



Multi-criteria Decision-making for Selection of Wind Turbine with Rated Power of 1000 KW using Dubois and Prade Fuzzy Operator

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Abstract: Wind energy is a promising alternative to fossil fuels for providing cheap and clean energy. One important issue in the study of wind energy harnessing is efficient design of wind farm. This design requires several objectives to be satisfied simultaneously. One objective is the selection of the turbine type that would be the most suitable choice for a specific wind farm site. The selection of an optimal turbine out of a number of different turbine types is complex task since a number of decision criteria need to be considered simultaneously. This decision requires consideration of best trade-off between the criteria such that all criteria are satisfied to the best possible extent. Two most important criteria in the decision process are hub height and rated output percentage. This paper addresses the issue of wind turbine type selection while considered the two aforementioned criteria while using fuzzy logic. The decision process is carried out using the Dubois and Prade's fuzzy aggregation operator. Results indicate that the Dubois and Prade's operator effectively finds the best turbine out of the given choices.

Keywords: Wind turbine, Automated decision-making, Fuzzy logic, Dubois and Prade Operator.

1. INTRODUCTION

The ever increasing demand for energy has resulted in fast depletion of fossil fuels, which has prompted energy producers to find out alternative sources of energy. Such sources include wind, solar photovoltaic, solar thermal, geothermal, biogas, tidal, wave, etc. which are available globally, both on-shore and off-shore [1]. The emergence wind and solar energy systems is one major step towards employing alternative energy resources. These alternative energy resources have already started to change the dependency on traditional fossil fuels. The renewable energy resources not only promise to provide cheap power, but are also environmental friendly, which is another important factor advocating their use.

Among the aforementioned alternative energy resources, wind energy, in particular, has received significant attention at a global scale. This interest lies in its economic and commercial feasibility, free availability, and eco-friendliness [1]. As reported in Global Wind Energy Council Report [2], the world's wind power capacity grew by has reached to 369,553 MW which is a considerable share of the total global power generation.

Although extraction of wind power is not a big challenge, it is a daunting task to manage the quality and throughput of wind power. This is caused by intermittent and fluctuating nature of wind speed. Numerous factors including time, location, and height above ground level (AGL) substantially contribute to the variation in wind speed. Wind speed measurements are typically taken at 10 meters AGL. However, the rotor of the wind turbines rests at a much higher altitude on towers (also known as hub). Hub height plays a crucial role in wind absorption. Higher hubs can absorb more power and vice versa. However, the hub height cannot exceed a certain level due to economical, installation, and maintenance issues and limitations. Thus, it is essential to have an accurate knowledge of optimal or near optimal hub height, so that maximum energy can be produced at an affordable cost and with easy maintenance and repair. In order to address the concerns related to quality of wind power, the rated energy output of the wind turbine should be maximized. This signifies that hub height and energy output are conflicting with each other since wind power is stronger at higher hub heights. Therefore, it is not possible to achieve improvement without negatively affecting the other. The most suitable solution to this is to find the best balance



between the two criteria, such that the best possible value of each criterion is found. This paper addresses this issue through multi-criteria decision-making (MCDM) using fuzzy logic. [1]

Different variants of the turbine selection problems have been reported in literature [3-7]. The foundations of the work reported in this paper are drawn from an earlier work [1] which formulated the underlying multi-criteria decision-making technique using fuzzy logic, while considering the Unified And-Or (UAO) [18] fuzzy aggregation operator. The current work assumes the same decision-making problems and attempts to solve it using the Dubois and Prade (DP) fuzzy operator.

The rest of this paper is organized as follows. Section 2 provides the details on fuzzy logic approach to multi-criteria wind turbine selection problem while considering the DP operator as the decision function. This is followed by results and discussion in Section 3. Conclusions are given in Section 4.

2. FUZZY LOGIC BASED MULTI-CRITERIA DECISION-MAKING FOR WIND TURBINE SELECTION

During the design phase of a wind farm, several issues need to be considered for efficient design that would generate maximum energy at minimum possible cost. Energy maximization depends on several factors, one of which is rated output percentage (ROP). Rated output percentage refers to the duration of time during the year for which the wind turbine generates power at its maximum rated capacity. Thus, ROP requires maximization. On the other hand, cost needs to be minimized. One major contributing factor is the cost of the hub on which the turbine is mounted. 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%. Therefore, it is desired to keep this height as low as possible.

It can be easily perceived that increasing hub height should also increase ROP, since at a higher altitude, more wind is available, resulting in more absorption by the turbine. However, higher altitude means higher hub height, resulting in more cost. Therefore, it is not possible to simultaneously optimize hub height and ROP. A suitable approach in this scenario is find the best balance between the two factors, so as to satisfy both criteria to the best possible extent. This can conveniently be done with multiple criteria decision-making (MCDM) using fuzzy logic.

In multiple criteria decision making (MCDM) problems, decisions need to be made in presence of multiple and conflicting criteria [9]. The concept of MCDM comes from the field of decision sciences, where, in many cases, decisions need to be made about selecting

the best solution from a set of available feasible solutions. In majority of MCDM problems, the data associated with criteria are non-commensurate due to different units and magnitudes. Fuzzy logic [8] is one approach that has been effectively used to solve a number of MCDM problems involving these issues [9-18].

To apply fuzzy logic to MCDM problems, criteria need to be combined to form an overall decision function through mathematical representation. This mathematical decision function generates answers in form of a scalar value. A primary concern in this process is what should be the structure of this mathematical function that represents the true insight of the decision problem being studied. There is a wide variety of fuzzy functions available, and it is a difficult task to choose the most appropriate function. Usually, the objective in MCDM problems is to satisfy all criteria simultaneously, resulting in the “pure ANDing” operation. One such function is the Dubois and Prade (DP) operator.

A. Dubois and Prade Operator for the underlying problem

To employ the DP operator for the proposed problem, two linguistic variables, namely, “Hub Height” and “Rated Output Percentage” are defined. Our interest is in the terms “low hub height” and “high rated output”. Since the two criteria conflict with each other, the objective is to find the optimal ratio that provides the best balance between the hub height and rated output percentage. For this purpose, the following fuzzy rule is defined.

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

In the above rule, X refers to a combination that has resulted due to a certain value of rated output percentage and its corresponding hub height. The terms “low hub height”, “high rated output”, 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 hub heights. Each fuzzy subset is defined by a membership function μ . The membership function maps to 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 DP operator as follows:

$$\mu(x) = \frac{\mu_{RO}\mu_{HH}}{\max(\mu_{RO}, \mu_{HH}, \beta)} \quad (1)$$

where $\mu(x)$ is the membership value for combination x in the fuzzy set *good combination*. Furthermore, μ_{RO} and μ_{HH} denote the membership values of rated output percentage and hub height for combination x in the fuzzy sets *low hub height* and *high rated output percentage*

respectively. The solution which results in the maximum value for (1) is reported as the best solution found.

B. Membership functions for rated output percentage and hub height

The membership functions for the two criteria are found as follows. For RPO, the upper and lower limits for rated output need to be defined. From the available data, it is observed that the rated output varies between 0.12% and 4.35%. Therefore, to accommodate this range, the lower limit, “RMin”, is taken as 0.0% whereas the upper limit, “RMax”, is defined as 5%. The corresponding membership function is shown in Figure 1, where *x-axis* represents the rated output percentage and the *y-axis* represents the membership value.

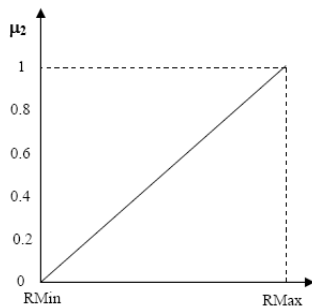


Figure 1. Membership function for rated output percentage

The membership function for hub height can be determined in the same manner as above through finding the upper and lower limits. In real wind farm designs, the hub height generally varies between 40 m and 120 m. Therefore, the lower limit, “HMin” is defined as 30m while upper limit, “HMax” is defined as 120m. The corresponding membership function is shown in Figure 2, where the *x-axis* represents the hub height and the *y-axis* represents the membership value.

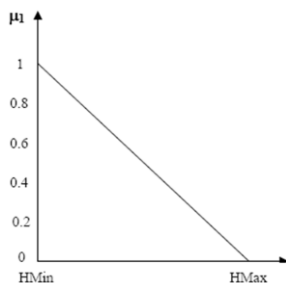


Figure 2. Membership function for hub height

3. RESULTS AND DISCUSSION

The study was done on an experimental site near the eastern part of Saudi Arabia. Data spanning a period of almost five years was gathered. The collected data was

first filtered and relevant useful information was extracted which was the rated output percentage measured with a step size of 5 meters. The data was then submitted to a software program exclusively developed to perform the multi-criteria decision-making calculations and provided the fuzzified output. For each set of data associated with a specific turbine, the combination which generated the highest fuzzified value was chosen as the best tradeoff solution. Four different turbine types with rated power of 1000 KW were used in the study. Technical specifications of these turbines are listed in Table 1.

TABLE I. TECHNICAL SPECIFICATIONS OF THE WIND TURBINES

Turbine	Rotor Diameter (m)	Cut-in Wind Speed (m/s)	Rated Wind Speed (m/s)	Rated Power (kW)
AAER A-1000	58	4	12	1000
Mitsubishi MWT62-1000	61.2	3.5	12.5	1000
Nordex N54/1000	54	3.75	14	1000
Suzlon S.61/1000	62	3	12	1000

Tables II to V show the results for the four turbines used in the study. In each table, columns 1 and 2 represent the Hub Height and Rated Output Percentage, respectively. Columns 3 and 4 give the individual membership values for the two criteria as μ_{HH} for Hub Height, and μ_{RO} for Rated Output percentage, respectively. The overall membership value obtained through aggregation using the DP operator is given in the last column of each table and is denoted by μ_{DP} . In these tables, note that the measurements of ROP were taken starting from a minimum hub height applicable to that turbine and relative to the rotor diameter. For example, AAER A-1000 has a rotor diameter of 58 meters. Therefore, for this turbine, measurements were taken starting with hub height of at least 60 meters. With the same approach, minimum hub heights for other three turbines were taken accordingly.

It is observed from Tables II to V that for three turbines, namely, AAER A-1000, Mitsubishi MWT62-1000, and Suzlon S.61/1000, the best overall membership values (given in boldface in the tables) are associated with the lowest hub height applicable to that turbine. This indicates that, in general, the performance of a specific turbine in terms of ROP is better at low hub heights than those at high hub heights. However, there was an exception from the above trend in case of Nordex N54/1000 where the best results were obtained at a mid-level hub height of 75 meters.



TABLE II. RESULTS FOR AAER-A 1000. HH = HUB HEIGHT, RO = RATED OUTPUT, μ_{HH} = HH MEMBERSHIP, μ_{RO} = RO MEMBERSHIP, μ_{DP} = OVERALL MEMBERSHIP USING DUBOIS AND PRADE OPERATOR. BEST OVERALL MEMBERSHIP IS IN BOLD.

HH	RO	μ_{HH}	μ_{RO}	μ_{DP}
60	1.95	0.667	0.390	0.2600
65	2.09	0.611	0.418	0.2554
70	2.21	0.556	0.442	0.2456
75	2.36	0.500	0.472	0.2360
80	2.52	0.444	0.504	0.2240
85	2.7	0.389	0.540	0.2100
90	2.89	0.333	0.578	0.1927
95	3.11	0.278	0.622	0.1728
100	3.3	0.222	0.660	0.1467
105	3.5	0.167	0.700	0.1167
110	3.75	0.111	0.750	0.0833
115	4.06	0.056	0.812	0.0451
120	4.35	0.000	0.870	0.0000

TABLE III. RESULTS FOR MITSUBISHI MWT62-1000. HH = HUB HEIGHT, RO = RATED OUTPUT, μ_{HH} = HH MEMBERSHIP, μ_{RO} = RO MEMBERSHIP, μ_{DP} = OVERALL MEMBERSHIP USING DUBOIS AND PRADE OPERATOR. BEST OVERALL MEMBERSHIP IS IN BOLD.

HH	RO	μ_{HH}	μ_{RO}	μ_{DP}
65	1.5	0.611	0.300	0.1833
70	1.63	0.556	0.326	0.1811
75	1.75	0.500	0.350	0.1750
80	1.86	0.444	0.372	0.1653
85	2	0.389	0.400	0.1556
90	2.14	0.333	0.428	0.1427
95	2.28	0.278	0.456	0.1267
100	2.43	0.222	0.486	0.1080
105	2.6	0.167	0.520	0.0867
110	2.78	0.111	0.556	0.0618
115	2.95	0.056	0.590	0.0328
120	3.17	0.000	0.634	0.0000

TABLE IV. RESULTS FOR NORDEX N54/1000. HH = HUB HEIGHT, RO = RATED OUTPUT, μ_{HH} = HH MEMBERSHIP, μ_{RO} = RO MEMBERSHIP, μ_{DP} = OVERALL MEMBERSHIP USING DUBOIS AND PRADE OPERATOR. BEST OVERALL MEMBERSHIP IS IN BOLD.

HH	RO	μ_{HH}	μ_{RO}	μ_{DP}
55	0.21	0.722	0.042	0.0303
60	0.25	0.667	0.050	0.0333
65	0.28	0.611	0.056	0.0342
70	0.33	0.556	0.066	0.0367
75	0.37	0.500	0.074	0.0370
80	0.4	0.444	0.080	0.0356
85	0.45	0.389	0.090	0.0350
90	0.51	0.333	0.102	0.0340
95	0.56	0.278	0.112	0.0311
100	0.62	0.222	0.124	0.0276
105	0.67	0.167	0.134	0.0223
110	0.72	0.111	0.144	0.0160
115	0.81	0.056	0.162	0.0090
120	0.89	0.000	0.178	0.0000

TABLE V. RESULTS FOR SUZLONS. 61/1000. HH = HUB HEIGHT, RO = RATED OUTPUT, μ_{HH} = HH MEMBERSHIP, μ_{RO} = RO MEMBERSHIP, μ_{DP} = OVERALL MEMBERSHIP USING DUBOIS AND PRADE OPERATOR. BEST OVERALL MEMBERSHIP IS IN BOLD.

HH	RO	μ_{HH}	μ_{RO}	μ_{DP}
65	2.08	0.611	0.416	0.2542
70	2.2	0.556	0.440	0.2444
75	2.35	0.500	0.470	0.2350
80	2.51	0.444	0.502	0.2231
85	2.68	0.389	0.536	0.2084
90	2.88	0.333	0.576	0.1920
95	3.09	0.278	0.618	0.1717
100	3.29	0.222	0.658	0.1462
105	3.49	0.167	0.698	0.1163
110	3.74	0.111	0.748	0.0831
115	4.03	0.056	0.806	0.0448
120	4.33	0.000	0.866	0.0000



TABLE VI. BEST RESULTS FOR EACH TURBINE

Turbine	Rated power (KW)	HH	RO	μ_{HH}	μ_{RO}	μ_{DP}
AAER A-1000	1000	60	1.95	0.667	0.390	0.2600
Mitsubishi MWT62-1000	1000	65	1.5	0.611	0.300	0.1833
Nordex N54/1000	1000	75	0.37	0.500	0.074	0.0370
Suzlon S.61/1000	1000	65	2.08	0.611	0.416	0.2542

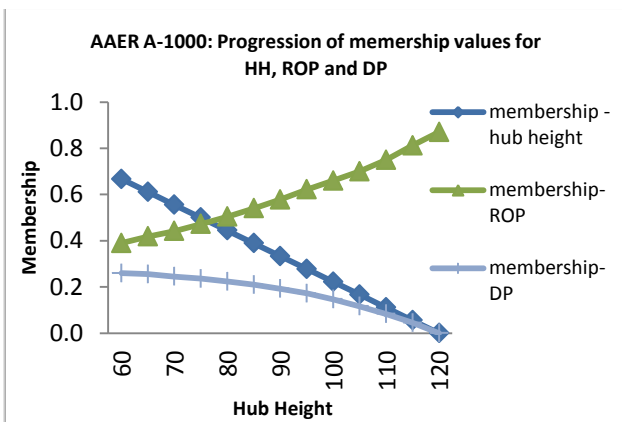


Figure 3. Membership plots for HH, RO, and DP for AAER A-1000

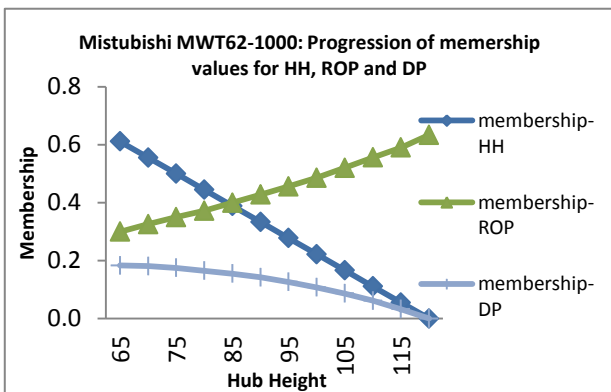


Figure 4. Membership plots for HH, RO, and DP for Mitsubishi MWT 62 -1000

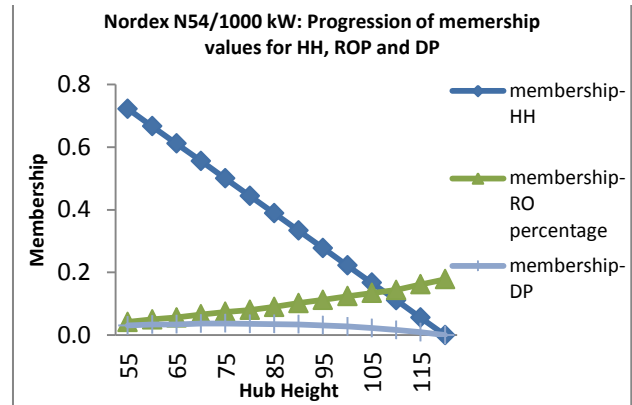


Figure 5. Membership plots for HH, RO, and DP for Nordex N54/1000

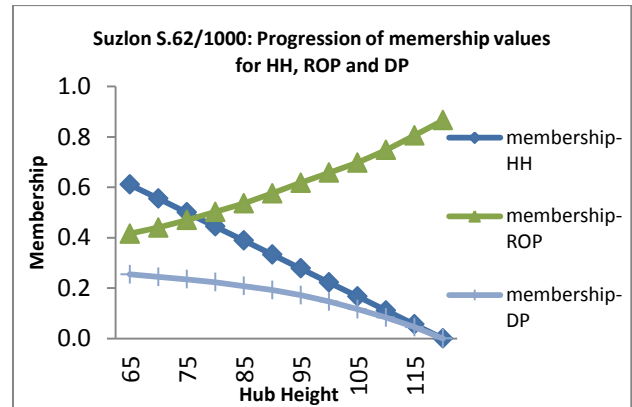


Figure 6. Membership plots for HH, RO, and DP for Suzlon S.62/1000

Figures 3 to 6 display the behavior of the overall membership (μ_{DP}), along with membership of μ_{HH} and μ_{RO} for each turbine. The figures show that the behavior for AAER A-1000, Mitsubishi MWT 62-1000, and Suzlon S.62/1000 have more or less the same behavior of μ_{DP} with respect to μ_{HH} and μ_{RO} . In contrast, Nordex N54/1000 shows a different behavior for the three membership values.

4. CONCLUSION

An important phase in the design of wind farms is the selection of appropriate turbine that suits the landscape and wind conditions of that site. Two factors that contribute heavily in this selection are the Hub Height and Rated Output Percentage. These parameters play a vital role in the decision making process. This paper presented a decision-making approach based on fuzzy logic to select the most suitable turbine out of many available options. Data was collected from a real site.

The two criteria were aggregated into a scalar decision function using Dubois and Prade fuzzy operator. The effectiveness of the approach was validated through application on various turbines with rated output of 1000 KW. Results suggested that AAER A-1000 had the best performance, with Suzlon S.61/1000 being a strong alternative. Another important finding from the study was that, in general, the best balance between the hub height and percentage of rated power output was found when the lowest hub height for that particular turbine was considered.

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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 and Network Technology*, Vol. 3, No.2, May 2015.
- [2] 'Global Wind Energy Council (GWEC)," <http://www.gwec.net/index.php?id=180> Access Feb. 2015.
- [3] S. Perkin, D. Garrett, P. Jensson. Optimal wind turbine selection methodology: A case-study for Búrfell, Iceland, *Renewable Energy* 75: 165-172, Elsevier, 2015.
- [4] C. Nemes and F. Munteanu. Optimal Selection of Wind Turbine For a Specific Area, In proceeding of IEEE 12th International Conference on Optimization of Electrical and Electronic Equipment (OPTIM 2010), pp. 1224-1229, 2010.
- [5] S. Chowdhury, J. Zhang, A. Messac, L. Castillo. Optimizing the arrangement and the selection of turbines for wind farms subject to varying wind conditions, *Renewable Energy*, Vol. 52, pp. 273 – 282, 2013.
- [6] 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.
- [7] Salman A. Khan and Shafiqur Rehman. On the Use of Werners Fuzzy Aggregation Operator for Multi-criteria Decision Making in Wind Farm Design Process Using Wind Turbines in 1000 KW - 1200 KW Range, In proceedings of 2012 International Conference on Clean Energy, Canada, 2012.
- [8] L. Zadeh, "Fuzzy Sets", *Information and Control.*, vol. 8, pp. 338-353, 1965.
- [9] A. Barin, L. N., K. Magnago, A. da Rosa Abaide, and B. Wottrich, "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.
- [10] Salman. A. Khan and Zubair A. Baig, "On the use of Uni_ed And-Or fuzzy operator for distributed node exhaustion attack decision-making in wireless sensor networks" in IEEE International Conference on Fuzzy Systems, 2010, pp. 1 - 7.
- [11] D. Ruan, J. Lu, E. Laes, G. Zhang, F. Wu, and F. Hardeman, "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, 2007, pp. 496-501.
- [12] H. Zimmermann and H. Sebastian, "Intelligent system design support by fuzzy-multi-criteria decision making and/or evolutionary algorithms", in IEEE International Conference on Fuzzy Systems, 1995, pp. 367-374.
- [13] C. Lin, "New product portfolio selection using fuzzy logic", IEEE International Conference on Industrial Engineering Management, 2007, pp. 114- 118.
- [14] M. Abdelbarr and Salman. A. Khan, "Design and analysis of a fault tolerant hybrid mobile scheme", *Information Sciences*, vol. 177, no. 12, pp. 2602-2620, 2007.
- [15] Salman. A. Khan and M. Abdelbarr, "On the use of fuzzy logic in a hybrid scheme for tolerating mobile support station failure", in IEEE International Conference on Fuzzy Systems, 2002, pp. 717- 722.
- [16] K. Sedki and V. Delcroix, "A hybrid approach for multi-criteria decision problems", in IEEE Annual Meeting of the North American Fuzzy Information Processing Society, 2010, pp. 1-6.
- [17] S. Moaven, J. Habibi, H. Ahmadi, and A. Kamandi, "A Fuzzy Model for Solving Architecture Styles Selection Multi-Criteria Problem", in Second UKSIM European Symposium on Computer Modeling and Simulation, 2008, pp. 388 - 393.
- [18] 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.



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