatra, Papua, West Papua, Maluku and East Nusa Tenggara provinces, respectively. The geographic locations are shown in Fig. 3.

The hierarchical fuzzy DEA gave South Sumatra the highest priority to build a wind farm. The results from the PCA show that the ratio of free usage area and total cost of infrastructure have significant influence on the result in district level. This is because the ratio of free usage area in South Sumatra is high. It shows that more space area in one region is advantageous due to

Table 8

Top 5 hierarchical Scores from the hierarchical fuzzy DEA.

No	Province	Efficiency	District	Efficiency	Combined score Step 1	Combined score Step 2	Combined score Step 3	Combined score province level
1	South Sumatra	0.725	Palembang	0.6076	4.9965	3.6238	13.1317	2.626
			Pagar Alam	0.0000	0.0001	0.0001	0.0000	
			Lubuk Linggau	0.0001	0.0010	0.0007	0.0000	
			Prabumulih	0.0001	0.0010	0.0008	0.0000	
			Lahat	0.0002	0.0013	0.0010	0.0000	
2	West Papua	0.729	Manokwari	0.1218	0.7429	0.5414	0.2931	1.979
			Sorong	0.0001	0.0004	0.0003	0.0000	
			Fakfak	0.0005	0.0032	0.0024	0.0000	
			Sorong City	0.6972	4.2520	3.0989	9.6031	
			Bintuni	0.0002	0.0015	0.0011	0.0000	
3	Papua	0.885	Jayapura	0.0017	2.9959	2.6500	7.0227	1.695
			Merauke	0.0002	0.3528	0.3121	0.0974	
			Biak Numfor	0.0000	0.0487	0.0431	0.0019	
			Nabire	0.0002	0.3285	0.2906	0.0844	
			Mimika	0.0007	1.2740	1.1269	1.2700	
4	Maluku	0.908	Ambon	0.6807	1.5134	1.3738	1.8874	1.388
			Seram	0.0002	0.0004	0.0003	0.0000	
			Tual	0.7079	1.5738	1.4287	2.0413	
			Aru	0.8598	1.9117	1.7355	3.0118	
			Buru	0.0003	0.0008	0.0007	0.0000	
5	East Nusa Tenggara	0.639	Kupang	0.0030	3.2750	2.0918	4.3758	0.938
			Alor	0.0003	0.3644	0.2327	0.0542	
			Belu	0.0003	0.3631	0.2320	0.0538	
			Ngada	0.0005	0.5607	0.3581	0.1283	
			Southwest Sumba	0.0004	0.4368	0.2790	0.0779	

Table 9
PCA result.

Province	Province efficiency	District	District efficiency	Combined score Step 1	Combined score Step 2	Combined score Step 3	Hierarchical score
South Sumatra	0.949	Palembang	1.000	2.325	2.208	4.874	1.340
		Pagar Alam	0.136	0.316	0.300	0.090	
		Lubuk Linggau	0.338	0.786	0.747	0.557	
		Prabumulih	0.256	0.595	0.565	0.319	
		Lahat	0.420	0.978	0.928	0.862	
West Papua	1.000	Manokwari	0.301	0.483	0.483	0.233	1.339
		Sorong	0.110	0.176	0.176	0.031	
		Fakfak	1.000	1.605	1.605	2.576	
		Sorong City	0.705	1.131	1.131	1.280	
		Bintuni	1.000	1.605	1.605	2.576	
Papua	1.000	Jayapura	0.358	1.049	1.049	1.100	1.166
		Merauke	0.243	0.713	0.713	0.508	
		Biak Numfor	0.260	0.760	0.760	0.578	
		Nabire	0.240	0.703	0.703	0.495	
		Mimika	0.606	1.775	1.775	3.150	
Maluku	1.000	Ambon	0.687	1.041	1.041	1.083	1.105
		Seram	0.348	0.527	0.527	0.278	
		Tual	0.719	1.089	1.089	1.187	
		Aru	1.000	1.514	1.514	2.293	
		Buru	0.547	0.828	0.828	0.686	
East Nusa Tenggara	1.000	Kupang	0.201	0.653	0.653	0.427	1.101
		Alor	0.251	0.818	0.818	0.669	
		Belu	0.467	1.519	1.519	2.308	
		Ngada	0.248	0.805	0.805	0.649	
		Southwest Sumba	0.370	1.204	1.204	1.450	

Table 10
Comparison of the ranks based on the hierarchical fuzzy DEA and the PCA.

Province	Scores from hierarchical fuzzy DEA	Rank	Scores from PCA	Rank
South Sumatra	2.626	1	1.340	1
West Papua	1.979	2	1.339	2
Papua	1.695	3	1.166	3
Maluku	1.388	4	1.105	4
East Nusa Tenggara	0.938	5	1.101	5

Pattern Matrix^a

	Component		
	1	2	3
Tot_Cost_Inf	.922	-.058	.042
Tertiary	.922	-.058	.042
Secondary	.903	.060	-.038
Primary	.878	.035	-.027
Land_Cost	-.040	.912	.052
Population	.037	.899	-.050
Ratio_of_Free_Space	.006	.006	.998

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.^a

a. Rotation converged in 3 iterations.

Fig. 1. Pattern matrix of level 1 (district) criteria.

the lower land cost. Also, South Sumatra has good primary and secondary road infrastructure, and do not need to build additional infrastructure for tertiary road. This decreases the total cost of infrastructure, which contributes to the high efficiency score. This result is similar to the result from [Aktak and Kabak \(2016\)](#) where land cost and operational cost are two of the most important factors for choosing location of wind turbines.

Pattern Matrix^a

	Component		
	1	2	3
Population	.896	.147	-.004
Elec_Consumption	.883	-.019	-.078
Earthquake	.620	.352	.482
Flood	-.567	.463	-.037
Wind_Velocity	.551	-.018	-.301
Vol_Eruption	.012	.853	-.010
Landslide	.060	.836	-.069
Total_Area	-.159	-.154	.867

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.^a

a. Rotation converged in 6 iterations.

Fig. 2. Pattern matrix of level 2 (province) criteria.

In the province level, some criteria such as population, electricity consumption and occurrence of natural disaster have the most influence on the total efficiency score. This result is similar to the result from [Seiford and Zhu \(2002\)](#). In South Sumatra, it shows that having high spreading population can help decrease the transportation and accommodation cost of labors. Electricity consumption demand in South Sumatra is also high, as a result, the establishment of wind farm in South Sumatra can help fulfill the electricity demand. The third influence criterion in South Sumatra is the occurrence of natural disaster. The South Sumatra is geographically located in the Sumatra Island, this region has less occurrence of landslide, earthquake and volcanic eruption. Due to the reasons, South Sumatra is considered as the most suitable location to build a wind farm power plant.

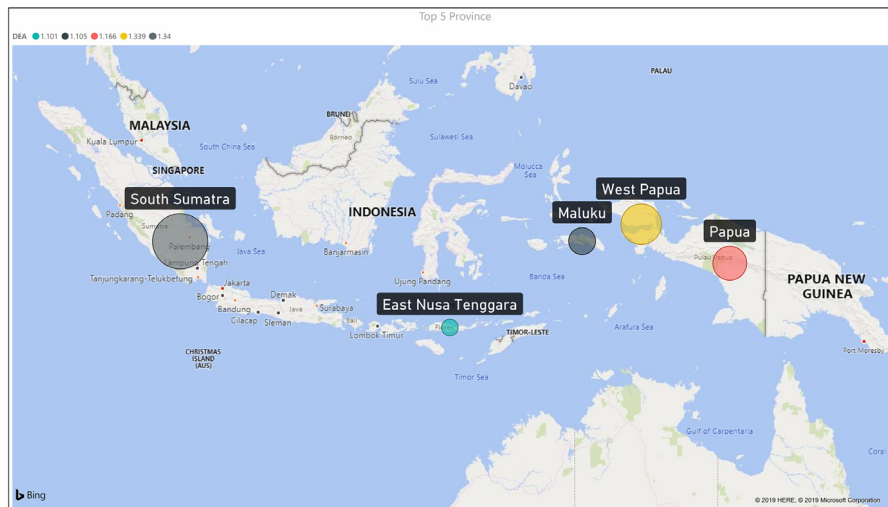


Fig. 3. Top five selected provinces in Indonesia.

5. Conclusion

In this study, we proposed a hierarchical fuzzy DEA approach to determine the integrated efficiency scores of DMUs from both district and province levels. The integrated efficiency scores from district and province levels based on the hierarchical fuzzy DEA were determined. HFLTS was used for determining the different levels of importance of the criteria based on the responses from experts. The validation of the significant criteria is based on the PCA. The final results show that the South Sumatra province has the highest efficiency score and is the most economical location for constructing a wind farm. The most significant criterion that has influence on wind turbine site selection at the district level is the ratio of free usage area, followed by total cost of infrastructure.

In this research, key criteria were selected and included in the analysis, however, additional criteria specification that includes social, environmental, economic, and technical aspects would make the analysis more accurate. Furthermore, the final site selection will be more practical, if opinions from experts, policy makers, government, and private stakeholders are also considered in the analysis.

References

- Afshartous, D., Guan, Y., Mehrotra, A., 2009. US Coast Guard air station location with respect to distress calls: a spatial statistics and optimization based methodology. *European J. Oper. Res.* 196, 1086–1096.
- Aktak, A., Kabak, M., 2016. A model proposal for locating wind turbines. *Procedia Comput. Sci.* 102, 426–433.
- Azadeh, A., Ghaderi, S.F., Nasrollahi, M.R., 2011. Location optimization of wind plants in Iran by an integrated hierarchical Data Envelopment Analysis. *Renew. Energy* 36 (5), 1621–1631.
- Azadeh, A., Golkhandan, A.R., Moghaddam, M., 2014. Location optimization of wind power generation–transmission systems under uncertainty using hierarchical fuzzy DEA: A case study. *Renew. Sustain. Energy Rev.* 30, 877–885.
- Bhatnagar, R., Sohal, A., 2005. Supply chain competitiveness: measuring the impact of location factors, uncertainty and manufacturing practices. *Technovation* 25, 443–456.
- Chiciudean, G.O., Harun, R., Arion, F.H., Chiciudean, D.I., Oroian, C.F., Muresan, I.C., 2018. A critical approach on sustainable renewable energy sources in rural area: Evidence from North-West region of Romania. *Energies* 11, 2225.
- Choudhary, D., Shankar, R., 2012. An STEEP-fuzzy AHP-TOPSIS framework for evaluation and selection of thermal power plant location: A case study from India. *Energy* 42, 510–521.
- Dutu, R., 2016. Challenges and policies in Indonesia's energy sector. *Energy Policy* 98, 513–519.
- Ertek, G., Tunç, M.M., Kurtaraner, E., Kebude, D., 2012. Insights into the efficiencies of on-shore wind turbines: A data-centric analysis. In: *International Symposium on Innovations in Intelligent Systems and Applications*. Trabzon.
- Gamboa, G., Munda, G., 2007. The problem of wind farm location: a social multicriteria evaluation framework. *Energy Policy* 35, 1564–1583.
- Hasan, M.H., Wuzammil, W.K., Mahlia, T.M.I., Jannifar, A., Hasanuddin, I., 2012. A review on the pattern of electricity generation and emission in Indonesia from 1987 to 2009. *Renew. Sustain. Energy Rev.* 16 (5), 3206–3219.
- Haydar, A., Senol, E., Eylem, K., 2004. Multi-criteria selection for a wind observation station location using analytic hierarchy process. *Renew. Energy* 29, 1383–1392.
- Lee, A.H.I., Kang, H.Y., Lin, C.Y., Shen, K.C., 2015. An integrated decision-making model for the location of a PV solar plant. *Sustainability* 7, 13522–13541.
- Mujiyanto, S., Tiess, G., 2013. Secure energy supply in 2025: Indonesia's need for an energy policy strategy. *Energy Policy* 61, 31–41.
- Rehman, S., Khan, S.A., 2016. Fuzzy logic based multi-criteria wind turbine selection strategy—A case study of qassim, Saudi Arabia. *Energies* 9, 872.
- Sağlam, Ü., 2016. A two-stage data envelopment analysis model for efficiency assessments of 39 state: wind power in the United States. *Energy Convers. Manage.* 146, 52–67.
- Seiford, L.M., Zhu, J., 2002. Modeling undesirable factors in efficiency evaluation. *European J. Oper. Res.* 142 (1), 16–20.
- Sueyoshi, T., Goto, M., 2010. Measurement of Returns to Scale and Damages to Scale for DEA-based operational and environmental assessment: how to manage desirable (good) and undesirable (bad) outputs. *European J. Oper. Res.* 211 (1), 76–89.
- Wang, C., Huang, Y., Chai, Y., Nguyen, V.T., 2018. A multi-criteria decision making (MCDM) for renewable energy plants location selection in Vietnam under a fuzzy environment. *Appl. Sci.* 8, 2069.
- Wang, C., Yang, C., Cheng, H., 2019. Fuzzy multi-criteria decision-making model for supplier evaluation and selection in a wind power plant project. *Mathematics* 7, 7417.
- Wu, Y., Hu, Y., Xiao, X., Mao, C., 2016. Efficiency assessment of wind farms in China using two-stage data envelopment analysis. *Energy Convers. Manage.* 123, 46–55.
- Yavuz, M., Oztaysi, B., Onar, S.C., Kahraman, C., 2015. Multi-criteria evaluation of alternative-fuel vehicles via a hierarchical hesitant fuzzy linguistic model. *Expert Syst. Appl.* 42, 2835–2848.