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TRILHA PRINCIPAL

Development of an advanced power curve for performance monitoring of wind turbines

Antonio Carlos de Barros Neiva[1*]

Ricardo Linden[1]

Vanessa Gonçalves Guedes[1]

Caio Leandro Suzano Massa[1]

[1]CEPEL – Centro de Pesquisas em Energia Elétrica
Avenida Horácio Macedo, 354 - Cidade Universitária, Ilha do Fundão
Rio de Janeiro - RJ - 21941-911

***Abstract*— Maintenance is an important step that must be performed as soon as possible, to minimize the impact of failures. In this paper we discuss the concept of power curve fitting and deviation calculation to detect failures that cause the wind turbines to misperform (the here denominated Type I failures). As mathematics and software applications evolution for predictive maintenance is growing fast, simple considerations will be made to enable the development of an advanced individual power curve, so the real time turbine performance analysis may be as accurate as possible.**

Past environmental and production data is subjected to outlier filtration and statistical analysis, prior to creation of a best fit that would allow for future failures to be detected early. The innovation relies on segregating a power curve for each directional sector and on the correction of the influence of the temperature on the power production, achieving an advanced power curve that really mimics as close as possible the real operational output.

***Keywords:* Predictive maintenance, wind power curve fitting, failure detection.**

I. INTRODUCTION

QUALITY is a key factor for the satisfaction of the stakeholders on any business and this is also true for a wind farm, as well as for any industrial process. Quality has strong connections with the effective control of the machines used to generate the company's product, and the maintenance of these machines is a necessary step for both productivity and product quality.

Given that wind has become the renewable energy with the largest production worldwide, and also that it is growing very fast, considerable effort has been dedicated to overcome the youthfulness of the technology, that faces strong innovations and few learned lessons. Experience from other engineering sectors, such as aerospace, Oil&Gas and conventional energy production is not always immediately applicable, but indeed must be studied to steepen the learning curve.

This study was developed to bring information that shall be useful to build a better knowledge base for wind engineers interested on the development of turbine monitoring, based on power output of the wind turbines. The database used is from a wind park with more than 30 turbines in Latin America, placed in flat terrain, with 10-minute stepped database of four-year period.

To do so, this paper is organized as follows. Section II discusses the concepts of success and failure in wind energy production. Section III brings a brief report of the state of the art, and in Section IV it is explained how new parameters will be used to create an advanced power curve, while Section V discusses the idea of curve fitting in order to find an ideal power curve specific for the realities of the wind farm. Section VI discusses the effects of temperature and how its impact on the power curve was considered, while Section VII concentrates on the application of the methods using SCADA data. Finally, section VIII concludes with some remarks and ideas for future work.

II. SUCCESS AND FAILURE

A. Failure detection

The study of mechanisms inherent to failures and their detection is of foremost importance to predictive maintenance. Early failure detection allows evaluation of component remaining useful life, maintenance scheduling, and the decrease of its financial impact on the business.

The use of SCADA real time data collected directly from the plant for maintenance planning is nowadays common practice in most industrial activities, including wind power generation. The failure of a component of a complex machine may be detected using real time data acquisition by analyzing one or more of the measured parameters (such as temperature, vibration, etc.) or by reading the final production output of the machine. Based on these concepts, the failure types may be

* Corresponding author, e-mail: neiva@cepel.br

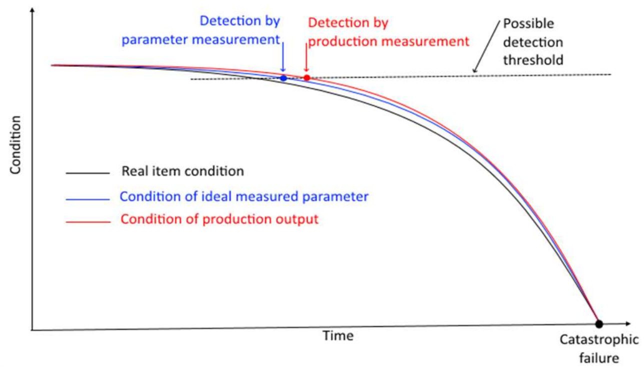

Fig. 1. Item and measured condition for Type 1 failures.

classified in two types:

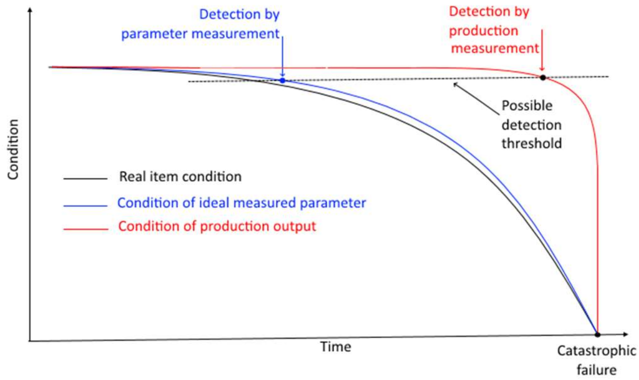

Fig. 2. Item and measured condition for Type 2 failures.

Type 1 – Failures that result in perceptible reduction of the production output of the machine since early stages of failure development;

Type 2 – Failures that only affect the production output very close to the actual catastrophic functional failure event.

Figure 1 shows an example of typical Type 1 failure behavior, and on Figure 2 the typical behavior of condition 2 may be seen. The failure classification shown has the goal of explaining the procedure described in this paper, since there are infinite failure types in between the above extremes. In some cases, there is no ideal parameter condition that can be measured to predict failure with the required anticipation. Hence, in these cases the maintenance scheduling forecast shall be based on the production output. From the figures 1 and 2, it may be seen that analyzing production output is useful only for Type 1 failures. The present study is devoted to a detailed investigation of the factors influencing the energy production output of each turbine of a wind farm, and the development of a system able to detect the development of a potential failure through statistical comparison.

Analyzing the production output also has the advantage of possible prediction of a more general family of failure causes, while parameter measurement will probably be useful for one or two failure causes.

B. Wind power production

The power generated by a given wind turbine is proportional to the cube of the wind speed and to the air density. Turbulence is another important and complex factor influencing power output and may be due to the surrounding physical characteristics (orography, surface roughness, obstacles and wake from other wind turbines) and atmospheric stability condition.

The expected production of a wind turbine is represented by its power curve, which the power output is a function of the wind speed, as shown in Figure 3.

It may be seen that the power curve has four regions, region 1 is the region where the wind speed is below the called cut-in speed, where no power production is expected. Region 2 is between the cut-in and rated wind speed, form which the wind turbine can produce its nominal power. Before reaching region 3, Jonkman *et al.* [1] defines a transitional region 2½, where the behavior does not follow the available power curve, and smoothly follows the constant power behavior of Region 3, which is limited by the electric generator capacity of the turbine, and the excessive power must be discarded. Due to safety considerations, above the cut-out wind speed the wind turbine must be turned off, and no energy can be produced in this 4th region of wind speeds. Most works devoted to power curve determination methods (including the present one), are dedicated to the region 2 of the power curve, since the other regions are constant. Region 2½ has specific constrains, as the torque slope is corresponding to the slope of an induction machine and there is need to limit tip speed (and hence noise emissions) at rated power [1]. As will be shown, this region it is also a challenge for the curve fitting process.

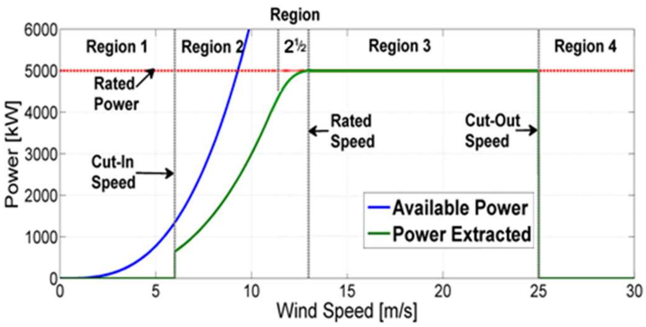

Fig 3. NREL's 5 MW Wind Turbine Power Curve [2, 1]

Although the turbine manufacturer supplies standard power curves for their products, the IEC 61400-12 [3] states that the real power curve is site dependent, and the purpose of the standard curve is only the establishment of an ideal power curve for all the installed wind turbines of the site.

The real power curves can change, due to the factors mentioned above in this text. Each turbine will be subjected to different topological and turbulence conditions, and therefore their power curve will not be exactly equal to the ideal one presented by the manufacturer or measured by IEC 61400-12. A high precision power curve, herein called Advanced Power Curve, is useful for evaluation of the actual production and fail prediction of the wind turbine and also for calculation of the energy that was not produced during downtime, either for maintenance or curtailment reasons. Hence, the interest in its determination.

III. Related Work

Many authors recognized the differences between the real power curves and the ones defined by the manufacturers and dealt with the problem of modelling real output conditions in their ways. In this section, we are going to offer a small report of the state of the art and their relationship to our work. Raj et al [4] offered a very quick review to some of the main models used, which is quite sketchy, but serves its purpose as an introduction. Another quick introduction can be found in Shokrzadeh et al. [5], which also shows a small practical application of some of the main methods to real data, which can be helpful for understanding.

Zhao et al. [6] excluded outliers to improve their power curve model. They first used a quartile approach to exclude the small clusters of outliers (which they called “sparse outliers”) and then used a density-based approach to exclude large clusters of outliers that do not correspond to correct operational circumstances. Our method is similar to their first approach and based on our results, we can consider that the large clusters are mostly eliminated with the first approach as well.

Marvuglia et al. [6] evaluated three different intelligent methods with high degree of accuracy. Nevertheless, the authors performed no initial cleaning of the data and the curves shown in their papers seemed to be rather ideal. They have single data points that they labeled as “out of control”, which seemed to be detected using deviation analysis, but they are rather sketchy in the details about this. Goudarzi and Ghayoor [7] have a similar take on the problem and are even sketchier on how they deal with outliers (seemingly, they don’t), but their intelligent method combines a sum of sine waves with Particle Swarm Optimization. Since they do not show any curves and report only absolute errors, it is difficult to have a correct view of their success. In this line of work, Renani et al [8] compare multi-layered perceptrons with traditional ARMA methods, without ever mentioning the concept of non-ideal data and even though they mention that their data was collected from a real wind farm, the curves shown in the paper seem rather ideal.

Yesilbudak [9], on the other hand, concentrates on detecting outliers using K-Means clustering and afterwards analyzing the distance from each point to the centroid of the group to which it belongs. His cluster techniques seem to divide the curve into regions and visually there seems to be no advantages from a simple density approach. One could even argue that, given that the author’s clusters merely reflect the division of the curve into regions, his examples sustain the simpler approach.

Wang et al. [10] propose a method that is based on splines, with the justification that the errors were characterized by heteroscedacity. Another paper from the main authors [11] justify this claim with an analysis of the error, showing that it does not fit into a gaussian distribution.

Looking into our data (figures 4-7) shows little evidence of this characteristics and even for the data these authors presented, heteroscedacity needs a little stretch. Besides their theoretical analysis [8] shows a long tail, which is normal since the wind farm tends to underperform instead of overperfoming. Besides, their work seems to include the outliers in the error distribution determination. Almost all papers (including ours) exclude outliers, for they are clearly not related to the curve. Wang et al [11] use an elaborate confidence method to find and exclude them, but it is not clear from their results how much of an improvement they get over simple standard deviation methods.

There is also the issue that the data [10] point to larger errors in regions 2, 2½, and 3, which is reasonable, for the power output is not constant in those areas. Nevertheless, separating the data into “changing” and “constant” regions will solve the problem with no further complication.

The long tail is the main challenge for the prediction model based on gaussian processes described by Pandit and Infield [13] and by Guo and Infield [14], which is also based on a comparison between binning and gaussian processes effectiveness by the same authors [15]. Nevertheless, their work shows an interesting characteristic in that they adjusted their curves for air density, something that may be an upgrade for our process in future works. Since we use a technique which is similar to binning, an analysis of changing it to a gaussian processes may also be beneficial in the future.

IV. Advanced Power Curve

The proposed methodology evaluates the power curve considering important environmental factors, to achieve a power curve obtained from stored measured data, for each turbine of a wind farm.

Finding a curve based on stored data is an approach that considers that the real data stores the subjacent relationship between the points, that is, the function is implied in each data point. Therefore, if we have enough data points, we can fit the real curve with good precision, even taking account local errors due to faulty measurements, outside influences and others, that change each data point. Given that all other influences can be considered stochastic, we can consider that their influence will amount to null when the number of data points grows (the actual zero influence can only be achieve with infinite data points, but for the effects intended, this supposition is not far-fetched for tens of thousands of data points).

We are considering that the power output is a function not only of the wind speed, but also of important factors that must be taken into consideration.

The first factor considered is the wind direction. The direction of the wind brings information about the physical turbulence, due to wake of nearby wind turbines, roughness, orography, and some influence of the atmospheric stability, as the cold fronts, for instance, usually come from a probable given direction, and the turbulence, wind shifts and gusts are characteristic of that direction, with some given probability.

The second factor considered is the air temperature. The temperature has direct influence on the air density, which can be easily calculated. But the temperature also brings indirect information about the turbulence because the convective effect on the atmosphere is generated by sun radiation that directly affects the temperature.

After careful analysis, we understood that the best approach is two-fold. The influence of the wind direction is considered for each turbine, while the temperature correction is applied to all power curves of the site, as function of the wind speed as shown below. Both direction and temperature also bring information about the wind shear, that is the speed difference due to the height above the ground, that affects the power production.

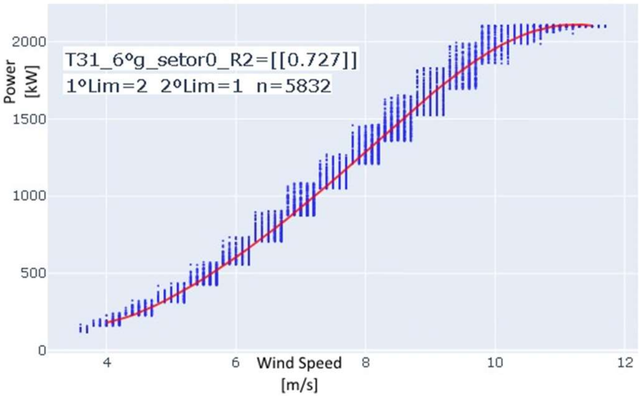

Fig. 4. Fitted curve for wind Turbine 31 at sector 0º - 30°, with 6º degree eqn., filters w/ SD=2 and SD=1

V. Statistical Process and Curve Fitting

In this section we will describe the process we used to fit the data, the steps taken and the improvement each new idea offered to the final fitted curve.

A. Wind Direction Sectors

As the proposed system will be handled by automatic digital analysis, having multiple power curves for each wind turbine is not a problem, as long as the final results offer a better perspective of the real behavior of the wind turbine.

Hence, we defined twelve wind sectors of 30° on the present study, so 12 power curves will be built for each turbine. The historical data of four years with 10 min resolution of a wind farm is used to adjust the curve, and each data point comprises the wind speed and power in the respective directional sector.

The selected time series, for a given wind sector, is transformed on a table with wind speed bins of 0,5 m/s, containing average Power [kW] and standard deviation (SD, [kW]) of power, found on the respective wind speed bin. Using this Power-SD table, the dataset may be analyzed, and a filtration with standard deviation thresholds may be used for exclusion of outliers for generation of a power curve. Several different threshold levels were tested in this work and their exclusion is necessary because a very discrepant number is usually due to errors in measurement or aberrant conditions that were usually analyzed by the human operators and their inclusion in the analysis tend to distort the curve in their direction. Given that they tend not to represent a real instance of the curve, but rather a non-significative response, this distortion would only generate imprecision in the fitting to the actual meaningful data, and hence, their exclusion is quite justified. As the Power-SD table has bins of 0,5 m/s, the graphs that shows the time series data filtered points forms little rectangles in each bin, as may be seen in Figures 4-7.

The search of the wind speed of the time series on the Power-SD table was developed based on vectorization, for operational efficiency. Please notice that the algorithm is quite efficient, and a curve fitting can be performed in a few minutes with a regular home computer. Given that the actual operational fitting will occur only sporadically (when the curves cease to offer a precise response), this efficiency is considered sufficient for the purposes of the application.

B. Data Exclusion and Statistical Filtration

Erratic data was excluded before the statistical analysis, excluding odd values when offset from nacelle to wind direction is large, system not OK is trigged, when grid connection is off even for a few seconds and other spurious data usually generated by sensors or other electronic system. These exclusions are not whimsical, but rather represent actual error conditions either of the SCADA systems or the turbine itself. Hence, the data is not representative and should be excluded from the sample used for learning purposes.

On the developed system, two filtration stages were used as suggested by [11], and after the first filtration a new Power SD table is generated from the first filtration, and the threshold for the second filter is different from the threshold of the first one. Increasing restriction at one filtration stage does not achieve the same effect as two stage filtrations, because a new standard deviation parameter is calculated so the next level will result in a more normalized distribution.

After the process, the resulting time series gathers a new column with the parameter SD for the Standard Deviation [kW] of the measured power with respect of the specific power bin. This standard deviation was used to exclude outlier data, for the reasons described above.

C. Power Curve Fitting

With the new time series containing the statistical filtered data and the Standard Deviation, the program uses a curve fitting module available in the Python: SciPy package. An equation must be supplied, as well as initial parameters, so that the fitted curve parameters may be calculated.

The traditional equation for the power curve is the polinomial expression, with grades from 4^{th} to 8^{th}. In the studied case it was found that in the region, from 10 to 12 m/s (Region 2½), the polynomial curve has difficulty to fit points cloud. To force the fit in this region, and to make the tangency of the curve to the horizontal line which represents the behavior above nominal win speed, we adopted the strategy of adding many points close to the nominal wind speed with given power values. This forces the fitting method to flatten the curve in that region and better fit the artificially generated data.

The equations given to the curve fitting were polynomials of grade 4^{th} to 8^{th} and the sigmoid logistic function; but only some combination of equations and SD threshold (the standard deviation at with the data was cut out of the data) combinations were tried (given that the results found were of sufficient quality for the intended purposes), so a more detailed study of this topic was left for future work.

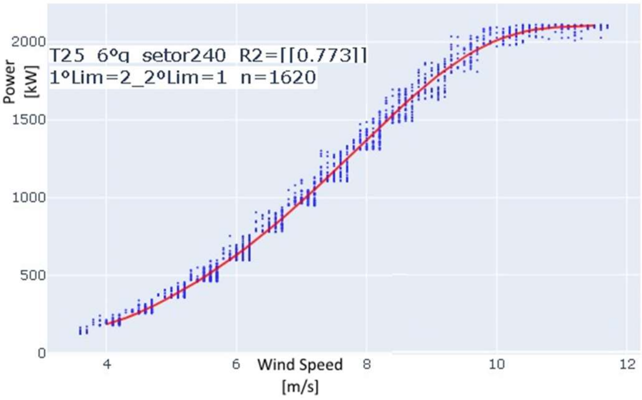

Fig. 5. Fitted curve for wind Turbine 25 at sector 240º - 270º, with 6º degree eqn., filters w/ SD=2 and SD=1

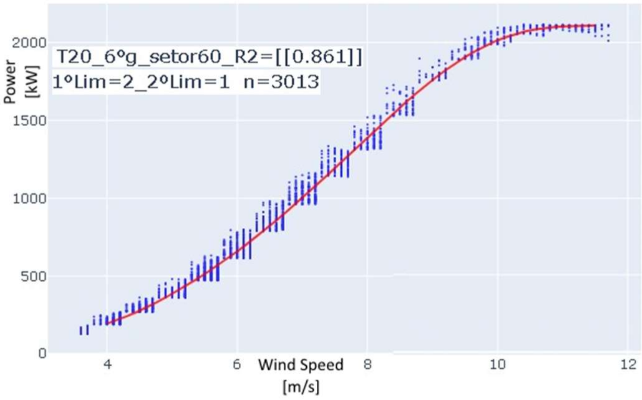

Fig. 6. Fitted curve for wind Turbine 20 at sector 60º - 90º, with 6º degree eqn., filters w/ SD=2 and SD=1 qual unidade de SD?

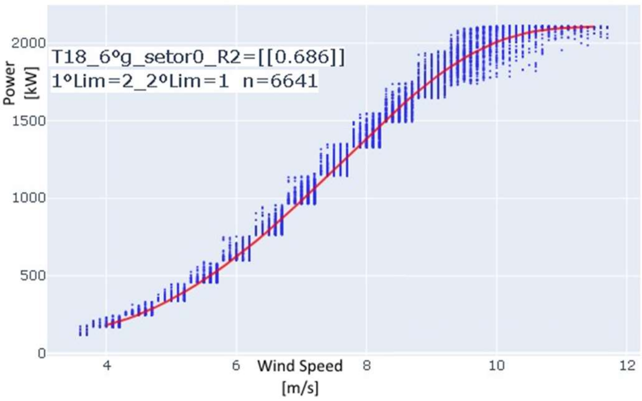

Fig. 7. Fitted curve for wind Turbine 18 at sector 0º - 30º, with 6º degree eqn., filters w/ SD=1 and SD=2

It was found a good fitting for the 6th degree polynomial and the first SD threshold at 2 and on the second run, we also tried with a smaller cut-out, nominally, SD = 1. Figures 5-7 shows graphics of the filtered data and the fitted curve.

Given the natural logistic shape of the power function, it would seem reasonable that the best fit would be found with a logistic curve. Nevertheless, all results showed that this was not true and that the polynomial curve was a better fit for the data. It is not clear why this happens, but the main assumption is that the derivatives of the power curve are not as steeped as the ones of the sigmoid function in the "middle" of the operational interval and do not change as much for all the active power region. Besides, the cut-off of the power curve is more abrupt, making it more difficult to fit a smoother logistic curve.

We have also found that the parameter R^2 alone was not a good measure of the quality of the fit; and the topic of ideal parameter to measure fitting quality for power curves is also open for further development.

D. *Standard Deviation*

The same algorithm that performs the curve fitting process also determine the standard deviation for each dataset. The Standard Deviation (SD) of the power was calculated for each speed bin. It was found that for a given database, SD varies according to the wind speed (s), which may be due for increased turbulence and chaotic wind behavior as the wind speed increases. The typical behavior of the SD curve is shown in Figure 8.

The 3rd degree polynom was found to fit reasonably well the SD plot, as can be seen on the example, so this equation type and initial parameters were given to the curve fitting process, and four parameters were obtained for each run of the program.

It is important to remember that each wind turbine is depicted in 12 wind sectors and the results are obtained for the whole wind park (as an aggregation of the individual curves), containing 12 lines for each turbine, with the number of points used for the fitting, the seven parameters for the power curve, the maximum power for the set, the correlation coefficient R^2 for the power curve fitting, the average temperature for the set and the four parameters to determine SD of the power as a function of the wind speed.

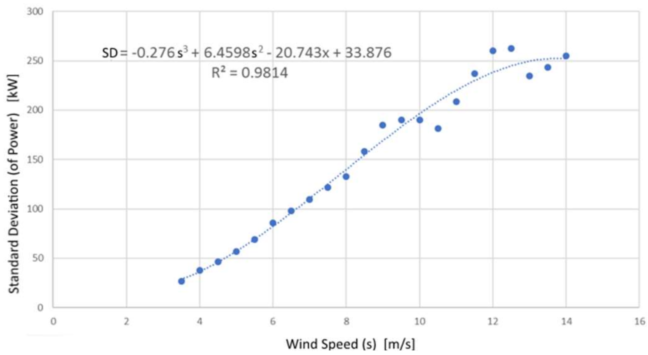

Figure 8 – Typical SD curve as function of wind speed.

VI. TEMPERATURE

At higher temperatures the air density decreases, and during hot sunny days, convective flows induced by sun radiation increases turbulence. Both factors induce smaller power production for the same wind speed.

Our goal initially was to create a different power curve for each different temperature bin (defined arbitrarily) but we noticed that this would shrink the amount of data available for each different fitting process. Hence, we changed the approach and decided to model the relationship between temperature and power production.

For the sake of simplicity and due to the nature of the curves seen in figure 9, it was assumed that the Power-Temperature correlation, for a given wind speed, is linear (P = aT + b). The power in figure 9 is dimentionless on base of T=10°C as reference.

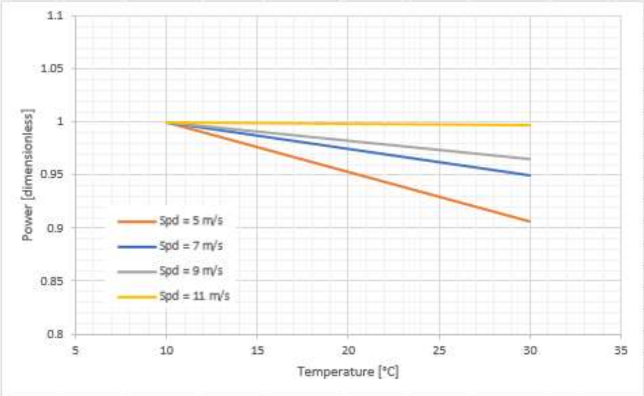

Fig. 9. Average power produced by the wind turbines, on four year period of the wind farm, as function of temperature, for four wind speeds.

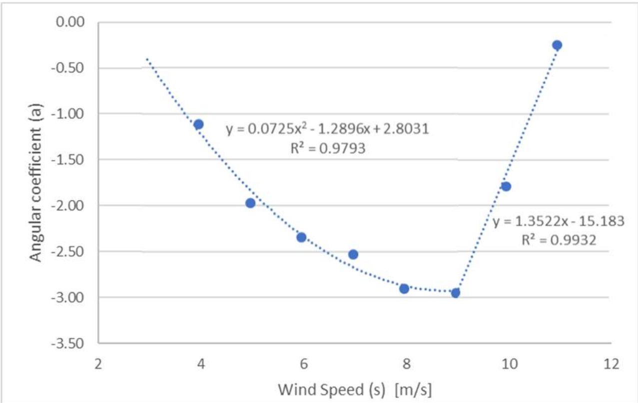

Fig. 10. Angular coefficient (a) as function of the wind speed, for the same data shown in figure 9.

Based on four years of data collected at the SCADA historic database, it was found that the influence of temperature on power production depends of the wind speed, *i.e.*, the angular coeficient a of the Power-Temperture varies with the wind speed as shown in figure 10. The linear coeficient b may be easily found when temperature correction is applied to the calculated power curve, but the angular coeficient a deserves some study.

The discontinuity observed at v=9 m/s induced us to use a quadratic relation for 4<v<9 m/s, and a linear relation for 9≤ v < 12 m/s. These curves give us then the coefficient of the linear function that will be used to adjust the fitted power curve according to the temperature measured at the moment of interest.

It is difficult to explain the abrupt change of behavior of the relationship at this wind speed without a thorough physical and climatic analysis of the process. Nevertheless, we can offer a hypothesis that suggests that this change is due to the big change on the derivative of the power function at Region 2 ½. Nevertheless, this function deserves more studies which should be performed in future work.

VII. Application to SCADA Data

There are two results obtained from the previous analysis applied to a given wind farm: The power curve table for each wind turbine by directional sectors, containing also the Standard Deviation; and the temperature correction function, which will be applied to all power curves of the site.

A. *Temperature correction*

To perform the analysis of real time measured data for a wind turbine, the input parameters are the power output, the wind direction and the air temperature. From the wind direction reading, the proper power curve parameters can be found so the power curve equation may be used, and the expected power and the Standard Deviation can be calculated for the given wind speed.

Maybe the simplest way to explain the application of temperature correction of the predicted power is to show an example, which can be seen in. Figure 11

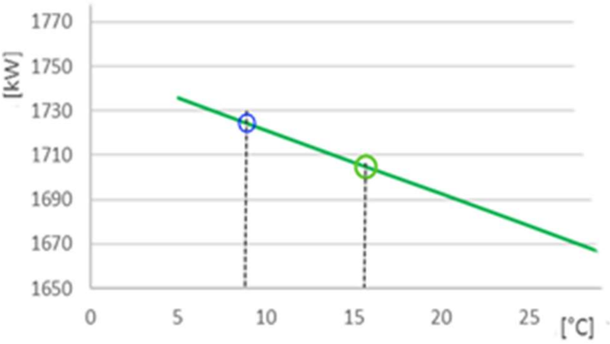

Fig 11. Temperature correction example

Given the current wind speed and direction, the power obtained from the equation resulted in 1705 kW, and the reference temperature for the dataset is 16°C as shown in the green circle. The green line is drawn for the current wind speed with the angular coefficient a, obtained from the temperature correction equation, for the given wind speed, containing the point (16, 1705). The real temperature where we want to evaluate the turbine performance is 9°C, so the corrected predicted power for this temperature is 1725 kW, signed in the blue circle.

It is not coincidental that when the temperature in the examples decreased, the power output increased. This effect is evident in all curves shown in Figure 9 and is a consequence on the increased turbulence and lower air density for hotter temperatures, as described in section V of this document.

B. *Power Curve*

The power curve table shows the power and standard deviation functions for each turbine, including reference temperature, R^2 and the number of points considered for curve fitting, for the 12 wind sectors. Having a reading of wind speed and direction, and produced power, it is possible to calculate the expected production, as well as a parameter called SC, that stands for Shewhart Control, calculated as shown in Equation (1) :

$$SC = \frac{P_R - P_E}{SD} \quad (1)$$

Where

P_R is the real measured produced power, available from SCADA;

P_E is the predicted power, calculated from the parameters from the table developed from the historical data.

SD is the standard deviation calculated form the parameters from the table developed from the historical data.

The value SC will then be applied to analyze the current status of the power plant based on the concept of Process Control Charts.

Process Control Charts were introduced by Prof. Walter Shewhart in 1931 and are also known as Shewhart Charts [16]. This tool is widely used mainly on industrial process control, to:

- Show evidence that the process is operating under statistical control;
- Detect cause of variations;
- Monitor and improve measurement procedures.

Upper and lower control limits may be stablished, depending on process characteristics, based on standard deviation; and rules for alarms may be established. Although there is vast literature and standards [17, 16], it is so process-specific that does not deserve further detail here. Figure 12 shows typical control chart, with data distribution. Notice that at each specific point we have the deviation of the current data point to the required one (in the case of our process, the point returned from the fitted power curve), measured at units of SDs (hence, it becomes an non-dimensional number).

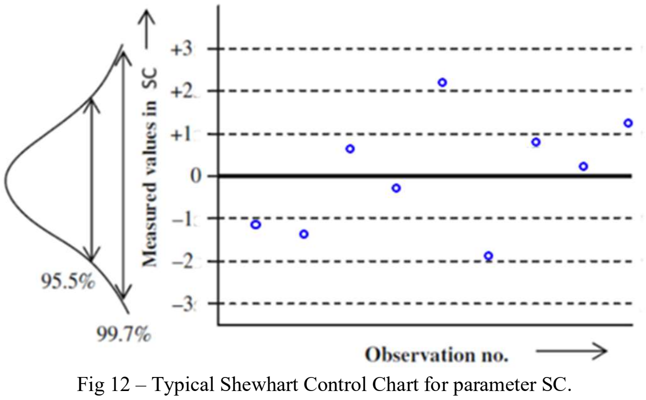

Fig 12 – Typical Shewhart Control Chart for parameter SC.

The parameter SC may be plotted on the chart, and when the value SC is zero, it corresponds to the situation when the real power equals the predicted fitted value for that wind speed and direction. There are some well-established rules to analyze the evolution of a Shewhart Chart for early failure prediction, which are described at length in industry standards [17, 16], and being able to plot from a power curve fitting is a great benefit for the wind industry.

C. Results

The application of the power curves obtained with this method relies on digital analysis of real time data. Once the Shewhart Chart tendency rules are defined, as the system acquires a new point the analysis of the behavior may trigger a pop-up of the graph on the maintenance and operator computer screens; so that detailed evaluation checks can be made to determine if maintenance actions will be recommended.

The definition of the tendency rules for general statistical process control is stablished in literature and standards, but it is recommended that the user develop its own rules, based on practical experience and application of the system.

Figures 13-14 shows the process charts of power production for selected wind turbines.

These figures are shown for visualization of the process control and do not show failure tendencies.

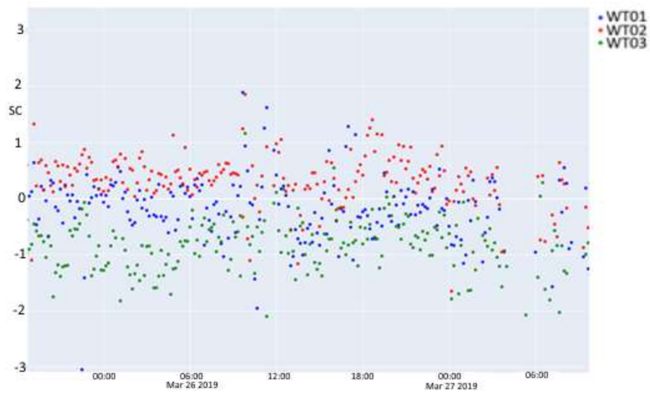

Fig. 13. Shewhart Control Chart for Power production of three wind turbines.

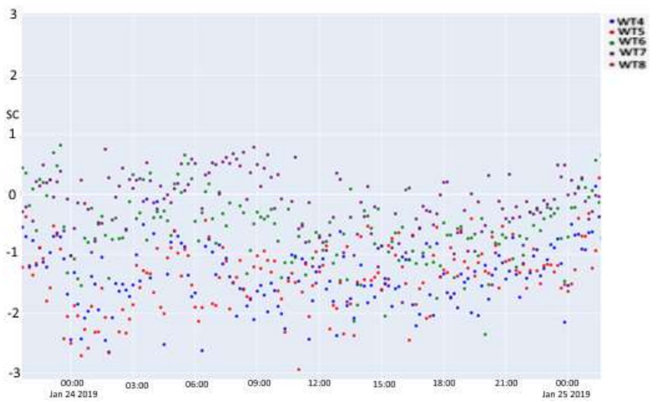

Fig. 14. Shewhart Control Chart for Power production of five wind turbines.

VIII. Final Remarks

The present study showed the current development state of each method applied. We are aware that there are possible new forms of combining known statistical and digital tools in order to achieve a better reading of what really happens on energy producing wind turbines.

Nevertheless, innovation relies in application of easily accessible digital programming to enrich wind turbine power curve application for predictive maintenance with wind direction and air temperature information and the results found in this paper show a lot of promise in increasing awareness to the current operational state of the wind power plant.

The fitted curves show that it is possible to mine the data and discover a functional relationship that describes the actual conditions of the wind power plant. We need these adjustments, given that the graphs provided by the manufacturer do not adapt to the real orography and wind conditions.

One of the most important achievements of this paper was the adjustment curve found for temperature data. As discussed, temperature is one of the factors that influence air flow and turbine efficiency, and it may be very hard to come with equations that model this air flow precisely. Hence, approximation methods are terribly important.

The mere separation of data into smaller groups might render the data mining and data fitting techniques less effective, for we would have smaller data sets for each condition. Hence, we proposed this curve adjustment which was obtained from the whole data set.

We used a linear adjustment model for temperature for it is the simplest. There is no claim that temperature affects the power output in a linear fashion, and further studies should be considered to find a model that may be more accurate. Nevertheless, even with such a simple curve fitting, we achieve interesting results in our fitting process.

The method needs to be validated in the long run in actual production situations, but it is promising enough to be deployed in an actual wind farm.

As discussed inside the paper, there is still a long way to run. As future work, we need to test other parameter configurations and understand better the change in the linear coefficient behavior, when mapping the relationship between power output and temperature. Besides, we can consider other methods of error treatment to eliminate outliers and improve the curve fitting process to achieve the Advanced Power Curve.

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