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Emerging challenges in wind energy forecasting for Australia

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Growing concern about climate change has led to significant interest in renewable energy resources such as wind energy. However, such non-storable energy sources present a significant issue – how to maintain continuity of supply in the event of possible disturbances to power production. For example, in the case of wind energy, such disturbances can result from extreme weather events due to frontal systems or rapidly evolving low pressure systems. Such events cannot be avoided, but if they can be accurately forecast, their impact can be minimized by ensuring that alternative sources are available to make up any power shortfalls. Thus as wind energy makes up an ever greater component of our energy supply, there is greater interest in developing models to produce accurate, local scale, wind-focused forecasts for wind farm sites that push the boundaries of current weather prediction techniques. In this article we present a case study focusing on the Woolnorth wind farm on the northwest tip of Tasmania, to highlight some of the key challenges that will be involved in developing such forecasts.

Introduction

Global warming and diminishing fossil fuel resources are driving the greatest shift in energy supply in the history of human society. As a result, renewable resources such as wind energy are making ever greater contributions to electricity production worldwide (Sanchez 2006). Australia is blessed with substantial wind resources due to its latitude, extensive coastline and vast unpopulated areas, and these resources have the potential to contribute significantly to our future electricity supply (Archer and Jacobson 2005). However, wind energy is not quite as simple to implement as some other energy sources. Unlike a coal-fired power station, for example, where power only stops being produced when the coal supply runs out, or there is a maintenance issue, wind farm production stops if the wind is too strong, not strong enough or suddenly changes direction. This added variability, and the inherently non-storable nature of wind energy, presents a major challenge for power system operation – how do we prevent fluctuations in the power production of a wind farm from affecting the continuity of electricity supply to the consumer?

Unfortunately, we can't control the weather, and so we need strategies to work around it instead. This can be achieved in two steps. The first is to predict the weather as accurately as possible, aiming to know any weather-related lapses in power production well in advance. The second is to use that knowledge to arrange for other sources to make up the shortfall at the appropriate time. At first sight, this might seem rather troublesome, but the energy industry already does exactly this to some extent. The operation of non-renewable resources is guided by accurate weather forecasting; for example, on a very hot day, power producers will increase supply to account for increased loads due to higher than normal usage of air conditioners. The use of an electric-

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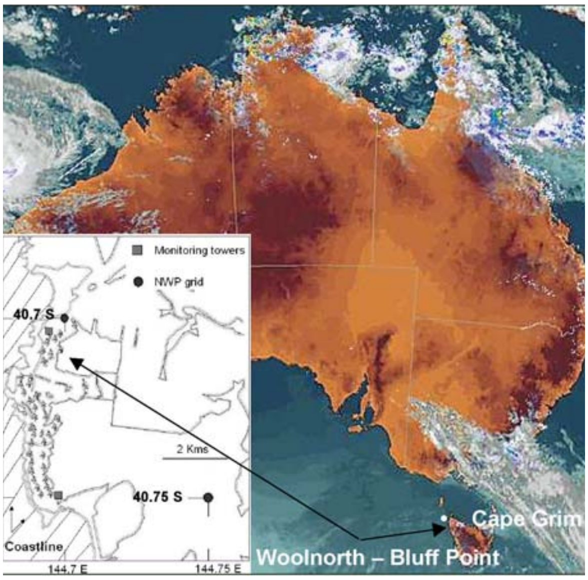


Fig. 1 Location of Woolnorth and Cape Grim on the north western tip of Tasmania. Inset shows the location of the wind turbines, monitoring towers and NWP grid for the Bluff Point wind farm (shaded region indicates coastline).

ity 'grid' – a widespread network linking numerous power producers to customers in a highly interconnected way – ensures supply continuity in the event of minor hiccups such as a power-station going off-line, by allowing one producer to make up the shortfall of another.

However, wind energy still leads to substantial new forecasting requirements to account for the weather's impact on supply, additional to its impact on consumption, for which well established models exist. The purpose of this paper is to identify and highlight some of these new forecasting requirements, particularly in the context of predicting the large changes in wind energy production that have a more profound effect on power system operation. To facilitate this, we will present a case-study of a wind farm located at Woolnorth on the northwestern tip of Tasmania (see Fig. 1), which has been operated by the Roaring 40s company since 2004.

The wind farm at Woolnorth

The Woolnorth wind farm is the largest operating in the southern hemisphere (Roaring 40s 2007) with a maximum generation capacity of 140 MW. It was developed in three stages across two nearby sites known as Bluff Point and Studland Bay. The Bluff Point site has a generation capacity of 65 MW, achieved using 37 Vestas wind turbines each supplying 1.75 MW, and was completed in 2004. The Studland Bay site consists of 25 Vestas V90 wind turbines, each supplying 3 MW for a total capacity of 75 MW, and was completed in 2007.

This case study will focus on the Bluff Point site alone, the layout of which is shown in Fig. 1 (inset). The 37 turbines are arranged in two rows running 5-6 km along the west-facing coastline at a latitude of 40.7°S. There is a pair of meteorological (met) masts located at the northern and southern tips of the wind farm (squares in Fig. 1 (inset)) to provide overall weather monitoring for the site. An added feature of this wind farm is its close proximity to the Cape Grim Baseline Air Pollution Station, jointly managed by the Bureau of Meteorology and the Commonwealth Scientific and Industrial Research Organisation (CSIRO), located 2 km north of the wind farm, which has its own met mast from which further useful data for this case study was obtained.

Each of the three met masts take measurements of wind speed and direction at a height of 50 m above ground level (agl), with the Bluff Point met masts (optoelectronic anemometers are Vaisala WAA151 and wind vanes are Vaisala WAV151) taking data at 2.5 min intervals, and the Cape Grim met mast (Vaisala WAA15 anemometers and WAV15 wind vanes) taking data at 1 minute intervals. Additional data can be obtained from the sonic anemometers mounted on the nacelle behind the blades (60 m agl) on each turbine. The turbine anemometers obtain data at 10 minute intervals, and so the met mast data used here has all been averaged over the preceding 10 minutes (Cripps and Dunsmuir 2003) to provide data-sets with consistent data time intervals. Wind speed and direction data has been collected for 2005, 2006 and six months of 2007.

How the weather affects wind farm output

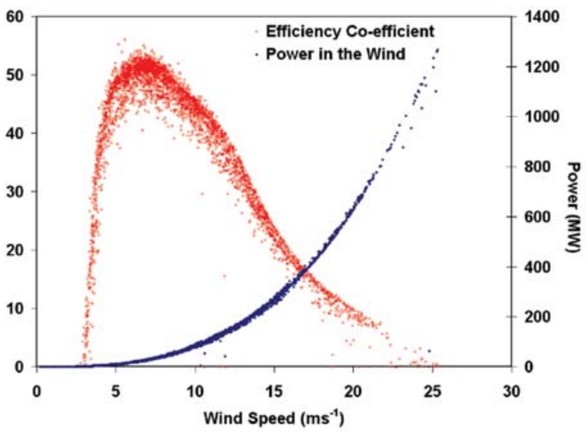
The basic relationship between the wind's speed and its power capacity is non-linear (see Fig. 2) and is given by:

$$P = \frac{1}{2}\rho A v^3 \qquad \ldots(1)$$

where P is the wind power in Watts, ρ is the density of dry air in kgm^{-3}, A is the swept area of the turbine and v is the wind velocity in ms^{-1}. This wind power is captured by the turbine, which is connected via a gearbox to an electrical generator to produce an electrical power output. Naïvely, one might expect that higher wind speed means more power; however, the turbine's conversion efficiency (i.e. the ratio of electrical power output to wind power input) is deliberately adjusted to maintain the turbine at its rated power output, with the efficiency maximised in light wind conditions and reduced for stronger winds. This is driven by integration issues (the need to control power input to the electricity grid) and is achieved using the turbine's gearbox and by adjusting the blade pitch. This is illustrated in Fig. 2, where we plot the conversion efficiency averaged over the 37 turbines at Bluff Point for one month as a function of wind speed. The conversion efficiency rises rapidly at ~3 ms^{-1}, reaches a maximum at ~5 ms^{-1} and is then gradually curtailed until it reaches zero for wind speeds greater than 25 ms^{-1}, where the turbine is shut-down to protect it from damage.

It is thus clear from Fig. 2, what three of the key weather-related issues for wind power generation are – wind speeds less than 3 ms^{-1} or greater than 25 ms^{-1}, where no power is produced, and wind speeds fluctuating sufficiently rapidly that the mechanisms for adjusting conversion efficiency cannot maintain sufficiently constant power output and the turbine needs to be disconnected from the grid. There is a fourth issue not illustrated by Fig. 2; large and rapid changes in wind direction. These require the turbine to rotate about its vertical axis, and given the large horizontal angular momenta generated by the rotating blades, this can require the turbine to be stalled (i.e., its rotation slowed by changing the blade pitch) to prevent damage to the turbine structure.

Fig. 2 The efficiency coefficient for one month for Bluff Point and the power in the wind as determined by the wind power formula.



An example of weather causing problems with wind power production

Returning to meteorology, there are a number of weather phenomena that have the ability to rapidly change the wind conditions and affect wind farm operation, but the two most common weather phenomena leading to the shut-down of turbines are (Cutler et al. 2007):

a) Frontal systems
b) Unstable low pressure systems, including cut-off lows

To demonstrate one such event, in Fig. 3(a) we show the wind speed and power output of the Bluff Point wind farm over a 48 hour period on 30 and 31 August 2005. The important features in Fig. 3(a) are the extreme variability in power output between 1900 and 2200 UTC on 30 August, and more

Fig. 3a Wind speed and power for 30-31 August 2005, showing the sudden swings in power related to changes in wind speed. Note that wind turbines typically shut themselves down at wind speeds of around 25m/s in order to protect the equipment.

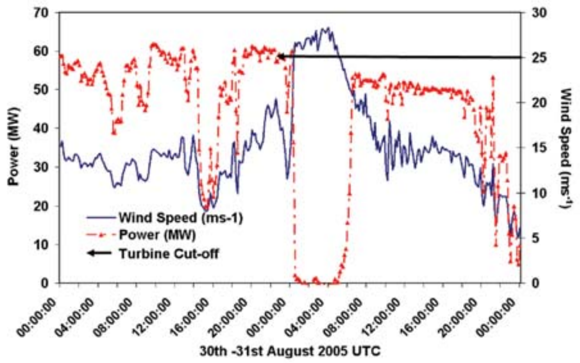
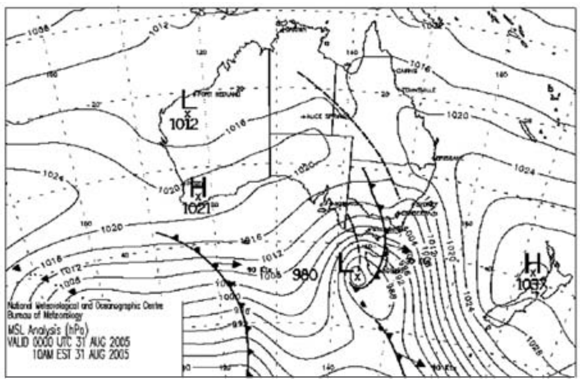


Fig. 3b MSLP chart for 31 August 2005 illustrating the synoptic situation that caused the rapid changes in power seen in Fig. 3(a).



significantly, the sudden and complete drop in power output around 0000 UTC on 31 August. The latter occurred because the wind speed exceeded 25 ms^{-1}, requiring the turbines to be shut-down to prevent them from being damaged. Figure 3(b) shows the MSLP chart for 31 August to illustrate the corresponding meteorology for the events in Fig. 3(a). The two features appearing in Fig. 3(a) are due to a deepening low pressure system, accompanied by a strong front and trough following closely behind, which kept winds high for a prolonged period.

Developing extreme event forecasting for wind power generators

It is clear from the example above how strong wind events can affect wind farm power output, but the question then becomes how we can best implement a forecasting system for such events? The example also demonstrates the extra layer of complexity that this problem adds to normal wind forecasting – the forecasts need to be geared towards accurate and detailed predictions on very short time scales (i.e. hours or even minutes) for small geographical areas (i.e. a few square km) and long continuous periods. This is clearly a task that would be highly desirable to automate; engaging the services of a meteorologist 24 hours a day, seven days a week to manage the weather related aspects of a wind farm would be expensive.

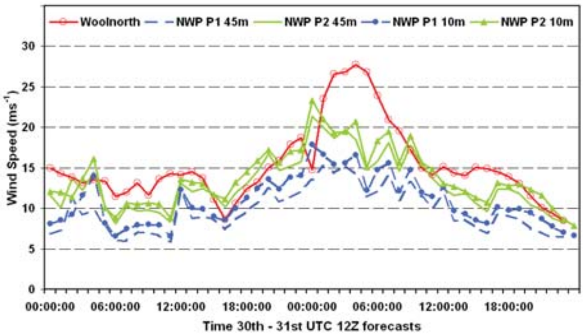
Numerical weather prediction

The usual route to automated forecasting is to use Numerical Weather Prediction (NWP) models; however, most NWP models are not geared towards the detailed wind predictions required for wind energy purposes (Archer and Jacobson 2005). Furthermore, the resolution of NWP models is often too coarse to predict the fine-scale winds affecting a specific wind farm. For example, the two NWP grid points nearest to the Woolnorth wind farm are shown in Fig. 1 (inset), with NWP P1 at 40.7°S 144.7°E and NWP P2 at 40.75°S 144.75°E. While NWP P1 is only 0.6 km northwest of the northern met mast, NWP P2 is nearly 5 km east, and well inland, of the southern met tower. However, it is the quality (or lack thereof) of the grid point forecasts that is more significant than their spatial separation from the wind farm, because this is what ultimately limits the accuracy of the model forecasts. To demonstrate this shortcoming in quality, we will now use an NWP model to try to predict the extreme events discussed earlier. We will do this using the Australian Bureau of Meteorology's MesoLAPS 5 km limited model domain over the Victoria/Tasmania region (Puri et al. 1998). Although we use a specific model here, it should be emphasised that this problem is not specific to that particular model alone; it is a generic issue of all NWPs where the grid spacing is large compared to the spatial extent of the wind farm.

In Fig. 4 we show the measured wind speed (red) along with the MesoLAPS predictions for NWP P1 (blue) and NWP P2 (green) for the same period presented in Fig. 3. For the NWP results, data is presented for heights of 10 m (lines with symbols) and 45 m (lines without symbols). Note that the 10 m level is what is normally considered as 'surface conditions' in forecasting, but the 45 m is at a level closer to the hub height of the wind turbines. Another important factor of the NWP data is its hourly time resolution, and we have plotted corresponding hourly measured wind speed readings in Fig. 4 for better comparison.

If we now consider the two events discussed earlier in Fig. 3, we can see that the NWP predicts neither. There are two separate problems that lead to the inability of the NWP to predict these events – temporal resolution and forecast accuracy – and they contribute to differing extents. The fluctuations between 1900 and 2200 UTC on 30 August are predominantly a time resolution issue. Comparing the measured wind speed data in Figs. 3 and 4, it is clear that

Fig. 4 NWP predictions and observations of wind speed beginning at 0000 UTC 30 August 2005 for a forecast of 48 hours. NWP predictions at two grid points (a north and south location referenced to the wind turbines) and two heights (approximately 10m and 45m).



the wind speed fluctuations are more or less invisible at an hourly scale. While the NWP does indicate some wind speed fluctuation in this period, it hardly has the temporal resolution to provide much assistance in managing its impact, and it doesn't help matters that it predicts the fluctuation 'out of phase' (i.e., predicts maxima where the real wind speed minima occurs), which is an accuracy issue. In contrast, the high wind speed shut-down at 0000 UTC on 31 August is almost entirely accuracy-related. This shut-down lasts for approximately five hours and is clearly evident and well represented in the hourly measured wind speed data in Fig. 4. The NWP has simply under-forecast the wind speeds involved in this event, and interestingly, the 45 m level is a less accurate predictor than the 10 m level in this particular case.

To determine whether the under-prediction of MesoLAPS (5 km domain) mainly occurs for high wind speed events, and investigate how often under-prediction occurs more generally, we have studied a more extended time-series consisting of approximately two months of data between 25 July and 13 September 2005. We found that MesoLAPS under-predicted the wind speed 88 per cent of the time for NWP P1 and 62 per cent of the time for NWP P2, which is surprising because NWP P1 is much better positioned than NWP P2 relative to the wind farm. This may come as no surprise to a modeller however, as sharp changes in actual topography (e.g. the cliff face close to Woolnorth) may not be well represented in the model topography. Further inland, where actual topography is undulating, the model topography is a better representation of the wind farm. Of course, there will be errors in any forecast, and it is important to consider their magnitude in any analysis. As will become evident in the next section, a discrepancy of 3 ms^{-1} can cause wind power predictions to be out by up to 30 per cent. Therefore we reanalysed these data looking for cases where the MesoLAPS model under-predicted the wind speed by more than 3 ms^{-1}. For NWP P1 and P2, approximately 58 per cent and 32 per cent of the under-predictions were greater than 3 ms^{-1}, respectively.

Together these problems highlight the key issues with implementing existing NWP models for wind energy forecasting. Correcting the time resolution issue comes at a significant computational cost that can only be mitigated by reducing the scale of the model, for example, using a microscale model such as The Air Pollution Model (TAPM) developed by CSIRO, run with inputs from a larger-scale NWP model. There are of course other alternatives being explored (Wadl et al. 2006; Mohrlen and Jorgensen 2006; Madsen et al. 1998; Lange and Focken 2005; Giebel et al. 2006). It is also possible to use ensemble forecasting (Jorgensen and Mohrlen 2008; Buizza 1997) or to apply statistics based on dynamical models (Sanchez 2006) to improve the accuracy of wind energy forecasts. However, there are downsides to these methods; for example, ensemble forecasting has much higher computational costs.

Is the problem with the models or the measurements?

A question that naturally follows, particularly from a forecast modeller's perspective, is whether the issues above are entirely the fault of the models used or whether they represent a problem with the measurements as well? There are two senses in which this question can be asked. The first is to ask: Is the data that we compare the models to 'correct'? In other words, how well does the measured data from the two met masts represent the overall behaviour of the region surrounding the wind farm? The second is to ask: What are the best measured data to use as inputs to the NWP models to improve their accuracy for this particular application? These two questions are intimately linked and lead us to a comparative statistical analysis of the various experimental data sources available for the wind farm and its locale.

We will now compare four available sets of data: measurements from the north and south met towers at either end of the wind farm, measurements from the Cape Grim station 2 km to the north of the wind farm, and the average of the readings of the 37 turbine-mounted anemometers at the wind farm itself. This will allow us to establish how well the met towers represent the wind farm and look at how wind conditions vary across the measurement sources.

Table 1 shows the percentage frequency occurrence of four wind speed categories for the four measurement sources for February and August 2005 (i.e. southern hemisphere summer and winter). The four categories coincide with important wind speed regimes for the turbines: the turbine cut-in regime (0 – 4 ms^{-1}), the maximum efficiency regime (7 – 13 ms^{-1}), the rated turbine power output regime (15 – 25 ms^{-1}), and the high-wind shut-down regime (> 25 ms^{-1}). As Table 1 shows, February exhibits a much greater occurrence of low wind speeds (< 4 ms^{-1}) than August by a factor of ~4, whilst periods of full power operation are ~5 times more likely in August than in February. Of the four categories, the maximum efficiency regime is significant because it is where the greatest variability in turbine output with wind speed occurs. As mentioned earlier, a change in wind speed of only 3 ms^{-1} in this regime can cause the power output to vary by as much as 31 per cent. For both months, wind speeds in

Fig. 5 Monthly statistics of average wind speed for the Woolnorth wind farm for 2005, 2006 and 6 months of 2007. Solid line is the climatology of average wind speeds for Cape Grim for comparison.

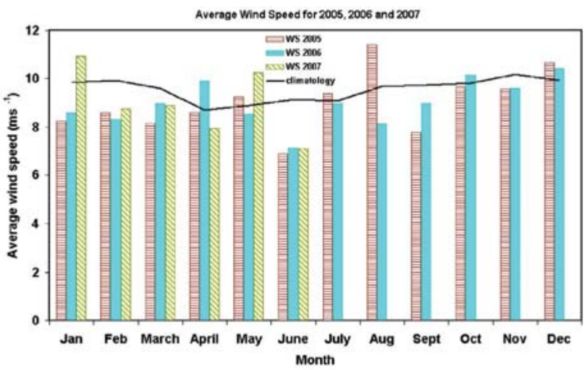


Table 1. Percentage (%) frequency of occurrence of different wind speed regimes for the four sites for February and August 2005

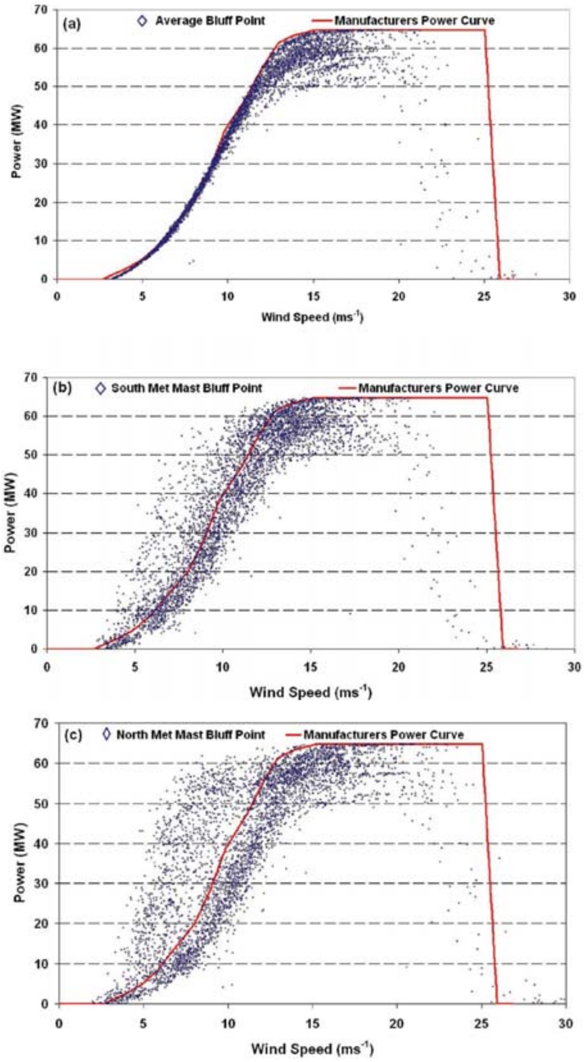
Wind Speed	Month	North Tower (% frequency of occurrence)	South Tower (% frequency of occurrence)	Woolnorth (% frequency of occurrence)	Cape Grim (% frequency of occurrence)
< 4 ms^{-1}	February	11.51	9.99	10.17	10.89
	August	3.27	2.73	2.71	2.17
7–13 ms^{-1}	February	58.43	63.79	63.90	60.34
	August	54.78	57.52	55.16	47.93
15–25 ms^{-1}	February	3.35	3.47	3.70	5.16
	August	19.00	14.18	18.66	29.37
> 25 ms^{-1} (cut-off)	February	0.00	0.00	0.00	0.00
	August	0.92	0.67	0.69	0.76

the 7-13 ms^{-1} range are most common, indicating significant potential for output variability issues for this wind farm site throughout the year. The Cape Grim measurements show a greater percentage of higher wind speeds than the three other sites, due to its more exposed location. At first glance these results appear to show that the wind farm is more productive in winter, whilst in summer the need for supplemental power from other sources would be more likely. However if we consider Fig. 5, which shows the average wind speed for each month in 2005, 2006 and six months of 2007, the first thing to notice is that on average wind speeds are higher in the warmer months and lower in the cooler months, noticeably in June. The 'extreme' event for August impacted on the statistics of that month, as the monthly wind speed average surpassed the value for 2006 as well as the climatology value for Cape Grim (which in general has higher average wind speeds than Woolnorth). These statistics for the period 2005 – June 2007 indicate that one would expect higher power output in October to December as opposed to June and July.

Although the values in Table 1 differ, ultimately it is rather difficult to assess how well the met towers represent the wind farm conditions from such a basic analysis. A better indication can be obtained by using a power curve analysis of time series data, as shown in Fig. 6. Fig. 6(a) shows the wind farm power output, as a function of the averaged turbine wind speed obtained from the 37 turbine mounted anemometers for the entire month of August 2005. Fig. 6(b) and (c) show the wind power output from Fig. 6(a), but this time against the measured south and north met tower wind speeds at the same point in time, respectively. The solid lines in both panels represent the manufacturer's specified power curve for the turbines, and represent the ideal, upper-limit relationship between power output and wind speed. The much greater data spreads in Fig. 6(b) and (c) indicate that the met tower data are not as good an indicator of wind speed conditions over the wind farm as the average of the 37 turbine-mounted anemometers. At first this might seem obvious, but in fact it is typically thought that the met mast data is superior instead, because the anemometer measurements are made behind the turbine blades and thus don't as accurately represent the free-stream winds experienced by the blades themselves. For this reason, met tower data is often used over turbine anemometer data for wind power performance testing of turbines (Smith et al. 2002). If the met mast is immediately adjacent to a single turbine it is certainly appropriate for this purpose, but our data indicate the opposite for wind energy forecasting when a larger number of turbines are involved – averaging over a larger number of measurements, despite some possible error due to blade turbulence, is clearly advantageous to a smaller number of measurements made in a 'clean' air-stream.

The idea of a clean air-stream however is still an important one however. Comparing Figs. 6(b) and (c) it is clear that the south met tower gives a more accurate representation of the wind farm than the north met tower, which is surprising given that the South met tower is actually further away from the coastline. The explanation for this lies in the data shown in Fig. 7, where we present polar-plots of percentage occurrence against direction for winds in (a) February and (b) August of 2005. In both cases the dominant wind direction is from the W to SSW. Considering the topography of the Woolnorth wind farm, for winds from these directions, the south met tower has a much cleaner air-stream than the north met tower, which experiences turbulence both from

Fig. 6 Power curves for the averages of (a) The Bluff Point wind farm for August 2005, (b) The south met mast for Bluff Point for August 2005 and (c) The north met mast for Bluff Point for August 2005. The solid line in (a), (b), and (c) represents the manufacturers power curve.

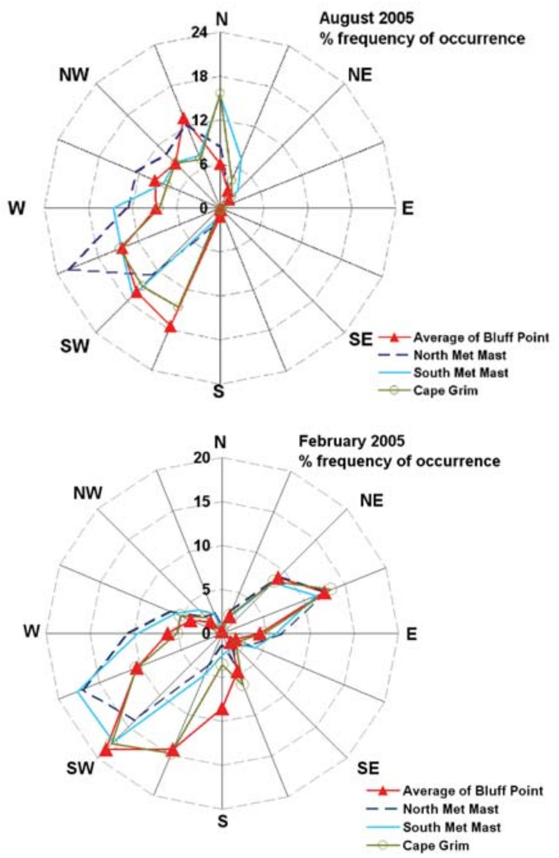


the land in front of it (Fig. 1 (inset) shows that the north met tower is 'effectively' far more inland than the south met tower), and up to a dozen turbines on its windward side. It is also interesting to note the correlation between the wind direction measurements from the four sources, which show good but not complete agreement, and the appearance of a distinct northeast component in summer, which occurs when a high pressure system is centred over the Tasman Sea to the east of Tasmania.

Discussion and conclusions

The ability to forecast the power output of a wind farm is vital to maintaining a stable and reliable electricity supply to the consumer. This presents a significant challenge from a meteorological perspective because it requires the development of models that can provide very accurate forecasts with high spatial and temporal resolution for relatively small geographical areas. Traditional NWP models are not geared to this, as demonstrated in our case study, where we used the limited domain mesoscale model MesoLAPS, which has a 5 km grid spacing, and found that it lacks the resolution, in both space and time, to provide sufficiently accurate forecast results. It will require the development of much smaller models focused specifically on forecasting wind conditions, possibly based on existing models such as TAPM or MALAPS (Vincent et al. 2008) and running in a nested manner under larger scale NWP models to provide inputs that allow larger scale weather phenomena to be accounted for at the local scale.

Fig. 7 The directional frequency for all four sites for (a) August 2005 and (b) February 2005.



However, the problem is not one of models alone. All NWP models require the input of measured atmospheric conditions, and the accuracy of these models is heavily dependent on the quantity and quality of these inputs. This provides a second important challenge for wind energy forecasting; the acquisition of accurate measurements that will in turn make the models more accurate. Our case study shows that the quantity and location of these measurements is extremely important, as is a consideration of obstructions on their windward side, which may lead to inaccuracies due to turbulence in their airstream. In particular, we found in our case study that a larger number of possibly less accurate, turbine-mounted anemometers are more effective than a smaller number of more accurate met towers located local to the wind farm for producing high-quality measurement data for wind energy forecasting.

Thinking beyond this work, an interesting question to ask is how the accuracy of wind energy forecasts can be improved upon beyond the development of smaller scale models and better quality measurements discussed above. This may be achieved by using statistical techniques, such as ensemble forecasting. Although ensemble forecasting is computationally expensive, judicious use during periods of rapidly varying weather and/or unstable atmospheric conditions may lead to improved accuracy for a more modest computational investment.

Ultimately however, it is clear that there is much work to be done in developing the ability to do wind energy forecasting well enough to enable wind energy to become a major contributor to electricity supply. This presents some important and interesting challenges for meteorologists, who will be called upon to develop highly accurate forecast models with unprecedented spatial and temporal resolution that push well beyond what is possible using existing forecasting techniques.

Acknowledgments

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