Application of cost functions for large-scale integration of wind power using a multi-scheme ensemble prediction technique

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PREPRINT

"Optimization Advances in Electric Power Systems"

Editor: Edgardo D. Castronuovo
Publisher: NOVA Publishers NY, USA
Submitted: 9th February 2008
Status: Accepted for publication (1.Q 2009)

Contents

0.1 ABSTRACT

The use of ensemble techniques for wind power forecasting aids in the integration of large scale wind energy into the future energy mix and offers various possibilities for optimisation of reserve allocation and operating costs. In this chapter we will describe and discuss recent advances in the optimisation of wind power forecasts to minimise operating costs by using a multi-scheme ensemble prediction technique to demonstrate our theoretical investigations. In recent years a number of optimisation schemes to balance wind power with pumped hydro power have been investigated. Hereby the focus of the optimisation was on compensating the fluctuations of wind power generation. These studies assumed that the hydro plant was dedicated to the wind plant, which would be both expensive and energy inefficient in most of today's and expected future electricity markets, unless the wind generation is correlated and has a very strong variability. Instead a pooling strategy is introduced that also includes other sources of energy suitable to balance and remove the peaks of wind energy, such as biogas or a combined heat and power (CHP) plant. The importance of such pools of energy is that power plants with storage capacity are included to enable the pool to diminish speculations on the market against wind power in windy periods, when the price is below the marginal cost and when the competitiveness of wind power as well as the incentives to investments in wind power become inefficient and unattractive.

It will also be shown that the correlation of the produced wind power diminishes and the predictability of wind power increases as the wind generation capacity grows. Then it becomes beneficial to optimise a system by defining and applying cost functions rather than optimising forecasts on the mean absolute error (MAE) or the root mean square error. This is because the marginal costs of up and down regulation are asymmetric and dependent on the competition level of the reserve market. The advantages of optimising wind power forecasts using cost functions rather than minimum absolute error increase with extended interconnectivity, because this serves as an important buffer not only from a security point of view, but also for energy pricing.

0.2 INTRODUCTION

Wind power is considered one of the most important renewable energy sources in the near future. In the past years the number of wind farms world wide increased strongly, with a total installed capacity of more than 94 GW by the end of 2007 [1], with about 50% distributed in Germany, Spain and the USA. This high concentration suggests that from a global perspective there is space for ample additional wind power. The issue is therefore not whether it is feasible, but rather what does it cost? The main focus in wind power integration in the past has been on producing the most accurate forecast with minimal average error, but experience has shown that this is not necessarily optimal from a cost perspective. Balancing costs will increase with increasing volumes of wind power. The larger the forecasted error (in MW), the higher the balancing costs.

Another aspect is the concentration level of wind power, which has a side effect from a forecasting perspective. This is the correlated generation and forecast error and is mainly relevant for large amounts of offshore wind power, as it is planned e.g. in the North Sea to in order to reduce transmission costs. Such scenarios make it unfeasible to run an electricity network with a forecast optimisation target of minimal mean absolute error, because it implies short periods during which GW of fossil fuel based power plants will have to be started with short notice. Germany is such an example, where it is the large errors that dominate the balancing costs of wind power. Skewness of the balancing costs of negative and positive reserve gives advantage to conservative forecasts in such areas and requires curtailment or other scheduled plants to stop generation with short notice. Such scenarios are also regularly experienced in Spain. An EU 6th-Framework project is assisting the Transmission System Operators (TSO's) in developing tools to handle such cases with a so-called cluster management [2].

From these experiences, it appears that cost functions will not only benefit the market prices and balancing costs, but also act as a means to increase system security. For those countries, where the installed capacity has gone beyond the 10 GW level, it has become an important consideration in the daily operation.

Whether intermittency poses technical limits on renewables in the future is certainly also of concern for other forms of renewable energy sources [3], since OECD (Organisation for Economic Cooperation and Development) Europe and IEA's (International Energy Agency) World Energy Outlook [4] project up to 23% market share of non-hydro renewable energy by 2030. Natural variations of resource availability do not necessarily correspond with the (also varying) need of the consumers. Balancing supply and demand is therefore a critical issue and potentially requires backup by other means of energy supply. The variations can occur at any time scale: hourly changes in output require balancing of short-term fluctuations by the so-called operational reserve, while days with low output require balancing of longer-term output fluctuations by so-called capacity reserves. Conversely, exceptionally windy days or rainy seasons can produce a surplus of supply and there might arise issues of handling excess capacity, where grids are not sufficiently interconnected. TSO's buy balance or reserve capacity in advance to ascertain secure grid operation. However, in addition to the anticipated cost savings, reliable forecasting aids in reducing the aforementioned problems, enabling high wind energy penetration and at the same time ensuring power system security and stability.

The development of wind energy is country dependent and the development structure is a function of the wind resource, the political environment, the electrical grid and the market. This means that different strategies are required to solve forecasting and, in a broader perspective, optimisation of energy systems in different countries.

Therefore, it seems to be natural to focus efforts on optimisation targets that can reduce the required reserve of the growing intermittent energy generation.

0.3 THE OPTIMISATION PROBLEM

Large amounts of wind power can not be integrated seamlessly into the electrical grid. There is a need for a combination of wind energy forecasting, interconnectivity and storage capacity to ascertain smooth operation. Today's market participants are not delivering this mixture of services and there are costs associated with each of these services. Forecasting is the cheapest solution and may in fact be sufficient to get a mix of power implemented in an optimal way.
The application of wind power forecasting can generally be divided into two different kinds. The first kind is to reduce the need for balancing energy and reserve power, i.e., to optimise the power plant scheduling. The second kind is to provide forecasts of wind power feed-in for grid operation and grid security evaluation. Wind power forecasting may well be one of the most direct and valuable ways to reduce the uncertainty of the wind energy production schedule for the power system. Therefore, the objectives of a wind power forecast depend on the application [5]. It in fact has to be separated between the following targets:

- For optimised power plant scheduling and power balancing, an accurate forecast of the wind power generation for the whole control area is needed. The relevant time horizon depends on the technical and regulatory framework; e.g., the types of conventional power plants in the system and the trading gate closure times.

- For determining the reserve power that has to be held ready to provide balancing energy, a prediction of the accuracy of the forecast is needed. As the largest forecast errors determine the need for reserve power, these have to be minimised.

- For grid operation and congestion management, the current and forecast wind power generation in each grid area or grid connection point are needed. This requires a forecast for small regions or even single wind farms.

0.3.1 Energy Prices and Market Structures

Competitive energy prices in a globalised world require a mix of multiple sources of energy. This is in fact a prerequisite in order to keep the energy generation process cost efficient. Shortage of components or resources will increase the price of a given energy generation method, if there is major concurrent demand. Renewable energy systems are therefore likely to be more expensive to install, whereas they are cheaper to operate. This is also due to fear of increasing prices of fossil fuel, further destruction of our environment and climate change.

The different marginal costs for different generation is another argument that points towards highly mixed energy systems. The future of energy will therefore most likely contain a more complex mixture of energy generation and development, possibly with the exception of regions with excessive resources of one particular energy source. Consequently, we have to expect that the electricity systems are going to become more complex to manage.

There is a strong trend that the society is in favour of supporting new developments of renewable energy and in particular non-scheduled intermittent sources such as wind energy. We therefore focus on how to keep a sustainable price for wind power. The optimisation strategies that will be presented hereafter may result in higher energy prices in the short-term, but a relatively lower energy price in the long-term compared to non-cost optimisation scenarios. The optimisation target here is therefore to the benefit of the entire society, but first of all to the current wind farm owners in markets, where wind power is frequently the price maker.

There may be other valid optimisation targets such as minimal emissions. This would however favour nuclear energy and lead to the dependency on one natural resource, unknown issues regarding the nuclear waste and therefore risk of high energy prices. In addition, nuclear energy is not a flexible energy generation mechanism, which could effectively complement the intermittent energy units. Either the nuclear or the intermittent generator would have to generate less power than they potentially could, each one at their standard marginal cost.

0.4 OPTIMISATION OBJECTIVES

Production incentives naturally help to increase the amount of renewables. These incentives are typically defined on the national level. The incentives are in most cases not important for the optimisation problem, but they may encourage a phase shift of the generation by using a storage unit and thereby maximising the production while the market price is highest instead of delivering power when the intermittent power generation is natively highest.

0.4.1 Market Considerations

Differences in the market structures, politically defined support systems, demand profiles and the inertia level of the scheduled power generation does make the optimisation problem specific for each region, if not even for each end-user. However, there are some basic difficulties, which all markets will experience once the volume of intermittent energy resources reaches during certain time periods “price maker levels”. The physical nature of the difficulties are in fact independent of how and by whom the energy is traded.

Our aim is therefore to present an optimisation strategy that works equally well in systems, where wind power is handled centralised or de-centralised, regardless whether it is managed by a TSO or not. The basic strategy is the same. The fundamental problem is how to trade the varying amount of wind power on the market and to determine the value. The value depends on how well the intermittent energy satisfies the demand, the predictability of the weather and also how eager the scheduled generators are to deliver power. The difficulty increases with the ratio between intermittent generation and demand, apart from the eager scheduled power generators such as CHP plants that also need to generate heat and therefore have very low marginal costs for electricity generation.

0.4.2 Transition from fixed Prices to the liberalised Market

The incentive to operate wind optimal from an economic perspective might however not always be given, if there is a fixed price policy and the consumers are enforced to pay over tariffs. It is very difficult to clarify in such cases, whether the system can be optimised. The alternative approach is then to leave it up to the wind generation owners to optimise the system. Fixed price policies may also be limited to either a number of years or are valid only until a certain number of MW-hours has been produced. Wind farm owners are usually thereafter enforced to trade their energy on market terms. The transition to market terms can be difficult, if there is a public monopoly that dumps the price with wind energy and takes the loss back over tariffs. This is especially the case on markets that operate with the price-cross principle on the day ahead spot market (e.g. the Nordic states). This leaves almost no possibility to get a good price for the energy produced, if the monopoly has enough volume to meet the demand. Wind power that has to be traded on market terms could in such cases in the future also be traded outside the market directly to other participants, which may be capable to absorb the energy in their energy pool. There are in fact also initiatives in Germany to get the possibility to trade wind energy directly on the market, although wind energy is by law traded by the TSO's and paid by a fixed price tariff [6]. While it is not yet clear how such models will be implemented into the legislation, they are a signal that there is an interest by the society in optimising the cost of clean (wind) energy.

Even though price dumping, as described above, is neutral for the end-users if there is no or little export, it nevertheless significantly lessens the value of renewables and in particular wind energy for the wind turbines/farms that operate on the market without the possibility to get a fixed price. If price dumping leads to export, then the importing party is receiving energy not only as clean energy, but also for a very low price, partially because it is paid over governmental subsidy in the area where it was produced. It is expensive for a society in the producing area to practise such export in the long run. It also means that such a country either has to produce the bulk of energy from renewables, or otherwise it will create a negative imbalance in the country's allowance of carbon emissions when exporting renewables.

In other words, price dumping prevents wind energy from becoming competitive and to develop to a non-subsidised energy source, at least in Europe. This is in the longer term not in the society's interest.

To conclude, a single wind power plant on its own will not be able to compete with a pool of many plants, unless it is located in unusual predictable weather conditions and hence could be considered a semi-scheduled plant. However, there are also means to operate as an individual on the market by outsourcing the handling of the wind power trading to parties that are specialised in this and may pool the energy of their aggregated customer's power to a larger portfolio. Sufficiently large wind generators may in the future also consider to forecast and trade themselves in order to get the market price in addition to some incentives, but also the penalties. Nevertheless, this is expected to be the most profitable way forward for wind energy in the future.

0.4.3 The skew Competition in the Trading of Wind

The wind generators are some of the weakest parties on the energy market seen from a trading perspective. Everybody with a good weather forecast and with a reasonable approximation and experience on the market can predict the wind energy generation in windy periods and therefore also the impact on the market price from wind. This is not so much a problem as long as the fraction of wind energy of the total generation is less than $\sim 10\%$. Above this level, this becomes a more serious problem, since the wind power traders are forced to bid on the energy to a relatively low price or the traders risk to be forced to sell the energy to a pool for a lower price after gate closure.

As previously mentioned, it may be the most beneficial way to trade wind energy with a pool that contains sufficient storage to create additional uncertainty on the market regarding the available energy than what the weather forecast provides. In such cases, the market can no longer predict the energy generation from wind power and speculate as aggressively against the wind power trader. The market can as an example not know, if the wind energy pool decides to store energy for some hours instead of delivering the power and thereby take the peak off the wind power generation. The scheduled generators can in time periods of strong wind speculate against the wind power trader by setting a price that lies below the marginal costs, because they know that the wind will be available for a marginal price, if the wind generation was bid in with a higher price than their own. If the scheduled generators know that wind generation may not be available for a near zero price, because it may be withheld from the market for storage, then the risk becomes too high and the scheduled generator will stop such speculations.

Pooling can hence be regarded as a security measure against unfair speculation. The pool will in that case be used in daily operation to phase shift wind generation such that the correlation between the demand and total output of the pool is highest.

0.4.4 Uncertainty Considerations

Another factor that has impact on the market price and competition level is the uncertainty of the weather forecast. Uncertain weather requires that more energy generation is active, either as primary energy or as reserve. This again increases the average energy price, because a larger fraction of the available generation will be required for balancing.
Steep ramping of wind power is an indicator of uncertainty in the weather and often even a cause of such. Nevertheless, steep ramping requires more scheduled capacity online, because the efficiency of the ramping generators is lower during the ramp.
On the other hand, there are also times of low uncertainty and high wind power generation. In these times, the traders of wind energy have to do something extraordinary to get rid of the energy. Although it may still be possible to bring the energy into the market by using dumping prices, it may not cover the marginal costs anymore. However, once a certain percentage of the total consumption is exceeded, other methods will have to be applied. These include energy pooling, export, methods to increase the demand and other trading strategies.

0.5 OPTIMISATION SCHEMES

In this section we describe a number of optimisation schemes that are either already in operation, or are likely to become part of the near future's energy trading at the markets.

0.5.1 Pooling of Energy

The optimisation problem when looking at pools of energy is relatively complex. Therefore, an example will be used in the following to illustrate the optimisation targets and possibilities of this scheme.
Let us introduce the Balance Responsible Party (BRP) as the party that ascertains that the wind together with other generation units in a pool follows the planned schedule for the pool. The BRP may not be a generator, but some party that has the required tools to effectively predict and manage the different pool members in an optimal way seen from the pool members point of view.
The first milestone for the BRP is to bring together a sufficient amount of uncorrelated wind power in the pool. The lower the correlation on timescales greater or equal than an hour, the lower the forecasting error and the higher the energy price. Low correlation means that the area aggregation over individual sites gives a smoother output signal, which is easier to forecast. The same smoothing is then implicitly applied to the forecast. The net result is that the phase on the shortest timescale of the individual wind farms is invisible on the aggregated power generation.
A large volume of wind power also helps to level out negative impact from problems due to restrictions on the grid or reduced turbine availability, although these may

only appear as small errors in a large pool.
One of the key parameters for a BRP is to secure a permanently high level of uncertainty of when and how much energy the pool is delivering to the network. As discussed earlier, this is because the wind power trading becomes vulnerable to speculation from stronger market participants, if it can easily be derived how much wind energy needs to be traded on the market. This is not a trivial task for the BRP, because there are also other constraints, which limit the possible "confusion" level introduced to the market.
Hence, the major tools that the BRP needs apart from the wind farm capacity are:

- A storage unit
- An ensemble prediction system for the difference between demand and wind power
- A short-term prediction system for wind power and demand
- An optimisation tool

An optimisation tool hence should combine forecasts with grid constraints, market trends and the physical constraints of the storage unit. Congestion on the grid is a typical reason for higher prices, but mostly to the disadvantage of the energy pool, if it is dominated by wind power. The optimisation problem is in theory global, but in practise a limited area problem, because the global problem extends to political decisions that would have to be modelled by stochastic processes. Instead, optimisation should be applied on the local grid. For this, time dependent boundary conditions are required. These should in theory contain the large-scale global trends, but at some stage approach the average trends for the season. The optimisation tool will have to comprise a set of partial differential equations including the storage unit, a portion of the grid and the intermittent energy sources. The partial differential equations describe the total output and exchange between storage units and the intermittent source. The accuracy of the numerical solution is partially determined by the extent of the domain of dependence for the partial differential equations. The domain increases with forecast horizon and can well reach part of the boundary, if the boundary values are accurately predictable by a simple function or some other prediction tool.
An example of a predictable boundary condition could be the large-scale electricity demand, which could be approximated with a periodic function to simulate the diurnal cycle. The large scale demand will after some hours have an influence on how the storage system should be scheduled, but the time derivatives of our intermittent energy is then likely to be the dominant forcing term on the storage equation.
The domain of dependence for the solution increases with the forecast horizon, partly because the dependency domain of the weather forecast increases. However, such an

energy system has as a good approximation no feedback on the weather, thus this system can be one way coupled. Also, trading of oil and the transmission of gas have both an influence on the pricing. Conflicts between employers and their labour (e.g. strikes), unavailability of multiple plants and extreme weather at offshore platforms can cause peaks in the spot market prices of gas and oil and consequently also electricity. Such peaks can have a dominant negative impact on the average market value of wind power, if there would be imbalance in the pool during an interval with high prices.

An objective optimisation process would hence require an algorithm that carries out simulations in a closed system, but with the possibility to control the time dependent boundary conditions. Typically, a strike would be known in advance and the time dependent boundary conditions could be manually adjusted by the user to take account for such effects. Although the optimisation problem should ideally encompass the entire globe, it appears that the impact from far distances on the next couple of days can be modelled equally well by subjective boundary conditions, as with attempts to objectively model such effects. The conditions that take place at far distances are rather consequences of unpredictable events that have spurious nature. Any objective algorithm would have to be tuned to discard observations that conflict with the present state of the system to prevent that the large scale numerical solution would become unstable. Large scale waves would propagate through the system and trigger new waves on the local scale and the final solution would destabilise the energy system and the result would be higher balancing costs. It is important that objective systems only accept observations that are likely to be correct. They must lie within an a priori defined uncertainty interval or be discarded.

Spurious waves in an objective system are worse than no waves, even if they would be correct, because the user does often not know of the source of the observations and it may be difficult to trace back. It is therefore most important in the design of the optimisation tool that the end-user can work with and define a robust set of boundary conditions and can explore the sensitivity of the solution to a number of incidents that are each relatively unlikely events.

0.5.2 The "Price Maker" Optimisation Problem

If the optimisation target is to predict an optimal price in an area between two market systems with a price difference due to a limited interconnection capacity between the two markets, it is considered a "price maker problem". This is because the energy would flow from the low price area to the high price area and the BRP would try to sell the energy in the direction of the high price area like other participants and there would be some likelihood of congestion on the line.

The "price maker" must therefore continuously predict the price of the neighbouring areas with more inertia and try to trade in the direction of the highest price. This involves usage of weather forecasting on larger scales and computation of demand

and intermittent energy generation. In this case, it is no longer sufficient to just predict what may be correct for the BRP itself. Other market participants might have access to different forecast information and may conclude very different or similar scenarios. This is thus an application, where ensemble forecasting is helpful. Depending on the ensemble spread, the likelihood of high or low competition can be determined and therefore also the price level on the market.
The weather determines the upper limit for what the BRP can sell. Before gate closure a decision has to be taken on the basis of weather forecast information. However, the BRP may decide to sell less or more than he expects to be produced, depending on the likelihood of the weather and the expected balancing costs. The "price maker" is likely to also cause the bulk of the imbalance and therefore also the bulk of the balancing costs. The "price makers" sign of the error will correlate with the sign of the total imbalance. This means that the error in every settlement interval counts as a cost, while this is not so for the "price taker" party whose sign is maybe 50% opposite to the "price makers" sign. The BRP has therefore an incentive to keep the balancing costs at zero and let other parties carry the balancing costs. The BRP can achieve this by using the ensemble minimum as a safe base generation. However, this principle leaves some excess energy at times, that needs to be traded with short notice on average under the sport market price scheme.

0.5.3 The "Price Taker" Optimisation Problem

A small pool (in MW) can be traded and optimised with a so called "price taker" policy. This means, that the pool does not necessarily need price predictions, but only needs to keep the generation profiles according to their schedule. The "price taker" can assume a diurnal cycle of the demand and a pricing that follows this pattern. As a refinement, the "price taker" can try to predict the generation profile of competing intermittent generation and from this compute a new price profile of the trading interval. This would in some cases encourage to reschedule generation to achieve the highest possible price. Thus, instead of predicting the price for the bid, the "price taker" predicts the intervals with highest prices and schedules the generation, so that most hours are delivered during the high price time interval. This strategy secures that the "price taker" will get rid of the energy at the highest possible price. However, it also means that the "price taker" needs a rather flexible pool of generating units.

0.5.4 The Combi-Pool Optimisation Scheme

The lower the predictability of the energy pool the better. Pumped hydro energy is one of the key storage units along with combined heat and power (CHP) and in smaller portions with biogas (e.g. [7], [8], [9]). In a CHP plant the energy can be stored as heat, if the energy regulations allow to do this on market terms. It is however useful to introduce the concept of scheduled demand, which is a better

description of what such a "combi-pool" needs to include. Some markets do not allow direct coupling of generation and demand. It is nevertheless the most efficient way to level out differences between demand and generation.
Generally, the system operators often export imbalances and there seems to be a trend that larger markets work with increased import and export. This is on the one hand levelling prices out and helping non-scheduled generation and it may in many cases even be a better alternative to use scheduled demand. This would mean that heavy industry could benefit from low prices. Using both would allow for more intermittent energy on the grid.
What is going to increase the efficiency of a BRP is therefore a number of inventive solutions. The difficulty in predicting the price and output from a BRP increases with the amount of negative scheduled MWh and MW in the pool. However, information of the pool needs to be kept highly confidential for maximum competitiveness, which is under strong debate in Europe at present [10], if the BRP are TSO's.
Last but not least, the question has to be raised whether it is scientifically correct to optimise a system with a mechanism, where the primary target is to generate confusion for the market participants? The answer is yes, because this is the primary principle of the free market to maintain fair competition. Wind power does not operate under such fair competition, because it is exposed to the world via weather forecasts, which is strictly speaking against market principles.

0.6 WIND POWER FORECASTING METHODS

Now that various optimisation strategies have been discussed, it is important to get an understanding of the forecasting methodologies and possibilities to set up optimisation functions for the trading of wind energy. Therefore, the following sections will provide various approaches of wind power forecasting and discuss the error that the forecasting process is subject to. An error decomposition is used to give insight into the forecasting problem, but also into the limitations of forecasting. These limitations are the prerequisite to build up an optimisation system that benefits from this information to predict the required reserve to balance the intermittent energy source.
Following these principles, two different types of optimisation schemes for existing BRP's are described and demonstrated. These are discussed and conclusions are drawn to allow other optimisations scenarios to be set up as described above.

0.6.1 Different Approaches to Forecast Power Output

The aim of a wind power forecast is to link the wind prediction of the NWP model to the power output of the turbine. Three fundamentally different approaches can be distinguished (e.g. [5], [11], [12]):

- The physical approach aims to describe the physical process of converting wind to power and models all of the steps involved.

- The statistical approach aims at describing the connection between predicted wind and power output directly by statistical analysis of time series from data in the past.

- The learning approach uses artificial intelligence (AI) methods to learn the relation between predicted wind and power output from time series of the past.

In practical applications these methods are sometimes combined or mixed. The different types of wind power forecasting methods and systems currently in use worldwide were summarised by Giebel et al. [11].

It should be noted that, whenever possible, dispersion of wind power over large areas should be performed, as the aggregation of wind power leads to significant reduction of forecast errors as well as short-term fluctuations. In countries with a longer tradition and fixed feed-in tariffs this seems to be the natural way wind power is deployed. However, in countries, where wind power is relatively new and where larger single wind farms have been and are being built, developers, TSO's, authorities and policy makers will have to consider in the future pooling of energy sources not only to it's technical and economic feasibility, but also to allow for and set rules for such approaches, if efficient and environmentally clean deployment of renewables, especially wind energy, is a target.

0.6.2 Ensemble Prediction Systems

The use of ensembles is intended to provide a set of forecasts which cover the range of possible uncertainty, recognising that it is impossible to obtain a single deterministic forecast which is always correct [13]. An ensemble prediction system (EPS) is one that produces a number of numerical weather forecasts, as opposed to a single, deterministic forecast. Ensemble techniques have been employed for some time in operational medium-range weather forecasting systems [14]. Three approaches dominate the field: (1) Ensemble Kalman Filter (EnKF) approach (e.g. [15], [16], [17]), (2) Singular vector (SV) approach (e.g. [18], [19], [20]) and (3) Breeding approach (e.g. [21], [22]). There are two other ensemble methods, the multi- model approach (e.g. [23], [24], [25], [26], [27], [28]) and the multi-scheme approach. These are discussed and tested in several studies of their feasibility (e.g. [27], [29], [30], [31], [32]). The multi-model method results in independent forecasts, but the exact reason of the independent solutions will never be understood. Similar arguments do not apply to other ensemble prediction methods.

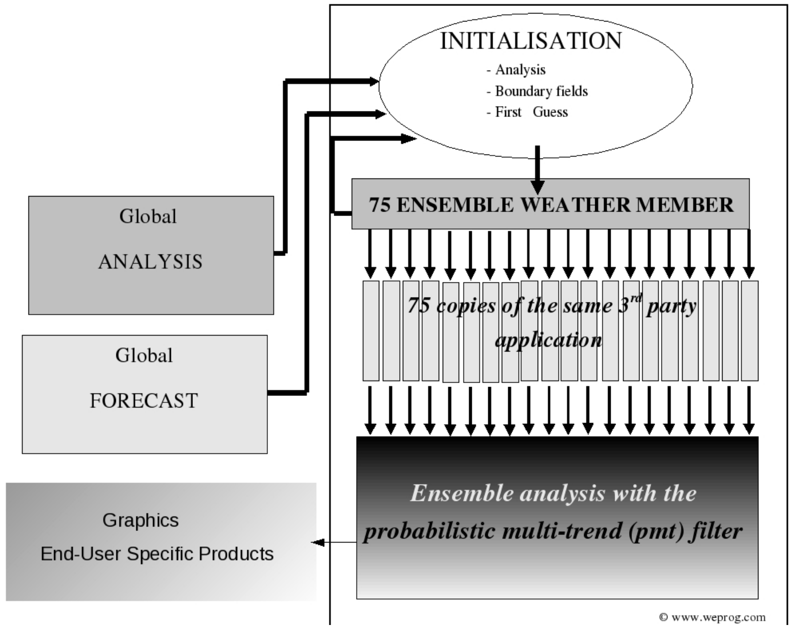

Figure 1: Schematic of the MSEPS ensemble weather & wind power prediction system.

0.6.3 The MSEPS Forecasting System

The Multi-Scheme Ensemble Prediction System (MSEPS) that has been used for our studies and which will be described later in this chapter, is a limited area ensemble prediction system using 75 different NWP formulations of various physical processes. These individual "schemes" each mainly differ in their formulation of the fast meteorological processes: dynamical advection, vertical mixing and condensation. The focus is on varying the formulations of those processes in the NWP model that are most relevant for the simulation of fronts and the friction between the atmosphere and earth's surface, and hence critical to short-range numerical weather prediction. Meng and Zhang [31] found that a combination of different parameterisation schemes has the potential to provide better background error covariance estimation and smaller ensemble bias. Using an EPS for wind power prediction is fundamentally different from using one consisting of a few deterministic weather prediction systems, because severe weather and critical wind power events are two different patterns. The severity level increases with the wind speed in weather, while wind power has two different ranges of winds that cause strong ramping, one in the middle range and a narrow one just around the storm level (the cutoff level). Wind power forecasting models therefore have to be adopted to the use of the ensemble data. In general, a wind power prediction model or module, that is directly implemented into the MSEPS is different from traditional power prediction tools, because the ensemble approach is designed to provide an objective uncertainty of the power forecasts due to the weather uncertainty and requires adaptation to make use of the additional information provided by the ensemble. Figure 1 shows the principle of the MSEPS wind power forecasting system. Apart from the direct implementation (e.g. [33], [34], [35]), some effort has been made in recent years by adopting traditional wind power prediction tools to ensemble data from the MSEPS system in research projects and studies (e.g. [36], [37], [38]).

0.7 ASPECTS OF THE FORECASTING ERROR

There is still a prevailing opinion in the wind energy community that the wind power prediction error is primarily generated by wrong weather forecasts (e.g. [11], [39]). From a meteorological perspective, this is a statement that may cause misunderstanding, because part of the error is due a complex mixture of weather related errors. The weather forecast process itself can only be blamed for the linear error growth with forecast length. We have therefore conducted an error decomposition in order to quantify the different error sources with a large ensemble of MSEPS weather forecasts. Traditionally, increased spatial weather prediction model resolution has been said to provide better forecasts (e.g. [40], [41]), but the shortest model waves may anti-correlate with the truth and cause double punishment in the verification (e.g. [32],[42]) and thereby additional model error. An ensemble prediction approach is another way to improve forecasts with fewer anti-correlation hours and the possibility to predict and understand forecast errors.

0.7.1 Wind Power Error Decomposition

In order to understand the forecasting error in wind power, we have carried out a decomposition of the influencing components that have let to misunderstanding in the past. The analysis to do this includes forecasts generated in 6 hour frequency. This means that one particular forecast horizon will verify at four different times each day. The forecast error was accumulated in 6 hour bins with centre at 3, 9, ..., 45 hour prediction horizon for additional smoothing. This hides the disturbing diurnal cycle arising from verification once per day. Thereby a linear error growth with prediction horizon is achieved. Figure 2 shows such an error decomposition for a 1-year verification over the forecast length 3-45 hours with data from the western part of Denmark. By generating a decomposition of the forecasting error it can be illustrated, which parts of the error can actually be due to the weather forecast process. In Figure 2, we have split the error into a background error and a prediction system error with a linear error growth. We illustrated the potential improvements from the weather part with “good forecast”, “average forecast” and “poor forecast”, which differ to a certain degree. However, when looking at the background error,

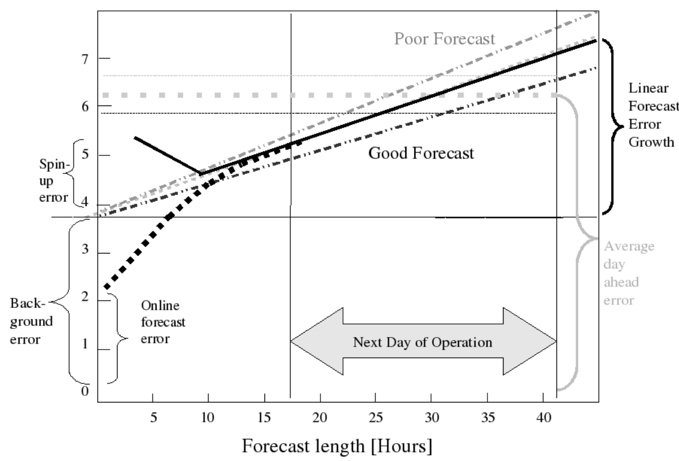

Figure 2: Error decomposition example generated with 1-year of data from the western part of Denmark.

then the differences between a "good forecast" and a "poor forecast" is less significant. The background error is not directly "felt" by end users, because this initial error is in the daily operation either recovered by short-term forecasts with use of online measurements or if this is not available, by extrapolating the online measurements a few hours ahead. In the day-ahead trading, which takes place in most countries approximately 12 hours before the time period at which the bids have to be given on the market, the first few hours of the forecast are also irrelevant. The light gray line represents a typical pattern of an online forecast. This forecast has a steeper error growth, but starts from zero. A short-term forecast 1-2 hours ahead is typically close to the persistence level except in time periods, where the wind power ramps significantly.

The linear error growth indicates that the weather forecast is responsible for about 1/3 of the error in the forecast for the next day and the remainder is a background error originating from different sources. These additional error sources were found to be due to: (i) the initial weather conditions; (ii) sub grid scale weather activity; (iii) coordinate transformations; (iv) the algorithm used to compute the wind power; (v) imperfection of turbines and measurement errors. The question remains, which fraction of the background error is caused by imperfect initial conditions of the weather forecast and which fraction is due to erroneous wind power parameterisations. By extrapolating the linear forecast error growth from 9-45 hours down to the 0 hour forecast, the background mean absolute error (MAE) could be estimated to be just under 4% of installed capacity. Therefore, we added an additional fixed uncertainty band of +/- 4% of the installed capacity to the native MSEPS ensemble uncertainty to account for the background error that exists in addition to the weather forecast generated error. With this band, we achieved that 8120 hours out of 9050 hours or 89.7% of the hours are covered by the predicted uncertainty interval. The remaining 10% have numerically large errors that are only partially covered by the MSEPS uncertainty prediction. Figure 3 shows a scatter plot of this test. The x-axis shows the measured wind power [MWh] and the y-axis the mean absolute error (MAE) in % installed capacity. The black crosses are those forecasts that deviate less than +/- 4% from the measurements. Here 8120 hours are equivalent to 89.7% of the time. The gray crosses towards the top show those errors that are greater than +4% and are measured for 576 hours, equivalent to 6.4%. The gray crosses towards the lower boundary are 354 hours and equivalent to 3.9% of the time.

A 4% constant background error is a poor approximation and probably the explanation why 10% of the error events are unpredicted. Part of the background error is due to the computation of the wind power. The inherent error from the conversion of wind to power of course also has an impact on the error, not only the weather forecast. The difference of different methodologies for different forecast problems can be quite large. We will therefore demonstrate this difference in the next section. The following list shows the methodologies that have been used in this demonstration. The power prediction methods can be distinguished as follows:

- Method 1: Direction and time independent simple sorting algorithm.
- Method 2: Time dependent and direction independent least square algorithm.
- Method 3: Direction dependent least square algorithm.
- Method 4: Direction dependent least square algorithm using combined forecasts.
- Method 5: Same as method 4, but including stability dependent corrections.
- Method 6: 300 member ensemble forecast of method 5 - all farms are handled individually and 6 parameters for each one of the 75 members are used to compute the power.

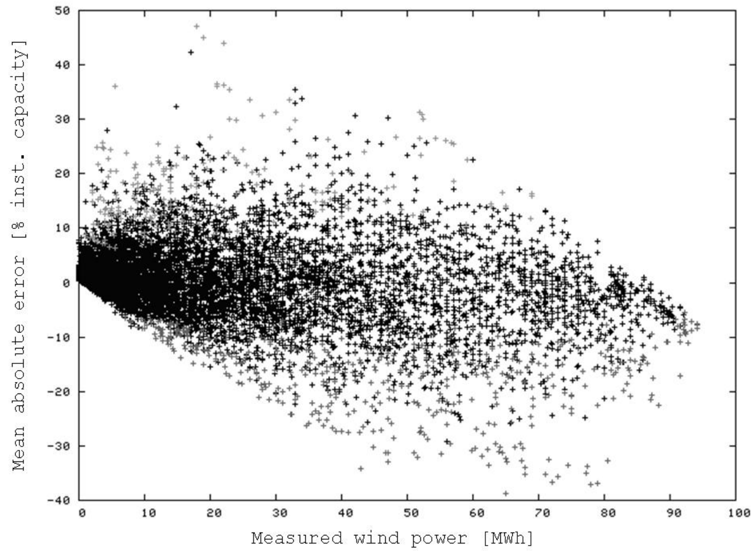

Figure 3: Scatter Plot of the mean absolute error (MAE)with a constant background error of 4% added to the native forecast of the EPS mean. The black crosses are EPS mean forecasts +/- 4% error, while the gray crosses display the errors that lie outside this band.

Note, when considering the results from investigating these different power prediction methods, all values are given as the improvement in % to the mean absolute error (MAE) for the day-ahead forecasts based on only one daily (00UTC) forecast performed with the basic power prediction (method 1).

To verify the impact of the conversion from meteorological parameters to wind power on the forecasting error, we use these 6 different methods to convert wind and other weather parameters into wind power output. Table 1 shows the results of the different power prediction approaches based on the same weather data.

Each result differs only in the level of detail of the statistical computation of wind power. The verification for Ireland took place for a period of 1-year (2005) for 51 individual wind farms of a total capacity of 497 MW, the Danish verification of aggregated wind power was up-scaled from 160 sites and took place for the period 09/2004-10/2005 and in Germany the verification was conducted for Germany as a whole and three individual TSO's for a 10-month period with the up-scaled online measurements valid for approximately 19 GW from estimated measurements published by the three TSO's (01/2006-10/2006). It can be seen from Table 1 that the forecast quality has been improved significantly for all investigated areas from a relatively simple power curve conversion method (i.e. method 1) to a more complex

method (e.g. method 5 or 6), when making use of the additional information from the ensemble. The relatively low improvement in Australia is due to the fact that the background error is higher for only 6 wind farms in comparison to the areas with a large number of farms.
Three major results can be drawn from from this investigation:

- The advanced methods, using several parameters and EPS information are providing superior results to using simple methods.
- The forecasting error is dependent on the location, the size and the load of the farms/areas.
- Detailed measurements can significantly reduce the forecast error.

Table 1: Statistics of the investigation of different wind power forecast methodologies in various countries.

Method	Ireland	Australia	Denmark	Germany	E.ON	VE	RWE
Cap [MW]	497	388	1830	19030	7787	7486	3464
Load [%]	33	30	21	16	16	15	16
1	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2	2.18	3.01	8.52	1.40	1.09	2.11	2.26
3	9.34	1.51	9.87	12.32	8.30	12.05	15.44
4	14.44	4.38	12.41	12.32	8.30	12.05	15.44
5	15.29	6.58	13.60	15.41	11.57	14.80	16.95
6	17.23	9.18	n/a	n/a	n/a	n/a	n/a

0.8 RESERVE PREDICTION AND OPTIMISATION

The economic value of wind power is related to the predictability of the weather and hence the wind power. The required forecast horizon depends on the market structure and the inertia of the conventional power plant. An economic benefit from uncertainty predictions can in the most static markets only be achieved, if the prediction ranges up to 48 hours ahead. The trading of up-regulation and down-regulation can then be synchronised with the trading of the total generation and therefore the handling costs of wind power on the grid can be optimised.
This creates not only an economic advantage for the system operator, but also a fair strategy for the intermittent energy source, as it prevents dominant generators with large market shares gaining exclusive contracts caused by the imbalance from wind generation. In addition to the economic benefit, there is a security benefit of trading reserve capacity in advance, as the capacity can then be scheduled with the focus on grid security.

0.8.1 Optimisation of Reserve Predictions: Example Denmark

Next an example of a reserve prediction scenario is presented, based on a situation in which there is knowledge of the uncertainty of the wind power forecast in advance. This assumption is reflected by the statistical scores.
The up-regulation and down-regulation has been counted separately, because of the asymmetry in the market pricing structure. Note however, that for convenience, the computation of the *optimal forecast* in the example below is for simplicity based on the assumption that the price of up-regulation and down-regulation is the same, which would normally not be the case. It should in most cases be more efficient to trade with a lower prediction of future production of wind power than expected and arrange for down-regulation, when the wind power production increases above the predicted power, because down-regulation is in many markets n average only 25% of the price for up-regulation.
In our example, we compared different forecasting scenarios:

1. Scenario: Use of the optimal forecast and reserve prediction for next day's wind generation.

2. Scenario: Use of the optimal forecast for next day's wind generation, where reserve is only allocated on the next day according to the demand.

3. Scenario: Use of the Ensemble average forecast for next day's wind generation, where reserve is only allocated on the next day according to the demand.

The scenarios in this example were constructed for a fully competitive market, where reserve capacity is traded day-ahead. In this example, we used the same single forecast in both scenario no. 1 and no. 2. In scenario no. 1 we allocated reserve capacity in a market with competition on reserve. In case no. 2 and no. 3 all regulation was traded according to the demand on the short-term spot market.

Scenario no.	1	2	3
EPS configuration	optimal*	optimal	average
Number of Hours	2331	2331	2331
Forecasted Mean	27.01	26.6	26.7
Bias	-0.77	-1.19	-1.02
Mean Absolute Error	2.72	5.30	5.83
Stdev Error	5.39	7.60	8.32
Correlation	0.977	0.953	0.946

Table 2: Results of the 3 scenarios of using and not using spinning reserve predictions in the wind power production forecasts for the western part of Denmark in the period January to April 2005. All statistical quantities are given as [%] of installed wind power capacity of Western Denmark

Table 2 shows the results of the 3 scenarios. Note, that all values are in units percent of installed capacity. The numbers are taken from prioritised production in the western part of Denmark in the period January to April 2005. The forecast horizon is 17 to 41 hours until daylight saving starts, then the forecast horizon changes to 16 to 40 hours. The total prioritised production is rated at 1900 MW in this period, which is almost equivalent to the minimum consumption in this area.
It can be seen in Table 2 that (scenario no. 1) using the optimal forecast and reserve prediction for next day's wind generation almost halves the mean absolute error (MAE) of both scenario no. 2 and scenario no. 3 and hence the costs for expensive spinning reserve for unexpected events (errors). The root mean square scores are slightly lower, but still of the order 30% and 40% better for scenario 1 than for scenario 2 and 3, respectively. The lower improvement in the root mean square (RMSE) is related to the fact that the prediction of the forecast error removes the smaller errors in a band-like way around the optimal forecast. Since the RMSE is more sensitive to the larger errors, the improvement is lower.

Table 3 shows the percentage of reserve of installed capacity that is required, predicted and non-predicted in scenario 1. It can be observed that the predicted up-regulation provided better results than the down-regulation. This is the result of optimising the forecast towards the less costly reserve.

Regulation type	Regulation magnitude	description
Average Up	2.40	required regulation
Average Down	3.43	required regulation
Predicted Up	1.43	traded day ahead
Predicted Down	1.68	traded day ahead
Unpredicted Up	0.98	traded on the day or handled by flexible contracts
Unpredicted Down	1.75	traded on the day or handled by flexible contracts
Unused	0.91	unnecessary regulation capacity

Table 3: Results of the verification of the predicted regulative power on a long-term basis for the Western part of Denmark in the period January to April 2005. The regulation magnitude is given as % of installed wind power capacity. The results correspond to scenario no. 1.

The average of the ensemble has a score of 5.83%. This is approximately the same score as the best single ensemble member. The *optimal forecast* gives the same period 5.35% absolute error. In the above example we found that if we add the uncertainty band and trade the predicted amount of reserve for both up-regulation and down-regulation on the market, we can reduce the error to 2.72%. This means that we have to trade regulation for only 2.72% of the capacity instead of 5.35% in the short-term spot market with high prices.

In this computation, it is assumed that there is no error when the error of the *optimal forecast* lies within the predicted uncertainty band. This increases the correlation significantly, which indicates that a large fraction of the forecast errors within the uncertainty band are completely unpredictable. We suggest that these errors are handled most efficiently by being balanced with pre-allocated constant reserve.

To be able to estimate the impact of such a pre-allocation, we considered 5 cases, with different percentages of pre-allocation and computed the amount of hours, where the pre-allocation accounts for the forecast error. With these results, it becomes feasible to set up a cost analysis of the optimal amount of pre-allocation. Our intention here is however merely to demonstrate how to design an optimised prediction system for a specific problem.

In the following we have therefore constructed 4 cases, where a fixed fraction of the installed capacity is pre-allocated as reserve with a long term contract and additional capacity is assumed to be allocated in a market with competition according to the predicted requirement (see scenario 1 above).

1. Case: Additional long-term contract for reserve of 0.8% of the inst. capacity

2. Case: Additional long-term contract for reserve of 1.6% of the inst. capacity

3. Case: Additional long-term contract for reserve of 3.2% of the inst. capacity

4. Case: Additional long-term contract for reserve of 6.4% of the inst. capacity

5. Case: Additional long-term contract for reserve of 12.8% of the inst. capacity

The following equation has been used to compute the number of hours when the pre-allocated reserve accounts for the forecast error:

$$R = max(R_{pre}, a_{stability}x + b_{stability}) \qquad (1)$$

where R_{pre} is the pre-allocated reserve from Table 4 and x is the ensemble spread. The sum of the hours, where the resulting pre-allocated reserve fully covers the forecast error is shown in Table 4. It can be seen in the table, how well the ensemble spread covers the forecast error for different levels of pre-allocation. The validation also reveals that only 3 hours out of 2331 hours (97 days) had forecast errors that were not covered by the reserve given by equation 1 when using a 12.8% pre-allocation.

case no.	pre-allocated reserve %	no reserve required hours	percent coverage [%]
1	0.8	1049	45%
2	1.6	1439	62%
3	3.2	1696	73%
4	6.4	1990	85%
5	12.8	2228	96%

Table 4: Number of hours out of 2331 hours where no additional reserve to the day-ahead and pre-allocated reserve is required for different levels of constant pre-allocation.

A pre-allocation of nearly 13% to reach 96% coverage by using this type of reserve is quite a large amount compared to the mean absolute error (MAE) of the forecast (¡ 6%). It is therefore recommended to study and evaluate from case to case and with real market data, if more than 10% of pre-allocation is a reasonable result of the optimisation. However, since there exists a pronounced price difference between up-regulating and down-regulating reserve, this amount could still proof as the most cost efficient.
It should also be noted, that this procedure does not eliminate the forecast error. Nevertheless, the reserve is traded more competitively than without using the predictions and hence the balancing costs can be reduced significantly.
Another aspect that may be of relevance in other countries is the combination of wind power and large power plants with respect to reserve requirements. In the western part of Denmark for example, the largest plant is 640 MW and corresponds to 33% of the prioritised wind generation. When this plant is in operation, then reserve requirements for wind power will never exceed the reserved 640 MW of up-regulation, which is required for this plant. A combination of wind power forecast failure and a 640 MW plant failure could of course cause a problem for grid security. However, it becomes clear from this example, that in a grid with large plants, it is not the amount of installed wind power that is responsible for the maximum reserve requirement and often also not for the large balancing costs. However, the shown methodology may also only provide a first step in how to combine the reserve allocation of larger power plants and wind power within an acceptable risk management structure and well working interconnections to cover parts of missing power in case of correlated failures.

0.8.2 Optimisation of the Reserve Prediction: Example Canada

As described above, the reasoning for using cost functions rather than standard statistical measures is that the uncertainty in the weather is random. Converted to wind power, the weather uncertainty is sometimes found to be very low and sometimes found to be very high. In the long-term and if a reasonable amount of wind power is installed in an area, a constant reserve would consequently be inefficient and expensive. Additionally, full coverage of all forecast errors is expensive, also because there is always a risk of non-weather related accidents during operation. The following is an example of an area, where the weather is highly variable and so is the wind power production. Within Alberta Electric System Operator's AESO's wind power pilot study [43] it has also been found that strong ramping is not seldom. In such areas larger amounts of constant reserve allocation are very expensive. The investigated scenarios are therefore based on this experience and the next step in benchmarking and adopting a forecasting system no longer to a low mean absolute error (MAE), but rather to the conditions under which the wind power integration takes place and optimise the forecasting system with this knowledge.

Optimisation Scenarios

1. Scenario: Static Regulation
   In this scenario the upper limit for reserve allocation from the error statistic of one forecast over 1 year has been determined. The actual reserve allocation is limited by the forecast with the following restriction:

   $$FC + R < UB \tag{2}$$

   and

   $$FC - R > LB \tag{3}$$

   with

   $$FC - R < G < FC + R \tag{4}$$

   Here, FC is the forecast, R is the reserve, G is the actual generation, UB is the upper bound of full generation and LB is the lower bound of no generation. R is chosen to secure that the generation is always lower than the sum of the forecast and reserve and higher than the forecast without reserve, which is supposed to historically always be valid (here: 90%).

2. Scenario: Deterministic Forecast Regulation
   In this scenario the reserve R is chosen as a fixed reserve allocation for upward and downward ramping. We chose +/-11% of installed capacity, which is equivalent to the mean absolute error (MAE).

3. Scenario: Security Regulation
   In this scenario, the reserve R is computed from the difference between minimum and maximum of the ensemble in each hour of the forecast. There may however be areas, where it will be necessary to adopt the difference of minimum and maximum in such a way that single outliers are not increasing the spread unnecessarily.

4. Scenario: Economic Regulation
   In this scenario, an optimisation of scenario 3 is used, where the unused reserve allocation is reduced for economic reasons. As a first approximation the 70% quantile of the level in Scenario 3 was used. In a future optimisation, the skewness of the price of positive and negative reserve also would have to be considered.

The data that were used to simulate different scenarios was 1-year (2006) of forecasting data for two regions in Alberta, the South-West region and the South-Centre region, where 5 wind farms with a combined installed capacity of 251.4 MW were used. The simulation was carried out with 12-18 hour forecasts issued every 6th hour. The forecasting model system was run in 22.5 km horizontal resolution and the wind power forecast was a probabilistic forecast generated with 2 combinations of different power conversion methods each using 300 weather parameters from the 75 member MSEPS ensemble system.
In Table 5 statistics of the aggregated forecasts for the 5 wind farms are displayed.

Table 5: Statistics of wind power forecasts without reserve prediction.

Statistics Parameter	% rated capacity
Bias (FC)	-2.10
Mean absolute Error (FC)	11.60
RMSE (FC)	16.80
Correlation (FC)	0.85

In Table 6 all parameters are given in % of installed capacity. The relative cost of various types of reserve was not taken from market reports, but estimated as a percentage relative to urgent reserve on the spot market, which was set to 1.0. This gives the following estimates:

- Urgent reserve = 1.0%

- Unused passive reserve = 0.1%

- Allocated reserve = 0.6%

The "allocated reserve" is the reserve that is allocated according to the forecasts and assumed to be bought day-ahead. The statistical parameter in the first rows of Table 6 are based on the forecasts including a reserve allocation. This means that the estimated error is added or subtracted from the forecast according to the used optimisation scheme. Therefore, these parameters have an index FCR (forecast + reserve), while the statistical parameters in Table 5 are based on the raw forecasts and indexed FC. These FC forecasts were optimised on the mean absolute error (MAE) to the observations.

There are furthermore output results of three types of reserve in the table, the required reserve, the predicted reserve and the unpredicted reserve, respectively. These are named UpReg for up-regulation or DownReg for down-regulation of the power on the electricity grid because of incorrect forecasts. Although the difference in price for up-regulation and down-regulation, where down-regulation is often a factor of 3-5 cheaper than up-regulation, was not accounted for in these simulations, the cost function is more favourable towards down-regulation than up-regulation. This can be seen in scenario 2 and 4, which are more cost efficient and use less up-regulating expensive reserve.

Table 6: Optimisation Scenarios for the AESO area.

Optimisation	Scenario 1	Scenario 2	Scenario 3	Scenario 4
	Static Reserve [% rated cap.]	Determin. FC Res. [% rated cap.]	Security Reserve [% rated cap.]	Economic Reserve [% rated cap.]
Reserve Predictor	75% reserve	FC+/-11%	max-min	0.7*(max-min)
Bias (FCR)	0.00	-0.85	-0.50	-0.80
MAE (FCR)	0.00	4.54	1.40	2.50
RMSE (FCR)	0.00	10.15	5.40	7.22
Correlation (FCR)	1.00	0.95	0.99	0.97
Required UpReg (7)	4.70	4.70	4.70	4.70
Required DownReg (8)	6.80	6.80	6.80	6.80
Predicted UpReg (9)	4.70	2.84	4.20	3.83
Predicted DownReg (10)	6.80	4.10	5.80	5.13
Unpredicted UpReg (7-9)	0.00	1.80	0.50	0.87
Unpredicted DownReg (8-10)	0.00	2.70	1.00	1.67
Unused Regulation	32.30	3.30	9.30	5.67
Effective cost	15.90	10.80	11.40	10.83
Hours covered by reserve	100.00	64.50	85.10	76.00

Table 6 also shows the significant difference in effective costs for the first scenario, the purely static reserve allocation, in comparison to the other 3 scenarios. However, when comparing the hours covered by the reserve, then it becomes clear that the coverage and the effective cost are cross-correlated for this type of optimisation. Scenario 2 is for example equally cost efficient than scenario 5, but covers only 64.5% of the hours, while scenario 4 covers 76% of all hours. Although the security scenario (no. 3) is slightly less cost efficient, the covered hours are quite significantly higher than for scenario 2 and also scenario 4 (85% versus 76% and 64,5%). Looking at the mean absolute error (MAE) or the root mean square error (RMSE), scenario 3 seems to also outperform scenario 2 and 4. However, when comparing the unused regulation, then the security scenario has almost double the amount of scenario 4,

and three times as much unused regulation as scenario 2. Dependent on the pricing structure of the market, which was excluded in this experiment, this could even change the effective cost levels of the scenarios,
‘ The results of the Canadian example demonstrate once again that the statistical error measures are not capable of providing a complete answer for an optimisation target. However, the results do provide an insight of the complexity of the optimisation of cost functions of reserve to end-users requirements.

0.9 SUMMARY AND DISCUSSION

The ensemble prediction method has a number of applications in wind energy integration and in energy in general. From the discussion in this chapter it can be concluded that energy markets can benefit from using ensemble predictions. Table 7 shows a general description of which forecasts from an ensemble forecasting system should be chosen for minimal costs. We have assumed that the capacity of wind power is sufficient for wind to be the “price maker” when the wind conditions are optimal. It can be seen in Table 7 that the forecast with the lowest mean absolute error (MAE) is not always the forecast that will generate the lowest cost of integration.
Although the original scope of ensemble prediction was to be able to conduct risk analysis of severe weather, it appears that the application in energy is not limited to grid security, but extends to trading and management of weather dependent energy generation systems. This includes all generation methods except nuclear power after the Kyoto protocol has become effective. Nuclear power generators do not have a CO_2 problem and have therefore the least incentive to participate in the balance of wind power. In the future, even nuclear plants may however need forecasts to be able to give bids on the market and to operate efficiently.

Table 7: Summary of the cost optimised forecast selection.

Predicted load factor in [%]	Competition on regulation	Forecast choice	Reserve allocation
0-10	Good on down-regulation	EPS minimum	Downward
70-100	Good on up-regulation	EPS maximum	Upward
20-70	Good for up and down	Best forecast	Down and up

The electricity price has a high volatility level because of the limited storage capacity and the strong relationship to oil prices, political disputes and not to forget the uncertainty in the weather development.
An increasing number of people around the world make their living on trading and because of the automatisation fewer people are required in today’s production

processes. This means that in the future, increasing volatility of stocks and energy can and have to be expected.
However, the volatility of the energy pricing may increase more than that of stocks for two reasons:

- The amount of intermittent renewables will increase more than the available storage capacity.
- The energy markets are developing slowly with new trading options.

Increased volatility on pricing will result in increased volatility on the generation as well, and consequently lower efficiency and higher costs. Increased volatility can also trigger instabilities on the grid. A typical example could be two competing generators that have to ramp with opposite sign to stay in balance. Increased volatility implies that the frequency of ramps will increase. Such ramps are not dangerous, but certainly do not add to the system security. The generators will bare the loss during the ramp, because of the higher average price.
The optimisation strategies that we have presented here serve to dampen volatility and the intermittent energy price. The main ingredients in this optimisation is ensemble forecasting, which increases the robustness of the decision process. Decisions will be taken on the basis of many results that are generated by some kind of perturbation. The market participants will, with the help of ensemble predictions in the future know in which range competing parties plan to set their bid on the market. There is also more continuity in time by using ensemble forecasting, because the decision process changes slowly hour by hour. This leads to a more stable decision process. Ensemble forecasting makes market participants aware of the risk of any speculation, although it may not be enough to prevent speculations.
A cost efficient way to dampen volatility is to allocate reserve in advance according to the uncertainty forecast for the intermittent energy source. The pre-allocation of reserve secures that a high level of competition can be achieved and last-minute volatility will be reduced.
A next step to reduce volatility is to create energy pools that allow phase shifting in time for intermittent energy. This will cap some of the price off the intermittent energy, because the balancing parties in the pool will demand a higher price than the intermittent generators. The more uncertainty there is on the pool's output for other market participants, the better for the pool. There is an incentive to make the pool members dynamic, so the other market participants cannot guess how much the pool is dependent on the intermittent generation pattern.
An additional step is required to secure fair prices during periods, where the intermittent energy is in excess. The market will often know the periods, where the weather is well predictable and the market price drops. Trading the intermittent energy several days in advance will allow scheduled generators to reduce their emissions and withhold their own generation. Their incentive to do so increases, if they

can schedule the production well in advance and thereby cut the marginal costs down.
Trading of intermittent energy requires therefore a special effort and forecasts with an ensemble technique along with temporary pooling with other energy sources will aid in achieving efficiency and stable prices.

0.10 CONCLUSION

The major benefit of ensemble prediction methods is that weather dependent energy generation can be classified as certain and uncertain. It has been tradition to not separate between certain and uncertain generation in the trading, because day-ahead markets were used to sell according to one best possible forecast only.
A creative trader could still trade strategically on the basis of a deterministic forecast and pool the deterministic forecasts with ancillary services and bid in the sum of the intermittent and ancillary service generation with a higher price.
Ensemble forecasting however opens possibilities for more creative and efficient trading strategies. Additionally, the trading process is going to become more complex and in fact too complex for a subjective decision process in the future. The objective decision process then has to be done on a computer based on predefined criteria.
The analysis in this chapter suggests that the model for the objective decision process has to be kept small. This secures fast convergence of the solution as well as the possibility for the trained user to redefine boundary conditions and test the solution's sensitivity to various likely and less likely events.
Another result that can be derived from our analysis is that a balance responsible party for intermittent energy should issue regular tenders on pool participation. This will allow an energy pool to deliver power according to a different profile than the weather allows for. Typically the generation should be phase-shifted to match the demand better. The net result is then that the market can no longer force the intermittent generator to bid in with low prices. The intermittent generator thereby gains freedom with the dynamically changing "cocktail" of pooled energy, weather uncertainty and advances trading according to the ensemble minimum. The more degrees of freedom, the higher the price for the intermittent energy, which is critical for the success rate in the future energy markets, because it can not be expected that the required investments in renewable energy will increase or even be kept at today's rate without an economic incentive in addition to the environmental benefits.

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