Applied Artificial Intelligence
An International Journal

ISSN: 0883-9514 (Print) 1087-6545 (Online) Journal homepage: https://www.tandfonline.com/loi/uaai20

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To cite this article: Shafiqur Rehman & Salman A. Khan (2019) Goal Programming-Based Two-Tier Multi-Criteria Decision-Making Approach for Wind Turbine Selection, Applied Artificial Intelligence, 33:1, 27-53, DOI: 10.1080/08839514.2018.1525525

To link to this article: https://doi.org/10.1080/08839514.2018.1525525

APPLIED ARTIFICIAL INTELLIGENCE
2019, VOL. 33, NO. 1, 27–53
https://doi.org/10.1080/08839514.2018.1525525

Goal Programming-Based Two-Tier Multi-Criteria Decision-Making Approach for Wind Turbine Selection

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ABSTRACT

Wind energy has emerged as a potential replacement of conventional fuel sources. One key factor that contributes to efficient harnessing of wind energy depends heavily on the turbine type. However, the task of selecting an appropriate, site-specific turbine is a complex one. It is due to the fact that several decision criteria, which are also mutually conflicting, are involved in the decision process. Important criteria energy output, cut-in speed of wind, rated speed of wind, hub height, turbine's power rating, and energy output. Therefore, a desired decision is the one that gives the best trade-off between the selection criteria. With the inherent complexities encompassing the decision-making process, this study develops a two-tier multi-criteria decision strategy for turbine selection founded on the concepts of fuzzy goal programming. The effectiveness of the proposed methodology is assessed through its application to a potential site located in Dhulom, Saudi Arabia. Results reveal the effectiveness of the proposed methodology in finding the most suitable turbine for the said site, from a pool of 20 turbines with different capacities and vendors.

Introduction

Due to exponentially growing population, materialistic life styles, and fast industrialization, the energy requirement has been increasing at faster pace. Furthermore, the awareness and sensitivity of deteriorating environmental changes have led the people from all walks of life to use renewable and cleaner sources of energy to safeguard the life on the earth and conserve the fossil fuel for future generations. In recent times, tremendous scientific efforts and engineering development have been made on the utilization of renewable energy sources which include wind, solar, geothermal, hydro, and biomass, to name a few. Of these energy sources, wind power technology has become competent to the traditional fossil fuel-based energy generation and has been accepted commercially (Baseer et al. 2015, 2016; Rehman et al.

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2016). Compared to other traditional methods of power generation (e.g. coal, gas, or nuclear plants etc.), it is easier and less complex to deploy wind turbines which require minimal operation and maintenance attention and cost. Furthermore, the operational age of turbines lasting between 20 and 25 years. Additionally, wind power harnessing is not restricted by geographical boundaries (Khan 2015; Rehman and Al-Abbadi 2009).

Recent statistics (Global Wind Statistics, GWEC 2016) indicate that a number of countries have made notable progress in generation and utilization of wind energy. The global generation of wind energy reached 486,600 MW at the end of 2016. This signifies an increase of about 2696.6% over a period of 17 years as shown in Figure 1. Compared to 2015, the cumulative wind power generation increased by 12.5% from 432,680 MW in 2015 to 486,749 MW in 2016. China holds the highest stake in global market with new addition of 23,328 MW generation capacities to the grid in 2016. This was followed by the USA, Germany, India, and Brazil which added 8,203, 5,443, 3,612, and 2,014 MW, respectively, in year 2016. Furthermore, France, Turkey, Netherlands, United Kingdom, and Canada took 6th to 10th place with new wind power capacity additions of 1,561, 1,387, 887, 736, and 702 MW. It is worth to mention here that India took fourth place in year 2016 with new capacity buildup compared to its fifth place in the previous years. The situation in Africa and the Middle East is improving, though the contribution from these regions is still small. The highest stake is of South Africa which is contributing 418MW.

Despite the fact the extraction of wind energy is easy, one main obstacle diminishes the effect of this fact. A key challenge is the maximization of energy output from the turbines which is negatively affected by the fluctuations arising in the speed of wind. The speed of wind depends heavily on geographical location, climatic conditions, topography, and height above ground level (AGL). In a typical setup, speed of wind is measured between 8 and 12 m AGL. Furthermore, multi-megawatt wind turbines are installed at heights ranging typically between 80 and 120 m. The tower height at which the turbine rotor is mounted is commonly known as *hub height*. While a high hub height is generally desired for more absorption of wind, the maximum hub height is restricted by a limit due to installation, technical, maintenance, and economic issues. Therefore, for maximum energy output from a turbine, a precise knowledge of most appropriate hub height is crucial pertaining to a particular type as well as location of wind turbine (Global Wind Statistics, GWEC 2016). To address the issues associated with quality and availability of wind power, maximization of the rated output of a wind turbine is desired (Global Wind Statistics, GWEC 2016).

The development of a wind farm deals with various important issues. These include identification of a proper site for the wind farm, layout design, and assortment of appropriate turbines that so as to maximize power generation.

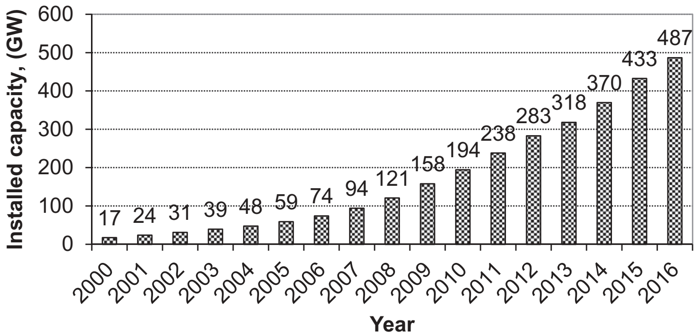

Figure 1. Global wind energy generation capacities (cumulative).

Installation of a wind turbine is a crucial task since transportation, maintenance, and installation costs along with technical challenges are involved in the process of positioning the tower and then mounting the turbine on it. Thus, an important concern is minimization of the overall financial cost. The tower is an important part of the whole structure, and therefore contributes significantly to the overall cost. The overall cost increases in the range of 6–16% with increment in the hub height by only 10 m (Khan and Rehman 2013). Therefore, it is necessary to reduce this cost, thus signifying that the hub height should be kept as minimal as possible. In contrast, an essential demand by the operator of a wind farm is maximization of power generation from the wind farm. However, several factors, such as unavailability losses, electrical losses, wake effect losses, zero output percentage, and rated output percentage, negatively affect the yearly mean energy output. Mean energy output refers to the energy available to the grid after taking into account the aforementioned losses. This energy output should be maximized as much as possible.

The maximization of energy output requires higher hub-heights which should be kept minimal due to other constraints as stated earlier. This points toward the conflicting nature of hub height and energy output as decision criteria. Therefore, optimization of both criteria simultaneously is not possible. Furthermore, wind speeds at specific hub heights also contribute to the amount of energy extracted. Apart from hub height and energy output, several turbine-specific factors such as cut-in speed of wind, rotor diameter, and rated speed of wind have an impact on energy extraction. These factors are also in mutual conflict. That is, improvement in one factor has a negative impact on another one. Lack of information on clear relationship between the factors also makes it difficult to decide about the suitability of a certain turbine. For example, turbines with bigger rotor diameter are considered appropriate since they have large swept area, which in turn generates more power. However, wind turbines having low rated and cut-in wind speeds are opted for higher wind energy generation and are more appropriate for low windy sites. Thus, there is a need for a decision approach in order to find an optimal trade-off between all the factors (a.k.a. decision criteria).

The rest of this paper is organized as follows. A review of relevant literature is given in the next section. Novelty of the proposed work is discussed in the section after the literature review. The section entitled "Research Methods" discusses the research methodology adopted in the paper. This is followed by a discussion on how goal programming is applied to the problem considered in the paper. The section entitled "Results and discussion" presents and analyzes the obtained results. Finally, a conclusion is given in the last section.

Literature Review

The wind turbine selection problem has received notable attention in the past many years. Sarja and Halonen (2013) conducted a qualitative approach by interviewing experts. They identified a number of turbine selection criteria such as product reliability, production volume of the manufacturer, availability factors, cost factors, and the maintenance organization. Perkin, Garrett, and Jensson (2015), identified various selection criteria such as rotor diameter, size of generator, hub height, and pitch angle. Genetic algorithm was employed to find the most suitable turbine. Nemes and Munteanu (2010) proposed methodology which utilized system reliability for comparison among nine different wind turbine models. Chowdhury et al. (2013) proposed a particle swarm optimization algorithm while using energy production capacity as selection criterion and considered a single turbine type. Firuzabad and Dobakhshari (2009) developed a probabilistic model for turbine type selection and used five turbine types. The proposed probabilistic model used turbine reliability in the selection process. Bencherif, Brahmi, and Chikhaoui (2014) developed a Weibull distribution-based analytical approach and used capacity factor as the selection criterion while considering 24 different turbine models in the decision process. Montoya et al. (2014) considered deviation in daily power output as well as power output as the decision criteria and proposed a Pareto ranking-based genetic algorithm to find the best turbine. Chowdhury et al. (2016) used cost of energy as the wind turbine selection criterion and considered over 120 different turbine models. Martin et al. (2007) developed a simple support tool with a hypothetical wind turbine to optimize the rotor-to-generator ratio using a range of wind conditions. Bekele and Ramayya (2013) proposed a genetic algorithm to find the appropriate wind turbine for a specific site, while considering blade design as the optimization factor. Helgason (2012) assumed cost of energy as the decision criterion and carried out a study on various potential sites in Iceland while considering 47 different turbine types. Eke and Onyewudiala (2012) proposed genetic algorithm for site-specific turbine selection using the thickness of the blade, the twist, and cord, as the decision criteria, with the objective of maximizing power generation. Jureczko, Pawlak, and Mezyk (2005) proposed a genetic algorithm for turbine design. Five design criteria were considered which are generated output, stability of blade structure, blade vibrations, blade material cost, and blade strength requirements.

Jowder (2009) proposed a turbine selection methodology using capacity factor as the selection criterion while using six commercially available turbines. El-Shimy (2010) proposed a turbine selection approach which was site-specific. The decision criteria were average power output, capacity factor, and turbine performance index. Dong et al. (2013) proposed three nature-inspired algorithms, namely, genetic algorithm, differential evolution, and particle swarm optimization for turbine selection while optimizing matching, turbine cost, and the integrated matching indices. Shirgholami, Zangeneh, and Bortolini (2016) proposed an analytic hierarchy process (AHP)-based approach (Saaty 1987) and identified over 30 decision criteria. However, as stated in their paper, only a subset of proposed criteria could be employed depending on certain conditions associated with the wind farm site. Bagočius, Zavadskas, and Turskis (2014) proposed a turbine selection approach specific to offshore wind farms using the weighted aggregated sum product assessment method, a method slimier to AHP. They assumed five criteria, which are the amount of energy generated per year, max power generated in the area, nominal power of the wind turbine, investments, and CO_2 emissions. Lee et al. (2012) proposed a multi-criteria decision approach while considering economic issues, environmental aspects, technical challenges, and machine characteristics as the major decision criteria. Only four turbines were considered, all of which had almost the same rated power. Du et al. (2017) proposed a turbine selection approach based on Supervisory Control And Data Acquisition (SCADA) data analysis.

Khan and Rehman (2012a, 2012b) employed multi-criteria decision-making (MCDM) using fuzzy logic for turbine selection problem considering three criteria. Subsequently, they proposed a turbine selection strategy considering six criteria while still using fuzzy logic (Rehman and Khan 2016). However, one limitation of these studies was the use of fuzzy decision-making in which selection of an appropriate fuzzy operator is a challenge, and different fuzzy operators may give different results. This issue is overcome in the current study by using goal programming which does not suffer from such issues.

Novelty of the Proposed Work

The literature review highlighted several limitations of the research carried out so far in the domain of wind turbine selection approaches. For example, many studies (Bekele and Ramayya 2013; Bencherif, Brahmi, and Chikhaoui 2014; Chowdhury et al. 2016, 2013; Firuzabad and Dobakhshari 2009;

Helgason 2012; Jowder 2009; Martin et al. 2007; Montoya et al. 2014; Nemes and Munteanu 2010) assumed a simple decision model in which a single criterion was assumed in the decision process. This approach affects the overall decision process and limits its effectiveness in real environments which depends on many factors in terms of decision. Another limitation observed was in terms of lack of use of computationally expensive techniques. Several studies reported the use of genetic algorithms, differential evolution, particle swarm optimization, and nonlinear programming (Bagočius, Zavadskas, and Turskis 2014; Bekele and Ramayya 2013; Chowdhury et al. 2016; Dong et al. 2013; Eke and Onyewudiala 2012; El-Shimy 2010; Helgason 2012; Jowder 2009; Jureczko, Pawlak, and Mezyk 2005; Lee et al. 2012; Martin et al. 2007; Shirgholami, Zangeneh, and Bortolini 2016). Although such approaches generally result in high quality solutions, their main drawback is computational complexity. Use of small number of turbines or lack of variety of turbines was also observed in various studies (Bagočius, Zavadskas, and Turskis 2014; Bekele and Ramayya 2013; Dong et al. 2013; Eke and Onyewudiala 2012; Helgason 2012; Jowder 2009; Jureczko, Pawlak, and Mezyk 2005; Khan 2015; Khan and Rehman 2012a, 2012b; Lee et al. 2012; Martin et al. 2007; Shirgholami, Zangeneh, and Bortolini 2016) whereby use of up to nine turbines was reported, despite that there are a large number and variety of turbines available. This aspect makes the concerned studies less comprehensive. Another concern that arises from the literature review is the selection of several decision factors for which information is not easily available (e.g. production volume, system reliability indices, organization of maintenance, blade shape, product reliability, visual impact, and political stability, among many others) (Bagočius, Zavadskas, and Turskis 2014; Bekele and Ramayya 2013; Chowdhury et al. 2013; Dong et al. 2013; Eke and Onyewudiala 2012; El-Shimy 2010; Firuzabad and Dobakhshari 2009; Helgason 2012; Jowder 2009; Jureczko, Pawlak, and Mezyk 2005; Martin et al. 2007; Nemes and Munteanu 2010; Perkin, Garrett, and Jensson 2015; Sarja and Halonen 2013; Shirgholami, Zangeneh, and Bortolini 2016). Use of such parameters has a negative impact on the selection approach, making it complex and in many cases, impractical. Finally, one major drawback of the reported studies which assumed MCDM did not focus on the fundamental requirement of conflict and incommensurability among the decision-criteria, while proposing the respective approaches (Dong et al. 2013; Eke and Onyewudiala 2012; El-Shimy 2010; Helgason 2012; Jureczko, Pawlak, and Mezyk 2005; Lee et al. 2012; Montoya et al. 2014; Perkin, Garrett, and Jensson 2015; Sarja and Halonen 2013; Shirgholami, Zangeneh, and Bortolini 2016). Conflict refers to the situation where improvement in one (or more) criterion (criteria) negatively affects the quality of other criteria. Incommensurability issues arise when decision criteria are of different magnitudes and units.

Noting the above issues, the work proposed herein has several novel aspects and addresses the concerns observed in the above studies. The proposed approach develops a turbine selection model considering six simple, yet important decision criteria, while taking into account the issues of conflict and incommensurability. These criteria are easily and readily available for any commercially available turbine, thus simplifying the proposed approach. The simplification of the proposed goal programming-based decision approach is further amplified by the fact that solutions are obtained in linear time, making the proposed approach computationally efficient. In addition, 20 turbines from a variety of manufacturers and rated outputs have been considered, thus enhancing the comprehensiveness of the proposed strategy. It is also important to mention that the proposed scheme is also scalable and robust; criteria as well as number of turbines can be added or deleted easily according to the requirements of the designer, without affecting the computational complexity.

Research Method

The research is based on an experimental study and uses real data collected from a potential site in western Saudi Arabia. Six important decision criteria are identified from the literature survey. The six decision criteria are speed of wind, hub height, mean energy output, rated speed of wind, cut-in speed of wind, and rotor diameter. Using these criteria, a hierarchical two-tier goal programming model is developed. Measurements were taken at hub heights between 30 and 120 m. These measured values of speed of wind at different AGL heights were used to obtain the local wind shear exponent. The speed of wind was interpolated or estimated at an interval size of 5 m using local wind shear exponent. For each decision criterion, the lower and upper bounds were determined using the data collected from the site under consideration. These limits play a pivotal role in developing the two-tier goal programming model for the problem considered herein. These bounds and the data collected from the site were used to form the membership functions for each criterion, and membership values were found and are used in the goal programming model according to the proposed approach.

Application of Goal Programming to Wind Turbine Selection

MCDM is frequently employed to solve decision problems where multiple and conflicting decision criteria are involved in the decision process. To apply goal programming to MCDM problems, a fundamental requirement is the aggregation of criteria such that an overall decision function is formed (represented as a scalar value). However, this process highlights the need to overcome incommensurability of criteria, due to which different criteria cannot be combined into a single decision function. Therefore it is necessary to convert all criteria to a unit-less, uniform scale. Goal programming (Gass and Saaty 1955) has been successfully employed to solve a variety of MCDM problems with the above issues (Du et al. 2017; Flavel 1976; Gass and Saaty 1955; Hannan 1981; Ignizio 1976; Jones and Tamiz 2010; Khan and Rehman 2012a, 2012b; Lee et al. 2012; Rehman and Khan 2016; Romero 1991; Tamiz, Jones, and El-Darzi 1993; Wolsey 1998).

As mentioned earlier, there are many variants of goal programming. In this work, fuzzy goal programming is adopted since its major benefit over other variants is its ability to deal with levels of imprecision in the goal programming model (Hannan 1981). The traditional fuzzy goal programming approach works by initializing a set of targeted goals. Each goal has a maximum achievement level that is determined a priori. The level of fuzziness around each goal is measured using a membership function. The membership function is used to express the achievement of a particular objective around the goal. Later, the deviational variable of each criterion is calculated. The deviational variable measures the distance of the achieved level from its desired goal. The aim is then to minimize the resulting total deviation.

The fuzzy goal programming approach proposed in this work follows a two-tier approach which is the major novelty of this work. In the first tier, fuzzy goal programming is employed considering hub height, speed of wind, and mean energy output as the decision criteria. To apply fuzzy goal programming to this tier, fuzzification of all three criteria is required to overcome incommensurability as well as uncertainties in the decision-making. To achieve this, the membership functions for the three criteria need to be defined. The purpose of the first-tier decision-making is to identify the best solution for each individual turbine type. In the second tier, additional criteria are combined with the outcome of the first tier to determine the best turbine type among all turbines. As with the first tier, fuzzification of these additional criteria is done at the second tier and results are aggregated with the outcome of the first tier. The criteria for the second tier are cut-in speed of wind, rated speed of wind, and rotor diameter.

Defining the Goals

Ideal values for each criterion should be stated in advance. Following this, the quality of the achieved level for each criterion is evaluated by calculating the deviation from its corresponding ideal value (i.e. the target). Lesser the deviation, the better is the solution. Therefore, the best deviation that can be achieved is 0 which signifies achieving the target.

Calculation of Membership Function

A membership function is used to assess the level of achievement of each criterion. This requires formation of membership functions for each criterion. The achieved satisfaction level is expressed using a membership value defined in the range of 0 to 1. A 0 indicates complete dissatisfaction, whereas a 1 signifies total satisfaction. A variety of membership functions (such as linear, triangular, trapezoidal, etc.) can be defined which are different from each other in their mathematical structure (Hannan 1981).

Fuzzy Goal Programming for the First Tier

To employ fuzzy goal programming for the first tier, the linguistic variables *Hub height, Speed of wind*, and *Mean energy output* are defined. For these linguistic variables, we are seeking the minimum values of speed of wind and hub height, and maximum value of mean energy output, respectively. Due to the mutual conflict among the three criteria, our objective is to achieve the optimal trade-off between the hub height, speed of wind, and energy output. This can be represented through the following rule.

Rule 1: IF for a solution Y, *hub height* is minimized AND *speed of wind* is minimized AND *mean energy output* is maximized THEN it is the best solution.

In the aforementioned rule, Y represents a solution that has resulted due to a certain value of hub height and its corresponding energy output and speed of wind. The phrases of *hub height, speed of wind, mean energy output*, and *best solution* are linguistic variables. Each linguistic variable is represented by a membership function which is represented as μ and lies in the interval [0,1] and expresses the level of satisfaction for the decision criterion under consideration. The process converts the actual values of the three decision criteria to unit-less values lying in a [0,1] range. The individual deviations are then calculated by taking the absolute difference between the target value and the actual value of each decision criterion.

The following subsections discuss as how the membership functions for the first-tier criteria are formed.

Membership Function for Hub Height

To form the hub height membership function, two extreme values (bounds) of the said criterion need to be defined. The two bounds (i.e. maximum hub height, H_{max} and the minimum hub height, H_{min}) are determined using the technical specifications of the turbine, as discussed in "Results and Discussion" section. The membership function, $\mu_H(x)$, is mathematically represented as follows.

$$\mu_H(x) = \begin{cases} 1 & if\ \text{Height}(x) \leq H_{min} \\ \frac{H_{max} - \text{Height}(x)}{H_{max} - H_{min}} & if\ H_{min} < \text{Height}(x) \leq H_{max} \\ 0 & if\ \text{Height}(x) > H_{max} \end{cases} \quad (1)$$

Membership Function for Speed of Wind

To form the membership function, $\mu_S(x)$, for the speed of wind, the upper and lower bounds, represented by S_{max} and S_{min}, respectively, are determined first. The two bounds are taken using the collected data (as discussed in "Results and Discussion" section). Mathematically:

$$\mu_S(x) = 1\begin{cases} \dfrac{S_{max} - \text{Speed}(x)}{S_{max} - S_{min}} & if\ \text{Speed}(x) \leq S_{min} \\ & if\ S_{min} < \text{Speed}(x) \leq S_{max} \\ 0 & if\ \text{Speed}(x) > S_{max} \end{cases} \quad (2)$$

Membership Function for Mean Energy Output

The membership function for mean energy output is constructed by defining the upper and lower bounds E_{max} and E_{min}, respectively. The bounds are determined using the collected data. Mathematically, the membership function for energy output, $\mu_E(x)$, is given as

$$\mu_E(x) = \begin{cases} 1 & if\ \text{Energy}(x) \geq E_{max} \\ \frac{\text{Energy}(x) - E_{max}}{E_{max} - E_{min}} & if\ E_{min} \leq \text{Energy}(x) < E_{max} \\ 0 & if\ \text{Energy}(x) < E_{min} \end{cases} \quad (3)$$

Computation of the Overall Deviation Function

After forming the membership functions, all deviational variables are calculated and aggregated through Rule 1. The deviational variable is 1 minus the membership value (i.e. $1 - \mu_H(x)$, $1 - \mu_S(x)$, and $1 - \mu_E(x)$). This is done through fuzzy goal programming approach which places all deviational variables into a single, normalized deviation function which measures the degree of minimization of overall deviational variables (Romero 1991). In short, the overall deviation function measures the "lack" or deviation of achieved goals. The mathematical representation of overall deviation, $\text{Dev}_O(x)$, is given in the following equation.

$$\text{Dev}_O(x) = \sigma_1(|1 - \mu_H(x)|) + \sigma_2(|1 - \mu_S(x)|) + \sigma_3(|1 - \mu_E(x)|) \quad (4)$$

In Equation (4) above, $\text{Dev}_{overall}(x)$ represents the overall deviation of all objectives collectively. σ_1, σ_2, and σ_3 are weights associated with each deviation to give preference to a criterion over the others. In this work, all three criteria are given equal preference, although the decision-maker can adjust the weights according to his/her requirements. The solution which results in the minimum value for Equation (4) is reported as the best solution.

Fuzzy Goal Programming for the Second Tier

The result of the first tier provides the best solution for each individual turbine type with respect to hub height, speed of wind, and mean energy output. However, these three criteria are used to select a turbine from a pool of turbines possessing near equal rated power, but not sufficient to select the best overall turbine. It is because the turbine types have been divided into three categories (500–700, 1000–1250, and 2000 kW). Each category is has its own suitable range of hub height, suitable range of speed of wind, and above all, its own mean energy output range. Therefore, there is a need to have more criteria to consider the influence of difference in rated energy output of different turbines, which justifies the need to have the second tier of decision-making. This prompts the application of fuzzy goal programming also at the second tier. In the second tier, the decision criteria of cut-in speed of wind, rated speed of wind, and rotor diameter are considered. The approach is very similar to the one used at the first tier. That is, the membership functions for the three criteria are determined and aggregated through goal programming using the following rule.

Rule 2: IF for a solution Z, *cut-in speed of wind* is minimized AND *rated speed of wind* is minimized AND *rotor diameter* is minimized AND *first-tier deviation* is minimized THEN it is the best solution.

The membership functions for decision criteria at the second tier are formed as follows.

Membership Function for Rotor Diameter

The membership function for rotor diameter is formed by defining the upper and lower bounds. From Tables 1–3, it is observed that the turbines have their rotor diameters in the range of 33–93 m. Note that bigger diameter is desired due to its higher capability of absorbing more wind power. The lower limit, D_{min}, is taken as 30 m whereas the upper limit, D_{max}, is considered to

Table 1. Technical specifications of turbines in the range of 500–750 kW (Rehman and Khan 2016).

Turbine	Minimum hub height (m)	Rotor diameter (m)	Cut-in speed of wind (m/s)	Rated Speed of wind (m/s)	Rated Power (kW)
Fuhrlder FL 600	50	50	2.5	11	600
Hyosung HS50	50	50	3.5	11	750
RRB Energy PS 600	48	47	3.5	15	600
Suzlon S.52/600	75	52	4	13	600
Unison U57	68	57	3	10.5	750
Vestas V47	55	47	4	13	660
Windflow 500	29	33	6	14	500

Table 2. Technical specifications of turbines in the range of 1000–1250 kW (Rehman and Khan 2016).

Turbine	Minimum hub height (m)	Rotor diameter (m)	Cut-in speed of wind (m/s)	Rated speed of wind (m/s)	Rated power (kW)
AAER A-1000	70	58	4	12	1000
DeWind D6 64m	60	64	2.5	12.3	1250
Mitsubishi MWT62	69	61.4	3.5	12.5	1000
Nordex N54/1000	60	54	3.75	14	1000
Suzlon S.62/1000	65	62	3	12	1000
Vensys 62-1200	69	62	2.5	11.5	1200

Table 3. Technical specifications of wind turbines with rated power of 2000 kW (Rehman and Khan 2016).

Turbine	Minimum hub height (m)	Rotor diameter (m)	Cut-in speed of wind (m/s)	Rated speed of wind (m/s)	Rated power (kW)
AAER A-2000-84	65	84	3.25	12	2000
DeWind D8.1	80	80	3	13.5	2000
Ecotecnia 80/2000	70	80	3	12	2000
REpower MM92	79	92	3	12.5	2000
Suzlon S.88/2000	80	88	4	14	2000

be 95 m. Mathematically, the corresponding membership function, $\mu_D(x)$, is represented as follows.

$$\mu_D(x) = \begin{cases} 1 & \textit{if } \text{Diameter}(x) \geq D_{max} \\ \frac{\text{Diameter}(x) - D_{min}}{D_{max} - D_{min}} & \textit{if } D_{min} \leq \text{Diameter}(x) < D_{max} \\ 0 & \textit{if } \text{Diameter}(x) < D_{min} \end{cases} \tag{5}$$

Membership Function for Cut-In Speed of Wind

The membership function for the cut-in speed of wind, $\mu_C(x)$, is developed by utilizing the extreme bounds of cut-in wind speeds of all turbines. Tables 1–3 indicate that the turbine cut-in speed of wind varies between 2.5 and 6 m/s. Accordingly, the upper bound, C_{max}, is set at 7 m/s whereas the lower bound, C_{min}, is set as 2 m/s. Mathematically:

$$\mu_C(x) = \begin{cases} 1 & \textit{if } \text{CutIn Speed}(x) \leq C_{min} \\ \frac{C_{max} - \text{CutInSpeed}(x)}{C_{max} - C_{min}} & \textit{if } C_{min} < \text{CutIn Speed}(x) \leq C_{max} \\ 0 & \textit{if } \text{CutIn Speed}(x) > C_{max} \end{cases} \tag{6}$$

Membership Function for Rated Speed of Wind

The membership function for rated speed of wind is defined by using the upper and lower limits, represented by R_{max} and R_{min}, respectively. These are taken from the data in column 5 of Tables 1–3. As observed in the tables, the range of rated speed of wind is between 15 and 10.5 m/s. Therefore, the upper limit is set at 16 m/s while the lower limit is set at 10 m/s. Mathematically, the membership function for rated speed of wind, $\mu_R(x)$, is given as

$$\mu_R(x) = \begin{cases} 1 & if \text{ Rated Speed}(x) \leq R_{min} \\ \frac{R_{max} - \text{RatedSpeed}(x)}{R_{max} - R_{min}} & if\ R_{min} < \text{Rated Speed } (x) \leq R_{max} \\ 0 & if \text{ Rated Speed}(x) > R_{max} \end{cases} \tag{7}$$

Calculation of the Total Deviation Function

The next step is to aggregate all deviational variables at the second tier as well as the overall deviation from the first tier. The strategy is similar to the one adopted in tier 1. The resulting mathematical expression is for total deviation, $Dev_T(x)$, is given as

$$Dev_T(x) = \gamma_1(|1 - \mu_D(x)|) + \gamma_2(|1 - \mu_C(x)|) + \gamma_3(|1 - \mu_R(x)|) + \gamma_4(Dev_O(x)) \tag{8}$$

In Equation (4), $Dev_T(x)$ represents the total deviation of all objectives at the second tier as well as the collective deviation from tier 1. Similar to tier 1, weights γ_1, γ_2, γ_3, , and $\gamma_4$are assigned to each second tier deviation and the overall deviation from first tier, respectively, to signify the preference of a criterion over other criteria. As done at tier 1, equal consideration is given to each criterion during the decision process (although the decision-maker can adjust the weights as required). The solution resulting in the minimum value for Equation (8) is considered the best solution.

Results and Discussion

The study was carried out for a potential site of Dhulom located in the western region of Saudi Arabia. Dhulom has an altitude of 1117 m above sea level. The data for the study was collected over a period of 4 years, and information relevant to the study was extracted from the data. This information composed of speed of wind and mean energy output for different turbines and was measured at a step of 5 m for hub height. A C++-based program was developed to perform the simulations. The simulator performs the MCDM calculations using the input data and applies the proposed goal programming approach to generate the decision output. For each set of turbine-specific data, the value which produced the lowest overall deviation was declared as the best solution (which corresponds to the best trade-off between the three decision criteria). Twenty different turbine models from having different rated powers and manufacturers were considered. Of the 20 turbines, seven turbines had rated power output in the range of 500–750 kW, 6 turbines had rated power in the range of 1000–1250 kW, while the other 7 turbines possessed rated power output of 2000 kW. Tables 1–3 provide the technical specifications of these turbines.

Selection of Turbines in 500–750 kW Range

Tables L1–L7 in Appendix A show the results for the turbines given in Table 1. In each table, columns 1 to 3 enlist the actual values of the three decision criteria, namely, hub height, speed of wind, and mean energy output, respectively. The developed simulator takes these values as inputs. The deviations specific to each of the three criteria are given in columns 4, 5, and 6, respectively. The overall deviation of a solution is then found using Equation (4). The overall deviation is shown in the last column of each table. It is worth mentioning that the hub height and its corresponding speed of wind and energy output were measured based on the minimum hub height associated with that turbine as specified by the manufacturer. As an example, the minimum hub height for Hyosung HS50 is 50 m and for Unison U57 is 68 m. Therefore, the measurements were taken with their lower limits of 50 and 65 m, respectively. Similar measurements were done for the other turbines. Furthermore, 120 m was taken as the maximum hub height for all turbines.

Tables L1–L7 reveal that for each turbine, the best (minimum) overall deviation is associated with high hub heights, in the range of 110–120 m. More specifically, the hub height of 120 m was ideal for Hyosung HS50, Unison U57, and Vestas V47. For RRB Energy PS 600, Suzlon S.52/600, and Windflow 500, the hub height of 110 m was the best. There is one exceptional case of Fuhrlder FL 600 where hub heights of both 110 and 120 m produced the best results. However, hub height of 110 is preferred. The results indicate that the performance of turbines with respect to speed of wind and mean energy output was superior at higher hub heights rather compared to that at lower hub heights.

Relative performance assessment for turbines was also done. For each turbine, the best results are shown in Table 4. These results have been

Table 4. Comparison of turbines in 500–750 kW range.

Turbine	H	S	E	Dev_H	Dev_S	Dev_E	Dev_O
Fuhrlder FL 600	110	7.09	1,793,995	0.889	0.164	0.303	1.3562
Hyosung HS50	120	7.28	1,934,067	1.000	0.088	0.239	1.3275
RRB Energy PS 600	110	7.09	1,517,311	0.889	0.164	0.429	1.4822
Suzlon S.52/600	110	7.09	1,619,463	0.889	0.164	0.383	1.4356
Unison U57	120	7.28	2,453,002	1.000	0.088	0.003	1.0912
Vestas V47	120	7.28	1,675,558	1.000	0.088	0.357	1.4452
Windflow 500	110	7.09	751,474	0.889	0.164	0.778	1.8309

H: hub height in meters; S: speed of wind in m/s; E: energy output in kWh/year; Dev_H: hub height deviation, Dev_S: deviation in speed of wind; Dev_E: energy output deviation;, Dev_O: overall deviation.

reproduced from Tables A1 to A7 for clear understanding. It is from the tables that Unison U93 exhibited the best performance with respect to other turbines since Unison U93 achieved the best trade-off between the hub height, speed of wind, and energy output. This is indicated by its overall deviation value of 1.0912 which is minimum among all turbines in that category. The nearest competitors to Unison U93 were Hyosung HS50 and Fuhrlder FL 600 with overall deviations of 1.3275 and 1.3562, respectively. The poorest performance was shown by Windflow 500 due to its highest overall deviation of 1.8309.

Selection of Turbines in 1000–1250 kW Range

Results for the turbines in the range of 1000–1250 kW (mentioned in Table 2) are given in Tables A8–A13 in Appendix A. Similar to "Selection of Turbines in 500–750 kW Range" section, columns 1–3 of each table provide the crisp values of hub height, speed of wind, and mean energy output, respectively. Columns 4–6 enlist the individual deviations of the three decision criteria. The overall deviation of the solution is found using Equation (4) and is mentioned in column 7 of each table. Note that in Tables A8–A13, the measurements were taken with respect to the minimum hub height given in column 1 of Table 2.

Tables A8–A13 reveal some interesting trends. In general, the best results were achieved with hub heights of 105–120 m, corresponding to wind speeds from 6.99 to 7.28 m/s. One exception is the case of Vensys 62 where least overall deviation was obtained at hub height of 85 m and wind speed of 6.58 m/s. The above results, in general, suggest that better performance of turbines was observed at higher hub heights compared to lower hub heights.

In terms of relative performance of the wind turbines, Table 5 depicts the best results for each turbine. The results have been taken from Tables A8 to A13 for better understanding. The results in Table 5 indicate that Vensys 62-1200 produced the minimum overall, signifying its best performance compared to other turbines in the category. The nearest competitor to Vensys 62-1200 was Suzlon S.62/1000 with an overall deviation of 1.0461.

Table 5. Comparison of turbines in 1000–1250 kW range.

Turbine	H	S	E	Dev_H	Dev_S	Dev_E	Dev_O
AAER A-1000	110	7.09	2,480,708	0.889	0.164	0.019	1.0720
DeWind D6 64 m	115	7.18	2,518,312	0.944	0.128	0.003	1.0750
Mitsubishi MWT62	105	6.99	2,485,984	0.833	0.204	0.017	1.0542
Nordex N54/1000	120	7.28	2,105,646	1.000	0.088	0.185	1.2731
Suzlon S.62/1000	105	6.99	2,543,787	0.833	0.204	0.009	1.0461
Vensys 62-1200	85	6.58	2,527,765	0.611	0.368	0.002	0.9808

H: hub height in meters; S: speed of wind in m/s; E: energy output in KWh/year; Dev_H: hub height deviation; Dev_S: deviation in speed of wind; Dev_E: energy output deviation; Dev_O = overall deviation.

Furthermore, Nordex N54/1000 had the poorest performance due to the highest overall deviation of 1.2731.

Selection of Turbines with Rated Output of 2000 kW

Tables A14–A20 in Appendix A depict the results for the turbines given in Table 3. As before, columns 1–3 in the tables show the crisp values of each decision criteria, whereas columns 4–6 provide the specific deviations of the three decision criteria, respectively. The overall deviation of the solution is obtained using Equation (4). Also, the measurements were done considering the minimum hub height applicable to that turbine.

The results in Tables A14–A20 are quite noteworthy. It is observed that all best performances were achieved at hub heights of 120 m corresponding to wind speed of 7.28 m/s. Thus, it is very clear from the trends that the best results for each turbine are obtained at the maximum hub height considered in this study as far as 2000 kW turbines are considered.

As far as the relative performance of each turbine is concerned, results in Table 6 suggest that Vestas V90 demonstrated the best performance due to the lowest deviation of 1.4874 it achieved. Furthermore, the worst performer was DeWind D8.1 due its (relatively) highest overall deviation of 1.7744.

Overall Best Performance of Wind Turbines

The results in the above three sub-sections provide the performance of each turbine in within the three ranges of rated power output which are 500–750, 1000–1250, and 2000 kW. However, the results do not provide sufficient information in deciding as which turbine among all the considered 20 turbines would be the most suitable for the site considered in this study. To reach this conclusion, more information is needed, which leads us to additional criteria given in Tables 1–3. These criteria are rotor diameter, cut-in speed of wind, and rated speed of wind. These criteria have a crucial role in selecting a suitable wind turbine in terms of economical energy yield, as well as maintenance and installations ease. For example, bigger rotor diameter indicates higher swept

Table 6. Comparison of turbines with rated power of 2000 kW.

Turbine	H	S	E	Dev_H	Dev_S	Dev_E	Dev_O
AAER A-2000–84	120	7.28	5,547,161	1.000	0.088	0.437	1.5250
DeWind D8.1	120	7.28	3,975,781	1.000	0.088	0.686	1.7744
Ecotecnia 80/2000	120	7.28	4,868,568	1.000	0.088	0.545	1.6327
REpower MM92	120	7.28	5,666,828	1.000	0.088	0.418	1.5060
Suzlon S.88/2000	120	7.28	5,666,828	1.000	0.088	0.418	1.5060
Unison U93	120	7.28	5,460,613	1.000	0.088	0.451	1.5387
Vestas V90	120	7.28	5,783,740	1.000	0.088	0.399	1.4874

H: hub height in meters; S: speed of wind in m/s; E: energy output in kWh/year; Dev_H: hub height deviation; Dev_S: deviation of speed of wind; Dev_E: energy output deviation; Dev_O: overall deviation.

area which facilitates more power generated from the turbine. However, a diameter beyond a certain threshold point is not feasible which limits the generated energy by the turbine. Furthermore, smaller values of rated speed of wind and cut-in speed are also desired since they result in higher energy production. As a matter of fact, these low values are desired for less windy sites.

For an effective decision, goal programming has also been utilized according to the approach presented in "Fuzzy goal programming for the second tier" section. This approach would incorporate the cumulative results from Tables 4–6 combined with the deviation of each of the three aforementioned second-tier criteria using Equation (8). Table 7 shows the individual deviation for the three criteria of rotor diameter, cut-in speed of wind, and rated speed of wind, along with the overall deviation from results presented earlier in the above three sub-sections.

It is observed from this table that Windflow 500 has the minimum total deviation of 2.410, suggesting that this is the best turbine for the wind farm site considered herein. The turbine is in the 500–750 kW turbine range. The table also indicates that two possible alternatives to Windflow 500 are RRB Energy PS 600 and Nordex N54/1000, with total deviations of 2.610 and 2.626, respectively. Furthermore, Unison U93 is the worst turbine for the underlying site with the highest total deviation of 4.141. Another notable trend is that, in general, turbines with rated power of 2000 kW are not apposite for the concerned wind farm site since all turbines have a higher total deviation, whereas most turbines in 500–750 kW are having low total deviation indicating their suitability, in general, for the site.

Table 7. Total deviation (Dev_T) for all turbines.

Turbine	Diameter (m)	Cut-in WS (m/s)	Rated WS (m/s)	Dev. Diameter	Dev. Cut-in Speed	Dev. Rated Speed	Dev_O	Dev_T
Windflow 500	33	6	14	0.05	0.20	0.33	1.831	2.410
RRB Energy PS 600	47	3.5	15	0.26	0.70	0.17	1.482	2.610
Nordex N54/1000	54	3.75	14	0.37	0.65	0.33	1.273	2.626
AAER A-1000	58	4	12	0.43	0.60	0.67	1.072	2.769
Vestas V47	47	4	13	0.26	0.60	0.50	1.445	2.807
Mitsubishi MWT62	61.4	3.5	12.5	0.48	0.70	0.58	1.054	2.821
Suzlon S.52/600	52	4	13	0.34	0.60	0.50	1.436	2.874
Suzlon S.62/1000	62	3	12	0.49	0.80	0.67	1.046	3.005
DeWind D6 64m	64	2.5	12.3	0.52	0.90	0.62	1.075	3.115
Vensys 62-1200	62	2.5	11.5	0.49	0.90	0.75	0.981	3.123
Hyosung HS50	50	3.5	11	0.31	0.70	0.83	1.328	3.169
Unison U57	57	3	10.5	0.42	0.80	0.92	1.091	3.223
Suzlon S.88/2000	88	4	14	0.89	0.60	0.33	1.506	3.332
Fuhrlder FL 600	50	2.5	11	0.31	0.90	0.83	1.356	3.397
Vestas V90	90	4	12	0.92	0.60	0.67	1.4874	3.677
DeWind D8.1	80	3	13.5	0.77	0.80	0.42	1.7744	3.760
AAER A-2000-84	84	3.25	12	0.83	0.75	0.67	1.525	3.772
REpower MM92	92	3	12.5	0.95	0.80	0.58	1.506	3.843
Ecotecnia 80/2000	80	3	12	0.77	0.80	0.67	1.6327	3.869
Unison U93	93	3	11	0.97	0.80	0.83	1.5387	4.141

Conclusion

A fundamental requirement of an effective design of a wind farm design is the selection of most suitable turbines that are capable of harnessing maximum power with minimal effort and cost. However, selection of a site-specific, effective wind turbine from a pool of off-the-shelf available turbines is a not an easy task since the decision-making process is governed by many criteria. Among several decision criteria, six important criteria are hub height, speed of wind at the site, mean energy output, rotor diameter of the turbine, cut-in speed of wind of the turbine, and rated speed of wind of the turbine. This study proposed a two-tier MCDM approach for the turbine selection problem using fuzzy goal programming. The proposed approach was tested on real data collected from Dhulom, Saudi Arabia. The usefulness of the two-tier strategy was analyzed with its application to a number of wind turbine types with rated power categorized in three groups which were 500–750, 1000–125, and 2000 kW. The results indicate that Windflow 500 was the best turbine, followed by RRB Energy PS 600 and Nordex N54/1000.

As a future work, we intend to perform an analysis of preferences assigned to different criteria as mentioned in the context of Equations (4) and (8). Furthermore, we plan to apply the proposed methodology to different potential wind turbine sites in Saudi Arabia.

Funding

This work was supported by Deanship of Research at King Fahd University of Petroleum & Minerals, Saudi Arabia, under project number IN 141039.

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Appendix A

Table A1. Results of Fuhrlder FL 600.

Hub height (HH) m	Wind speed (WS) m/s	Mean energy output (EO) kWh/yr	Dev_H	Dev_S	Dev_E	Dev_O
50	5.72	1,083,218	0.222	0.712	0.627	1.5612
55	5.86	1,155,425	0.278	0.656	0.594	1.5278
60	5.99	1,226,658	0.333	0.604	0.562	1.4990
65	6.12	1,296,319	0.389	0.552	0.530	1.4708
70	6.24	1,363,920	0.444	0.504	0.499	1.4476
75	6.36	1,428,832	0.500	0.456	0.470	1.4256
80	6.47	1,490,901	0.556	0.412	0.441	1.4089
85	6.58	1,549,771	0.611	0.368	0.414	1.3936
90	6.69	1,605,127	0.667	0.324	0.389	1.3800
95	6.79	1,657,198	0.722	0.284	0.366	1.3718
100	6.89	1,705,938	0.778	0.244	0.343	1.3652
105	6.99	1,751,535	0.833	0.204	0.323	1.3599
110	7.09	1,793,995	0.889	0.164	0.303	1.3562*
115	7.18	1,833,787	0.944	0.128	0.285	1.3576
120	7.28	1,871,031	1.000	0.088	0.268	1.3562*

Dev_H: hub deviation hub height; Dev_S: deviation for speed of wind; Dev_E: energy output deviation; Dev_O = overall deviation. Best (minimum) Dev_O is marked with asterisk.

Table A2. Results for Hyosung HS50.

Hub height (HH) m	Wind speed (WS) m/s	Mean energy output (EO) kWh/yr	Dev_H	Dev_S	Dev_E	Dev_O
50	5.72	1,037,081	0.222	0.712	0.648	1.5822
55	5.86	1,112,113	0.278	0.656	0.614	1.5476
60	5.99	1,186,734	0.333	0.604	0.580	1.5171
65	6.12	1,260,729	0.389	0.552	0.546	1.4870
70	6.24	1,333,776	0.444	0.504	0.513	1.4613
75	6.36	1,405,168	0.500	0.456	0.480	1.4363
80	6.47	1,474,607	0.556	0.412	0.449	1.4163
85	6.58	1,541,805	0.611	0.368	0.418	1.3972
90	6.69	1,606,377	0.667	0.324	0.389	1.3794
95	6.79	1,668,169	0.722	0.284	0.361	1.3668
100	6.89	1,727,064	0.778	0.244	0.334	1.3555
105	6.99	1,783,072	0.833	0.204	0.308	1.3456
110	7.09	1,836,071	0.889	0.164	0.284	1.3370
115	7.18	1,886,419	0.944	0.128	0.261	1.3336
120	7.28	1,934,067	1.000	0.088	0.239	1.3275*

Dev_H: hub deviation hub height; Dev_S: deviation for speed of wind Dev_E: energy output deviation; Dev_O: overall deviation. Best (minimum) Dev_O is marked with asterisk.

Table A3. Results for RRB energy PS 600.

Hub height (HH) m	Wind speed (WS) m/s	Mean energy output (EO) kWh/yr	Dev_H	Dev_S	Dev_E	Dev_O
50	5.72	899,610	0.222	0.712	0.711	1.6448
55	5.86	959,200	0.278	0.656	0.683	1.6172
60	5.99	1,017,946	0.333	0.604	0.657	1.5940
65	6.12	1,075,749	0.389	0.552	0.630	1.5712
70	6.24	1,132,272	0.444	0.504	0.605	1.5531
75	6.36	1,187,275	0.500	0.456	0.580	1.5356
80	6.47	1,240,650	0.556	0.412	0.555	1.5228
85	6.58	1,292,141	0.611	0.368	0.532	1.5109
90	6.69	1,341,565	0.667	0.324	0.509	1.5000
95	6.79	1,388,843	0.722	0.284	0.488	1.4940
100	6.89	1,433,882	0.778	0.244	0.467	1.4890
105	6.99	1,476,720	0.833	0.204	0.448	1.4851
110	7.09	1,517,311	0.889	0.164	0.429	1.4822*
115	7.18	1,555,901	0.944	0.128	0.412	1.4841
120	7.28	1,592,431	1.000	0.088	0.395	1.4831

Dev_H: hub deviation hub height; Dev_S: deviation for speed of wind; Dev_E: energy output deviation; Dev_O: overall deviation. Best (minimum) Dev_O is marked with asterisk.

Table A4. Results for Suzlon S.52/600.

Hub height (HH) m	Wind speed (WS) m/s	Mean energy output (EO) kWh/yr	Dev_H	Dev_S	Dev_E	Dev_O
80	6.47	1,323,506	0.556	0.412	0.518	1.4851
85	6.58	1,380,130	0.611	0.368	0.492	1.4709
90	6.69	1,433,796	0.667	0.324	0.467	1.4580
95	6.79	1,484,555	0.722	0.284	0.444	1.4504
100	6.89	1,532,358	0.778	0.244	0.422	1.4442
105	6.99	1,577,309	0.833	0.204	0.402	1.4393
110	7.09	1,619,463	0.889	0.164	0.383	1.4356*
115	7.18	1,659,182	0.944	0.128	0.365	1.4371
120	7.28	1,696,442	1.000	0.088	0.348	1.4357

Dev_H: hub deviation hub height; Dev_S: deviation for speed of wind; Dev_E: energy output deviation; Dev_O: overall deviation. Best (minimum) Dev_O is marked with asterisk.

Table A5. Results for Unison U57.

Hub height (HH) m	Wind speed (WS) m/s	Mean energy output (EO) kWh/yr	Dev_H	Dev_S	Dev_E	Dev_O
70	6.24	1,832,874	0.444	0.504	0.286	1.2340
75	6.36	1,914,782	0.500	0.456	0.248	1.2043
80	6.47	1,992,038	0.556	0.412	0.213	1.1807
85	6.58	2,064,617	0.611	0.368	0.180	1.1592
90	6.69	2,132,604	0.667	0.324	0.149	1.1398
95	6.79	2,195,970	0.722	0.284	0.120	1.1265
100	6.89	2,254,928	0.778	0.244	0.093	1.1152
105	6.99	2,309,751	0.833	0.204	0.068	1.1058
110	7.09	2,360,766	0.889	0.164	0.045	1.0981
115	7.18	2,408,482	0.944	0.128	0.023	1.0959
120	7.28	2,453,002	1.000	0.088	0.003	1.0912*

Dev H: hub deviation hub height; Dev S: deviation for speed of wind; Dev E: energy output deviation; Dev_O: overall deviation. Best (minimum) Dev_O is marked with asterisk.

Table A6. Results for Vestas V47-660.

Hub height (HH) m	Wind speed (WS) m/s	Mean energy output (EO) kWh/yr	Dev_H	Dev_S	Dev_E	Dev_O
55	5.86	976,605	0.278	0.656	0.675	1.6093
60	5.99	1,040,608	0.333	0.604	0.646	1.5837
65	6.12	1,103,700	0.389	0.552	0.618	1.5585
70	6.24	1,165,579	0.444	0.504	0.589	1.5379
75	6.36	1,226,052	0.500	0.456	0.562	1.5179
80	6.47	1,284,766	0.556	0.412	0.535	1.5027
85	6.58	1,341,543	0.611	0.368	0.509	1.4884
90	6.69	1,396,085	0.667	0.324	0.484	1.4751
95	6.79	1,448,504	0.722	0.284	0.461	1.4668
100	6.89	1,498,581	0.778	0.244	0.438	1.4596
105	6.99	1,546,135	0.833	0.204	0.416	1.4535
110	7.09	1,591,584	0.889	0.164	0.395	1.4483
115	7.18	1,634,618	0.944	0.128	0.376	1.4483
120	7.28	1,675,558	1.000	0.088	0.357	1.4452*

Dev_H: hub deviation hub height; Dev_S: deviation for speed of wind; Dev_E: energy output deviation; Dev_O: overall deviation. Best (minimum) Dev_O is marked with asterisk.

Table A7. Results for Windflow 500.

Hub height (HH) m	Wind speed (WS) m/s	Mean energy output (EO) kWh/yr	Dev_H	Dev_S	Dev_E	Dev_O
40	5.42	264,386	0.111	0.832	1.000	1.9429
45	5.58	294,264	0.167	0.768	0.986	1.9209
50	5.72	325,336	0.222	0.712	0.972	1.9063
55	5.86	357,650	0.278	0.656	0.957	1.8911
60	5.99	391,034	0.333	0.604	0.942	1.8795
65	6.12	425,401	0.389	0.552	0.927	1.8674
70	6.24	460,620	0.444	0.504	0.910	1.8589
75	6.36	496,566	0.500	0.456	0.894	1.8501
80	6.47	533,021	0.556	0.412	0.877	1.8451
85	6.58	569,820	0.611	0.368	0.861	1.8398
90	6.69	606,734	0.667	0.324	0.844	1.8346
95	6.79	643,553	0.722	0.284	0.827	1.8334
100	6.89	680,131	0.778	0.244	0.811	1.8323
105	6.99	716,169	0.833	0.204	0.794	1.8314
110	7.09	751,474	0.889	0.164	0.778	1.8309*
115	7.18	785,834	0.944	0.128	0.762	1.8348
120	7.28	819,310	1.000	0.088	0.747	1.8351

Dev_H: hub deviation hub height; Dev_S: deviation for speed of wind; Dev_E: energy output deviation; Dev_O: overall deviation. Best (minimum) Dev_O is marked with asterisk.

Table A8. Results for AAER A-1000.

Hub Height (HH) m	Wind Speed (WS) m/s	Mean energy output (EO) kWh/yr	Dev_H	Dev_S	Dev_E	Dev_O
70	6.24	1,791,257	0.444	0.504	0.324	1.2727
75	6.36	1,888,275	0.500	0.456	0.281	1.2373
80	6.47	1,983,264	0.556	0.412	0.239	1.2068
85	6.58	2,075,571	0.611	0.368	0.198	1.1775
90	6.69	2,164,749	0.667	0.324	0.159	1.1496
95	6.79	2,249,912	0.722	0.284	0.121	1.1275
100	6.89	2,330,669	0.778	0.244	0.086	1.1073
105	6.99	2,407,769	0.833	0.204	0.051	1.0888
110	7.09	2,480,708	0.889	0.164	0.019	1.0720*
115	7.18	2,549,751	0.944	0.128	0.011	1.0838
120	7.28	2,613,887	1.000	0.088	0.040	1.1278

Dev_H: hub deviation hub height; Dev_S: deviation for speed of wind; Dev_E: energy output deviation; Dev_O: overall deviation. Best (minimum) Dev_O is marked with asterisk.

Table A9. Results for DeWind D6 64m.

Hub height (HH) m	Wind speed (WS) m/s	Mean energy output (EO) kWh/yr	Dev_H	Dev_S	Dev_E	Dev_O
60	5.99	1,409,148	0.333	0.604	0.493	1.4306
65	6.12	1,512,491	0.389	0.552	0.448	1.3885
70	6.24	1,617,410	0.444	0.504	0.401	1.3496
75	6.36	1,723,268	0.500	0.456	0.354	1.3103
80	6.47	1,829,377	0.556	0.412	0.307	1.2749
85	6.58	1,935,012	0.611	0.368	0.261	1.2397
90	6.69	2,039,363	0.667	0.324	0.214	1.2051
95	6.79	2,141,511	0.722	0.284	0.169	1.1755
100	6.89	2,240,925	0.778	0.244	0.125	1.1470
105	6.99	2,337,116	0.833	0.204	0.083	1.1200
110	7.09	2,429,685	0.889	0.164	0.042	1.0946
115	7.18	2,518,312	0.944	0.128	0.003	1.0750*
120	7.28	2,602,263	1.000	0.088	0.035	1.1226

Dev_H: hub deviation hub height; Dev_S: deviation for speed of wind; Dev_E: energy output deviation; Dev_O: overall deviation. Best (minimum) Dev_O is marked with asterisk.

Table A10. Results for Mitsubishi MWT62-1000.

Hub height (HH) m	Wind speed (WS) m/s	Mean energy output (EO) kWh/yr	Dev_H	Dev_S	Dev_E	Dev_O
70	6.24	1,855,558	0.444	0.504	0.296	1.2442
75	6.36	1,957,530	0.500	0.456	0.251	1.2067
80	6.47	2,056,154	0.556	0.412	0.207	1.1746
85	6.58	2,150,965	0.611	0.368	0.165	1.1442
90	6.69	2,241,526	0.667	0.324	0.125	1.1157
95	6.79	2,327,615	0.722	0.284	0.087	1.0931
100	6.89	2,409,060	0.778	0.244	0.051	1.0726
105	6.99	2,485,984	0.833	0.204	0.017	1.0542*
110	7.09	2,558,363	0.889	0.164	0.015	1.0681
115	7.18	2,626,581	0.944	0.128	0.045	1.1178
120	7.28	2,690,849	1.000	0.088	0.074	1.1618

Dev_H: hub deviation hub height; Dev_S: deviation for speed of wind; Dev_E: energy output deviation; Dev_O: overall deviation. Best (minimum) Dev_O is marked with asterisk.

Table A11. Results Nordex N54/1000 kW.

Hub height (HH) m	Wind speed (WS) m/s	Mean energy output (EO) kWh/yr	Dev_H	Dev_S	Dev_E	Dev_O
60	5.99	1,264,923	0.333	0.604	0.557	1.4944
65	6.12	1,344,717	0.389	0.552	0.522	1.4627
70	6.24	1,423,468	0.444	0.504	0.487	1.4354
75	6.36	1,500,953	0.500	0.456	0.453	1.4087
80	6.47	1,576,803	0.556	0.412	0.419	1.3867
85	6.58	1,650,851	0.611	0.368	0.386	1.3655
90	6.69	1,722,840	0.667	0.324	0.354	1.3452
95	6.79	1,792,633	0.722	0.284	0.324	1.3298
100	6.89	1,860,165	0.778	0.244	0.294	1.3155
105	6.99	1,925,023	0.833	0.204	0.265	1.3024
110	7.09	1,987,833	0.889	0.164	0.237	1.2901
115	7.18	2,048,008	0.944	0.128	0.211	1.2831
120	7.28	2,105,646	1.000	0.088	0.185	1.2731*

Dev_H: hub deviation hub height; Dev_S: deviation for speed of wind; Dev_E: energy output deviation; Dev_O: overall deviation. Best (minimum) Dev_O is marked with asterisk.

Table A12. Results for Suzlon S.62/1000.

Hub height (HH) m	Wind speed (WS) m/s	Mean energy output (EO) kWh/yr	Dev_H	Dev_S	Dev_E	Dev_O
65	6.12	1,814,551	0.389	0.552	0.314	1.2548
70	6.24	1,917,802	0.444	0.504	0.268	1.2167
75	6.36	2,018,572	0.500	0.456	0.224	1.1796
80	6.47	2,116,326	0.556	0.412	0.180	1.1479
85	6.58	2,210,498	0.611	0.368	0.139	1.1178
90	6.69	2,300,636	0.667	0.324	0.099	1.0895
95	6.79	2,386,216	0.722	0.284	0.061	1.0672
100	6.89	2,467,184	0.778	0.244	0.025	1.0469
105	6.99	2,543,787	0.833	0.204	0.009	1.0461*
110	7.09	2,615,877	0.889	0.164	0.041	1.0935
115	7.18	2,683,944	0.944	0.128	0.071	1.1432
120	7.28	2,747,937	1.000	0.088	0.099	1.1871

Dev_H: hub deviation hub height; Dev_S: deviation for speed of wind; Dev_E: energy output deviation; Dev_O: overall deviation. Best (minimum) Dev_O is marked with asterisk.

Table A13. Results for Vensys 62.

Hub Height (HH) m	Wind Speed (WS) m/s	Mean energy output (EO) kWh/yr	Dev_H	Dev_S	Dev_E	Dev_O
70	6.24	2,195,417	0.444	0.504	0.145	1.0938
75	6.36	2,308,736	0.500	0.456	0.095	1.0512
80	6.47	2,419,618	0.556	0.412	0.046	1.0137
85	6.58	2,527,765	0.611	0.368	0.002	0.9808*
90	6.69	2,632,449	0.667	0.324	0.048	1.0387
95	6.79	2,732,892	0.722	0.284	0.092	1.0987
100	6.89	2,829,192	0.778	0.244	0.135	1.1568
105	6.99	2,921,131	0.833	0.204	0.176	1.2131
110	7.09	3,008,410	0.889	0.164	0.214	1.2672
115	7.18	3,091,285	0.944	0.128	0.251	1.3235
120	7.28	3,169,765	1.000	0.088	0.286	1.3737

Table A14. Results for AAER A-2000/84.

Hub height (HH) m	Wind speed (WS) m/s	Mean energy output (EO) kWh/yr	Dev_H	Dev_S	Dev_E	Dev_O
65	6.12	3,647,325	0.389	0.552	0.739	1.6794
70	6.24	3,862,170	0.444	0.504	0.704	1.6529
75	6.36	4,071,559	0.500	0.456	0.671	1.6272
80	6.47	4,274,031	0.556	0.412	0.639	1.6066
85	6.58	4,468,238	0.611	0.368	0.608	1.5873
90	6.69	4,652,922	0.667	0.324	0.579	1.5696
95	6.79	4,827,433	0.722	0.284	0.551	1.5574
100	6.89	4,991,003	0.778	0.244	0.525	1.5470
105	6.99	5,145,701	0.833	0.204	0.501	1.5380
110	7.09	5,287,602	0.889	0.164	0.478	1.5310
115	7.18	5,421,911	0.944	0.128	0.457	1.5293
120	7.28	5,547,161	1.000	0.088	0.437	1.5250*

Dev_H: hub deviation hub height; Dev_S: deviation for speed of wind; Dev_E: energy output deviation; Dev_O: overall deviation. Best (minimum) Dev_O is marked with asterisk.

Table A15. Results for DeWind D8.1.

Hub height (HH) m	Wind speed (WS) m/s	Mean energy output (EO) kWh/yr	Dev_H	Dev_S	Dev_E	Dev_O
80	6.47	2,771,537	0.556	0.412	0.878	1.8451
85	6.58	2,934,746	0.611	0.368	0.852	1.8307
90	6.69	3,095,943	0.667	0.324	0.826	1.8167
95	6.79	3,254,233	0.722	0.284	0.801	1.8071
100	6.89	3,408,598	0.778	0.244	0.776	1.7982
105	6.99	3,558,373	0.833	0.204	0.753	1.7900
110	7.09	3,702,783	0.889	0.164	0.730	1.7826
115	7.18	3,842,009	0.944	0.128	0.708	1.7801
120	7.28	3,975,781	1.000	0.088	0.686	1.7744*

Dev_H: hub deviation hub height; Dev_S: deviation for speed of wind; Dev_E: energy output deviation; Dev_O: overall deviation. Best (minimum) Dev_O is marked with asterisk.

Table A16. Results for Ecotecnia 80 2.0.

Hub height (HH) m	Wind speed (WS) m/s	Mean energy output (EO) kWh/yr	Dev_H	Dev_S	Dev_E	Dev_O
70	6.24	3,257,516	0.444	0.504	0.800	1.7488
75	6.36	3,443,583	0.500	0.456	0.771	1.7269
80	6.47	3,626,566	0.556	0.412	0.742	1.7094
85	6.58	3,805,086	0.611	0.368	0.713	1.6926
90	6.69	3,978,094	0.667	0.324	0.686	1.6767
95	6.79	4,144,626	0.722	0.284	0.660	1.6658
100	6.89	4,304,263	0.778	0.244	0.634	1.6560
105	6.99	4,456,541	0.833	0.204	0.610	1.6474
110	7.09	4,601,143	0.889	0.164	0.587	1.6400
115	7.18	4,738,633	0.944	0.128	0.565	1.6377
120	7.28	4,868,568	1.000	0.088	0.545	1.6327*

Dev_H: hub deviation hub height; Dev_S: deviation for speed of wind; Dev_E: energy output deviation; Dev_O = overall deviation. Best (minimum) Dev_O is marked with asterisk.

Table A17. Results for REpower MM92.

Hub height (HH) m	Wind speed (WS) m/s	Mean energy output (EO) kWh/yr	Dev_H	Dev_S	Dev_E	Dev_O
80	6.47	5,029,270	0.556	0.412	0.519	1.4867
85	6.58	5,218,761	0.611	0.368	0.489	1.4682
90	6.69	5,396,551	0.667	0.324	0.461	1.4515
95	6.79	5,562,950	0.722	0.284	0.434	1.4407
100	6.89	5,718,625	0.778	0.244	0.410	1.4315
105	6.99	5,863,344	0.833	0.204	0.387	1.4241
110	7.09	5,998,321	0.889	0.164	0.365	1.4182
115	7.18	6,124,347	0.944	0.128	0.345	1.4178
120	7.28	6,242,483	1.000	0.088	0.327	1.4146*

Dev_H: hub deviation hub height; Dev_S: deviation for speed of wind; Dev_E: energy output deviation; Dev_O: overall deviation. Best (minimum) Dev_O is marked with asterisk.

Table A18. Results for Suzlon S.88/2000.

Hub height (HH) m	Wind speed (WS) m/s	Mean energy output (EO) kWh/yr	Dev_H	Dev_S	Dev_E	Dev_O
80	6.47	4,332,565	0.556	0.412	0.630	1.5973
85	6.58	4,531,511	0.611	0.368	0.598	1.5773
90	6.69	4,721,851	0.667	0.324	0.568	1.5586
95	6.79	4,902,704	0.722	0.284	0.539	1.5455
100	6.89	5,073,855	0.778	0.244	0.512	1.5339
105	6.99	5,235,760	0.833	0.204	0.486	1.5237
110	7.09	5,387,983	0.889	0.164	0.462	1.5151
115	7.18	5,531,715	0.944	0.128	0.439	1.5119
120	7.28	5,666,828	1.000	0.088	0.418	1.5060*

Dev_H: hub deviation hub height; Dev_S: deviation for speed of wind; Dev_E: energy output deviation; Dev_O: overall deviation. Best (minimum) Dev_O is marked with asterisk.

Table A19. Results for Unison U93.

Hub height (HH) m	Wind speed (WS) m/s	Mean energy output (EO) kWh/yr	Dev_H	Dev_S	Dev_E	Dev_O
80	6.47	4,150,121	0.556	0.412	0.659	1.6263
85	6.58	4,348,443	0.611	0.368	0.627	1.6063
90	6.69	4,537,239	0.667	0.324	0.597	1.5879
95	6.79	4,715,641	0.722	0.284	0.569	1.5752
100	6.89	4,884,221	0.778	0.244	0.542	1.5640
105	6.99	5,042,503	0.833	0.204	0.517	1.5544
110	7.09	5,190,828	0.889	0.164	0.494	1.5464
115	7.18	5,329,715	0.944	0.128	0.471	1.5439
120	7.28	5,460,613	1.000	0.088	0.451	1.5387*

Dev_H: hub deviation hub height; Dev_S: deviation for speed of wind; Dev_E = energy output deviation; Dev_O = overall deviation. Best (minimum) Dev_O is marked with asterisk.

Table A20. Results for Vestas V90-2.0 MW.

Hub height (HH) m	Wind speed (WS) m/s	Mean energy output (EO) kWh/yr	Dev_H	Dev_S	Dev_E	Dev_O
80	6.47	4,527,240	0.556	0.412	0.599	1.5664
85	6.58	4,719,473	0.611	0.368	0.568	1.5474
90	6.69	4,901,363	0.667	0.324	0.539	1.5301
95	6.79	5,072,866	0.722	0.284	0.512	1.5185
100	6.89	5,234,066	0.778	0.244	0.487	1.5084
105	6.99	5,385,068	0.833	0.204	0.463	1.5000
110	7.09	5,526,439	0.889	0.164	0.440	1.4931
115	7.18	5,659,247	0.944	0.128	0.419	1.4916
120	7.28	5,783,740	1.000	0.088	0.399	1.4874*

Dev_H: hub deviation hub height; Dev_S: deviation for speed of wind; Dev_E: energy output deviation; Dev_O: overall deviation. Best (minimum) Dev_O is marked with asterisk.