INTERMITTANCY REDUCTION: WIND TIME-SERIES CLASSIFICATION.

Kheirreddine SARI,Montpellier Recherche en Economie (MRE), +33619139353, kheirreddine.sari@etu.umontpellier.fr

Overview

Wind energy is a volatile electricity production. In France and worldwide, the development of renewable energy sources (RES) is increasing the energy system costs. These will increase further to reach the wind energy target of 33.2 GW of installed capacity by 2028.

However, intermittency decreases as the installed capacity is geographically dispersed [1], mainly due to the presence of different weather regimes [2]. Hence the importance of adopting new wind deployment strategies in locations that are complementary.

The objective of this research is to identify these complementary locations by analysing wind time series, which is challenging due to its variability. Therefore, we considered both “feature-based” and “instance-based” classifiers and opted for the one that meets our research objective.

Methods

The data used are mainly wind speed measurements. These measurements are carried out at 373 weather stations at 10 meters height, located in the North-West and South-East of France. The measurement is in hourly time steps and extends from 2016 until 2018.

Initially, we used Principal Component Analysis (PCA) as a feature-based classifier. In order to project the whole sample, we considered an algorithm [3] that extracts wind time series features (e.g., autocorrelation and autoregressive processes) while preserving as much information as possible. In this way, the unique values obtained for each series will be represented as variables in an orthogonal plane, thus facilitating their visualization.

Subsequently, we used various instance-based classifiers (e.g., “Dynamic Time Warping” [4] and “Shape Based Distance” (k-shape) [5]) and selected the highest scoring classifier for our sample. Due to the computational capacity and time required for these methods, we have used weekly observations, which allows us to get an overall idea of the wind speeds over a given period.

Results

The « time-features » are generated for all 373 meteorological measurement stations. The first 2 axis of the analysis express 51.46% of the total variability of the cloud of individuals (and variables) that are represented in this plane. While the first axis (Dimension 1) is more representative of the potential of the wind sites, the second axis (Dimension 2) shows the stability of the wind occurrence. As shown in Fig.1, we also find 3 groups of individuals. Among them, the third one is the most productive as it is located next to "eff_winter" and “eff_summer". On the other hand, Group 1 and 2 are less productive and more volatile as they are located in the opposite of “eff_summer” and “eff_winter” and closer to “spike” and “crossing points”.

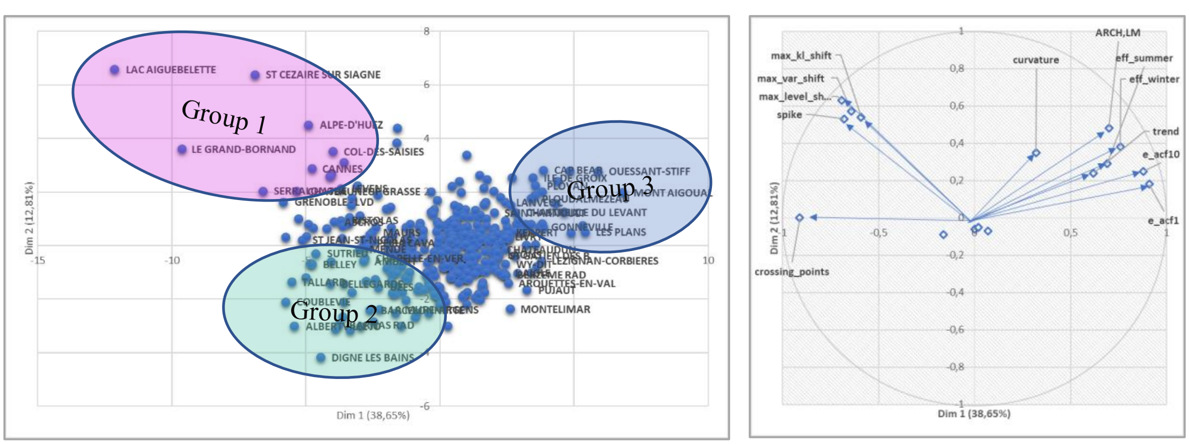

Fig.1: Principal component (PCA) output. Individuals’projection (left) and Variables’ projection (right)

Labelled individuals and variables are those with the highest contribution in the plane composition.

To select the most performing instance-based classifier for the current dataset, we measured several indicators. Results show that “k-shape” obtained a better score than “Dynamic Time Warping” (DTW). The reason for this is that it directly aligns the values of the time series, whereas DTW twists the points in the middle of the time series which gives a reduced classification quality.

Fig.2: Cluster members (left) and weekly average wind speeds of individuals from cluster 9 and 4 (right).

We obtained 12 clusters, among them, some have a complementary shape, i.e., cluster 9 and 4 are the most dissimilar (cf. Fig.2 left). After selecting two individuals from these clusters we notice that during the weeks when the average wind speed is lowest at “Villefranche” the average is highest at “St Jean St-Nicolas” and vice versa (cf. Fig 2 right).

Conclusions

Intermittency phenomenon is increasing proportionally with RES increase and must be treated while installing additional RES capacities, especially wind energy.

In this application, the key point is to be able to cluster wind sites with sufficient production potential, which can abound throughout the year, whether in winter or summer. "Feature based classification did not enable us to discriminate among these endowed sites, which are likely to produce in a complementary way. Indeed, it is a method that classifies according to features and not wind speed values.

In contrast, the instance-based method selected (k-shape) showed better results. Indeed, since it is a method that classifies based on the values of the time series, by aligning them, it allowed us to group wind sites that are likely to provide balanced electricity production. Although it is more accurate to classify sites on an hourly time steps, nevertheless the weekly observations provided an idea of the potential for complementarity and showed that weather patterns in France are diversified sufficiently for such a scheme to be implemented (i.e., complementary wind production).

References

[1] Hannele Holttinen; Juha Kiviluoma; Alain Forcione; Michael Milligan; Charles J. (2016) Design and operation of power systems with large amounts of wind power. Final summary report, IEA WIND Task 25, Phase three 2012-2014. VTT Technical Research Centre of Finland Ltd, éd. Finland. Online: https://www.vttresearch.com/sites/default/files/pdf/technology/2016/T268.pdf.

[2] Christian M. Grams; Remo Beerli; Stefan Pfenninger; Iain Staffell; Heini Wernli (2017) Balancing Europe’s wind-power output through spatial deployment informed by weather regimes. In : Nature Climate Change, vol. 7, n° 8, p. 557–562. DOI: 10.1038/nclimate3338.

[3] Fulcher, Ben D.; Jones, Nick S. (2014) Highly Comparative Feature-Based Time-Series Classification. In : IEEE Transactions on Knowledge and Data Engineering, vol. 26, n° 12, p. 3026–3037. DOI: 10.1109/TKDE.2014.2316504.

[4] Aghabozorgi, Saeed; Seyed Shirkhorshidi, Ali; Ying Wah, Teh (2015) Time-series clustering – A decade review. In : Information Systems, vol. 53, p. 16–38. DOI: 10.1016/j.is.2015.04.007.

[5] Yang, Junjing; Ning, Chao; Deb, Chirag; Zhang, Fan; Cheong, David; Lee, Siew Eang et al. (2017) k-Shape clustering algorithm for building energy usage patterns analysis and forecasting model accuracy improvement. In : Energy and Buildings, vol. 146, p. 27–37. DOI: 10.1016/j.enbuild.2017.03.071.