Department of Mechanical and Aerospace Engineering

Analytical Techniques of SCADA Data to Assess Operational Wind Turbine Performance

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Copyright Declaration

Signed: Preetcharan Singh Date: 13th September 2013

Abstract

Global Perspective

The wind turbine industry is currently growing on a global scale in order to meet governmental energy targets and to create a more sustainable future [1]. Operators are required to account for every kW generated (or indeed lost) with a current estimation of global underperformance to the tune of €500m annually [9]. It has therefore become increasingly important to the industry to develop sophisticated analytical tools to assess performance and efficiency of wind turbine operations.

Aims of the Study

The aim of this study is to further develop a procedure adopted by Natural Power to assess the performance characteristics of wind turbine operations. The study will focus on better identifying those turbines within a wind farm that are performing sub-optimally. The methodology for the study will utilise '10-minute SCADA Data' and 'Downtime Reporting Logs' to develop an analytical tool.

Development of Procedure to Identify Under-Performing Turbines

Data from downtime reporting logs was analysed to identify those turbines that were the least efficient in generating power. Specific Key Performance Indicators (KPIs) were studied to isolate those most effective in improving analytical techniques currently used to identify inefficient turbines. The KPIs studied include power curve shape, energy ratio, pitch behaviour, yaw effect and rotor speed of turbine blades.

Application of Procedures Developed to Wind Turbine Operations

New procedures developed during this study has led to operational events being identified with significant energy losses previously unidentified. This has proved beneficial to the wind turbine operations management consultancy, Natural Power, to better identify performance characteristic changes. The framework thus established can be further developed for wind turbine operations in general. The study has additionally highlighted the need to develop a complex automated algorithm that interconnects multiple KPIs simultaneously due primarily to poor performance being related directly to specific operational faults.

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Family and friends who helped and encouraged me in so many ways.

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Nomenclature

KPIs	Key Performance Indicators
kW/MW/GW	Kilowatt(s)/Megawatt(s)/Gigawatt(s)
PCYA	Post Construction Yield Analysis
RPM	Revolutions Per Minute
SCADA	Supervisory Control and Data Acquisition
T	Abbreviation for Turbine, eg T1 = Turbine 1

1 Introduction

With wind farm installation growing on a global scale to move towards a sustainable future, it is becoming ever more important to understand and analyse the performance of operational wind turbines in order to account for every kW generated. In recent years the development of wind turbine technology, resulting in a greater complexity of subsystems, has led to traditional performance monitoring techniques becoming outdated [2].

In 2012, the UK added 3.2GW of installed capacity from renewables, 57% which came coming from wind power technologies [4]. More relevantly, of the 41,258GWh generated from renewables in 2012, almost half was generated from wind power, highlighting the UK's investment into wind energy, both on and offshore. It is predicted that by 2020, 22GW of installed capacity from wind alone will be added to the renewable energy portfolio in the UK [1].

On a global scale, China, USA, Germany, Spain, India and UK, respectively, are the 6 main world leaders in wind power and continue to significantly invest in wind power. 2012 saw record development in the USA, adding 13.1GW of new wind power capacity, coming from 190 projects leveraging $25 billon of investment [1].

In consideration of the global renewable energy market outlook for the foreseeable future [5], wind energy is predicted to remain one of the main renewable energy sources. With this sheer scale in mind, it is therefore of great importance to take advantage of the extensive data available from commercially operational wind turbines, to be able to carry out detailed performance analysis in order to maximise the operation of wind turbine generation. For a consultancy managing multiple wind farms, it could prove beneficial to rank a type of analysis to efficiently improve the performance of wind turbines and consequentially that of the wind farm. It is estimated by a leading wind energy consultancy that the wind industry is underperforming by €500m per year [9]. If on a global scale the performance of wind turbines are analysed and improved, the wind energy sector can be of more value both economically and environmentally for countries working to meet energy targets.

Using 10-minute SCADA data and downtime reporting logs for an operational onshore wind farm of 60 turbines, the aim of this project is to further develop an existing procedure that assesses operational wind turbine performance. Currently, at Natural Power, the assessment of performance of turbines mainly involves analysing power characteristics along with downtime, whilst in specialised PCYA (Post Construction Yield Analysis) reports, other KPIs (Key Performance Indicators) are included. This thesis aims to develop new assessment procedures for analysing the performance of wind turbines. The main objectives of this project are to:

- Perform downtime analysis, in order to analyse the performance and reliability of the wind turbines
- Investigate specific KPIs that affect turbine performance, including:
    - Power Curve Shape
    - Energy Ratio
    - Pitch Curve
    - Yaw Effect
    - Rotor & Generator Speed
    - Torque Characteristics

The downtime analysis covers a detailed overview of the wind farm operation, which makes use of downtime logs, listing any time the turbine was not able to operate. This data can be analysed to identify over a long period of time which factors contributed to downtime the most. At this stage, the operational availability of the turbines and the wind farm can be calculated, by comparing the duration of time that the turbines were operating to the times they were not.

Downtime normally accounts for ~1-10% of the duration of the operation of the wind farm. Of the other ~90-99% of the time, it is important to assess the efficiency of the turbines whilst they are running. The data available from turbine SCADA systems are extensive and so it is important to identify which parameters are of most use in performance analysis. In the first instance, obtaining power curves (plotting wind speed v active power) for each turbine over a period of time is useful in determining performance characteristics of each turbine. Additionally, by filtering out anomalies found from any bad data found in the plots, such as failed anemometry, icing or uncharacteristic performance, the actual performance of the turbines can be seen, and this can be compared to turbine manufacturer warranty data. By reviewing monthly power curves for each turbine for the duration of the operation of the wind farm, noting changes in power curve shape, power curtailments and any other uncharacteristic performance, specific turbines can be identified for further investigation. Additionally, after comparing the actual energy output to that predicted by the manufacturer, the revenue gains/losses can be calculated, which is of great interest to a wind farm owner.

From the power curve study of turbines requiring further investigation, analysis can be carried out on the aforementioned KPIs, to establish the root cause of the performance change. However, in some cases, reviewing power curve plots does not highlight every performance issue. This current investigation will therefore cover other KPIs that are useful in highlighting performance changes. This report will discuss the procedure to calculate performance losses in energy and monetary terms from any significant performance changes seen in the research.

2 Operational Wind Turbines Overview

When assessing the performance of a turbine, it is important to have a good understanding of turbine subsystems. This makes it easier to understand the way in which the data available in the SCADA system is interlinked and how it can be subsequently analysed to result in useful information for operators.

In this section, an overview of turbine subsystems and some key factors in turbine design relevant to this project will be discussed.

2.1 Turbine Subsystems

Generally, all wind turbines work in the same way, by harnessing the power of the wind by converting aerodynamic lift generated by airflow over the blades to turn a shaft connected to a generator, which can convert the mechanical energy to electrical energy. There are differences between turbine design styles, including:

- Blade orientation (horizontal/vertical)
- Number of blades
- Method of power control (stall/pitch regulation)
- Rotor configuration (fixed/variable)

Figure 2.1 shows a typical configuration of a commercial wind turbine, namely, a three bladed, pitch-regulated horizontal axis turbine, similar to the configuration of the turbines used to formulate the results presented in this thesis.

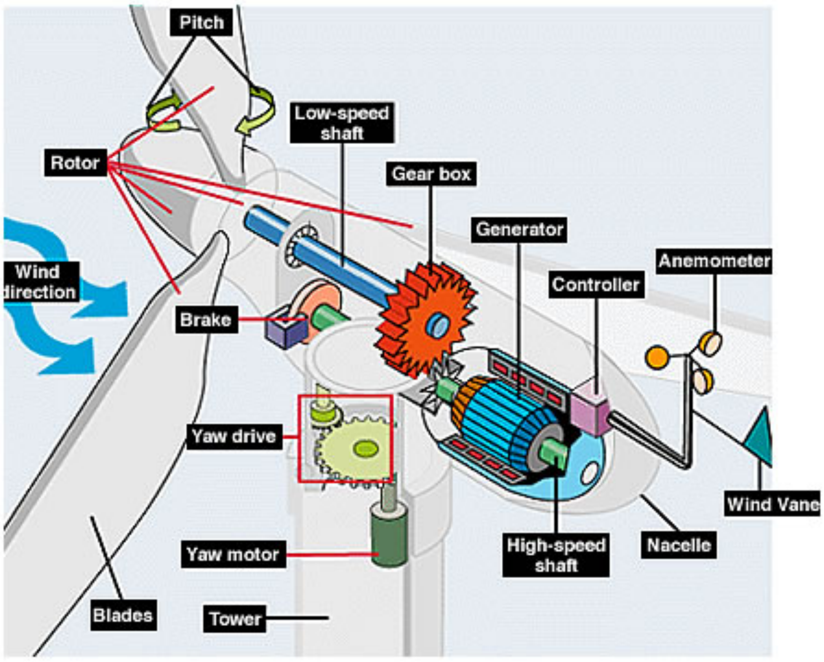


Figure 2.1 Typical Commercial Wind Turbine Subsystems Diagram, courtesy of Turbines Info [7]

Most of the components of the turbine shown above are self-explanatory, however listed below are the key functions of some of the subsystems [8]:

- Anemometer (Nacelle): Measures wind speed
- Pitch Regulation: Twisting of the blades, changing the aerodynamic interaction with the wind, therein controlling rotor speed to regulate power output
- Wind Vane: Measures wind direction and communicates with the yaw drive to rotate the turbine into the direction of the wind

The nacelle anemometer sends wind speed data to a controller that controls the pitch actuation, to regulate power output. Wind speed measurements can be used in conjunction with average active power output to generate power curves, an important and useful tool for performance analysis.

Pitch curve (wind speed v average pitch angle) analysis is an important KPI investigated in this project, as pitching correctly is related to performance [2]. The wind vane is an important component as it provides the data for the turbine to adjust yaw so that it is facing oncoming wind flow, for maximum power output. If the wind vane is misaligned, it can lead to a possible reduction in power and also fatigue the structure, leading to losses in revenue from reduced, sub-optimal performance and downtime.

2.2 Power Control

Wind turbines are designed to operate over a range of wind speeds. Shown in Figure 2.2 is a typical power curve, showing three distinct regions. The operating range is said to occur between the cut-in and cut-out speeds. At wind speeds in region I, the turbine is run at maximum efficiency to extract as much energy as possible [6]. In region II, the wind speeds are such that the turbine is able to reach its rated power. In region III, the turbine is controlled such that the energy extracted remains at the rated power. After the cut-out speed, the turbine will shut down as high wind speeds could damage the turbine.

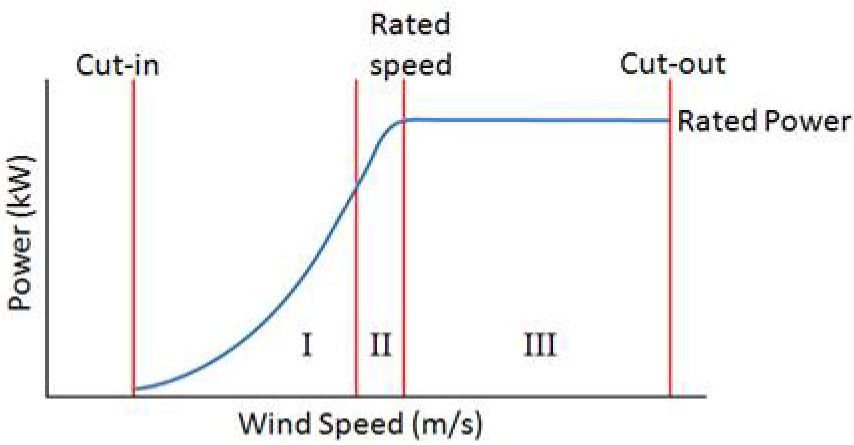


Figure 2.2 Wind Turbine Power Curve, courtesy of NI [6]

In region III, the power output is controlled by either the stall or pitch regulation of the blades, in order to constrain it to rated power.

3 Performance Analysis Literature Review

In the early stages of the project, a literature review was carried out to find which KPIs that effectively and efficiently identify sub-optimal performance of turbines would be of interest to investigate. Papers and conference presentations were reviewed of several industry leading consultancies, including GL Garrad Hassan[2][9][18], RES Group [11] and Sgurr Energy [19], to name a few.

The aforementioned consultancies utilise data from similar SCADA systems for the analysis of turbines. From the literature reviewed, similar KPIs were suggested by the consultancies to be effective in identifying sub-optimal performance. Garrad Hassan, known to be the world's largest renewable energy consultancy [20], provided the majority of the foundation knowledge required to develop the procedures presented in this research. No detailed methodologies were found in the literature review, for the likely reasons of the organisations wanting to protect their valuable information. However, the papers reviewed did highlight and give examples of what performance changes can look like in the KPIs chosen for study in this project. This provided sufficient grounding to develop the analysis in further sections of the report.

As mentioned in the introduction, a power curve analysis study was carried out first. This method was found to be a commonly used tool to identify performance changes in turbines. Using Natural Power's existing methods as a foundation, further methodologies were developed, revealed in Section 8. Subsequently however, the KPIs analysed were the development of new methodologies based primarily on the literature review carried out.

4 Data Acquisition & Analysis

In the storing of large data sets, elaborate, robust and effective data management systems are required. In collecting years of operational wind farm data for multiple wind farms, millions and millions of rows of information are stored and so security measures for the protection of that data is also important. It is also required that analysts can efficiently retrieve the relevant data, to be able to carry out reporting to the wind farm owner/client, and also to carry out more detailed analysis like in this project.

SCADA (Supervisory Control and Data Acquisition) is a system, which is used on wind turbines to monitor and acquire data, measuring all aspects of the turbine subsystems.

Microsoft SQL Server is a relational database management system, which is used to create, read, update and delete data, sorted by rows and columns in tables. SQL (Structured Query Language) is a programming language used to manage the data in the database to carry out create/read/update/delete operations. The wind farm data used in this project was acquired and analysed using Microsoft SQL Server 2008 and SQL in unison.

For the protection of the original data, a new database was set up for this project and the relevant data for each wind farm copied. This allowed full administrative rights over the data allowing appropriate manipulation of this data as required.

In utilising data acquired from SQL Server, some data can be copied into Microsoft Excel and with the use of appropriate tools (for instance equation and graphing tools), it can be analysed. Additionally, Python is used to plot large data sets that Excel cannot handle. As Python is able to communicate and retrieve data from SQL Server databases directly, this allows for the automated generation of multiple plots.

Windographer is an industry-leading tool for analysing wind resource data. By importing 10-minute data from an SQL database, it is simple to plot and manipulate data to provide useful results for analysis, rather than using manual plotting technique (like in Excel). Windographer was used in the KPI study to plot the parameters mentioned in the introduction.

5 Wind Farm Sites

For the purposes of data protection, the name and specific location of the site from which data is used will not be disclosed in this thesis. However, it is the analysis and procedures developed in this investigation that is of value and these can be applied to any wind farm rendering the site specific details irrelevant.

For clarity, the name “Wind Farm A” will be assigned to the wind farm used in this project. The wind farm is in the UK and some of its details are listed below:

Wind Farm A:

- 60 x 2.3MW turbines
- Operational data available from August 2010 to June 2013
    - 2040 turbine months of data

This specific wind farm was chosen to carry out a performance analysis study on for several reasons. It was important to pick a wind farm that had been operational for 2+ years in order to have extensive data for analysis, to enable potential performance changes to be found. This also offered the opportunity for the project to assess the potential for fatigue effects. With this wind farm housing 60 turbines, there were plenty of opportunities to be made between the turbines.

Additionally, it is challenging to isolate performance issues due to any one parameter in the SCADA data, as quite often performance changes can be the result of the effect of multiple parameters. It is therefore important to pick a wind farm that has as few external factors affecting performance as possible, to give the best opportunity to make sense of performance changes without blurring the analysis. Wind Farm A was chosen as it is not subject to noise curtailments and shadow flicker curtailments.

6 Methodology of Analysis

Developing the ideas discussed in the introduction, analysing power curves as a first port of call is useful in performance analysis [12]. As an existing method of analysis, reviewing monthly power curves for a turbine and noting any changes showing non-standard behaviour can identify performance issues [2]. After filtering out any "bad data", leaving only representative data points for the performance of the turbine for a given period, an operational power curve can be generated for that turbine, showing its actual performance, by averaging the active power output for a wind speed bin [10]. This is an important factor in the performance analysis study, because it compares the theoretical power attained from the operational power curves before and after a performance change is identified, and this allows for energy losses and therefore revenue losses to be calculated. This will be discussed more in detail in a further section on power curve analysis.

A monthly power curve can be generated by obtaining the wind speed and the corresponding average active power for a 10-minute period, and by plotting wind speed v average active power output for every 10-minute record in a month [2]. Wind speed measurements should be corrected for air density to generate accurate power curves. In this study, it was assumed that applying this correction factor would not affect the aims of the project (to develop new methodologies of performance analysis) therefore to save time, the measured wind speed was used.

A change seen in the power curve could be the result of a corresponding downtime event, and so by identifying the time period when the change occurred and consulting downtime alarm logs, it can be relatively straight forward to find the root cause of that performance change. However, the root cause of a change can sometimes be unclear. In some cases, no change can be seen by visually inspecting a monthly power curve however a change in another parameter during the same month could highlight a performance change. It is for this reason that it is important to analyse other parameters available in the SCADA 10-minute data available. This makes it more probable to find performance changes and identify the root cause of the change, as later sections in the report will discuss.

For each KPI analysed, the expected range and standard operation should be identified. This in turn allows the analyst to fully categorise non-standard operational events. The KPIs chosen for study have been identified from carrying out a literature review on analytical techniques for performance analysis of turbines [9] [11]. Following sections based on operational data analysed will detail the standard operation of the said parameter, also showing examples of changes in performance and how this translated to an energy loss. Firstly, the next section will cover an analysis carried out on the downtime of Wind Farm A over its entire operation.

7 Downtime Analysis Study

7.1 Contribution to All Downtime

When considering all downtime, three key relevant data sets were retrieved for all 60 turbines belonging to Wind Farm A since the beginning of operation, as follows:

1. Number of Downtime Events
2. Duration of Events
3. Duration of Time between Events

The data retrieved from the SQL Database has previously been analysed by wind analysts producing monthly reports over the duration of operation. All downtime logs have gone through a quality control process, as it is the client who uses the downtime log reports as an important reference, for understanding the reasons why their 'assets' did not produce energy and what factors are responsible for those downtime events. Therefore, it was possible to retrieve the data from the database without the requirement for quality control.

Using the three datasets listed above, the contribution of downtime made by each turbine is illustrated in Figure 7.1. The table below summarises the three turbines that contributed to downtime the most. Note that the duration between events should be maximised.

WTG	Number of Events (Descending)	% of Total
16	793	2.31%
34	756	2.20%
6	733	2.13%
WTG	**Total Duration of Downtime (Descending) (Days)**	**% of Total**
18	97.1	4.97%
3	72.6	3.72%
35	67.7	3.47%
WTG	**Total Duration between Events (Ascending) (Days)**	**% of Total**
18	932	1.55%
3	961	1.60%
35	963	1.01%

Table 7.1 Contribution to Total Downtime for Total Operation of Wind Farm A

Table 7.1 shows that with regards to the total amount of downtime, Turbine 18, 3 and 35 contributed most to downtime, respectively. These turbines reappear in the listing of duration between events, confirming that not only are these turbines contributing most to downtime, but also that the duration between events were relatively shorter.

In the calculation of duration between events, there were some events that gave a negative duration, meaning that an event was logged for a turbine during a currently active one for that same turbine. This was considered an error and these two events were equated to zero. The error calculated from making these changes is negligible (0.00012%).

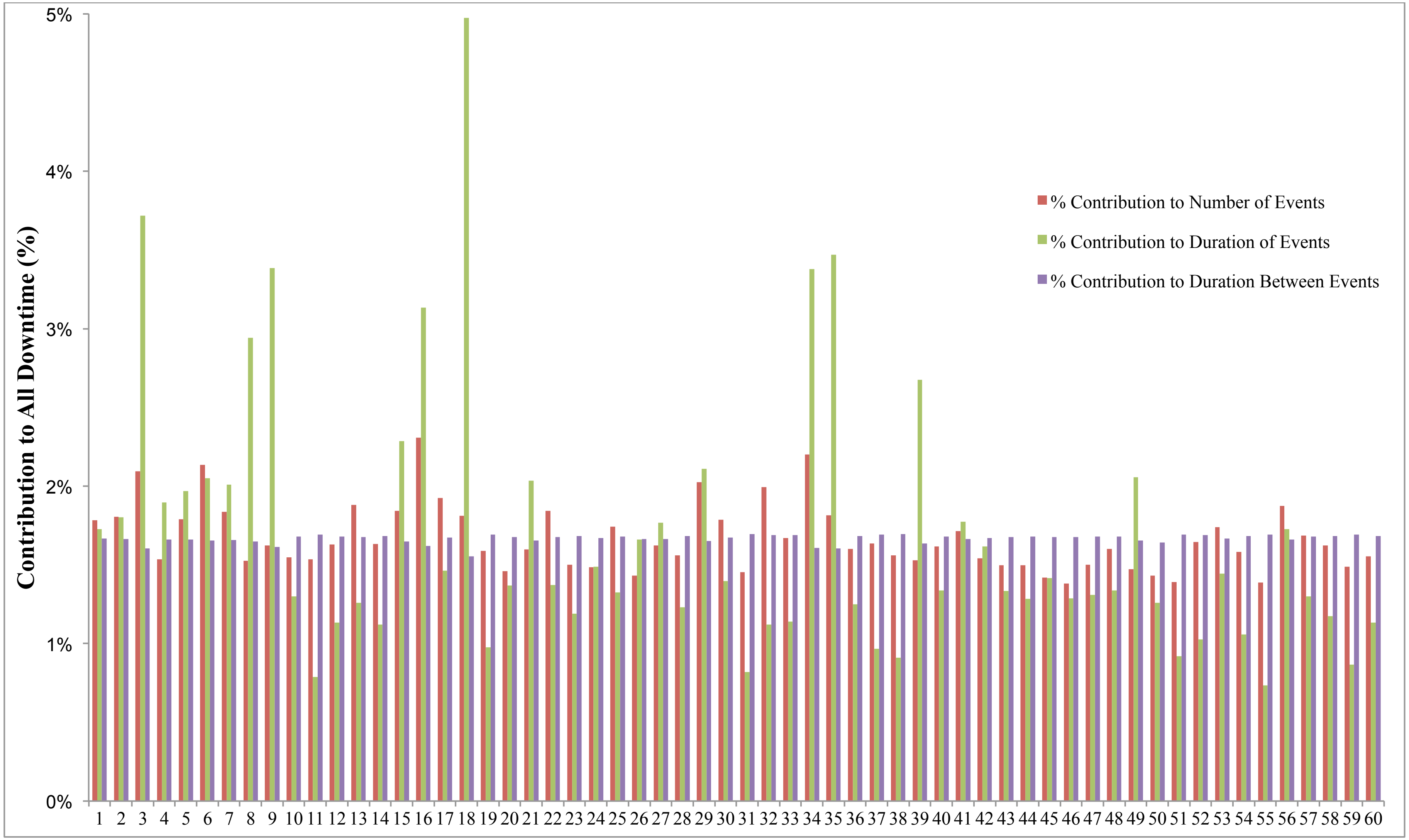


Figure 7.1 Contribution to All Downtime Wind Farm A

Table 7.2 summarises the most occurring Alarm IDs (in bold) for those turbines that contributed most to the duration of downtime. Listed below the Alarm IDs are the comments that were flagged as contributing the most to that Alarm ID. Of all Alarm IDs, the Manual Stop Alarm ID contributed the most (23%) at Wind Farm A. The generically named Alarm ID is not very useful, so the top comments for that Alarm ID allow for the analyst to understand in more detail what specific events contributed.

<table>
<tr><th></th><th colspan="3">Alarm ID (Most Occurring in Duration Order)</th></tr>
<tr><th>WTG</th><th>1st</th><th>2nd</th><th>3rd</th></tr>
<tr><td rowspan="2">18</td><td>Manual Stop
(1001) – 60 days</td><td>Grd Inv Comm Error
(13122) – 18 days</td><td>LMU Alarm Overspeed
(6101) – 7 days</td></tr>
<tr><td>▪ Inspect and test transformer – 51 days
▪ LMU (Line Matching Unit) fault - 1 day
▪ Change parameters converter System – 1 day
▪ Replace 230V-27.5V power supply unit A12 cabinet – 1 day</td><td>▪ Inspect and test transformer – 17 days
▪ Replacement of TS18/2 33kV switchboard – 1 day</td><td>▪ LMU error – 1 day
▪ Remove and replace centre plate low speed – 1 day
▪ LMU fault – 1 day
▪ Investigate fault in LMU over speed – 0.5 days
▪ Replace IO board in A3 panel - 0.5 days</td></tr>
<tr><td rowspan="2">3</td><td>Mainbreaker Cut Out
(13106) – 12 days</td><td>Remote Stop - Owner
(1007) – 9 days</td><td>Manual Stop (1001) – 9 days</td></tr>
<tr><td>▪ Replace trip unit on turbine – 5 days
▪ Replacement of main breaker – 3 days
▪ Main breaker related issues – 3 days</td><td>▪ HV switching to restore part of array - 6 days
▪ Grid transformer fault – 1 day</td><td>▪ Replacement of switch board – 1 day
▪ Servicing related downtime – 2 days
▪ 120 other downtime event contributions</td></tr>
<tr><td rowspan="2">35</td><td>Manual Idle Stop (1015) – 18 days</td><td>Manual Stop (1001) – 12 days</td><td>Brakepressue Too Low
(9303) – 7 days</td></tr>
<tr><td>▪ Check delta modules – 14 days
▪ Inverter fault – converter calibration & test – 4 days</td><td>▪ Electrical fault finding on delta modules – 4 days
▪ Replace hydraulic motor – 2 days
▪ 93 other downtime event contributions</td><td>▪ Replace hydraulic motor – 7 days</td></tr>
</table>

Table 7.2 Most occurring Alarm IDs (duration) for top 3 turbines contributing to downtime for total operation of Wind Farm A (Alarm ID in brackets, duration of alarm ID downtime in days, rounded to the nearest day)

Overall, this analysis provides the starting point for identifying which turbines and downtime Alarm IDs to consider for further investigation.

7.2 Contribution to Downtime – Turbine Category Only

The above analysis considered all downtime, including Grid, Infrastructure and Environmental Categories. In a similar method, the number of events, duration of events and duration between events was considered for the Turbine Category only, to assess what downtime was due to the turbine alone. This was important as manufacturers can be held responsible for energy not exported to the grid if it is due to unexpected problems with the turbines themselves. Even though current monthly reporting covers this information to account for lost energy due to turbine faults, one of the research objectives in this project is interested in the long term performance of the wind farm. Figure 7.2 illustrates the results for this analysis, along with Table 7.3 summarising the top three turbines contributing to Turbine Category downtime below:

WTG	**Number of Events (Descending)**	**% of Total**
16	640	2.39%
34	632	2.36%
29	604	2.25%
WTG	**Total Duration of Downtime (Days)**	**% of Total**
35	59.9	5.56%
34	57.3	5.32%
9	44.3	4.11%
WTG	**Total time between Events (Days)**	**% of Total**
18	848.0	1.55%
3	868.9	1.60%
44	879.5	1.01%

Table 7.3 Contribution to Turbine Category Only for Total Operation of Wind Farm A

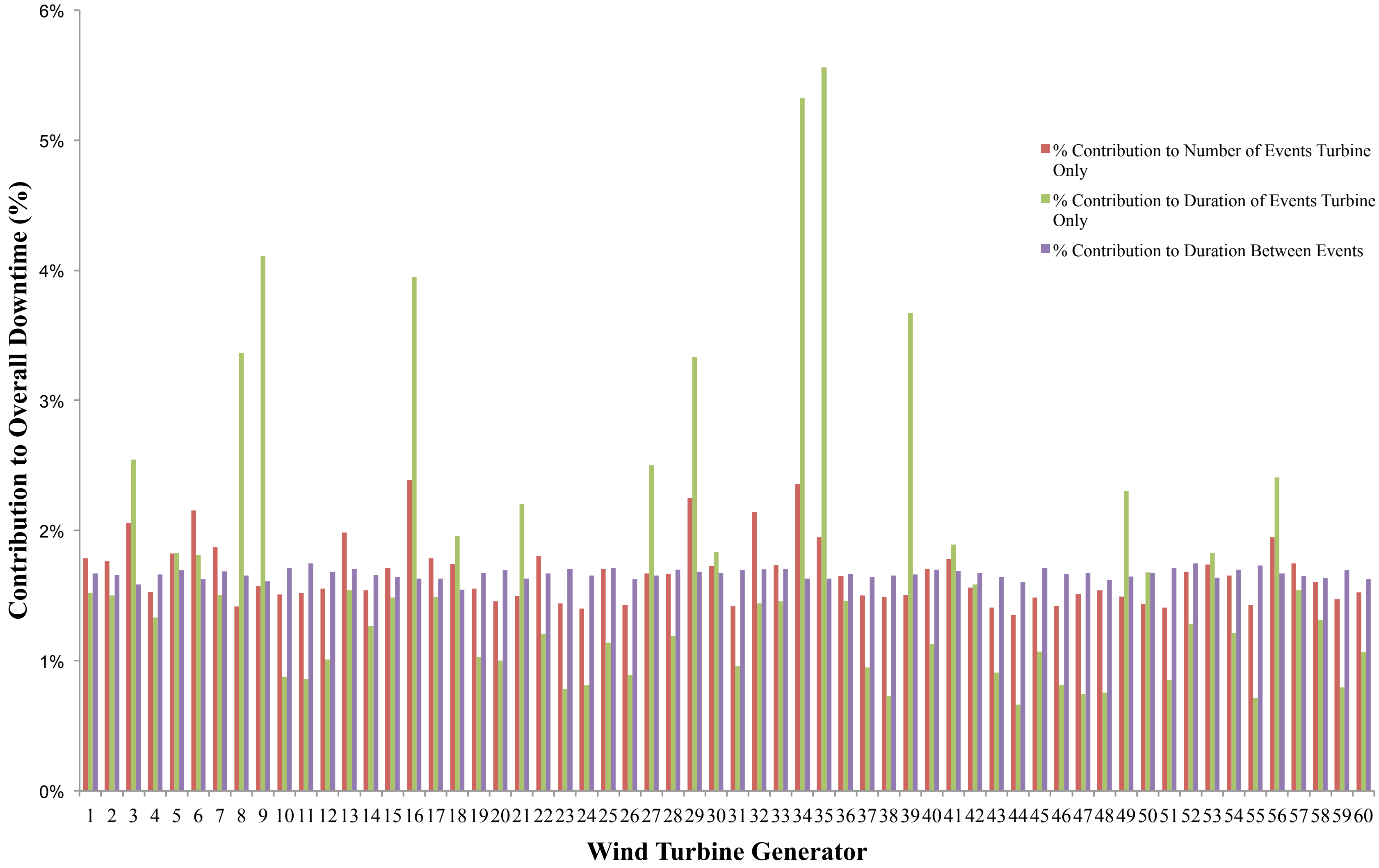


Figure 7.2 Contribution to Turbine Downtime Wind Farm A

Comparing these results to total downtime from the previous section, it can be seen that there are some similarities, however in the case of total duration, Turbine 35 is now the biggest contributor, with Turbine 34 and 9 following, respectively. In the case for number of events and time between events, the results have slighted changed, nevertheless, it is the duration of downtime that is of most interest.

Again, similar errors were found with events being logged during already active events for that turbine, giving negative durations. These entries were equated to zero. The error was found to be 0.001%, which can be considered as negligible.

Table 7.4 on the following page lists the top Alarm IDs for turbines that contributed most to downtime for the Turbine Category alone. As discussed previously, because the Alarm ID names are often generic, the top event comments contributing to that ID are listed too.

Overall, this procedure provides a useful tool for knowing which factors related to the turbine subsystems affect downtime the most. Further investigation could be carried out to improving the efficiency of the turbines by preventing the most significant events occurring in the future.

	Alarm ID (Most Occurring in Duration Order)		
WTG	**1st**	**2nd**	**3rd**
35 (in previous table)	**Manual Idle Stop (1015) – 18 days**	**Manual Stop (1001) – 12 days**	**Brake Pressure Too Low (9303) – 7 days**
	▪ Check delta modules – 14 days ▪ Inverter fault – converter calibration & test – 4 days	▪ Electrical fault finding on delta modules – 4 days ▪ Replace hydraulic motor – 2 days ▪ 93 other downtime event contributions	▪ Replace hydraulic motor – 7 days
34	**DC Fuse Blown (13110) – 21 days**	**Manual Stop (1001) – 11 days**	**Brake Pressure Too Low (9303) – 10 days**
	▪ Replacement of delta modules – 21 days – 5th Dec 2010	▪ Delta module replacement – 4 days – 26th Dec 2010 ▪ 157 other downtime event contributions	▪ No comments found
9	**Manual Stop (1001) – 17 days**	**Manual Idle stop(1015) – 13 days**	**Remote Stop – Owner (1007) - 8 days**
	▪ Generator related problems – 3 days ▪ Fault in a12 cabinet – 2 days ▪ Replacement of generator – 2 days ▪ 78 other downtime event contributions	▪ Generator replacement – 11 days (related event to manual stop downtime)	▪ HV switching to restore part of array (infrastructure related downtime) - 6 days

Table 7.4 Most occurring Alarm IDs (duration) for top 3 turbines contributing to **turbine downtime** for total operation of Wind Farm A (Alarm ID in brackets, duration of Alarm ID downtime in days, rounded to the nearest day)

7.3 Contribution to Downtime - Turbine Only - Split by Category

The analysis carried out to create Figure 7.3 below is useful in determining which specific Turbine Categories contributed to downtime for each turbine on the wind farm.

This figure shows specific downtime in seconds, unlike any of the other figures displayed in this section. This is required in this specific analysis, to give an accurate illustration of the categories contributing to downtime, rather than a relative distribution. Additionally, it can be seen that this graph is essentially the same as the green dataset (duration) from Figure 7.2 however broken up by category.

By using the information that is known from the analysis in the previous section that Turbine 35, 34 and 9 had the most amount of downtime attributed to the Turbine Category, this further analysis can show that for Turbine 35 and 34, that downtime is mainly due to the Electrical System. When retrieving data from the database the Alarm ID duration for Turbines 35 and 34 associated with the Electrical System alone, it is evident that all the time was due to a Manual Idle Stop and DC Fuse Blown, respectively, meaning that the those two Alarm IDs can be attributed to Electrical System faults, as might be expected. For Turbine 9, it is an unlogged manual stop that is attributed to the Alarm ID (which happens to be called Manual Stop). The uninformative manual stop alarm ID can be investigated further by reviewing work order comments in the downtime log, as completed in Table 7.4 above.

Overall, this procedure allows the analyst to hone in on what specific Turbine Categories affect turbines with extensive downtime and connect Turbine Categories with specific Alarm IDs.

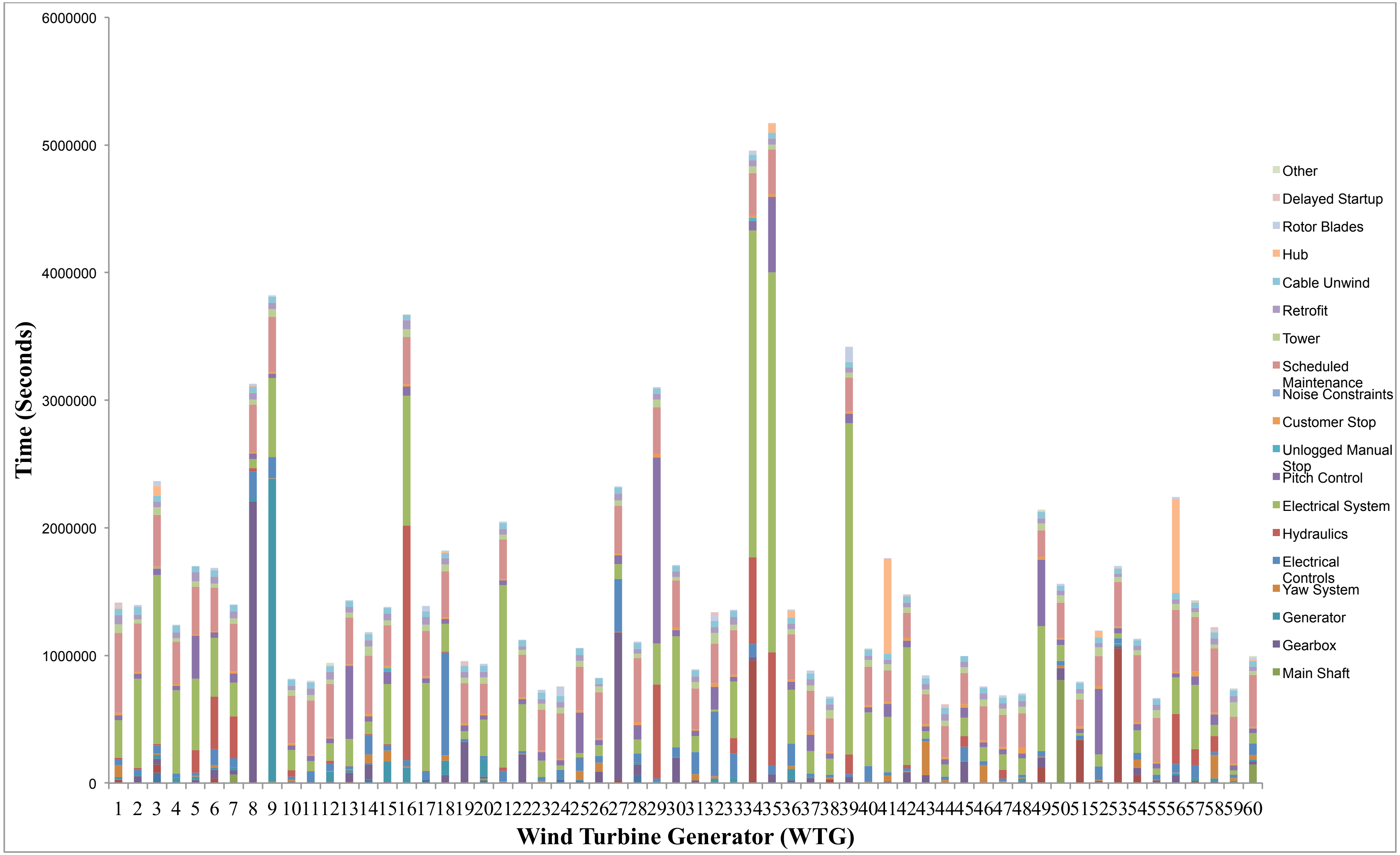


Figure 7.3 Contribution to Downtime – Turbine – Split by Turbine Category Wind Farm A

7.4 Contribution of Downtime per Turbine Category

Instead of analysing each turbine and plotting the relevant data, it is useful to see the distribution of Turbine Category downtime to understand what subsystems of a Turbine contribute to downtime the most.

In Figure 7.4, the duration of downtime and the number of events are plotted for each Turbine Category. The figure is sorted by duration of downtime, showing that the Electrical System Category has contributed the most to downtime for this wind farm over its operation. It is of interest to note the number of events alongside the duration to identify whether a period of downtime is due to several shorter events or longer less occurring events. This information could be useful in the planning of upgrades to subsystems of the most problematic turbines.

Even though the scheduled maintenance and cable unwind Turbine Categories are unavoidable and necessary downtime events for any wind turbine, they have been plotted to show what duration they take up relative to the other categories. Since scheduled maintenance is the second biggest contributor to downtime, it could be the topic of a separate investigation to ensure this procedure is carried out efficiently and effectively.

It should be noted that the Turbine Category 'OK' was set to equal 0, to allow the graph to represent the categories that were detrimental to energy generation. For the majority of the time the turbines are operational, therefore the duration of the 'OK' Turbine Category is significantly larger than any of the other categories.

If this analysis were to be carried out on every turbine across multiple sites, it would be beneficial to compare the performance of one wind farm to the results found across multiple sites. This would be useful for a wind farm owner who owns multiple sites, or a consultancy for assessing the downtime of a site in comparison to others.

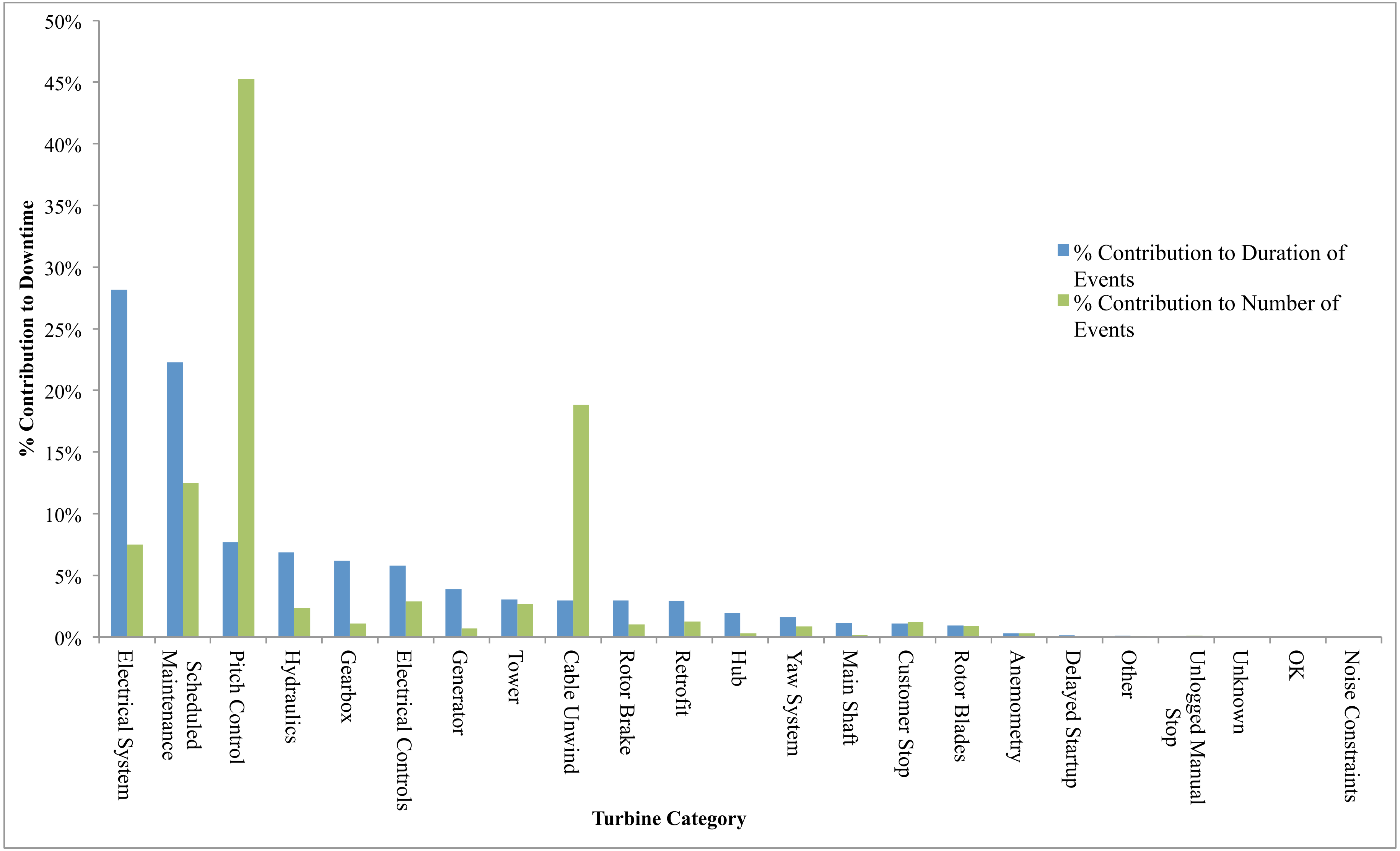


Figure 7.4 Contribution of Downtime per Turbine Category Wind Farm A

7.5 Summary

Firstly, turbines were identified from Wind Farm A that contributed to downtime by duration, number of events and duration between events. For those turbines contributing to downtime the most, the corresponding Alarm IDs and work order comments were identified, showing the cause of downtime.

Secondly, the downtime was analysed for the turbine and its subsystems only, making it clear which turbines had more downtime due to technical issues associated with the turbine alone. By organising this analysis according to turbine category, the specific components/factors affecting downtime for those turbines could be identified. Again, these categories could be associated with an Alarm ID, to hone in on the root cause of the overall downtime.

Finally, the Turbine Categories were analysed to show which turbine subsystems contributed to downtime the most for all turbines over the entire operation of the wind farm.

This analysis allows the wind analyst and client to identify which turbines have been most detrimental to energy generation and forms an important element in the overall performance analysis investigation.

8 Power Curve Analysis

8.1 Overview

As previously discussed, it is important to identify the standard operation of the performance indicator to be able to identify when a change occurs. In Figure 8.1, a power curve is shown for a turbine during one month's normal operation, plotted by running a python script that retrieves the required data from MS SQL Server. Each blue point represents one record for a 10-minute period. It should be noted that a specific filter is applied to specifically plot records that have a full 10-minute duration, so that erroneous records and downtime is not plotted. The red line is the warranted power curve, supplied by the manufacture, giving the estimated performance of the turbine that is taken from wind tunnel testing under specific conditions [13].

It is normal for the general trend of the operational data to be offset to the left of the warranted power curve. This is due to the wind speed being measured behind the rotor, normally at the back of the nacelle, so the wind speed recorded is marginally less for the corresponding active power measurement at the rotor.

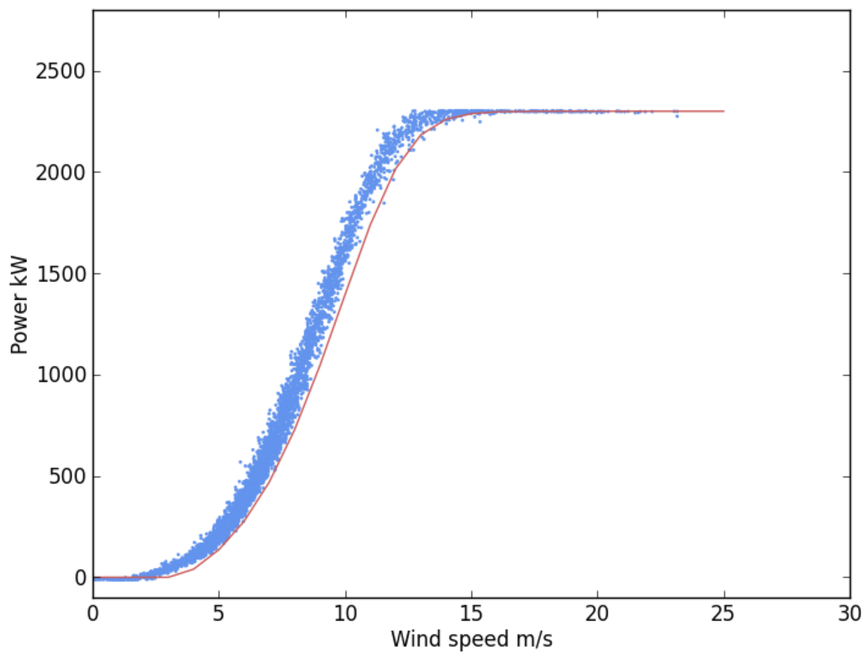


Figure 8.1 Monthly Turbine Power Curve – Normal Operation

In Figure 8.2 below, two examples of monthly power curves for a turbine show apparent changes in performance. The power curve on the left shows an example of bad data (the data circled in red), which can be due to faults in the measurement, or faults with the turbine system(s). In this particular plot, when looking at the corresponding month in the downtime alarm logs, it was found that there was some downtime for diagnosing a potential problem with the hydraulic pitch system. It would need to be investigated exactly when in the month this bad data occurred to ensure that the root cause of the bad data seen is due to the hydraulic pitch system downtime, nevertheless the purpose of discussing this particular power curve is to highlight how bad data can appear on a power curve. In the right hand power curve, the highlighted area shows an example of power curtailment, which is when the turbine is forced to de-rate its performance, to perhaps control power output to the grid for supply-demand matching.

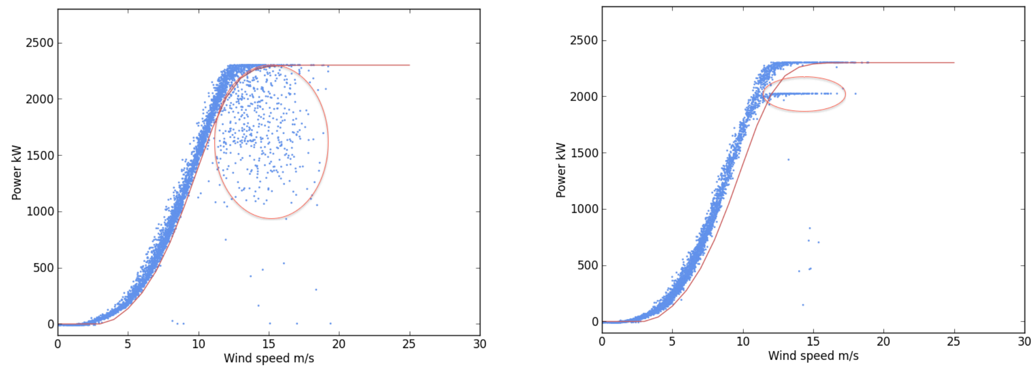


Figure 8.2 Monthly Power Curve Examples of Bad Data and Curtailment, respectively

As discussed previously in the methodology of analysis, for each monthly power curve plot, any bad data or curtailment needs to be filtered out, in order to be able to generate an accurate operational power curve for each turbine. This in turn will affect the accuracy of the theoretical power values calculated. The theoretical power is the calculated theoretical value for active power output from the operational power curve, for a given wind speed.

Filtering out uncharacteristic performance data for 34 months of operation for 60 turbines (2040 plots) is a time consuming process and so a simple filtering tool was developed for this filtering process, discussed in the next sub-section.

8.2 Power Curve Filtering Process

Filtering of data is carried out by applying SQL queries to the database table of operational data to attribute data outside defined limits to be excluded from characteristic operation. In this case, a column was added in this table called “filter bad data” and any data to be filtered was assigned the value 0 in this “filter bad data” column. The data left to be included in calculating theoretical power and generating operational power curves is assigned the value 1 in the “filter bad data” column. For efficiency, by plotting the data for the entire operation for a turbine and filtering out uncharacteristic performance, all monthly power curves plotted by default became filtered. Two methods were used in this filtering process, detailed below.

8.2.1 Filtering by Warranted Power Curve

Since the general trend of data points are offset to the left of the warranted power curve for most of the turbines at Wind Farm A, for any data points to the right of the warranted power curve (which are probably not part of the trend), a mathematical query to assign those data points to be attributed to 0 in the “filter bad data” column can be carried out. This is done by selecting data points that are less than ~90-99% of the warranted power curve.

Figure 8.3 shows an example of three iterations carried out to filter out uncharacteristic data by attributing data that is less than percentage of the warranted power curve to be equal to 0 in the “filter bad data” column. When filtering, the analyst must be careful not to select data that is part of the trend, so the 1st iteration was carried out from 0-11m/s at 95%, the 2nd iteration from 11-14m/s at 97% and the 3rd iteration from 14-25m/s at 99% to filter out the rest of the data.

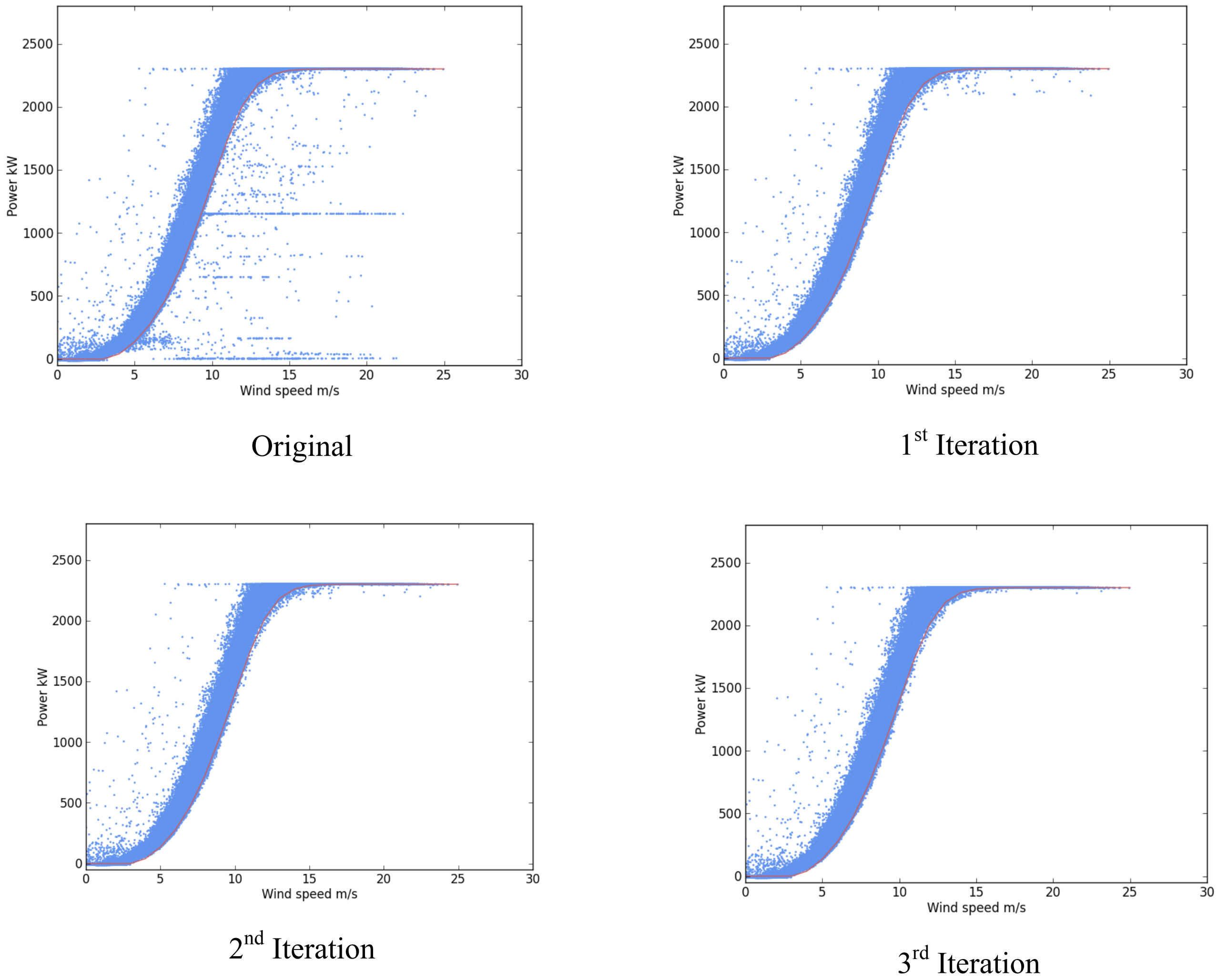
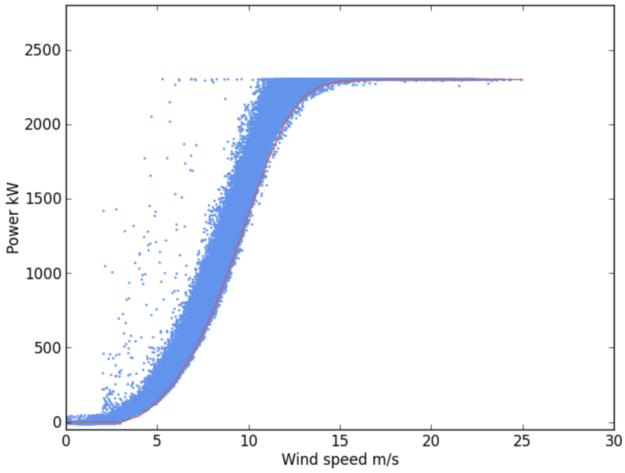


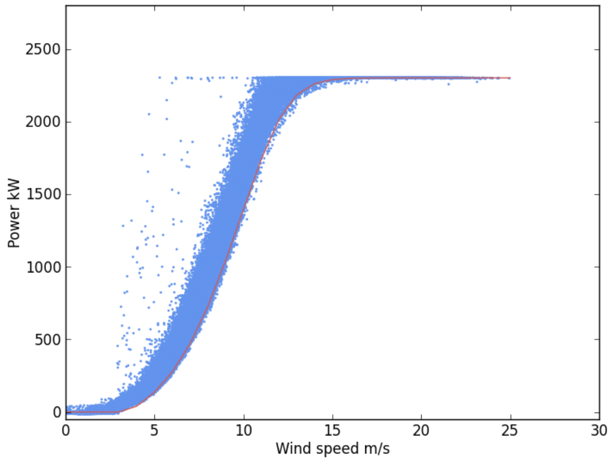
Figure 8.3 Power Curve Filtering Iteration using Warranted Power

8.2.2 Filtering by Standard Deviation

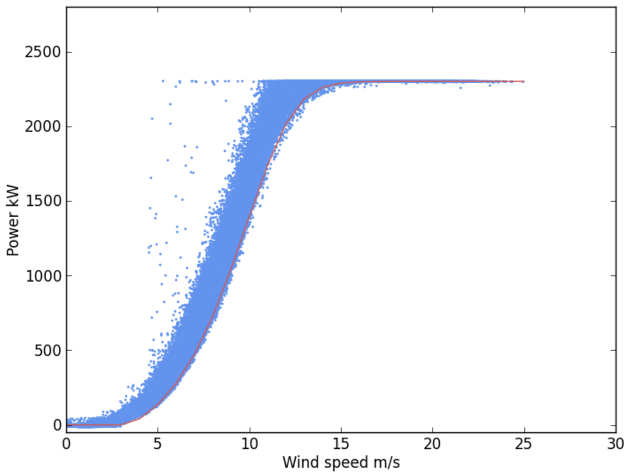
It is difficult to precisely know what percentage to the left of the warranted power curve that the general trend ends, to be able to capture the data points to be filtered accurately. Data can be selected by choosing above/below a certain wind speed and above/below a certain active power to be filtered, however this is very time consuming. Therefore, a tool based on standard deviation was developed to cater for this. By selecting data by small wind speed bins and calculating the standard deviation for that bin, data outside 2-4 standard deviations outside those limits is easily selected as uncharacteristic data and can be filtered out. An Excel tool was developed to visually show the points being selected and a corresponding SQL query was used to execute the calculation to filter out the data in the database. The Excel tool was important in this process to ensure that data inside the general trend was not selected, because if the query was run in the database to filter out that characteristic data, the standard deviation of those points within that bin changes and so it would be difficult (not impossible) to attribute the wrongly filtered data back to being part of the trend. Nevertheless, this tool saved a great deal of time in the filtering process. Using a similar tool or developing this one further is essential for carrying out performance analysis on other wind farms, especially with wind farms growing in size (US & Offshore) [1]. An example below in Figure 8.4 shows the iterations continued from Figure 8.3 to complete the filtering process for this turbine for its entire operation.



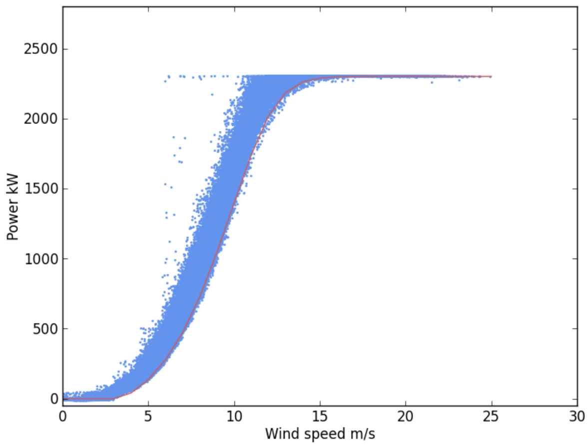
1st Iteration



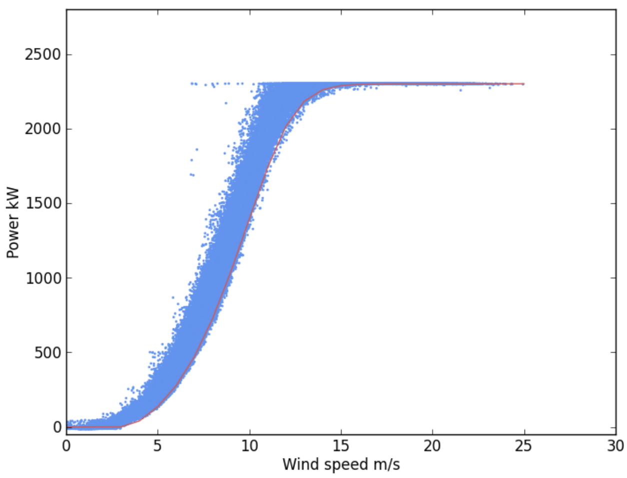
2nd Iteration



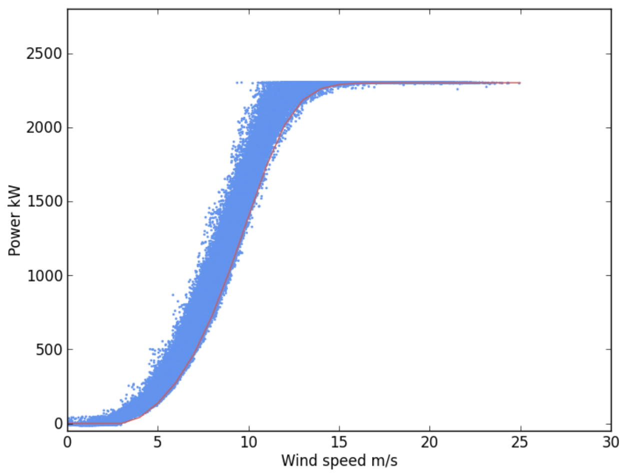
3rd Iteration



4th Iteration



5th Iteration



Final Filtered Power Curve (entire operation)

Figure 8.4 Power Curve Filtering Iterations based on Standard Deviation Tool

8.3 Operational Power Curve

After completing the filtering process for all turbines, an operational power curve can be generated for each turbine. This can be achieved by running a code on the operational data to calculate the average active power for each wind speed bin over the entire operation. Figure 8.5 shows the generated operational power curves plotted for T1-T5 as an example. The warranted power curve is also plotted to show the comparison in operational performance to the manufacturer's power curve.

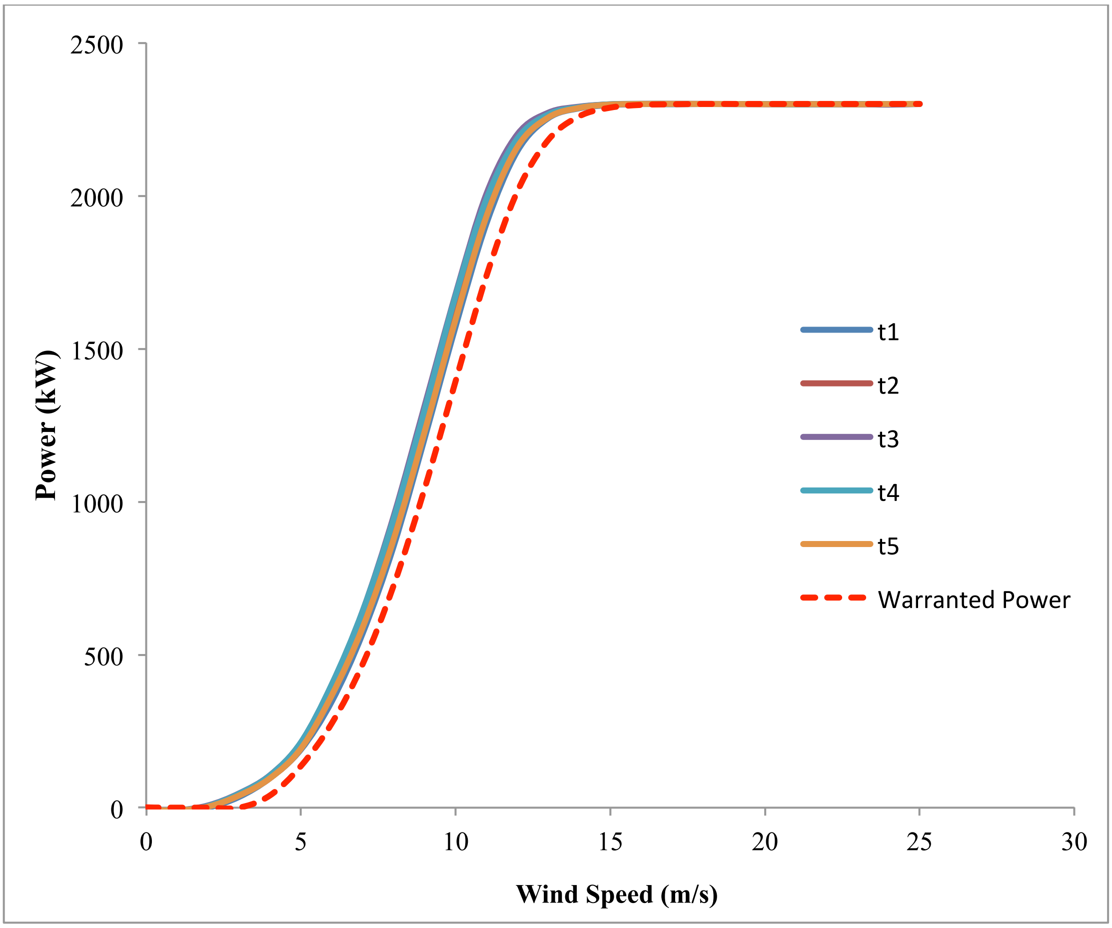


Figure 8.5 Operational Power Curve T1-T5 Wind Farm A

Operational power curves can be used to compare the performance of turbines against each other. Additionally, operational power curves can be plotted on a wind direction basis. Figure 8.6 below shows the operational power curves for T1 on a 30° basis (12 sectors), again with the warranted power curve plotted as a reference. Plotting by sector is useful in identifying if performance changes are due to the turbine operating in any particular sector.

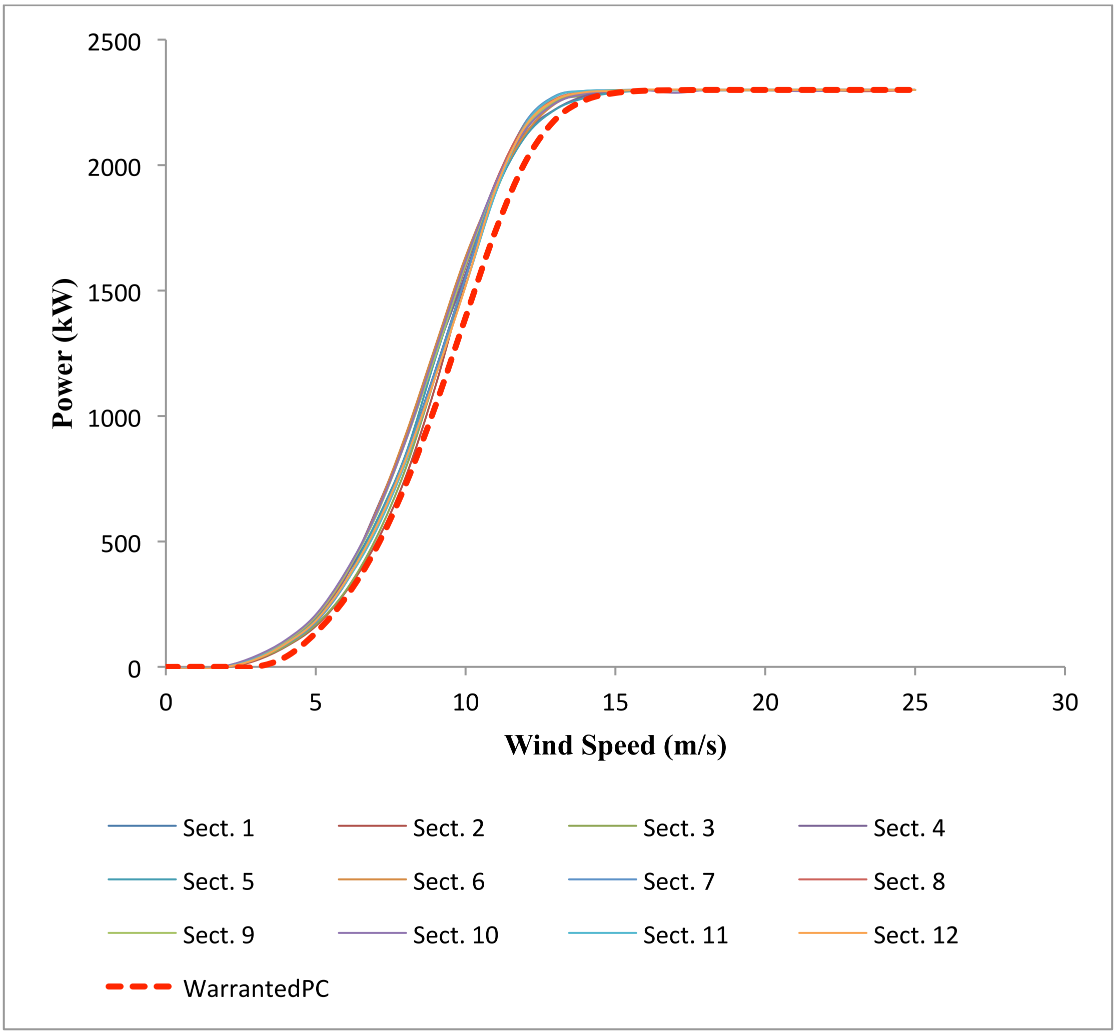


Figure 8.6 Sectorwise Operational Power Curve T1

As previously discussed, plotting operational curves is an important process of performance analysis as this step leads into calculating theoretical power, discussed in the next section.

8.4 Theoretical Power

After calculating the operational power curve for each turbine, a code can be run on the 10-minute operational data to calculate the active power output that could theoretically be generated based on the operational power curve for that turbine. This is denoted as the theoretical power.

Theoretical power can be used in calculating the energy loss/gain from a performance change. When calculating the operational curve values for each turbine as carried out in the previous section, the data from the entire operation of the turbines are used. However, if the time of change of the performance of a turbine is known, then an operational power curve can be generated for the operation before the change and after the change. From this, the theoretical power for each 10-minute value can be calculated based on both operational power curves for the entire operation of that turbine. Therefore, by comparing the theoretical power between the two different operational curves after the performance change occurred, the theoretical energy loss can be calculated. By applying a £/MWh rate to this energy lost, the consequence of the performance change in a financial context can be obtained. An example of this methodology will be developed in further sections.

8.5 Summary

Power curve analysis is a key factor in performance analysis of wind turbines. By noting changes in power curve characteristics, most but not all performance issues can be found. By correlating any changes with downtime alarm logs, the root cause of events can in most cases be identified.

It is from power curve analysis that leads performance changes to being contextualised into energy loss/gains and hence revenue loss/gains.

Finally, this analysis leads into other studies and even in studying other KPIs, referring back to the power curve is important in building up the entire picture when diagnosing a performance change. The analysis carried out in this section is from carrying out existing techniques, adding the filtering process as a new tool for time saving. The following sections on other KPIs are developing new methods of analysis, having identified these KPIs in the literature review to be of benefit for performance analysis.

9 Energy Ratio

The energy ratio KPI relates closely to power curve analysis and is a relatively quick tool for performance analysis. The energy ratio is simply the active power divided by the theoretical power. Since active power records from the SCADA system are in 10-minute periods, active and theoretical power values should be divided by 6 to convert the power units into energy units (kWh). In this case no difference is made to the results, as it is the ratio that is of interest. Figure 9.1 illustrates an example of the energy ratio calculated for a selection of turbines at Wind Farm A on a monthly basis for the operation of the wind farm.

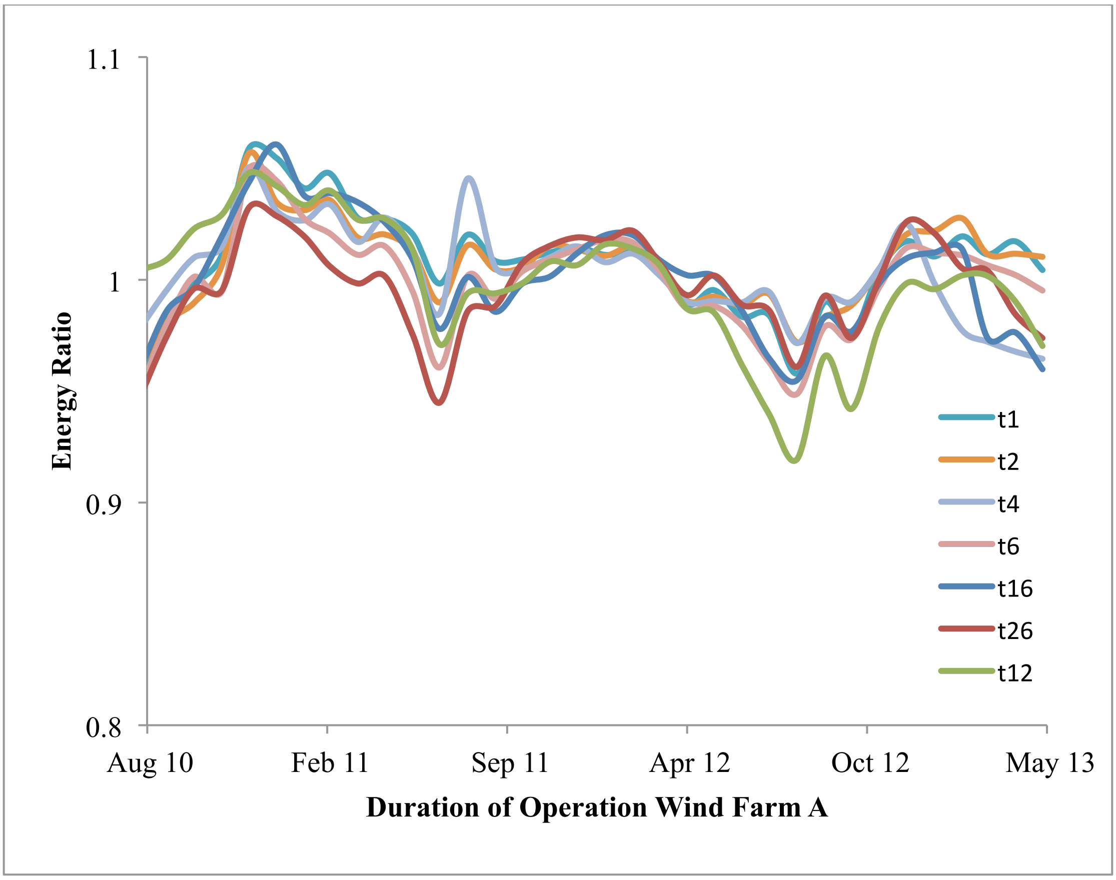


Figure 9.1 Energy Ratio Wind Farm A (Selection of Turbines)

This KPI is useful in comparing turbines from the same site against each other to identify turbines with a relatively lower performance. For example, T12 in August

2012 is seen to have a lower energy ratio than the other selection of turbines plotted. When reviewing the corresponding power curve for this month, this relative performance decrease is not easily identifiable. This issue requires further investigation to find the root cause as it is not clear if any downtime event has contributed to this change. This case shows an example of an event found relatively simply that went unidentified from the power curve analysis.

Using the energy ratio could also become a useful tool in assessing the performance of the turbines over a long period of time (years), with regards to the deterioration of turbines that are deterring due to fatigue.

Overall, this KPI is a useful representation of showing performance of the turbines. This analysis can highlight turbines in periods of poor performance that power curve analysis cannot. However, using power curve analysis and downtime logs alongside the energy ratio KPI is useful in confirming performance changes identified. The analysis is quick to implement and it would be relatively simple to automate an energy ratio plotting tool into monthly reporting of turbine performance.

10 Wind Vane Misalignment

When plotting wind speed against KPIs (power, pitch, rotor speed etc) changes in performance found can be due to the turbine having a misaligned wind vane. This is because if the wind vane is misaligned with the turbine, the measured wind direction will be offset to the actual yawed position of the turbine. This will manifest in any parameter plotted against wind speed as the turbine will be not be pointing in the correct direction.

Plotting the measured wind direction against a neighbouring turbine or a meteorological reference mast is a good way to check if a turbine has a misaligned wind vane. When correlating the wind direction of turbines, the analyst has to be careful that the wind direction data is correct. At Wind Farm A, some turbine correlations showed offsets of more than 100°. This is more likely due to a correction factor not being implemented on the data, rather than a misaligned wind vane. Of the analysis carried out, an example of a misaligned wind vane was not found.

Figure 10.1 below shows an example of a turbine having a misaligned wind vane, offset by 30°, resulting in an estimated loss of €150,000 per year [9]. Misaligned wind vanes can also increase the fatigue affects on the turbine, and therefore can effectsthe long-term performance of the turbine [14].

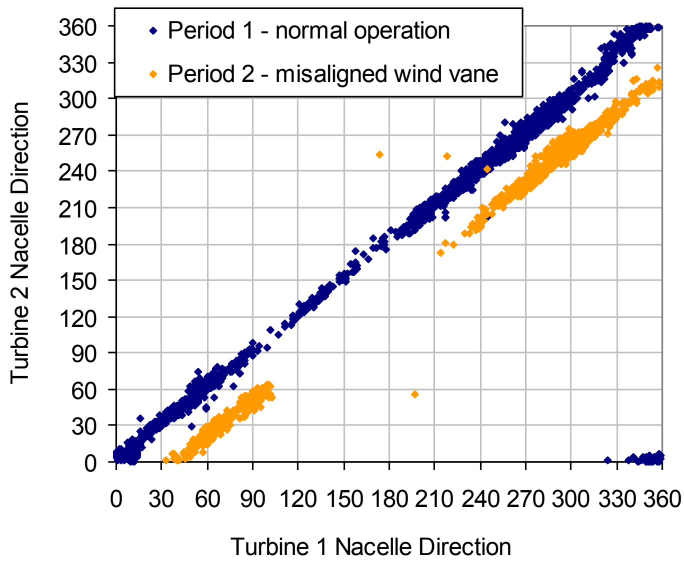


Figure 10.1 Example of Misaligned Wind Vane, courtesy of Garrad Hassan [9]

It is therefore of great important to ensure that turbines have well aligned wind vanes. This can be achieved by using advanced technologies, like LiDAR [15][16]. Moreover, if performance changes are identified in other KPIs, it should be checked if the change is due to a misaligned wind vane, before moving forward in investigating other possible root causes.

11 Pitch Curve Analysis

11.1 Overview

This section will detail how analysing the pitching of the blades of a turbine can identify performance changes. In a similar methodology to power curve analysis, it is important to identify characteristic operation of the parameter of study. Figure 11.1 shows a monthly pitch curve (winds speed v pitch angle) and represents standard operation for this specific turbine manufacture. The pitch angle is calculated by averaging the angles of the three blades. The plot was exported from Windographer.

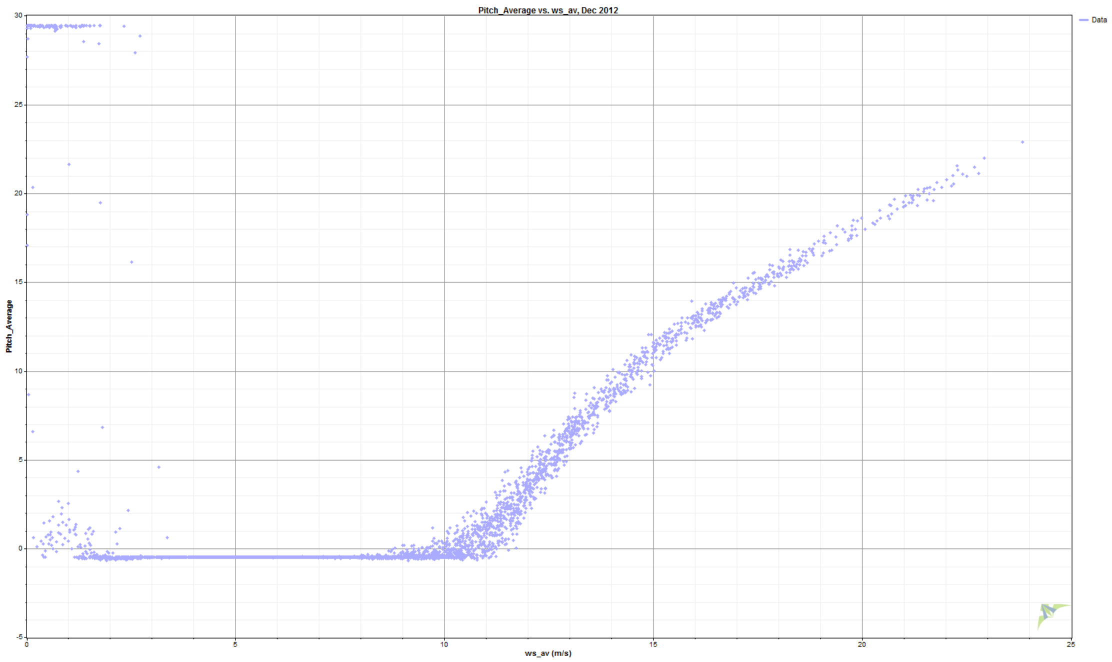


Figure 11.1 Monthly Turbine Wind Speed v Pitch Angle Curve – Normal Operation

In a similar fashion to the power curve analysis, changes in characteristic operation in monthly pitch curves can be noted and for any significant changes, further investigation can be carried out. Analysis was carried out on a cluster of 15 turbines at Wind Farm A to find performance changes in the pitch curve. In this section, one example of a change in pitch characteristics is discussed.

11.2 T30 Pitch Curve Characteristic Change

The example in question is a change in the pitch curve observed during November 2012 for T30. Figure 11.2 below shows that a step change occurred during this month, highlighted by the arrows pointing to the step change in the trend.

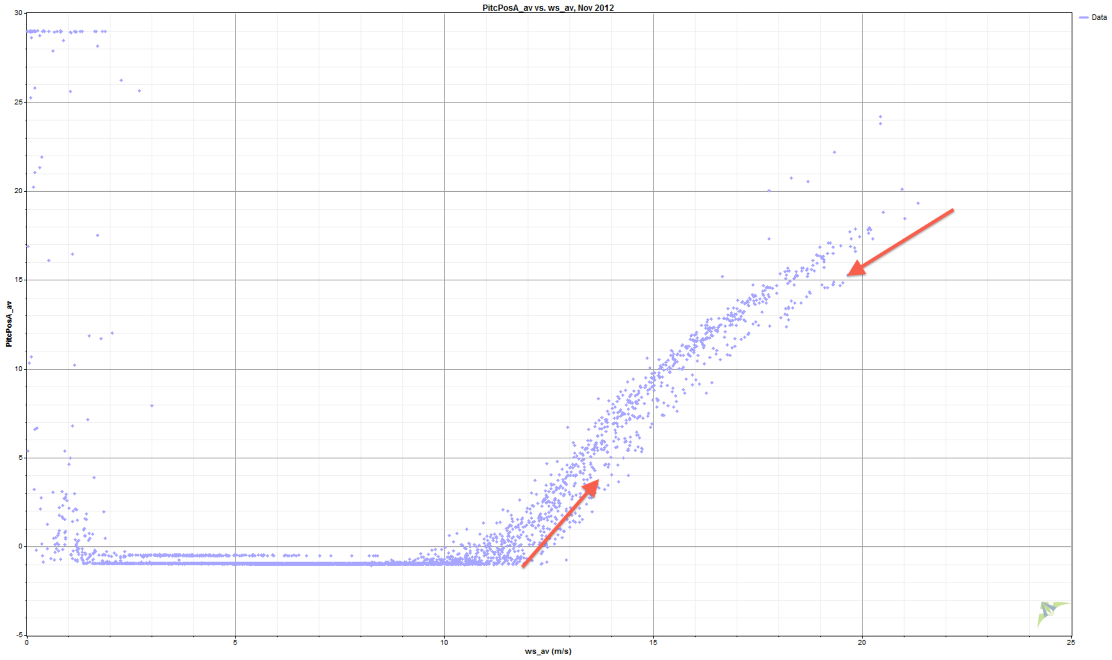


Figure 11.2 Step Change Observed (wind speed v pitch angle) T30 November 2012

The corresponding power curve for this month for T30 shows a move of the trend to the right compared to normal operation and more of a scatter of data. Apart from this, the power curve does not reveal much more about this performance change, shown in Figure 11.3.

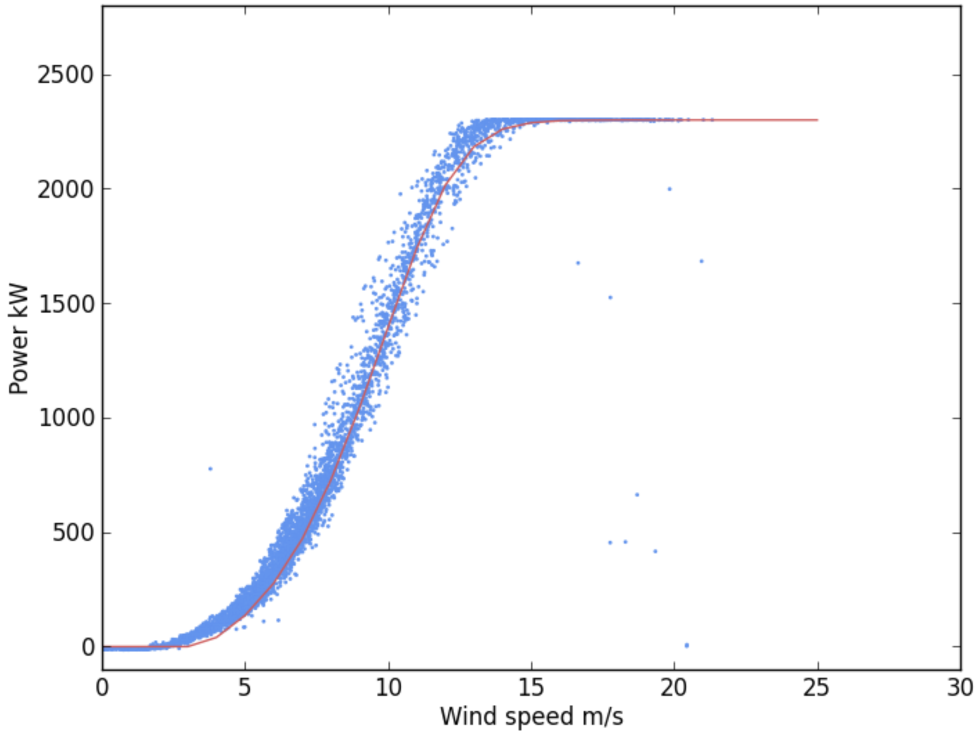


Figure 11.3 Power Curve T30 November 2012

The next step in diagnosing this performance change is to identify when specifically in the month that the change occurred. This information can be useful in identifying if any particular downtime event that may have caused the step change. After some investigation, the following analysis in Figure 11.4 shows that the change occurred on 21st November 2012 and thereafter, the new mode of operation commenced.

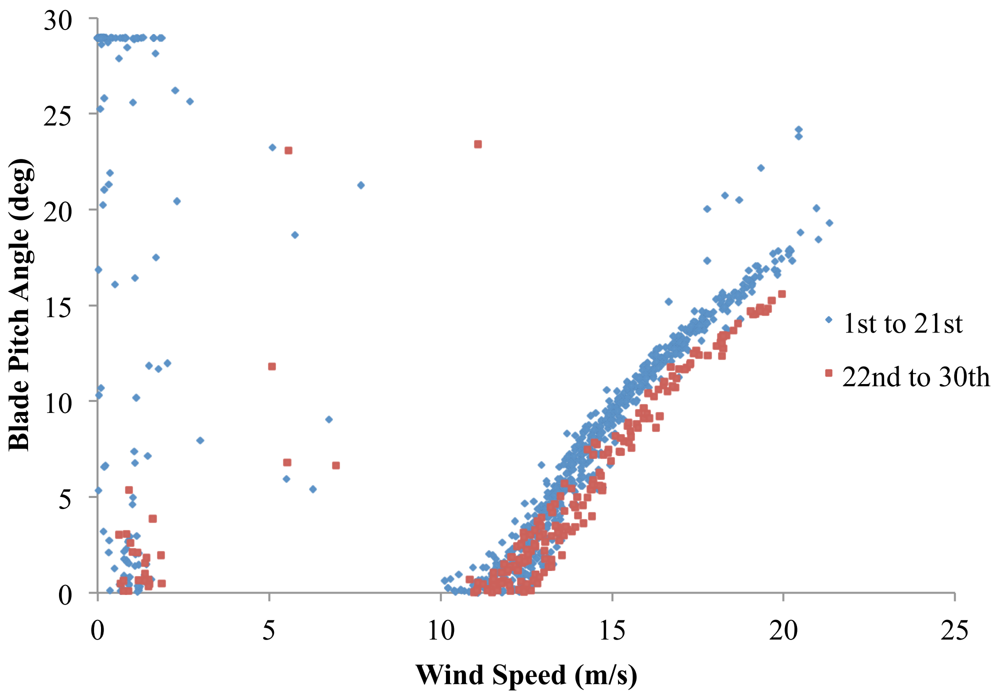


Figure 11.4 Pitch Curve T30 November 2012 – Identifying period of change

After consulting downtime logs, it was found that on 21st November, a transformer was replaced in the A2 cabinet, which is part of the control system. It can therefore be assumed that this event is related to this performance change. It is then of interest to ascertain whether the change returned to normal operation or if this is a new operation. In this case, from 22nd November 2012 to the end of May 2013 (the latest operational data available), the pitch characteristics remained in the new operation. Therefore, with this new operation, the next analysis carried out was to identify what the energy losses/gains were as a result of this change. Before this, it is important to check that this performance change is not due to a misaligned wind vane, which the next subsection will discuss.

T30 Wind Direction Study

To rule out that the pitch change was not due to a misaligned wind vane, Figure 11.5 shows that a direct correlation between T30 and T29, a neighbouring turbine, is similar before and after the change occurred. For the red data points (T30), the majority of the records are between 180° and 360°. This is simply due to a prevailing westerly wind direction.

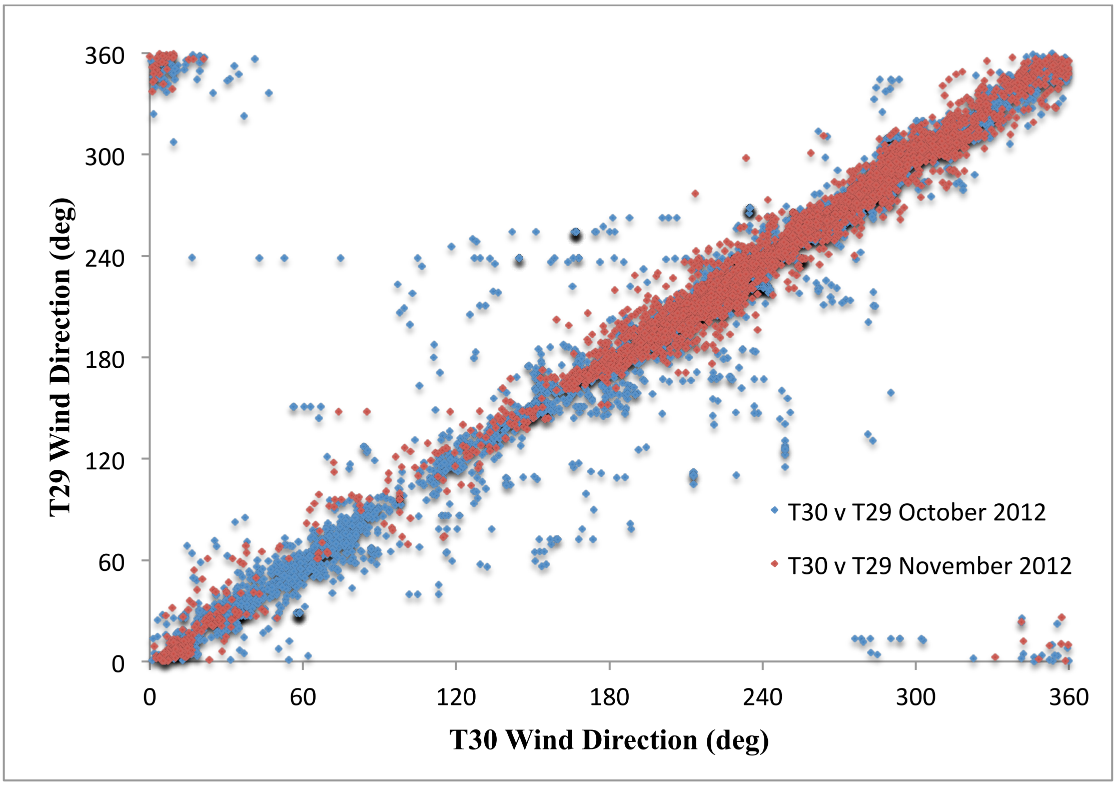


Figure 11.5 T30 v T29 Wind Direction Correlation

11.3 Consequence of Pitch Characteristic Change

Having identified the date of change in the pitch curve and checking that the change was not due to a misaligned wind vane, the energy loss/gain can be calculated.

Following the procedure discussed in the power curve analysis section, an operational power curve is derived for T30 before and after the change, shown below in Figure 11.6. It can be seen that the operational power curve representing the characteristics of T30 after the pitch change is offset slightly to the right of the operation before the change.

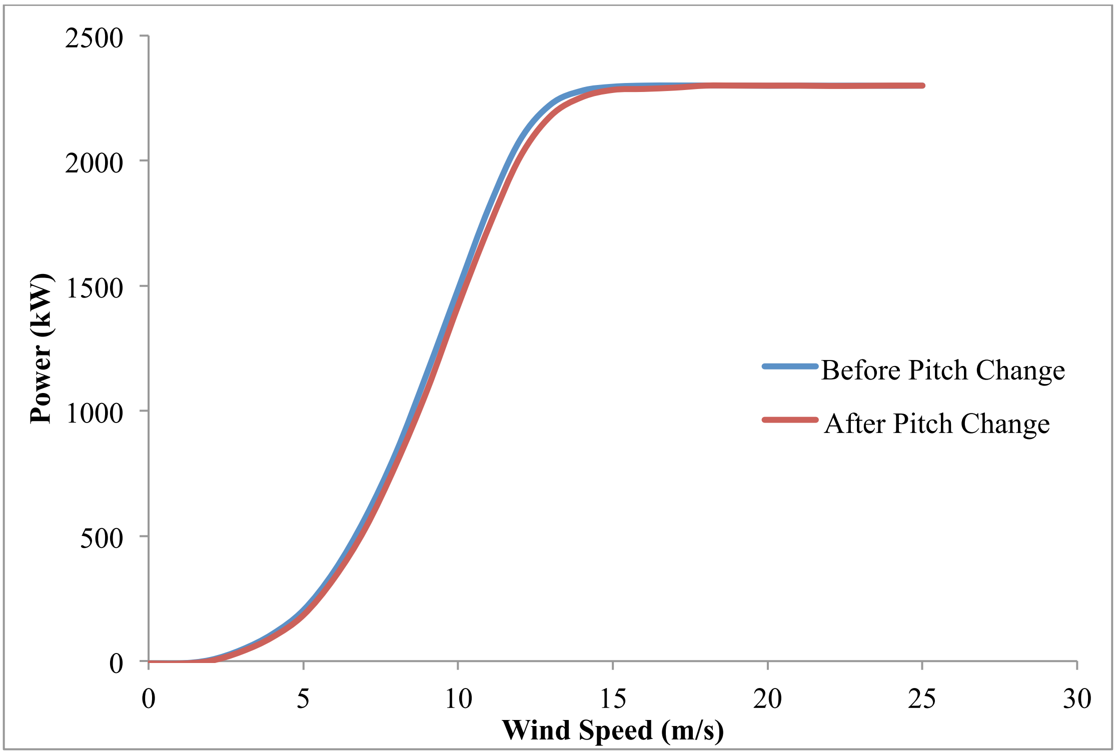


Figure 11.6 Operational Power Curve T30 Before/After Pitch Change on 22nd Nov 2012

The next step is to calculate the theoretical power values for the wind speed data after the change, based on both operational curves. Then by taking the difference between the total theoretical power available for the duration after the pitch change, the energy loss/gain can be calculated. The theoretical power is divided by 6 to convert the 10-minute average power values into kWh energy units.

$$\frac{\Sigma\, Theoretical\ Power_{orig\ op\ pc}}{6} - \frac{\Sigma\, Theoretical\ Power_{new\ op\ pc}}{6}$$

where "op pc" = operational power curve

Based on this calculation, if T30 continued to perform based on the operational power curve before the change occurred, it was calculated that theoretically, another

111MWh of energy could have been generated from November 2012 to May 2013. This counts for a 2.78% decrease in performance over the 6 month period.

If the price of energy sold to a utility is £75/MWh, which is an estimate taken from an energy marketing website for UK (bmreports.com), the estimated loss in revenue is £8,300 over the 6 month period analysed after the change.

11.4 Summary

Analysing pitch characteristics is very useful in identifying performance changes in turbines. For the example with T30 discussed in this report, the power curve for when the performance change occurred did not give any indication of what the root cause may be. By plotting wind speed v pitch angle, it was possible to find the root cause and calculate the loss in energy due to the change.

It should be noted that in calculating the energy loss from the change, it had to be checked that no other performance issues developed, so that the loss in energy calculated was a true representation of that one change found and not an amalgamation of a number of changes in performance.

To ensure that the procedure carried out in this section is replicable, similar methods were carried out on another cluster of turbines at Wind Farm A, and several performance changes were flagged.

12 Rotor Speed Analysis

In this section, rotor speed is investigated to identify performance changes at Wind Farm A. Figure 12.1 below shows a plot of rotor speed v active power for a month and represents normal operation.

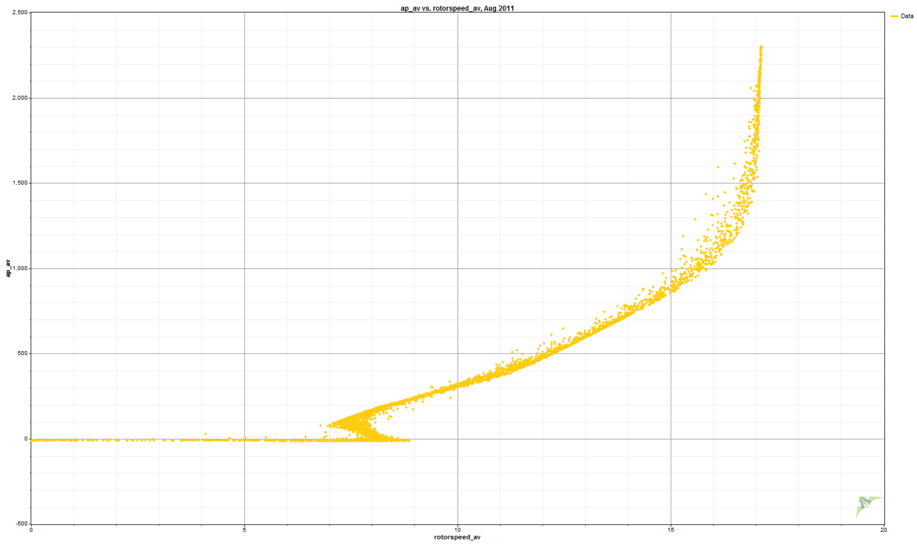


Figure 12.1 Monthly Turbine Rotor Speed v Active Power Curve – Normal Operation

When reviewing monthly rotor speed curves, a small change was found in September 2011, as highlighted in Figure 12.2 below.

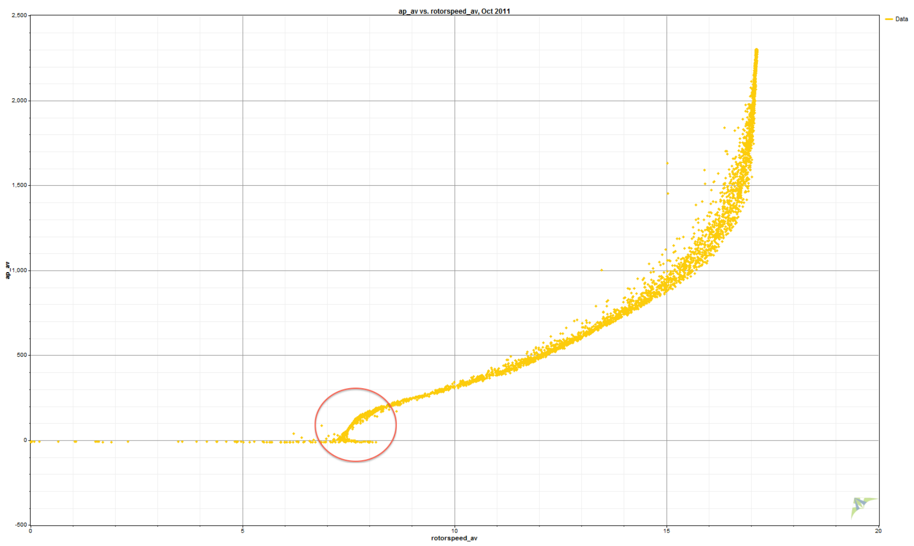
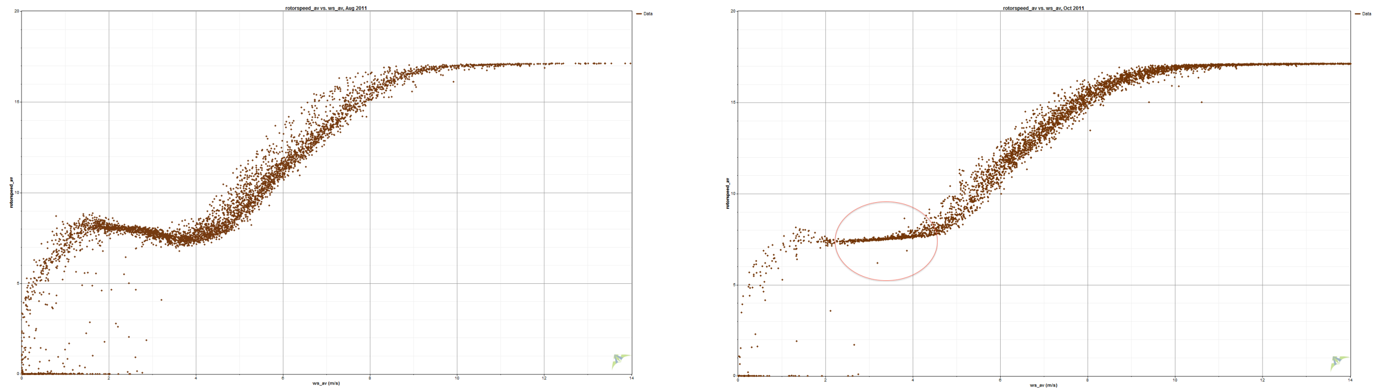


Figure 12.2 Rotor Speed v Active Power T28 – Change observed September 2011

Further investigation was carried out to identify the specific date of change. It was found that the date of change corresponded with a downtime event, which was a software update carried out on all 60 turbines. This change was not observed when reviewing the corresponding power curve, however when plotting wind speed v rotor speed, the performance change can be seen, shown in Figure 12.3.



Before Software Update — After Software Update

Figure 12.3 Monthly Wind Speed v Rotor Speed before/after software update

12.1 Consequence of Software Update

To calculate the energy loss/gain from this software update, the same procedure as in the pitch curve was carried out.

The energy difference was estimated to be 16MWh for the 20 months following the software update for T10. On a yearly basis, that energy loss converts to £720/year/turbine based on a £75/MWh rate.

Even though the downtime logs showed that all 60 turbines received the software updates, it was 24/60 turbines that the change in rotor speed plot was observed. So even though the loss in energy due to the software update was calculated to be a 0.33% annual performance decrease, when multiplying by 24 turbines, losses are calculated to be £17,000/year.

12.2 Torque Characteristics

During initial research in this project, it was found that software updates can have an affect rotor torque characteristics [2]. No changes were seen in any of the turbines at Wind Farm A when reviewing torque v active power plots, hence why it was not included as a section in this report. However, it is important to mention in this section that if in the future, a software update is seen in the downtime alarm logs, both rotor speed and torque parameter should be checked, as the software update may affect both. According to a study carried out by Garrad Hassan [2], a software update affecting torque characteristics gave an energy loss of approximately 1% on an annual basis, resulting in a substantial impact on the financial performance of the project. Figure 12.4 shows how the torque curve changed. The report reads that only a very subtle change was observed in the power curve, which may have left the issue undetected for a long period of time.

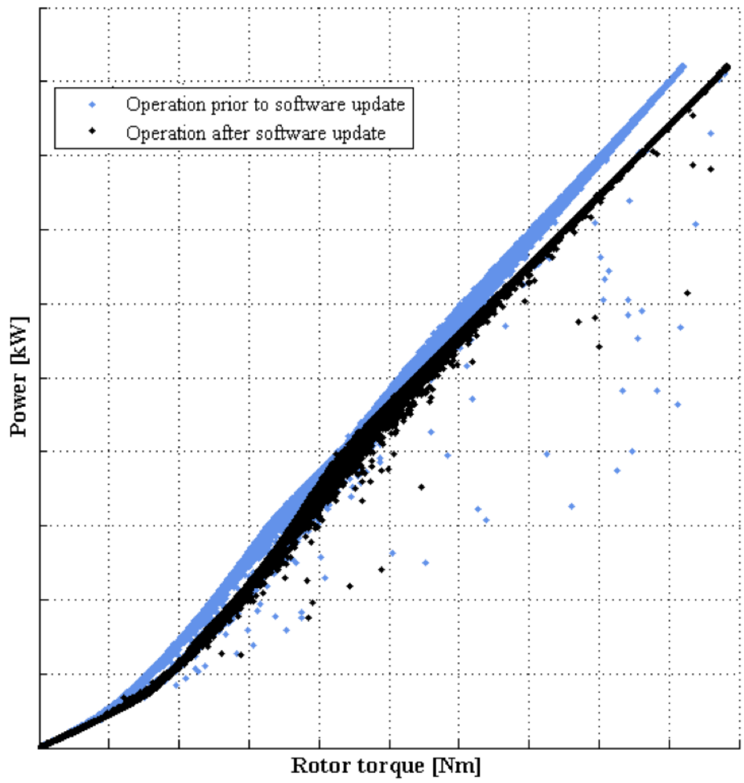


Figure 12.4 Rotor Torque v Power performance change due to software update, courtesy of Garrad Hassan [2]

12.3 Summary

Of all KPIs investigated in this project, the software update downtime event appeared to affect only rotor speed. When plotting wind speed v generator speed and generator speed v active power, a similar change was observed. This should be expected as the generator and rotor are directly connected by a shaft and gearbox, so the only difference is the scale (generator rpm is higher than rotor rpm).

The purpose of the software update was unknown and so if this was investigated further, a better understanding of effects rotor speed could be gained. If a software update is found in the downtime logs in the future, investigating both rotor speed and torque proves to be useful in identifying any performance changes.

13 Discussion & Conclusions

The research carried out during this project resulted in the successful development of existing procedures to assess operational wind turbine performance, making use of available SCADA 10-minute data and downtime logs. The procedures carried out have aided Natural Power to identify many changes found in the performance characteristics of turbines at Wind Farm A, previously unidentified. The framework established in this research can be further developed to apply to other wind farms.

This section will summarise the key findings of the analysis carried out during this project and will discuss the development and challenges for performance analysis of wind turbines.

13.1 Downtime Study

Carrying out a downtime analysis was useful in analysing the reliability and performance of the turbines at Wind Farm A. Analysing one wind farm's downtime would not act as a benchmark to compare to another site, however developing this new tool further could contribute towards a future benchmarking application, if the analysis was carried out over multiple sites. However, in order to compare the duration of downtime and number of events to another site, common themes would be required. For example, only the same turbine manufacturers could be compared. Additionally, correlation factors would need to be built into the tool to account for varying wind distributions across sites. Moreover, it would be relatively simple to compare the analysis of turbine categories across different sites, discussed in Section 7.4 (p31). The downtime study was not used in the KPI analysis using the 10-minute SCADA data, and so it can be said that this is a separate analysis.

13.2 KPI Study

Investigating power curve characteristics proved to be a very useful parameter in analysing the performance of turbines. Many performance issues were flagged by reviewing monthly power curves. Additionally, by using wind speed, active power and the warranted power curve data, the energy loss/gains from any performance change could be calculated. However, resorting to reviewing power curves alone did not highlight all performance issues, hence the requirement to take full advantage of all the data available from the SCADA system to analyse other parameters.

From reviewing monthly wind speed v pitch curves, many changes in performance were flagged. T30 was a good example of how analysing the pitch curve allows for the analyst to identify the root cause by finding the date of change and consulting downtime alarm logs. T30 was chosen as an example as the root cause was found and no other changes in performance in other parameters were observed, so the process to calculate the energy loss was straightforward. Often, there are not corresponding downtime events for observed changes in performance. Also, work order comments are not always included, giving less context to the downtime log. To investigate any flagged changes would require consultation with the wind farm manager.

In investigating the rotor speed parameter, the only change that was seen was as a result of a software update. Generator speed is related to rotor speed, with a higher order of magnitude of rpm, so the change can be seen in generator speed plots too. If another software update is carried out on the turbines, it is important to monitor rotor/generator speed. Along with this, rotor torque should be monitored, as software updates have been found to affect torque [2]. Even though the energy loss calculated was relatively small, because the loss can be multiplied across multiple turbines, the losses can accumulate to become significant.

13.3 Developing an Automated Algorithm to Detect Performance Changes

With an objective to formulate the interconnectivity between the KPIs to develop an automated algorithm to detect sub-optimally performing turbines, it was found that events identified which highlight poor performance are directly related to the type of fault. Therefore, to have a system that can detect any type of fault, a complex algorithm to check multiple KPIs simultaneously, rather than a linear procedure would be required.

13.4 Challenges of Data Analysis

In this project, getting from the raw data acquired from the SCADA system to useful results required a significant amount of time and effort. Data was analysed using a mixture of Python code, Excel and Windographer. To repeat such a study for another wind farm, the framework developed from this project should be used to develop an automated process to carry out many of the time intensive procedures, e.g. power curve filtering.

Importing the SCADA data into a relational database software tool like SQL Server is good as it provides quick access to all the data in a logical way, however good understanding of SQL and the way the data is built up in the database is required, which comes with time and experience.

The SCADA systems that provide the raw data for analysis are not standardised between wind turbine manufacturers. Therefore, if this research was to be repeated at another wind farm consisting of a different turbine manufacturer to that at Wind Farm A, it would be challenging for the analyst to understand the data and prepare it for analysis. Additionally, if the framework developed in this research to assess wind turbine performance were coded to have an automated software tool, the representation of data from SCADA would have to be considered for each wind turbine manufacturer. As the wind farm industry grows, so do the databases that store the information; it is becoming more important to assess the current structure and lack of standardisation of SCADA data. To show how current this aspect of performance analysis is, a conference organised in Hamburg, Germany for Late September 2013 has a workshop dedicated to discussing data management and standardisation of SCADA [17].

14 Future Work

Due to time constraints during this investigation, there are several areas of research that could be conducted to continue the development of a performance analysis tool.

14.1 Downtime Analysis

As mentioned earlier in the report, carrying out a downtime analysis on multiple sites and using that as a benchmark to compare to single sites would prove useful in the analysis of sites. When considering duration of downtime and number of events, the tool would need to ensure that the same type of turbine from the same manufacturer are compared.

Scheduled maintenance was found to be a large contributor to downtime. It could be the topic of a separate investigation to ensure that downtime for maintenance is carried out efficiently and effectively. A consultancy managing multiple sites may be able to assess the efficiency of external maintenance companies.

14.2 Automation

The findings of this project were as a result of the development of a new methodology to assess wind turbine performance. The procedures were executed manually, which was an ineffective and time consuming process, but a necessary one to develop the framework. For these findings to be of maximum benefit to a renewable energy consultancy like Natural Power, who manage multiple wind farms, the procedures would need to be developed into an automated software tool. The tool would ideally run an algorithm through the 10-minute SCADA data to automatically detect faults so that they can be dealt with immediately after the event is detected. Garrad Hassan make use of Changepoint Analysis for the automatic monitoring of turbine performance analysis [2]. Such a system used on large datasets is computationally intensive, however as computer power becomes more affordable, it would be beneficial to develop a robust tool that can handle growing databases.

Additionally, developing the power curve filtering algorithm to become automated when monthly data becomes available would save considerable amount of time for generating operational power curves.

14.3 Other Performance Monitoring Research

This research focused on analysing 10-min operational SCADA data. However, other SCADA-based data is available which would be useful for condition monitoring, including temperatures of turbine subsystems, voltages/currents and high frequency vibration data. Garrad Hassan in a paper presents how the monitoring of gearbox temperatures at high frequency to predict performance changes can be beneficial for flagging turbines with developing performance issues [18]. Developing a similar tool to prevent faults before they occur would be of great benefit both to a consultancy to offer the service and of course to a wind farm owner who could likely save money due to unnecessary downtime. Such research was beyond of the scope of this project, however to be able to develop a system that integrates not only 10-minute SCADA data but data of other frequencies would be valuable.

15 References

[1] Global Wind Energy Council. (2012). *Global Wind Report - Annual Market Update 2010.* Available: http://www.gwec.net/wp-content/uploads/2012/06/Annual_report_2012_LowRes.pdf. Last accessed 10th July 2013.

[2] Lindahl, S & Harman, K. (2012). *Analytical Techniques for Performance Monitoring of Modern Wind Turbines.* Available: http://www.gl-garradhassan.com/assets/downloads/Analytical_Techniques_for_Performance_Monitoring_of_Modern_Wind_Turbines.pdf. Last accessed 10th July 2013.

[3] Scottish Renewables. (2013). *Scotland's Renewable Energy Sector in Numbers.* Available: http://www.scottishrenewables.com/scottish-renewable-energy-statistics-glance/. Last accessed 11th July 2013.

[4] Department of Energy & Climate Change. (2013). *Renewables Electricity Capacity and Generation (ET 6.1).* Available: https://www.gov.uk/government/publications/renewables-section-6-energy-trends. Last accessed 11th July 2013.

[5] Bloomberg New Energy Finance. (2013). *Global Renewable Energy Market Outlook 2013 - Fact Pack.* Available: http://about.bnef.com/presentations/global-renewable-energy-market-outlook-2013-fact-pack-2/. Last accessed 11th July 2013.

[6] National Instruments. (2008). *Wind Turbine Control Methods.* Available: http://www.ni.com/white-paper/8189/en/. Last accessed 29th July 2013.

[7] Turbines Info. (2011). *Horizontal Axis Wind Turbines - HAWT.* Available: http://www.turbinesinfo.com/horizontal-axis-wind-turbines-hawt/. Last accessed 6th August 2013.

[8] U.S. Department of Energy. (2013). *The Inside of a Wind Turbine.* Available: http://www1.eere.energy.gov/wind/inside_a_wind_turbine.html. Last accessed 6th August 2013.

[9] Graham Gow. (2011). Fully Exploiting SCADA And Its Data. *GL Garrad Hassan Conference, Copenhagen*. ( ), .

[10] Gill, S & Stephen, B. (2012). Wind Turbine Condition Assessment Through Power Curve Copula Modeling. *IEEE TRANSACTIONS ON SUSTAINABLE ENERGY*. 3 (1), p94-p101.

[11] Atkinson, N. (2012). *Using SCADA Data to Assess Turbine Performance.* RES Group

[12] McLaughlin, D; Clive, P; McKenzie, J. (2010). *Staying Ahead of the Wind Power Curve.* Available: http://www.renewableenergyworld.com/rea/news/article/2010/04/staying-ahead-of-the-wind-power-curve. Last accessed 3rd Sep 2013.

[13] Provided by manufacturer in warranty documents - confidential material. Power Curve based on set air density, temperature, clean rotor blades and a defined wind shear exponent and turbulence intensity.

[14] Bossanyi, E. (2012). *Current perspectives on wind turbine control.*Available: http://www2.hull.ac.uk/administration/pdf/talk-Ervin_Bossanyi.pdf. Last accessed 7th September 2013.

[15] Kragh, K.A; Hansen, M.H; Mikkelsen, T. (2011). Improving Yaw Alignment Using Spinner Based LIDAR. *AIAA*. 264.

[16] Wagner, R. (2012). *Nacelle lidar for assessing wind turbine performance.* Wind Power Forum: Convention Hamburg

[17] Wind Power Events. (2013). *Wind Farm Data Management & Analysis.*Available: http://www.windpowermonthlyevents.com/events/wind-farm-data-management-analysis-2013/programme-32/. Last accessed 8th Sep 2013.

[18] Wilkinson, M; Darnell, B; Delft, T.V; Harman, K. (2013). *Comparison of Methods for Wind Turbine Condition Monitoring with SCADA Data.* Available: http://www.gl-garradhassan.com/assets/downloads/Methods_for_Wind_Turbine_Condition_Monitoring_with_SCADA_Data.pdf. Last accessed 8th Sep 2013.

[19] Clive, P.J.M; McLaughlin, D; McKenzie, J.H. (2008). *Making the most of SCADA data: wind farm performance assessment.* Available: http://www.taplondon.co.uk/bwea30/pdf/3_Dave%20mcLaughlin-web.pdf. Last accessed 10th Sep 2013.

[20] GL Garrad Hassan. (2013). *About GL Garrad Hassan.* Available: http://www.gl-garradhassan.com/en/aboutus.php. Last accessed 11th Sep 2013.