Favorable wind states in wind energy production at La Rumorosa I wind farm

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Abstract

This work introduces a statistical method that identifies wind states present in the wind farm La Rumorosa by analyzing wind speed and nacelle position (wind direction). These states contribute to the generation of wind power in microscale, mesoscale, and macroscale phenomena. The data were obtained from five wind turbines at the onshore and anemometric tower in La Rumorosa located on the border with the state of California, USA. The contribution of wind states and their impact on the annual power production in the wind farm was observed using this method. It is concluded that the method reliably identifies wind patterns with low computational effort.

1 Introduction

One sustainable development goal of the 2030 agenda of the United Nations [6] is to use affordable and non-polluting energy. Thus, many countries worldwide have pledged to reduce emissions to the atmosphere and bet on clean energy. California State has embarked on an ambitious effort to achieve very high levels of clean energy to minimize greenhouse gas emissions. It established an aspirational goal of 100% clean energy in all sectors by 2045 [10]. Wind energy is one of the most common clean energies that has been developed significantly in the world [11]. Hence, wind speed prediction is identified as one of the critical inputs for wind farm power dispatching and maintenance planning. Generating power not only depends on an intermittent and variable wind resource but also on complex non-linear atmospheric interactions on various spatial and time scales, both within and outside the wind farm [7].
In this work, a statistical analysis of the wind states [9] present in a wind farm was performed by the authors. In particular, the states present are microscale (valley and mountain winds), mesoscale (Santa Ana winds), and macroscale (Meteorological Fronts) [12]. They contribute to the generation of wind power and have been previously studied to know how much wind energy they contribute and their general behavior. Santa Ana winds and meteorological fronts are the phenomena with higher wind speeds and appear in a dominant quadrant in the direction of the winds. These events were analyzed at the La Rumorosa I [5] Wind Farm. Santa Ana winds have been studied for their periodicity [8], and for environmental impacts in Southern California [3], they are dry, low relative humidity and come from a single quadrant and cold fronts provide precipitation, low temperature and occur every winter [2]. The data used were obtained from five wind turbines at the onshore wind farm “La Rumorosa I” and anemometric tower in La Rumorosa. The geographical location of the five turbines can be seen in Figure 1 in blue, and the anemometric tower in red. La Rumorosa is one of the best areas for wind power generation in Mexico. It is located in Baja California, Mexico, on the border with California, United States.

Figure 1: “La Rumorosa I” its geographical coordinates are 32°29'51.03"N and 116°5'33.88"O

2 Objectives

The main objective of this work is to analyze the contribution of wind turbine power production for all wind states found in the site. This includes the local conditions that correspond to valley and mountain winds, Santa Ana winds, midlatitude cyclones, and meteorological fronts, which provide wind power energy in La Rumorosa wind farm.

3 Methodology

We present a stochastic analysis for wind classification and identification based on a Gaussian Mixture Model (GMM) [1] data clustering using wind speed and wind direction data. This allows us to characterize wind behavior over several years in any part of the world through finding and classifying the local wind states. The method we are proposing is based on previous work [9], where the concept of wind states, was introduced. They appear in the two-dimensional velocity vector plane understood as a phase space for the wind speed data. In such work, it was defined that “a wind state is a region in the velocity phase space that contains the accessible wind velocities having a common probability distribution function that characterizes them as a
cluster.” It was postulated that wind states physically exist but are determined in a stochastic way by the site’s geographical and climatic conditions.

It is challenging to model wind states using fundamental hydrodynamic equations. Hence, clustering methods constitute an alternative to discover wind states in long-period data series. If the clusters preserve the relationship with the physical wind state, then they could be the base for automatic recognition of wind speed patterns. Thus, clustering is used as a method for discovering real states. GMM is based on a probabilistic analysis employing a parametric mix or combination of physical variables related to wind behavior. This method is convenient when the data one intends to model is very complex, such as when it is not possible to represent it in the form of a simple distribution. Then these data could be displayed in a multimodal form. This means there are various high probability clustering regions and other of less probability clustering in the midpoint. In this situation, we could model data in terms of several component blends, where each one has a simple parametric form (as a Gaussian one). Therefore, it is possible to define as a probabilistic one to represent the presence of subcategories contained in a cluster. The blended methods are employed to create statistic inferences, approximations, and predictions about the subgroup properties. Therefore, the GMM is a function of parametric probabilistic density represented as the sum of the Gaussian components’ density [1].

Once the method identifies the clusters, these clusters are aligned with the wind states that correspond in magnitude and wind direction, according to the time series of the conditions of each of the meteorological phenomena. In this case, we had previously identified the behavior of each of these phenomena. To a proper validation of the identification method, previous knowledge of the regional winds is needed and should be provided by meteorologists and aligned with the results. For La Rumorosa case study, the months with the most considerable influence of macroscale phenomena were identified. It was also possible to identify that January is the month with the highest production of wind energy due to external phenomena. In total two analyses were carried out, one for January and another for the entire year. January has the highest incidence of macroscale phenomena and little presence of local conditions.

4 Results and discussion

4.1 Results for January

According to the statistical method, six wind states were found in January in the anemometric tower located next to the wind farm, see Figure 2, “Wind states.” The wind rose of the anemometric tower of January was plotted in Figure 2, “Wind Rose,” according to the behavior of the wind states. The wind state that most prevailed in January was the Santa Ana Winds with 48% of presence; the cold fronts with 27% of occurrence, and with less incidence “mid-latitude cyclones” with 9%. It is essential to mention that wind states change throughout the year. For wind turbine 1, with the data provided by the anemometric tower, each of the six wind states’ behavior was obtained, see Figure 3. The power output curve for wind turbines and the energy contribution of each wind state is plotted until they reach the nominal power of 2 MW in the power curve.

The results of each wind state of the anemometric tower are shown in the classification of “wind states” and “Presence of states winds in January”, and wind energy production of turbine 1 in “Wind energy production” in Table 1.
The results shown in Table 1 correspond to wind states of Wind Turbine 1 in January. The conditions of mesoscale phenomena of Santa Ana winds and macroscale phenomena of Meteorological Fronts and Midlatitude Cyclones contribute with 97% of the wind energy production in a wind turbine. On the other hand, the local conditions and the states found as in transition corresponds to 16% of these wind states. Nonetheless, they represent only 3% of the wind energy production of the wind turbine; during its presence, the wind speed is lower, so the energy production will be lower, or possibly the wind turbine is out of operation.

The results are shown in Figure 2, and Figure 3 analyzes the wind states for January, one of the months with the highest incidence of Santa Ana winds [4]. The presence of the Santa Ana winds and cold fronts in January is more significant than the rest of the year due to the increase of other meteorological phenomena.
| TOTAL | States Winds (SW) | Color code | Presence of SW in January (%) | Wind turbine energy production (kW) | Wind turbine energy production (%) |
|-------|------------------|------------|-------------------------------|------------------------------------|-----------------------------------|
| Local conditions | 1 Lilac | 9 | 36902 | 2 |
| Transition state 1 | 2 Green | 2 | 10964 | 1 |
| Midlatitude cyclone | 3 Cyan | 9 | 333921 | 20 |
| Transition state 1 | 4 Red | 5 | 4041.86 | 0 |
| Cold front | 5 Magenta | 27 | 645114 | 38 |
| Santa Ana winds | 6 Blue | 48 | 672981 | 39 |
| Total | 100 | | 1703923.21 | 100 |

Table 1: Classification of wind states and their wind power energy contribution for January 2011

4.2 The annual Wind States

The following section shows the results of the wind states for a full year, which considers the data obtained from 5 turbines in the wind farm and the anemometric tower on one side. Due to the availability of the data, the information from 2016-2017 was used. The analysis to observe the influence of larger-scale meteorological phenomena in a winter month was carried out in January. When reviewing for one year, the average values decrease. The following graphs depict the wind states’ results for five wind turbines and an anemometric tower that is 104 m from Turbine 1 and 184 degrees.

According to the results of Figures 4, 5, 6, 7, 8 and 9, it is possible to see that the wind states of wind turbines 3 (Figure 6) and 5 (Figure 8) are similar to each other. It is also clear that wind turbines 2 (Figure 5) and 4 (Figure 7) are similar to each other. If the graph of the wind turbine 1 (Figure 4) rotates 180 degrees (due to the position correction of the nacelle), it and the anemometric tower (Figure 9) have a high similarity, even more significant than the other pairs of wind turbines mentioned. Site topography may affect differences in wind states patterns in wind turbines. The behavior is similar in the figures of wind states ), knowing that the turbines’ separation is approximately 200 meters between them. In these figures, the increase of magnitudes is represented by the distance from the origin; it is possible to see the grouping of the states and their magnitude concerning zero. Tables 2 and 3 show the results of the five wind turbines and the wind states classified for each one and the power generated. The changes between each state were classified as another wind state, called transition.

The results of the wind states of Turbine 1 must be discussed because, in this turbine, there was an error in the reading of the wind direction (according to the operators of the wind Farm). The problem was a delay of 180 degrees of the north as it can be seen in Figure 4, and in the results, that error was present in the year 2016 to 2017. So the method will always identify the wind states according to their behavior pattern, no matter if the wind vane is outdated or if there is a problem with the geographical north indication.

This can be specified in wind turbine 1, where Figure 4 is the other way around. The turbine presents a lag in the Nacelle position data record. Still, as seen in Table 3, it is the one that produces most of the wind energy in the entire wind farm, our method can identify the 180-degree lag in the wind direction by patterns in groupings of wind states.

One question to answer is why it would be essential to know this method in wind farms? The short-term wind energy production projection as 24 hours or 48 hours. This projection could be made if the variables of speed, direction, relative humidity, atmospheric pressure, and temperature are found at the moment and compare historical data to see in which state of the wind is being operated. A shift could be made to the data of the 72 previous hours, to see the behavior of the current wind state, and to support the prediction of wind power production in the previous 24 hours.
Also, it is essential to carry out a study of previous wind analysis, on the meteorological events that affect the area to identify and cross information with this method. The advantage of the method is that one gets results in a short time. It is also applicable for any data sample from any...
part of the world, where there is already an analysis of the wind and the meteorological events present in the area.

According to the results, the wind turbine that generates more wind power production is Turbine 1. The advantage of the method is that it identifies patterns according to the wind speed and direction variables. By adding more variables, one could have a more thorough analysis. We only obtained wind speed and wind direction by the arrangement of the data, the wind power produced by the five wind turbines, and the data of an anemometric tower.

### Table 2: Percentage of wind energy production annually

| States Winds (SW)          | States by wind turbine | % of wind energy production annually |
|----------------------------|------------------------|--------------------------------------|
|                            | Aero1 | Aero2 | Aero3 | Aero4 | Aero5 | Aero1 | Aero2 | Aero3 | Aero4 | Aero5 |
| Local condition (Day)      | 2     | 5     | 6     | 4     | 4     | 0.4%  | 3%    | 8%    | 2%    | 11%   |
| Local condition (Night)    | 6     | 1     | 2     | 5     | 5     | 18%   | 14%   | 15%   | 19%   | 17%   |
| Midlatitude cyclone        | 4     | 4     | 5     | 1     | 6     | 39%   | 27%   | 37%   | 29%   | 38%   |
| Cold Front                 | 1     | 6     | 1     | 6     | 3     | 10%   | 28%   | 11%   | 22%   | 11%   |
| Santa Ana Winds            | 3     | 2     | 4     | 2     | 2     | 19%   | 17%   | 11%   | 18%   | 9%    |
| Transition State           | 5     | 3     | 3     | 3     | 1     | 12%   | 13%   | 16%   | 14%   | 14%   |

Table 3: Wind Energy Production by Wind Turbine of Wind Farm (MW)

| States Wind (SW)          | Wind Energy Production by Wind Turbine of Wind Farm (MW) |
|----------------------------|----------------------------------------------------------|
|                            | Aero1 | Aero2 | Aero3 | Aero4 | Aero5 |
| Local condition (Day)      | 503.065 | 708.94 | 2399.99 | 593.37 | 3139.81 |
| Local condition (Night)    | 5562.41 | 3863.8  | 4218.72 | 5473   | 4880.26  |
| Midlatitude cyclone        | 12217  | 7437.6  | 10647.93 | 8345   | 10858.97 |
| Cold Front                 | 3258.76 | 7763    | 3032.51 | 6364   | 3061.42  |
| Santa Ana Winds            | 5827.9 | 4717    | 3200.09 | 5302   | 2445.50  |
| Transition State           | 3754.31 | 3546.3  | 4680.74 | 4025   | 4160.55  |
| Total production MW        | 31172  | 28035   | 28692.76 | 29029  | 28752.45 |

Figures 10 - 13 show the behavior of the wind turbine power curve. In these wind turbine power curves, the most energetic states are shown: those that deliver the highest wind power with speeds above $10 \text{ m/s}$. In Figure 10, the power curve for wind turbine 3 is observed, it is possible to notice that the state with the highest generation of wind energy in the pink state that corresponds to the Midlatitude cyclone state.

The percentage of the wind energy of the wind states is described in Table 2. According to all the wind farm data, six wind states were classified, and their power generation is observed in the power curve of each wind turbine by color.

Figure 10: Power output curve for wind turbine 3 for 2016-2017

Figure 11: Power output curve for wind turbine 3 only for state 5 (Midlatitude cyclone)
5 Conclusions

The first result corresponds to January of wind turbine 1 (subsection 4.1). The macroscale wind states in January represent 97%. The analysis carried out for this turbine allowed us to know the wind energy contribution of the wind states and their behavior. It was found that the mesoscale and macroscale phenomena provide more wind energy during this month. However, in June and July, when the local conditions predominate, then the local power generation is more significant.

Since the power delivered by the wind states can vary in the wind farm, due to the wake conditions or the distribution of the wind farm itself, this type of analysis is essential to know the behavior and contribution of these phenomena throughout the year. In this work, only two variables were used in the method. For future studies, it is recommended to use three to five variables. According to the results obtained for the full year with the Gaussian Mixing Method using averages of wind power production throughout the wind farm, the local conditions of valley and mountain winds (day and night), and the transition state, represent 35%, see Table 3.

The Midlatitude cyclone wind status is cataloged according to the method using two variables and represents 34%. These macro-scale events coming from the United States represent more wind energy production for the region than the local conditions of valley and mountain winds. It is important to remark that in this study, only two variables were used for the classification of winds due to the availability of data, and these were wind speed and direction. If more variables such as relative humidity, atmospheric pressure, and the temperature had been used, the classification could have been more exhaustive, and events cataloged in this state could go to local conditions. This is under discussion yet; if more data were available, the result could be confirmed or reaffirmed. Cold fronts (16.3%) and Santa Ana winds (14.7%) on average throughout the wind farm represent 31% of the power generated at the site. The exciting fact is that the wind conditions per year represent 65%, and they represent 97% during January, which is when there is a more significant presence of these events. Wind states’ classification contributes to the knowledge of the duration, presence, and amount of wind energy that different meteorological phenomena or wind states contribute to the generation of wind power generation in a wind farm. Knowing these wind states in detail could support the program of preventive and corrective maintenance, the position of a turbine in a certain period, or during the presence of the wind state (they occur in a dominant quadrant). Furthermore, the power output curve’s visualization for a wind turbine that contains the wind states could help both the decision-making process of the wind farm operation and the analysis of the data.

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