Development of a new low-cost procedure for wind farm maintenance with a view to decrease soil pollution

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ABSTRACT: The purpose of this article is to present the development of a wind farm, with a condition monitoring system (CMS) based on control charts as the algorithm, centred on a new index, to prevent soil pollution by oil spills in wind farms. To this end, temperature sensors can be considered as one of the more significant sensors to be employed in this study, because the information obtained with regard to anemometers and electrical power output counters can be employed by the control system. As a result, among the other variables, oil temperatures sampled in multipliers used in the wind turbines of a real wind farm were employed. Statistical analyzes were developed and the relationship between wind farm maintenance (usually related to wind farm oil spills) and oil temperature was obtained. Furthermore, a practical case study, centered in the statistical process control, based on the low-cost sample variable was developed and showed that this new procedure would improve deficiencies in the maintenance process, thus, reducing the failure detection time under low sensor cost, as also the related soil pollution.

Keywords: applied probability, decision analysis, oil spill, maintenance, wind warm.

INTRODUCTION

According to the American Lung Association, "Climate, energy, and clean air are inexorably linked". Solutions that lead to cleaner air must be included in any approach to a cleaner, more efficient energy use and a reduction in global warming. In October 2009, the National Academy of Sciences issued an important study that examined the hidden costs of energy to society. Such hidden costs, often called "externalities," include, lung damage, asthma, and premature death from air pollution; birth defects from a mercury fallout; and damage to buildings, timber harvests, and ecosystem services from acid rain. Even though they are very real, they are not reflected or "internalized" in the market prices. In effect, they are a hidden subsidy for polluting energy sources. According to the US Department of Energy, one of the obvious benefits of wind energy is that the production of electricity from this source involves zero direct emissions of air pollutants. In contrast, fossil fuel-fired electric generation from coal, oil or natural gas results in substantial direct emissions of numerous air pollutants that have adverse impacts on public health and the environment (Wind Energy Foundation, 2014).

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Wind energy generation results in the reduction of air emissions because of the manner in which the electric power system works. Wind energy is a preferred power source on an economic basis, as the operating costs to run the turbines are very low and there are no fuel costs. Thus, when the wind turbines produce power, this power source will displace the generation of fossil-fueled plants, which have higher operating and fuel costs (Wind Energy Foundation, 2014).

On the other hand, oil spills from a wind turbine multiplier are the highest source of pollution of this so-called clean energy source, and to date, there is a lack of solution to reduce this (Philip, 1995; Etkin, 2008).

One of important aims of this article is to present the development of a new low-cost procedure for wind farm maintenance with a view to decrease soil, with the help of a condition monitoring system (CMS), which is a tool that describes the present condition of the components of a system. At present, there is a need to develop an efficient fault prediction algorithm that will form the basis for the CMS. Furthermore, one of the main algorithm sources is the quality process control of the different indices.

The statistical process control (SPC) is the applied science that helps to collect, organize, and interpret a wide variety of information available on engineering applications (Harris et al., 1999; Kumar Sharma et al., 2008). SPC can help to understand and reduce the variation in any business process, thus, leading to less expenditure of money and time on rework and waste. Above all, control charts show how consistently a process performs and compares it with the customer requirements, providing an index that functions as an indicator for improvement of quality. Finally, the resulting process-capability index facilitates a quick evaluation of the results of the quality initiatives designed to improve the process consistency.

These types of statistical studies can be developed automatically by computers, in real time (Kumar Sharma et al., 2008). In this sense, as concluded in the recent research studies (Vosniakos and Wang, 1997; Lee et al., 2003; Louit et al., 2009), a computer that collects information in real time can detect very subtle changes in a process and can even give a warning in time, to prevent process errors before they occur.

In this is view, programming languages allow power station operators to adjust real sampling data to each particular situation. For example, Microsoft (MS) VBA is a very simple language to converse with Excel and also a user-friendly programming language that can be easily used by engineers who are interested in and ready to spend some time in a very rewarding and enabling learning process(Verma, 2003; Verhoefa et al., 2007; Wu and Liua, 2007).

Once an algorithm is proposed, it must be employed over some indices (UNEEN, 2008). These indices are usually obtained from the operators' experience and are usually defined as a function of the standard indicators. An indicator is a numerical parameter that provides information on the critical facilities identified in the processes or in individuals with regard to their expectations or perceptions of cost, quality, and lead times. Care must be exercised in choosing the indicators, as there is a risk involved in using a lot of numbers that do not provide any useful information.

The Computerized Maintenance Management System (CMMS) is being used today in many other applications; however, in the wind power industry, it is relatively new, so it is very interesting to analyse a practical case study that allows to define the main parameters to be considered (Verbruggen, 2003; Orosa et al., 2010).

On the other hand, the second purpose of this article is to develop a wind farm (CMS) methodology, based on control charts, as an algorithm of a new index that has not been employed before in wind

farms; wind turbine multiplier temperature. The main advantage of this research is that the information obtained from these low-cost sensors, like PT-100, can be employed by the control system as regard of anemometers and electrical power output counters. In consequence, between the other variables, the oil temperatures sampled in the multipliers used in the wind turbines of a real wind farm during a continuous study periods will be employed.

For the purpose of this study, data were obtained from the existing control system installations; furthermore, a statistical analysis was conducted and the main results were presented in an easy manner. When the multipliers' oil temperature was demonstrated as a new control parameter, a practical case study based on this theory

was developed, showing the feasibility of this new maintenance control procedure.

MATERIALS

Multipliers in wind turbines

In a wind turbine, we can find different components like multipliers, generators, couplings, breaks, and sensors, as shown in Figure 1. The coupling between the gearbox and the generator is elastic and capable of absorbing misalignments during a continuous operation. The mechanical brake is mounted on the speed shaft and consists of a disk on which a fail-safe hydraulic calliper operates. Finally, all these components and more sensors that measure velocities, temperatures, and position every 10 minutes, were located within an evolvement called 'housing' or 'gondola', as shown in Figure 1.
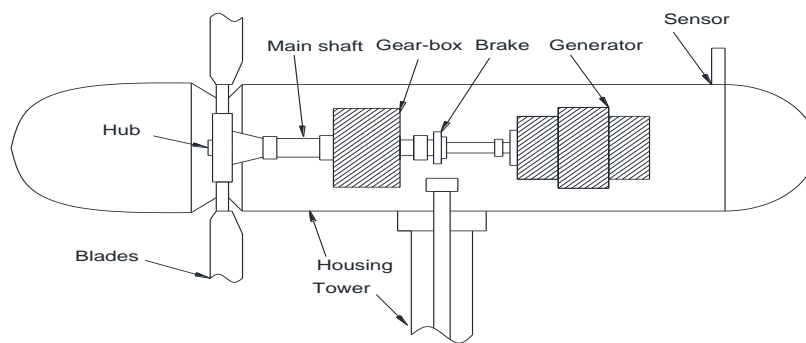

Fig. 1. Main structural components of a horizontal-axis wind turbine (HAWT)

The multiplier is designed to convert low revolutions that pass the hub per minute into high revolutions, as they are needed by the generator, to work. It is composed of a series of gears in several stages, between 3 and 4, which increase the revolutions and connect the output shaft of the gearbox to the generator shaft. Therefore, the input stage is usually between 15 and 25 rpm, and the output stage is between 1200 and 1800 rpm. As a consequence, among other things, the main functions of a multiplier are to transmit the rotational rotor power to the generator, to multiply the revolutions, and to let us obtain an evolutionary adaptation to demand.

In particular, we will analyse the

behaviour of a planetary gearbox type. The planetary gearbox is a kind of multiplier to be imposed at present because of its characteristics, such as, high transformation ratio, several multiplications, less workspace, and finally, because it supports heavy loads.

At the same time, a multiplier is where the greatest loss of turbine performance lies. As a consequence, to minimize these losses significantly, all the gears are usually immersed in lubricating oil, which at the same time, is circulated through a circuit that filters, cools, and is shared by all the moving parts. This circulation system consists of different elements like a pumping unit, which pumps oil to circulate

through the circuit toward an intercooler, and a filter with a sensor that alerts a high amount of deposited impurities. This oil is the source of the different oil spills that we can find in the wind farm soil, as a consequence of different breakdowns and their related maintenance tasks. In particular, the main oil spill occurs when the wind turbine works under very high wind velocities and housing vibrations.

In this study, the multiplier will be analysed to relate to the wind farm maintenance and its related oil spills, with its main control parameters that will be defined in the next sections.

METHODS

Variables Control Charts

In any production process, there is always some unavoidable variation. This is a normal variation and the cumulative effect of many small uncontrollable causes. When the variation is relatively small and associated with unforeseen causes in a stable system, it is considered acceptable in the course of the normal operation of the process and is treated as if it is within the statistical control limits. In contrast, there are other causes of variation produced by these assignable causes that are usually large compared to the normal process variations. Consequently, the process attains an unacceptable level of performance and is treated as a process out of control. Statistical process control is basically intended to detect the presence of assignable causes calling for corrective action.

As it has been explained, the control chart is one of the most important and commonly used in the Statistical Quality Control (SQC) methods, for monitoring process stability and variability (Montgomery, 1991). It is a graphical display of a process parameter plotted against time, with a center line and two control limits (Jennings and Drake, 1997).

In our case study, we were able to measure some continuously varying quality characteristics of interest and eventually the variable control charts were selected.

Once we measured the time evolution of the different indicators, a statistical process had to be developed to establish the control limits. These limits were usually set above and below the mean value equivalent, to thrice the standard deviation of the process.

The calculation of the average of all measures, and the upper and lower control limits are given by:

$$UCL = \mu + 3 \cdot \sigma \tag{1}$$

$$LCL = \mu - 3 \cdot \sigma \tag{2}$$

where

μ is the mean of each indicator.

σ is the standard deviation of each indicator.

Once the information is analysed in a control chart, we can determine if each of the indicators is under control or out of control, in accordance with the previous rules. If the process is out of control, we only have to eliminate the assignable causes. If the process is not capable of controlling each indicator within the control limits, we must take a general decision over the process. On the other hand, if the process is capable of controlling the indicators within the control limits, we must try to optimize the process. If the process is centered within the control limits, it means that optimization is obtained.

Parameters of interest

As it has been explained earlier, wind multipliers present a number of temperature sensors that collect and send signals in real time to data storage files, to record the operating status of the tower in time periods of fractions of an hour. Power output, wind velocity, housing temperature, multiplier temperature, and ambience temperature are the main parameters considered to be analysed in this process, as they are usually considered in these types of power stations. In accordance with
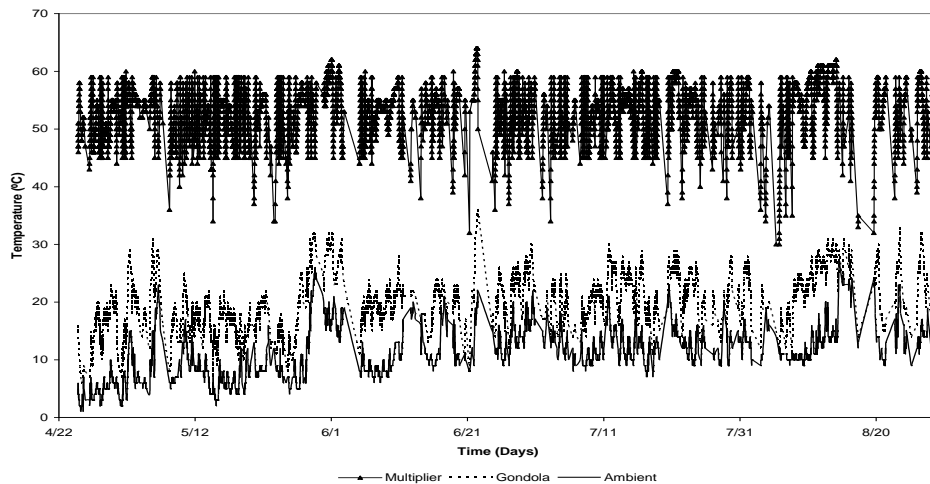
Fig. 2. Real sampled data of a wind turbine

the general maintenance procedures (Teresa, 2007; Tavner, et al., 2007) real sampled data have been obtained for a six-month period of time, with a sampling frequency of 10 minutes of each variable, as has been commented before (Fig. 2).

Once the main data were obtained, their relationship had to be defined by general correlation factor studies of the real sampled data. This correlation resulted from a special interest between the power output and wind velocity and between the power output and multiplier oil temperature. At the same time, a correlation factor of 0.8 was obtained between the housing and ambient temperature. It was a clear example of heat transfer through housing evolvement that had to be analysed in future research studies; in turn, it could generate interferences in the control process.

From these correlation factors, we can conclude that the power output depends on wind velocity and moist air ambient temperature. Furthermore, because of the moist air density calculation, a low variation during the sampling process was found and a curve fitting the power output and wind velocity was proposed.

Results showed an adequate correlation factor as a function of cubic power of velocity; it was similar to the theoretical studies on wind power potential (Fig. 3).
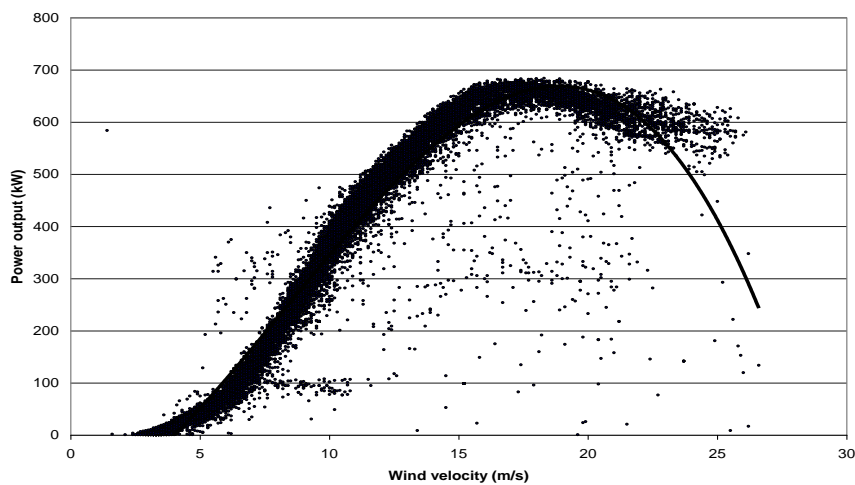

Fig. 3. Correlation between power output and wind velocity

The relationship between power output and wind velocity is represented in Equation 3, with an adequate correlation factor of 0.9483.

$$P = -0.1817 \cdot V^3 + 4.557 \cdot V^2 + 22.105 \cdot V - 149.98 \quad (3)$$

where

P is the power output (kW)

V is the wind velocity (m/s)

In accordance with the previous results on the correlation factor between the real sampled data, a curve fitting between the power output and wind turbine multiplier temperature was obtained, with an adequate correlation factor of 0.9345, as shown in Figure 4 and Equation 4.
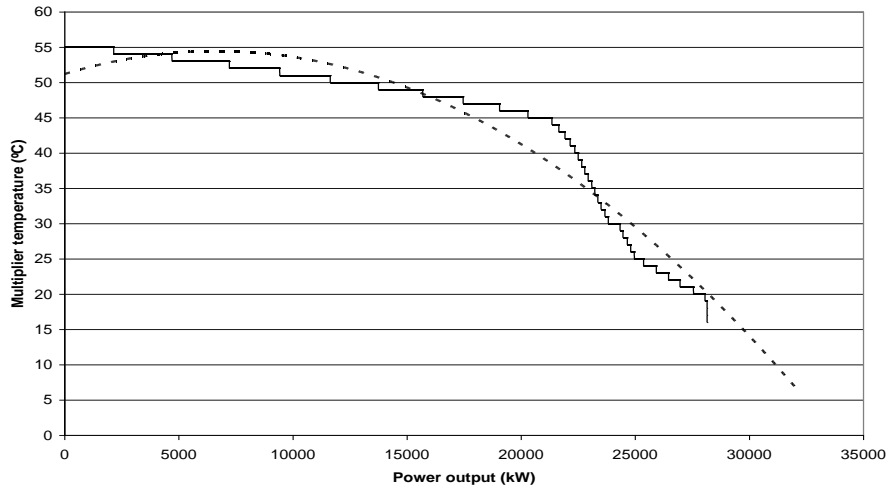

Fig. 4. Correlation between multiplier temperature and power output

$$T_{multiplier} = -7 \cdot 10^{-8} \cdot P^2 + 0.001 \cdot P + 51.216 \quad (4)$$

where

P is the wind turbine power output (kW)

$T_{multiplier}$ is the wind turbine multiplier temperature (°C)

As it shown before, it is possible to relate the weather conditions with the power output. In this energy transformation process, a new step forward, defining a relationship between multiplier temperature and power output has been developed. Now, the next step in this investigation is to define a new control system centred in these low-cost sensors that can be developed for the maintenance of wind turbines, as will be shown in the real case study and discussed in the next section.

RESULTS

A practical case study of multiplier temperatures as a low-cost control

parameter was developed in this section to reduce maintenance time detection, and as a consequence, to reduce oil spills. In particular, the purpose of this detailed analysis is to identify the trends of the multiplier temperatures and give details of their possible deviations, with the goal of finding remedial measures to limit the misuse of the optimum operating temperature for each power range.

Real sampled data

In the following table (Table 1), there is an example of data obtained from the control system of a real wind farm. Parameters such as, time, average power, wind speed, temperature, and multiplier room temperature were sampled. These data were collected and ordered in different average power ranges.

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Table 1. Statistical process control

Average power output (kW)	Average temperature (ºC)	Standard deviation	UCL	LCL	Counter	Counter (%)
455	51.06	3.22	57.49	44.63	329	97.34%
465	51.06	3.29	57.65	44.48	321	97.57%
475	51.17	3.05	57.28	45.07	312	96.89%
485	51.75	3.08	57.91	45.58	378	94.26%
495	51.83	2.94	57.71	45.94	346	96.92%
505	52.04	2.97	57.99	46.09	377	95.93%
515	51.87	2.83	57.54	46.20	322	97.87%
525	52.40	3.00	58.39	46.40	379	97.93%
535	53.01	3.14	59.30	46.72	342	97.99%
545	52.84	2.88	58.60	47.08	362	96.28%
555	52.96	3.12	59.20	46.71	336	96.28%
565	53.60	2.95	59.50	47.70	314	96.62%
575	53.77	3.29	60.35	47.20	362	95.51%
585	54.08	3.21	60.50	47.67	439	97.34%
595	54.84	3.52	61.88	47.80	477	95.59%
605	55.12	3.57	62.26	47.98	560	97.22%
615	54.98	3.17	61.32	48.64	646	98.48%
625	55.25	3.12	61.50	49.01	707	95.67%
635	55.22	2.46	60.15	50.30	753	98.17%
645	54.83	2.16	59.14	50.52	660	98.36%
655	54.47	1.89	58.25	50.69	530	97.79%
665	53.84	1.18	56.20	51.47	205	95.79%
675	53.63	0.93	55.48	51.78	25	92.59%
				Total	**9482**	**96.99%**

In this table, the calculations are made according to the power ranges described in the first two columns. The third column expresses the average value of this range, the fourth column shows the average temperature that exists in each power range, and the fifth column represents the standard deviation of the multiplier temperature.

In accordance with the previous research studies (Harris et al., 1999; Kumar Sharma et al., 2008), if random factors play a role in a process, any variable can create a normal distribution, with a mean and standard deviation. As a result, the distribution is located around the average plus or less than three times the standard deviation

Therefore, the sixth and seventh columns are the upper (UCL) and lower (LCL) control limits, respectively. The last columns are counters that show the number of values that are within the control limits and the percentage of these sampled values.

After setting the control limits, it is necessary to define when a process is said to be out of control. To do this, we define A, B, and C as the regions between one, two, and three times the standard deviation, over and below the mean, and we apply the following rules:

- Two of three points in a row, in area C.
- Four of five points in a row, in zone B or beyond.
- Six straight points up or down.
- Eight consecutive points outside area A, on both sides of the center line.

In any case, we must consider the presence of patterns or trends in the control charts, 2009.

As a result, for one simple multiplier, we have obtained Figure 5, which shows each control limit, central line, and each instantaneous value, as a cloud of points representing the temperatures in each power range limit.
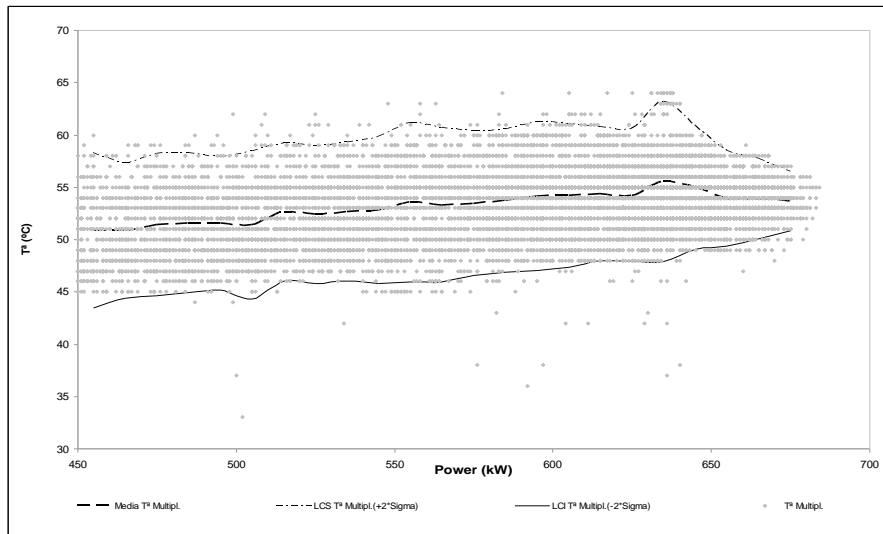
Fig. 5. Statistical process control of data from one multiplier

For a specific multiplier of this machine, we can obtain a polynomial valid operating range of temperatures, as shown in Equation 5.

$$T_{Central\ line} = -9 \cdot 10^{-05} x^2 + 0.1218x + 14.113 \qquad (5)$$

At the same time, the polynomials that yield a smooth operation can be given by the calculated control limits, which are shown in Equations 6 and 7.

$$T_{UCL} = -0.0003x^2 + 0.3061x - 28.069 \qquad (6)$$

$$T_{LCL} = 8 \cdot 10^{-05} x^2 - 0.0626x + 56.294 \qquad (7)$$

Statistical process control of a wind farm

The same real case study, developed for only one multiplier, can be now developed for all the multipliers of a wind farm, with the aim of showing the behavior of each one with respect to the average value. As a consequence, the mean of means and new standard deviations have been obtained. Furthermore, new control limits have been obtained, as shown in Figure 6.
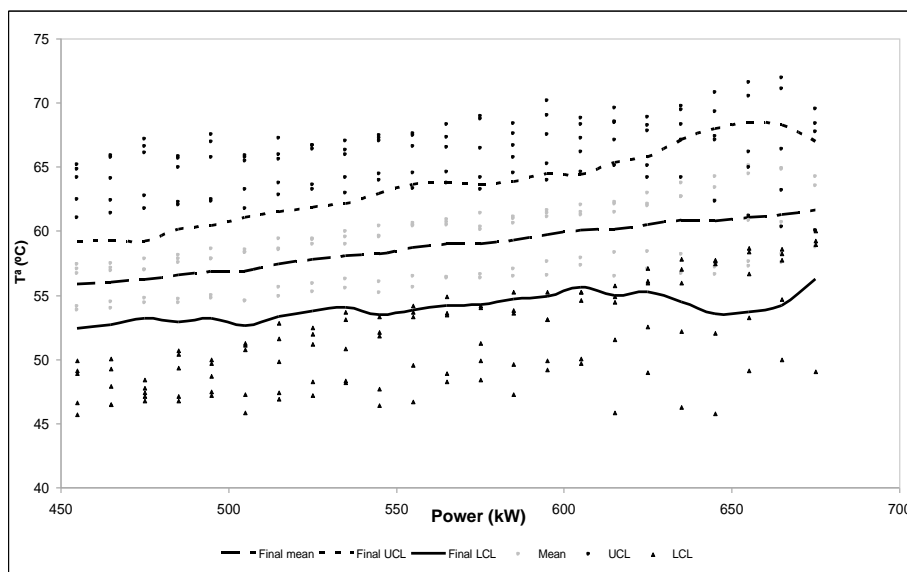

Fig. 6. Upper and lower wind farm control limits

As a result of this correlation, the optimal operating temperature for wind farm multipliers is given by one polynomial for any global multiplier of this wind farm, as shown in Equation 8.

$$T_{Central\ line} = -8 \cdot 10^{-05} x^2 + 0.1055x + 18.39 \qquad (8)$$

Furthermore, it is important to know when a multiplier operates within the adequate temperature. It is defined by the control limits defined in Equations 9 and 10.

$$T_{UCL} = -0.0001x^2 + 0.1642x + 3.0862 \qquad (9)$$

$$T_{LCL} = -3 \cdot 10^{-05} x^2 + 0.0468x + 33.693 \qquad (10)$$

Once the wind farm control limits are defined, we can calculate the real optimum operating temperature for these types of multipliers, in this particular wind farm. As a consequence, we can compare the performance of any wind turbine in the wind farm and form an impression on whether the operation is normal or abnormal.

An example of an abnormal situation caused by the multiplier mean temperature exceeding the upper control limit of the temperatures of the wind farm is shown in Figure 7. From this, we can see clearly that the multiplier is operating under an "abnormal" condition, so we can verify that

we have some kind of problem in this wind turbine, despite the fact that no alarms were raised against such a failure. Furthermore, despite the fact that nowadays there is no kind of sensor to detect oil spills, some kind of oil spill is always expected under these conditions. Once its operation is defined as unsuccessful, we can look for some evidence of this temperature increase. In this regard, tests such as spectral analysis and video endoscopy were performed.

In the spectral analysis, an increase in the vibration was noted and it was associated with the contact between the teeth of the gears in the planetary stage. Furthermore, a slight increase in the vibration was associated with the activity of the gears in the intermediate stage, bearings of the planetary stage, misalignment of the coupling, and the passage of the rotor bars of the generator, and finally, the oil spills.

On the other hand, a video endoscopy review determined that the multiplier had been generating chip signals, resulting in two broken teeth. The final conclusion of this was that the multiplier had to be replaced by another. Despite this, it could be repaired because of fast failure detection.
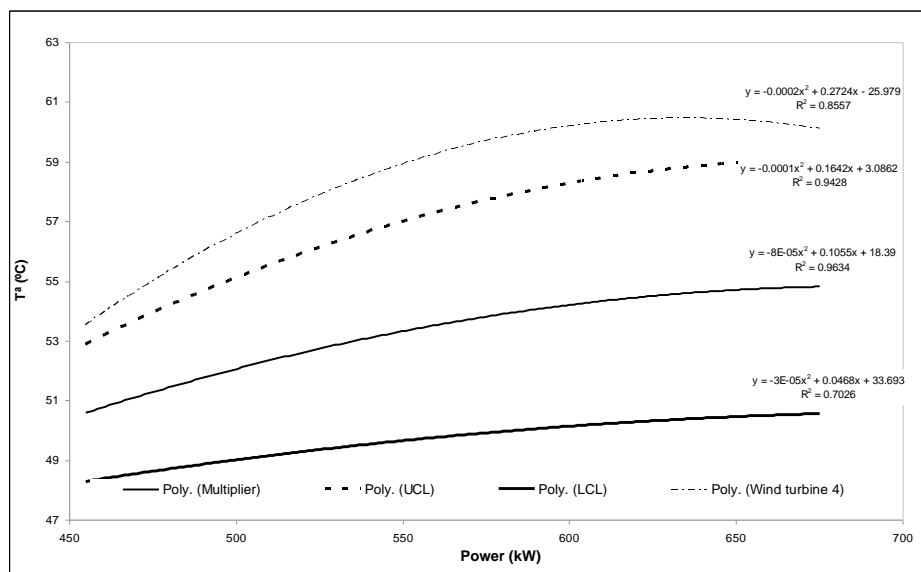

Fig.7. Statistical process control for a wind farm with respect to a wind turbine

As a consequence of this result, further maintenance procedures had to be employed in future statistical control methods in real wind farms, and particularly, an in-depth analysis of housing insulation had to be done to reduce failure detection time and the consequences of pollution.

CONCLUSIONS

Multipliers are a major cause of failures in wind farms. In the present article, a clear relationship between the wind turbine power output and multiplier temperature was obtained. As a consequence, the implementation of control systems with optimal operating temperatures in these elements was proposed in this study. In particular, control charts of multipliers' temperatures, based on real sampled data of each wind turbine of a real wind farm were employed, to compare the average value of wind farms. The results showed a clear reduction in the failure detection time and an improvement in wind turbine maintenance. Another advantage of this methodology, as compared to the vibration analysis typically employed in these studies, was its response speed and cost-effectiveness; this advantage was because of its low-cost temperature sensors.

More interesting correlations between the sampled data were obtained. For example, a clear correlation between power output and wind velocity was obtained and a correlation factor of 0.8 between housing and ambient temperature was obtained; this was a clear example of heat transfer through housing evolvement. Furthermore, an improvement in housing or multiplier insulation, with respect to outdoor ambience, allowed us to improve this control method toward lower detection time periods, and as a consequence, lower maintenance costs.

As a consequence of the time reduction in failure detection and vibration reduction, a reduction of oil spills, which is one of the more important contamination sources in a wind farm, is expected (Philip, 1995; Etkin, 2008). It must be analyzed in future research studies.

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