The Importance and Accuracy of Wind Power Forecasts

AUTHOR

LIAM DISKIN

A THESIS SUBMITTED FOR THE MASTER OF SCIENCE IN
ENVIRONMENTAL SYSTEMS,
AT THE COLLEGE OF ENGINEERING,
GALWAY MAYO INSTITUTE OF TECHNOLOGY, IRELAND

SUPERVISOR

DR. DENIS O'MAHONEY

DEPARTMENT OF MECHANICAL & INDUSTRIAL ENGINEERING,
GALWAY MAYO INSITUTE OF TECHNOLOGY, IRELAND.

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The substance of this thesis is the original work of the author and due reference and acknowledgement has been made, when necessary, to the work of others. No part of this thesis has been accepted for any degree and is not concurrently submitted for any other award. I declare that this thesis is my original work except where otherwise stated.

Name of Candidate	Name of Supervisor
Liam Diskin	Dr. Denis O'Mahoney

Date

Abstract

Due to the global crisis of climate change many countries throughout the world are installing the renewable energy of wind power into their electricity system. Wind energy causes complications when it is being integrated into the electricity system due its intermittent nature. Additionally winds intermittency can result in penalties being enforced due to the deregulation in the electricity market.

Wind power forecasting can play a pivotal role to ease the integration of wind energy. Wind power forecasts at 24 and 48 hours ahead of time are deemed the most crucial for determining an appropriate balance on the power system. In the electricity market wind power forecasts can also assist market participants in terms of applying a suitable bidding strategy, unit commitment or have an impact on the value of the spot price. For these reasons this study investigates the importance of wind power forecasts for such players as the Transmission System Operators (TSOs) and Independent Power Producers (IPPs). Investigation in this study is also conducted into the impacts that wind power forecasts can have on the electricity market in relation to bidding strategies, spot price and unit commitment by examining various case studies. The results of these case studies portray a clear and insightful indication of the significance of availing from the information available from wind power forecasts. The accuracy of a particular wind power forecast is also explored. Data from a wind power forecast is examined in the circumstances of both 24 and 48 hour forecasts. The accuracy of the wind power forecasts are displayed through a variety of statistical approaches. The results of the investigation can assist market participants taking part in the electricity pool and also provides a platform that can be applied to any forecast when attempting to define its accuracy.

This study contributes significantly to the knowledge in the area of wind power forecasts by explaining the importance of wind power forecasting within the energy sector. It innovativeness and uniqueness lies in determining the accuracy of a particular wind power forecast that was previously unknown.

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Chapter One

"If you have to forecast, forecast often..."

- Edgar R. Fiedler

1.0 Introduction

1.1 Background

Due to increasing concern over global climate change, many policy makers worldwide have accepted the importance of reducing greenhouse gas emissions, in particular from the electricity industry. As a result, there has been an international movement in the promotion of policy mechanisms of clean renewable technologies for electricity generation such as wind, solar, tidal and wave generation. The Kyoto protocol has been the main motivation behind the impetus of renewable energy. In this protocol the European Commission has set targets to increase the gross energy consumption from 6% in 1997 to 12% by the end of 2010 for the share of renewables (European Commission, 2001). Wind energy is currently the leader in renewable energy as it is the most integrated renewable in the electricity system and at a more advanced stages in development in comparison to tidal or wave energy. Wind energy is currently the fastest growing renewable in the energy sector with an annual growth of 27%.

Large nations such as Denmark, Spain and Germany have become the market leaders for integrating wind energy into their electricity system. In Ireland's circumstance the geology of Ireland containing good rock and gently sloping valleys makes Ireland perfect a natural energy source for wind and as a result of this and additional factors such as the Kyoto protocol, has led Ireland to set a target of 40% of their electricity supply to be generated from renewables. Wind energy will supply the majority of this target (Ireland, Department of Environment, 2006).

At present the majority of wind generation is from on-shore developments, however, in the future I believe that a large share of the wind power that will be generated will be from off-shore projects. Off-shore wind farms have the benefits of having greater and more frequent high winds available in comparison to on-shore wind farms (Pryor & Bathelmie, 2001). In addition to this the wind farms located off-shore are out of sight from the publics view and hence less likely to cause any planning application difficulties. Horns Rev, figure 1.1, on the west coast of Denmark is currently one of the world's largest off-shore wind farms that is able to produce 160 MW from 80 competent wind turbines. The aim of the Danish government is the ambitious target that by 2030 to have 4000 MW of wind energy generated from the Danish waters under the Horns Rev project (www.hornrev.dk).

Figure 1.1 *Horns Rev in Denmark (www.rechargenews.com)*

Whether on-shore or off-shore developments are selected by governments throughout the world, the main problem each government will face is the difficulties of managing wind power in their electricity system. Unlike conventional energy sources wind power is intermittent and as a result causes various snags for Transmission System Operators (TSOs) when trying to seek a balance between wind power and conventional energy sources. For example in circumstances when the wind doesn't blow reserves, conventional sources are required to deliver the demand levels that are required. The use conventional sources cause a negative effect on the principle reason for integrating wind power i.e. to minimise CO_2 emissions. This is why the forecasting of wind power production is considered necessary. Wind power forecasts assist TSOs in the management of electricity grids and also the market participators for trading in the electricity pools.

1.2 Research Question

The question below is divided into two parts and is the fundamental subject matter that will be examined in this thesis and is essentially the leading light of this research.

Why are wind power forecasts so important and how good is the accuracy of a particular wind power forecast?

1.3 Principle Aims

The principle aim of this thesis is to determine the accuracy of a particular wind power forecasts and additionally to describe the importance of wind power forecasts. To achieve the principle aim of the thesis analysis is conducted into the information of a particular wind power forecast from data supplied by Bord Na Mona. To illustrate the accuracy of the wind power forecasts I have decided to calculate the accuracy of the wind power forecasts for two periods i.e. 0 - 24 and 25 - 48 hours ahead as these are the most crucial hours for wind power forecasts in the energy sector.

As a second aim of this thesis, I proposed to display the benefits and impacts of wind power forecasts to illustrate why wind power forecasting is so important. I explain the benefits of having wind power forecasts for such players as the Transmission Systems Operators (TSOs) and Independent Power Producers (IPPs) and to demonstrate the importance of wind power forecasts I use case studies to display the effect wind power forecasts can have on the market for example in terms of bidding strategies and spot prices.

1.4 Structure of Thesis

This thesis is separated into the following chapters and is structured as follows;

Chapter two explains the chief problem associated with wind power being its variability and intermittent nature. Additionally in this chapter the importance of wind power forecasts to TSOs and IPPs is examined while to further emphasise to significance of its importance a case study is analysed that describes scenarios without the benefit of wind forecasts and then analyses the same scenario with wind power forecasting present. The benefits of wind power forecasts for wind storage and surplus wind energy are also briefly discussed. The current research and analysis that has been conducted into wind power forecasts in regard to impacts on electricity market in term of bidding strategies and spot price is also examined. Finally, this chapter delves into research conducted on the effect of wind power forecasts on unit commitment and economic dispatch.

Chapter three determines the accuracy of the particular wind power forecast supplied by Bord Na Mona and additionally details a brief description of the two main models for wind power forecasts i.e. statistical and physical. For determining the accuracy of the wind power forecast data a broad range of statistics were calculated to display such results as mean error per hour, probability, mean absolute error (MAE), root mean square error (RMSE), inter-quartile range and the probability distribution function.

Chapter four contains discussions and a summary of the overall conclusion from the research presented in this thesis.

Chapter five details recommendations for further work based on the research conducted in this thesis.

Chapter Two

"It is far better to foresee even without certainty than not to foresee at all..."

- Henri Poincare

2.0 Wind Power Forecasting

2.1 Introduction

In the eighties research began into the area of wind power forecasting (M^{c}Carthy, 1998). Ever since then there has been huge investment by companies throughout the world into techniques to enhance the accuracy of prediction models in different time scales. The times scale can be from up to a few minutes ahead, 48 – 72 hours or longer time scales such as 5 – 7 days ahead. The forecasts up to a few minutes ahead can be used for the turbine active control, 48 - 72 hours ahead are required for power system management or energy trading, while 5 – 7 days ahead is needed for servicing of wind farms (Pinson, 2006).

2.2 Wind Power: The Problem

Wind power is not similar to conventional power sources as it is created by changing climate conditions and results in an intermittent and highly variable power source, in comparison to conventional thermal plant such as fossil-fired steam plants or gas turbines. Conventional sources are required to intervene as a reserve for the electricity network if actual wind power generated is less than predicted (Bindner & Lundsager, 2002). Fluctuations of wind speed are the key characteristic to the variation of wind power output (Albadi & Saadany 2008).

2.2.1 The Variable Nature of Wind

Classification of Variability

Albadi and Saadany (2009) attempted to categorize the classification of variability by stating that the high variability of wind is what characterises its wind speed both spatially and temporally. Spatial variability, on a global scale, is recognised to the fact that there are various climate areas throughout the world influenced by the altitude and solar insulation. On a regional scale, the geographical location can cause variance to wind speed due to different types of terrain such as land, sea and mountains.

Finally on a local viewpoint, the main effects on wind speed can be vegetation and topography.

Enduring temporal wind fluctuations, at a specified location, explains the fact that the quantity of wind may differ per annum. Despite this there have been various studies conducted that has reached the conclusion that from one 20 year period to the next the average wind power output has a maximum standard deviation as low as 10% (Ackermann, 2005). Therefore, these results indicate the ambiguity of wind power production isn't huge during the existence of a wind turbine.

In contrast to annual fluctuations, seasonal fluctuations are easier to forecast. Wind speed synoptic fluctuations connected with the passage of weather systems aren't extremely predictable more than a couple days beforehand. Diurnal variations, wind variations with the time of day are less complicated to forecast. Both synoptic and diurnal fluctuations can have an effect on power balancing needs. Fluctuations of wind speed in relation to minutes and seconds are known as turbulences (Ackermann, 2005).

Synoptic, diurnal and turbulent effects related to clear peaks are illustrated below in figure 2.1;

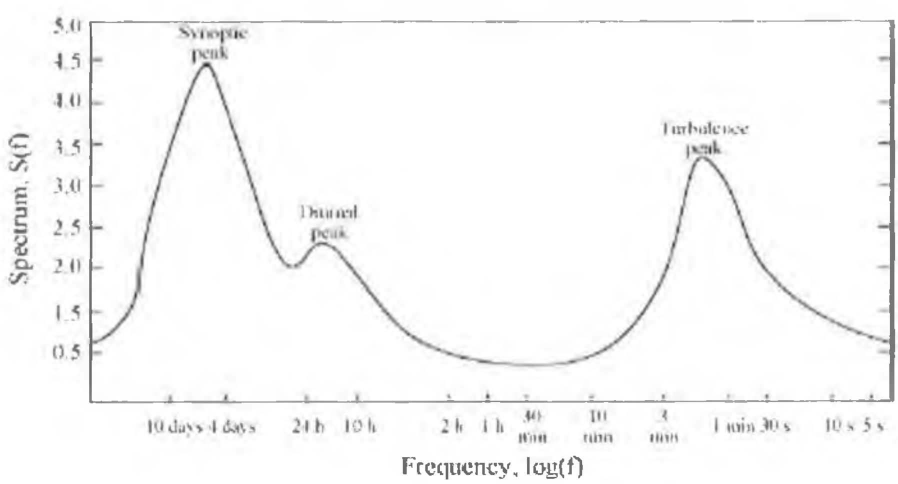

***Figure 2. 1** Wind Spectrum (V.D Hoven, 1957)*

Aggregation Effect on Variability

The temporal volatility of wind power is minimised by aggregation of wind turbine outputs in two aspects as demonstrated by Albadi and Saadany (2009):

1. Amplified number of turbines on a wind farm
2. Spatial distribution of wind generation resources

When additional turbines are increased on a wind farm, gusts of wind don't strike each turbine independently resulting in reduction of turbulent wind effect. Actually a minimal number of turbines (n) are required to attain a considerable smoothing result, as the percentage variation of power is reduced to $n^{-1/2}$, preferably. While in the other scenario, on a wind farm where wind turbines are wider geographically dispersed, the impact of synoptic and diurnal fluctuations are reduced. For wind farms, with specific aggregate capacity spatial distribution has a great deal lower up and down ramping rate requirements compared to a large single wind farm having a similar capability (Ackermann, 2005). Table 2.1 below displays a summary of wind speed variability.

***Table 2. 1** Summary of Wind Speed Variablity (Albadi & Saadany, 2009)*

Classification	**Predictability**	**Aggregation Effect**	**Impacts on Power Systems**
Annual	Not predictable but small	N/A	Reliability/adequacy
Seasonal	Predictable	Limited	
Synoptic	Predictable few days ahead	Through wider geographical dispersion	Unit commitment/reserves
Diurnal	Predictable		
Turbulences	Not predictable	Ideally in rule	Power quality

2.3 The Importance of Wind Power Forecasting

2.3.1 Transmission System Operators (TSOs) and Independent Power Producers (IPPs)

Pinson (2006) examined the importance of wind power forecasting in terms of the Transmission System Operators (TSOs) and Independent Power Producers (IPPs), he started that the responsibility of overseeing the electricity stability on the grid is with the TSOs. The TSOs, in Ireland is Eirgrid, has the task to ensure that electricity production is to equal consumption 24 hours a day. For that reason, the type of production is planned beforehand to act in response to load profiles. The total electricity consumption throughout the grid relates to the load. For day-ahead predictions high accuracy for load profiles are in the region of 98-98.5% can be forecasted, while week-ahead forecasts don't normally exceed a forecast error of 5%. Despite this high level of accuracy there is still constant research being conducted to enhance this small error as a minimal reduction of the amount of forecast error will result in considerable savings for utilities that manage large interconnected systems.

When TSOs are calculating their daily schedule, they can decide to use their power production means if they are available or if they can obtain power generation for IPPs and utilities through electricity pools. In the circumstance of deregulation, additional players can come onto the market, which cancels the previous situation of local monopolies of vertically-integrated utilities (Pinson, 2006).

The electricity market is composed of two procedures;

1. Spot market
2. Balancing of power generation

Pinson (2006) explained the two procedures by stating that in the first procedure, spot market, players offer amounts of energy at a stated production cost for the following day. A structure similar to an auction allows an electricity spot price to be agreed for different times depending on the different price offered. The organisation of the TSOs is required for the second procedure, the balancing of power generation. If there are power plant failures or as a result of the intermittent nature of wind there becomes a deficit or surplus of energy, it is the responsibility of the TSOs to decide on the fines that will have to be paid by the IPPs who are in breach of their proposed requirement. Because of this players in wind power generation have a large amount of their production that can be subject to penalties and as a result are punished by this market system. In some countries that aim to develop wind power generation guaranteed grid entry has been approved from electricity that has been created from wind farms, in addition as to enforce the acquisition of all wind generation at a guaranteed price, also know as feed-in-tariff (Butler & Neuhoff, 2004). Spain, who has also been one of the leaders in the wind market industry, has decided to promote wind power generation by adding a premium to market clearing prices. The premium represents ecological benefits of that renewable energy (Barquero & Segurado, 2004). The amount of energy can't be anticipated by the IPPs without knowing what will the output of his wind farm. Wind power forecasting greatly improves the revenue for the IPP for bidding in the electricity market (Usaola et al., 2004). It is also advisable to take into account the related uncertainty approximations for essentially the best possible participation approaches, this topic is reviewed later in this chapter.

2.3.2 Wind Power Penetration

Despite a large focus being placed on wind power generation throughout Europe wind generation still remains low in a large majority of countries of the total electricity production. However, in countries such as Denmark the opposite can be stated as wind power generation can be high and this causes complications for management of the grid. Therefore, it is crucial to be able to deal with circumstances when errors in forecasts occur due to decreases in wind speed or times when there is excess production.

When analysing the first scenario, decreases in wind speed, the task is to calculate the reserve requirement that will be needed to compensate for a deficit of the wind that is anticipated to be produced. A major disadvantage when having to use a large quantity of reserves is that conventional methods of electricity generation are used and hence cause an increase in CO_2 emissions. Research has been conducted on potential approaches for determining the way conventional power plants and wind power can partake in the electricity market, which is explained in a case study by Doherty et al., (2004).

Case Study – Irish Electricity System

Introduction

Research conducted by Doherty et al., (2004) examined potential approaches for determining the way conventional power plants and wind power generation may contribute in the electricity market. Their research was based on the all Ireland electricity system and was set up to show the effect that different models of system operation can have on the successful integration of significant quantities of wind power. Their analysis is based on a usual day, 24 hour period, on the system and the results demonstrate the comparative qualities of various operational situations. This research displays the importance of wind power forecasting as it analyses scenarios without the benefit of wind power forecasts and then analyses the same scenario with wind power forecasting present.

Test Day System

As mentioned above the test is based on the all Ireland electricity system that compromises of approximately 7000 MW and an inter-connector to Scotland. The analysis is based during a common 24 hour period containing an assumed 1500 MW installed wind capacity. 525 MW is the average hourly wind generated for the day, resulting in a wind capacity factor of .35. Figure 2.2 displays the load and wind power production for the 24 hour period.

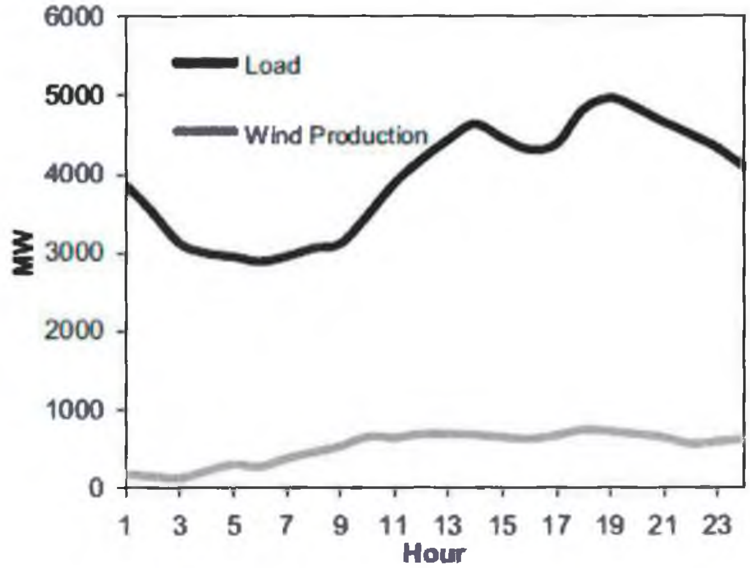

Figure 2.2 *Load ad Wind Power Production for the 24 Hour Period System Operation Scenarios (Doherty et al., 2004)*

For the 24 hour period that is being analysed there are three different situations examined to display the effects on the system operational modes have on the successful integration of wind power generated. The three situations are outlined below;

1. *No Wind Scenario*; this situation is used as the fundamental case to evaluate the effect of the wind power generated. No wind capacity is held on the system. Conventional generation is total generation and reserve generation.

2. *Fuel Saver Scenario*; this situation works on the basis that generation and reserve needed on the system is intended with no contemplation specified to the forecasted wind production. The intention of this situation is for the system to use only conventional plant and when wind power is available to reduce the quantity of conventional plant generation. The conventional plant is never turned off, it is reduced to its minimal operating point. Wind power generation is curtailed if conventional generation isn't possible to reduce beyond its minimum operating limit.

3. *Forecasted Scenario*; this situation takes into account the forecasted wind power to be generated and forecasts errors the system requires to meet the consumption and reserve requirements e.g. reduction in conventional plant generation due to wind power generation and increased quantity of reserve due to ambiguity of the wind power generation forecasts. Wind forecasting is essential in this form of approach as the errors in wind power forecasts decrease in error with time e.g. the forecast two hours ahead is more accurate than the forecast two days ahead. This dictates the amount of reserve required.

Results

The results of this analysis by Doherty et al., (2004) focus on the effects on reserves and conventional generation while also producing information on other impacts of system operation e.g. effect on best new entrant and dynamic system issues.

As described earlier the analysis was based on the situation of "no wind", "fuel saver" and "forecasted", which was broken down into two variations. In the first forecast variation the forecast is set at the start of each hour while the second variation is forecasted 24 hours ahead i.e. forecasted one day ahead.

Concentrating on the reserve requirements table 2.2 illustrates the results of the case study in terms of the mean quantity of each scenario and additionally displays the rates paid for the various operations of reserve on the system.

Table 2. 2 *Mean Reserve Required (Doherty et al., 2004)*

			Reserve (MW)			
Category	**Rate (€)**	**Time Scale**	**No Wind**	**Fuel Saver**	**Forecasted Hour-Ahead**	**Forecasted Day-Ahead**
Primary	1.73	15 Sec	309	322	322	322
Secondary	1.57	90 Sec	315	329	329	329
Teritary 1	1.43	5 min	401	417	417	417
Teritary 2	1.43	20 min	420	441	441	441
One Hour	1.08	1 hour	455	978	491	626

Table 2.2 illustrates a minimal rise between 4 - 5% for all operation scenarios for primary, secondary and tertiary reserves. This small increase is due to the variation on

the system caused by the wind capacity. This rise reveals the detail that the biggest section of the reserve is approved to protect the loss of the biggest generation units. A rise of 455 – 491 MW (8%) increases the requirement for one hour reserves is displayed on the forecasted hour ahead operation. This additional rise is again the result of this more variation on the system. The forecasted day ahead on the one hour reserve an increase from 455 – 626 MW (38%) is experienced. While a part of this is due to the extra variation for wind, the system must also take into account for uncertainty of the wind forecast error that will occur between 24 hours ahead and the actual one hour ahead. The largest increase on the one hour reserve system is on the fuel saver reserve, 455 – 978 MW (116%). The main cause for this high reserve is due to the fact that the fuel saver method, although reduces the conventional plant when wind is available, never turns off the conventional plant and it must always remain online.

The quantity of conventional generation required to reach the generation and reserve requirements throughout the day is illustrated in figure 2.3. Each operational scenario is represented, the "no wind" scenario is equal to "fuel saver".

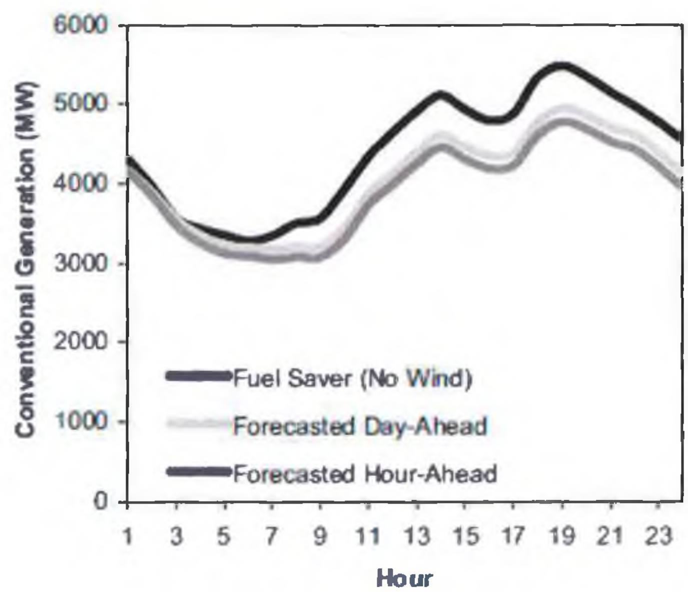

Figure 2. 3 *Conventional Generation Capacity under the Various System Operations (Doherty et al., 2004)*

Figure 2.3 displays the "forecasted hour ahead" requires the least conventional generation in comparison to the system operations of "forecasted day-ahead" and "fuel saver/no wind". The system operation of "fuel saver/no wind" entails the largest use of conventional generation followed by "forecasted day ahead".

As figure 2.3 displays the reduced quantity of conventional generation required due to impact of wind power generation. However, it is very complicated to determine the external costs of wind power production e.g. planning, installation and operation. Doherty et al., (2004) used an approximation to display the impact of system operation capacity to give an indication of the reserve availability payment throughout the year. To calculate the cost of reserve throughout the year they based their assumptions on a normal day for the load system and average day wind power generation and then used this day to determine the total cost for the year. Table 2.3 illustrates the cost results of the reserve payments on the all Ireland system throughout the year.

Note: The rates in table 2.3 are based on those shown in table 2.2

Table 2. 3 *Cost of Reserve Availability per year (Doherty et al., 2004)*

Scenario	**Cost of Reserve (€m/year)**	**% Increase in Cost over No Wind Case**	**Cost Imposed per MW Installed Wind Capacity for 1500MW (€/year)**
No Wind Capacity	23.6	N/A	N/A
Fuel Saver	29.4	24.7	3888
Forecasted Hour-Ahead	24.8	5.1	804
Forecasted Day-Ahead	26.1	10.5	1656

Table 2.3 shows that a cost of €5.8 million/yr in additional reserve availability payments is the cost of using "fuel saver" approach based on 1500 MW of wind capacity. Significant enhancements are made on the €5.8 million/yr when adopting the forecasted techniques. The "forecasted day ahead" costs €2.5 million/yr while "forecasted hour ahead" costs €1.2 million/yr. The forecasted figures represent the advantages of planning the system over shorter time frames when the error in forecast is minimised. The rise in cost, for each operational system, of reserve availability per MW of installed wind capacity for a total installed wind capacity is also shown in table 2.3. This illustrates that a 25 MW wind farm would be likely to inflict approximately €20,000/yr in further reserve accessibility costs for the hour ahead

forecast scenario while in the region of €115,000 /yr would be the cost of the "fuel saver" option.

Conclusion

The results of this analysis by Doherty et al., (2004) gives a quality insight of throughout the year of the comparative performance of the various system operation strategies. The "fuel saver" option has shown that on the system results in over-commitment of conventional generation in times of large wind power production and consequently leads to a non-economic system and can alleviate some probable advantages of reducing CO_2 emissions in comparison to using wind power. As Ireland is attempting to reduce carbon emissions to meet requirements such as the Kyoto protocol it is impractical to adopt the "fuel saver" option for the all Ireland electricity system. However, the option of the forecasted techniques illustrated the enhancements that can be made by incorporating wind power generation into the system. This is mainly due to the fact that the forecasted technique permits a reliable system to be maintained while conventional plant generation can be turned off.

2.3.3 Wind Storage

The storage of wind energy is another option to balance the negative effect of wind power being an intermittent source. The IPPs would benefit greatly from the storage of wind, in regard to the electricity market, as it would minimise the risk of penalties due to not being able to meet their projected amount of energy to the market. The storage of wind can make strong economic sense if wind power can be stored in periods of high winds or times of low electricity prices as this wind energy could then be available to sell at times when prices are high on the electricity market, resulting in a profit for the IPPs. Advanced wind power forecasts would result in the best possible results and advantages for such methods of wind storage. Despite this advantage wind storage isn't a common practice throughout the world at present due the huge expense associated with the facilities to incorporate wind storage such as hydro-storage plants (Barton & Ingfield, 2004).

2.3.4 Surplus Wind Generation

As mentioned earlier in parts of Western Denmark often a surplus quantity of wind power produced exceeds consumption required. This can result in wind power generated being wasted. This scenario can provide to be difficult for TSOs to manage. Interconnection to adjoining grid systems is the best option to deal with the management of surplus wind power production. Advanced forecasts can provide key assistance in these circumstances of high wind power generation to arrange exportation of the additional wind power (CEPOS, 2009).

2.4 Wind Power Forecasts on the Electricity Market

In this section the effects of wind power forecasts have on the market are demonstrated by displaying how they impact on the value of spot prices on the electricity market and additionally displays the role wind power forecasts can play in bidding strategies in the electricity pool.

The variability nature and introduction of wind power into the electricity market causes numerous challenges for TSOs who have the task to manage this variability and ambiguity of wind power production for their judgment in scheduling and dispatch. As mentioned earlier, in section 2.3.1, to assist the TSOs organise their scheduling and dispatch in a competent manner wind power forecasts plays a pivotal role. In recent times the introduction of deregulation has seen significant change in electricity markets throughout the world. The most noteworthy alteration has been the implementation of wholesale electricity markets, where electricity is bid and sold by distributors and producers. But in this scenario the prices are not easily forecasted as it is extremely difficult to comprehend as it is not totally known the movement of the spot prices. However, for scheduling, trading and risk management it is vital to have knowledge of the movement in these prices.

Many circumstances result in difficulty of predicting spot prices, for example anti-gaming guidelines together with the immediate features of electricity and limitations on its transmission result in taking advantage of a price difference between two or more markets over time and space is virtually unfeasible. Also from a short-term viewpoint the demand for electricity is unaffected when the supply and demand price changes.

Wind energy is bid into markets on the basis of using advanced wind power generation forecasts. Research has been conducted by Chevallier et al., (2007) into perfecting the bidding strategies of wind power in the deregulated electricity market with the foundation of their analysis being based on wind power forecasts. Their case study on the evaluation of bidding strategies in a Dutch electricity pool is analysed later in section 2.4.1. This research doesn't take into account that possible effects on its prices, it focuses on wind power as a price taker. Later in section 2.4.2 analysis of a case study conducted by Madsen et al., (2009) on the Nord Pool's Elspot market, showing wind as the price maker, considering the effects of wind power forecasting on prices.

2.4.1 Trading of Wind Power Generation on the Electricity Markets

The Market

It is possible to deem electricity markets as a substitute solution to power unit scheduling, given that they assure a cost-effective equivalent amid supply and demand bids. Every electricity pool is unique in regard to such items as the purchase and sale of electricity and the agreement of prices (Chevallier et al., 2007). In many countries legislation has been incorporated to ensure the use of wind power to use wind power on the system when it is available, with the aim being to reduce CO_2 emissions.

The participants in the electricity mix, the sellers and buyers, propose their price bids in the day ahead market prior to gate closure. Program Time Unit (PTU) is the term given to the time after the gate closure. To establish the market spot price, the bids are coordinated through a solitary auction procedure and the PTU program for each participant is created. This is now a type of contract in the sense that the sellers are now financially accountable if they don't comply with their bid. In some electricity markets there is "intraday markets". In the Intra market it is achievable to make remedial actions. The reason for this is due to the possible delay of 12 – 14 hours between the start of the delivery of energy and gate closure. A time limit between thirty minutes and two hours prior to delivery of energy is when gate closure occurs on the intraday markets. The TSOs is then responsible to ensure that there is a real time balance for production to meet consumption.

Bidding Strategies

Assumptions

When strategies are being developed to bid in the electricity pool, wind power generation producers must make some assumptions how the wind power will impact the behaviour of the market. The following points below are some of the common assumptions that are made in regard to advanced bidding strategies;

1. In the long-term it is anticipated that the mean spot price on the electricity pool will be reduced if a large quantity of wind power generation is brought onto the power system (Murphy, 2003).

2. A single wind power producer hasn't any market power, and the bidding policy of this wind power producer cannot single-handedly cause disproportion to the price (Bathurst et al., 2002).

3. Wind power producers don't have an advantage from derogatory rules, every wind power producer acts as conventional producers in the electricity market. Also, in relation to the intraday market it is assumed that they don't submit no bids for regulation, reserve power or corrective actions (Chevallier et al., 2007).

Case Study – Bidding Strategies on the Dutch Electricity Pool in 2002

The Market and Wind Producer

This case study is based on data replicated from the Dutch electricity pool in 2002 researched by Chevalier et al., (2007). The day ahead market is called APX (Amsterdam Power Exchange), which is linked to the TenneT, which is the TSO for the Netherlands. 10:30 is the time of gate closure on the APX for the following day.

1 hour is the length of time specified for the PTU. There is no restriction on the sign or scale of disproportion on prices due to the fact that both APX spot and TenneT are independent. Regulation unit costs, $\pi_k{}^{*+}$ and $\pi_k{}^{*-}$, are possible to contain a minus. When this occurs electricity becomes a waste good. At first this may seem unusual however, it is effortlessly expandable due to the non-flexible generators that must always be in operation. As a result negative prices are adequate to the power suppliers as the costs associated with a shutdown phase are often more costly.

Data for the mean spot and regulation prices are displayed in table 2.4 for the entire 2002 period and additionally containing data in a monthly and quarterly formation.

Table 2. 4 *Market Characteristics 2002 (Chevallier et al., 2007)*

Month	π_k**c+ (M.)**	$\pi_k{}^{*-}$ **(M.)**	$\pi_k{}^{*+}$ **(M.)**	$\pi_k{}^{c}$ **(Q.)**	$\pi_k{}^{*-}$ **(Q.)**	$\pi_k{}^{*+}$ **(Q.)**	$\pi_k{}^{c}$ **(Y.)**	$\pi_k{}^{*-}$ **(Y.)**	$\pi_k{}^{*+}$ **(Y.)**
1	14.5	-2.1	18.29						
2	10	-0.67	17.96	11.65	0.33	16.22			
3	10.43	3.77	12.4						
4	17.92	-6.66	18.49						
5	39.21	0.93	9.06	38.38	1.34	11.13			
6	58.02	9.74	5.83				29.99	4.03	10.93
7	48.56	12.97	2.9						
8	41	23.06	-4.3	41.17	8.22	8.51			
9	33.94	-11.38	26.93						
10	38.25	9.61	6.38						
11	29.09	-4.4	18.92	29.38	6.97	7.61			
12	20.81	15.71	-2.47						

From figure 2.4 it is illustrated that the regulation prices related to positive imbalances tend to be greater than those related to negative ones but this is highly variable from month to month. From January to February (months 1 - 4) the mean spot prices on the day-ahead market are less than the mean regulation unit costs for downward regulation, in this circumstance deviations from contract are more penalised, while also in the three of the four months negative values are present for the unit costs of upward regulation. When analysing the remaining months of the year it can be noticed that in August and December (months 8 and 12) the exact opposite occurs, low prices for positive imbalances and high prices for negative imbalances. It is possible to suggest for these occurrences that the imbalances are intended by the participants. However, research by Boogert and Duport (2005) states that strategies of this kind aren't profitable due to the fact that it would be required to anticipate at least the sign of the entire system disproportion to validate theses approaches, which isn't possible.

A wind farm in Ireland is also analysed for the purpose of this research by Chevallier et al., (2007). The operator of this wind farm has a capacity to produce 15 MW. The Fuzzy-Neutral Networks (Fuzzy-NN) system was used as the forecasting system to determine the 48 hour ahead point predictions. The aim of this research is to contrast the advantages in using advanced forecast methods in comparison to Persistence and perfect forecasts. In this circumstance the Persistence method involves using the last measured power value as a prediction for hours of times that lay ahead, the time for the Persistence forecast is 10:00 am. By using these forecasts, Persistence and Perfect, for trading wind power generation both negative and positive views are obtained. The income of these forecasts will identify an envelope in which the income from the use of advanced methods is anticipated to be positioned.

A 15 minute PTU is the time limit on the TenneT regulation market. This results in presuming that on the spot market the amount of energy can be split into four equal quantities of energy for the TenneT PTU. A comparable assumption is made for the precise amount for assessment amid contracted and actual levels of energy.

Figure 2.4 illustrates a graph of a 48 hours ahead probabilistic forecast containing 10% ranges from 10% - 90% from the Fuzzy-NN point forecasts

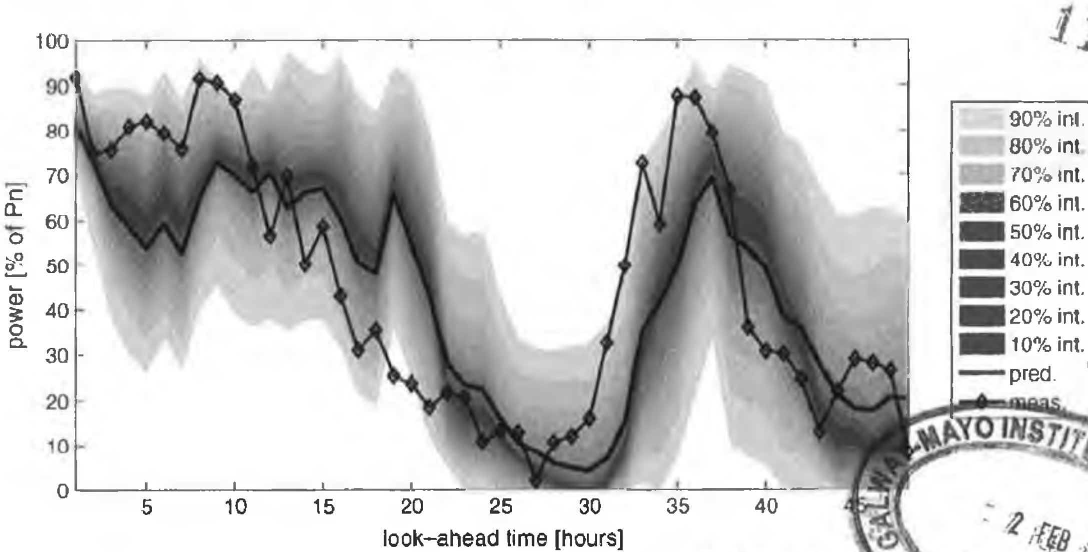

***Figure** 2.4 A 48 Hour ahead Probabilistic Forecast of Normalised Wind Power for a 15 MW Wind Farm (Chevallier et al., 2007)*

The assumption is made by Chevallier et al., (2007) for the regulation costs that estimates can be made for the quarterly and annual trends. As a result of this two PC strategies PC1 and PC2 are calculated. PC1 is based on a single loss function throughout the year, while PC2 is based on four individual loss functions for the four quarters of the year 2002. Results depend on the assumption that it is possible for regulation unit costs to be correctly predicted trends.

Results

A summary of the variety of strategies together with Persistence, Fuzzy-NN, PC1 and PC2 forecasts are displayed in table 2.5

Table 2. 5 *Results for Persistence, Fuzzy-NN, PC1 and PC2 from 2002 (Chevallier et al., 2007)*

	Persistence	Fuzzy-NN	PC1	PC2	Perfect predictions
Contracted energy (GWh)	44.37	45.49	57.23	62.37	46.41
Surplus (GWh)	18.12	9.87	5.19	4.89	0
Shortage (GWh)	16.08	8.95	16.03	20.85	0
Down-regulation costs (10^3 €)	195.72	119.99	55.92	42.61	0
Up-regulation costs (10^3 €)	79.59	52.01	87.15	61.46	0
Total revenue (10^3 €)	1041.38	1145.69	1173.62	1212.61	1317.69
Av. down regulation unit cost (€/MWh)	10.8	12.15	10.77	8.71	0
Av. Up-regulation unit cost (€/MWh)	4.95	5.81	5.44	2.95	0
Av. regulation unit cost (€/MWh)	8.05	9.13	6.74	4.04	0
Av. energy price	22.44	24.68	25.29	26.13	28.37
Part of imbalance (% of produced energy)	73.69	40.55	45.72	55.46	0
Performance ratio (%)	79.1	86.99	89.99	92.1	100

Analysis of Strategies Based on Point Predictions

For the prediction of the Persistence and the Fuzzy-NN based techniques, they are equal to 4.4% and 1.98% of the energy created. Both techniques are faintly below the actual wind power generated. The wind farm operator is likely to be liable to penalties due to the surplus being higher than the shortage. Additionally, when combining this with the reality that unit costs for positive deviations from contract are bigger than those for negative deviations results in the regulation costs linked to the energy in surplus are a lot greater than the one connected to shortage. Nevertheless, the total regulation costs are considerably minimised, by 38%, because of the advanced technique, Fuzzy-NN, instead of Persistence due to the fact that of Fuzzy-NN taking preference for regulation costs.

Advanced forecasts have an advantaged over reference methods due to their greater accuracy. The quantity of energy subject to regulation is decreased with advanced forecasts. Therefore, a greater improvement in comparison to Persistence, even though the market 48 hours ahead is quite comparable. In this case study by Chevallier et al., (2007) there is a reduction from 73.69% - 40.55% of produced energy when using bids for predictions from Fuzzy-NN in comparison to Persistence. Therefore, the financial implementations for the participant in the market are minimised by availing of advanced forecasts.

When assessing the mean price produced it is €28.37 /MWh under perfect predictions. In times when the market clearing price is low large amounts of wind power generation are sold and the opposite occurs when the market clearing price is high i.e. small quantities are sold. Due to regulation costs the mean price per produced MWh for Persistence and Fuzzy-NN are decreased to €22.44 and €24.68. When focusing attention on the mean regulation cost it is visible that Persistence is lower than Fuzzy-NN, €8.05/MWh and €9.13/MWh, even when the quantity of energy in imbalance is a lot greater throughout the year.

Analysis Based on Probabilistic Forecasts

The performance ratio of PC1 and PC2 out performs both Persistence and Fuzzy-NN. In relation to PC1 the performance ratio is 89.14% and increase of 10.04% and 2.15% on Persistence and Fuzzy-NN respectively. Due to the significance variations of regulation unit prices, defining different loss functions depending on the period of the year allows one to further increase the resulting income for PC2 when applying this strategy it reaches 92.1%. Therefore, when comparing the PC2 strategy and Fuzzy-NN, the regulation costs are reduced by 39% when choosing PC2 in place of Fuzzy-NN.

By minimising the quantity of energy imbalance the income of the wind power producer is not enlarged. The opposite occurs. For the bidding strategy for Fuzzy-NN it increases to 40.55% while for PC1 and PC2 strategies it increases to 45.72% and 55.46%. It is preferable to put forward amounts of energy that are perhaps subject to shortage than to excess regulation as the unit costs for positive imbalances are greater on average than those for negative imbalances. This is beneficial for TSO and wind power producers as imbalance penalties also directly reflect the sensitivity of the TSO to balance the system. Therefore, for the other electricity markets with different behaviours, or if given regulation market behaviour evolves, it can be accounted for by modifying the loss function (Chevallier et al. 2007).

The cost sustained by the wind power producer during the year 2002 for upward and downward regulation is entirely dissimilar. When analysing the bidding strategies based on Fuzzy-NN forecasts to PC1 and PC2 the costs for upward regulation are a little greater in comparison to downward regulation, when focusing on PC strategies, albeit the amount of energy in shortage is a lot higher. Additionally when taking into account the best possible bidding strategies the cost of a regulated MWh decreases.

The cost per MWh that is subject to regulation, on average, is divided by more than two when applying the PC2 bidding strategy (€4.04/MWh) in contrast to the Fuzzy-NN prediction. The mean cost of regulation produced per MWh, in this circumstance, which is stated as the variation amid the mean energy price attained by using a specified bidding strategy and by using perfect predictions ranges from €2.24/MWh for PC2 and for the Persistence prediction based policy is €5.93/MWh.

Conclusion

The research by Chevailler et al., (2007) has shown that for wind power producers participating in the electricity pool wind power forecasting plays a significant role. As wind forecasts contain a certain percentage of error, regulation costs will always be present because of these errors. The market value of wind power forecasts can be increased by incorporating an uncertainty data from the forecasts in the decision making procedure. As a result of this a general method for the best possible strategies has been analysed, which displayed the calculation of forecast errors and the variation of market cost due to regulation.

2.4.2 Effect of Wind Power Forecasts on Spot Prices

While the research analysed in section 2.4.1 focused optimising the bidding strategies of wind power forecasts into deregulated electricity markets it didn't take consideration of its potential effect on prices as they had wind power as the price taker. In this section I portray research that was conducted by Madsen et al., (2009) that examines the case of the Western Danish price area (DK-1) of the Nord Pool's Elspot market, where analysis is conducted on how electricity spot prices are impacted by wind power forecasts. The wind forecasting tool in this case study was generated by WPPT. The question that is really being answered in this case study is "what will the price of electricity spot prices be if it is anticipated that the wind will or will not blow?"

Case Study – Nord Pool's Elspot

Research conducted by Madsen et al., (2009) is based on data from Nord Pool's Elspot. The Elspot market is used throughout Scandinavia and is a day-ahead physical delivery market from electricity.

The Market

In the Elspot market all spot prices are set by a market equilibrium model. In this model all market contributors for the supply and demand curves are coordinated on a day ahead structure. At 12:00 PM everyday gate closure occurs. The publication of prices occurs later in the day with a price indicated for each individual hour. To calculate the prices per hour the supply and demand curves are combined based from the market contributors bids and ask prices. The area prices are defined from the bids of the market participants of the system price (Nord Pool Spot AS, 2006a / 2006b).

There are several price areas in the Elspot due to transmission restraints. The outer bounds of each price area can be defined by the physical constraints on transmission, therefore, giving the indication that the transmission capacity contained within an area can be considered as unlimited. The same method to calculate the system price is used for determining the area spot prices, however, only the bids are considered inside the area together with achievable operation of the transmission lines to neighbouring surroundings. Therefore, the area prices can vary significantly between each specific location. Jutland, Funen and the islands towards the west of the Green Belt makes up the price area of the DK-1.

The Data

Throughout the period of January 4th 2006 to October 31st 2007 is when the analysis of this research occurred (Madsen et al., 2009). The data is representative of spot prices per hour together with measurements of the consumption per hour and wind forecasts (MW). The forecasts were based on the WPPT forecast model and are displayed at 7:00 on the day prior delivery for lead times up to 48 hours ahead (Nielsen et al., 2002).

The Effect of Forecasts on Mean Price

Madesen et al., (2009) stated that the area spot price is subject to substantial vagueness on a day-ahead source. As a result of this it can be stated that there is an unknown distribution associated with the future spot price.

For DK-1, the time of day and wind energy forecasted to be generated are used as a function, in MWh per hour, to estimate the mean spot price. This is demonstrated in figure 2.5;

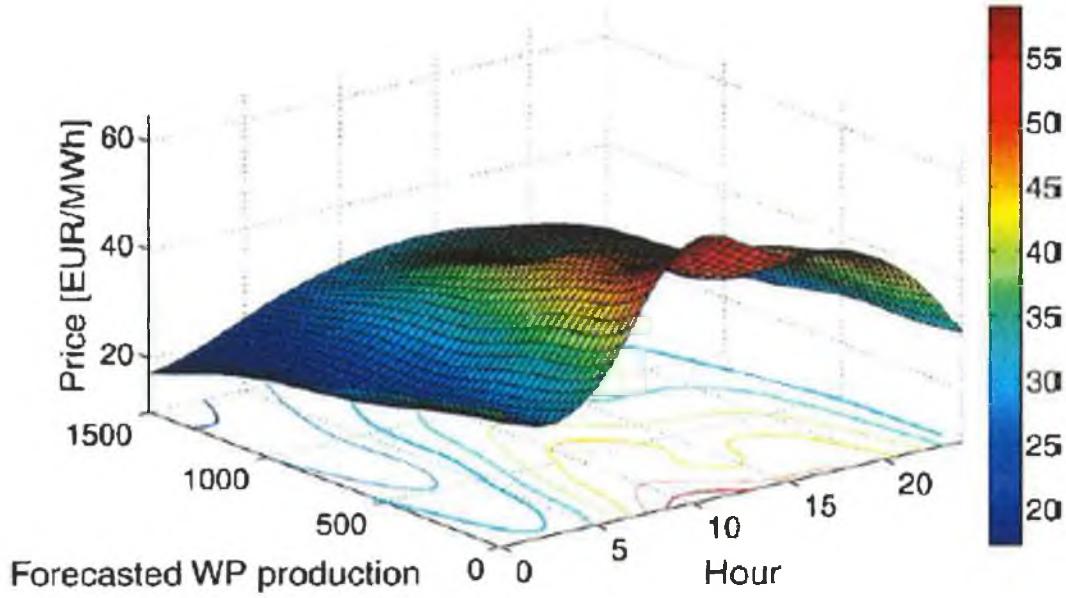

Figure 2. 5 *Reliance of the Spot Prices on Forecasted Wind Power Production and its Deviation all Through the Day (Madsen et al., 2009)*

Figure 2.5 illustrates the forecasts of large quantities of wind power production per hour will consequently result in a reduced lower spot price during that hour. This can be seen by following the "Forecasted WP production axis" results in a low price on the "Price [EUR/MWh]" axis. In terms of price per MWh, a mean price during the night varies from €18/MWh, when there is large quantity wind power production forecasted, to €30/MWh in times of a low quantity of wind power production forecasted. While at times during the day the price per hour is amplified to approximately €55/MWh to €30/MWh.

The results from the research by Madsen et al., (2009) shows that in the hours of the day when electricity consumption achieves its peak it is noticeable that the daily price increase flattens out as wind power production in the system is enlarged. This is due to the fact that wind turbines have practically no marginal cost, which causes the supply curve to move to the right when additional wind power is generated and consequently requires more consumption to attain the steep end of it. What this means is basically that the amplified generation from wind turbines results in plants that aren't as economical covering the base load in only times of peaks. As a result of this it avoids less cost efficient generators from being in operation in the hours when demand peaks.

The amount of wind energy produced can have diverse effects on the price of electricity depending on the time or day of the week due the various demand requirements for electricity not being constant. The majority of electricity demand is higher during the day and evening than at night. It is in this time, during the night, there is a large quantity of wind energy generated and throughout these hours will constitute for a larger allocation of the total demand than the same quantity would during the day. As a result of the balance between the supply and demand curves will be placed lower in the night that it would during the day. To remove these effects, to a certain degree, include the wind power forecasts as the proportional contribution to the total supply instead of its absolute contribution. Basically, in substituting the forecasted wind power production (Vt) with the forecasted wind power penetration ($Vt^{(p)}$) into the equation $Vt^{(p)} = Vt / Lt$, where Lt is the predicted load, a more accurate prediction of the price equilibrium is achieved from the wind power forecasts (Madsen et al., 2009).

In relation to time of day and forecasted wind power, a smooth estimate of spot price is illustrated in figure 2.6;

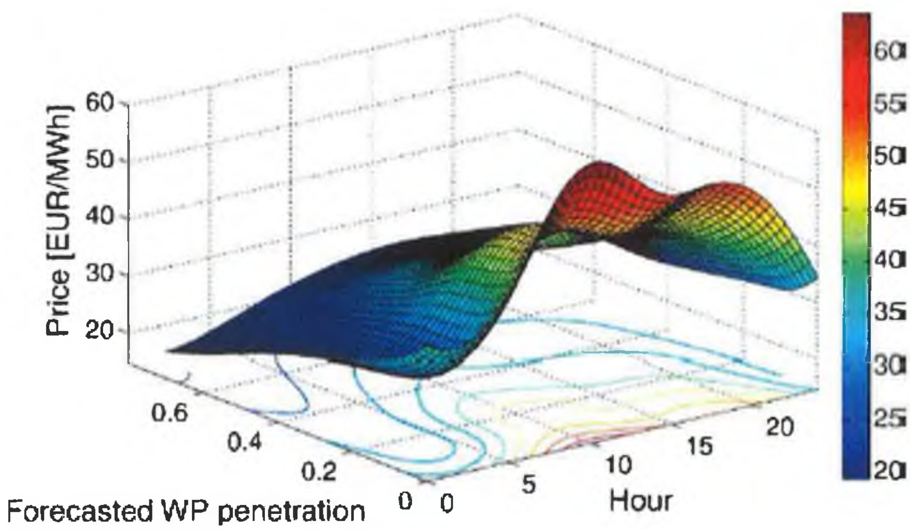

***Figure 2. 6** Reliance of the Spot Prices on Forecasted Wind Power Penetration and its Deviation all Through the Day (Madsen et al., 2009)*

Figure 2.6 is similar to figure 2.5 as the same axes are used with the exception of wind penetration being used instead of wind power production. In comparing figure 2.5 and figure 2.6 it is noticeable that the equivalent actual production now has diverse effects depending on what time of the day and week production takes place, due to the deviation in the load. This results in a more graphical result in figure 2.6. In similar circumstances to figure 2.5 the spot prices were significantly less when the wind power forecasted to be generated is high. When there is no amount of power supplied by wind power, during the day, the mean spot price is at a maximum between €55 - €60/MWh. As the forecasted wind power penetration begins to increase towards 40% the mean spot prices decrease to within the region of €30 - €35/MWh. It is also illustrated that as the forecasted wind power penetration continues to increase towards 80%, a mean spot price of a minimum between €20 - €25/MWh is achieved.

The effect of wind power forecasts on mean spot prices are undoubtedly displayed in figures 2.5 and 2.6. Despite these illustrations it is difficult to see the actual extent of the wind power forecasts on the spot prices. Figure 2.7 removes this ambiguity and displays in the form of a bar chart the forecasted wind power penetration in comparison to the price in DK-1.

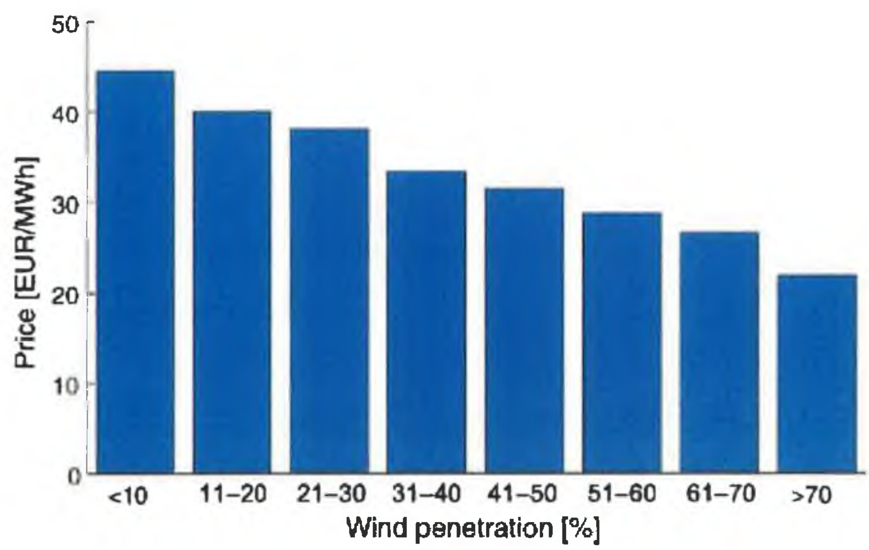

Figure 2. *7 Mean Spot Prices V Internals of Forecasted Wind Power Penetration (Madsen et al., 2009)*

disadvantage to any form of power plant as it is likely to see a decrease to the large initial investment to these power plants made by investors. Additionally, the continuation of different power plants that create electricity at large marginal costs is in doubt due to cheaper electricity. This would place a significant question mark over the safety of any countries security of energy as the power plants provide the reliability to maintain a secure source of energy.

Distribution of the Price Caused by Wind Power Forecasts

While the previous section dealt with the impact of forecasted wind power penetration on the average spot price in DK-1. Madsen et al., (2009) equipped with further wide-ranging information regarding the connection amid price unpredictability and wind power forecasts attempted to explain and estimate better the future unpredictability in the statistical manner of non-parametric. In this distribution analysis the data consisting of between 25000 – 3000 measurements for each bin are represented in the form of histograms. The histogram in figure 2.9 displays the distribution of prices for different intervals of forecasted wind power penetration.

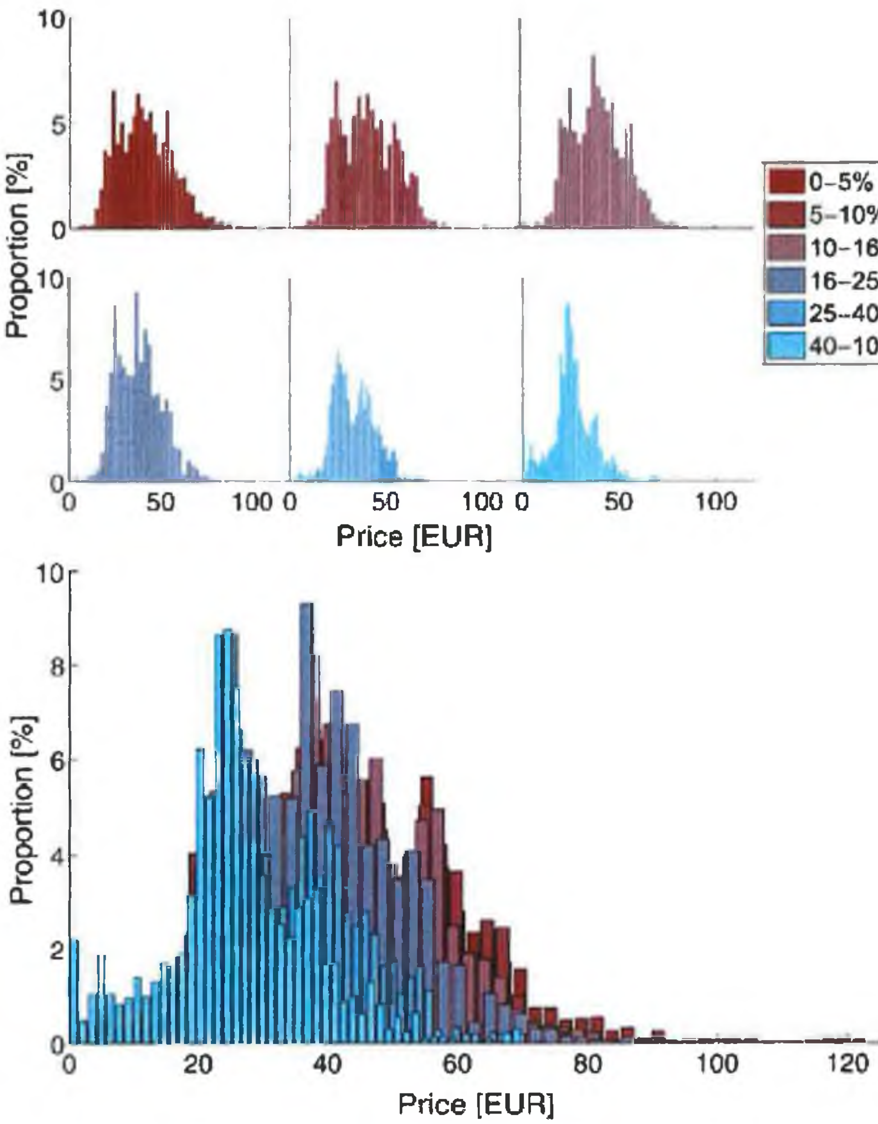

Figure 2. 9 *Distribution of Prices at Various Levels of Forecasted Wind Power Penetration (Madsen et al., 2009)*

Figure 2.9 reemphasises the fact that as the forecasted wind power penetration increases it has a knock on impact that decreases the mean spot price. Additionally figure 2.9 illustrates that the histogram becomes narrower as the forecasted wind power penetration is increased. This gives further evidence that it is less likely that high prices will occur when large quantities of wind power generation are forecasted. Another factor that proves to be interesting from analysis of figure 3.7 is in the highest penetration level, 40 – 100%, where large shares of prices are equal to zero. In times the wind penetration is above 40% electricity spot prices are €0 /MWh over 2% of the time. This statistic is in contrast to the forecasted wind power penetration of 25

– 40%, where it is visible from figure 2.9 that the spot price of €0 /Mwh is seldom evident. The increase of €0 /Mwh is also seldom evident in the remaining four lower limit proportion sections but it can be seen that as the forecasted wind penetration is increased the occurrence of €0 /MWh is more frequent. The significance of the spot price being €0 /MWh is a negative cash flow for producers subject to unevenness expenditure during that hour will be achieved. This means that it will be an advantage for producers, even though they may not have any marginal production costs, to decline in creating electricity. This fact is additional evidence to support the statement at the end of the section prior to the disadvantage, under the current market circumstances, of having an amplified quantity of wind power penetration in the system.

Table 2.6 displays the statistics of mean and standard deviation for each distribution. When analysing the mean it is clear of the reduction as the proportion is increased. While the standard deviation sees a reduction that illustrates less unpredictability of the prices.

Table 2. 6 *Statistics of Mean Spot Price Distribution of Forecasted Wind Power Penetration (Madsen et al., 2009)*

	0-5%	5-10%	10-16%	16-25%	25-40%	40-100%
Mean	42.98	41.13	40.26	38.1	33.24	26.02
Standard Deviation	16.95	15.32	14.18	13.08	11.35	11.23

From the analysis of the research by Madsen et al. (2009) in this section it would be credible to state that from a modelling viewpoint, predicting intervals based on forecasted wind power penetration is very significant due to the variation of the spot price distribution amid various levels of forecasted wind power penetration.

Conclusion

This case study by Madsen et al., (2009) has shown the effects of forecasted wind power penetration can have on both spot prices and the distribution effect on prices. The results have displayed that the spot price is likely to decrease with a large quantity of wind power forecasted, while wind power forecasts have additionally illustrated that the distribution of prices for example with €0 /MWh appearing in times of forecasted wind power penetration being 40 – 100%.

It is credible to state the effects of forecasted wind power in this case study of the Nord Pool's Elspot would have similar outcomes in other countries such as Spain and Ireland where there is a significant quantity of wind power on their system.

This research has also produced attention-grabbing facts in terms of market design. As countries throughout the world are aiming to increase their wind power generation on their system, for example Ireland have set a target of 40% renewable by 2020 with the majority of the 40% consisting of wind power production, as with the current market structure of marginal bidding increased wind power is likely to see more frequent occurrences of prices in the region of €0 /MWh. Taking this into account careful consideration should be acknowledged when considering increasing the share of wind power on the system.

2.5 The Impact on Unit Commitment and Economic Dispatch due to Wind Power Forecasts

Unit commitment and economic dispatch are effected due to the intermittent nature of wind power that is being used on the electricity system. The main effects on unit commitment and economic dispatch are required to be altered to facilitate the renewable energy of wind. For example, as discussed previously, wind forecasting isn't 100% accurate and therefore consists of errors that cause difficulties for the TSOs. The wind may decrease unexpectedly causing the system requirements to change and also the wind could increase unanticipated causing the curtailment of wind power resulting in a waste of renewable energy. Additionally, unit commitment and economic dispatch may have to be altered due to scheduling the required generation. The TSOs aims to avail of wind power as frequent as possible due to the unit commitment of wind power having a zero operating cost. Hence, the objective of the TSOs is to minimise the supply cost to reach the requirements of the system load. As a result of this, due to the variability of wind, the conventional energy sources are required to be scheduled competently by unit commitment and dispatch.

In section 2.5.1 I focus on the impact of wind forecasting errors on the power system operation based on a case study by Wang et al., (2009) that proposes two separate methods of unit commitment i.e. stochastic and deterministic, to examine the prospect of availing of other options for scheduling to deal with the intermittent nature of wind power. Where the solution for unit commitment is achieved from unit commitment trials using a wind power forecast, an economic dispatch model is attempted to explore the impact of the wind forecasts errors can have in the system.

2.5.1 Case study

Assumptions

A hypothetical power system was used for this case study by Wang et al., (2009) for a period of 30 days with the aim bring to replicate the effect of various wind power forecasts and operating reserves for day ahead unit commitment.

The load profiles are obtained from previous data sourced for the month of January from the state of Illinois, USA. The load profiles are based on an hourly profile. The peak load of the system is 1500 MW. In similar circumstances previous data is sourced to determine the wind power that was generated on the system. 400 MW is the maximum capacity assumed and this is taken as being one wind farm. There is a 40.1% wind power capacity factor and 13.8% of this load is reached by wind power. Figure 2.10 illustrates the load/wind power in during the 30 days at hourly intervals.

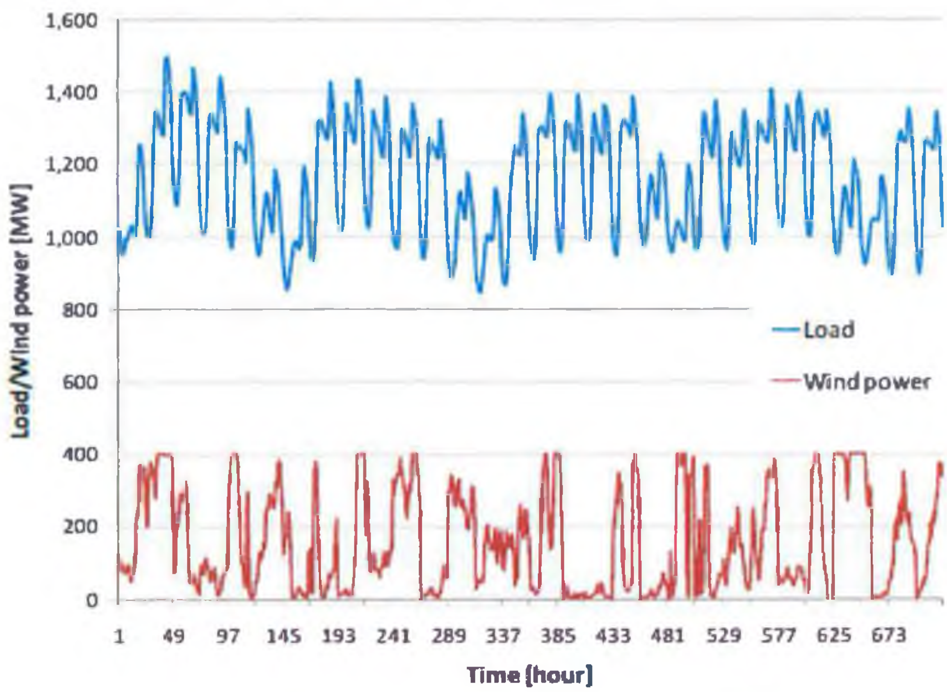

Figure 2. 10 *Load / Wind Power During 30 Day Simulation at Hourly Intervals (Wang et al., 2009)*

Figure 2.11 illustrates the day ahead wind power forecast based on day 15 of the case study. The graph displays the actual generated wind in comparison to point forecast and 10 individual scenarios.

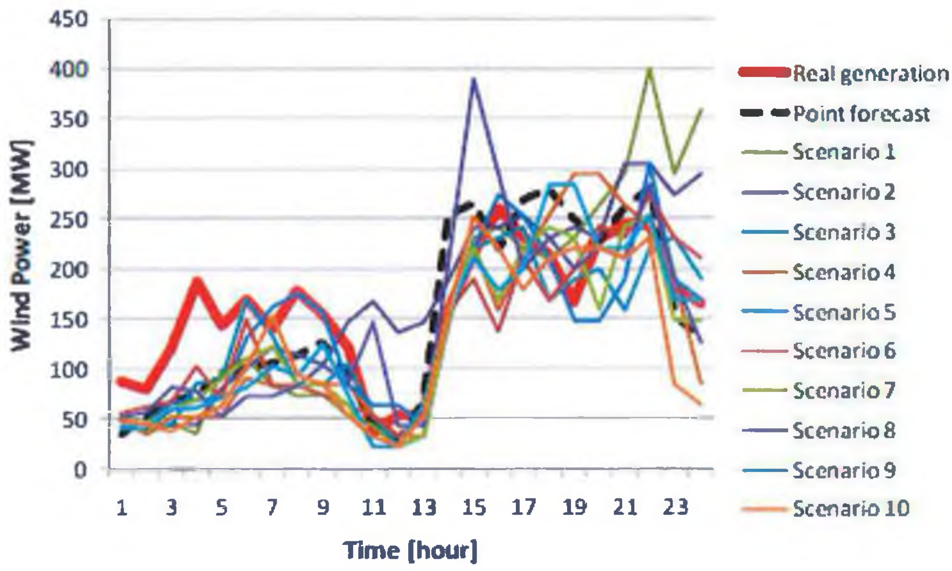

Figure 2. 11 *Wind Power Forecast of Day 15 (Wang et al., 2009)*

When analysing figure 2.11 it is can be seen that up to hour 10 of the day all forecasts remain below the actual wind power generated. After hour 10 the forecasts become more accurate to the actual wind power produced. The mean absolute error (MAE) for the point forecast, during the 30 day period, is between 6.3% and 12.6%.

The assumptions for thermal power plants are shown in tables 2.7 and 2.8. Four blocks of equal size are assumed for each unit. From unit 1 to unit 10 the production cost increases.

Table 2. 7 *Thermal Power Plant Assumptions (Wang et al., 2009)*

Unit	PTj (MW)	PTj (MW)	Rj (MW)	Tjup (MW/h)	Tjdn(h)	In. state (h)
1	455	150	200	8	8	8
2	455	150	200	8	8	8
3	130	20	100	5	5	-5
4	130	20	100	5	5	-5
5	162	25	100	6	6	-6
6	80	20	80	3	3	-3
7	85	25	85	3	3	-3
8	55	10	55	1	1	-1
9	55	10	55	1	1	-1
10	55	10	55	1	1	-1

Note: Start-up and shut-down ramps, SUj and SDj, are equal to the ramp rate RLj.

Where:

PTj = Capacity, thermal unit j

PTj = Minimum output, thermal unit j

Tjup = Minimum up-time, thermal unit j

Tjdn = Minimum down-time, thermal unit j

RLj = Ramping limit (up/down), thermal unit j

SUj = Start-up ramp limit, thermal unit j

SDj = Shut-down ramp limit, thermal unit j

Table 2. 8 *Thermal Power Plant Assumptions (Wang et al., 2009)*

Unit	a_i ($/h)	b_j ($/MWh)	c_i ($/MW^{2}h)	CC_i ($/h)	HC_j ($/h)	T_j^{cold} (h)
1	1000	16	0.00048	9000	4500	5
2	970	17	0.00031	10000	5000	5
3	700	30	0.002	1100	550	4
4	680	31	0.0021	1120	560	4
5	450	32	0.004	1800	900	4
6	370	40	0.0071	340	170	2
7	480	42	0.00079	520	260	2
8	660	60	0.0041	60	30	0
9	665	65	0.0022	60	30	0
10	670	70	0.0017	60	30	0

Where:

j = Index for thermal unit, j = 1.J

a,b,c = Unit production cost function coefficients

CCj = Cold start cost, thermal unit j

HCj = Hot start cost, thermal unit j

Tjcold = Time for cold start cost (in addition to min downtime), thermal unit j

At present the there is 10.1% greater capacity of installed capacity of thermal units in comparison to peak load. A quite low system reserve margin is increased to 16.1% if the capacity value of 20% is created for wind power capacity.

A value of 10% is set as a default value for the operating reserve (spinning) requirement in the unit commitment formulation. In this case study by Madsen et al., (2009) the results of changing the reserve requirement in the unit commitment, with both stochastic and deterministic unit commitment strategies are examined.

Simulated Cases

Using both stochastic and deterministic unit commitment and the results of using various wind forecasts are analysed. In table 2.9 is a summary of each individual simulated case.

Table 2. 9 *Summary of Simulated Cases (Wang et al., 2009)*

Case	Description	UC	Forecast	Reserve
D1	Det. UC w/perfect forecast	Det.	Perfect	10%
D2	Det. UC w/point forecast	Det.	Point	10%
D3	Det. UC w/additional reserve	Det.	Point	15%
D4	Det. UC w/no forecast	Det.	No	10%
S1	Stoch. UC w/regular reserve	Stoch.	Scenarios	10%
S2	Stoch. UC w/lower reserve	Stoch.	Scenarios	8%

From table 2.9 it can be seen that case D1 deals with a perfect wind forecast, while cases D2 and D3 deal with deterministic point forecast with a different reserve requirements at the unit commitment stage. D4 differs from the above in the form that no wind power is considered. In the final two cases, S1 and S2, stochastic unit commitment with regular and reduced unit commitment reserve requirement.

Results

To display information regarding the short-term effects of the various systems scheduling techniques and additional long-term statistics with the different wind power forecasts considered, the dispatch results are provided in this section for the total 30 days and also a single day i.e. day 15.

I) Day 15 Results

In figure 2.12 the dispatch results for day 15 are illustrated. Cases D2, D3 and S1 are shown. The reason these three particular cases are shown are due to the fact that they are the best representations of how the integration of wind power forecasts into the unit commitment by TSOs.

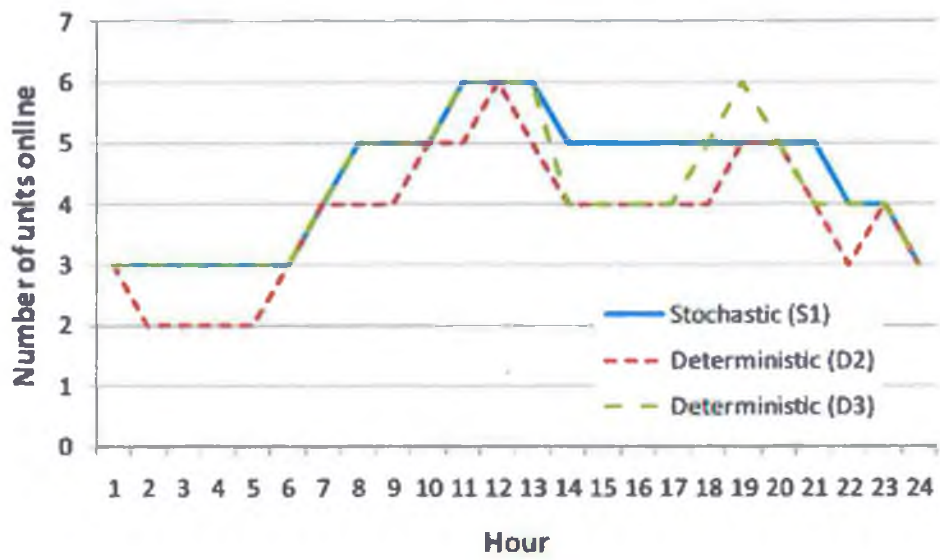

Figure 2. 12 *Day 15 On-line Units (Wang et al., 2009)*

When analysing figure 2.12 it can be seen that on-line units of D2 is at the bottom while D2 and S1 are higher on the graph. The reason for this is because S1, stochastic approach, takes into account numerous situations. Therefore, additional units are required to be on-line to be able to deal with the various scenarios represented in figure 2.11. Similar results are obtained from case D3 due to the additional increase of 5% reserve in comparison to case D2. This statement is supported by figure 2.13 that illustrates the reserves available throughout the day, as S1 and D3 display a greater quantity of reserves in comparison to D2. It is also important to note that all three cases are above the 10% real-time dispatch.

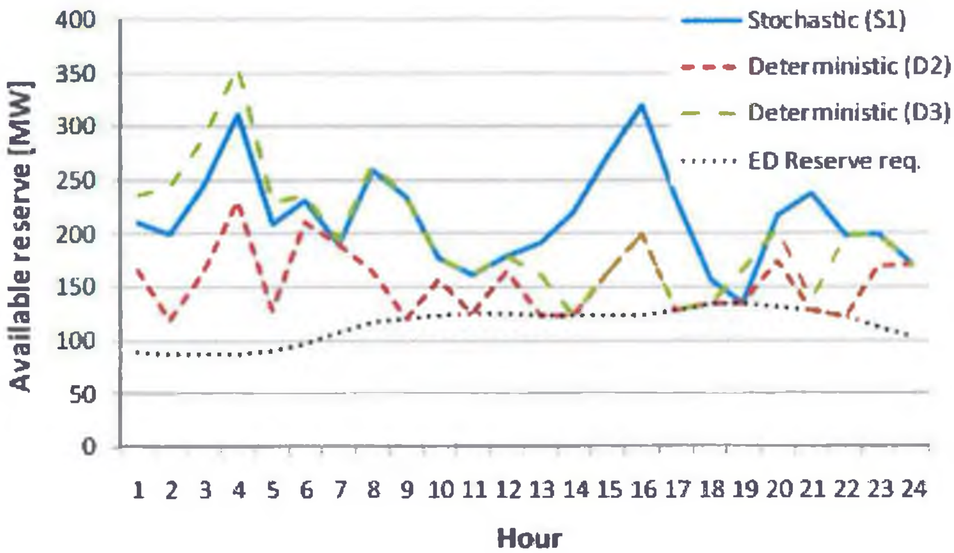

Figure 2. 13 *Day 15 Operation Reserves (Wang et al., 2009)*

II) 30-Day Simulation Results

Total Hours of Commitment

The results of the research by Wang et al., (2009) for ten thermal units table 2.10 displays the total hours of commitment.

Table 2. 10 *Thermal Units Total Hours of Commitment (Wang et al., 2009)*

Unit	D1	D2	D3	D4	S1	S2
1	720	720	720	720	720	720
2	720	720	720	720	720	720
3	394	396	447	605	429	390
4	237	265	308	434	324	297
5	568	585	619	720	585	581
6	242	253	340	358	255	222
7	68	89	159	195	114	100
8	40	49	87	71	44	38
9	10	8	30	15	13	14
10	1	0	8	5	15	19

The units are positioned in correspondence of their production cost. For all six cases (D1 to S2) units 1 and 2, which are the cheapest, are committed all the way through the simulation phase. In contrast the most high-priced unit, unit 10, is only committed for a restricted number of hours. It can be noticed that in the case of unit 10 cases S1 and S2 are in use more regularly in comparison to the four deterministic cases. This is due to the fact that when using the stochastic approach for unit 10 it is needed to be on to offer extra ramping capacity to manage the inconsistency nature of wind power being generated. The commitment levels for D1 and D2 are quite comparable. This is due to the only difference between the two being the replacement of point and perfect forecast. While in the case of D3 when units 3 – 10 are dispatched more repeatedly, the reason for this is due to the necessity for higher reserve. As the wind power is not being taken into account in the unit commitment D4 results in having the greatest number of hours in commitment. Hence, additional units are required to supplement the wind power that is accessible in the five other circumstances. The significance of this is that it shows that over commitment of thermal units can be caused if system operators are not availing of the data available from a wind power forecast. When assessing S1 and S2 the only comment that can be made in comparing the two is that as the reserve requirement is less in S2 due to the reserve requirement being lower i.e. 10% for S1 and 8% for S2.

Average Dispatch of Thermal Units

The results of the average dispatch of thermal units for the 30 day simulation are illustrated in table 2.11.

Table 2. 11 *Average Dispatch for Thermal Units (Wang et al., 2009)*

Unit	D1	D2	D3	D4	S1	S2
1	453.20	453.20	453.20	451.7	453.20	453.20
2	404.10	402.50	400.80	390.30	401.50	401.50
3	58.50	57.90	59.20	62.70	58.80	55.80
4	35.10	35.90	37.80	40.80	39.80	36.60
5	38.30	37.60	31.40	35.80	33.60	39.90
6	7.00	7.30	9.60	10.00	7.30	6.50
7	2.40	3.10	5.50	6.80	4.00	3.50
8	0.60	0.70	1.20	1.00	0.60	0.50
9	0.10	0.10	0.40	0.20	0.20	0.20
10	0.00	0.00	0.10	0.10	0.20	0.30

When contrasting the results for the average dispatch for thermal units in comparison to the total hours of unit commitment it is noticeable that the small quantities are in dispatch. This is as a result of the equal realised wind generation output is used in the real-time dispatch for all cases i.e. D1 – S2. Hence, although dissimilarities exist in commitment the resulting average thermal plant are fairly alike for all situations. As units 8,9,10 are being dispatched for most of their time at a minimum level and as a result of the effect on the average dispatch is rather limited.

Operating Costs

In regard to operating costs such as fuel, start up and curtailment are displayed below in table 2.12 while table 2.13 displays the results by Wang et al., (2009) of other factors such as number of start ups, load curtailment, average available reserve and average energy price.

Table 2. 12 *Operating Cost Results (Wang et al., 2009)*

Scenario	Fuel Cost (M$)	Start-up cost (M$)	Curt. Cost (M$)	Total cost (M$)
D1	15.80	0.08	0.00	15.88
D2	15.85	0.08	0.84	16.76
D3	16.13	0.08	0.04	16.25
D4	16.50	0.06	0.00	16.56
S1	15.97	0.09	0.21	16.27
S2	15.88	0.08	0.99	16.96

Table 2. 13 *Additional Results (Wang et al., 2009)*

Scenario	No. of start ups	Load Curtailment (MWh)	Avg. Avail. Reserve (MW)	Avg. Energy Price ($/MWh)
D1	165	0.8	162.5	30.5
D2	163	836.7	175.6	80.1
D3	197	0.1	214.3	29.5
D4	154	0.0	281.5	25.1
S1	190	210.3	191.0	43.5
S2	199	991.7	178.5	123.1

When analysing the results in both tables 2.12 and 2.13 it is evident that, as expected, the lowest operating cost is present in D1. The reason this result is expected is as the D1 scenario predicts the perfect forecast i.e. no forecast errors. This means that there is no requirement to alter the dispatch from the unit commitment for the real time economic dispatch. There is an increased cost associated with D2 chiefly due to the cost of load curtailment caused by the impact of forecast errors. As additional units are online in scenario D3, the load curtailment is more or less non existent. While the fuel cost is greater in D3 in contrast to D2 the most significant value is the total cost that results in D3 being more favourable. This means that by raising the reserve requirements in the deterministic method has the consequence of improving the approach to tackle wind inconsistency and ambiguity as additional units are necessary to be online to offer as reserves. As a result of this in table 2.13 it is visible that the energy prices is less and greater available reserve in D3 in contrast to D2 and D1. When assessing the results of D4 it is a plausible statement to make that this scenario is the most cautious approach to dispatch the units in the regard that the presence on wind power being generated is not considered. As a result if this load curtailment is minimal and results are in a high operating reserve when comparing the other scenarios. Due to the additional generating units being dispatched than required the fuel cost is highest in D4. This is significant as the total cost doesn't reflect well on D4 displaying the wastefulness of not availing of the data portrayed in wind power forecast for unit commitment. Despite this the result of the average energy process displayed in table 2.13 illustrates that scenario D4 is the lowest price, chiefly due to the curtailed wind loads. This demonstrates the effects of various system preparation approaches in regard to system dispatch cost and energy prices.

For S1 the total cost is nearly the exact same as for the D3 scenario, which contains a greater proportion of available reserves. This shows that both scenarios, S1 and D3, are using different options to combat the variability of wind power production. When analysing the particulars of each case it can be seen that the fuel cost for S1 is lower than D3, however S1 contains a higher curtailment cost. Additionally, further details display a greater price and reduced reserve for S1 in contrast to D3. For the stochastic approach S2 contains the highest average price and curtailment cost in comparison to the other five approaches. This is due to the S2 reduction in operating reserve requirement results in a low level of realised reserves.

In terms of the number of start up costs for all scenarios it can be seen that D4 has the lowest number of start ups followed by D2 and D1 that have quite similar figures. In third place is S1 and second place is D3 while the most amount of start ups goes to S2.

The data produced in the results in tables 2.12 and 2.13 shows the significance of having a unit commitment plan and the reserve requirements has a vital impact on cost and dependability of functioning power systems with large quantities of wind power generation. The ramping capability and reserves supplied by online units are to a great level decided by these aspects, which consequently affects the real-time dispatch results to a large scale.

Conclusion

This case study produced by Wang et al., (2009) has described the effects on unit commitment and dispatch due to wind power forecasting by using two unit commitment methods in six individual scenarios. The results of the case study have shown that the errors that are present in wind power forecasts encompass large effects for the real time dispatch. The results have illustrated that each wind forecast method used produced unique results. When analysing the stochastic unit commitment method the cost and consistency was very impressive. While the deterministic unit commitment approach with amplified reserve requirement is comparable to the stochastic method. The importance of wind power forecasting on unit commitment and dispatch can be identified when comparing cases where the perfect wind forecast is used and compared to the no wind power forecast scenario as the perfect wind forecast illustrated the reduced system dispatch.

2.6 Concluding Remarks

This chapter displayed that wind power forecasting plays a significant role in the energy sector. The chief concern of wind power is its variable intermittence that causes distress to TSOs for operating the electricity grid. This intermittent nature, whether it is a surplus or a decrease in the forecasted MW, requires component management of conventional power sources to act as reserves whether that it is by connecting to surrounding grids or wind storage. Wind power forecasting plays a crucial role for applying any of the management control measures and in particular forecasting the anticipated errors of the forecasts.

Chapter Three

"An unsophisticated forecaster uses statistics as a drunken man uses lamp-posts - for support rather than for illumination..."

- Andrew Lang

3.0 The Accuracy of Wind Power Forecasts

3.1 Introduction

The wind power industry is rapidly expanding and accurate wind power forecasting is crucial, particularly when up to two days ahead is documented as a chief contribution for consistent large-scale wind power integration. As discussed previously, wind power forecasts are used as contributions for a variety of simulation tools, including market operation, unit commitment and economic dispatch. For that reason, the short term wind power predictions are essential in the overall operation of the wind power industry.

There are various forecasts models that operators have the option of choosing e.g. MoreCare, Previento, Prediktor, WPPT and AWPPS. During the last 10 years there have been large enhancements in wind power forecasts. The majority of forecast models use a similar framework of an amalgamation of statistical and physical models to predict wind power output over a set period e.g. 24, 48 and 72 hours. While the accuracy is reasonably sufficient in these models there is still improvement required. Models find it difficult to foresee rapid alterations in the output of wind farms or ramping events. Additionally a significant restraint on the technical side of forecasts is that many wind farm operators use rotating cup anemometers and wind-vanes, placed on the back of the turbine, behind the rotor blades, to measure the wind and control their turbines. The difficulty with this is that its often imprecise measurements are created by the instrumentation, using turbulent wind, which is distributed as it passes through the turbine blades (Pinson, 2006).

This chapter examines and describes the two most common forms of wind forecasting models, physical and statistical, and also investigates the accuracy of a particular wind power forecasting data supplied by the Bord Na Mona Energy Department PowerGen, for 24 and 48 hour forecasts (at half hour intervals) throughout forty random days that were selected during the months of February, March, April and May, 2010. The information revealed in this data analysis displays the following;

- Accuracy of 24 and 48 hour forecasts i.e. total wind power forecasted V total wind power generated.
- Likelihood error of wind power forecast, taking into account the frequency, probability and the range of the error in both 24 and 48 hour forecasts.
- Mean forecast error per hour.
- Statistical data for both 24 and 48 hour forecasts e.g. mean absolute error (MAE) and root mean square error (RMSE).

3.2 Wind Power Forecast Modelling

3.2.1 Introduction

A wind forecasting tool consists of downscaling, power curves, modelling and model output statistics. Each one is expected to contribute to accomplish a minimal error and acceptable accuracy.

Physical Method

Wind forecast modelling is generally either physical or statistical. The principle scheme of the physical method is to process the Numerical Weather Predictions (NWPs) to establish the wind field surrounding the wind farm, focusing on such physical features of the terrain such as roughness and orography. The next step, after the wind at the level of the wind farm and hub height is know, is to transform the wind speed to wind power (Pinson, 2006). This is conducted by using a theoretical power curve, similar to the one displayed in figure 3.1.

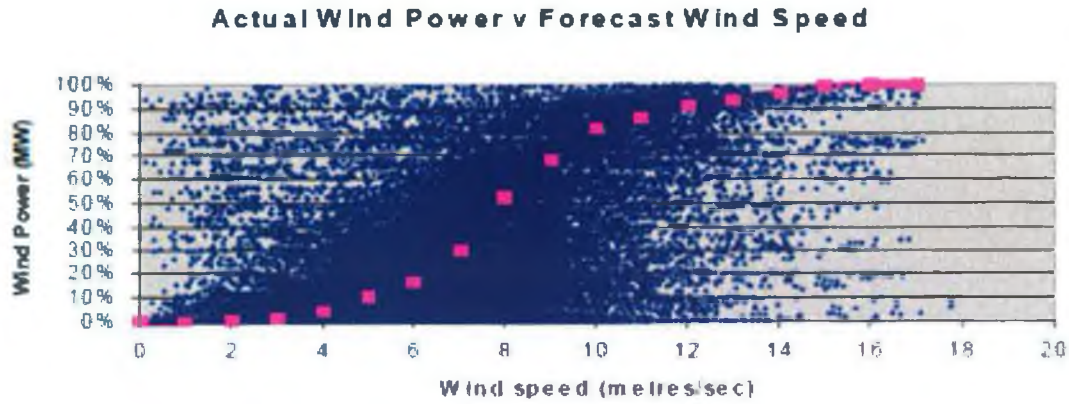

Figure 3. 1 *Actual Wind Power V Forecast Wind Speed Power Curve (www.eirgrid.com)*

In figure 3.1 the power curve of the turbine is represented in pink while the various wind speeds are represented in blue.

Statistical Method

The foundations for statistical approach methods are on one or numerous models that attempt to ascertain the relation amid past values of power, as well as previous forecast values of descriptive variables and wind power measures. The physical conditions aren't considered. Model limits are set from a set of previous accessible data and they are frequently updated throughout online procedures by taking note of any up-to-date obtainable data i.e. meteorological forecasts and power measurements (Pinson, 2006).

Types of statistical models are generally either linear or non-linear but can additionally be black-box or structural types of models. Black-box models entail minute subject-matter understanding and are created from figures in a reasonably mechanical method. Support Vector Machines (SVMs) and Neural-Networks are examples of the artificial-intelligence-based black-box models. Structural type models depend on the analyst's proficiency of observance awareness. These types of models include a modelling of the diurnal wind speed deviations or an unequivocal function of meteorological inconsistent estimations (www.wapedia.mobi/en/Wind_Power_Forecasting).

In recent times, progress in statistical forecasting focus on using numerous meteorological forecasts, from various meteorological offices, for combining forecast data.

3.3 Data Analysis

3.3.1 Data Description

The data used in this research was generated from the Single Electricity Market Operator (SEMO) wind power 48 hour rolling wind power forecast. The SEMO is the market operator that has the responsibility for the administration of the Single Electricity Market (SEM) in the All-Ireland electricity market. Both Eirgrid PLC and SONI Limited are joined contractually to manage the SEMO organisation.

The wind power forecast data is published at 6:00 AM each morning, containing the wind power expected to be generated during the next 48 hours. The data is forecasted at delivery intervals every half hour, with each forecast illustrating the individual wind power forecast for Northern Ireland and the Republic of Ireland.

The data used in this research was collected during the months of February, March, April and May 2010. The wind power generated during this period was generally low, due to the good weather conditions Ireland was experiencing. However, there was still a number of high wind power generation days and ramping events present. From these months, February to May 2010, forty random days were selected and this is the data that produced the results of this research. The forty random days that were selected are displayed in table 3.1:

***Table 3. 1** Forty Days Randomly Selected for Analysis*

February	March	April	May
2^{nd}	2^{nd}	2^{nd}	1^{st}
6^{th}	3^{rd}	3^{rd}	3^{rd}
7^{th}	4^{th}	11^{th}	5^{th}
9^{th}	16^{th}	15^{th}	14^{th}
13^{th}	18^{th}	17^{th}	15^{th}
14^{th}	26^{th}	18^{th}	16^{th}
15^{th}	28^{th}	19^{th}	18^{th}
22^{nd}	29^{th}	22^{nd}	19^{th}
23^{rd}		27^{th}	20^{th}
26^{th}			25^{th}
			28^{th}
			30^{th}

The data included a total of 7680 individual forecasts at half hour intervals for both Northern Ireland and the Republic of Ireland.

The aim of this analysis is to define the accuracy of the 24 and 48 hour forecast based on the information supplied to Bord Na Mona by the SEMO forecast. Therefore, the data supplied was separated into a 0 – 24 hour forecast and 25 – 48 hour forecast. To display the accuracy of the forecasted wind generated in comparison to actual wind generated (this data was sourced from the Eirgrid website) a line graph was plotted, for both the 24 hour and 48 hour forecasts to display the difference between the forecasted wind power and actual wind power generated. Additionally, to determine the accuracy of the forecasting data a histogram was plotted to display the probability of the error for each individual 24 and 48 hour forecast. Average hourly forecast errors are also analysed to demonstrate the mean error in forecast for each hour of the total forty days selected for this research. Various statistics for both forecasts were also calculated to provide unambiguous details of the accuracy in results of the forecast analysis. The statistics calculated include the median and inter-quartile ranges and the Cumulative Distribution Function (CDF) graph. CDF completely describes the probability distribution of a real-valued random variable X, which is in this situation wind power. Other statistics calculated included;

- Mean Absolute Error (MAE); measures the average magnitude of the errors in a set of forecasts, without considering their direction.
- Standard Deviation; is a statistic that states how tightly all the various forecasts are clustered around the mean in a set of data.
- Maximum Error; the maximum forecasted error.
- Minimum Error; the minimum forecasted error.
- Root Mean Square Error (RMSE); measures the average magnitude of the error.

3.3.2 24 Hour Forecast Data Analysis Results

Total Forecasted V Total Generated

To illustrate visibly the discrepancy in the amount of wind power forecasted in comparison to actual wind power generated the data displayed in the graphs below, figures 3.2 and 3.3 has been divided into two groups i.e. 1-20 day analysis and 21 – 40 day analysis.

Note: A full list of the statistics regarding figures 3.2 and 3.3 are available on the CD-ROM at the back of this thesis.

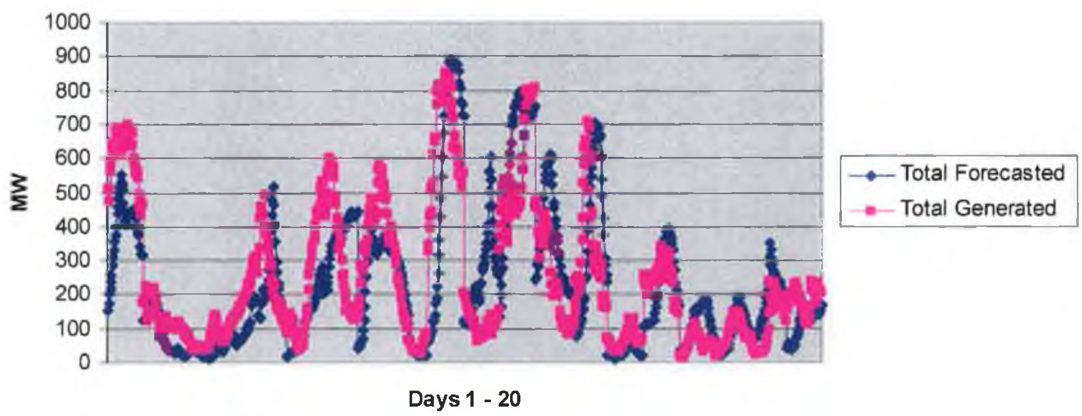

Figure 3. 2 *Day 1 - 20 Total Wind Power Forecasted V Total Wind Power Generated*

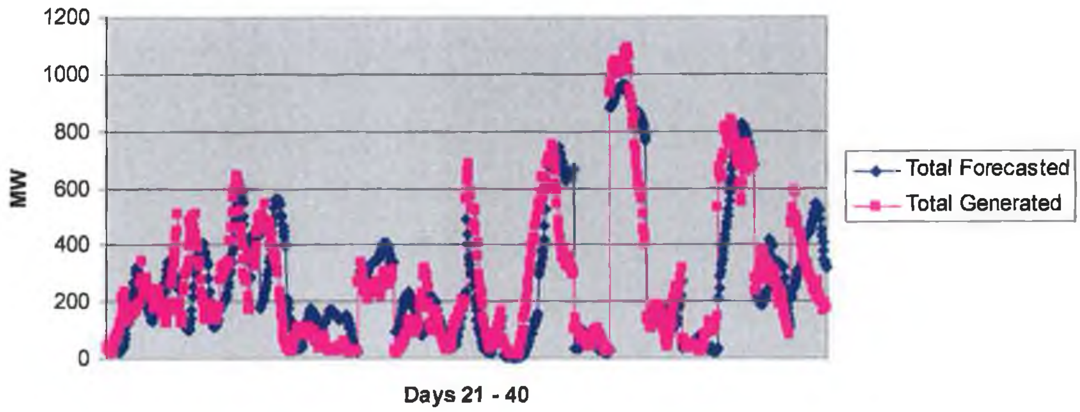

Figure 3. 3 *Day 21 - 40 Total Wind Power Forecasted V Total Wind Power Generated*

On visual inspection of figures 3.2 and 3.3 it appears that the total forecasted in comparison to total generated is quite good but it is difficult to evaluate the accuracy of the forecasts based on these graphs alone.

Probability

To illustrate the accuracy of the forecasts I complied the data supplied into ranges between 15 MW and then calculated the frequency occurrence of the probability error of the forecasts. The outcome of this data is display below in figure 3.4;

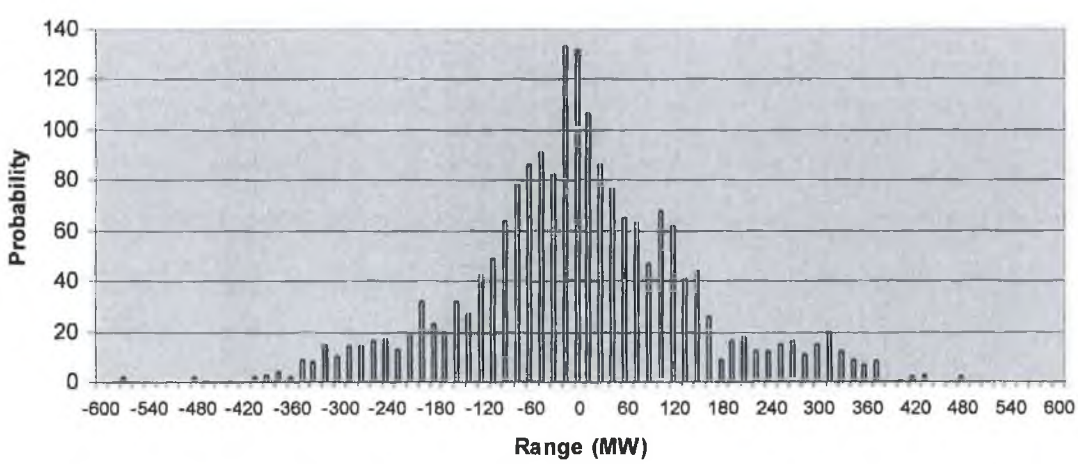

Figure 3. 4 *Probability Error of 24 Hour Forecast*

Figure 3.4 displays evidence that the 24 hour forecast has the most frequent error of between the range of -15 and -30 MW with this forecast error occurring 133 times. The second highest frequency was between the range of 0 and -30 MW, with a total of 132 occurrences followed in third place by +15 and +30 on 107 frequencies. Table 3.2 below contains a list of the top 10 most likely frequencies;

Note: A full list of the frequencies can be found in Appendix A.

Table 3. 2 *Top 10 Forecast Errors*

Rank	Range (MW)	Frequency
1	-15 to -30	133
2	0 to -30	132
3	+15 to +30	107
4	-45 to -60	91
5	+15 to +30	86
6	-60 to -75	86
7	-30 to -45	82
8	-75 to -90	78
9	+30 to +45	77
10	+105 to 120	68

The histogram also illustrates that the normal distribution or gaussian distribution as it is also known occurs. The graph of the linked probability density function is "bell-shaped" with peak at the mean and is known as the gaussian function or bell curve. The normal distribution for the wind power forecasts, for example, is able to determine what the probability that the forecast error will be between 15 - 30 MW. Figure 3.5 displays the 24 hour forecast probability distribution function for the 24 hour forecast.

Note: For a full list of data corresponding to figure 3.5 see Appendix A.

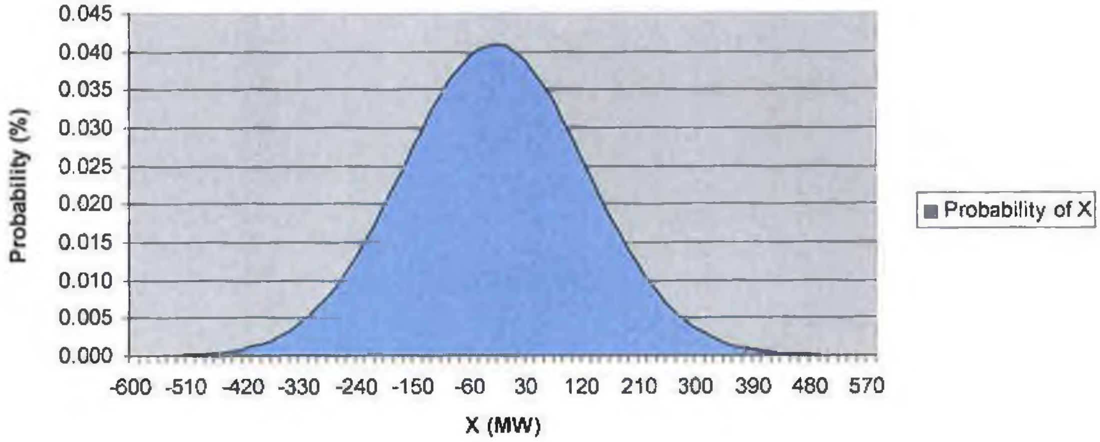

Figure 3. 5 *24 Hour Forecast Normal Distribution Function - Probability Distribution Function*

Mean Forecast Error per hour

To display the mean forecast error for each hour of the 24 hour forecast the absolute mean error for each hour was individually separated and from this it was possible to determine the mean error per hour, the results can be seen in figure 3.6;

Note: For a full list of data corresponding to figure 3.6 see Appendix A.

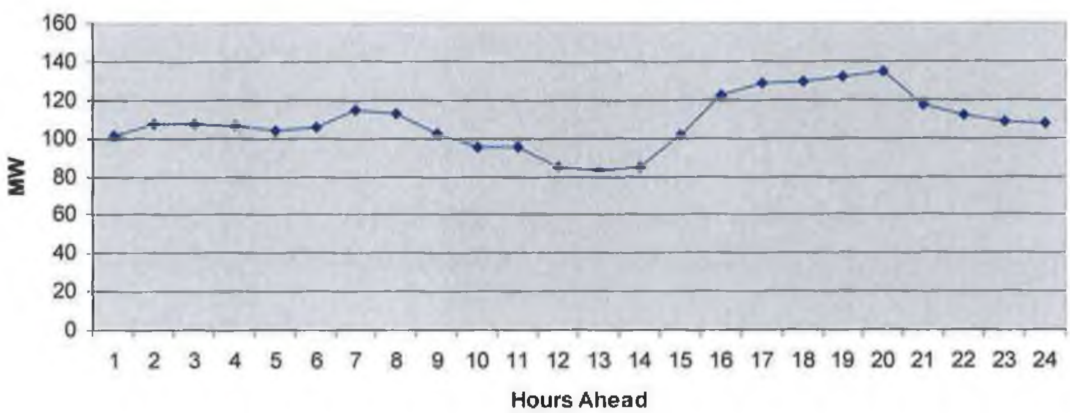

Figure 3. 6 *Mean Forecast Error per hour - 24 Hour Forecast*

The results of figure 3.6 are surprising as it would be expected for the forecast to begin with the smallest error and then for the error to increase constantly. However, a pattern is created that begins with an error of 101 MW at 1 hour ahead then increases steadily to 114 MW at 7 hours ahead before deceasing in error a total of 31 MW between 7 and 13 hours ahead on the x-axis, which is the minimum mean error of 83 MW. The mean error increases again between 13 and 20 on the x-axis to the maximum mean error of 135 MW before decreasing in error towards 24 hours ahead. The total mean error per hour for the 24 hour forecast is 108 MW.

Additional Statistics

Statistical analysis for the data is crucial to determine the overall accuracy of the wind power forecast and to give and clear indication of the errors present in the 24 forecast. Table 3.3 displays the statistics figures for the 24 hour forecast of the data supplied.

Table 3. 3 *Statistics of 24 Hour Forecast*

24 Hour Forecast	MW
Mean Absolute Error (MAE)	115.141
Root Mean Square Error (RMSE)	145.910
Standard Deviation	145.794
Maximum Error	-573.933
Minimum Error	0.061
Median	-10.831

Usually, the mean absolute error (MAE) and root mean square error (RMSE) are the most common statistics to distinguish errors in wind power forecasts. In this analysis the MAE, average magnitude of errors in forecast, is calculated to be 115.141 MW and the RMSE, magnitude of error, is 145.910 MW. The standard deviation is 145.910 MW this gives great measure to see if our mean actually represents our forecast errors, which in this circumstance proves to be correct. The maximum error in the 24 hour forecast is a massive -573.933 MW. This error occurred on March 16th during a ramping event when the actual wind generated was 761 MW and only 187 MW was forecasted. The minimum error was a mere .061 MW. This displays the potential accuracy of the forecast. The minimum error occurred on the 18th April during a period of low wind pressure, the actual wind generated was 133 MW when

133.061 MW was forecasted. The result of the maximum and minimum error results in a range in forecast error of 573.872 MW. It is important to note that the results of the maximum and minimum error indicate the forecasts are more reliable in periods of low winds in comparison to high winds such as the ramping event that occurred on April 18th.

The median and inter-quartile ranges were calculated from the data supplied on Microsoft Excel (available on CD-ROM at back of thesis) and resulted in the Cumulative Distribution Frequency (CDF) graph below in figure 3.7

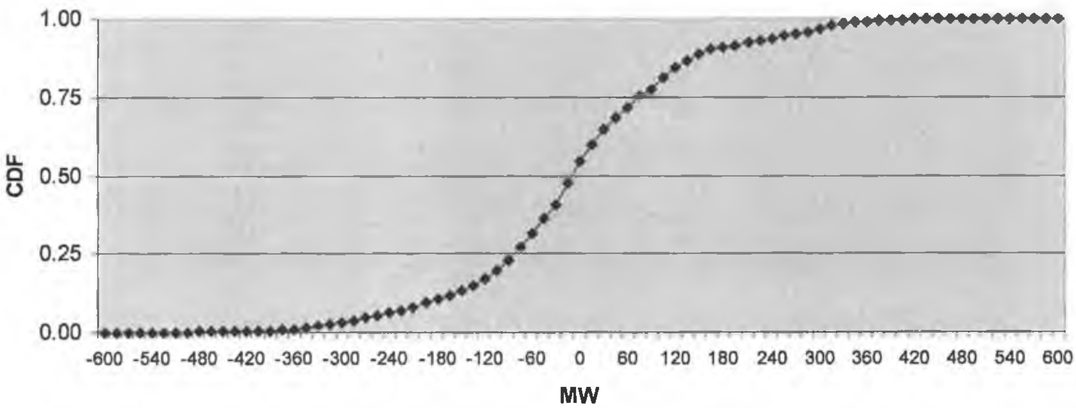

Figure 3. *7 CDF*

The median is the middle value of the forecasts. Half the values are above and below the forecast. The median for the 24 hour forecast is -10.831 MW. The inter-quartile range (IQR) is a measure of statistical dispersion being equal to the difference between the third and first quartiles. In this circumstance the quartile ranges are .25 and .75. The value for the quartile range at .25 is equal to -82.873 MW, while the quartile range at .75 is equal to 74.161 MW. Therefore, between these two values 50% of the forecast errors are present. This results in the IQR being equal to 157.033 MW. A summary of these results are displayed below in table 3.4

Table 3. *4 CDF Statistics*

24 Hour Forecast	MW
Median	-10.831
Lower Quartile	-82.873
Upper Quartile	74.161
Inter Quartile Range	157.033

3.3.2 48 Hour Forecast Data Analysis Results

The same format of data analysis was applied to the 48 hour forecast as the 24 hour forecast analysis.

Total Forecasted V Total Generated

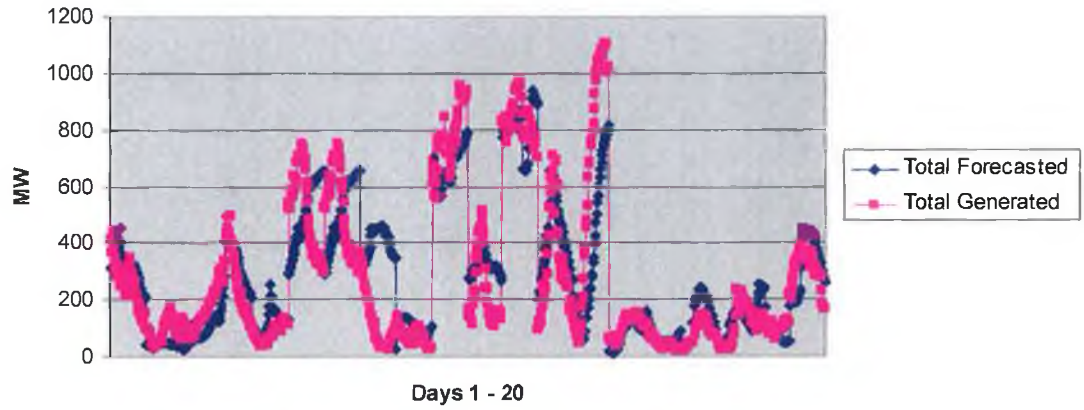

Figure 3. 8 *Day 1 - 20 Total Wind Power Forecasted V Total Wind Power Generated*

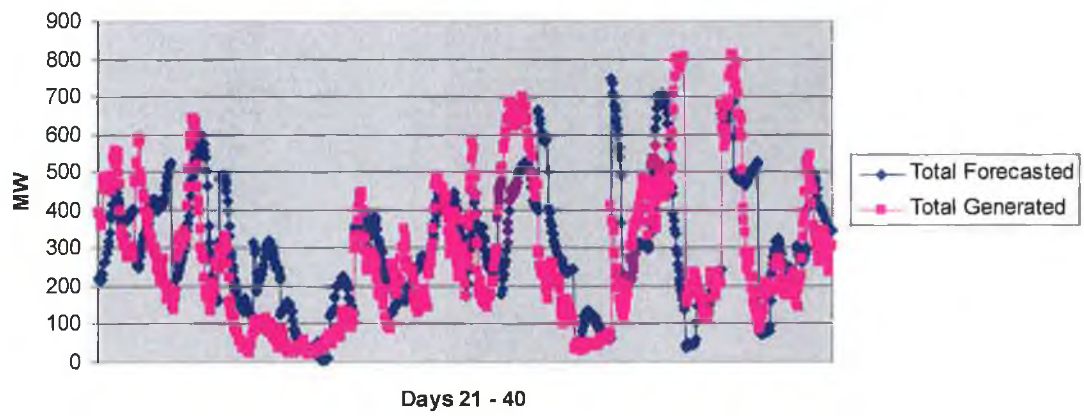

Figure 3. 9 *Day 21 - 40 Total Wind Power Forecasted V Total Wind Power Generated*

Similar to the 24 hour forecast graphs the total forecasted v total generated is difficult to judge the accuracy as it is not clearly illustrated in figures 3.8 and 3.9.

Note: A full list of the statistics regarding figures 3.8 and 3.9 are available on the CD-ROM at the back of the thesis.

Probability

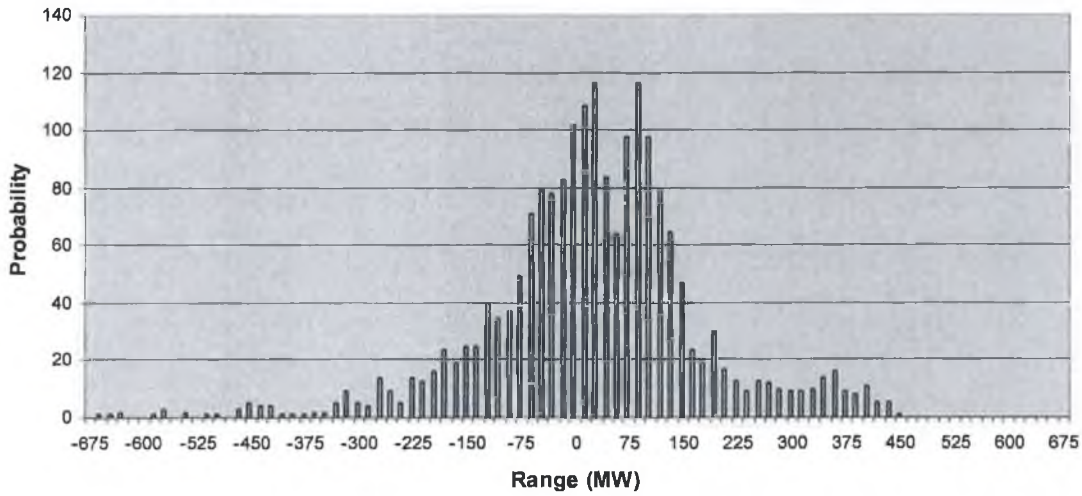

Figure 3. 10 *Probability Error of 48 Hour Forecast*

The histogram in figure 3.10 displays that the most frequent occurrence occurs between the ranges 90 – 105 MW and 30 – 45 MW, with both having a frequency of 116 times. Followed by the range 15 – 30 MW with 109 occurrences and 0 – 15 MW with 102. A list of the top ten frequencies is displayed below in table 3.5.

Note: A full list of the frequencies can be found in Appendix A.

Table 3. 5 *Top 10 Forecast Errors*

Rank	Range (MW)	Frequency
1	+90 to +105	116
2	+30 to +45	116
3	+15 to +30	109
4	0 to +15	102
3	+75 to +90	98
6	+105 to +120	98
7	-15 to -30	83
8	-75 to -90	80
9	-45 to -60	79
10	-30 to -45	78

The distribution of the histogram is a normal distribution. Therefore, it is possible to calculate the normal distribution function. Figure 3.11 displays the results.

Note: The data list for figure 3.11 is in Appendix A.

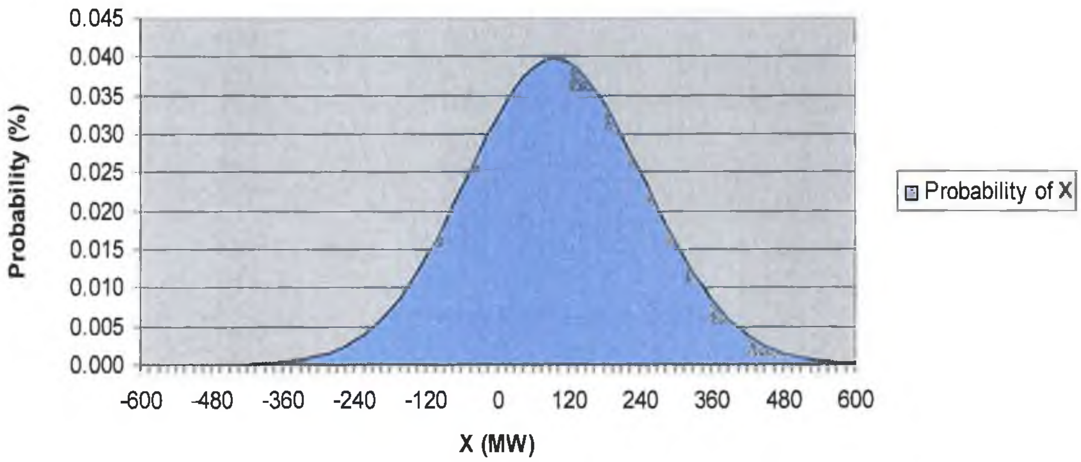

Figure 3. 11 *48 Hour Forecast Normal Distribution - Probability Distribution Function*

Mean Forecast Error per hour

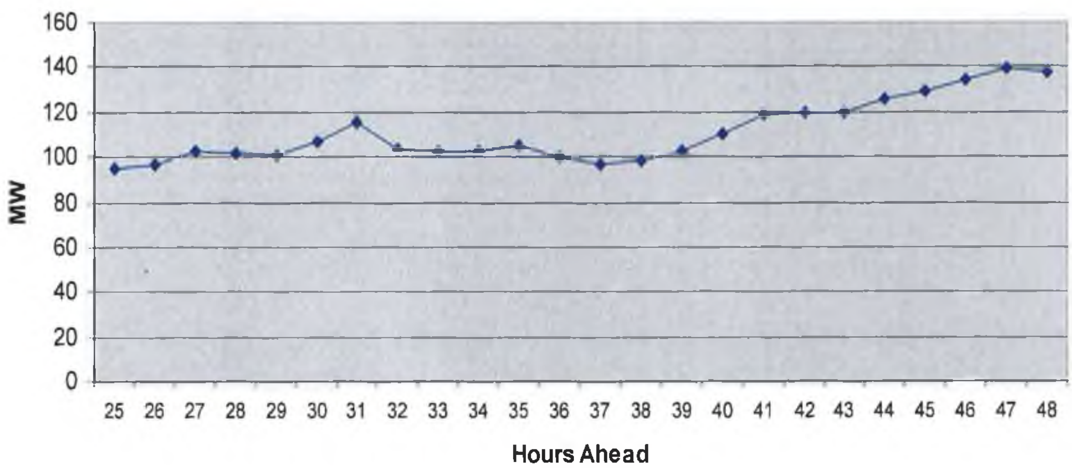

Figure 3. 12 *Mean Forecast error per hour - 48 Hour Forecast*

Figure 3.12 displays a pattern that would be expected i.e. a gradual increase from start to finish, despite a minor deviation at 30 – 32 and 36 - 37 hours ahead. The minimum mean value error per hour, 95.151 MW, is at 25 hours ahead and the maximum mean error value per hour is at 48 hours ahead with a value of 138 MW. The average mean error per hour for the 48 hour forecast is 111 MW.

Note: A full list of the statistics regarding figure 3.12 is in Appendix A

Additional Statistics

Table 3. 6 *Statistics of 48 Hour Forecast*

48 Hour Forecast	**MW**
Mean Absolute Error (MAE)	110.135
Root Mean Square Error (RMSE)	151.543
Standard Deviation	150.369
Maximum Error	669.931
Minimum Error	0.029
Median	90.19

The MAE for the 48 hour forecast is 115.141 MW, a surprising 5 MW decrease on the MAE of the 24 hour forecast, while and RMSE and standard deviation are 151.543 MW and 159.369 MW respectively. The maximum error is a massive 669.931 MW while the minimum error is .029 MW. This gives a range of 669.931 MW. The maximum error occurred on March 30th during a period a high winds while the minimum error occurred on April 20th during a period of low winds, this gives further evidence that the forecast are more reliable in times of low wind in contrast to high winds.

In the same manner as the 24 hour forecast the median and inter-quartile ranges were calculated from the data supplied on excel (available on CD-ROM at back of thesis) and resulted in the Cumulative Distribution Frequency (CDF) graph in figure 3.13;

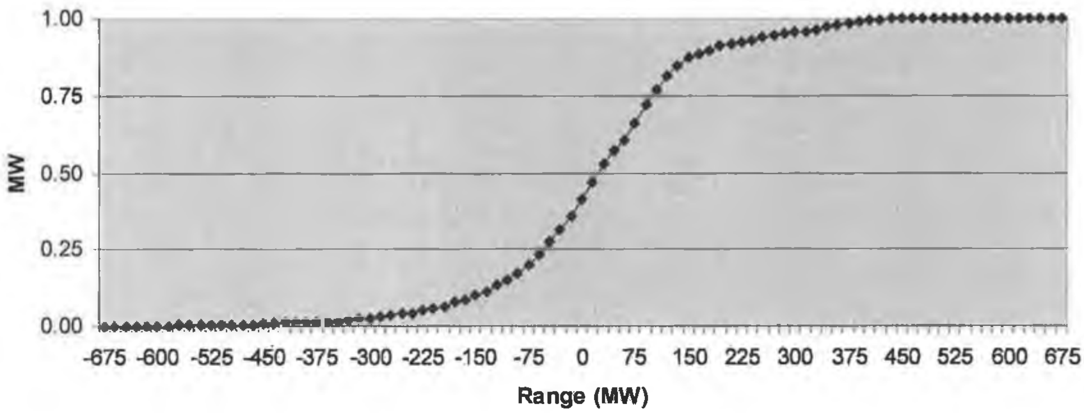

***Figure 3. 13** CDF*

The median for the 48 hour forecast is 90.10 MW. The lower quartile results in a value of -54.379 MW, while the upper quartile value is equal to 97.799 MW. This results in an IQR of 152.178 MW. This means that 50% of the forecast error is within the range of -54.379 to 97.799 MW. A summary of these result are available in table 3.6:

***Table 3. 7** CDF Statistics*

48 Hour Forecast	MW
Median	90.10
Lower Quartile	-54.379
Upper Quartile	97.799
Inter Quartile Range	152.178

3.4 Conclusion

This chapter gave an insight into the two most common forms for wind power forecast models, statistical and physical, and it also investigated the accuracy of 24 and 48 hour wind power forecasts from the information available to Bord Na Mona.

The statistical model approaches are based on values of past information of power and additional past forecasts values of descriptive variables and wind power measures. The values in the models are set from power measurements and meteorological forecasts, no physical conditions are considered. While the physical approach is based on the terrain associated with each individual wind farm location.

The results of the analysis of the 24 and 48 hour forecasts were quite interesting. Prior to conducting the research into the forecasts I would have expected the results of the 24 hour forecast to be much more accurate in comparison to the 48 hour forecast. Despite the 24 hour forecast being overall more accurate I envisaged there being a greater difference in results. For example when contrasting the values of the mean forecast error per hour. The mean value error for the 24 hour forecast is 108 MW while the 48 hour forecast mean error is 111 MW, a mere difference of just 3 MW. I had expected that the minimal forecast error per hour would be at 1 hour prior to actual time and that with each hour thereafter the forecast mean error would gradually increase. However, this is not the case and it is illustrated in figure 3.6. This means that the forecast error does not follow the anticipated sequence and is just as likely to have the same error at 36 hours ahead as at 1 hour ahead. Further evidence to support the lack of anticipated sequence is displayed in the mean absolute error (MAE). The MAE for the 24 hour forecast is 115 MW while the MAE for 48 hour forecast is 110 MW, which suggests that the MAE for the 48 hour forecast is on average 5 MW more accurate than the 24 hour forecast. Therefore, the average forecast error per hour at anytime is 113 MW throughout the 0 – 48 hour forecast period.

Both forecasts display evidence of being able to calculate high accuracy as both have a minimum error of .061 MW and .029 MW respectively. However, both forecasts are susceptible to high forecast errors as the maximum errors for each forecast are as large as -574 MW and -669 MW. The minimal forecast errors were in times when low wind speeds are present while the maximum errors were in times of high winds, hence this indicates that the forecasts are more accurate in times of low winds. Additionally, it should be noted that the majority of forecasts errors are deemed to be forecasted below that actual wind power produced.

The cumulative distribution function graphs (figures 3.7 and 3.12) display the inter-quartile ranges (IQR) for both the 24 hour and 48 hour forecasts. The IQR for the 24 hour forecast is 157 MW while the 152 MW is the IQR for the 48 hour forecast.

I believe the probability distribution functions for both 24 hour and 48 hour forecast (figures 3.5 and 3.11) to be the key findings of this research and analysis as it determines the probability of the forecast error in percentage terms within a range of 15 MW. Therefore, by establishing figures 3.5 and 4.11 I have achieved my objective to determine the accuracy of the 24 hour and 48 hour forecast e.g. it can be stated that there is a 4% chance of there being a forecast error between 75 – 90 MW.

Chapter Four

"My interest is in the future because I am going to spend the rest of my life there..."

- C.F. Kettering

4.0 Discussion and Conclusion

4.1 Introduction

The overall aim of this thesis is to determine the accuracy for a particular wind power forecast and to investigate the importance of wind power forecasts for such aspects as the transmission system operators (TSOs), biddings strategies and spot prices. This research into wind power forecasting is of huge interest to all participants in the electricity market especially since there is now a major emphasis being placed on countries to incorporate renewable energy systems into their electrical system due to the crisis facing plant earth of climate change. This thesis provided an insight into the benefits, impacts and accuracy of wind power forecasts. The benefits were examined in terms of TSOs, Independent Power Producers (IPPs), wind storage and trading wind energy with neighbouring countries. The impacts of wind power forecasts on the electricity markets was explained by using previous case studies on bidding strategies, spot prices, unit commitment and economic dispatch. Finally, the accuracy of wind power forecasts, for 24 and 48 hour forecasts, for a particular set of data was explored by using various statistical analysis methods to illustrate the precision of the particular wind power forecast.

In this chapter I discuss all the aspects explained and researched in this thesis by describing the different strategies I used, what methods worked, what didn't and why. I also highlight areas where I feel a better solution may be reached and the success of what this thesis has achieved. The final section in this chapter details a general conclusion of my work conducted in this thesis.

4.2 Discussion

4.2.1 Benefits

The benefits of wind power forecasting were explained in this thesis in terms of TSOs, IPPs and a case study examining the advantages of using forecasting techniques instead of other methods such as the fuel saver option.

The chief concern of wind power is its variable intermittence that causes distress to TSOs for operating the electricity grid. This intermittent nature whether it is a surplus or a decrease in the forecasted MW requires component management of conventional power sources to act as reserves, connecting to surrounding grids or wind storage. Wind power forecasting plays are crucial role for applying any management control measures and in particular forecasting the anticipated errors of the forecasts.

The benefits of wind power forecasts are best described in the case study analysed by Doherty et al., (2004) as it portrays the advantages in the management of the grid system by availing of forecasted techniques in comparison to the fuel saver option. The results show that the forecasted techniques option is significantly less expensive in comparison to the fuel saver options in terms of cost of reserve per year, percentage increase in cost over the no wind case and cost imposed per MW. Therefore, it would be improbable to suggest that the fuel saver option should be implemented and consequently brainless to conduct further research into that option. As the forecasted system permits the conventional plant to be switched off, this results in a proficient management method for the incorporation of wind power into the electricity system as there still remains a sufficient amount of reserves for the errors that are likely occur in the wind power forecasts.

At present the storage of wind energy is not common in many countries mainly due to high costs associated with construction and installation for hydro-storage. However, I believe that with improved technology and reduced costs wind storage will result in it being introduced into various countries developing their renewable infrastructure. Wind forecasts will play a pivotal role for achieving the best possible results.

4.2.2 Impacts

This thesis has examined the impact of the wind power forecast chiefly on the electricity market in relation to bidding strategies and spot prices while analysis was also given to the effects of unit commitment and economic dispatch.

It is evident from the research explained in this thesis that wind power plays a pivotal role for wind power producers taking part in the electricity pools. Unfortunately, there will always be the attachment of regulation costs due to the error that is present in all wind power forecasts. This is implausible to change in the coming years as it is not expected for wind power forecasts to radically advance in the near future. The market value of wind power forecasts could be amplified by incorporating the uncertainty information into the decision making procedure.

In terms of wind power forecasts effect on spot prices this thesis has demonstrated by the case study in the Nord Pool by Madsen et al., (2009) that the prediction of wind power to be generated can have remarkable impact on the level of spot prices. Generally the spot price decreases in times when there is a large quantity of wind power forecasted. The results of the case study support the research conducted by Bunn and Karakatsani and (2007) in that portions of the plant dynamics should be considered when models of the short-term dynamics of the electricity spot prices are to be derived. The results of the case study by Madsen et al., (2009) additionally support the conclusions of previous studies such as Wang and Bottererud (2009) that the impact of wind power forecasts on the electricity market has a major effect on the electricity prices for the day ahead.

In terms of the unit commitment and economic dispatch the results illustrated that errors in wind power forecasts have a significant effect on the scheduling of generating units in the day ahead market with consequences for the dispatch in real-time. For cost and reliability the stochastic approach for unit commitment showed quality results. Ultimately the benefit of wind power forecasting was made definite when the results of the perfect forecast were contrasted to the no wind forecast. The results displayed that a good wind forecast can reduce the system dispatch.

4.2.3 Accuracy

For determining the accuracy of the wind power forecast from the data supplied by Bord Na Mona the results were produced in various forms of statistical and graphical formats. In comparing the results of the two forecasts, the first element I found surprising was the fact that there was very little difference between the overall accuracy of the two individual forecasts when assessing the results of the mean error per hour. I would have expected the results to illustrate a distinct higher degree of accuracy however, this was not the case as little difference existed between the two forecasts. For the 24 hour forecast no unambiguous pattern developed in the results of the mean error per hour For example it would have been anticipated that the forecast one hour ahead would be more accurate than the forecast at fifteen hours ahead however, the results displayed that the forecast of 15 hours ahead is just as likely to be as accurate as the one hour ahead forecast. While in the 48 hour forecast the results of the mean error forecast per hour produced a pattern that illustrated that the forecasted error increased as time elapsed.

The results of the particular wind power forecast used in this thesis is quite poor in comparison to the wind power forecast supplied by Eirgid on their website, www.eirgird.com. I conducted preliminary research into the accuracy of the wind power forecast data available based on 24 hour forecast data. The results proved to have greater accuracy from the Eirgrid forecast. For example, the mean absolute error (MAE) was equal to 53 MW from the Eirgrid wind power forecasts in comparison to a MAE error of 115 MW, a difference of 62 MW, from the wind power forecast available to Bord Na Mona. These results would encourage me to carry to further research into the wind power forecasts data available from Eirgird in a similar method to the data analysis conducted in this thesis and to contrast the differences in results of the two forecasts available. This topic is discussed further in chapter five recommendations.

As stated previously I believe the key findings of my research to be the graphs for both the 24 and 48 hour forecasts that illustrate the probability distribution function. These graphs determine the percentage probability of the forecast error within a range of bins of 15 MW. The information displayed in each of these graphs would be extremely beneficial for any IPPs or TSOs to schedule their bidding strategy or to balance their grid system. I initially selected thirty days to base the results from the wind power forecasts on however, I added an additional random ten days to the calculations. The reason I used an extra ten days was to increase the shape of the histogram of a bell curve for the 48 hour forecast. The probability distribution function for the 24 hour forecast gave an appropriate bell shaped curved however, while the 48 hour forecast curve had a resemblance to a bell curve it wasn't as smooth in comparison to the 24 hour forecast curve. Therefore, I increased the number of days analysed to forty in an effort to investigate if the additional ten days would create a smoother histogram. The additional ten days proved to be effective and a suitable bell curve was formed on the histogram to portray a normal distribution.

4.3 Limitations of Research

Despite my research giving a distinct examination of the benefits and impacts of wind power forecasts, I feel that the data analysis section would have benefited from assessing the results of the particular wind power forecast throughout a twelve month period, January to December, in comparison to the random forty days that were assessed between February and May. The reason for only assessing forty days was due to time restrictions, of three months, from start date to completion date of this thesis. The time limit of three months was simply not long enough to feasibly carry out analysis for the full twelve month period. I believe that an assessment of the wind power forecast during a full calendar year would have given a truer reflection on the wind power forecasts as it would have included all four seasons that contain the various climatic conditions associated with wind.

4.4 Strengths of Research

This study has contributed significantly to display the importance of wind power forecasts and it illustrated various methods to demonstrate the results of a particular wind power forecast. Its innovation lies in how it displays the various methods of the accuracy for a wind power forecast and consequently describes the impacts that wind power forecasts can have for participants in the energy sector.

Ultimately, this research acknowledges the role wind power forecasts play in the energy sector and additionally describes the accuracy of a particular wind power forecast via statistical methods. Therefore, this research contributes to portraying the role wind power forecasts can play in industry and can display a method to show how to define the accuracy of any wind power forecast.

4.5 Conclusion

This thesis has proposed a methodology for the benefits, impacts and accuracy of a wind power forecast. Going further, I clearly demonstrated the various patterns and statistical analysis of a particular wind power forecast. When I began my research into wind power forecasts in May no results were available on the accuracy of the wind power forecasts assessed in this thesis. I explained and illustrated by various means, such as mean forecast error per hour, probability distribution function and by various statistics the accuracy of the particular wind power forecast. The results have provided meaningful information for a particular wind power forecast as they provide results of data that prior to this research didn't exist. The fact that this research was not previously conducted was a key factor for my motivation as I knew I was determining something that was innovative, technically challenging and most of all a thesis that would be beneficial in industry and provide a foundation for further developments in the area of wind power forecasts.

In order to give the reader an overview of wind power forecasting I deemed it necessary in the first stage to give an insight into the topic. For that reason I explained the background into wind energy in general terms. I then progressed into discussing the problem with wind power. Many people hear through the media the great benefits associated with wind power and rarely are the negative effects analysed, I felt it was important to state the chief problems that are associated with wind power i.e. its intermittent and variable nature. Next, I discussed the importance of wind forecasting for such participants as TSOs e.g. planning their schedules and IPPs e.g. the quantity of wind power anticipated to be generated. The importance of this was further verified in the case study assessed in which forecasting techniques in the research by Doherty et al., (2004) were contrasted against other methods such as the fuel saver option. A strong focus of the impact of wind power forecasts in the electricity market, in relation to bidding strategies and spot prices, was described by using two case studies based in both the Netherland's and Denmark's electricity markets respectively. Both these case studies displayed the significant role wind power forecast can play on the electricity market. Finally, I examined the accuracy of a particular wind power forecast through a variety of methods. The variety of methods used illustrated a group of individual results each of which are of benefit to participants in the wind energy market.

To conclude, I firmly believe I have achieved the objective set out in the research question, see below, and also set a foundation for further work to be undertaken.

Why are wind power forecasts so important and how good is the accuracy of a particular wind power forecast?

Chapter Five

"Prediction is very difficult, especially if it's about the future..."

- Nils Bohr

5.0 Recommendations

5.1 Introduction

After an abundant quantity of analysis, research and data in relation to wind power forecasting the following chapter hereby makes recommendations for further work.

5.2 Recommendations for Further Work

There are various aspects that can be recommended for further work from the analysis in my research. The first recommendation would be to conduct research as a case study on the Irish electricity system in terms the effect of wind forecasting on price due to day ahead forecasts. As the Irish electricity market is going to increase with the quantity of wind power generated on the grid in the coming years, I believe it would be worthwhile to develop a case study over a period of twelve months to evaluate the distributional properties of the spot prices under different scenarios of wind power forecasts. Additionally, the markets response to other sources of renewable energy such as wave and solar could be monitored. The results of this proposed case study would be extremely relevant to any participant taking part in the electricity pool in Ireland by assisting them in their bidding strategy and to portray an idea of spot price in different scenarios. The data analysis of my particular wind power forecast assessed in this thesis would provide a baseline for the case study proposed to develop the results of any wind power forecast against the effect on spot prices. Therefore, I suggest further study being carried out on the distributional properties of the spot prices under different scenarios of wind power forecasts in the Irish electricity market.

Another opportunity I believe to exist from the finding of this research, which was mentioned earlier in the discussion section 4.2, is to investigate other types of wind power forecasts that are available and hence determine the wind power forecast that has the greatest accuracy. The data analysis section investigated in this thesis could be applied to the other wind power forecasts available e.g. Eirgrids wind power forecast. This proposed study would be of benefit to participants in the renewable wind energy sector by assisting them in their bidding strategies and in the operation of thermal plant by defining the most accurate wind power forecast available. This proposed study could also delve further into the types of wind forecasts models being used whether it is physical or statistical. The conclusions of this proposed study would eliminate the wind power forecasts generating the least reliable results and therefore, highlight the most accurate forecast to assist the participants in the wind energy sector.

Finally, I would additionally suggest further work be investigated to study the impacts for wind power forecasts on power system scheduling as an Irish system case study. This proposed study would take into account market conditions of the Irish electricity market and include the most favourable scheduling options for reserve. A host of the wind power forecasts could be examined and the results could illustrate the impact of each forecast has on the scheduling.

It is my intention that the recommendations outlined in this report will encourage further research into the area of wind power forecasting.

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3.2 Total acreage of Athlone borough 1831-1901, including separate acreage totals for Athlone, Co. Westmeath and Athlone, Co. Roscommon.

3.3 Population proportions by religious denomination, Athlone town, Athlone Co. Westmeath and Athlone Co. Roscommon.

3.4 Population change by religious denomination in Athlone 1861-1901, Athlone, Co. Westmeath 1861-1901, Athlone, Co. Roscommon 1861-1901
Overall trend by religious denomination Athlone, Athlone Co. Westmeath and Athlone Co. Roscommon 1861-1901.

3.5 Proportion of Athlone's religious denominations by sex 1861-1901.

APPENDIX 4: POLITICS

4.1 MPs elected for Athlone Borough 1837-1885.

4.2 MPs elected for the constituencies of South Roscommon and South Westmeath 1885-1900.

APPENDIX 5: MISCELLANEOUS

5.1 Map of Athlone showing a number of important structures.

5.2 Additional photographs and images.

5.3 Information relating to Athlone Union Workhouse.

5.4 Census form used in the compilation of housing statistics.

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Appendices

Appendix A: The Models and Accuracy of Wind Power Forecasts

NB: Further information from the data analysis of the wind power forecast is available on the CD-ROM attached at the back of this thesis.

1) Full index of results relating to data from figures 3.4 and 3.10. (Frequency of forecast errors)

24 Hour Forecast

Range	Frequency
-600	0
-585	0
-570	2
-555	0
-540	1
-525	0
-510	1
-495	0
-480	2
-465	1
-450	0
-435	1
-420	0
-405	2
-390	3
-375	4
-360	2
-345	9
-330	8
-315	15
-300	10
-285	14
-270	14
-255	16
-240	17
-225	13
-210	19
-195	32
-180	23
-165	20

48 Hour Forecast

Range	Frequency
-675	0
-660	1
-645	1
-630	2
-615	0
-600	0
-585	1
-570	3
-555	0
-540	2
-525	0
-510	1
-495	1
-480	0
-465	3
-450	5
-435	4
-420	4
-405	1
-390	1
-375	1
-360	2
-345	2
-330	5
-315	9
-300	5
-285	4
-270	14
-255	9
-240	5

-150	32
-135	27
-120	42
-105	49
-90	64
-75	78
-60	86
-45	91
-30	82
-15	133
0	132
15	107
30	86
45	77
60	65
75	63
90	47
105	68
120	62
135	41
150	44
165	26
180	9
195	16
210	18
225	12
240	12
255	15
270	16
285	11
300	15
315	20
330	12
345	9
360	7
375	8
390	0
405	1
420	2
435	3
450	0
465	0
480	2
495	0
510	0
525	0
540	0
555	0
570	0
585	0
600	0

-225	14
-210	13
-195	16
-180	24
-165	19
-150	25
-135	25
-120	40
-105	35
-90	37
-75	49
-60	71
-45	79
-30	78
-15	83
0	102
15	109
30	116
45	84
60	64
75	98
90	116
105	98
120	80
135	65
150	47
165	24
180	20
195	30
210	17
225	13
240	9
255	13
270	12
285	10
300	9
315	9
330	10
345	14
360	16
375	9
390	8
405	11
420	5
435	5
450	1
465	0
480	0
495	0
510	0
525	0

2) Full index of results relating to data from figures 3.5 and 3.11. (Probability distribution function)

24 Hour Forecast Data from Figure 3.5;

X (MW)	Normal Distribution	Probability	Percentage (%)
-600	0.000		
-585	0.000	0.000	0.001
-570	0.000	0.000	0.002
-555	0.000	0.000	0.003
-540	0.000	0.000	0.005
-525	0.000	0.000	0.007
-510	0.000	0.000	0.010
-495	0.000	0.000	0.014
-480	0.001	0.000	0.020
-465	0.001	0.000	0.027
-450	0.001	0.000	0.038
-435	0.002	0.001	0.051
-420	0.003	0.001	0.069
-405	0.003	0.001	0.093
-390	0.005	0.001	0.122
-375	0.006	0.002	0.160
-360	0.008	0.002	0.206
-345	0.011	0.003	0.264
-330	0.014	0.003	0.334
-315	0.018	0.004	0.418
-300	0.024	0.005	0.518
-285	0.030	0.006	0.636
-270	0.038	0.008	0.771
-255	0.047	0.009	0.926
-240	0.058	0.011	1.100
-225	0.071	0.013	1.293
-210	0.086	0.015	1.504
-195	0.103	0.017	1.730
-180	0.123	0.020	1.970
-165	0.145	0.022	2.220
-150	0.170	0.025	2.475
-135	0.197	0.027	2.730
-120	0.227	0.030	2.979
-105	0.259	0.032	3.218
-90	0.294	0.034	3.439
-75	0.330	0.036	3.636
-60	0.368	0.038	3.804
-45	0.407	0.039	3.939
-30	0.448	0.040	4.035
-15	0.489	0.041	4.090
0	0.530	0.041	4.102
15	0.570	0.041	4.070
30	0.610	0.040	3.997
45	0.649	0.039	3.884
60	0.686	0.037	3.734

75	0.722	0.036	3.552
90	0.755	0.033	3.343
105	0.787	0.031	3.114
120	0.815	0.029	2.870
135	0.841	0.026	2.617
150	0.865	0.024	2.361
165	0.886	0.021	2.108
180	0.905	0.019	1.862
195	0.921	0.016	1.628
210	0.935	0.014	1.408
225	0.947	0.012	1.205
240	0.957	0.010	1.020
255	0.966	0.009	0.855
270	0.973	0.007	0.709
285	0.979	0.006	0.581
300	0.983	0.005	0.472
315	0.987	0.004	0.379
330	0.990	0.003	0.301
345	0.993	0.002	0.237
360	0.995	0.002	0.184
375	0.996	0.001	0.142
390	0.997	0.001	0.108
405	0.998	0.001	0.082
420	0.998	0.001	0.061
435	0.999	0.000	0.045
450	0.999	0.000	0.033
465	0.999	0.000	0.024
480	1.000	0.000	0.017
495	1.000	0.000	0.012
510	1.000	0.000	0.008
525	1.000	0.000	0.006
540	1.000	0.000	0.004
555	1.000	0.000	0.003
570	1.000	0.000	0.002
585	1.000	0.000	0.001
600	1.000	0.000	0.001

48 Hour Forecast Data from Figure 3.11;

X (MW)	Normal Distribution	Probability	Percentage (%)
-600	0.000		
-585	0.000	0.000	0.000
-570	0.000	0.000	0.000
-555	0.000	0.000	0.000
-540	0.000	0.000	0.000
-525	0.000	0.000	0.001
-510	0.000	0.000	0.001
-495	0.000	0.000	0.002
-480	0.000	0.000	0.002
-465	0.000	0.000	0.004
-450	0.000	0.000	0.005
-435	0.000	0.000	0.008
-420	0.000	0.000	0.011
-405	0.000	0.000	0.015
-390	0.001	0.000	0.021
-375	0.001	0.000	0.029
-360	0.001	0.000	0.039
-345	0.002	0.001	0.052
-330	0.003	0.001	0.070
-315	0.004	0.001	0.092
-300	0.005	0.001	0.121
-285	0.006	0.002	0.156
-270	0.008	0.002	0.201
-255	0.011	0.003	0.255
-240	0.014	0.003	0.320
-225	0.018	0.004	0.399
-210	0.023	0.005	0.491
-195	0.029	0.006	0.599
-180	0.036	0.007	0.724
-165	0.045	0.009	0.866
-150	0.055	0.010	1.026
-135	0.067	0.012	1.203
-120	0.081	0.014	1.396
-105	0.097	0.016	1.605
-90	0.115	0.018	1.827
-75	0.136	0.021	2.058
-60	0.159	0.023	2.296
-45	0.184	0.025	2.537
-30	0.212	0.028	2.775
-15	0.242	0.030	3.005
0	0.274	0.032	3.222
15	0.309	0.034	3.420
30	0.344	0.036	3.595
45	0.382	0.037	3.741
60	0.420	0.039	3.855
75	0.460	0.039	3.933
90	0.499	0.040	3.973
105	0.539	0.040	3.973
120	0.579	0.039	3.934

135	0.617	0.039	3.857
150	0.655	0.037	3.745
165	0.691	0.036	3.599
180	0.725	0.034	3.425
195	0.757	0.032	3.227
210	0.787	0.030	3.010
225	0.815	0.028	2.781
240	0.840	0.025	2.543
255	0.863	0.023	2.303
270	0.884	0.021	2.064
285	0.902	0.018	1.832
300	0.919	0.016	1.610
315	0.933	0.014	1.401
330	0.945	0.012	1.207
345	0.955	0.010	1.030
360	0.964	0.009	0.870
375	0.971	0.007	0.727
390	0.977	0.006	0.602
405	0.982	0.005	0.494
420	0.986	0.004	0.401
435	0.989	0.003	0.322
450	0.992	0.003	0.256
465	0.994	0.002	0.202
480	0.995	0.002	0.157
495	0.996	0.001	0.122
510	0.997	0.001	0.093
525	0.998	0.001	0.070
540	0.999	0.001	0.053
555	0.999	0.000	0.039
570	0.999	0.000	0.029
585	1.000	0.000	0.021
600	1.000	0.000	0.015

3) Full index of results relating to data from figures 3.6 and 3.12 (Mean error forecast per hour).

24 and 48 Hour Forecast Data from Figure 3.6 and 3.12;

24 Hour Forecast

Hour Ahead	MW
1	101.447
2	107.536
3	107.729
4	106.455
5	103.649
6	105.517
7	114.441
8	112.886
9	102.064
10	95.517
11	95.517
12	85.123
13	83.446
14	84.742
15	101.632
16	122.684
17	128.877
18	129.422
19	132.427
20	134.758
21	117.524
22	111.859
23	108.338
24	107.260

48 Hour Forecast

Hour Ahead	MW
25	95.151
26	96.389
27	102.911
28	101.404
29	100.722
30	107.144
31	115.269
32	103.110
33	102.559
34	102.621
35	105.487
36	100.528
37	96.851
38	98.136
39	102.749
40	110.159
41	118.820
42	119.623
43	119.927
44	125.512
45	129.119
46	134.033
47	139.822
48	137.998