Assessment of Wind Farm Allocation Criteria

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Abstract

In keeping with the urgent goals of maintaining a healthy environment and providing clean energy alternatives at reasonable prices, Saudi Arabia is moving towards electricity generation using wind. Selecting optimal wind farm locations is an important challenge in which one seeks to reduce the levelized cost of electricity. A four-level multi-criteria decision-making model was developed that used the analytic hierarchy process to consider wind availability, electricity demand, employment costs, maintenance costs, infrastructure costs, sale prices, and energy production capabilities to optimize wind farm locations. In addition, this study introduced multiple factors that affect wind farm success. In this study, the analytical hierarchy process was implemented using mathematical simulations to compare three wind farm locations in Saudi Arabia.

Keywords:
Analytic Hierarchy Process (AHP), Renewable Energy, Wind Farm, Vision 2030.

1. Introduction

The Saudi Arabia 2030 Vision supports the advancement of the renewable energy industry and seeks to increase the renewable energy capacity within the Kingdom to 9.5 GW by 2023 (General Authority of Statistics 2016). On July 23, 2018, the Renewable Energy Project Development Office at the Ministry of Energy, Industry, and Mineral Resources of Saudi Arabia hosted bids for the first utility-scale wind farm in the country. It is expected to cost approximately $500 million and generate 400 MW of wind power to supply up to 70,000 Saudi households (Saudi Arabia Ministry of Energy 2018). In addition, the wind energy industry is growing. Recently, it has grown by approximately 16% per year, reaching 435 GW of installed capacity at the end of 2015 (World Wind Energy Association 2016). The invention of electric cars is one of the initiatives that have been made. In addition, new techniques have been implemented to exploit energy from renewable sources.

Recently, the level of discussion regarding shifts from classical to renewable energy within Saudi Arabia has increased. Thus, there is ongoing research on renewable energy sources such as wind. Optimization of wind turbine locations is important to power generation and the turbine life cycle. In particular, selecting an optimal site maximizes the benefits of wind farms (Ali et al. 2018). Several factors affect wind farm location decision-making. Cost is important — this includes maintenance and infrastructure costs, as well as labor costs. The latter can include uncertainty in currency fluctuations, economic changes, and political situations (Almaktoom et al. 2016). In addition, the quantity of energy produced affects location decision-making regardless of cost. Decision-makers also consider the opportunities associated with each location. These opportunities include energy demand (the number of households in the area) and wind availability as measured via wind speed. Opportunities, costs, and energy output significantly influence location decision-making.

This study sought to rank the criteria used in selecting an optimal wind farm location in Saudi Arabia by importance via the analytic hierarchy process (AHP). This paper establishes a four-level model that includes wind farm selection criteria, sub-criteria, and alternatives such as locations A, B, and C. The AHP model used to rank these criteria was developed based on Saaty (1980). The rest of this paper is organized as follows: Section 2 analyzes applications of AHP. Section 3 introduces the wind farm criteria ranking method. Section 4 includes a case study of criteria ranking for wind farm location optimization. Finally, a summary is provided with recommendations and further work.

2. Application of the Analytic Hierarchy Process

The AHP is one of the most commonly used multi-criterion decision-making (MCDM) tools. According to Saaty (2008), "Decisions involve many intangibles that need to be traded off" and the AHP facilitates decision-making using qualitative or quantitative factors. In order to limit inconsistencies and improve AHP-based judgments, "the derived priority scales are synthesized by multiplying them by the priority of their parent nodes and adding for all such nodes" (Saaty 2008).

The AHP has been used in several applications, including wind farms. For example, Aras et al. (2004) studied the process of identifying the most suitable location for a wind observation station via AHP. They considered the potentiality of the wind power, wind speed, and wind path in order to choose the location. Moreover, they considered the amount of energy produced and selected a wind turbine. Another example of AHP implementation is the strategic selection of a wind farm in China (Lee et al. 2009). These researchers developed a model based on the benefits, opportunities, costs, and risks of each location and used it to assist in choosing the most suitable wind farm project. A similar study was conducted in the northwest of Jordan. It considered wind speed, rainfall, slope, altitude, and land use. The criteria were ranked based on expert opinions (Al-Shabeeb et al. 2016).

In addition, the AHP is used in many other applications. It can be applied to the critical concept of supply chain finance (Lin and Lin, 2016) and to engineering education (Kousalya et al. 2012). Moreover, AHP was used to identify the top areas in the Abidjan district of West Africa for flood risk (Danumah et al. 2016). Another study evaluated the benefits of using the AHP in real decision problems (Ishizaka et al. 2011).

3. Wind Farm Criteria Ranking Using AHP

This study ranked wind farm factors to help in choosing an optimal wind farm location. Several factors that influence the location have previously been studied. In addition, several studies have been performed in order to enhance renewable energy utilization using various methods. For example, Helgason (2012) studied 48 sites round Iceland and 47 different wind turbines using the Weibull distribution and simulation. These factors included the expected annual energy output (in GWh), capacity factor (in % of maximum energy possible to generate), and cost of energy (ce /kWh). The study concluded that the calculated cost of wind power was significantly higher than those of other renewable energy sources in Iceland. Zhao and Huang (2011) developed a multi-objective decision-making model for wind power project valuation using the AHP. They considered operational feasibility, as well as economic, social, and synthetic factors in their model. A study in South Korea by Ali et al. (2017) identified an optimal wind farm location using various parameters and weights alongside MCDM and a geographic information system. They considered several parameters, including the slope of the land, road network, wind speed, and presence of cities with populations greater than 10,000. Decision-makers should consider several factors that play significant roles in wind farm projects, including wind resources, land availability, topography, etc. These factors are associated with significant uncertainty (Chen, 2013).

In this study, pairwise comparison (PWC) was used to check the consistency of the weighting selection criteria. The implementation of the AHP used in this study is based on Saaty (1980).. This decision-making method helps to organize complex, multi-criteria decision problems into hierarchies. The AHP incorporates the evaluations of all decision makers into a final decision without having to compare utility functions that contain subjective and objective criteria by comparing alternatives in pairs (Saaty, 1990). The consistency ratio (CR) was calculated for expert opinions and tested to see if it was less than or equal to 0.1 in order to verify the suitability of each pairwise comparison matrix for AHP analysis.

AHP requires the following steps: Establishing a pairwise comparison matrix A. In this matrix, C1, C2, ..., Cn refer to the set of elements, while aij denotes a quantified judgment of a pair of elements Ci, Cj. The relative importance of two elements is classified using a value scale that includes 1, 3, 5, 7, and 9. In this case, 1 indicates 'equally important', 3 refers to 'slightly more important', 5 equals 'significantly more important', 7 represents 'demonstrably more important', and 9 denotes 'absolutely more important'. This yields an *n*-by-*n* matrix A, which is shown here as matrix (1).

$$A=[a_{ij}]\begin{array}{c} \\ C_1 \\ C_2 \\ \vdots \\ C_n \end{array}\begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_n \end{array} \\ \begin{bmatrix} 1 & a_{12} & \dots & a_{1n} \\ 1/a_{12} & 1 & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/a_{1n} & 1/a_{n2} & \dots & 1 \end{bmatrix} \end{array} \tag{1}$$

$$a_{ij} = 1 \tag{2}$$

$$a_{ij} = 1/a_{ij}\ , i, j = 1,2, \dots, n. \tag{3}$$

where (2) and (3) are in matrix A (1). The problem becomes one of assigning a set of numerical weights $W_1, W_2, \dots, W_n$ that reflect the recorded judgments to the n elements $C_1, C_2, \dots, C_n$. If A is a consistency matrix, the relationships between weights W_i and judgments a_{ij} are given by equation (4) and matrix *A* (5*)*

$$\frac{W_i}{W_j} = a_{ij}(\text{for } i, j = 1,2, \dots, n) \tag{4}$$

$$A=\begin{array}{c} \\ C_1 \\ C_2 \\ \vdots \\ C_n \end{array}\begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_n \end{array} \\ \begin{bmatrix} w_1/w_1 & w_1/w_2 & \dots & w_1/w_n \\ w_2/w_1 & w_2/w_2 & \dots & w_2/w_n \\ \vdots & \vdots & \ddots & \vdots \\ w_n/w_1 & w_n/w_2 & \dots & w_n/w_n \end{bmatrix} \end{array} \tag{5}$$

Saaty (1990) suggested that the largest eigenvalue λ_{max} would be equation (6)

$$\lambda_{max} = \sum_{j=1}^{n} a_{ij} \frac{W_j}{W_i} \tag{6}$$

If A is a consistency matrix, the eigenvector X can be calculated using equation (7)

$$(A - \lambda_{max} I)\chi = 0 \tag{7}$$

Saaty (1990) proposed using the consistency index (CI) and CR to verify the consistency of the comparison matrix. The CI is defined in equation (8), while the CR is defined in equation (9). RI represents the average CI over numerous random entries of reciprocal matrices with the same order.

$$CI = \frac{(\ell_{max} - n)}{(n-1)} \tag{8}$$

$$CR = \frac{CI}{RI} \tag{9}$$

$$CR \leq 0.1 \tag{10}$$

Either the inequality from equation (10) is true or new comparison matrices are calculated until equation (10) becomes true.

4. Case Study

The goal of this study was to rank the criteria involved in selecting a wind farm location so that one could choose an optimal site. Evaluating the opportunities, costs, and outputs enhances the ability of decision makers to evaluate wind farm locations and make the best decision.

Figure 1 describes a hierarchical model that seeks to identify the optimal wind farm location and is divided into levels of criteria, sub-criteria, and alternatives. Logically, the optimal location is the one with the highest opportunities and outputs and the lowest cost.

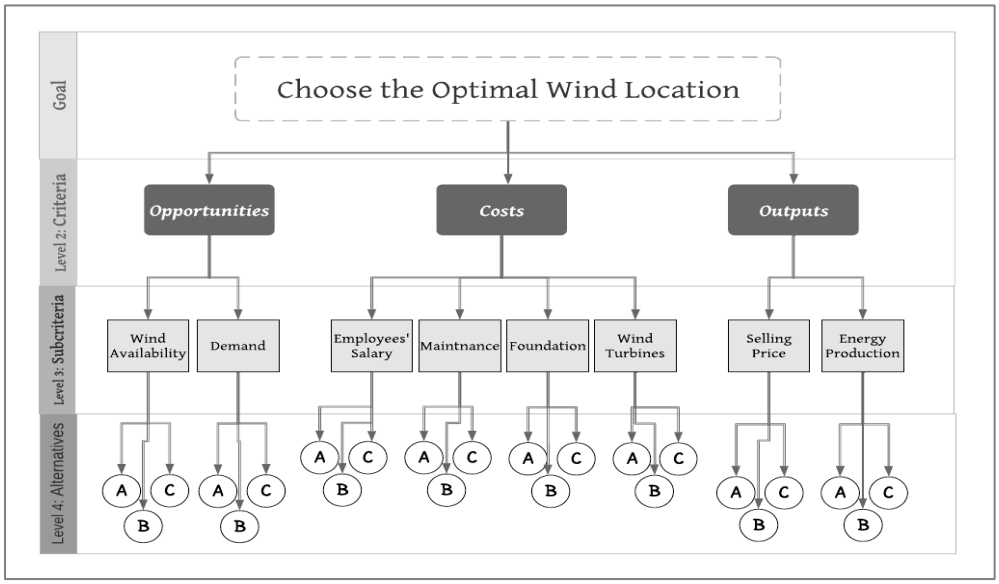

Figure 1. AHP model for wind farm location selection

The criteria include sub-criteria which affect the final decision (Figure 1):

A. Opportunities:
- Wind availability: wind speed and direction, etc. vary by location.
- Demand: the demand depends on the local population.

B. Costs:
- Employee salary: Salaries for Saudi and non-Saudi laborers vary. In addition, accommodations and transportation costs should be considered and vary by location.
- Maintenance: the cost of maintenance is often linked to the wind turbine type and depends on the turbine quality, life cycle, and performance.
- Foundation: the cost of buildings and infrastructure.
- Wind turbine: affected by wind productivity. The cost depends on the height and wing width, as well as power generation.

C. Outputs:
- Selling price: the cost in terms of Saudi hlala / kilowatt / hour.
- Energy production: the amount of energy produced in megawatts.

The case study locations are A, B, and C and are in Saudi Arabia. Location A is to the west, near the sea. It has mid-range winds and the highest population of the three locations. Location B is to the north. It has the highest wind speed and a mid-sized population. Location C is to the south and has a mid-range wind speed, but has the smallest population.

4.1 Discussion and Analysis

This case study considered three criteria in order to determine the optimal location. These criteria were chosen based on previous studies and application of the AHP. Opportunities, costs, and outputs were considered to help the

decision-makers achieve the overall goal of choosing the location with the lowest costs and highest energy production and sale price.

Information on wind farm project performance with respect to various criteria were collected from previous papers that included expert interviews. All sub-criteria are quantitative data. For opportunity and output criteria, high values reflect high wind farm efficiency. For cost-related criteria, higher values indicate lower efficiency.

Table 1. Pairwise comparison method scale (adapted from Saaty's (1980) AHP theory)

Intensity of Importance	**Definition**	**Explanation**
1	Equal importance in a pair	Two criteria contribute equally to the objective
3	Moderate importance	Judgment and experience slightly favor one criterion over another
5	Significant importance	Judgment and experience significantly favor one criterion over another
7	Very strong importance	Judgment and experience very strongly favor one criterion over another
9	Extreme importance	The evidence favoring one criterion over another is of highest possible validity
2, 4, 6, 8	Intermediate values	Used when compromise is required
Reciprocals	Values for inverse comparison	If criterion i had one of the above numbers assigned to it when compared to criterion j , then j has the reciprocal value when compared to i.

The AHP method is based on the construction of a series of pairwise comparison matrices (PCMs), which are used to compare all of the criteria to each other. All possible pairs of criteria in the PCM are compared in order to determine which has the highest priority. A PCM element comparison scale is shown in Table 1. A value of 1 indicates that the criteria are equally important, while 9 indicates that the criterion under consideration is extremely important compared to the other criteria. PCMs include a consistency indicator used to control errors and calculate a consistency ratio. According to Malczewski (1999) and Saaty (1990), there are three main phases used to make decisions based on PCMs in the AHP:

1) Identification of important criteria and the problem (wind turbine sites).
2) Assessment of the relative importance of each criterion. This is usually performed by experts using a scale from 1 to 9.
3) Evaluation of consistency by using pairwise comparisons to assign a CR. This step includes the following:
   - Calculating the priority vector for a criterion.
   - Computing the eigenvalue factor (λ max).
   - Computing the CI.
   - Determining the appropriate random consistency ratio (RI) value.

- Calculating CR. This includes the average random consistency indices using N number of criteria (N = 1 up to N = 8) (Table 2).

Table 2. Average random consistency indices (RI) for different numbers of criteria

Number of criteria (N)	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Random consistency indices (RI)	0	0.0	0.58	0.90	1.12	1.24	1.32	1.41

- Criteria level:

1- The model uses the AHP to rank criteria from 1–9 based on Saaty theory. The structure was built using AHP structure levels (Figure 3).
2- Criteria comparisons (opportunities, costs, and outputs) were scaled from 1–9 based on previous papers. For example, experts rated costs as being less important than opportunities and outputs. Therefore, Table 3 shows that opportunities and outputs are 4 times and 5 times more important than costs, respectively. Outputs have moderate importance compared to opportunities.
3- The criteria are normalized so that they have similar weights (Table 4).

4- CR evaluation. In Table 5, *Wsum* and *Ws* 1/W* are calculated using Eq. (4) and (5). *RI* is defined in Table 2. *Lambda* is calculated using Eq. (6), the CI is calculated using Eq. (8), and the *CR* is calculated using Eq. (9). Thus, the *CR* has been calculated and is within the acceptance level ($0 > CR < 0.1$).

Table 3. Pairwise comparison matrix for criteria comparison

(PCM)	OPPORTUNITIES	COSTS	OUTPUT
OPPORTUNITIES	1.00	4.00	0.33
COSTS	0.25	1.00	0.20
OUTPUT	3.00	5.00	1.00

Table 4. Criteria comparison after normalization

Normalized PCM	OPPORTUNITIES	COSTS	OUTPUT	Criteria Wgt. (W)
OPPORTUNITIES	0.24	0.40	0.22	0.28
COSTS	0.06	0.10	0.13	0.10
OUTPUT	0.71	0.50	0.65	0.62
Total	**1.00**	**1.00**	**1.00**	**1.00**

Table 5. CI and CR values

Criteria	*Wsum*	*Ws* 1/W*			
OPPORTUNITIES	0.88	3.083283		RI=	0.58
COSTS	0.29	3.021662		lambda max=	3.09
OUTPUT	1.95	3.155127		N=	3
				CI=	0.043
				CR=	0.075
				Consistency	OK

As a result, the criteria can be ranked by importance. The outputs, opportunities, and costs have weights of 62%, 28%, and 10%, respectively.

- Sub-criteria level:
  1- Sub-criteria are ranked by importance from 1–9 based on expert opinions from previous papers. For instance, Table 6 shows that wind available in a location is 4 times more important than the demand for energy in that location. Data normalization also takes place (Table 6).
  2- The same calculations are performed for all other sub-criteria and are shown in Tables 7 and 8. Consistency calculations are also performed, except when sub-criteria contain only two evaluation measures. When there are only two elements to compare (such as opportunities and outputs) the respective comparison matrices will always be consistent (CR = 0). However, consistency must be checked if the number of elements compared pairwise is three or more (Mu and Pereyra-Rojas 2017).

Table 6. Sub-criteria of opportunities: comparison and normalization

PCM	Wind Availability	Demand		Normalized	Wind Availability	Demand	Criteria wgt. (w)
Wind Availability	1.00	4.00		Wind Availability	0.80	0.80	**0.80**
Demand	0.25	1.00		Demand	0.20	0.20	**0.2**

Table 7. Sub-criteria of costs: comparison and normalization

PCM	Emp. Sal	Maintenance	Foundation	Wind Turbines		Normalized	Emp. Sal	Maintenance	Foundation	Wind Turbines	*Criteria Wgt (W)*
Emp. Sal	1.00	0.33	0.33	0.33		Emp. Sal	0.10	0.04	0.18	0.07	0.10
Maintenance	3.00	1.00	0.20	0.50		Maintenance	0.30	0.12	0.11	0.10	0.16

Foundation	3.00	5.00	1.00	3.00	Foundation	0.30	0.60	0.54	0.62	0.51
Wind Turbines	3.00	2.00	0.33	1.00	Wind Turbines	0.30	0.24	0.18	0.21	0.23

Table 8. Sub-criteria of outputs: comparison and normalization

PCM	Sale Price	Energy Prod	Normalized	Selling Price	Energy Production	*Criteria Wgt (W)*
Sale Price	1.00	0.33	Selling Price	0.25	0.25	0.25
Energy Production	3.00	1.00	Energy Prod	0.75	0.75	0.75

The resulting sub-criteria percentages and ratios are shown in Tables 6, 7, and 8. In order to link the sub-criteria to the criteria, one must weigh the former according to the main criteria weights (Figure 2).

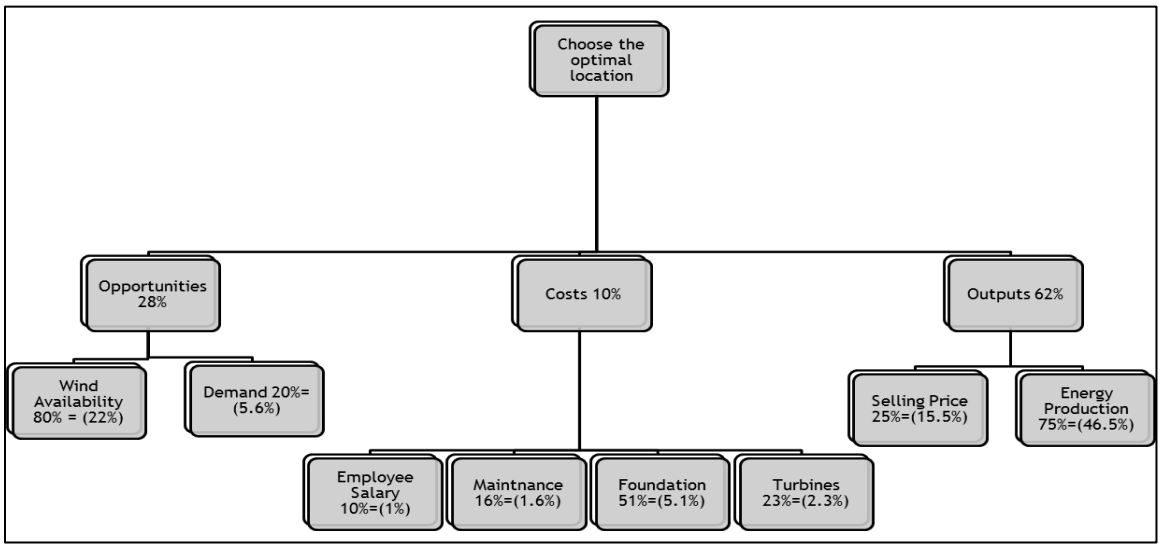

Figure 2. AHP model for wind farm location selection with criteria and sub-criteria weights.

In order to choose the optimal wind farm location using the AHP method, the sub-criteria information must be determined for each location and the weights summed. The location with the highest weight is the best. However, this method is most effective when the sub-criteria are qualitative. In this case study, the sub-criteria such as wind availability, employee salaries, etc. are all quantitative. In conclusion, the AHP is not sufficient for identification of a suitable wind farm location. Further studies should be performed. Thus, this area of research will continue to adopt other techniques to achieve its objectives.

5. Conclusions

Wind farm turbine technology can make important contributions to the energy needs of Saudi Arabia. This study presented a model that can be improved to help in developing a model that help in reducing energy costs. This study used the AHP, which is an MCDM method, to rank and evaluate wind farm allocation criteria. Due to the weaknesses of the AHP in multi-level ranking and dealing with quantitative data, further studies should integrate other methods to help achieve better rankings. It is recommended to extend the study and use other MCDM techniques that are more effective in ranking multi-level problems using qualitative and quantitative data. To overcome this gap, the technique for order of preference by similarity to ideal solution (TOPSIS) described in Choudhary and Shankar (2012), Roszkowska (2011), Srikrishan et al. (2014), and Ahmadi et al. (2013) should be integrated with AHP. It is also suggested to conduct further studies that consider the effects of uncertainty like Almaktoom (2017), Almaktoom and Krishnan (2016), Wang et al. (2013, 2014), and Krishnan et al. (2016) on optimal location selection.

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7. Biographies

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