RESEARCH ARTICLE OPEN ACCESS

# Sustainable Energy Farm Location: A case study considering Wind Farm

Tapaswini Routray[1], Chakradhar Karan[2], Gangadhar Das[3], Sujata Singh[4]

[1,3,4]*Assistant Professor, Department of Electrical Engineering, Gandhi Institute for Technology, Bhubaneswar, India*

[2]*Assistant Professor, Department of Electrical & Electronics Engineering, Gandhi Engineering College, Bhubaneswar, India*

**ABSTRACT:** Wind farm siting can be considered as Multi Criteria Decision Making (MCDM) problem that consists of set of alternative locations and set of selection criteria. This study applied multi-criteria decision making approach using Analytical Hierarchy Process with Ordered Weigh Averaging AHP-OWA aggregation function to derive wind farm land suitability index and classification under Geographical Information System(GIS)environment.Linguisticquantifier'sversionofAHP-OWAaggregationfunctionwasusedto classify lands based on their suitability for wind farm installation. Different selection criteria were considered including economical (distance to road, terrain slope), social (urban area), environmental (historical locations, wildlife and natural reserves) and technical (wind power density, energy demand matching, percentage of sustainable wind, turbulence intensity, sand dunes). A case study of the proposedapproachisimplementedandpresentedforOman.

## INTRODUCTION

In general, decision making is considered as a process for selecting one alternative from a group of other alternatives which involve uncertainties about their outcomes with respect to certain considerations such as economical, environmental, social and technical [1] through aggregated scores [2].

Depending on the degree of the optimism of the decision maker, the best alternative is then selected based on its degree of satis- faction with the decision criteria. The most commonly used aggregationoperatorsare'AND'(satisfactionofallcriteria)and'OR' (satisfaction of any criteria) operators, which are used to represent two extremes. However, in some cases, decision makers may want to perform an aggregation which lies in between these two extreme cases. The Ordered Weighted Average (OWA) and Analytical Hier- archy Process (AHP) are two approaches that provide weighted summation procedure [3]. The derived weights are used to rank the alternatives based on their degree of satisfaction to the decision criteria in a way that satisfaction degree lies in between these two extreme cases "AND" and"OR".

Recently, an extension of AHP aggregation function was intro- duced in Ref. [4]using OWA operator with fuzzy logic linguistic quantifier [4]. An implementation of this extension (AHP-OWA combination) was presented in Ref. [5] under GIS environment. It each criterion as exclusion zone, less suitable, suitable, moderate suitable, highly suitable or extremely suitable. Weights are then calculated using the pairwise matrix.

GIS-based environmental assessment of wind energy system was presented in Ref. [13]. Potential environmental criteria of wind assessment were identified according to the Turkish legislation and previous studies. Based on the Turkish wind maps, areas with low potential were excluded initially and then linguistic quantifier guided OWA was used to calculate the suitability index based on the environmentalcriteria.

Withrespecttotheaggregationfunction,itcanbeseenthatsimple aggregation function was used in Refs. [10,11]. More advanced ones were used in Refs. [12,13]. With respect to the evaluation criteria, mostlysocial,environmentalandeconomicalrelated criteriawere [illegible]

include technical aspects which affect the wind farm output such as energy demand matching, percentage of sustainable wind and turbulence intensity. Furthermore the analysis was based on wind speeddataanddidnotconsiderthewindpowerdensity distribution. Wind power which considers the variation in air density is more informative and representative for wind energyanalysis.

The main objective of this paper is to use the new aggregation operator extension (AHP-OWA combination) for wind farm land suitability indexing compared to the aggregation functions used in

the literature. With respect to the selection criteria additional

power density distribution, energy demand matching, percentage of sustainable wind and turbulence intensity are included as selection criteria. The multi-criteria approach using (AHP-OWA) operator is implemented under GIS environment as a case study of wind energy forOman.

The rest of the paper is organized as follow: Section 2 reviews the AHP and OWA aggregation functions; Section 3presents the proposed methodology and procedure; Section 4discusses the results and Section 5 concludes thepaper.

the intensity of the importance of one element with respect to another element is subject to expert's judgment.

After calculating the weight at each level of the hierarchy (i.e. objectives, criteria), then the global weight of each criterion can be calculated by means of sequence of multiplications of matrices of relative weights at each level of the hierarchy. The global weight of a criterion $j$ ($w^g_j$) is the results of multiplying its own weight by the weight ofthe objective which belong to:

$$w^g_j = w_q \times w_{j(q)} \quad (1)$$

Finally, the overall score $R_i$ of the $i$th alternative is defined as the summation of the product of weight of each criterion by the performance of the alternative with respect to that criterion.

$$R_i = \sum_{j=1}^{n} w^g_j x_{ij} \quad (2)$$

*2.2. Ordered weighted averaging (OWA)*

OWAisafamilyormulticriteriacombinationprocedureintro- duced by Yager [14]in 1988. An aggregation operator $F: I^n \to I$ is calledorderedweightedaveragingoperatorofdimension$n$ifithasaweightingvector $W = \{w_1, w_2, \ldots, w_n\}$ suchthat

$w_i \in [0;1]$ and $\sum w_i = 1$ and:

1. Aggregationmethods

1.1. *Analytical hierarchy process(AHP)*

AHP was introduced by Saaty in 1980 [6]based on linear

$$F(a_1; a_2; \ldots; a_n) = \sum^n w_j b_j \quad (3)$$

where $b_j$ is the $j$th largest of $a_i$.

A key step of this aggregation is the re-ordering of arguments $x_i$ in descending order so that the weights $w_i$ is associated with the ordered position of the argument. Different OWA operators are distinguished by their weighting functions that can be expressed by its "*orness*"

weighted average model for complex decision makingproblems. AHP structure the decision making problem into hierarchical

framework [5]. The overall goal is broken down into set of objec-tives,criteriaandalternatives.Asetof$m$alternatives denotedby$A_i$for$i = 1,2, \ldots, m$areevaluatedwithrespecttto$p$objectives$O_q$for $q = 1,2, \ldots, p$.Theobjectivesaremeasuredintermoftheirattributes (criteria).Thesetof$n$criteriaisdenotedby$C_j$for$j = 1,2, \ldots, n$.Asubset of the criteria associated with $q$th objective can be defined anddenotedby$C_{j(q)}$for$k = 1,2, \ldots, l; l \leq n$. The importance of the objectives is defined by the set of weights set of weights

$W_q$¼($w_1$,$w_2$, … ,$w_p$).Theweightshavethefollowingproperties:

$w$ 0 1 and $w$ 1. Similarly, the importance of thecriteria $q$ ¼1

for objective $q$ is defined by the set of weights $W_{k(q)}$ ¼ ($w_{1(q)}$, $w_{2(q)}$,

… ,$w_{l(q)}$)with $wk\check{o}q$Þ ∈ [0;1]and $wk\check{o}q$Þ¼1.

Theperformanceofalternatives$A_i$withrespecttocriteria$C_j$is describedbyasetofcriteriavalues$X$¼[$x_{ij}$];$x_{ij}$ ∈ [0;1]for$i$¼1,2, … , $m$and$j$1,2, … ,$n$.

The required weights at each level can be derived through the use of pairwise comparison approach. Once the pairwise matrix of the level is constructed, the weights can be derived by calculating the eigenvector associated with the maximum eigenvalue of the pairwise matrix. Saaty [9]demonstrated mathematically that the eigenvector solution was the best approach. It is worth notice that

measure which measures the degree to which the aggregation is like '*or*' operation.

The OWA aggregation defined by Eq. (3), doesn't include any information regarding the importance of the criteria, therefore anotherfamilymemberofOWAofalternative$i$canbe defined[14,15]:

$$\mathrm{OWA}_i ¼ \sum_{j¼1}^{n} \frac{u_j w_j}{\sum_{j¼1}^{n} u_j} z_{ij} \qquad (4)$$

thesetoforderedcriterionweightsand$z_i$($z_{i1}$, … $z_{ij}$)isthe sequence obtained by reordering the attributes or alternative $i$ for each criterion $j$.

It is important to differentiate between two types of weights (criterion weights and order weights) [16]. Criterion weights are assigned to indicate the importance of each criterion. Therefore all alternatives are assigned the same weight on the $j$th criterion. On the other hand, order weights are associated with criterion value for each alternative. Therefore, the $i$th ordered weight (decreasing) isassignedtothe$i$thalternativeforallcriteria.

Different approaches have been proposed to generate the ordered weights. Constrained nonlinear optimization approach was suggested by[17e21].

In Ref. [22], Yager introduced a new method to obtain the OWA weightsusingfuzzylinguisticquantifiers.RegularIncreasingMono-tone(RIM)identifierswasproposedbyYager[22]andmostlyused [16] for generating OWA weights. One family members of RIM is:

$$Q\,\check{o}p\text{Þ} ¼ p^{a};a>0 \qquad (5)$$

which represent a fuzzy set of interval [0, 1] and the parameter a represent the degree of the optimism of the design maker as shown in Table 1[16,23].

Table 1
RIM quantifier for different values of a

| a | Quantifier(Q) | Optimisticsituation |
|---|---|---|
| a→0 | Atleastone | Optimism |
| a¼0.5 | Few | |
| a¼0.7 | Some | |
| a¼1 | Half(identity) | Neutral |
| a¼1.5 | Many | Pessimism |
| a¼2 | Most | |
| a→N | All | |

Thus, OWA is redefined using RIM as:

$$¼ \sum_{j¼1}^{n} \left( \sum_{k¼1}^{j} u_k - \sum_{k¼1}^{j-1} u_k \right) z_{ij}$$

2. Modelingapproach

Theprocedureconsistsofdatapreparationandthenprocessingin Geographical Information System (GIS). The required data include different factors such as physical, socio-economic, technical and environmental. For data processing to evaluate the land suitability, different parameters are considered, namely wind power density at different heights above the ground, distance to road, urban area, sand dunes, wind speed occurrence and turbulence intensity.These parameters are first normalized then processed according to maxi- mization or minimization criteria with assigned weights.

*2.1. PreparationofGISdataforOmancasestudy*

*2.1.1 Wind power density(WPD)*

Using wind power density as selection criteria is more informative than using wind speed data only. WPD considers the air density variation which impacts the power output of the wind turbine. WPD data for Oman was generated from Numerical Weather Prediction (NWP) models using nested ensemble approach [24], which reduces the uncertainty of the NWP models. COSMO [24,25] model at 2.8 km resolution was used to generate WPD data for different heights above the ground namely 50 m, 80 m, 100 m and 150 m. Fig. 1(a) shows the normalizedscoresforWPDat50mabove the ground.Thisisamaxi- mization criterion. Therefore, areas with higher power density gets higher scores. This criterion represents one GIS layer called"WPD".

*3.1.2. Wind speed occurrence (WSO)*

Itisimportantforthedailywindfarmoperationtoanaly zethe

typical cut-in (5 m/s) and cut-off (20 m/s) wind speeds [26]. WSO data is calculated from the COSMO model output for two wind

classes. Wind speed class between 5 m/s and 20 m/s and wind speed class 20 m/s are considered as two different criteria called WSO_GTE05 and WSO_GTE_20 respectively. Wind speed occur- rence between 5 m/s and 20 m/s is considered as a maximization criterion. Therefore, areas with high occurrence of this wind speed class gets higher scores. On the other hand, areas with high occurrence of wind class 20 m/s get low scores. Fig. 1(b) and (c) show the normalized scores for WSO_GTE05 and WSO_GTE_20 layers respectively at 50 m above the ground.

*3.1.3. Turbulenceintensity*

High turbulence intensity can affect the power output of windturbines [26,27]. Therefore, turbulence intensity is considered as a minimization criterion and is used as a GIS criterion layer called "TI". Turbulence intensity data is also calculated from the COSMO model output. Fig. 1(d) shows the normalized scores for turbulence intensity layer at 50 m above theground.

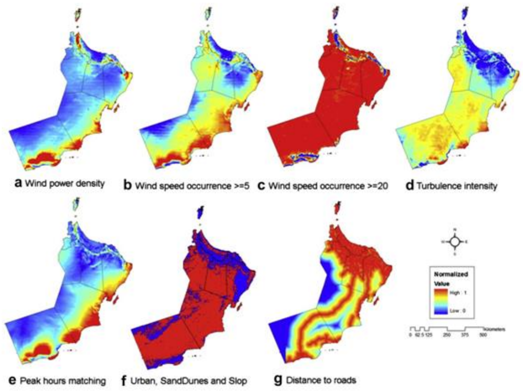


Fig. 1. Normalized criteria scores as GIS layers

*3.1.4. Load power demand peak hoursmatching*

Due to the seasonal climatology of Oman, higher load power demand is normally experienced during summer. Peak hours are typically between 3pm and 5pm and again between 11pm and 4am during summer [28]. The higher the wind speed during the peak hours, the higher the power generation from the wind turbine. Therefore, peak hours matching is a maximization criterion. Areas with higher mean wind speed during the peak hours get the higher scores. Fig. 1(e) shows the normalized scores for the mean wind speed during the peak hours at 50 m above the ground. Thus, the mean wind speed during the peak hours is also considered as one GIS criterion layer.

*3.1.5. Sanddunes*

It was shown experimentally [29]that dust can affect the performance of wind turbine by increasing the blades surface roughness. Oman has sand dunes especially in Al-Sharqiyah region and Empty Quarter desert, where, sand and dust storms are re- ported during windy days. Therefore, a buffer of 1 km exclusion zone is created around sand dunes.

316. *Terrainslope*

According to the technical questionnaire in Ref. [10], the maximum grade slope of the terrain should not exceed 10%. Beside the accessibility issues, sharp changes in slopes can also cause turbulences. Therefore, area with slope greater than 10% are excluded. The slope information are generated by surface analysis of Oman Digital Elevation Model (DEM) at 40 m resolution.

317. *Urban and sensitiveareas*

Due to the noise and vibration generated from wind turbines it is important to ensure that wind farms are located outside the residential area. In addition, wind turbines are known to cause bird mortality especially during migration seasons. Since Oman has a variety of birds and wildlife species in certain regions classified as protected and natural reserves, it is important to avoid these regions. Therefore, a 2 km [10] exclusion buffer is created around the urban and sensitive areas. In order to reduce the complexity of the problem, it is important to minimize the number of criteria by merging some of them together. Therefore, urban and sensitive areas, sand dunes and terrain

slope data are merged to create anew GIS layer called "Urban_Sand_Slope". Areas inside the exclusion bufferaregivenavalueof"0"andareasoutsidetheexclusionbuffer

are given a value of "1" as shown in Fig. 1(f). Note that the Urban_Sand_Slope criterion is a maximization criterion which means that areas far from exclusion zones get higher scores.

318. *Distance toroads*

Duetoaccessibilityandeconomicalconsiderations,thedistance- to-roads is considered also as a criterion in this land suitability study.InRef.[10],itwassuggestedthatsuitablelocationsshouldnot exceed10kmfromtheroads.Ontheotherhand,itwas suggested [12]thatthesiteshouldnotbelocatedwithin500m distancefrom the road for safety consideration. Hence, distance-to-roads is consideredtobeaminimizationcriterioninthisstudy.Thecloser thedistancetoroads,thehigherthescoreitgets.Fig.1(g)showsthe normalized scores for the distance-to-roadslayer.

AfterpreparingallrequiredGIScriterionlayers,thenextstepis to aggregate and process these layers using the multi-criteria analysis approach definedbelow

2.2. AHP-OWAaggregation

landforwindfarminstallationinOman.Forthat,twoobjectivesare considered namely technical objective and combined Social, Economical and Environmental (Soci-Econ-Env) objective. The technical objective is measured in term of five criteria: (i) wind power density, (ii) peak hours matching, (iii) wind occurrence of wind class between 5 m/s and 20 m/s, (iv) turbulence intensityand
(v) wind occurrence of wind class 20 m/s. The Soci-Econ-Env objective is measured in term of two criteria: (i) urban, sand and terrain slope, and (ii) distance to road. The GIS-based AHP-OWA operator structure is shown in Fig. 2.

To achieve the final goal, it is required to assign the relative importance (weights) for the objectives and criteria levels of the hierarchy. At the objectives level, it is judged that the technical objective is six times more important than the Soci-Econ-Env objective. This judgment is made based on the fact that wind power is much more important than the other criteria for Oman. Table 2shows the pairwise comparison matrix for the objectives level and the calculatedweights.

The Soci-Econ-Env objective is measured by two criteria. It is judged that protecting urban area which includes (residential, historical, natural, wildlife) locations is five times more important than being close to the roads.

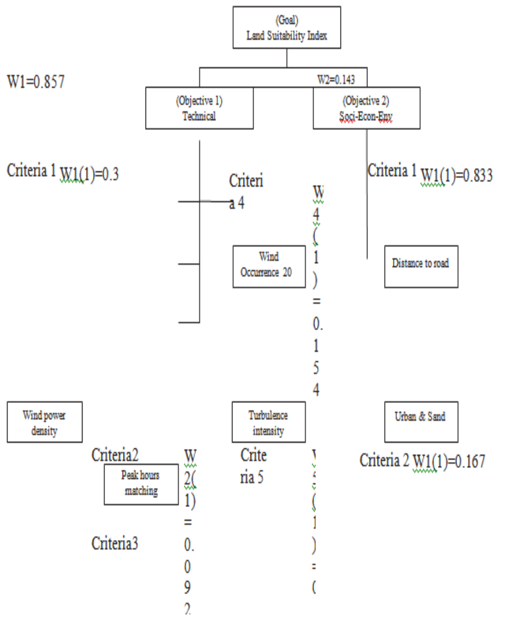


**Fig. 2.** GIS-based AHP-OWA operator structure.

Table 2 Pairwise comparison matrix for the objectives level and the calculated weights.

| | Technical | Soci-Econ-Env | Weight |
|---|---|---|---|
| Technical | 1 | 6 | 0.857 |
| Soci-Econ-Env | 0.167 | 1 | 0.143 |

Table 3
Pairwise comparison matrix for the Soci-Econ-Env attributes and the calculated weights.

| | Urban & sand | Distance to road | Weight |
|---|---|---|---|
| Urban & Sand | 1 | 5 | 0.833 |
| Distance to road | 0.2 | 1 | 0.167 |

Table 3shows the pairwise comparison matrix for the Soci- Econ-Env attributes and the calculatedweights.

On the other hand, technical objective is evaluated by six criteria. Table 4shows the pairwise comparison matrix for the technical attributes and the calculatedweights.

This paper applies the combination of AHP and OWA to aggre- gate the scores of different criteria to classify the land suitability for wind farms in Oman. This AHP-OWA combination is implemented as an extension module (FLOWA) [5] in ArcGIS 9.3.

OneadvantageofusingtheAHPOWAcombinationistheuseof linguistic quantifiers in generating the required weights. Linguistic quantifiers provide flexibility to decision maker based on the degree of the optimism that decision maker would like to use. AHP-OWA combination is able to aggregate the criteria's values considering "All", "Most", "Many", "Half", "Some", "Few" criteria or "At least one"criterion according to their relative weights.

This paper uses the linguistic quantifier "All" at all levels to analyze the land suitability for wind farms installation in Oman. After identifying the regions of high potential, an investigation of the effect of the degree of optimism on the final land suitability is carried out on a selected region using other combinations of linguistic quantifiers.

## RESULTS AND DISCUSSIONS

The seven criteria used in this study are input to the MCDMextension (FLOWA) in the GIS environment which calculates thesuitability index based on the relative weights of each criterion.Fig. 3.shows the calculation results of the land suitability index at50 m above the ground. The results are then reclassified with equalintervals into four classes namely "unsuitable", "marginally suit-able", "moderate suitable" and "mostly suitable" as shown in Fig. 4.Fig. 4shows the land suitability classification for differentheights above the ground namely 50 m, 80 m, 100 m and 150 m. Itshows that most of the land of Oman is unsuitable for wind farms applications. It can be seen that that only Dhofar and Wusta regionshas high land suitability index classified as "mostly suitable" below100 m. This is clearly due to the pattern of wind power distribution

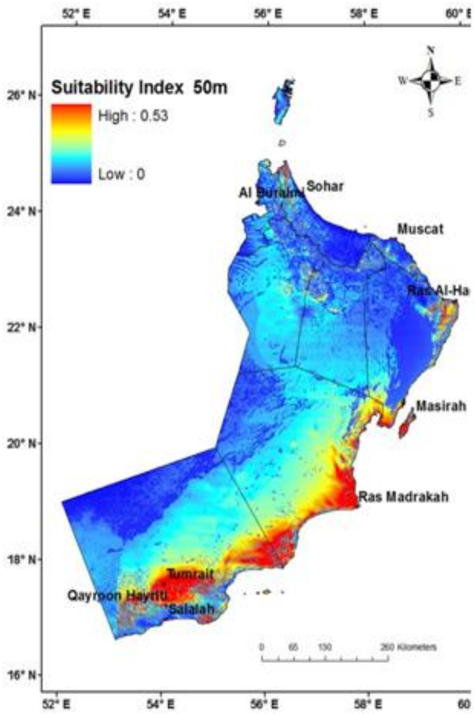


**Fig. 3**. Land suitability index at 50 m above the ground.

moderate suitability can be found in Dhofar, Wusta and Sharqiyah regions.

Asofthecurrenttechnicalfeasibility,windturbinesaretypically installed at 50e100 m above the ground. Land suitability map for height of 150 m above the ground can be used once such installa- tion is technically feasible. The area of "mostly suitable" lands represents 0.2% of the total country's area (308,376 km$^2$) at 50e150mabovethegroundasshowninTable5.

Fig. 4 and Table 5 show also that the land areas with moderate and marginal suitability classes expand more rapidly with height. They show also that the land with moderate suitability classifica- tion exists in many locations along Wusta coasts and in Masirah Island. The "moderate suitable"land class represents 0.4%, 1.4% and 2.5% at 50 m,100 m and 150 m, respectively.

Regionwise,theareasofthelandsclassifiedas "mostlysuitable" expressed with their percentages relative to the total region area are shown in Fig. 5. It can be seen from this figure that for 50 m height,the"mostlysuitable"landrepresents0.47 %oftotalDhofar region area. At 80 m, the "mostly suitable" land increases up to 0.67%forDhofarregion.Besides,itisnoticedtha

Table 4 Pairwise comparison matrix for the technical attributes and the calculated weights.

| Wind power density | Wind power density | Peak hours matching | Wind occurrence ≤5 | Turbulence intensity | Wind occurrence ≤20 |
|---|---|---|---|---|---|
| | 1 | 3 | 2 | 2 | 1 |
| Peak hours matching | 0.333 | 1 | 0.5 | 0.5 | 0.333 |
| WindOccurrence ≤5 Turbulence intensity | 0.5 0.5 | 2 2 | 1 1 | 1 1 | 0.5 0.5 |
| Wind Occurrence ≤20 Weights | 1 0.3 | 3 0.092 | 2 0.154 | 2 0.154 | 1 0.3 |

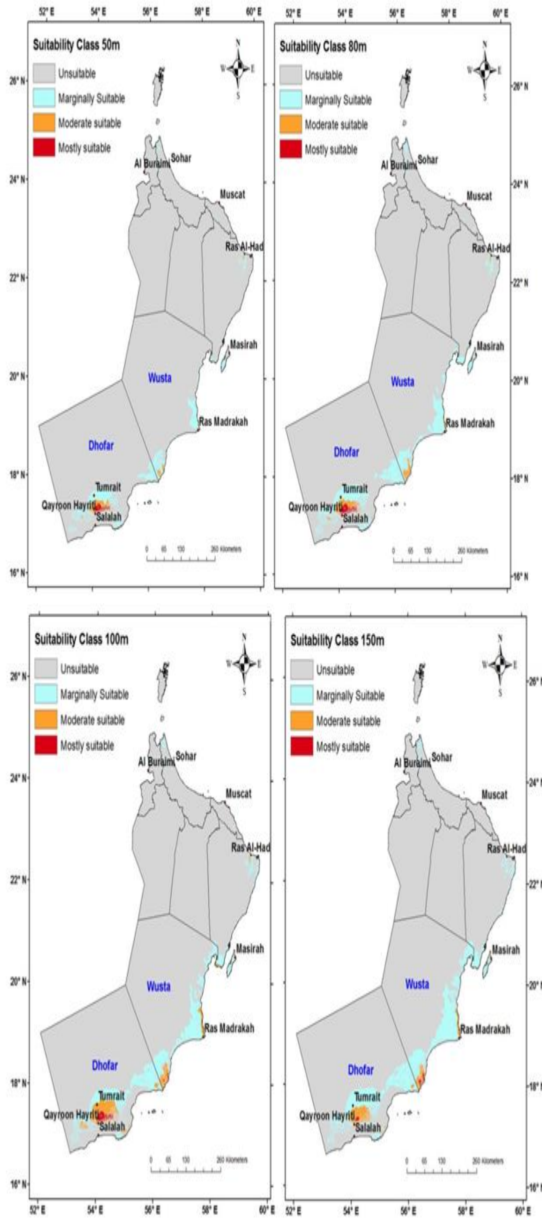


**Fig. 4.** Land suitability classification at 50 m, 80 m, 100 m and 150 m above the ground.

Table 5 Land percentage (%) from the whole country area for different suitability classification.

| Height | Marginallysuitable | Moderate suitable | Mostly suitable |
|---|---|---|---|
| 50m | 3.1 | 0.4 | 0.2 |
| 80m | 5.0 | 0.6 | 0.2 |
| 100m | 6.3 | 1.4 | 0.2 |
| 150m | 10.7 | 2.5 | 0.2 |

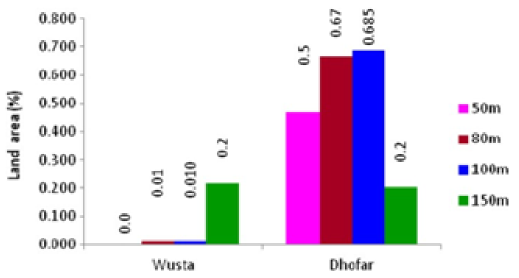


Fig. 5. Percentage of the mostly suitable land from the total region area.

suitable" areas have emerged in the Wusta region for 80 m height with about 0.01% land coverage. It is clearly seen that "mostly suitable" land distributions start moving from Dhofar to Wusta region at 150 m above the ground.

Lands with "marginally suitable"classification cover wider areas at lower heights. For example they represent 3% of the whole country at 50 m above the ground. In contrast to other land classes, thisclasscanbefoundinthenorthernpartofOmans uchasSurand north of Batinahregion.

From decision maker's perspective, providing alternativesbased on the degree of optimism (optimistic, neutral or pessimistic) gives better view of the potential solutions. Using the linguistic quanti-fiers. "All", "Most" and "Many" describe the least degreesof optimism(pessimism).Theybehavelikethe" AND"operator."Half" linguistic quantifier describes the neutral attitude. On the other hand, "Few" and "Some" describe higher degree of optimism.Theyareclosertothe"OR"operator.Finally, "Atleastone"representsthe "OR" operator which means that if any criterion (regardless of its weight) is satisfied then that site is considered to satisfy the final goal. This is not acceptable for the wind farm land suitability application. Therefore, these latest optimism quantifiers should not beused.

Dhofarregionisselectedforcarryingouttheinvestigationofthe degree of optimism effect because it has more sites with "mostly suitable" classification. Fig. 6 shows land suitability classification at 50m above the ground using different degrees of optimism for the Dhofarregion.

It can be seen that the area of higher suitability classes is expanding showing higher degree of optimism. Land suitability classification using All quantifier looks very much similar to the land classification using Most quantifier. Lands with moderate land classification expands 25% of region using Many quantifier. As we go more toward "OR" operator, the land classification becomes more similar. This can be seen using Half, Some, Few and at least one criterion.

## CONCLUSIONS

In this paper, the multi-criteria decision making approach based on the AHP-OWA aggregation function was used to derive wind farm land suitability index and classification. The AHP-OWA aggregation function was used to aggregate the scores for different criteria in the GIS environment. Different factors were considered as selection criteria including economical (distance to road, terrain slope), social (urban area), environmental (historical locations, wildlife and natural reserves) and technical (wind power density, energy demand matching, percentage of sustainable wind, turbulence intensity, sand dunes). Linguistic quantifiers for different degrees of optimism were also evaluated A case study of the approach and the selection criteria was conducted to study the wind farm suitability overOman.

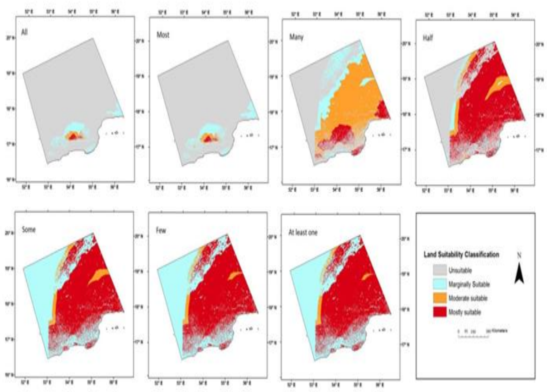


Fig. 6. Land suitability classification at 50 m above the ground using different degrees of optimism for Dhofar region.

Results of the case study show that lands with mostly suitable classification are located in Dhofar and Wusta regions. This land class represents about 0.2% of the total area of Oman. It was also shown that the higher suitability class areas expand with height.

Evaluating the degrees of optimism, it was clearly shown thatthe land suitability is proportional to the degree of optimism. The lower the degree of optimism, the smaller the area with "mostly suitable" class. It was also noticed that lower degrees of optimism (half,some, few, atleastone)shouldnotbeusedforwindfarmland suitability analysis because they behave like the "OR" operator and they can bemisleading.

## ACKNOWLEDGMENTS

AuthorsgratefullyacknowledgetheOmaniResearchCouncilforfundingthisresearchunderthegrant

RC/ENG/ECED/10/01.Thanks are also extended to Directorate General of Meteorology and Air Navigation for providing access to its PC Cluster to run the NWP models.

## REFERENCES

[1]. RanyardRob,CrozierWRay,SvensonOla.Decisionmaking:cognitivemodelsand explanations. London: Routledge;1997.
[2]. Delgado M, Verdegay JL, Vila MA. On aggregation operations of linguistic labels.InternationalJournalofIntelligentSystems1993;8:351e70.
[3]. Triantaphyllou Evangelos. Multi-Criteria decision making methods: acomparativestudy.Netherland:KluwerAcademicPublication;2000.
[4]. Yager RR, Kelman A. An extension of the analytical hierarchy process usingOWAoperators.JournalofIntelligentand FuzzySystems1999;7:401e17.
[5]. Boroushaki Soheil, Malczewski Jacek. Implementing an extension of the analyticalhierarchyprocessusingorderedweightedaveragingoperatorswithfuzzyquantifiersinArcGIS.Computers&Geosciences2008;34: 399e410.
[6]. Saaty TL. The analytic hierarchy process: planning, priority setting, resource allocation.NewYork,NY:McGraw-Hill;1980.
[7]. Schmitt,C.,Dengler,D.,Bauer,M.TheMAUT-Machine:anAdaptiveRecom- mender system. Proceedingof “Adaptivität und Benutzermodellierung in interaktiven Softwaresystemen ABIS” workshop, October (2002), Hannover, Germany.
[8]. OkurAyse,EfendiN,KilicMusa,YavuMurat.UsingOWAaggregation tech- nique in QFD: a case study in education in a textile engineering department. Quality and Quantity2009;43:999e1009.
[9]. Saaty TL. How to make a decision: the analytic hierarchy process. European Journal of Operational Research1990;48:9e26.
[10]. Serwan MJ, Parry Tim. Development and Apply a GIS-assisted approach tolocating wind farm in UK. RenewableEnergy 2001;24:59e71.
[11]. Sten Hansen Henning. GIS-based multi-criteria analysis of wind farm devel- opment,proceedingofScanGIS’2005.Sweden:Stockholm;13e15June2005.
[12]. AdulBennui,PayomR.,UdomphonP.,PornchaiP.,KanaditK.,Siteselectionfor large wind turbine using GIS. PSU-UNS international conference on engi-neeringandenvironment-ICEE2007,10e11May2007,Phuket,Thailand.
[13]. YoncaNazil,KentelElcin,DuzgunSebnem.GIS-basedenvironmentalassess- ment of wind energy system for spatial planning: a case study from Western Turkey. RenewableandSustainableEnergyReviews2010;14:364e73.
[14]. Yager RR. On ordered weighted averaged aggregation operator in multi- criteria decision making. IEEE Transaction on Systems and Cybernetic 1988; 18:183e90.
[15]. Bell David E, Raiffa Howard, Tversky Amos. Decision making: descriptive, normative, and prescriptive interactions. Press Syndicate of the University of Cambridge;1988.
[16]. Malczewski Jacek. Ordered weighted averaging with fuzzy quantifiers: GIS- based multicriteria evaluation for land-use suitability analysis. International JournalofAppliedEarthObservationandGeoinformation2006;8:270e7.
[17]. Fuller R, Majlender P. An analytic approach for obtaining maximal entropy OWAoperatorweights.FuzzySetsandSystems 2001;124:53e7.
[18]. Wang Ying-Ming, Parkan Celik. A minimax disparity approach for obtaining OWAoperatorweights.InformationScience2005;175:20e9.
[19]. Amin Gholam R, Emroizenejad Ali. An extended minimax disparity todeter-minetheOWAoperatorweights.Computerand IndustrialEngineering.2006; 50:312e6.
[20]. Wang Ying-Min, Luo Ying, Liu Xinwang. Two new models for determining OAW operator weights. Computer and Industrial Engineering2007;52:203e9.
[21]. Emroizenejad Ali, Amin Gholam R. Improving minimax disparity model to determine the OWA operator weights. Information Science 2010;180: 1477e85.
[22]. Yager RR. Quantifier guided aggregation using OWA operator. International Journal of Intelligent Systems1996;11:49e73.
[23]. Zarghami Mahdi, Szidarovszky Ferenc. Fuzzy quntifieres in sensitivity analysis of OWA operator. Computer and Industrial Engineering2008;54:1006e18.
[24]. Al-Yahyai Sultan, Charabi Yassine, Al-Badi Abdullah, Gastli Adel. Nested ensemble NWP approach for wind energy assessment. Renewable Energy 2012;37:150e60.
[25]. DomsG,SchattlerU.Adescriptionofthenonhydrostaticregionalmodel LM. Part I: dynamics and Numerics. s.l. : online;. Deutscher Wetterdienst, www.cosmo-model.org;2008.
[26]. DBD Energy Associates, “wind energy bible”, [online], http://energybible.com/

wind_energy/index.html, [accessed on10.10].
[27]. AWS scientific. Wind resource assessment handbook; fundamentals for con- ducting a successful monitoring program. TAT-5-15283-01. NewYourk: AWS Scientific Inc;1997.
[28]. AL-Badi AH, Malik A, Gsatli A. Assessment of renewable energy resources potential in Oman and identification of barrier to their significant utilization. Renewable and Sustainable Energy Review2009;13:2734e9.
[29]. Khalfallaha Mohammed G, Koliub Aboelyazied M. Effect of dust on the performanceofwindturbines.Desalination2007;209:209e20.