TRAINING A FUZZY SYSTEM IN WIND CLIMATOLOGIES DOWNSCALING

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Keywords: Wind Climate, Fuzzy Systems, Genetic Algorithm, Topography.

Abstract: The wind climate measured in a point is usually described as the result of a regional wind climate forced by local effects derived from topography, roughness and obstacles in the surrounding area. This paper presents a method that allows to use fuzzy logic to generate the local wind conditions caused by these geographic elements. The fuzzy systems proposed in this work are specifically designed to modify a regional wind frequency rose attending to the terrain slopes in each direction. In order to optimize these fuzzy systems, Genetic Algorithms will act improving an initial population and, eventually, selecting the one which produce the best aproximation to the real measurements.

1 INTRODUCTION

The knowledge of the wind resources available in a selected area is fundamental to evaluate the possible installation of wind turbines destinied to produce electrical energy. The models used in these evaluations needs high requirements to work and vagueness in terrain descriptions or errors in measurements affect considerably the reliability of the simulation. Hence the majority of information registered in a studied area, from stations destinied to agriculture, fire detection or pollution, will be rejected to be used in these estimations because of their low quality. A fuzzy wind model could be able to use all these excluded data reducing the requirements (and therefore the time and the costs) of the wind resource prospections.

The most of the numerous works that describe a mesoscalar wind potential evaluation in different areas of the world summarize the wind measured at the stations giving a general view of the wind conditions (Boehme, 2008). When a higher reliability is needed, the study is normally based on Computational Fluid Dynamics (CFD) (Palma, 2008) (Gastón, 2008) . CFD solves the fluid mechanic equations over a terrain with high computational cost (especially in this scale), and losing certainity when complex geography and chaotic dynamic arises. So, these estimations are slow and expensive.

Fuzzy Logic, Artificial Neural Networks and other adaptative tools are statistical structures able to work with low requirements and high tolerance to possible errors (Gutiérrez, 2006). Thus, using these techniques in the wind resource assessment, the data quality could be replaced with data quantity and the deterministic prediction with a probabilistic one, more inline with the atmospheric dynamic (Louka, 2008) (Cellura, 2008).

In this paper, Genetic Fuzzy Learning will be used to develope a fuzzy system able to transform a regional wind climate into a local one attending to basic aspects of the surrounding topography.

2 AREA AND WINDDATA

To illustrate this paper, measurements from a net of meteorological stations have been acquired. These stations are focused on agricultural parameters, so their locations and instruments are not optimized to the wind resource estimation. As it is shown in figure 2, the selected station is located at Jimena (Andalucia, Spain), inmersed in a complex terrain. The other three neighbor stations, with similar characteristics, have been collected to build a regional wind climate.

3 REGIONAL WIND CLIMATE

The regional wind climate, which will be forced by the terrain conditions, is generated as a linear

Agüera A., J. G. de la Rosa J., G. Ramiro J. and C. Palomares J. (2010).
TRAINING A FUZZY SYSTEM IN WIND CLIMATOLOGIES DOWNSCALING.
In *Proceedings of the 12th International Conference on Enterprise Information Systems - Artificial Intelligence and Decision Support Systems*, pages 238-243
DOI: 10.5220/0002899402380243

combination of real data registered at the stations around Jimena. This combination is based in interpolation functions for geostatistics variables (defined by G. Matheron (1963)), and its application to Atmospheric Sciences suggested by Thiebaux and Pedder (Thiebaux, 1987). Zekay Sen (Sen, 1998) have used these works to calculate the monthly mean wind speed in different areas in Turkye obtaining good results.

In this paper these techniques are used to generate a wind frequency rose calculating wind vectors in a point (v_{jimena}) as linear combination of real wind vectors recorded at the three stations mentioned before (v_1, v_2, v_3):

$$\vec{v}_{jimena} = a_1\vec{v}_1 + a_2\vec{v}_2 + a_3\vec{v}_3 \tag{1}$$

The coefficients a_i are normalized and indicate the contribution of each station to the final result. This coefficients will be calculated using studied geostatistic weighting functions and normalizing:

$$a_i = \frac{W(r_i)}{\sum_j W(r_j)} \tag{2}$$

Where r_i represents the distance between Jimena and the i*th* station, and $W(r_i)$ is the weight function which adopts this form (Thiebaux and Pedder):

$$W(r_i) = \begin{cases} \left(\dfrac{R^2 - r_i^2}{R^2 + r_i^2}\right)^{\alpha} & r_i < R \\ 0 & r_i > R \end{cases} \tag{3}$$

The parameter α can be changed in order to modulate the distribution, and R is the radius of action beyond that the evaluated point does not contribute. The values of this paramaters (R=50 Km, α=2) have been selected according with (Agüera, 2009). In this last work, it is possible to find detailed information of the interpolation system used here.

The result of this process is a temporal serie of wind vectors created with real information of the area. This serie can be analyzed in order to test the accuracy of the prediction. In figure 1 the real wind frequency rose at Jimena is compared with the rose of the regional wind climate generated by linear combinations of data from stations of the area.

As it is possible to see, the regional wind rose builded with this method gives an important aproximation of the real wind measured at the meteorological station of Jimena. But, in spite of this general similarity, there is an important difference when the expected incoming direction is E and the station measures SE. This is due to the linear interpolation predicts a theoretical wind whithout information of topography, roughness, obstacles, etc. However, the wind measured in a point is affected by local conditions and these effects may be evaluated in order to get a better prediction. So fuzzy systems will be used to transform the regional wind distribution into the real one evaluating relief parameters. To achieve this objective, the geographical information must be processed and inserted in a matrix builded as it is shown in the following section.

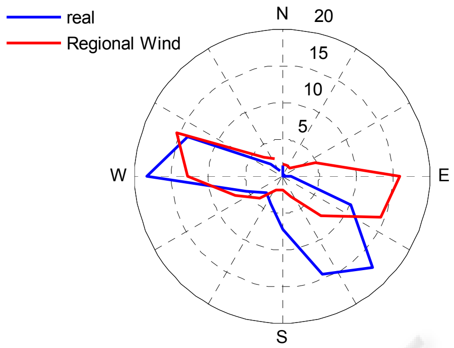

Figure 1: Real and Regional wind frequency roses.

4 TERRAIN

In figure 2 is represented the process through which an altimetric map image is transformed in the matrix used as terrain input in this model. In the altimetric image each colour is associated to a height above sea level. Then, reading the RGB components of each pixel, a height matrix of the area can be created and represented (figure 2a).

The wind measured in a point could be defined as a vector whith module and direction equal to wind speed and wind direction. Hence, the simmetry of this problem is radial and input arguments should be expressed in polar coordinates.

Figure 2b shows the mean heights of the digitized area, fractioned in sectors (M_{ij}) depending on the polar coordinates relatives to the central point (Jimena).

Each M_{ij} is obtained as the mean height of the n pixels inside the ij-sector (1):

$$M_{ij} = \frac{\sum_n h(r,\theta)}{n} \tag{4}$$

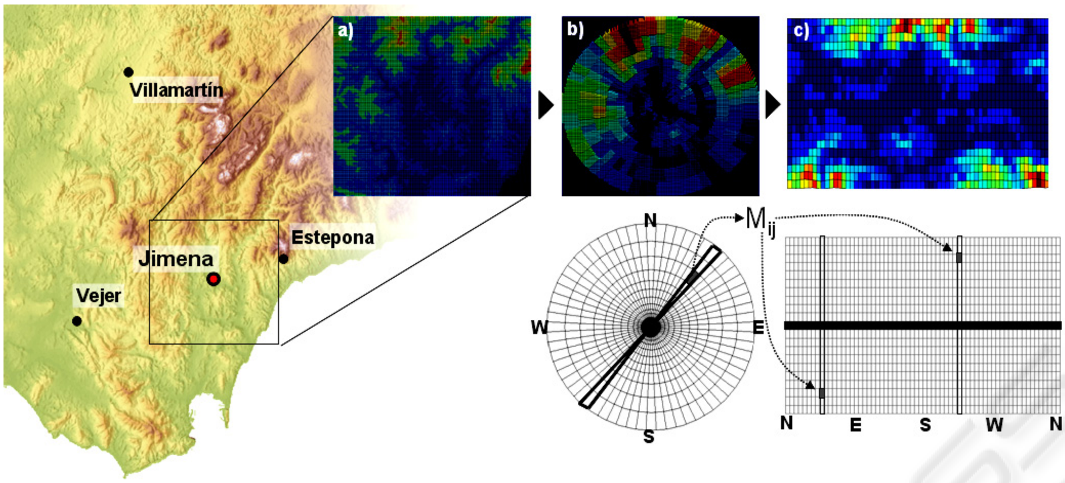

Figure 2: Area of Jimena and transformations to obtain the model terrain input from a map image.

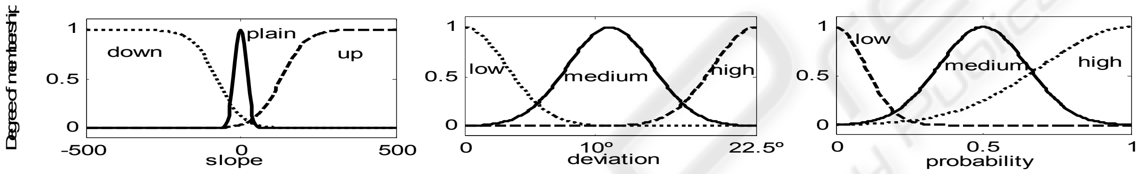

Figure 3: Possible description of the input and output domains using the proposed fuzzy sets.

The matrix M, composed of Mij, is represented in Figure 2c. As it is shown in the graphic explanation below, each column contains information of one direction. So a turn in the wind direction will be interpreted as a displacement in x-axis. M gives an usefull representation of the physical geography around the calculation point, adapted to the simmetry of the problem, and it is easily applied as input of fuzzy systems.

5 GENETIC FUZZY SYSTEM

The fuzzy system used in this problem pretends to connect the local wind conditions with terrain characteristics of the area. The vagueness in the terrain description in this scale, the quality of data recorded at the used stations, and the chaotic dynamics inherent to atmospheric events demand a fuzzy treatment of these elements. The proposed system will calculate the probability of possible changes in the direction of the wind analyzing the terrain in those directions. In order to simplify the problem only two inputs parameters will be proposed: the terrain will be described considering the “slope” and the wind behavior will be represented by a “deviation” in the incoming direction. In the same way, the output parameter will be represented by “probability”. References (Zadeh, 1997) (Sanchez, 1997) are fundamental bibliography to understand and study in depth the concepts used in this section.

5.1 Fuzzy Sets

Fuzzy Logic is based on the fuzzification of crisp variables obtaining fuzzy sets, so linguistic terms are generally used to build the new description. Each fuzzy set is defined in a domain and it is characterized by a membership function with values between 0 and 1 which indicates de degree of membership of an element to the concerned fuzzy set. For example, a fuzzyfication of the parameter “slope”, defined as the difference of heights between two relief elements in the range [-500m, 500m], could be done using these fuzzy sets [down, plain, up]. So the parameter “slope” could be fuzzyficated as it is shown in Figure 3.

In this figure is also represented a possible election of fuzzy sets for the parameter “deviation” ,[low, medium, high], defined between 0 and 22.5 degrees. “Probability”, whith range [0, 1] will be divided with three sets [low, medium, high].

5.2 Fuzzy Rules

Using these fuzzy sets it is possible to to build "IF-THEN" rules connecting the inputs with the output generating a knowledge base. For example: IF "deviation" is *high* and "slope" is *up* THEN "probability" is *low*.

Now it is possible to map crisp input values into output ones by using the processes of fuzzyfication, fuzzy inference and defuzzyfication. So, the fuzzy systems used in this work can be represented as follow:

$$p = fuzz(s,d) \tag{5}$$

Where s and d are the input values, p is the output and *fuzz* represents the processes of fuzzyfication and inference.

5.3 Genetic Algorithm

The membership functions, and fuzzy rules could be defined and adjusted by a human expert or founded using adaptatives tools. In this paper we will try to optimize the fuzzy system with Genetic Algorithms (GA).

So, we must encode the fuzzy system characteristics into a string of values which will be considered a genome of this system. Mutation and Crossover operators can act on these strings generating new fuzzy systems; and a selection operator can select individuals according to the values obtained from a fitness function or objective. The action of these operators brings an iterative process through which an initial population of fuzzy systems could be improved in order to obtain the best fitness value. We have chosen 22 parameters (genes) to characterize each fuzzy system. Eight of them are relationed with the position and shape of the memberships functions; so, they are continous. The other ones are discrete variables used to build the fuzzy rules of the system (Table 1).

5.4 Fitness Function

The prove suggested to rank the fuzzy systems involves the modification of the regional frequency rose by interaction with M, the matrix which contains the processed information of the map (Figure 4 c). This correction of the regional rose will be done using an iterative process which simulates the wind flowing over the matrix M from the bottom up. In each step the fuzzy system has to distribute the wind frequency in a selected direction (F) over the five upper elements attending to the slopes and possible deviations as figure 4 shows. The iteration of this process generates diagrams, like the one shown in figure 7, where probabilistic trajectories induced by the fuzzy system are represented, and the output distribution could be considered a corrected rose obtained from the regional one after the interaction with the topographic elements.

Table 1: Genes.

Gen	Values	Parameter
1	[0, 1]	Width Slope / down
2	[0, 1]	Width Slope / plain
3	[0, 1]	Width Slope / up
4	[0, 1]	Position Slope / down
5	[0, 1]	Position Slope / plain
6	[0, 1]	Position Slope / up
7	[0, 1]	Width Deviation / low-medium-high
8	[0, 1]	Width Probability / low
9	[0, 1]	Width Probability / medium
10	[0, 1]	Width Probability / high
11	0, 1, 2	Fuzzy rule 1 / input 1
12	0, 1, 2	Fuzzy rule 2 / input 1
13	0, 1, 2	Fuzzy rule 3 / input 1
14	0, 1, 2	Fuzzy rule 4 / input 1
15	0, 1, 2	Fuzzy rule 1 / input 2
16	0, 1, 2	Fuzzy rule 2 / input 2
17	0, 1, 2	Fuzzy rule 3 / input 2
18	0, 1, 2	Fuzzy rule 4 / input 2
19	0, 1, 2	Fuzzy rule 1 / output 1
20	0, 1, 2	Fuzzy rule 2 / output 1
21	0, 1, 2	Fuzzy rule 3 / output 1
22	0, 1, 2	Fuzzy rule 4 / output 1

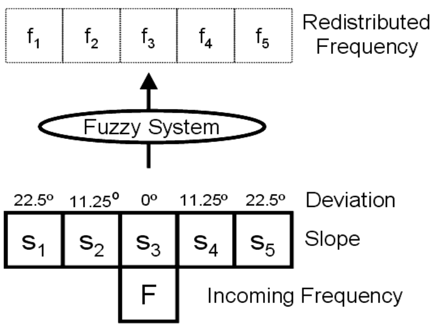

Figure 4: Corrections of directions using the fuzzy system, where "Inc" indicates the incoming direction, s_i and p_i the slope and probability in each direction. The deviations affect the five upper elements because, according to the fuzzy sets defined before, deviations are limited to 22.5º, and consecutive elements in a row represent deviations of 11.25º.

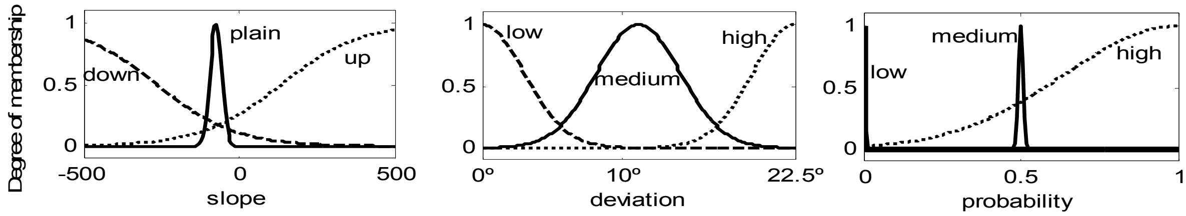

Figure 7: Optimized Fuzzy Sets.

Once the corrected rose is obtained, it will be compared with the real one evaluating the mean absolute error (*MAE*) in each direction:

$$MAE = \frac{\sum_{j=1}^{16} \left| FR_j - FS_j \right|}{16} \qquad (6)$$

Where *FR* represents the real frequencies measured at Jimena, *FS* the simulated ones and *j* is a parameter that covers the 16 sectors of the roses. *MAE* value will be used as a fitness value to rank the fuzzy systems.

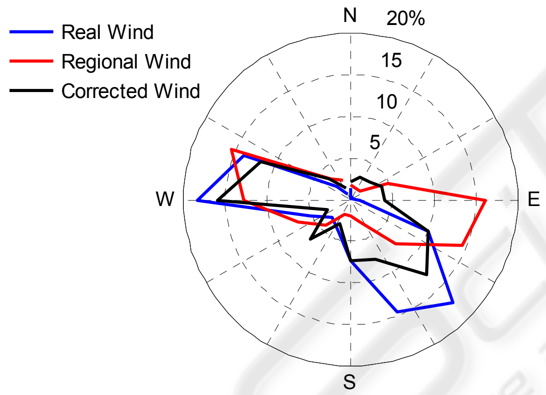

Figure 5: Real, Regional and corrected roses.

6 RESULTS

After the action of Genetic Algorithms, an optimized fuzzy system have been obtained. The correction of the probability distribution given by this fuzzy system is shown in figure 5. The MAE value obtained with this distribution is 2.35% that improve the 4.29% associated to the regional rose. As it was expected, the probabilistic trajectories simulated by the trained fuzzy system (Figure 6) describe a strong modification in the winds from E displaced to the S, in opposition to the ones from the W which are smoothly modified. These corrections are derived from the action of fuzzy rules and fuzzy sets summarized in table 2 and figure 8.

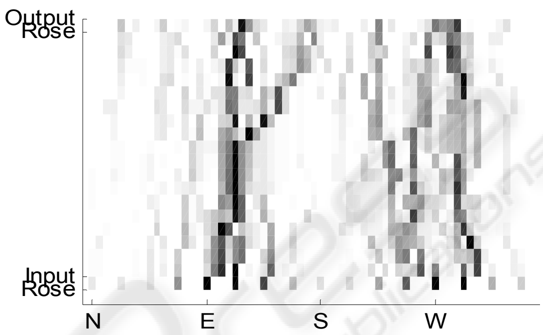

Figure 6: Density of trajectories.

Table 2: Fuzzy Rules.

	Slope	Deviation		Probability
IF	Plain	Medium	THEN	Medium
	Up	Medium		Low
	Down	High		Low
	Plain	High		Low

The inference surface builded with this information is showed in figure 8, where slope and deviation are connected to the output (probability, gray scale). The fuzzy system associates the highest probability to medium deviations when the slope is smoothly negative. Turns higher than 20º and positive and strongly negative slopes are not favored. Another minor effect observed is that wind tolerates a wider range of slopes while flowing in the same direction, that is, deviation 0º.

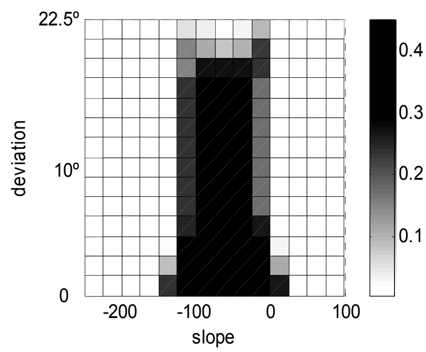

Figure 8: Inference surface.

7 CONCLUSIONS AND FUTURE WORK

The fundamental conclusion of this work is that the described process presents a way to train fuzzy systems in wind parameters downscaling. It is clearly visible the improvement of the obtained wind frequency distribution with regard to the regional one. This fact implies that the optimized fuzzy system contains information about how to correct the wind direction over Jimena using the terrain slopes. This acquired knowledge is the best statistical solution founded through Genetic Fuzzy Learning according to the variables and conditions imposed to solve this particular problem in this location. But the ultimate objective of this technique should be the development of a generalized fuzzy system able to work in many enviroments and expanded to correct the wind speed, the most important variable in wind resource evaluation. In order to get the best agreement, this system should evaluate more terrain characteristics as roughness, heights and distances from obstacles to the target point, topographic complexity, etc. Despite this parameter inclusion, this new extended problem is essentially similar to the one described in this paper. The differences are related to the number of inputs and outputs of the fuzzy system and the number and characteristics of the terrains used in the training process.

Since fuzzy logic is able to work with vague data, an interesting application of this technique lies in training fuzzy systems to work with low quality stations. In fact, the stations used in this study can be considered poor, because wind vanes and anemometers are placed at 2 meters above ground level and reported data could be affected by obstacles and roughness. Another problem is that the frequency of the provided mean wind speed and direction is daily, far from the recommended ten-minutes interval. In opposition to these inconvenients, the use of this information allows to acquire easily a considerable quantity of long term time series of real measurements of the area. So, once this general fuzzy system is obtained, the duration and requirements of the wind resource evaluation of large areas could be strongly reduced.

Finally, the technique exposed could be also applied to all that processes in which wind and terrain are closely relationed as fire propagation or erosion.

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