

Article

Fuzzy Logic Based Multi-Criteria Wind Turbine Selection Strategy—A Case Study of Qassim, Saudi Arabia

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Abstract: The emergence of wind energy as a potential alternative to traditional sources of fuel has prompted notable research in recent years. One primary factor contributing to efficient utilization of wind energy from a wind farm is the type of turbines used. However, selection of a specific wind turbine type is a difficult task due to several criteria involved in the selection process. Important criteria include turbine's power rating, height of tower, energy output, rotor diameter, cut-in wind speed, and rated wind speed. The complexity of this selection process is further amplified by the presence of conflicts between the decision criteria. Therefore, a decision is desired that provides the best balance between all selection criteria. Considering the complexities involved in the decision-making process, this paper proposes a two-level decision turbine selection strategy based on fuzzy logic and multi-criteria decision-making (MCDM) approach. More specifically, the fuzzy arithmetic mean operator is used in the decision process. The proposed approach is applied to wind data collected from the site of Qassim, Saudi Arabia. Results indicate that the proposed approach was effective in finding the optimal turbine from a set of 20 turbines of various capacities.

Keywords: wind turbine; wind energy; fuzzy logic; decision-making; fuzzy arithmetic mean operator

1. Introduction

Renewable sources of energy such as wind, solar photovoltaic, solar thermal, geothermal, biomass, municipal waste, tides and waves, and small and large hydro are being used globally to combat the deteriorating climatic conditions, and at the same time meeting the growing demand for energy. The renewable sources of energy are independent of the location and hence can be tapped anywhere, and can provide energy to people living in remote areas which are not connected to the grid. Of these clean and freely available sources of energy, wind has been accepted commercially [1–3] due to ease of installation, operation and maintenance, and availability of advanced wind turbines of all sizes from few kilowatts to multi-megawatt. It is easy and fast to deploy wind turbines requiring minimal attention. Furthermore, these turbines have a life span of 20 to 25 years. Beside all technical and commercial advantages, wind power harnessing does not need any kind of transportation and does not have geographical boundaries [4,5].

In recent years, wind power generation has emerged as the fastest growing source of energy on global scale. A recent report from Global Wind Energy Council (GWEC) [6] states that the cumulative global wind power installed capacity reached 432,419 MW at the end of 2015 compared to 17,400 MW in year 2000, showing an increase of about 2485.2% in a period of 16 years as depicted in Figure 1. The cumulative installed capacity increased from 369,695 MW in 2014 to 432,419 MW in 2015, which is approximately 17%. China leads the global share with addition of 30,500 MW capacities

in 2015. This was followed by the United States, Germany, Brazil, and India, which added 8598, 6013, 2754, and 2623 MW capacities, respectively. The situation in Africa and the Middle East is slow but improving, with South Africa, Ethiopia, and Jordan adding 483, 153, and 117 MW, respectively, bringing the total to 753 MW.

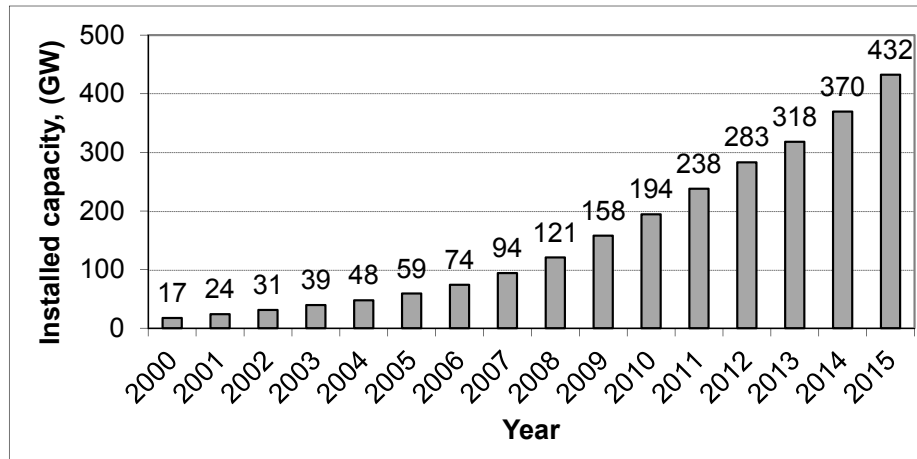


Figure 1. Global cumulative wind power installed capacities [6].

Although the wind power technology is simple and extraction of power from wind is easy, there are some challenges such as maximizing the output from the wind turbines and maintaining uninterrupted power due to intermittent and fluctuating nature of the wind. The wind speed is highly site dependent, and changes with time of the day, day of the year, height above ground level (AGL), and topography. Usually, the wind speed measurements are made at 8 to 12 m AGL, whereas the hub heights of the modern wind turbines of multi megawatt capacities vary from 80 to 120 m. Hub height refers to the height of the tower at which the turbine rotor is installed to harness the wind which can then be converted to energy. The hub height cannot exceed a threshold value due to technical, installation, economical, and maintenance issues. Hence, it is important to have an accurate knowledge of the suitable hub height for a particular location and for a particular type of wind turbine for maximum energy output from wind turbines [6].

In general, as the wind speed increases with height, the energy output from the turbine also increases. Therefore, for increased wind energy output from a selected wind turbine, the hub height should be as high as possible, both economically and technology wise. However, the hub height cannot be increased randomly. This implies that the two decision criteria of hub height and energy output are conflicting in nature, and it is not possible to optimize both criteria at the same time. In addition to these factors, other factors specific to the turbine such as rotor diameter, cut-in wind speed and rated wind speed contribute to the energy extraction. However, many of the aforementioned factors are conflicting with each other: improving one factor negatively affects the others. Moreover, there is no direct or indirect proportional relationship between some of these factors, which further adds to difficulty in choosing a suitable turbine. For example, some turbines have bigger rotor diameters, which is desired due to larger swept area and hence more power. Wind turbines with low cut-in and rated wind speeds are required for higher wind energy productions and are more suitable at low windy sites.

A possible approach to select the best turbine in presence of aforementioned conflicting factors is to opt for a solution that would provide an optimal balance between the all factors (also termed as decision criteria). An approach following this rationale was proposed in various studies [4,7,8], which was based on multi-criteria decision-making (MCDM) and utilized fuzzy logic to find the best balance between two criteria, i.e., hub height and rated power output/zero power output. The underlying fuzzy function to reach the decision was based on the Unified And-Or (UAO) operator [9] or Werners'

operator [10]. However, one potential drawback of the aforementioned operators is that the results are sensitive to the value of an operator-related parameter, and a minor change in the value of this parameter could reflect significant variations in the final decision. Similar concerns are associated with various other well-known operators such as Dombi's operator [11,12], Hamacher's operator [13], Frank's operator [14], Weber's operators [15], Dubois and Prade's operator [16], and Schweizer's operator [17], among many others. However, there is one fuzzy operator that does not contain any operator-related parameter, and therefore does not suffer from the issues that arise with fuzzy operators mentioned above. This operator is known as fuzzy arithmetic mean operator [18] and has been used in a number of MCDM problems. The fuzzy arithmetic mean operator provides motivation for its utilization for finding the best trade-off between the various relevant factors, which serves as the core of the proposed work to select the optimal turbine type for the underlying wind farm site.

The rest of this paper is organized as follows. Section 2 provides the current status of wind turbine selection problem. Contributions and novel aspects of the proposed approach are discussed in Section 3. Section 4 provides the discussion on the research method. In Section 5, discussion is provided as how fuzzy logic is applied to the underlying problem. The results and discussion are provided in Section 6. Finally, the paper concludes in Section 7.

2. Current Status of Wind Turbine Selection Problem

Efficient and effective wind farm development depends on various important factors. These factors may include the selection of potential windy site for the wind farm development, wind farm layout design, and selection of efficient wind turbines that would result in maximum power generation. Installation of a wind turbine involves the transportation of large and heavy turbine components to the site, laying the foundation and building the high towers, provision of appropriate and highly skilled installation crew, maintenance, and various other engineering challenges. The overall issue in this process is to minimize the total financial project cost. The cost of tower is an important element, contributing substantially to the overall cost. An increase by only 10 m in the hub height results in cost increment in the range of 6% to 16%, with an average increase of 10.33% [7]. Thus, it is important to optimize this cost, which in turn requires that the hub height be kept optimal.

In contrast to the above requirement, a wind farm operator demands maximum possible energy output from the wind farm. However, the annual energy output is adversely affected by unavailability, electrical and wake effect losses, zero output percentage (ZOP) and rated output percentage (ROP). Mean net energy output is defined as the energy available to the grid after taking in to consideration the various losses mentioned above. This energy output needs to be optimized while dealing with all prevailing favorable or unfavorable conditions.

As mentioned above, an efficient wind farm design depends on several major factors such as the selection of proper site, wind farm layout, and selection of appropriate wind turbines. Each of these factors is treated as a complex optimization and decision-making problem [19,20]. The complexity of these problems is further amplified by several other aspects [20], such as environmental, technical, and setback constraints. Since the focus of this study is on wind turbine selection and MCDM techniques, the literature review is divided into two parts. The first part is concerned with the use of MCDM techniques on the first two aspects, namely, site selection and layout optimization. The second part focuses on the turbine selection problem and evaluates different strategies adopted for the purpose, including the multi-criteria approaches.

2.1. Multi-Criteria Decision-Making Techniques for Site Selection and Layout Design

Due to the complexity of the aforementioned problems, substantial attention has been given in recent years to the use of computational intelligence (CI) techniques for dealing with these problems in a more systematic and efficient way. The problems can either be treated as single-criteria or multi-criteria. It has been shown [21] that these problems should better be solved as multi-criteria (also referred to as multi-objective) problems as it is a more logical and naturalistic approach to deal with these problems

and can result in better solutions. It is due to this fact that many researchers working in the field of wind farm design have resorted to the use of multi-criteria optimization and decision-making techniques. The primary motivation for the use of CI techniques is to develop automated decision-making techniques that are not only efficient, but replace the human-based decision making which are prone to inefficient, and rather wrong decisions. A variety of CI based MCDM techniques such as weighted aggregation [22], Pareto ranking [23], and fuzzy logic [24] have been employed by researchers in various sub-domains of wind farm design. For example, wind farm site selection problem has been treated as a MCDM problem in various studies. Some recent studies in this direction used weighted aggregation [25–28], fuzzy logic [29–32], and Pareto ranking [33]. A more comprehensive coverage of other relevant studies is given in a recent survey by Herbert-Acero et al. [19]. As far as wind farm layout is concerned, many studies have utilized the aforementioned multi-criteria approaches. Use of weighted aggregation has been reported in various studies [34–37], whereas Pareto ranking has also been used in a number of research works [38–42]. In addition, a comprehensive literature review covering various aspects of wind farm design has been reported in various research articles [19,21,43,44].

2.2. Approaches for Turbine Selection Problem

Considerable attention has also been given to the turbine type selection. Sarja and Halonen [45] performed a research with semi-structured interviews conducted with domain experts and identified several selection criteria such as product reliability, production volume, cost factors, availability factors, and the organization of maintenance. Based on the outcome of the interviews, selection criteria were ordered based on their importance. However, as stated in their article, it was not possible to form a detailed and prioritized list of selection criteria, but still some general themes emerged. The main limitation of their study was that it did not provide a mathematical model that would quantify the results which could facilitate the decision-making process. Perkin et al. [46] identified five selection criteria, namely, the diameter of rotor, generator size, hub height, pitch angle range, and rotations per minute (RPM) range. These criteria were embedded into the chromosome encoding of a genetic algorithm that was used to obtain the best turbine. This was an interesting approach, but was computationally expensive due to the use of genetic algorithm. Nemes and Munteanu [47] presented an approach based on system reliability indices which was used to compare nine different wind turbine types. Chowdhury et al. [48] carried out wind turbine selection based on a single criterion, energy production capacity, and particle swarm optimization algorithm was used as the underlying optimization algorithm. Furthermore, a single wind turbine type was assumed. Similar to the case of Perkin et al. [46], the concern in this situation was algorithmic and computational complexities associated with particle swarm optimization, along with the accuracy of the decision process due to a single criterion. Firuzabad and Dobakhshari [49] used a probabilistic model based on turbine reliability to select the turbine assuming five turbine types. The main limitation here was also that only a single-objective was considered in the decision process. Bencherif et al. [50] considered capacity factor as the decision criteria considering 24 turbine types. An analytical approach based on Weibull distribution was adopted for selection. Montoya et al. [51] proposed Pareto ranking-based genetic algorithms to get the best turbines considering power output and deviation in daily power output as the decision criteria. Chowdhury et al. [52] assumed optimization of cost of energy as the turbine selection criterion, while assuming 121 different turbine types. However, one issue with their proposed selection approach was its computational complexity.

Martin et al. [53] optimized the rotor-to-generator ratio for a hypothetical wind turbine using a range of wind conditions. However, it was stated that the approach can only serve as a support tool, rather than a complete selection method since many other important factors involved in the turbine selection process were not considered in the research. Bekele and Ramayya [54] proposed a site specific design for wind turbine considering blade design as the optimization factor. A genetic algorithm was used to optimize the blade shape. One potential drawback of this approach was that it

did not use off-the-shelf turbines, making the approach totally site specific. Helgason [55] conducted a study on several potential sites in Iceland using 47 different turbines. One optimization criterion, namely, minimum cost of energy was considered which was modeled as function of expected annual energy output, capacity factor, and cost of energy. Eke and Onyewudiala [56] had similar issues where the approach was to design a site specific turbine assuming shape parameters comprising the chord, the twist and the relative thickness of the blade. The idea was to modify these parameters of two existing turbines so that the modified design could generate more power. Genetic algorithm was used but it was not discussed as how the three decision factors were used in the optimization process. Jureczko et al. [57] proposed an approach based on genetic algorithm for turbine design considering blade vibrations, output generated, blade material cost, stability of blade structure, and strength requirements by the blade structure as the design parameters.

Jowder [58] proposed a selection approach that used capacity factor as the decision variable for a site in Bahrain. Furthermore, only six commercially available turbines were considered in the study. El-Shimy [59] proposed a site-specific turbine selection approach while considering capacity factor, normalized average power output, and turbine-performance-index. One drawback of the approach was its complexity and subjectivity in the sense that the results required in-depth interpretations by a domain expert and the interpretations could vary from person to person. Abul'Wafa [60] proposed a method of matching wind turbine generators to a site using turbine performance index (TPI) in conjunction with minimum deviation ratio (DR) between rated speed of wind turbine generator (WTG) and optimal speed and resulting in minimum cost of energy. Although the paper claims that twenty-five potential turbines were assessed, results and analysis of only a few turbines were given in the article. Dong et al. [61] proposed three criteria, namely matching index, turbine cost index and the integrated matching index for turbine selection. Three optimization algorithms were used which were particle swarm optimization, differential evolution, and genetic algorithm.

The most relevant study to the work proposed herein was by Shirgholami et al. [62] who identified more than 30 decision criteria as used in the literature. However, it was also identified that only a subset of the given criteria can be used under specific conditions. In their work, Shirgholami et al. used 11 decision factors which included capacity factor, availability, rotor efficiency, life time costs, initial capital costs, operating and maintenance costs, environmental issues, impact on wildlife, noise emission, visual impact, supplier performance, satisfaction level delivery, and political stability. Furthermore, only four wind turbine types were considered in the study. An Analytic Hierarchy Process (AHP) based approach [22] was used for the decision making process. Another similar study was done by Bagočius et al. [63] who proposed a turbine selection strategy for offshore wind farms. They used the WASPAS method, which is similar to the AHP approach. Five criteria, namely, nominal power of the wind turbine, max power generated in the area, the amount of energy per year generated in the area, investments, and CO₂ emissions were taken into consideration. Furthermore, only four turbine types were considered for assessment.

Lee et al. [64] presented a multi-criteria decision approach considering four major decision criteria namely machine characteristics, economic aspects, environmental issues and technical challenges. However, one major limitation of their study was that it was focused on rating the mutual importance of the four decision criteria, without showing the actual implementation of how this was applied to real turbine data. Since there were some very technical sub-criterion involved in the decision process, actual data for this sub-criterion was almost impossible to obtain from open sources or vendors, thus making the approach less practical. They assumed only four turbines of almost same rated power in their study.

Khan and Rehman [7,8] were the first in reporting the use of fuzzy logic based MCDM for turbine selection problem. However, the approach proposed therein had some limitations. For example, only three criteria were considered in the decision making process. In addition, the study in each paper was focused on a specific rated output range, limiting the variety of turbine types studied. Furthermore, as discussed in Section 1, the fuzzy operators used in those studies were less effective compared to the fuzzy operator used in the current study.

3. Novelty and Contribution of the Proposed Approach

From above literature review, the following limitations are observed.

- (1) Simple decision models. Majority of reviewed research [47–50,52–55,58] has been limited to using one decision criterion for the turbine selection process, which introduces limitations in the decision process.
- (2) Decision parameters that cannot be known by the developer. Most research papers assumed decision parameters for which information is not easily accessible (i.e., blade shape, product reliability, production volume, availability factors, organization of maintenance, system reliability indices, environmental issues, visual impact, political stability, among many others) [45–49,53–63]. Such parameters result in the selection approach being very complex and impractical.
- (3) Restriction to a small variety of turbine types. Many research papers [47–49,53,54,56,58,62–64] have used a small set of turbines type despite a huge variety of commercially available turbines.
- (4) Slow/inefficient optimization techniques (i.e., brute force calculations or iterative heuristics). Optimization techniques such as genetic algorithms, particle swarm optimization, non-linear programming, and other complex approaches are computationally less efficient. Despite this, such approaches have been frequently used in the turbine selection problems [46,48–57,59–61,64].
- (5) Failure to account for impact of changing hub height on cost and production. This important aspect has also been ignored in a number of studies [47–49,53,57,62].
- (6) Conflict and incommensurability of criteria. While a number of studies [45,46,51,55–57,59–62,64] have assumed multiple criteria for selection of the best turbine type, all of them have missed the two fundamental aspects of MCDM. These aspects are known as conflict between criteria and incommensurability. Note that the aim of MCDM is to make decision on finding the best solution from a pool of available alternatives. These decisions generally involve high degree of complexity since a number of conflicting criteria are involved in the decision making process. Conflict between criteria occurs when improvement in one (or more) criterion/criteria results in degradation in other criteria. Incommensurability refers to the decision criteria being in different units and magnitudes. The studies have not discussed (or even considered) these two aspects in proposing the turbine selection problem.

With the above observations, the contribution of this work lies in addressing the above issues and proposing a novel and simple turbine selection approach. The proposed approach would provide a decision model consisting of six important, yet simple decision criteria. These criteria can be easily obtained for any commercially available turbine, thus reducing the total time of the selection process. Furthermore, as opposed to computationally inefficient techniques, the proposed fuzzy logic based approach produces solutions in linear time. In addition, 20 turbines of different rated outputs and different vendors have been used, thus providing a variety in the selection process. The proposed fuzzy logic approach also inherently addresses the conflict and incommensurability issues.

It is also worth mentioning that the proposed approach is robust and scalable, as opposed to previous studies. That is, any number of criteria can be added or removed as per the designer's requirements, and any degree of mutual preference can be introduced among the criteria.

4. Research Method

The research follows a quantitative model and is based on an experimental study. From the literature survey, the important decision criteria have been identified. Based on these criteria, a two-level fuzzy logic model has been developed. Six decision criteria were considered in the model. These criteria include hub height, wind speed, mean net energy output, rotor diameter, cut-in wind speed, and rated wind-speed. The measurements were taken with a step size of 5 m for hub height. In order to develop the two-level fuzzy logic model for the underlying problem, the upper and lower

limits for each decision criteria were found using the data collected for the concerned site. Using these bounds and the data from the sites, fuzzy membership values for each criterion are computed and aggregated in form of an overall decision function according to the proposed approach.

The above approach was implemented as a computational program in C++. The program takes the site specific data as input and generates several solutions. The best (optimal) solution is also identified by the program based on the strategy discussed in Section 5. The site specific information focuses on data for wind turbines in the range of 600–2000 kW. Empirical analysis was performed, providing comparisons of different types of turbines for the site. Based on the outcomes of the analysis, interpretations and recommendations were made.

5. Application of Fuzzy Logic to Wind Turbine Selection

MCDM is a technique used in situations requiring decisions while considering multiple and “conflicting” decision criteria. Conflicting criteria are those criteria which negatively impact each other, i.e., improving the quality of one criterion degrades the quality of other(s). A fundamental requirement pertaining to the application of fuzzy logic to MCDM problems is that the criteria be aggregated to form an overall decision function, which is a scalar value. However, this raises the concern of “incommensurability” of criteria, a scenario arising due to the different units and magnitudes of the criteria. Due to incommensurability, different criteria cannot be aggregated into one decision function, and therefore it is essential to bring all criteria to a uniform, unit-less scale. Fuzzy logic [24] has been effectively used for decades to solve a number of MCDM problems involving the aforementioned issues [65–75].

The fuzzy logic approach proposed in this work is a two-level strategy. In the first level, fuzzy arithmetic mean operator is applied to three selection criteria which are hub height, wind speed, and mean energy output. In order to apply fuzzy arithmetic mean operator to this level, all three criteria need to be fuzzified to overcome the incommensurability issues. This is achieved through finding the membership functions for the three criteria. In the second level, the results of the first level are combined with additional criteria to find the best turbine among all turbines. Again, these additional criteria are first fuzzified and then aggregated with the results of the first level. The criteria for the second level include rotor diameter, cut-in wind speed, and rated wind speed.

5.1. Calculation of Membership Function

The achievement level of each criterion is evaluated through a membership function. Thus, a membership function should be defined for each criterion individually. The membership function takes a value that ranges from 0 to 1 to express the achieved satisfaction level. While the value of 0 indicates total dissatisfaction, the value of 1 indicates complete satisfaction. Several membership functions can be defined that differ in mathematical structure [76]. The structure of a membership function determines the penalization pattern of undesired deviation.

5.2. Application of Fuzzy Logic to the First Level

In order to utilize fuzzy logic for level one, three linguistic variables, namely, “Hub Height”, “Wind speed”, and “Mean Net Energy Output” are defined. Note that our interest is in the terms “low hub height”, “low wind speed” and “high mean net energy output”. It should be noted that there is no linear relationship among these parameters. Wind speed is exponentially dependent on height ratio and the wind shear exponent. The wind power density is directly proportional to the cube of mean wind speed and hence the mean energy output. In addition, note that the three variables (i.e., criteria) are mutually conflicting, since higher hub heights (which are not desired) will ideally give high energy output (desirable) at high wind speed (undesirable). Thus, improvement in energy output would mean higher hub heights and higher wind speeds. Accordingly, an optimal ratio is desired such the best balance between the hub height, wind speed, and energy output is achieved. This can be achieved by defining the following rule.

Rule 1: IF a solution X has low hub height AND low wind speed AND high mean net energy output THEN it is a good solution.

In the above rule, X refers to a solution (i.e., a ratio) that results due to the combined effect of certain value of hub height and its corresponding wind speed and energy output. The terms “low hub height”, “low wind speed”, “high mean net energy output”, and “good solution” are linguistic values, each of which defines a fuzzy subset of solutions. Each fuzzy subset is defined by a membership function, $\mu(x)$. The membership function returns a value in the interval $[0,1]$, describing the degree of satisfaction with the decision criterion under consideration. This process converts the crisp values of three decision criteria into a $[0,1]$ range, and without any units.

The membership functions for the three criteria at the first level are determined as follows.

5.2.1. Membership Function for Hub Height

The membership function for the hub height is formed by determining two extreme values (upper and lower bounds) for hub height. The two limits (i.e., the minimum hub height, $HMin$, and maximum hub height, $HMax$) are found based on the technical specifications of the turbines, as will be discussed in Section 5. The membership function for the hub height, $\mu_H(x)$, is mathematically represented as follows.

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

5.2.2. Membership Function for Wind Speed

The membership function for the wind speed is defined in a manner similar to that of hub height. The upper and lower bounds for wind speed are determined. The lower bound, $SMin$, as well as the upper bound, $SMax$, are found based on the collected data (as explained in Section 5). Equation (2) represents the membership function, $\mu_S(x)$, for the wind speed.

$$\mu_S(x) = \begin{cases} 1 & \text{if } Speed(x) \leq SMin \\ \frac{SMax - Speed(x)}{SMax - SMin} & \text{if } SMin < Speed(x) \leq SMax \\ 0 & \text{if } Speed(x) > SMax \end{cases} \quad (2)$$

5.2.3. Membership Function for Mean Net Energy Output

Finally, the membership function for mean net energy output can be formed as follows. The two bounds for energy output are determined first, using the collected data. Equation (3) represents the membership function, $\mu_E(x)$, for mean net energy output. In this equation, $EMax$ and $EMin$ correspond to the upper and lower bounds, respectively.

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

5.2.4. Calculation of the Overall Membership Function at Level 1

The next step is to aggregate all individual memberships for the three criteria. This is done using Rule 1, which is mathematically represented by fuzzy arithmetic mean operator. The operator places all membership functions into a single aggregation function that measures the degree of satisfaction of

the overall membership function. The mathematical representation of overall membership function for solution x , $OM(x)$, is given in the following equation.

$$OM(x) = \frac{\alpha_1\mu_H(x) + \alpha_2\mu_S(x) + \alpha_3\mu_E(x)}{3} \tag{4}$$

In Equation (4) above, $OM(x)$ represents the overall membership of the three criteria collectively. Furthermore, the coefficients α_1 , α_2 , and α_3 are weights used to indicate the priority of a specific design objective. In this work, a general problem is considered that gives equal consideration to all design objectives. The solution that results in the maximum value for Equation (4) is reported as the best solution found.

Let us take an example to see how the method works at the first level.

Example 1. Assume the data for Fuhrllder FL 600 in Table A1. We will take the data in the first two rows to illustrate how the approach works. The data in the two rows are as follows.

Row 1: Hub height = 50 m, Wind Speed = 4.51 m/s, and Mean Net Energy Output = 652,928 kWh/year

Row 2: Hub height = 55 m, Wind Speed = 4.63 m/s, and Mean Net Energy Output = 706,370 kWh/year

In order to calculate the memberships, Equations (1)–(3) should be used appropriately along with the upper and lower limits for each criterion (the upper and lower limits are given in Table 1).

From Equation (1), membership values for hub height in Row 1 = 0.778 and Row 2 = 0.772

From Equation (2), membership values for wind speed in Row 1 = 0.255 and Row 2 = 0.307

From Equation (3), membership values for energy output in Row 1 = 0.307 and Row 2 = 0.337

From Equation (4), the overall membership (OM) for Row 1 = $(0.778 + 0.255 + 0.307)/3 = 0.447$

Again from Equation (4), OM for Row 2 = $(0.772 + 0.307 + 0.337)/3 = 0.458$

As per the rules of fuzzy logic, since Row 2 has higher OM value than Row 1, data in Row 2 is a better choice than that of Row 1. Note that the approach is done to select the best combination of hub height, wind speed, and energy output for the same turbine. The procedure has to be repeated separately for each turbine as done in Tables A1–A20.

Table 1. Upper and lower bounds for level 1.

Turbine Rated Power Range (kW)	Hub Height (m)		Wind Speed (m/s)		Energy Output (kWh/Year)	
	Lower	Upper	Lower	Upper	Lower	Upper
500–750	30	120	4	6	100,000	1,900,000
1000–1250	30	120	4	6	500,000	2,200,000
2000	30	120	4	6	1,000,000	4,900,000

5.3. Application of Fuzzy Logic to the Second Level

The outcome of the first level identifies the most appropriate combination with respect to hub height, wind speed, and mean net energy output for each turbine. However, as mentioned earlier in Section 1, these three criteria are suitable for selecting a turbine from the same class of turbines with regard to the rated power output, but not adequate for selecting the best overall turbine in all three categories. It is due to the fact that there are three categories of turbines (500–750 kW, 1000–1250 kW, and 2000 kW) considered herein and each category has its own suitable hub height range, suitable wind speed range, and most importantly, mean net energy output. Therefore, more criteria are needed to appropriately consider the effect of difference in rated energy output of different turbines. This motivated the need for a second level of decision making, thus prompting the application of fuzzy arithmetic mean operator also to the second level while considering rotor diameter, cut-in wind speed, and rated wind-speed as the decision criteria. The approach follows the same methodology adopted

at the first level. This requires defining a second rule for the second level, finding the membership function for the three criteria, and aggregate them along with the overall membership of level 1 through fuzzy arithmetic mean operator.

Rule 2: IF a solution X has big rotor diameter AND low cut-in wind speed AND low rated wind speed AND high overall membership at level 1 THEN it is a good solution.

In order to utilize fuzzy logic for level 2, again three linguistic variables, namely, “Rotor diameter”, “Cut-in wind speed”, and “Rated wind-speed” are defined. The next step is to define three membership functions for the criteria at level 2, which is done as explained below.

5.3.1. Membership Function for Rotor Diameter

The development of membership function for rotor diameter requires the upper and lower bounds to be defined. Tables 2–4 indicate that the rotor diameter for all turbines varies between 33 and 93 m. Note that higher rotor diameter is desired since this allows more absorption of wind power. The upper limit, $DMax$, is taken as 95 m while the lower limit, $DMin$, is assumed to be 30 m. The membership function for the rotor diameter, $\mu_D(x)$, is represented as follows.

$$\mu_D(x) = \begin{cases} 1 & \text{if } Diameter(x) \geq DMax \\ \frac{Diameter(x) - DMin}{DMax - DMin} & \text{if } DMin \leq Diameter(x) < DMax \\ 0 & \text{if } Diameter(x) < DMin \end{cases} \quad (5)$$

Table 2. Technical specifications of the wind turbines in the range of 500–750 kW.

Turbine	Minimum Hub Height (m)	Rotor Diameter (m)	Cut-in Wind Speed (m/s)	Rated Wind Speed (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 3. Technical specifications of the wind turbines in the range of 1000–1250 kW.

Turbine	Minimum Hub Height (m)	Rotor Diameter (m)	Cut-in Wind Speed (m/s)	Rated Wind Speed (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 4. Technical specifications of the wind turbines with rated power of 2000 kW.

Turbine	Minimum Hub Height (m)	Rotor Diameter (m)	Cut-in Wind Speed (m/s)	Rated Wind Speed (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
Unison U93	80	93	3	11	2000
Vestas V90	80	90	4	12	2000

5.3.2. Membership Function for Cut-in Wind Speed

In order to define the membership function for cut-in wind speed, the two extreme values are determined first. It is observed from Tables 2–4 that the cut-in wind speed of turbines varies from 2.5 to 6 m/s. Therefore, the upper bound, C_{Max} , is taken as 7 m/s while the lower bound, C_{Min} , is taken as 2 m/s. The membership function for the cut-in wind speed, $\mu_C(x)$, is represented by Equation (6).

$$\mu_C(x) = \begin{cases} 1 & \text{if } CutIn\ Speed(x) \leq C_{Min} \\ \frac{C_{Max} - CutIn\ Speed(x)}{C_{Max} - C_{Min}} & \text{if } C_{Min} < CutIn\ Speed(x) \leq C_{Max} \\ 0 & \text{if } CutIn\ Speed(x) > C_{Max} \end{cases} \quad (6)$$

5.3.3. Membership Function for Rated Wind Speed

The membership function for the rated wind speed is determined using the upper and lower bounds of rated wind speeds of all turbines. The values are taken from the data in Column 5 of Tables 2–4. Since the rated wind speed varies between 15 and 10.5 m/s, the upper limit, R_{Max} , is taken as 16 m/s while the lower limit, R_{Min} , is taken as 10 m/s. Mathematically, the membership function for rated wind speed, $\mu_R(x)$, is represented as follows:

$$\mu_R(x) = \begin{cases} 1 & \text{if } Rated\ Speed(x) \leq R_{Min} \\ \frac{R_{Max} - Rated\ Speed(x)}{R_{Max} - R_{Min}} & \text{if } R_{Min} < Rated\ Speed(x) \leq R_{Max} \\ 0 & \text{if } Rated\ Speed(x) > R_{Max} \end{cases} \quad (7)$$

5.3.4. Calculation of the Total Membership Function

After the individual memberships at the second level are found, the next step is to aggregate all memberships as well as the overall membership from the first level, using Rule 2. Similar to level 1, this is done using the fuzzy arithmetic mean operator. The resulting mathematical expression is as given below.

$$TM(x) = \frac{\beta_1 \mu_D(x) + \beta_2 \mu_C(x) + \beta_3 \mu_R(x) + \beta_4 OM(x)}{4} \quad (8)$$

In Equation (8), $TM(x)$ signifies the aggregated memberships of all three objectives at the second level and overall membership from level 1. Moreover, the coefficients β_1 , β_2 , β_3 and β_4 are the weights that can be used to indicate the priority of a specific criterion. The solution which results in the maximum value for Equation (8) is recorded as the best solution found.

Let us now understand through an example as how the method works at the second level.

Example 2. Following the approach described in Example 1, let us assume that the best combination for each turbine type has been found (i.e., taking the best combination from each table in Appendix A). Then, the desire is to find the best overall turbine using the data for level 2 and the best result for level 1. As an example,

assume that we want to compare any two turbines, say Unison U93 and Vestas V90. From Table 5 we observe the following data:

For Unison U93: Diameter = 93 m, Cut-in wind speed = 3 m/s, Rated win speed = 11 m/s

For Vestas V90: Diameter = 90 m, Cut-in wind speed = 4 m/s, Rated win speed = 12 m/s

From Level 1, OM for Unison U93 = 0.543

From Level 1, OM for Vestas V90 = 0.577

To calculate the memberships, Equations (5)–(7) should be used appropriately as discussed above.

From Equation (5), membership for Diameter for Unison U93 = 0.97 and Vestas V90 = 0.92

From Equation (6), membership for Cut-in wind speed for Unison U93 = 0.8 and Vestas V90 = 0.6

From Equation (7), membership for Rated wind speed for Unison U93 = 0.83 and Vestas V90 = 0.67

From Equation (8), while assuming equal preference for all criteria, the total membership (TM) for Unison U93 = $(0.97 + 0.8 + 0.83 + 0.543)/4 = 0.786$

Again from Equation (8), with equal preference for criteria, TM for Vestas V90 = $(0.92 + 0.6 + 0.67 + 0.577)/4 = 0.692$

Since Unison U93 has higher membership value than Vestas V90 (i.e., 0.786 vs. 0.692), we conclude that Unison U93 is a better choice than Vestas V90 for the given site.

Table 5. TM for all turbines. OM = overall membership and TM = total membership.

Turbine	Diameter (m)	Cut-in Wind speed (m/s)	Rated Wind speed (m/s)	OM	Membership Diameter	Membership Cut-in Speed	Membership Rated Speed
Unison U93	93	3	11	0.543	0.97	0.8	0.83
Vestas V90	90	4	12	0.577	0.92	0.6	0.67

6. Results and Discussion

The study was performed on a potential experimental site of Qassim located in the central part of Saudi Arabia. The location has an altitude of 648 m above sea level. As discussed in Section 4 the simulator executes the MCDM calculations with the input data, and generates the output decision based on the two-level fuzzy logic approach described in Sections 5.2 and 5.3. With respect to first level of decision, for each set of data associated with a specific turbine, the value which generated the highest membership according to Rule 1 was chosen as the best solution (representing the best balance between the three decision criteria). Twenty different turbine types, with different rated powers were assumed. Of these, seven turbines were having rated power output in the range of 500–750 kW, six turbines were in the range of 1000–1250 kW, and the remaining seven turbines had rated power output of 2000 kW. Technical specifications of these turbines are given in Tables 2–4.

6.1. Selection of Turbines between 500 and 750 kW Rated Output

The results for the seven turbines mentioned in Table 2 are displayed in Tables A1–A7 in Appendix A. Columns 1–3 in each table enlist the first level decision criteria which are hub height, wind speed, and mean net energy output, respectively. These values were provided as input to the simulator. Columns 4–6 provide the individual membership values of the three decision criteria, respectively. The overall membership of the solution is thus found using Equation (4) by adding the individual deviations, and is given in the last column of each table. It is important to mention that, in Tables A1–A7, the measurements of hub height, and the corresponding wind speed and energy output, were taken based on the minimum hub height applicable to that turbine (i.e., as specified by the manufacturer). For example, the minimum hub height for Fuhrlder 600 is 50 m, for Vestas V47

is 55 m, and so on. Therefore, measurements were taken considering the minimum hub heights as the lower limit for each respective turbine. Similarly, the maximum hub height for all turbines was assumed to be 120 m.

Tables A1–A7 indicate that for all turbines, the best (maximum) overall membership is associated with highest hub height of 120 m, with the exception of Windflow 500 for which a hub height of 110 m produced the best solution. These results signify that the performance of turbines considering wind speed and energy output was better at higher hub heights than at lower hub heights.

The relative performance of the wind turbines was also assessed. Table 6 provides the best results for each turbine. These results have been reproduced from Tables A1–A7 for convenience. As observed from these tables, Unison U57 demonstrated the best performance among all turbines. It is due to the fact that Unison U57 achieved the best balance between the hub height, wind speed, and energy output, as indicated by highest overall membership value of 0.631. The other possible alternatives of Unison U57 were Fuhrlder FL 600 and Hyosung HS50 with overall memberships of 0.544 and 0.538, respectively. The worst performance was demonstrated by Windflow 500, which had the lowest overall membership of just 0.378.

Table 6. Comparison of turbines in 500–750 kW range. HH = Hub height in m, WS = wind speed in m/s, and EO = energy output in kWh/year, Mem HH = hub height membership, Mem WS = wind speed membership, Mem EO = energy output membership, and OM = overall membership.

Turbine	HH	WS	EO	Mem HH	Mem WS	Mem EO	OM
Fuhrlder FL 600	120	5.85	1,372,142	0.000	0.925	0.707	0.544
Hyosung HS50	120	5.85	1,339,670	0.000	0.925	0.689	0.538
RRB Energy PS 600	120	5.85	1,137,149	0.000	0.925	0.576	0.500
Suzlon S.52/600	120	5.85	1,212,688	0.000	0.925	0.618	0.514
Unison U57	120	5.85	1,843,128	0.000	0.925	0.968	0.631
Vestas V47	120	5.85	1,186,994	0.000	0.925	0.604	0.510
Windflow 500	110	5.70	410,844	0.111	0.850	0.173	0.378

6.2. Selection of Turbines between 1000 and 1250 kW Rated Output

Tables A8–A13 in Appendix A provide the results for the six turbines in the range of 1000–1250 kW mentioned in Table 3. Again, Columns 1–3 in Tables A8–A13 provide the values of the first-level decision criteria, i.e., hub height, wind speed, and mean net energy output, respectively. In addition, as before, Columns 4–6 provide the individual memberships of the three decision criteria, respectively. The overall membership of the solution is obtained by using Equation (4). The overall membership is given in the last column of each table. Note that in Tables A8–A13, the measurements of hub height, and the corresponding wind speed and energy output were taken based on the minimum hub height applicable to that turbine.

Tables A8–A13 show some interesting trends. All best results were obtained with hub heights of 120 m, corresponding to wind speed of 7.28 m/s. The above results clearly indicate that the performance of turbines considering wind speed and energy output was best at highest hub height considered in the measurements.

The relative performance of the wind turbines was also evaluated. Table 7 depicts the best results for each turbine. These results have been reproduced from Tables A8–A13 for the sake of completeness. As observed from Table 7, Vensys 62-1200 demonstrated the best performance among all turbines since it has the highest overall membership of 0.641, followed by Suzlon S.62/1000 with an overall membership of 0.588, and so on. The worst performance was shown by Nordex N54/1000, which had the lowest overall membership of 0.495.

Table 7. Comparison of turbines in 1000–1250 kW range. HH = Hub height in m, WS = wind speed in m/s, and EO = energy output in kWh/year, Mem HH = hub height membership, Mem WS = wind speed membership, Mem EO = energy output membership, and OM = overall membership.

Turbine	HH	WS	EO	Mem HH	Mem WS	Mem EO	OM
AAER A-1000	120	5.85	1,795,286	0.000	0.925	0.762	0.562
DeWind D6 64m	120	5.85	1,615,199	0.000	0.925	0.656	0.527
Mitsubishi MWT62	120	5.85	1,868,132	0.000	0.925	0.805	0.577
Nordex N54/1000	120	5.85	1,453,262	0.000	0.925	0.561	0.495
Suzlon S.62/1000	120	5.85	1,924,100	0.000	0.925	0.838	0.588
Vensys 62-1200	120	5.85	2,198,506	0.000	0.925	0.999	0.641

6.3. Selection of Turbines with 2000 kW Rated Output

Turbines with rated output of 2000 kW were also evaluated. Tables A14–A20 in Appendix A provide the results for the seven turbines mentioned in Table 4 where all turbines were having the same rated power of 2000 kW. Similar to previous sections, Columns 1–3 of each table enlist the three decision criteria of hub height, wind speed, and mean net energy output, respectively. In addition, as before, Columns 4–6 provide the individual memberships of the three decision criteria, respectively. The overall membership of the solution is obtained by using Equation (4) as given in the last column of each table. Similar to previous cases, the measurements of hub height, and the corresponding wind speed and energy output were taken based on the minimum hub height applicable to that turbine.

The results revealed by Tables A14–A20 are quite noteworthy. A pattern similar to what was observed in Section 6.2 is seen here as well. That is, all best performances were obtained at hub heights of 120 m where the wind speed was 7.28 m/s. With regard to the relative performance of each turbine, results in Table 8 indicate that REpower MM92 was the best performer as it resulted in the highest overall membership of 0.620 while DeWind D8.1 was worst in performance due its lowest overall membership deviation of 0.432.

Table 8. Comparison of turbines with rated power of 2000 kW. HH = Hub height in m, WS = wind speed in m/s, and EO = energy output in kWh/year, Mem HH = hub height membership, Mem WS = wind speed membership, Mem EO = energy output membership, and OM = overall membership.

Turbine	HH	WS	EO	Mem HH	Mem WS	Mem EO	OM
AAER A-2000-84	120	5.85	3,881,328	0.000	0.925	0.739	0.555
DeWind D8.1	120	5.85	2,443,060	0.000	0.925	0.370	0.432
Ecotecnia 80/2000	120	5.85	3,244,719	0.000	0.925	0.576	0.500
REpower MM92	120	5.85	4,649,758	0.000	0.925	0.936	0.620
Suzlon S.88/2000	120	5.85	3,934,755	0.000	0.925	0.753	0.559
Unison U93	120	5.85	3,748,612	0.000	0.925	0.705	0.543
Vestas V90	120	5.85	4,142,236	0.000	0.925	0.806	0.577

6.4. Overall Best Performance of a Wind Turbine

The results in Sections 6.1–6.3 assess the best turbine in three different ranges, namely, 500–750 kW, 1000–1250 kW, and 1000–2000 kW. However, the results do not classify the overall best turbine considering all turbines simultaneously. In order to make that decision, more information other than what has been presented and analyzed in Sections 6.1–6.3 is needed. That decision can be made with the factors presented in Tables 2–4. These factors include rotor diameter, cut-in wind speed, and rated wind speed. These factors play an important role in selecting a suitable wind turbine for a particular location from economical energy yield and ease of installation and maintenance. For example, larger the rotor diameter, more swept area and hence more power is expected from the wind turbine. However, there is a limit of the rotor diameter beyond which it will not be operational. Furthermore, lesser cut-in and rated wind speeds of a wind turbine would produce more energy, resulting in higher yields at low

windy sites. Again, the technical aspects of developing such wind turbine blades need more research and development work.

In order to make appropriate decision, again fuzzy logic has been employed here using the strategy presented in Section 5.3. This strategy incorporates the cumulative results from Tables 6–8 combined with the memberships of each aforementioned factor and implemented as discussed in Section 5.3.4. Table 9 displays the individual memberships for the three factors, i.e., rotor diameter, cut-in wind speed, rated wind speed, and rated power, combined with the overall memberships of Section 5. The resulting membership is calculated using Equation (8) and is referred to as the total membership (TM) in the last column of Table 9.

It is observed from Table 9 that the best turbine for the underlying site is Unison U93 with the highest TM of 0.791. This turbine has a rated output of 2000 kW. Two other turbines, namely, REpower MM92 and AAER A-2000-84, are also close in performance to Unison U93. Furthermore, Windflow 500 has the lowest TM of 0.239, indicating that this is the worst turbine for the underlying wind farm site. The turbine is in the 500–750 kW turbine range. Another trend observed in this table is that, in general, turbines with rated power of 2000 kW are most suitable for the wind farm site of Qassim because all turbines have a higher TM, while most turbines in 500–750 kW have low TM, indicating their unsuitability, in general, for the site.

Table 9. TM for all turbines. OM = overall membership and TM = total membership.

Turbine	Diameter (m)	Cut-in Wind Speed (m/s)	Rated Wind Speed (m/s)	Membership Diameter	Membership Cut-in Speed	Membership Rated Speed	OM	TM
Unison U93	93	3	11	0.97	0.8	0.83	0.543	0.786
REpower MM92	92	3	12.5	0.95	0.8	0.58	0.620	0.739
AAER A-2000-84	84	3.25	12	0.83	0.75	0.67	0.555	0.701
Vensys 62-1200	62	2.5	11.5	0.49	0.9	0.75	0.641	0.696
Vestas V90	90	4	12	0.92	0.6	0.67	0.577	0.692
Unison U57	57	3	10.5	0.42	0.8	0.92	0.631	0.691
Ecotecnia 80/2000	80	3	12	0.77	0.8	0.67	0.500	0.684
Fuhrlder FL 600	50	2.5	11	0.31	0.9	0.83	0.544	0.646
DeWind D6 64m	64	2.5	12.3	0.52	0.9	0.62	0.527	0.642
Suzlon S.62/1000	62	3	12	0.49	0.8	0.67	0.588	0.637
DeWind D8.1	80	3	13.5	0.77	0.8	0.42	0.432	0.604
Suzlon S.88/2000	88	4	14	0.89	0.6	0.33	0.559	0.596
Hyosung HS50	50	3.5	11	0.31	0.7	0.83	0.538	0.595
Mitsubishi MWT62	61.4	3.5	12.5	0.48	0.7	0.58	0.577	0.586
AAER A-1000	58	4	12	0.43	0.6	0.67	0.562	0.565
Suzlon S.52/600	52	4	13	0.34	0.6	0.50	0.618	0.514
Vestas V47	47	4	13	0.26	0.6	0.50	0.510	0.468
Nordex N54/1000	54	3.75	14	0.37	0.65	0.33	0.495	0.462
RRB Energy PS 600	47	3.5	15	0.26	0.7	0.17	0.500	0.407
Windflow 500	33	6	14	0.05	0.2	0.33	0.378	0.239

7. Conclusions

An efficient wind farm design primarily requires the deployment of appropriate turbines that suit the needs of the site. Selection of an appropriate wind turbine from many available alternatives is a difficult task and requires consideration of various factors in the decision-making process. Six key decision factors are hub height, wind speed, mean net energy output, rotor diameter, cut-in wind speed, and rated wind speed. This paper presented a fuzzy logic based two-level MCDM approach for the turbine selection problem. The proposed approach was applied to data collected from the potential site of Qassim, Saudi Arabia. The effectiveness of the approach was analyzed through application on various turbines with nominal power in the ranges of 500–750 kW, 1000–1250 kW, and 2000 kW. According to the obtained results, Unison U 93 turned out to be the best turbine while Windflow 500 was the worst turbine.

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Author Contributions: Shafiqur Rehman collected the data for the study and proposed the overall framework. He proposed the criteria for selection of turbines. He also performed part of the literature review and wrote Sections 1 and 2, and partially Section 3, as well as the Abstract. He also performed part of analysis of results. Salman A. Khan developed the fuzzy logic based two-level turbine selection strategy, including the development of fuzzy membership functions, and decision functions. He also analyzed the data and wrote Section 3 (partially), Sections 4–6, and the Appendix A.

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

Appendix A

Table A1. Results for Fuhrlder FL 600 (Fuhrlder, Haiger, Germany). Mem HH = membership for hub height, Mem WS = membership for wind speed, Mem EO = Membership for energy output, and OM = overall membership. Best OM which corresponds to the best solution(s) is in bold.

Hub Height (HH) (m)	Hub Height Wind Speed (WS) (m/s)	Mean Net Energy Output (EO) (kWh/Year)	Mem HH	Mem WS	Mem EO	OM
50	4.51	652,928	0.778	0.255	0.307	0.447
55	4.63	706,370	0.722	0.315	0.337	0.458
60	4.74	762,434	0.667	0.370	0.368	0.468
65	4.86	814,177	0.611	0.430	0.397	0.479
70	4.97	868,204	0.556	0.485	0.427	0.489
75	5.07	922,046	0.500	0.535	0.457	0.497
80	5.14	970,760	0.444	0.570	0.484	0.499
85	5.26	1,028,540	0.389	0.630	0.516	0.512
90	5.35	1,080,891	0.333	0.675	0.545	0.518
95	5.44	1,132,390	0.278	0.720	0.574	0.524
100	5.49	1,173,203	0.222	0.745	0.596	0.521
105	5.61	1,232,176	0.167	0.805	0.629	0.534
110	5.7	1,280,293	0.111	0.850	0.656	0.539
115	5.78	1,326,950	0.056	0.890	0.682	0.542
120	5.85	1,372,142	0.000	0.925	0.707	0.544

Table A2. Results for Hyosung HS50 (Hyosung Corporation, Seoul, Korea). Mem HH = membership for hub height, Mem WS = membership for wind speed, Mem EO = Membership for energy output, and OM = overall membership. Best OM which corresponds to the best solution(s) is in bold.

Hub Height (HH) (m)	Hub Height Wind Speed (WS) (m/s)	Mean Net Energy Output (EO) (kWh/Year)	Mem HH	Mem WS	Mem EO	OM
50	4.51	595,719	0.778	0.255	0.275	0.436
55	4.63	649,148	0.722	0.315	0.305	0.447
60	4.74	705,486	0.667	0.370	0.336	0.458
65	4.86	757,288	0.611	0.430	0.365	0.469
70	4.97	811,782	0.556	0.485	0.395	0.479
75	5.07	866,352	0.500	0.535	0.426	0.487
80	5.14	916,259	0.444	0.570	0.453	0.489
85	5.26	975,136	0.389	0.630	0.486	0.502
90	5.35	1,029,202	0.333	0.675	0.516	0.508
95	5.44	1,082,817	0.278	0.720	0.546	0.515
100	5.49	1,126,225	0.222	0.745	0.570	0.512
105	5.61	1,188,073	0.167	0.805	0.604	0.525
110	5.7	1,239,561	0.111	0.850	0.633	0.531
115	5.78	1,290,144	0.056	0.890	0.661	0.536
120	5.85	1,339,670	0.000	0.925	0.689	0.538

Table A3. Results for RRB Energy PS 600 (RRB Energy, New Delhi, India). Mem HH = membership for hub height, Mem WS = membership for wind speed, Mem EO = Membership for energy output, and OM = overall membership. Best OM which corresponds to the best solution(s) is in bold.

Hub Height (HH) (m)	Hub Height Wind Speed (WS) (m/s)	Mean Net Energy Output (EO) (kWh/Year)	Mem HH	Mem WS	Mem EO	OM
50	4.51	542,702	0.778	0.255	0.246	0.426
55	4.63	587,970	0.722	0.315	0.271	0.436
60	4.74	635,029	0.667	0.370	0.297	0.445
65	4.86	677,883	0.611	0.430	0.321	0.454
70	4.97	722,385	0.556	0.485	0.346	0.462
75	5.07	766,484	0.500	0.535	0.370	0.468
80	5.14	806,222	0.444	0.570	0.392	0.469
85	5.26	853,295	0.389	0.630	0.418	0.479
90	5.35	896,000	0.333	0.675	0.442	0.484
95	5.44	938,074	0.278	0.720	0.466	0.488
100	5.49	971,518	0.222	0.745	0.484	0.484
105	5.61	1,020,077	0.167	0.805	0.511	0.494
110	5.7	1,059,956	0.111	0.850	0.533	0.498
115	5.78	1,098,993	0.056	0.890	0.555	0.500
120	5.85	1,137,149	0.000	0.925	0.576	0.500

Table A4. Results for Suzlon S.52/600 (Suzlon, Ahmedabad, India). Mem HH = membership for hub height, Mem WS = membership for wind speed, Mem EO = Membership for energy output, and OM = overall membership. Best OM which corresponds to the best solution(s) is in bold.

Hub Height (HH) (m)	Hub Height Wind Speed (WS) (m/s)	Mean Net Energy Output (EO) (kWh/Year)	Mem HH	Mem WS	Mem EO	OM
80	5.14	833,566	0.444	0.570	0.408	0.474
85	5.26	888,092	0.389	0.630	0.438	0.486
90	5.35	937,648	0.333	0.675	0.465	0.491
95	5.44	986,305	0.278	0.720	0.492	0.497
100	5.49	1,025,036	0.222	0.745	0.514	0.494
105	5.61	1,080,418	0.167	0.805	0.545	0.505
110	5.7	1,125,783	0.111	0.850	0.570	0.510
115	5.78	1,169,886	0.056	0.890	0.594	0.513
120	5.85	1,212,688	0.000	0.925	0.618	0.514

Table A5. Results for Unison U57 (Unison, Gyeongsangnam-Do, Korea). Mem HH = membership for hub height, Mem WS = membership for wind speed, Mem EO = Membership for energy output, and OM = overall membership. Best OM which corresponds to the best solution(s) is in bold.

Hub Height (HH) (m)	Hub Height Wind Speed (WS) (m/s)	Mean Net Energy Output (EO) (kWh/Year)	Mem HH	Mem WS	Mem EO	OM
70	4.97	1,197,179	0.556	0.485	0.610	0.550
75	5.07	1,266,399	0.500	0.535	0.648	0.561
80	5.14	1,328,827	0.444	0.570	0.683	0.566
85	5.26	1,403,430	0.389	0.630	0.724	0.581
90	5.35	1,470,875	0.333	0.675	0.762	0.590
95	5.44	1,537,157	0.278	0.720	0.798	0.599
100	5.49	1,589,262	0.222	0.745	0.827	0.598
105	5.61	1,665,206	0.167	0.805	0.870	0.614
110	5.7	1,726,494	0.111	0.850	0.904	0.622
115	5.78	1,785,919	0.056	0.890	0.937	0.627
120	5.85	1,843,128	0.000	0.925	0.968	0.631

Table A6. Results for Vestas V47 (Vestas, Smed Hansensvej, Denmark). Mem HH = membership for hub height, Mem WS = membership for wind speed, Mem EO = Membership for energy output, and OM = overall membership. Best OM which corresponds to the best solution(s) is in bold.

Hub Height (HH) (m)	Hub Height Wind Speed (WS) (m/s)	Mean Net Energy Output (EO) (kWh/Year)	Mem HH	Mem WS	Mem EO	OM
55	4.63	576,683	0.722	0.315	0.265	0.434
60	4.74	627,796	0.667	0.370	0.293	0.443
65	4.86	674,633	0.611	0.430	0.319	0.453
70	4.97	723,647	0.556	0.485	0.346	0.462
75	5.07	772,467	0.500	0.535	0.374	0.470
80	5.14	816,847	0.444	0.570	0.398	0.471
85	5.26	869,067	0.389	0.630	0.427	0.482
90	5.35	916,763	0.333	0.675	0.454	0.487
95	5.44	963,831	0.278	0.720	0.480	0.493
100	5.49	1,001,605	0.222	0.745	0.501	0.489
105	5.61	1,055,687	0.167	0.805	0.531	0.501
110	5.7	1,100,406	0.111	0.850	0.556	0.506
115	5.78	1,144,187	0.056	0.890	0.580	0.509
120	5.85	1,186,994	0.000	0.925	0.604	0.510

Table A7. Results for Windflow 500 (Windflow Technology, Christchurch, Newzealand). Mem HH = membership for hub height, Mem WS = membership for wind speed, Mem EO = Membership for energy output, and OM = overall membership. Best OM which corresponds to the best solution(s) is in bold.

Hub Height (HH) (m)	Hub Height Wind Speed (WS) (m/s)	Mean Net Energy Output (EO) (kWh/Year)	Mem HH	Mem WS	Mem EO	OM
40	4.24	110,514	0.889	0.120	0.006	0.338
45	4.38	126,293	0.833	0.190	0.015	0.346
50	4.51	143,407	0.778	0.255	0.024	0.352
55	4.63	161,749	0.722	0.315	0.034	0.357
60	4.74	182,070	0.667	0.370	0.046	0.361
65	4.86	201,577	0.611	0.430	0.056	0.366
70	4.97	222,804	0.556	0.485	0.068	0.370
75	5.07	244,719	0.500	0.535	0.080	0.372
80	5.14	265,741	0.444	0.570	0.092	0.369
85	5.26	290,323	0.389	0.630	0.106	0.375
90	5.35	313,820	0.333	0.675	0.119	0.376
95	5.44	337,672	0.278	0.720	0.132	0.377
100	5.49	358,219	0.222	0.745	0.143	0.370
105	5.61	386,236	0.167	0.805	0.159	0.377
110	5.7	410,844	0.111	0.850	0.173	0.378
115	5.78	435,602	0.056	0.890	0.186	0.377
120	5.85	460,449	0.000	0.925	0.200	0.375

Table A8. Results for AAER A-1000 (AAER, Fort Lee, NJ, USA). Mem HH = membership for hub height, Mem WS = membership for wind speed, Mem EO = Membership for energy output, and OM = overall membership. Best OM which corresponds to the best solution(s) is in bold.

Hub Height (HH) (m)	Hub Height Wind Speed (WS) (m/s)	Mean Net Energy Output (EO) (kWh/Year)	Mem HH	Mem WS	Mem EO	OM
70	4.97	1,092,548	0.556	0.485	0.349	0.463
75	5.07	1,164,244	0.500	0.535	0.391	0.475
80	5.14	1,229,889	0.444	0.570	0.429	0.481
85	5.26	1,307,623	0.389	0.630	0.475	0.498
90	5.35	1,379,165	0.333	0.675	0.517	0.508
95	5.44	1,450,104	0.278	0.720	0.559	0.519
100	5.49	1,507,924	0.222	0.745	0.593	0.520
105	5.61	1,590,646	0.167	0.805	0.642	0.538
110	5.7	1,659,849	0.111	0.850	0.682	0.548
115	5.78	1,728,115	0.056	0.890	0.722	0.556
120	5.85	1,795,286	0.000	0.925	0.762	0.562

Table A9. Results for DeWind D6 64m (DeWind Co., Irvin Texas, TX, USA). Mem HH = membership for hub height, Mem WS = membership for wind speed, Mem EO = Membership for energy output, and OM = overall membership. Best OM which corresponds to the best solution(s) is in bold.

Hub Height (HH) (m)	Hub Height Wind Speed (WS) (m/s)	Mean Net Energy Output (EO) (kWh/Year)	Mem HH	Mem WS	Mem EO	OM
60	4.74	768,321	0.667	0.370	0.158	0.398
65	4.86	830,723	0.611	0.430	0.195	0.412
70	4.97	897,357	0.556	0.485	0.234	0.425
75	5.07	965,498	0.500	0.535	0.274	0.436
80	5.14	1,029,615	0.444	0.570	0.312	0.442
85	5.26	1,105,671	0.389	0.630	0.356	0.458
90	5.35	1,177,202	0.333	0.675	0.398	0.469
95	5.44	1,249,489	0.278	0.720	0.441	0.480
100	5.49	1,310,444	0.222	0.745	0.477	0.481
105	5.61	1,395,408	0.167	0.805	0.527	0.499
110	5.7	1,468,714	0.111	0.850	0.570	0.510
115	5.78	1,542,060	0.056	0.890	0.613	0.520
120	5.85	1,615,199	0.000	0.925	0.656	0.527

Table A10. Results for Mitsubishi MWT62-1000 (Mitsubishi Heavy Industries, Ltd., Yokohama, Japan). Mem HH = membership for hub height, Mem WS = membership for wind speed, Mem EO = Membership for energy output, and OM = overall membership. Best OM which corresponds to the best solution(s) is in bold.

Hub Height (HH) (m)	Hub Height Wind Speed (WS) (m/s)	Mean Net Energy Output (EO) (kWh/Year)	Mem HH	Mem WS	Mem EO	OM
70	4.97	1,107,203	0.556	0.485	0.357	0.466
75	5.07	1,186,578	0.500	0.535	0.404	0.480
80	5.14	1,259,280	0.444	0.570	0.447	0.487
85	5.26	1,344,546	0.389	0.630	0.497	0.505
90	5.35	1,422,785	0.333	0.675	0.543	0.517
95	5.44	1,500,184	0.278	0.720	0.588	0.529
100	5.49	1,562,804	0.222	0.745	0.625	0.531
105	5.61	1,651,587	0.167	0.805	0.677	0.550
110	5.7	1,725,379	0.111	0.850	0.721	0.561
115	5.78	1,797,630	0.056	0.890	0.763	0.570
120	5.85	1,868,132	0.000	0.925	0.805	0.577

Table A11. Results Nordex N54/1000 kW (Nordex SE, Hamburg, Germany). Mem HH = membership for hub height, Mem WS = membership for wind speed, Mem EO = Membership for energy output, and OM = overall membership. Best OM which corresponds to the best solution(s) is in bold.

Hub Height (HH) (m)	Hub Height Wind Speed (WS) (m/s)	Mean Net Energy Output (EO) (kWh/Year)	Mem HH	Mem WS	Mem EO	OM
60	4.74	733,028	0.667	0.370	0.137	0.391
65	4.86	789,610	0.611	0.430	0.170	0.404
70	4.97	849,597	0.556	0.485	0.206	0.415
75	5.07	910,199	0.500	0.535	0.241	0.425
80	5.14	966,311	0.444	0.570	0.274	0.430
85	5.26	1,032,431	0.389	0.630	0.313	0.444
90	5.35	1,093,755	0.333	0.675	0.349	0.453
95	5.44	1,154,895	0.278	0.720	0.385	0.461
100	5.49	1,205,141	0.222	0.745	0.415	0.461
105	5.61	1,275,903	0.167	0.805	0.456	0.476
110	5.7	1,335,783	0.111	0.850	0.492	0.484
115	5.78	1,394,937	0.056	0.890	0.526	0.491
120	5.85	1,453,262	0.000	0.925	0.561	0.495

Table A12. Results for Suzlon S.62/1000 (Suzlon, Ahmedabad, India). Mem HH = membership for hub height, Mem WS = membership for wind speed, Mem EO = Membership for energy output, and OM = overall membership. Best OM which corresponds to the best solution(s) is in bold.

Hub Height (HH) (m)	Hub Height Wind Speed (WS) (m/s)	Mean Net Energy Output (EO) (kWh/Year)	Mem HH	Mem WS	Mem EO	OM
65	4.86	1,102,522	0.611	0.430	0.354	0.465
70	4.97	1,178,155	0.556	0.485	0.399	0.480
75	5.07	1,254,238	0.500	0.535	0.444	0.493
80	5.14	1,324,060	0.444	0.570	0.485	0.500
85	5.26	1,407,119	0.389	0.630	0.534	0.517
90	5.35	1,483,631	0.333	0.675	0.579	0.529
95	5.44	1,559,639	0.278	0.720	0.623	0.540
100	5.49	1,621,174	0.222	0.745	0.660	0.542
105	5.61	1,709,142	0.167	0.805	0.711	0.561
110	5.7	1,782,225	0.111	0.850	0.754	0.572
115	5.78	1,853,952	0.056	0.890	0.796	0.581
120	5.85	1,924,100	0.000	0.925	0.838	0.588

Table A13. Results for Vensys 62 (Vensys Energy, Nonnweiler, Germany). Mem HH = membership for hub height, Mem WS = membership for wind speed, Mem EO = Membership for energy output, and OM = overall membership. Best OM which corresponds to the best solution(s) is in bold.

Hub Height (HH) (m)	Hub Height Wind Speed (WS) (m/s)	Mean Net Energy Output (EO) (kWh/Year)	Mem HH	Mem WS	Mem EO	OM
70	4.97	1,373,601	0.556	0.485	0.514	0.518
75	5.07	1,458,095	0.500	0.535	0.564	0.533
80	5.14	1,535,143	0.444	0.570	0.609	0.541
85	5.26	1,626,994	0.389	0.630	0.663	0.561
90	5.35	1,711,099	0.333	0.675	0.712	0.574
95	5.44	1,794,630	0.278	0.720	0.762	0.586
100	5.49	1,862,038	0.222	0.745	0.801	0.589
105	5.61	1,959,121	0.167	0.805	0.858	0.610
110	5.7	2,040,071	0.111	0.850	0.906	0.622
115	5.78	2,119,946	0.056	0.890	0.953	0.633
120	5.85	2,198,506	0.000	0.925	0.999	0.641

Table A14. Results for AAER A-2000-84 (AAER, Fort Lee, NJ, USA). Mem HH = membership for hub height, Mem WS = membership for wind speed, Mem EO = Membership for energy output, and OM = overall membership. Best OM which corresponds to the best solution(s) is in bold.

Hub Height (HH) (m)	Hub Height Wind Speed (WS) (m/s)	Mean Net Energy Output (EO) (kWh/Year)	Mem HH	Mem WS	Mem EO	OM
65	4.86	2,169,598	0.611	0.430	0.300	0.447
70	4.97	2,326,962	0.556	0.485	0.340	0.460
75	5.07	2,485,514	0.500	0.535	0.381	0.472
80	5.14	2,631,381	0.444	0.570	0.418	0.478
85	5.26	2,803,851	0.389	0.630	0.463	0.494
90	5.35	2,963,114	0.333	0.675	0.503	0.504
95	5.44	3,121,421	0.278	0.720	0.544	0.514
100	5.49	3,250,190	0.222	0.745	0.577	0.515
105	5.61	3,433,254	0.167	0.805	0.624	0.532
110	5.7	3,585,762	0.111	0.850	0.663	0.541
115	5.78	3,735,263	0.056	0.890	0.701	0.549
120	5.85	3,881,328	0.000	0.925	0.739	0.555

Table A15. Results for DeWind D8.1 (DeWind Co., Irvin Texas, TX, USA). Mem HH = membership for hub height, Mem WS = membership for wind speed, Mem EO = Membership for energy output, and OM = overall membership. Best OM which corresponds to the best solution(s) is in bold.

Hub Height (HH) (m)	Hub Height Wind Speed (WS) (m/s)	Mean Net Energy Output (EO) (kWh/Year)	Mem HH	Mem WS	Mem EO	OM
80	5.14	1,537,798	0.444	0.570	0.138	0.384
85	5.26	1,655,162	0.389	0.630	0.168	0.396
90	5.35	1,765,989	0.333	0.675	0.196	0.402
95	5.44	1,877,836	0.278	0.720	0.225	0.408
100	5.49	1,972,189	0.222	0.745	0.249	0.406
105	5.61	2,103,223	0.167	0.805	0.283	0.418
110	5.70	2,216,634	0.111	0.850	0.312	0.424
115	5.78	2,330,001	0.056	0.890	0.341	0.429
120	5.85	2,443,060	0.000	0.925	0.370	0.432

Table A16. Results for Ecotecnia 80/2000 (Alstom, Saint-Ouen, France). Mem HH = membership for hub height, Mem WS = membership for wind speed, Mem EO = Membership for energy output, and OM = overall membership. Best OM which corresponds to the best solution(s) is in bold.

Hub Height (HH) (m)	Hub Height Wind Speed (WS) (m/s)	Mean Net Energy Output (EO) (kWh/Year)	Mem HH	Mem WS	Mem EO	OM
70	4.97	1,904,075	0.556	0.485	0.232	0.424
75	5.07	2,039,396	0.500	0.535	0.267	0.434
80	5.14	2,159,080	0.444	0.570	0.297	0.437
85	5.26	2,311,168	0.389	0.630	0.336	0.452
90	5.35	2,447,356	0.333	0.675	0.371	0.460
95	5.44	2,583,036	0.278	0.720	0.406	0.468
100	5.49	2,689,181	0.222	0.745	0.433	0.467
105	5.61	2,851,752	0.167	0.805	0.475	0.482
110	5.7	2,984,441	0.111	0.850	0.509	0.490
115	5.78	3,115,523	0.056	0.890	0.542	0.496
120	5.85	3,244,719	0.000	0.925	0.576	0.500

Table A17. Results for REpower MM92 (REpower, Tripsrath, Germany). Mem HH = membership for hub height, Mem WS = membership for wind speed, Mem EO = Membership for energy output, and OM = overall membership. Best OM which corresponds to the best solution(s) is in bold.

Hub Height (HH) (m)	Hub Height Wind Speed (WS) (m/s)	Mean Net Energy Output (EO) (kWh/Year)	Mem HH	Mem WS	Mem EO	OM
80	5.14	3,336,809	0.444	0.570	0.599	0.538
85	5.26	3,528,408	0.389	0.630	0.648	0.556
90	5.35	3,700,502	0.333	0.675	0.692	0.567
95	5.44	3,868,852	0.278	0.720	0.736	0.578
100	5.49	4,001,539	0.222	0.745	0.770	0.579
105	5.61	4,194,667	0.167	0.805	0.819	0.597
110	5.7	4,351,165	0.111	0.850	0.859	0.607
115	5.78	4,502,963	0.056	0.890	0.898	0.615
120	5.85	4,649,758	0.000	0.925	0.936	0.620

Table A18. Results for Suzlon S.88/2000 (Suzlon, Ahmedabad, India). Mem HH = membership for hub height, Mem WS = membership for wind speed, Mem EO = Membership for energy output, and OM = overall membership. Best OM which corresponds to the best solution(s) is in bold.

Hub Height (HH) (m)	Hub Height Wind Speed (WS) (m/s)	Mean Net Energy Output (EO) (kWh/Year)	Mem HH	Mem WS	Mem EO	OM
80	5.14	2,669,926	0.444	0.570	0.428	0.481
85	5.26	2,846,288	0.389	0.630	0.473	0.497
90	5.35	3,008,305	0.333	0.675	0.515	0.508
95	5.44	3,168,669	0.278	0.720	0.556	0.518
100	5.49	3,298,395	0.222	0.745	0.589	0.519
105	5.61	3,483,031	0.167	0.805	0.637	0.536
110	5.7	3,636,630	0.111	0.850	0.676	0.546
115	5.78	3,787,344	0.056	0.890	0.715	0.553
120	5.85	3,934,755	0.000	0.925	0.753	0.559

Table A19. Results for Unison U93 (Unison, Gyeongsangnam-Do, Korea). Mem HH = membership for hub height, Mem WS = membership for wind speed, Mem EO = Membership for energy output, and OM = overall membership. Best OM which corresponds to the best solution(s) is in bold.

Hub Height (HH) (m)	Hub Height Wind Speed (WS) (m/s)	Mean Net Energy Output (EO) (kWh/Year)	Mem HH	Mem WS	Mem EO	OM
80	5.14	2,483,854	0.444	0.570	0.380	0.465
85	5.26	2,657,287	0.389	0.630	0.425	0.481
90	5.35	2,817,926	0.333	0.675	0.466	0.491
95	5.44	2,978,000	0.278	0.720	0.507	0.502
100	5.49	3,109,319	0.222	0.745	0.541	0.503
105	5.61	3,293,851	0.167	0.805	0.588	0.520
110	5.7	3,448,573	0.111	0.850	0.628	0.530
115	5.78	3,600,356	0.056	0.890	0.667	0.537
120	5.85	3,748,612	0.000	0.925	0.705	0.543

Table A20. Results for Vestas V90 (Vestas, Smed Hansensevej, Denmark). Mem HH = membership for hub height, Mem WS = membership for wind speed, Mem EO = Membership for energy output, and OM = overall membership. Best OM which corresponds to the best solution(s) is in bold.

Hub Height (HH) (m)	Hub Height Wind Speed (WS) (m/s)	Mean Net Energy Output (EO) (kWh/Year)	Mem HH	Mem WS	Mem EO	OM
80	5.14	2,860,836	0.444	0.570	0.477	0.497
85	5.26	3,042,369	0.389	0.630	0.524	0.514
90	5.35	3,208,220	0.333	0.675	0.566	0.525
95	5.44	3,371,863	0.278	0.720	0.608	0.535
100	5.49	3,503,124	0.222	0.745	0.642	0.536
105	5.61	3,690,773	0.167	0.805	0.690	0.554
110	5.7	3,845,304	0.111	0.850	0.730	0.564
115	5.78	3,995,923	0.056	0.890	0.768	0.571
120	5.85	4,142,236	0.000	0.925	0.806	0.577

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