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Application of Fuzzy Einstein Operator to Multi-Criteria Decision-Making for Selection of Wind Turbine Type with Nominal Power of 2000 KW

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Abstract: Wind energy has emerged as a potential alternative to traditional sources of fuel. One key factor that contributes to efficient harnessing of wind energy from a wind farm is the type of turbines used in that farm. However, selection of a specific wind turbine type is not a simple task due to several decision criteria, such as turbine's power rating, and height of tower on which a turbine is mounted, among others. This selection process is further complicated 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 presents a fuzzy logic based decision-making approach for selection of the most appropriate wind turbine for a specific wind farm using fuzzy Einstein operator. The proposed approach is applied to data collected from a potential site. Results indicate that the proposed approach was effective in finding the optimal turbine from a set of available turbines.

Keywords: Wind turbine, Automated decision-making, Fuzzy logic, Einstein Operator

1. INTRODUCTION

Since the discovery of fossil fuels, the requirement for energy has been ever increasing. This requirement is driven by the need for electricity which is now a vital part of survival of human race. Traditionally, fossil fuels have provided the most dominant share of this energy demand. However, these sources are depleting rapidly. Another concern with fossil fuels is the environmental pollution. These issues have compelled the energy providers to strive for alternative sources of energy so as to reduce the dependency on fossil fuels and to provide clean and green energy. This struggle has resulted in discovery of various alternatives sources of energy which are not only cheaper than fossil fuels, but also eco-friendly.

In recent year, wind energy has emerged as one of the potential alternatives to fossil fuel for power generation. The global attention being received by wind energy lies in its economic feasibility, environmental compatibility, and reliability. The advantages of wind energy are further signified by quick infrastructure development and deployment, augmented by negligible maintenance. Furthermore, there are minimal hindrances associated with political or geographical boundaries as far as wind energy is concerned [1]. According to Global Wind Energy Council Report [2], the world's wind power capacity grew by 44% in 2014 with addition of 51,477 MW to bring total installations to 369,553 MW. China leads the global market for wind power generation, accounting for 45% of the total market, adding 23,351 MW to its grid. This was followed by India which added 2,315 MW to its wind power sources. The growth of European market was also astonishing with 12,820 MW of new capacity. Out of this, Germany had the largest share with addition of 5,279 MW followed by UK (1,736 MW), Sweden (1,050 MW), and France (1.042 MW). The situation in Africa, though still having a small contribution to the total, was improving, with South Africa and Morocco adding 560 MW and 300 MW respectively, bringing the total to 934 MW. In South America, Brazil had new installations adding 3,749 MW, with Chile (506 MW) and Uruguay (405 MW) also making strong showings. In North America, US market added 4,854 MW, with Canada adding 1,871 MW, and Mexico with 522 MW. Australia's 567 MW also showed a promising growth.

Although extraction of wind power is easy, a major challenge is to manage its throughput and quality instigated by intermittent and fluctuating nature of wind speed. Numerous factors, such as location, time, and

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height above ground level (AGL) significantly contribute to the variation in wind speed. Wind speed measurements are usually taken at 10 meters AGL, whereas the rotor of the wind turbine is mounted on towers (also known as hub) at much higher altitudes. Hub height refers to the height of the tower on which turbine rotor is installed to absorb wind power (which is then converted into electrical energy). The hub height cannot exceed a threshold due to limitations in various economical, installation, and maintenance issues. Thus, for placement of a wind turbine in a wind farm, it is essential to have accurate knowledge of optimal (or sub-optimal) hub height - a height at which a turbine could produce maximum energy at a reasonable cost, with considerations of convenience in installation and maintenance [3].

To address the issues associated with quality of wind power, the rated energy output of the wind turbine ought to be maximized [3]. This maximization requires wind absorption at higher altitudes. However, higher altitudes require higher hubs (which is not desired). 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 other words, improvement in one criterion comes at the expense of the degradation of the other. A possible approach to resolve this issue is to opt for a solution that would provide an optimal balance between the two criteria. An approach following this rationale was proposed in [1][3][4] which was based on multi-criteria decision-making (MCDM) and utilized fuzzy logic to find the best balance between the two criteria. The underlying fuzzy function to reach the decision was based on the Unified And-Or (UAO) operator [25] or Werners' operator [26]. 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 [5, 6], Hamacher's operator [7], Frank's operator [8], Weber's operators [9], Dubois and Prade's operator [10], and Schweizer's operator [11], among many others. However, one operator, namely the Einstein operator, does not suffer from the drawback, since there is no operator-related parameter associated with that. This provides motivation for utilizing the Einstein operator for finding the best trade-off between hub height and rated output power, which serves as the core of the proposed work to select the optimal turbine type for a given wind farm site.

The proposed Einstein operator-based selection methodology is applied to selection of the best turbine from a set of different turbine types, all with nominal power of 2000 KW. Previous studies [1][3][4][28-30] compared turbines with different nominal powers, or did not specify even the turbine type [27]. In [28], only three different turbine types with different nominal powers (0.91 MW, 2 MW and 3 MW) were considered. In [29], nine different turbines were considered. However, these were coming from four different manufacturers, and the turbines were of different nominal powers, ranging from 1.5 MW to 3 MW. In [30], turbines of various capacities (1.8 MW to 3MW), all belonging to the same manufacturer were considered. In [31], five different turbines from two manufacturers were considered, with nominal power ranging between 1.5 MW to 3 MW. The work proposed herein compares seven turbines, all from different manufacturers, and all having the same nominal power of 2 MW, which is another novel aspect of the proposed work.

The rest of this paper is organized as follows. Section 2 provides the details of the wind turbine selection problem. A fuzzy logic based approach for wind farm selection is discussed in Section 3. Section 4 provides the results and discussion. Finally, conclusions are given in Section 5.

2. Wind Turbine Selection Problem

The development of a wind farm deals with various key issues. These include identification of a proper site for the wind farm, wind farm layout design, and selection of appropriate turbines that would result in maximum power generation. Installation of a wind turbine in a wind farm is a critical 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, one issue in this process is to minimize the overall financial cost. The cost of hub tower is an important element, contributing substantially to the overall cost. An increase by only 10 meters in the hub height results in cost increment in the range of 6% to 16%, with an average increase of 10.33% [3]. Therefore, it is important to reduce this cost, which in turn requires that the hub height is kept as low as possible.

In contrast, an essential demand by the operator of a wind farm is maximization of power generated by the wind farm. This power generation is affected by a numerous factors such as unavailability losses, electrical losses, wake effect losses, zero output percentage (ZOP), and rated output percentage (ROP). Rated output percentage is defined as the duration of time during the year for which the wind turbine output was at its maximum rated capacity [32]. ROP has a positive effect on the overall power generation, and therefore should be maximized as much as possible, to maximize the generated power.

It is logical to assume that increasing hub height should also increase ROP, since at higher altitudes, more wind is available and therefore high amount of wind is absorbed by the turbine. This results in higher amount of conversion of wind energy into electrical energy. However, as mentioned earlier, higher hub is difficult to manage due to technical and financial reasons. Therefore, it is not possible to have hub height and ROP optimized simultaneously. As stated in the previous section, both criteria would be satisfied to the best possible extent through the use of fuzzy logic based multi-criteria decision making, while employing Einstein operator in the process. The process is explained in the following section.

3. Application Of Fuzzy Einstein Operator To Wind Turbine Selection

Multi-criteria decision-making (MCDM) is a technique used in situations requiring decisions while considering multiple and conflicting decision criteria. Conflicting criteria are those criteria which have a negative impact on each other, i.e., improving the quality of one criterion degrades the quality of other(s). Another concern in MCDM problems is incommensurability of criteria, which arises due to the different units and magnitudes of the criteria. Due it incommensurability, different criteria cannot be aggregated into one decision function, and therefore it is essential to bring all criteria to a uniform scale, and without any units. Fuzzy logic [13] has been effectively used to solve a number of MCDM problems involving the aforementioned issues [12][14-23].

In order to apply fuzzy logic to MCDM problems, a fundamental requirement is that the criteria be aggregated to form an overall decision function which is a scalar value. One major concern with this process is how to select an appropriate function, since there are a number of fuzzy functions that can perform the aggregation. A number of such operators have been mentioned in Section 1. However, as mentioned in Section 1, Einstein operator has been selected for the underlying study due to the fact that the operator does not depend on the operator-related parameter, and therefore the results are not biased by any parameter. A detailed discussion and mathematical properties of the operator can be found in [24].

A. Einstein Operator for the underlying problem

In order to utilize the Einstein operator for the wind turbine selection problem, two linguistic variables, namely, "Hub Height" and "Rated Output Percentage" are defined. Note that we are interested in the terms "low hub height" and "high rated output percentage". Since the two criteria are mutually conflicting, the aim is to find the optimal ratio such the best balance is achieved between the hub height and rated output percentage. The following fuzzy rule is defined for this purpose.

Rule 1: IF a solution X has *low hub height* AND *high rated output percentage* THEN it is a *good solution*.

In the above rule, X refers to a decision (solution) that has resulted due to a combined effect of certain value of hub height and its corresponding rated output. The terms "low hub height", "high rated output percentage", and "good combination" are linguistic values, each of which defines a fuzzy subset of solutions. For example, low hub height is the fuzzy subset of solutions of low hub heights. Each fuzzy subset is defined by a membership function, μ. The membership function returns a value in the interval [0,1] which describes the degree of satisfaction with the decision criterion under consideration. Rule 1 can be mathematically represented using the Einstein operator as follows:

$$\mu_E = \frac{\mu_{HH}\mu_{RO}}{2-(\mu_{HH}+\mu_{RO}-\mu_{HH}\mu_{RO})} \quad (1)$$

In Equation (1), μ_E represents the membership value for a solution *x* in the fuzzy set *good solution*. The higher the value of μ_E, the better the solution (representing a good balance between hub height and ROP). Furthermore, μ_{HH} and μ_{RO} denote the membership values of the fuzzy sets *low hub height* and *high rated output percentage*, respectively. The solution that gives maximum value for (1) is reported as the best solution found.

The membership functions for the two criteria are determined as follows:

B. Membership function for hub height

To form the membership function for the hub height, two extreme values (upper and lower bounds) of hub height need to be determined. The lower bound (i.e. the minimum hub height), "HMin", is taken based on the technical specifications of the turbine (as mentioned in Column 2 of Table 1), while the upper bound, "HMax", is taken as 120 meters, which is the typical maximum height used for many turbines. Figure 1 depicts the membership function for the hub height. In this figure, x-axis represents the hub height and the y-axis represents the corresponding membership value.

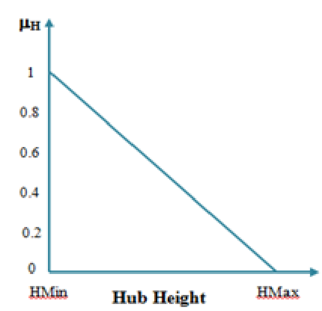

Figure 1. Membership function for hub height

C. Membership function for rated output percentage

The membership function for ROP can be formed following the same approach used for the membership function of hub height. The upper and lower bounds for ROP need to be determined first. The collected data reveals that ROP varies between 0.08% and 6.13%. Therefore, to accommodate this range, the lower limit, "RMin", is set at 0% whereas the upper limit, "RMax", is defined to be 7%. The corresponding membership function is shown in Figure 2. In this figure, x-axis represents the rated output percentage and the y-axis represents the corresponding membership value.

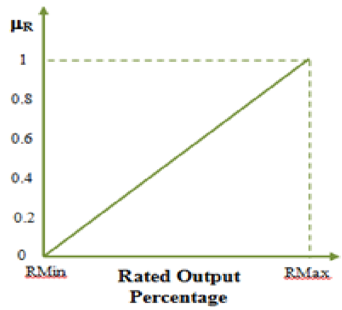

Figure 2. Membership function for rated output percentage

4. RESULTS AND DISCUSSION

The study was performed on a potential experimental site near the eastern coast of Saudi Arabia. The location has an altitude of 3 meters above sea level. The data for the study was collected over a period of five years, and information relevant to the study was extracted. This information comprised of rated output percentage for different turbines and was measured with a step size of 5 meters. A C++ based program was developed to perform the simulations. The simulator performs the multi-criteria decision-making calculations with the input data, and generates the fuzzified output based on the Einstein operator. For each set of data pertaining to a specific turbine, the value which generated the highest fuzzified value was chosen as the best solution (representing the best balance between the two decision criteria). Seven different turbine types, each from a different manufacturer were used. All turbines had a nominal power output of 2000 KW. Technical specifications of these turbines are given in Table 1.

TABLE I. TECHNICAL SPECFICATIONS OF THE WIND TURBINES

Turbine	Minimum hub height (m)	Rotor Diamter (m)	Cut-in Wind Speed (m/s)	Rated Wind Speed (m/s)
AAER A-2000-84	65	84	3.25	2
DeWind D8.1	80	80	3	13.5
Ecotecnia 80/2000	70	80	3	12
REpower MM92	79	92	3	12.5
Suzlon S.88/2000	80	88	4	14
Unison U93	80	93	3	11
Vestas V90	80	90	4	12

Tables II to VIII display the results for the seven turbines used in the study. In each table, columns 1 and 2 enlist the hub height and ROP, respectively. These values were provided as input to the simulator. Columns 3 and 4 provide the membership values for hub height (μ_{HH}) and ROP (μ_{RO}), respectively. The membership value for the overall solution, which is calculated through aggregation using the Einstein operator (denoted by μ_E), is given in the last column of each table. It is noteworthy that the measurements of ROP as listed in Tables 3 to 9 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 AAER A-2000/84 is 65 meters and for DeWind D8.1 is 80 meters. Therefore, the measurements were taken with their respective lower limits of 65 meters and 80 meters. Similar measurements were done for the other turbines.

Tables II to VIII alos reveal that for all turbines, the best overall membership values using the Einstein operator (given in boldface in the tables) are associated with the lowest hub height applicable to that turbine. For example, for AAER A-2000/84, the best results were obtained with hub height of 65 meters; for DeWind D8.1, the best balance was achieved at this minimum hub height of 80 meters, and so on. This signifies that at low hub heights, the performance of a specific turbine with respect to ROP is better than those at high hub heights.

TABLE II. RESULTS FOR AAER A-2000/84. HH = HUB HEIGHT, RO = RATED OUTPUT, μHH = HH MEMBERSHIP, μRO = RO MEMBERSHIP, μE = OVERALL MEMBERSHIP USING DUBOIS AND PRADE OPERATOR. BEST OVERALL MEMBERSHIP IS IN BOLD.

HH	RO	μ_{HH}	μ_{RO}	μ_E
65	2.1	0.611	0.300	**0.1441**
70	2.22	0.556	0.317	0.1352
75	2.37	0.500	0.339	0.1272
80	2.53	0.444	0.361	0.1186
85	2.71	0.389	0.387	0.1095
90	2.89	0.333	0.413	0.0989
95	3.12	0.278	0.446	0.0884
100	3.31	0.222	0.473	0.0745
105	3.51	0.167	0.501	0.0590
110	3.76	0.111	0.537	0.0423
115	4.08	0.056	0.583	0.0232
120	4.36	0.000	0.623	0.0000

TABLE III. RESULTS FOR DEWIND D8.1. HH = HUB HEIGHT, RO = RATED OUTPUT, μHH = HH MEMBERSHIP, μRO = RO MEMBERSHIP, μE = OVERALL MEMBERSHIP USING DUBOIS AND PRADE OPERATOR. BEST OVERALL MEMBERSHIP IS IN BOLD.

HH	RO	μ_{HH}	μ_{RO}	μ_E
80	0.13	0.444	0.019	**0.0053**
85	0.14	0.389	0.020	0.0049
90	0.16	0.333	0.023	0.0046
95	0.18	0.278	0.026	0.0042
100	0.21	0.222	0.030	0.0038
105	0.23	0.167	0.033	0.0030
110	0.26	0.111	0.037	0.0022
115	0.3	0.056	0.043	0.0013
120	0.33	0.000	0.047	0.0000

TABLE IV. RESULTS FOR ECOTECNIA 80/2000. HH = HUB HEIGHT, RO = RATED OUTPUT, μHH = HH MEMBERSHIP, μRO = RO MEMBERSHIP, μE = OVERALL MEMBERSHIP USING EINSTEN OPERATOR. BEST OVERALL MEMBERSHIP IS IN BOLD.

HH	RO	μ_{HH}	μ_{RO}	μ_E
70	0.46	0.556	0.066	**0.0258**
75	0.5	0.500	0.071	0.0244
80	0.55	0.444	0.079	0.0231
85	0.61	0.389	0.087	0.0218
90	0.67	0.333	0.096	0.0199
95	0.74	0.278	0.106	0.0178
100	0.79	0.222	0.113	0.0148
105	0.85	0.167	0.121	0.0117
110	0.94	0.111	0.134	0.0084
115	1.01	0.056	0.144	0.0044
120	1.1	0.000	0.157	0.0000

TABLE V. RESULTS FOR REPOWER MM92. HH = HUB HEIGHT, RO = RATED OUTPUT, μHH = HH MEMBERSHIP, μRO = RO MEMBERSHIP, μE = OVERALL MEMBERSHIP USING EINSTEN OPERATOR. BEST OVERALL MEMBERSHIP IS IN BOLD.

HH	RO	μ_{HH}	μ_{RO}	μ_E
80	3.43	0.444	0.490	**0.1697**
85	3.64	0.389	0.520	0.1564
90	3.86	0.333	0.551	0.1415
95	4.11	0.278	0.587	0.1256
100	4.39	0.222	0.627	0.1080
105	4.69	0.167	0.670	0.0876
110	5.02	0.111	0.717	0.0637
115	5.4	0.056	0.771	0.0352
120	5.8	0.000	0.829	0.0000

TABLE VI. RESULTS FOR SUZLON S.88/2000. HH = HUB HEIGHT, RO = RATED OUTPUT, μHH = HH MEMBERSHIP, μRO = RO MEMBERSHIP, μE = OVERALL MEMBERSHIP USING EINSTEN OPERATOR. BEST OVERALL MEMBERSHIP IS IN BOLD.

HH	RO	μ_{HH}	μ_{RO}	μ_E
80	3.32	0.444	0.474	**0.1631**
85	3.54	0.389	0.506	0.1510
90	3.76	0.333	0.537	0.1368
95	3.99	0.278	0.570	0.1208
100	4.25	0.222	0.607	0.1033
105	4.56	0.167	0.651	0.0841
110	4.89	0.111	0.699	0.0612
115	5.23	0.056	0.747	0.0335
120	5.62	0.000	0.803	0.0000

TABLE VII. RESULTS FOR UNISON U93. HH = HUB HEIGHT, RO = RATED OUTPUT, μHH = HH MEMBERSHIP, μRO = RO MEMBERSHIP, μE = OVERALL MEMBERSHIP USING EINSTEN OPERATOR. BEST OVERALL MEMBERSHIP IS IN BOLD.

HH	RO	μ_{HH}	μ_{RO}	μ_E
80	3.6	0.444	0.514	**0.1800**
85	3.82	0.389	0.546	0.1661
90	4.08	0.333	0.583	0.1520
95	4.33	0.278	0.619	0.1347
100	4.61	0.222	0.659	0.1156
105	4.94	0.167	0.706	0.0945
110	5.31	0.111	0.759	0.0694
115	5.71	0.056	0.816	0.0386
120	6.13	0.000	0.876	0.0000

TABLE VIII. RESULTS FOR VESTAS V90. HH = HUB HEIGHT, RO = RATED OUTPUT, μHH = HH MEMBERSHIP, μRO = RO MEMBERSHIP, μE = OVERALL MEMBERSHIP USING EINSTEN OPERATOR. BEST OVERALL MEMBERSHIP IS IN BOLD.

HH	RO	μ_{HH}	μ_{RO}	μ_E
80	1.34	0.444	0.191	**0.0587**
85	1.44	0.389	0.206	0.0539
90	1.54	0.333	0.220	0.0482
95	1.65	0.278	0.236	0.0422
100	1.79	0.222	0.256	0.0360
105	1.93	0.167	0.276	0.0287
110	2.07	0.111	0.296	0.0202
115	2.22	0.056	0.317	0.0107
120	2.38	0.000	0.340	0.0000

The relative performance of the wind turbines was also assessed in the study. Table IX provides the best results for each turbine. These results have been reproduced from Tables II to VIII for convenience. As observed from these tables, Unison U93 demonstrated the best performance among all turbines. It is due to fact that Unison U93 was able to achieve the best balance between the hub height and ROP, as indicated by its μ_E value of 0.1800. The nearest competitors to Unison U93 were REpower MM92 and Suzlon S.88/2000 who had μ_E = 0.1697 and μ_E = 0.1631, respectively. The worst performance was shown by DeWind D8.1 which had μ_E value of only 0.0053. Therefore, based on the results, Unison U93 could be recommended for deployment at the test site under study.

TABLE IX. BEST RESULTS FOR EACH TURBINE

Turbine	HH	RO	μ_{HH}	μ_{RO}	μ_E
AAER A-2000-84	65	2.1	0.611	0.300	0.1441
DeWind D8.1	80	0.13	0.444	0.019	0.0053
Ecotecnia 80/2000	70	0.46	0.556	0.066	0.0258
REpower MM92	80	3.43	0.444	0.490	0.1697
Suzlon S.88/2000	80	3.32	0.444	0.474	0.1631
Unison U93	80	3.6	0.444	0.514	0.1800
Vestas V90	80	1.34	0.444	0.191	0.0587

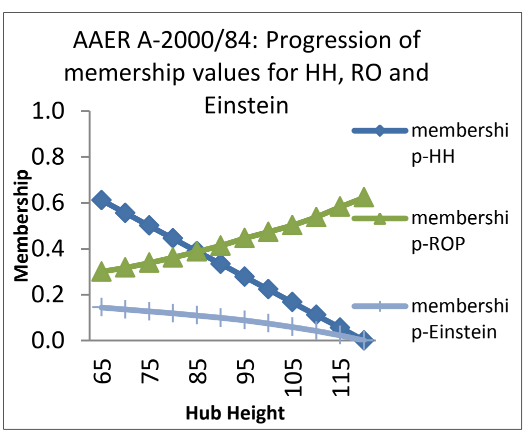

Figure 3. Membership plots for HH, RO, and E for AAER A-2000

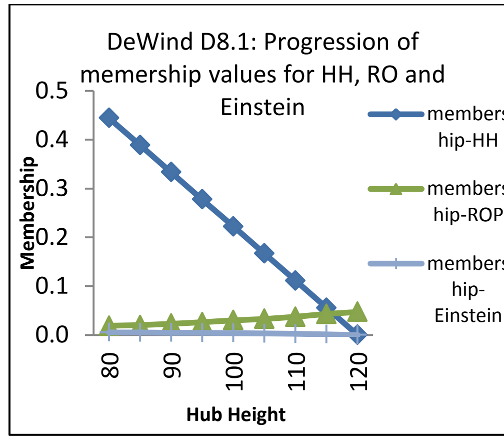

Figure 4. Membership plots for HH, RO, and DP for DeWind D8.1

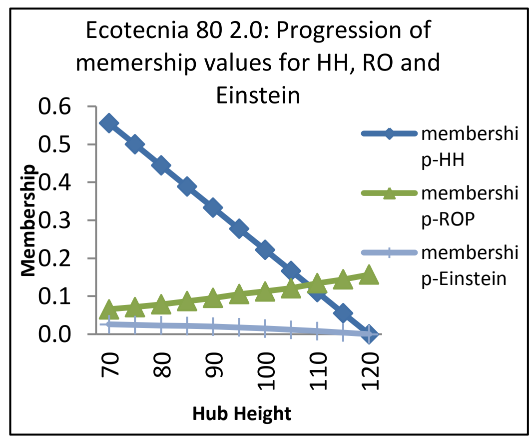

Figure 5. Membership plots for HH, RO, and DP for Nordex N54/1000

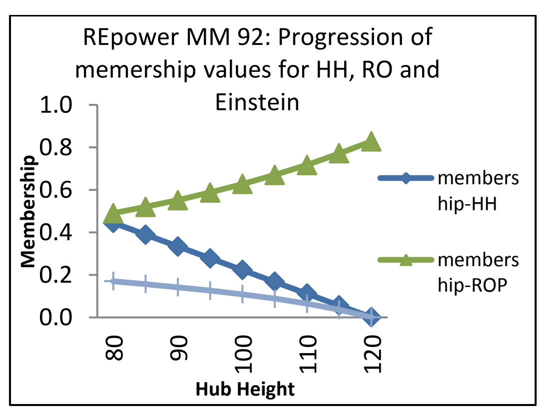

Figure 6. Membership plots for HH, RO, and DP for Suzlon S.62/1000

Figures 3 to 9 illustrates the behavior of μ_E as well as that of μ_{HH} and μ_{RO} for each turbine. With regard to μ_E, μ_{HH}, and $\mu_{RO,}$ similar patterns are observed for REpower MM92, Suzlon S.88/2000 and Unison U93 in Figures 6, 7, and 8 respectively,. These patterns confirm the comparable performance of the three turbines. Furthermore, the worst performance of DeWind D8.1 is also confirmed from Figure 4 which shows that μ_E stays near zero, and is almost insensitive to the values of μ_{HH} and μ_{RO}.

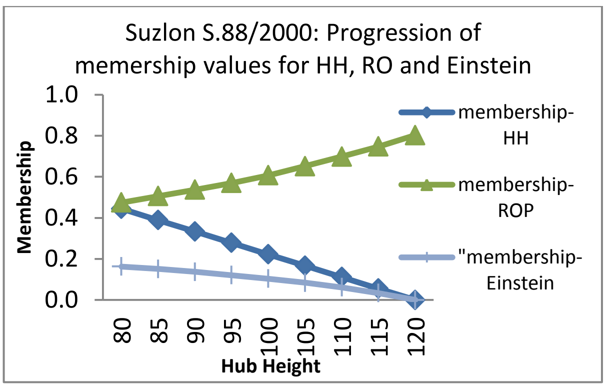

Figure 7. Membership plots for HH, RO, and DP for Suzlon S.62/1000

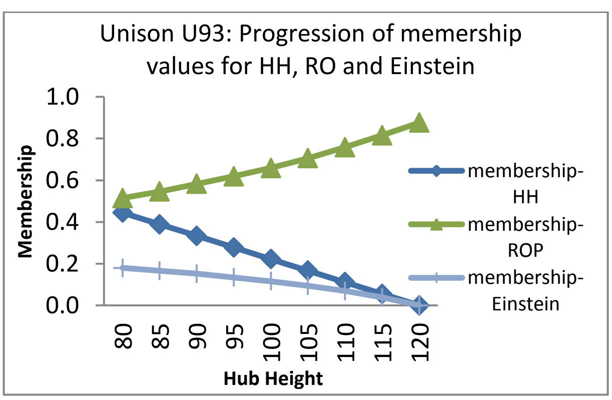

Figure 8. Membership plots for HH, RO, and DP for Suzlon S.62/1000

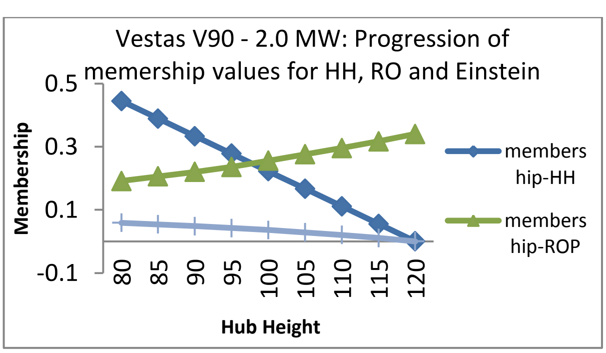

Figure 9. Membership plots for HH, RO, and DP for Suzlon S.62/1000

5. CONCLUSION

A fundamental requirement of an efficient wind farm design is deployment of appropriate turbines that suit the needs of the site. Selection of an appropriate wind turbine from many available choices is not an easy task and requires consideration of various factors in the decision-making process. Two key factors are hub height and rated output percentage. Hub height is related to the financial aspect of a turbine while rated output percentage governs the power generated by the turbine. This paper presented a fuzzy logic based multi-criteria decision-making approach, while utilizing the Einstein operator for the turbine selection problem. The proposed approach was applied to data collected from a real potential site. The effectiveness of the approach was analyzed through application on various turbines with nominal power of 2000 KW. According to the obtained results, Unison U93 turned out to be the best turbine, followed by REpower MM92 and Suzlon S.88/2000. Another noteworthy finding from the study was that for all turbines, the best balance between the hub height and rated output percentage was found when the lowest hub height for that particular turbine was considered, as evident from the μ_E values for each turbine.

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References

[1] S. A. Khan, "An automated decision-making approach for assortment of wind turbines – A case study of turbines in the range of 500 KW to 750 KW", International Journal of Computing & Network Technology, Vol 3., no. 2, pp. 75 - 81. May 2015.

[2] "Global wind energy Council (GWEC)," http://www.gwec.net/index.php?id=180 Accessed 25 Feb. 2015.

[3] S. A. Khan and S. Rehman, "On the Use of Unified And-Or Fuzzy Aggregation Operator for Multi-criteria Decision Making in Wind Farm Design Process Using Wind Turbines in 500 kW – 750 kW Range", IEEE International Conference on Fuzzy Systems, pp. 1-6, September 2012.

[4] S. A. Khan and S. Rehman, "On the use of Werners Fuzzy Aggregation Operator for Multi-Criteria Decision making in wind Farm Design Process using Wind Turbines in 1000kW-1200kW Range", Proceedings of International Clean Energy Conference, pp. 163-170, September 10-12, 2012. Canada

[5] J. Dombi. "A General Class of Fuzzy Operators: The De Morgan Class of Fuzzy Operators and Fuzziness Measures Induced by Fuzzy Operators", Fuzzy Sets and Systems, Vol. 8, pp. 149 -163, 1982.

[6] J. Dombi. "Basic Concepts for a Theory of Evaluation: The Aggregative Operator". European Journal of Operational Research, Vol 10, pp.282-293, 1982.

[7] H. Hamacher. "Ueber Logische Verknupfungen Unschalfer Aussagen und deren Zugehoerige Bewertungs-funktione". Progress in Cybernetics and Systems Research, Vol 3, pp. 276-288, 1978.

[8] M. Frank. "On the Simultaneous Associativity of F(x; y) and x + y - F(x; y)". Aequationes Mathematicae, Vol. 19, pp. 194 - 226, 1979.

[9] S. Weber. "A General Concept of Fuzzy Connectives, Negations and Implications Based on t-Norms and t-Conorms". Fuzzy Sets & Systems, Vol. 11, pp. 115-134, 1983.

[10] D. Dubois and H. Prade. "A Class of Fuzzy Measures Based on Triangular Norms". International Journal of General Systems, Vol. 8, pp. 105 -116, 1982.

[11] B. Schweizer and A. Sklar. "Associative Functions and Abstract Semigroups". Publicationes Mathematicae Debrecen, Vol. 10, pp. 69 - 81, 1963.

[12] L. A. Marks et al., "Multiple criteria decision making (MCDM) using fuzzy logic: an innovative approach to sustainable agriculture". IEEE Third International Symposium on Uncertainty Modeling and Analysis and Annual Conference of the North American Fuzzy Information Processing Society, pp.503-508, 1995.

[13] L. Zadeh, "Fuzzy Sets", Information and Control, Vol. 8, pp. 338-353, 1965.

[14] A. Barin et al., "Multicriteria decision making for management of storage energy technologies on renewable hybrid systems - the analytic hierarchy process and the fuzzy logic",in IEEE 6th International Conference on the European Energy Market, 2009, pp. 1 -6.

[15] S. A. Khan and Z. A. Baig, "On the use of Unifed And-Or fuzzy operator for distributed node exhaustion attack decision-making in wireless sensor networks", IEEE International Conference on Fuzzy Systems, pp. 1 – 7, 2010.

[16] D. Ruan et al., "Fuzzy Multi-criteria Group Decision Support in Long-term Options of Belgian Energy Policy", in IEEE Annual Meeting of the North American Fuzzy Information Processing Society, pp. 496-501, 2007,

[17] H. Zimmermann and H. Sebastian, "Intelligent system design support by fuzzy-multi-criteria decision making and/or evolutionary algorithms", IEEE International Conference on Fuzzy Systems, pp. 367-374, 1995.

[18] C. Lin, "New product portfolio selection using fuzzy logic", IEEE International Conference on Industrial Engineering Management, pp. 114- 118, 2007.

[19] M. Abdelbarr and S. A. Khan, "Design and analysis of a fault tolerant hybrid mobile scheme", Information Sciences, Vol. 177, No. 12, pp. 2602-2620, 2007.

[20] S. A. Khan and M. Abdelbarr, "On the use of fuzzy logic in a hybrid scheme for tolerating mobile support station failure", IEEE International Conference on Fuzzy Systems, pp. 717- 722, 2002.

[21] K. Sedki and V. Delcroix, "A hybrid approach for multi-criteria decision problems", IEEE Annual Meeting of the North American Fuzzy Information Processing Society, 2010, pp. 1-6.

[22] S. Moaven et al. "A Fuzzy Model for Solving Architecture Styles Selection Multi-Criteria Problem", Second UKSIM European Symposium on Computer Modeling and Simulation, pp. 388 – 393 , 2008.

[23] E. Shragowitz, J. Lee, and E. Kang, "Application of Fuzzy Logic in Computer-aided VLSI Design", IEEE Transactions on Fuzzy Systems, vol. 6, no. 1, pp. 163 - 172, 1998.

[24] H. Li and V. Yen, "Fuzzy Sets and Fuzzy Decision-Making". CRC Press, 1995

[25] S. A. Khan and A. P. Engelbrecht, "A New Fuzzy Operator and its Application to Topology Design of Distributed Local Area Networks", Information Sciences, vol. 177, no. 12, pp. 2692-2711, 2007

[26] B. Werners, "Aggregation models in mathematical programming" G. Mittra, H. Greenberg, F. Lootsma, M. Rijckaert, and H. Zimmerman (Eds.) Mathematical Models for Decision Support, Springer, Vol 48, pp. 295-305, 1988.

[27] J. Sarja and V. Halonen, "Wind Turbine Selection Criteria: A Customer Perspective", Journal of Energy and Power Engineering, Vol 7, pp. 1795-1802, 2013.

[28] S. Perkin, D. Garrett, and P. Jensson. "Optimal wind turbine selection methodology: A case-study for Búrfell, Iceland", Renewable Energy Vol. 75, pp. 165-172, 2015.

[29] C. Nemes and F. Munteanu. "Optimal Selection of Wind Turbine For a Specific Area", IEEE 12th International Conference on Optimization of Electrical and Electronic Equipment (OPTIM 2010), pp. 1224-1229, 2010.

[30] S. Chowdhury et al. "Optimizing the arrangement and the selection of turbines for wind farms subject to varying wind conditions", Renewable Energy, Vol. 52, pp. 273 – 282, 2013.

[31] M. Firuzabad, and A. Dobakhshari. "Reliability-based Selection of Wind Turbines for Large-Scale Wind Farms", World Academy of Science, Engineering and Technology, Vol. 49, pp. 734-740, 2009.

[32] S. Rehman et al. "Assessment of wind power, wind exponent, local air density and air turbulence intensity for an isolated site". International Journal of Sustainable Energy, Vol. 28, No. 4, pp. 217–230, 2009.

[33] http://www.thewindpower.net/turbine_en_108_aaer_a2000-84.php Accessed 15 February 2015

[34] http://en.wind-turbine-models.com/turbines/1010-dewind-d8 Accessed February 2015

[35] http://en.wind-turbine-models.com/turbines/572-ecot-cnia-eco-80-2000 Accessed February 2015

[36] http://www.thewindpower.net/turbine_en_15_repower_mm92.php Accessed February 2015

[37] http://en.wind-turbine-models.com/turbines/476-suzlon-s.88-2000 Accessed February 2015

[38] http://www.thewindpower.net/turbine_en_80_unison_u93.php Accessed February 2015

[39] https://www.vestas.com/en/products_and_services/turbines/v90-2_0_mw Accessed February 2015

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