Effects of improved wind forecasts on operational costs in the German electricity system

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Abstract

The low predictability of wind power causes additional costs for the operation of electricity systems that integrate large amounts of wind energy. This is due to a higher demand for balancing power and short-term unit-commitment with more frequent part-load operation and start-ups. A simulation of short-term wind forecast errors in combination with a stochastic unit-commitment model for Germany allows examining these additional costs. The paper has three focuses. First, a statistical analysis of short-term forecast errors based on real data and literature. Second, the generation of discrete forecast scenarios that fit to the found statistical parameters of real forecast errors and that are needed for the stochastic optimization in an unit-commitment model. Third, discussion of results of the latter model with different assumptions of forecast qualities. This finally allows deriving operational cost reductions in the German electricity system due to improved wind forecast techniques.

1 Introduction

In the past years wind power has become one of the most important renewable energy sources in the electricity sector. Especially in Germany wind power has benefited from the renewable energy law granting fixed payments to wind farms and has produced more electricity than any other renewable energy source in 2006. And more installed wind power capacities are to be expected. Several studies forecast an installed wind power capacity of over 40 GW in Germany for the year 2020. Even though such a growth can be seen to be optimistic especially offshore wind power has a great potential. Being a CO_2-free and resource independent power source the contribution of wind farms to electric power supply are welcomed. But some difficulties arise during integration of wind power into the electric grids. Its concentration in Northern Germany and its fluctuating character could be mentioned here. Another important issue is wind power forecasting. As wind is not perfectly predictable wind power integration suffers from forecast errors. In order to cope with forecast errors conventional units in the power system have to operate more flexibly to maintain the stability of the power system. Eventually power plants have to start up fast to compensate an previous overestimation of wind power. Another example is an underestimation of wind power that leads to curtailing wind power or operating conventional plants in part-load. Such changes in the operation of power plants can result in additional costs in the power system. The effects become more important with increasing wind power capacities. Hence more accurate forecast techniques reduce operation costs and improving forecast quality is of value.

Assessment of this value is similar to the assessment of the integration costs of wind energy. The larger part of recent research on wind power integration involving conventional unit commitment has focused on deterministic approaches, compare e.g. Krämer (2004) or Lund (2005). These approaches disregard the uncertainty in predicting wind power production. Probabilistic approaches like in Dena (2005) or Doherty and O'Malley (2005) quantify reserve requirements due to wind integration but do not consider forecast errors during unit-commitment. Fabbri et al. (2005) assess costs of wind prediction errors by means of market prices for reserve energy. Other approaches involve forecast errors in unit commitment but wind power forecasts are only represented by their expected value, compare e.g. Ummels et al. (2007). Hence, the obtained unit commitment represents a local optimum only valid for the assumed wind power forecast. By contrast stochastic programming explicitly takes into account the distribution of uncertainties like wind power forecast errors, compare Birge and Louveaux (1997). Thus, obtained results are robust towards all possible realizations of wind power, not only for the expected value of forecasts. Stochastic modelling has already been used in the past to consider other not perfectly predictable parameters like load in unit commitment, compare Wallace and Fleten (2003) for an overview. Swider and Weber (2007) present a stochastic model that optimises endogenously the future power plant portfolio with respect to future wind power extensions. This paper is based on a electricity market model that concentrates on the operational integration of wind energy and the stochastic optimization of unit-commitment, compare Barth et al. (2006). As a matter of fact wind forecast suppliers have started to deliver not only expected values but also estimations of error distributions in their forecasts, compare e.g. Pinson et al. (2006) where the value of distribution forecasting is also assessed by market prices.

Hence, a correct representation of forecast errors in electricity models gets more important. The main focus of the paper is the statistical analysis of real wind forecast errors and their simulation with scenario trees. A state of the art of and introduction into wind forecasting is delivered by Giebel (2003). Marti et al. (2006) and Lange and Focken (2006) deliver indications about current forecast qualities and a profound explanation of statistical relations in wind forecasting. Knowledge about the statistical properties of forecast errors enables their correct simulation for stochastic programming. In fact, stochastic programming requires the translation of uncertainties in discrete scenarios or scenario trees. Due to calculation time only few scenarios can be computed in the model. Soeder (2004) presents an approach to simulate wind forecast errors by many scenarios. These many scenarios can then be reduced to a scenario tree according to Dupacova et al. (2003). Here scenario trees representing wind forecast errors will be generated by moment-matching. This approach adapts statistical properties of the scenario tree to the statistical parameters of the considered variable, compare Høyland and Wallace (2001).

The generated scenario trees are applied in the used electricity market model that calculates hourly operational costs and power plant scheduling by cost minimization. Thereby the model has no perfect knowledge about the future and must cope with forecast errors. But it is assumed that the model knows the distribution of errors and that it is able to perform a stochastic optimization. Thus the additional costs due to forecast errors can be calculated. To assess the value of improved forecasts the operational costs in the German electricity system depending on wind forecast quality are estimated. The market model calculates hourly operational costs by cost minimization and for a given power plant mix and given fuel prices. Thereby minimum operation and start-up times of power plants as well as start-up and part-load costs are taken into account. As wind and load series depend not only on day and night but also on seasons, the operational costs over one whole year are calculated.

The paper is organized as follows. In chapter 2 the applied electricity market model is described. In chapter 3 statistical properties of wind forecast errors derived from data analysis and literature indications are assorted. In chapter 4 the generation of scenario trees by moment matching and generation results are presented. In chapter 5 the generated scenario trees are applied in the market model and the value of improved forecast quality is assessed. In chapter 6 conclusions are drawn.

2 The electricity market model

It is a speciality of electricity markets that electric production must equal electric load demand in every moment, as no large amounts of electricity can be stored. Moreover unit-commitment has to be planned in advance, as many power plants need some hours to start-up. In Germany, a day-ahead market for physical delivery of electricity accomplishes this planning of unit commitment for the following day. The market is cleared at 12 o'clock each day. Forecasts of load demand and wind power are needed for the scheduling at the day-ahead market. But there are always uncertainties in the forecasts. Therefore, intra-day markets and reserve capacities are introduced to handle deviations between production agreed upon the day-ahead market and the actual needed production in the operation hour.

The fundamental market model analyses power markets based on an hourly description of generation, transmission and demand, combining the technical and economical aspects and derives hourly electricity market prices from marginal system operation costs. This is done on the basis of an optimisation of the unit-commitment. The model is defined as a stochastic linear programming model, confer for example Birge and Louveaux (1997) or Kall and Mayer (2005). For every hour the inflexible demand for electricity is covered by the commitment of the available power plants. Hereby the costs of unit-commitment are minimized. The electricity demand is given exogenously. The stochastic part is presented by a scenario tree for possible wind power generation forecasts for the individual hours. The technical consequences of the consideration of the stochastic behaviour of the wind power generation is the partitioning of the decision variables for power output, for the transmitted power and for the loading of storages and use of heat pumps: one part describes the different quantities of power sold or bought at the day-ahead market. Thus they are fixed and do not vary for different scenarios. The other part describes contributions at the intraday-market both for up and down regulation. The latter consequently depends on the scenarios. So for the power output of the unit group i at time t in scenario s we find $P_{i,s,t} = P_{i,t}^{DAY\_AHEAD} + P_{i,s,t}^{+} - P_{i,s,t}^{-}$. The variable $P_{i,t}^{DAY\_AHEAD}$ denotes the energy sold at the day-ahead market and has to be fixed the day before. $P^{+}_{i,s,t}$ and $P^{-}_{i,s,t}$ denote the positive and negative contributions to the intra-day market. The decision variables for the transmitted power and for the loading of storages and for the use of heat pumps are defined accordingly.

To cover a simulated time period of for instance one year, the model uses a multi-stage recursion approach with rolling planning, confer Buchanan et al. (2001). In stochastic multi-stage recourse models, there exist two types of decisions: decisions that have to be taken immediately and decisions that can be postponed. The first kind of decisions are called root decisions and have to be decided before the uncertain future is known. The second kind of decisions is called recourse decisions. They are taken after some of the uncertain parameters are known and can include actions which might possibly revise the root decisions. In the case of a power system with wind power, the power generators have to decide on the amount of electricity they want to sell at the day-ahead market before the precise wind power production is known (root decisions). In most European countries this decision has to be taken at least 12 - 36 hours before the delivery period. And as wind power prediction is not perfect actions are necessary when the delivery period is in the near future and the wind power forecast becomes more accurate (recourse decisions).

In general, new information about the operational status of the electricity systems arrives on a continuous basis. Hence, an hourly basis for updating information would be most adequate. However, stochastic optimisation models quickly become intractable. It is therefore necessary to simplify the information arrival and decision structure in a stochastic model. Hence, the model steps forward in time using rolling planning with a 3 hour step holding the individual hours. This decision structure is illustrated in Figure 1 showing the scenario trees for four planning periods covering half a day. For each planning period a three-stage, stochastic optimisation problem is solved having a deterministic first stage covering 3 hours, a stochastic second stage with five scenarios covering 3 hours, and a stochastic third stage with 10 scenarios covering a variable number of hours according to the rolling planning period in question. In the planning period 1 the amount of power sold or bought from the day-ahead market is determined. In the subsequent replanning periods the variables standing for the amounts of power sold or bought on the day-ahead market are fixed to the values found in planning period 1, such that the obligations on the day-ahead market are taking into account when the optimisation of the intra-day market takes place.

More detailed descriptions of the model can be found in Barth et al. (2006), Meibom et al. (2007) or Brand et al. (2005).

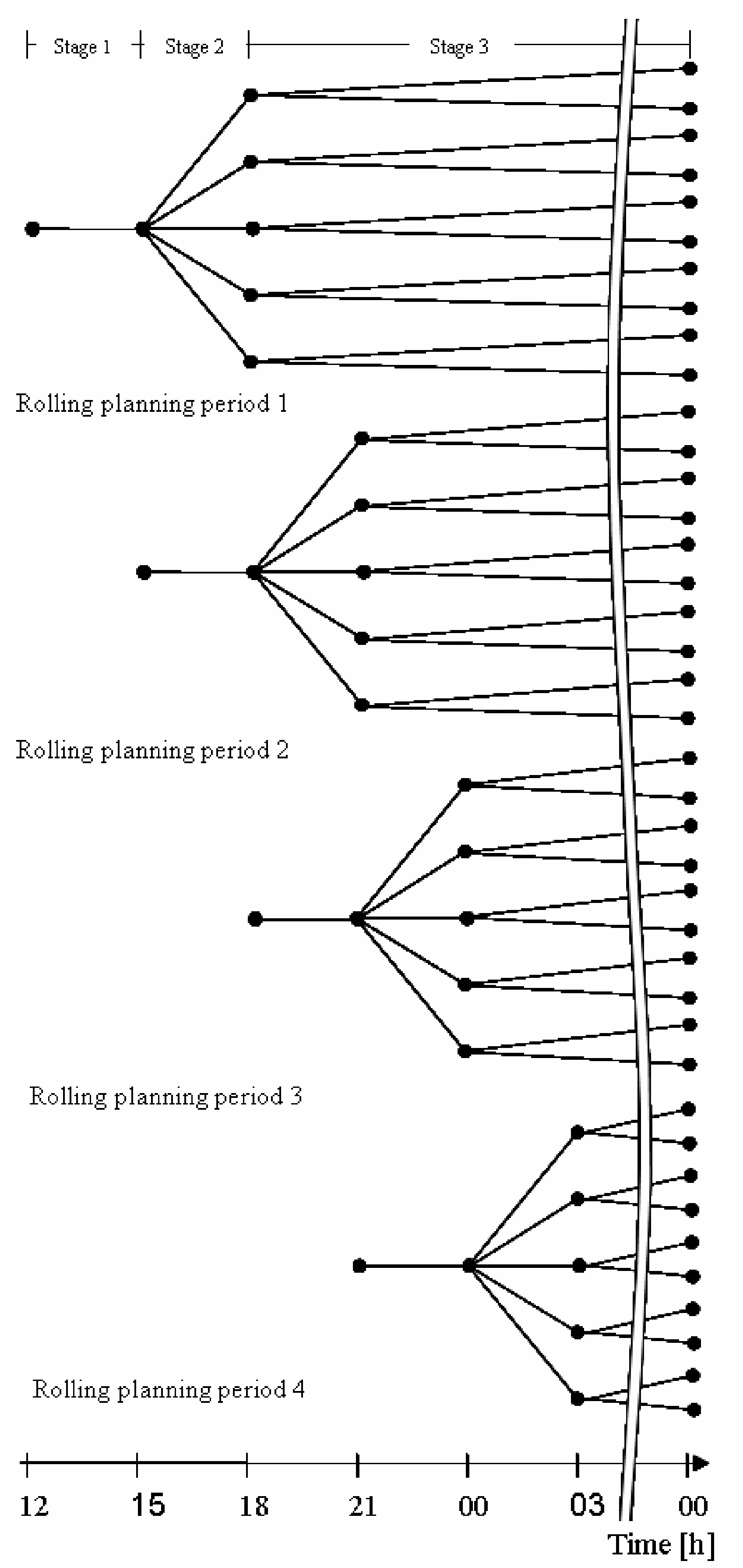

Figure 1: Rolling planning

3 Analysis of wind forecast errors

The presentation of the electricity market model showed that wind power forecast errors are included in the model in form of scenario trees. The creation of scenario trees demands both a sound statistical knowledge of real forecasts and a good translation of the real forecast errors to scenario trees. This chapter presents a statistical description of real forecast errors.

There are different approaches of wind power forecasting. Most models forecast wind speed at single wind turbines by means of physical models that take into account numerical weather forecasts and the specific surroundings at the wind farm. Including the power curve of the turbine power output can then be calculated. Figure 2 shows a typical power curve.

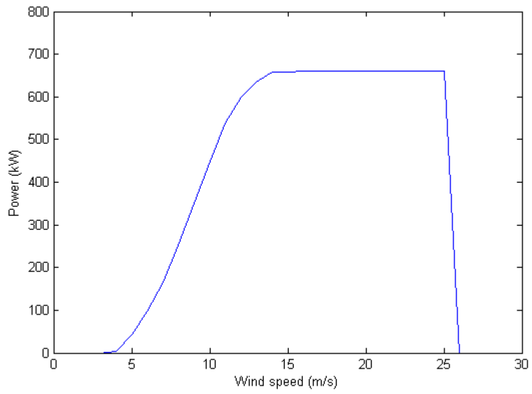

Figure 2: Typical power curve

Most of the times system operators are interested in the wind power output in a region. Hence, models gross up forecasts at different representative wind farms to a power output of the whole region. At all states of the models diverse statistical methods are used. Thereby, currently measured data of power output at wind stations can be helpful. These online measurements can enter into regression or neural network models to improve forecasting. Further descriptions of wind forecasting and forecast models can be found in Giebel (2003) or Landberg et al. (2003).

The analysis concentrates mainly on available data of speed forecasts at different wind farms. Lange and Focken (2006) show that the standard deviations of wind speed forecast errors do not change in a systematic way with the forecasted speed level. This means that forecast errors are not greater in case of higher forecasted speed levels. The forecast errors can hence be approximated by being independent of the speed forecast itself. This is not the case for power forecasts, as Marti et al. (2006) demonstrate. Another advantage of concentrating on speed forecast errors is their distribution. According to Lange (2005) and Giebel (2000) wind speed forecast errors can be fitted by a normal distribution which may be useful in simulation. The transformation of wind speed to power changes the original distribution due to the nonlinear power curve.

A common description of forecast quality is the root mean square error (RMSE). Mean square error (MSE) stands for the expected value of the square of error and RMSE is the root of the MSE. The RMSE is composed of the standard deviation and mean value of the forecast error.

Equation 1 explains the connection where e_i is a single error, n the number of observations and μ_e and σ_e the mean value and standard deviation of the error.

$$\mathrm{RMSE}^2 = \sum_i \frac{e_i^2}{n} = E(e^2) = (E(e))^2 + E(e^2) - (E(e))^2 = \mu_e^2 + \sigma_e^2 \qquad (1)$$

Consequently standard deviations are an important component to assess forecast quality. Figure 3 shows the standard deviations of forecast errors depending on the forecast horizon. The forecast errors at six differently located wind farm stations were examined. Beside the results of a real forecast model in operation that doesn't cover the first five forecast hours the corresponding values of a simulated persistence forecast are given. A persistence forecast assumes that the present values will not change. As Figure 3 shows the persistence forecast becomes quickly bad and is only reasonable for a very short forecast horizon. The quality of the forecast error (if transformed to power forecast errors) corresponds to indications in literature like for example Marti et al. (2006) or Giebel (2003) although the quality of the forecast model at hand seems to belong to the less performing ones. By combining the results of the real and persistence forecasts a typical curve of standard deviations over the forecast horizon can be derived (dot-dashed line).

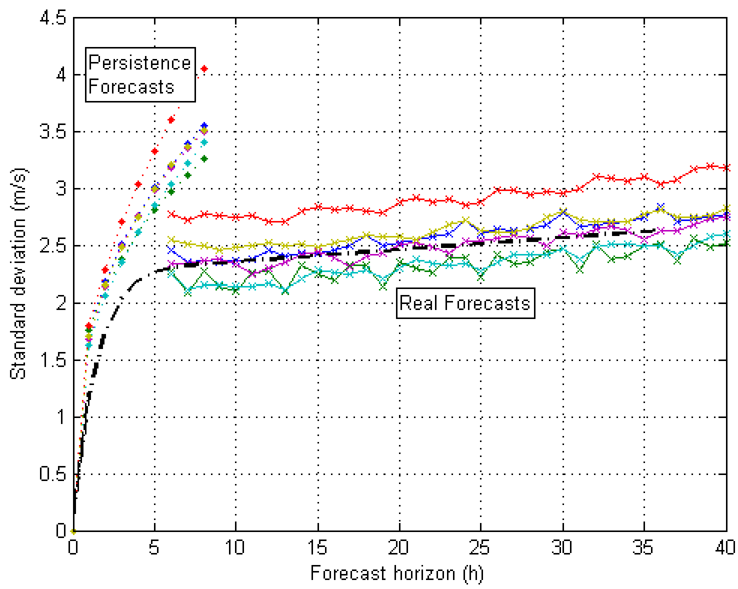

Figure 3: Standard deviations of wind forecasts

The mean values of forecast errors are quite different between the six wind stations. For some stations the mean values are negatives for all forecast horizons and for others positive. According to Lange and Focken (2006) the sign of the mean value of forecast errors can depend on the wind farms terrain. Here, the objective is to find a general description of forecast errors and therefore a mean value of zero is assumed. Moreover the positive and negative deviations at different stations can level themselves. For a single station a description of forecast errors with a assumed mean value of zero results in overestimating forecast quality.

To simulate forecast errors in a scenario tree (see chapter 4) it is important to know how strong a forecast error for a certain forecast hour depends on the error of the precedent forecast hour. In other words, it has to be examined whether the forecast error of one forecast stays positive (or negative) over the whole forecast horizon or rather oscillates. This can be quantified by the autocorrelations of the error. Figure 4 represents the correlation of the error of a forecast hour with the error of one (lag equal one) or four (lag equal four) forecast hours later. The autocorrelations of the same six wind farms are shown at each case. As the difference between autocorrelations at lag 1 and 4 indicate autocorrelation decrease quickly with increasing lags. For a lag of two they are located around 0.6 and for a lag of eight they move only around 0.25. Concluding it can be said that the forecast error is clearly correlated with the precedent one but does not depend strongly on earlier ones.

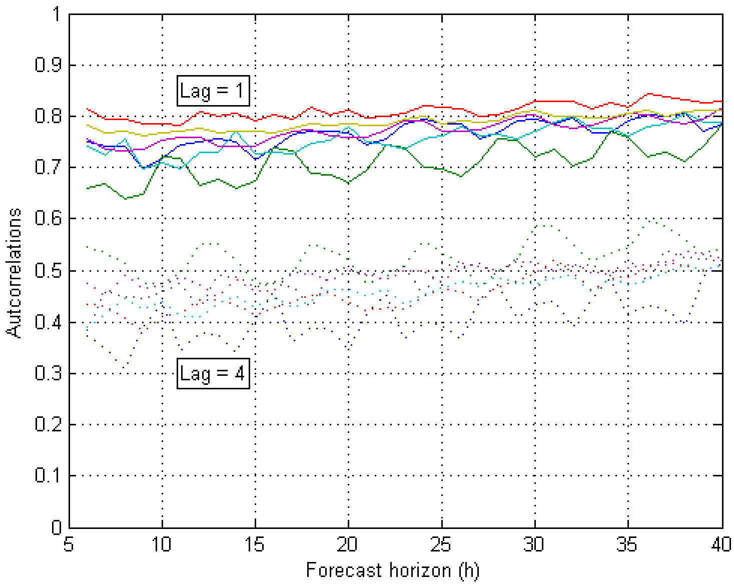

Figure 4: Autocorrelations of forecast error

Normally, not only the forecast error at one wind farm but at several ones is of interest. Then it is important to consider correlations between these forecast errors. This is important as forecast errors at different locations can level each other to a certain extent when summing up the power output of the concerned wind farms. Only perfectly correlated forecast errors would not level each other. The correlation between the errors at several wind stations is calculated. For each possible pair of wind farms there is an error correlation in dependence of the forecast horizon and the distance between the two stations. For a very short forecast horizon the results of an adapted persistence forecast were used. The graphical representation of the correlations results in a three dimensional mesh. To generalize the results a fitted mesh was generated. Figure 5 shows the correlations for different station pairs. The grey mesh is composed of empiric data points and the dark (coloured) smooth mesh is derived from fitting.

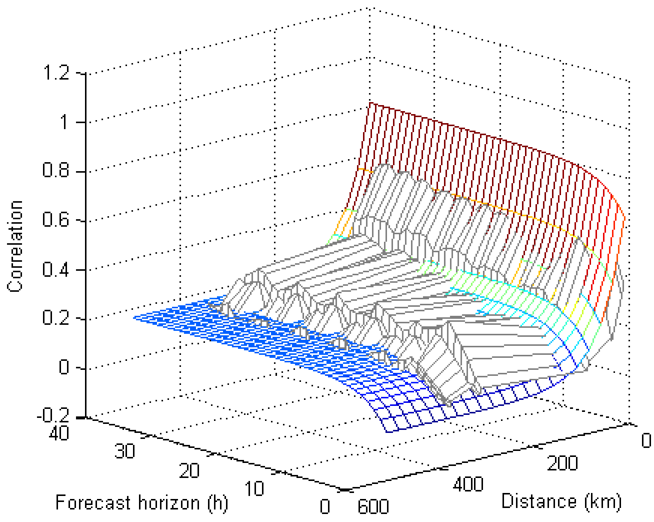

Figure 5: Spatial correlations

On the one hand correlations should become zero when the distance goes to infinity. On the other hand correlations are also likely to approach zero for forecast horizons near zero as for these cases a disturbance at one location causing the forecast error and propagating finitely fast does not affect the other location. For these reasons two superposed exponential functions were chosen to fit the correlations. A least-square fitting results in the smoothed mesh of Figure 5 respectively in equation 2:

$$\rho_{i,j}(h) = 0.17 - 0.25 \cdot \exp(-0.23 \cdot h) + 0.63 \cdot \exp(-0.02 \cdot d_{i,j}) \qquad (2)$$

$\rho_{i,j}$ stands for the error correlation between two stations with distance $d_{i,j}$ in kilometre. The forecast hour is represented by h. This formula can only give a rough indication about the correlations. As only distances between 40 and 550 kilometres are important here fitting was above all adjusted to this relevant area. Beyond these limits the equation is not necessarily valid.

Until now only forecast errors at single wind stations and their correlations were described. But usually the power output of a whole region is of interest. As already indicated, forecast errors at single stations can partially level themselves and the relative quality of a region forecast is better than for a single wind farm. The quality of a power forecast is normally standardised to installed power capacity. The following refers to normalised power forecast errors. In a certain region compensation of forecast errors depend on the number of installed wind farms and the region size as correlations depend on distances. If only few wind farms are situated in the region, every additional wind farm reduces the forecast error of the total region. Focken et al. (2002) show that this error reduction does no longer increase when a certain number of installed wind farms has been achieved. In a region, different distances between different pairs of wind farms are represented. If all stations are distributed randomly the distribution of existing distances in the region does not change anymore after a certain number of wind farms. Then there are no more correlation effects with further installed wind farms and the error reduction in regional forecasting only depends on the region size. So there is a saturation value of error reduction for each region. A large region leads to a greater error reduction as correlations decrease with distance. For more than 100 installed wind farms it can be assumed that the error reduction matches well the saturation value. Considering 1.5 MW wind turbines this corresponds with a installed capacity of 150 MW in a region. Figure 6 represents the saturation value of error reduction in dependence of the region size. Region size is expressed by the diameter of the area in kilometre. $\sigma_{ensemble}$ is the standard deviation of the forecast error for the whole region and σ_{single} is the error standard deviation of the underlying power forecast error at a single station. Standard deviations are normalised to installed capacities.

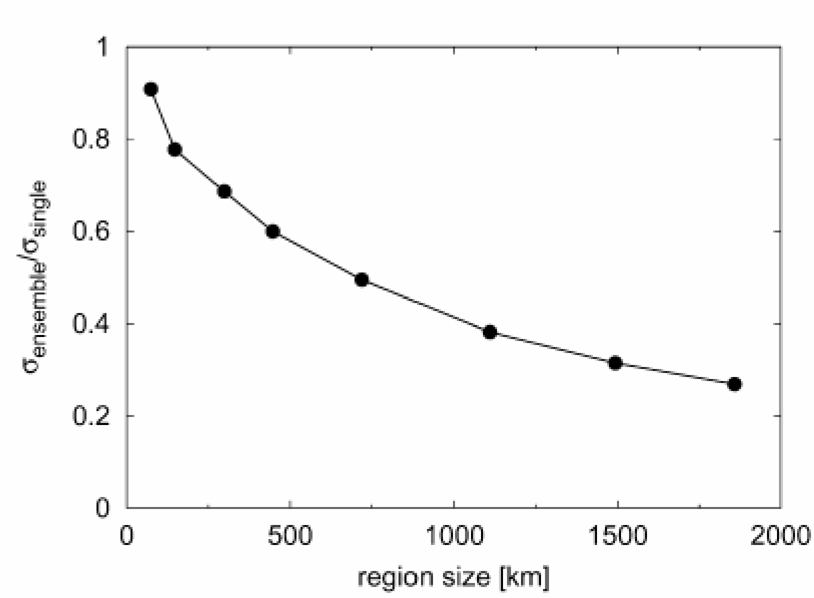

Figure 6: Regional wind power forecasts, Focken et al. (2002)

The simulation of forecast erros in the next chapter is based on wind speed forecast errors. Figure 6 above refers to power forecast errors. It is therefore useful to have an indication about the relation between standard deviations of speed and power forecast errors for one station. For different wind series at turbine height a normally distributed speed forecast error is simulated. After transformation to power by means of a typical power curve the standard deviation of the power forecast error is calculated and normalised to the installed capacity. Figure 7 shows the relation of the accordant standard deviations of forecast errors for different wind series. Standard deviations of speed forecast errors are given in meter per second. The relation is not linear due to the form of the power curve. It depends not only on the assumed power curve but also on the underlying wind series. The latter can be described by mean annual wind speeds. The legend gives these annual wind speeds in meter per second. The first two dotted lines and the dashed one (all three in grey) represent artificially created wind series with very low respectively high mean wind speeds. They demonstrate that the shown relation of standard deviations depends on the underlying wind series. The other mean wind speeds are those of real wind series and are situated in the typical range of mean annual wind speeds at turbine height. Based on the applied power curve a mean wind speed of 3.68 m/s results in 530 full load hours and a mean wind speed of 8.77 m/s in 3750 full load hours. Hence, nearly all speed series of existing wind farms can be situated in the sector of the solid lines. The relation of standard deviations depends also on the applied power curve but normally wind turbine power curves have a similar shape.

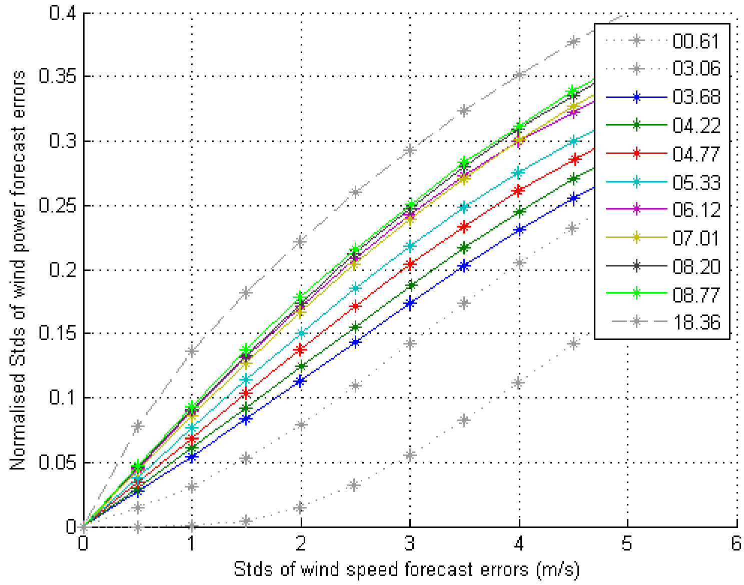

Figure 7: Relation between standard deviations of speed and power forecast errors

The analysis in this chapter creates the basis to simulate typical wind forecast errors. Depending on the optimization approach to be used in the market model a single forecast error scenario is simulated representing a simple forecast or a bunch of scenarios is simulated representing a forecast that gives information about the error distribution. A typical curve of standard deviations is given in Figure 3. The standard deviations of error can be adapted to the size of the region at hand by means of Figure 6 and Figure 7. The deduced standard deviations will then be less than the original ones depending on the size of the given region. Correlations between forecast errors at different locations are reproduced in Figure 5 or by equation 2. Furthermore an indication for the autocorrelations of forecast errors is given in Figure 4.

4 Generation of forecast error scenarios

The applied market model is able to execute a stochastic optimization several times a day. At each execution the model looks up to 36 hours into the future. Stochastic optimization requires that probabilities of all scenarios are known. Thereby each scenario represents a certain wind forecast error process. Knowing those scenarios the simulation of a single forecast error scenario for a non stochastic optimization is simple, as it is sufficient to draw randomly one scenario from the scenario tree by taking into account all probabilities. Due to calculating time the number of scenarios is limited when executing a stochastic optimization. The chapter describes how scenario trees of forecast errors can be created with respect to the statistical characteristics found in chapter 3. The model works with a 1-5-2 scenario tree, which results in 10 scenarios at the end. In the first branching 5 scenarios emerge and each of the scenarios divides again in two scenarios. The first three hours, so the actual hour and the first two look-ahead hours, are deterministic and there is only one scenario in the tree. Figure 8 shows the tree. This structure was found to be reasonable by experience as a tree with more scenarios is not practical for this model due to calculation time. Naturally the representation of forecast errors by one scenario in the first stage is meaningless and only due to calculation time in the model.

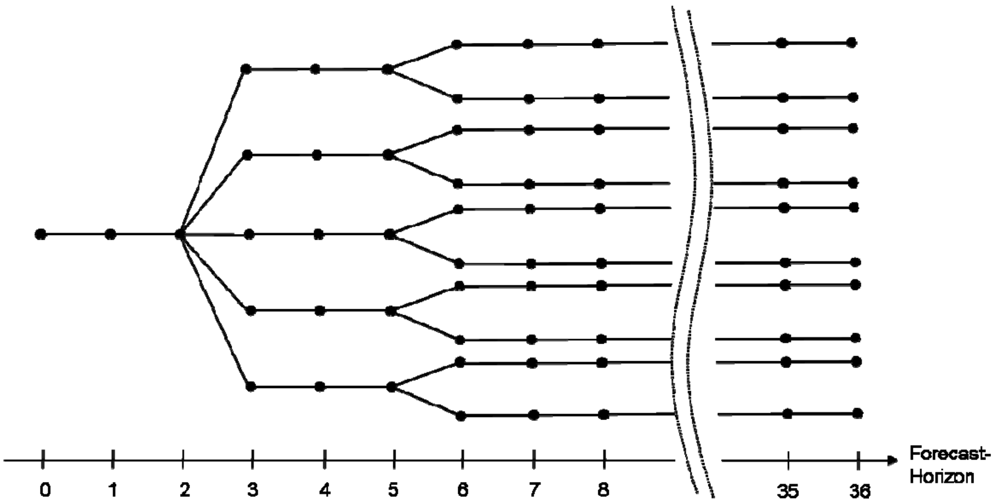

Figure 8: Scenario Tree

The first step to include scenarios into the model is to decide which parameter should be represented by the scenarios. There are three possibilities due to wind data processing in the model. First wind speed series for single stations are transformed to wind power series. The latter are then aggregated to wind power series for whole regions. Normally the fluctuations of wind power input for whole regions are less pronounced then fluctuations of wind power series of single stations. To consider this fact, wind power series are smoothed during the aggregation. Finally, the produced wind power in each region enters into the model. All series are in an hourly resolution. So there are three ways how the scenario tree can be put into the model. Either it stands for speed forecast errors or for power forecast errors at single stations or for power forecast errors for whole regions.

Here, scenarios represent speed forecast errors. This has the advantage that forecast errors are relatively independent of the predicted value as it was shown in the previous chapter. Therefore, it is possible to add one and the same scenario tree to all values of the speed series (naturally one has to take into account that predicted wind speed values can not be negative). Apart from this convenient characteristic the distribution of speed forecast errors is approximately Gaussian and the distribution of power forecasts is not well known. It can be advantageous to know the error distribution in other simulation methods like the one presented by Soeder (2004). For the actual simulation method explained below exact knowledge of the error distribution is not crucial. Last but not least statistical parameters like standard deviations are better known for speed forecasts than for forecasts covering whole regions. On the other hand scenario trees representing speed forecast errors must consider smoothing effects between regionally dispersed forecast locations.

The method to generate scenarios in this analysis is based on Høyland and Wallace (2001). The general approach is to match statistical properties of the scenarios in a best possible way with the corresponding properties of the concerned random variable. Therefore the square distances between the corresponding parameters are minimized which results in a nonlinear optimization problem.

$$\begin{aligned} &\min_{\mathbf{x},\mathbf{p}} \quad \sum_{i \in S} w_i (f_i(\mathbf{x},\mathbf{p}) - SV_i)^2 \\ &\text{s.t.} \quad \sum \mathbf{p} = 1 \\ &\qquad\;\; \mathrm{p} > 0 \end{aligned} \tag{3}$$

Generation of an actual tree with several branchings follows from the principal procedure. Equation 3 defines the optimization problem at hand. S is the set of statistical properties that one wants to consider. SV_i are the given or known statistical parameters of the random variable. By means of $f_i(\mathbf{x},\mathbf{p})$ the corresponding parameters of the tree are calculated. They depend on the values in the scenarios **x** and the scenario probabilities **p**. A minimization of the sum of square distances takes places. By means of w_i each parameter can be given another weight to set priorities to certain properties. All probabilities must sum up to one (first restriction) and each scenario probability must be greater than zero (second restriction). Typically mean value, variance and higher moments like kurtosis and correlations constitute the set S.

The generation of the scenario tree in Figure 8 with its defined structure follows a sequential approach. For every forecast hour an optimization takes place except for the first three hours where a forecast error of zero is supposed. After each branching new probabilities are calculated. So the first restriction becomes:

$$\sum_{i=1}^{b} {}^{\mathrm{p}_{i,k}}\!\big/_{\mathrm{p}_k} = 1 \text{ for each parent scenario k} \tag{4}$$

Thereby $p_{i,k}$ are the probabilities of the b scenarios that are brunched from the parent scenario k. According to the restriction a scenario must brunch into scenarios whose conditional probabilities sum up to one. If there is no branching from one forecast hour to the next one the total number of scenarios rests equal and so do all probabilities. The sequential approach generates only a suboptimal tree as probabilities are at least partially determined by foregoing steps. Another approach exists that optimizes the whole tree in one large optimization which results in a optimal tree but needs more calculating time. However, Gülpinar et al. (2004) test different scenario trees for a (financial) optimization software and show that scenario trees generated by an overall optimization approach lead only to slightly more accurate results in the end. Moreover, the end of the scenario tree representing long forecast horizons is not so crucial in the electricity market model than scenario values at the beginning. Facing a scenario tree for many stations with corresponding correlations a sequential approach was chosen here.

Wind power generation is modelled by 12 wind series. Therefore, twelve scenario trees have to be generated that simulate the speed forecast error at each wind station. Afterwards, the scenarios are added to the wind speed series to simulate the different speed forecasts. The values in each scenario tree can be different but the probabilities must be equal. According to the precedent chapter following statistical properties are considered: mean values, standard deviations, autocorrelation at lag one and correlations between different locations.

Consequently each scenario tree should match 14 statistical properties in every forecast hour as there a 11 neighbours for every station. In total there are 66 independent spatial correlation values for every forecast hour. Mean values and standard deviations (standing for forecast quality) were considered especially important in the applied model and were therefore considerably more weighted during tree generation.

Figure 9 shows the resulting scenario tree for station 7 for the first 10 forecast hours. As at the actual hour and the first two forecast hours the applied model is deterministic, a forecast error of zero is assumed. The forecast error of the next three forecast hours is reproduced in five scenarios. The legend indicates the probabilities of each scenario after the second branching at forecast hour five. The probabilities of the five scenarios at the second stage (forecast hour three to five) are the sum of the probabilities of the two corresponding child scenarios.

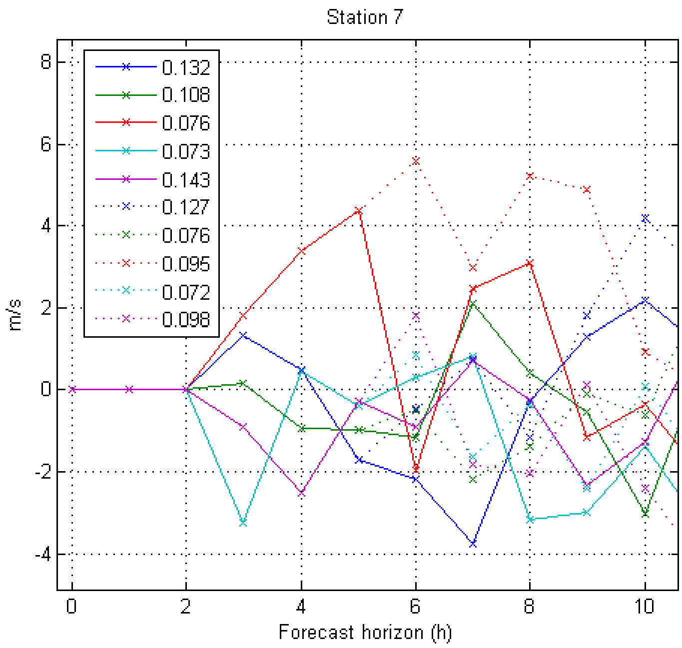

Figure 9: Forecast errors for station 7

In the following, several figures assess the quality of moment matching in the scenario trees. The specification of standard deviations follows the dashed line in Figure 3 but it was adapted to the region size that each wind station is supposed to represent (by means of Figure 6 and Figure 7). So the assumed standard deviations are less than in Figure 3. Mean value of the scenarios are defined as zero over the whole forecast horizon as explained in chapter 6. Currently, only autocorrelations at lag one can be considered in the scenario tree generation model. Assuming autocorrelations at lag one according to Figure 4 leads to scenarios that stay constant over the whole forecast horizon in an unrealistic way. Therefore, slightly lesser autocorrelations were assumed to make a compromise between autocorrelations at lag one and at lag four according to Figure 4. Then the resulting scenarios show a more realistic behaviour.

Figure 10 shows the specified properties and the corresponding properties in the scenario tree over the forecast horizon. Mean values are perfectly matched over all hours. Standard deviations are also perfectly matched except for the first three hours as there is only one scenario in the tree. Autocorrelations are taken into account as autocovariances. In Figure 10 their root (sign is retained) is presented, so that they are in the same range as the standard deviations. Each autocovariance indicates the covariance between the scenarios at this forecast hour and the scenarios at the precedent hour. For the first four hours simulated autocovariances are zero as there is only one scenario for the first three hours. The matching of autocovariances shows deviations which will be discussed below.

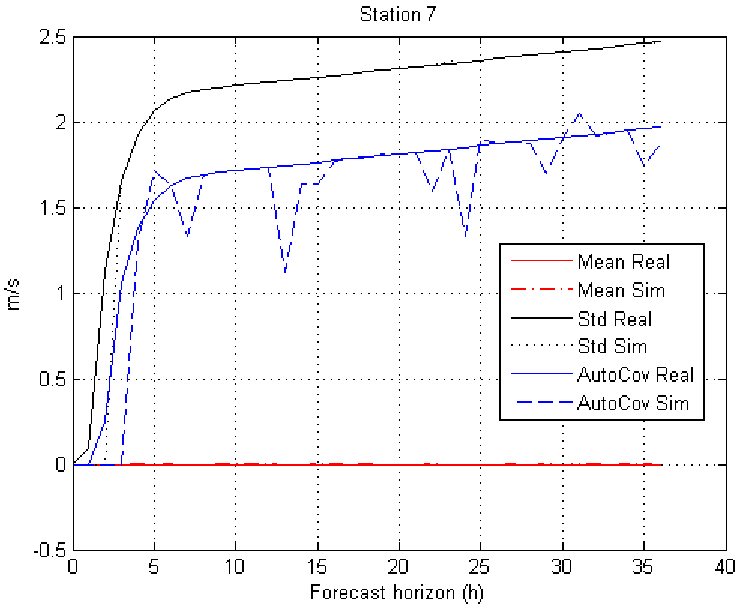

Figure 10: Results for station 7

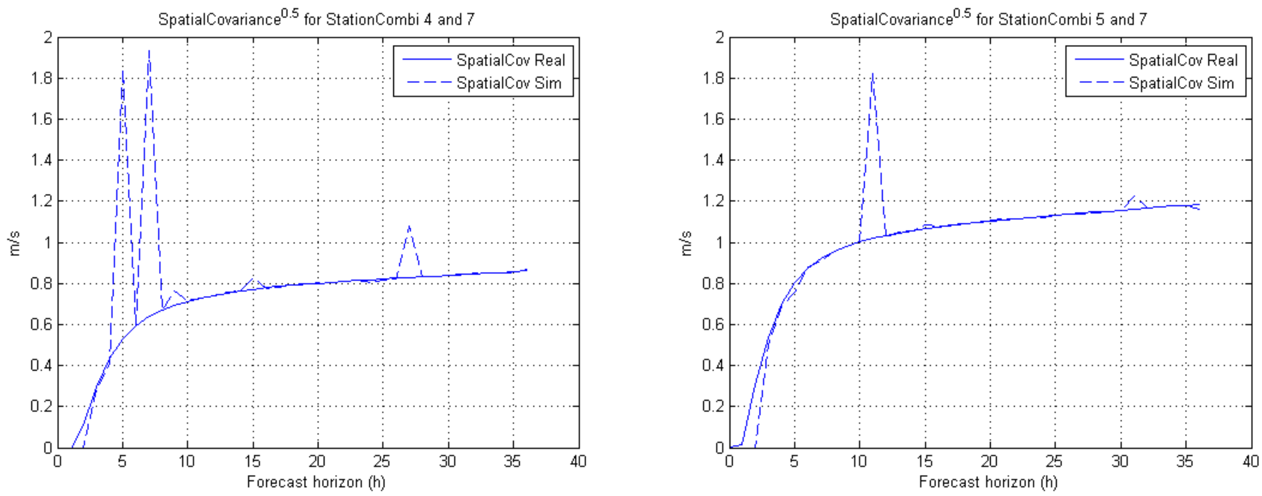

Figure 11: Spatial covariances for station 7

Spatial correlations between all stations could be calculated by formula 2 as all twelve station locations are known. Figure 11 shows how well the correlations between two combinations of stations (out of sixty-six) are matched in the scenario tree. Spatial correlations are expressed in the same manner as autocorrelations that is as roots of covariances. In general spatial covariances are matched well except for the first three hours and some exemptions.

The two precedent figures showed matching for the scenario tree at station 7. Figure 12 gives an indication how well properties were matched at all stations. It shows the mean of the absolute deviations for all four properties. For the first three time steps (forecast hour zero up to two) there are large deviations for all properties except for mean values as there is only one scenario. For all other steps there are nearly no deviations for standard deviations and mean values. This is due to the fact that these two properties were more weighted during tree generation. Autocovariances are not at all matched for the first four steps due to the one scenario stage. Autocovariances and spatial covariances are not well matched in the second stage with five scenarios and deviations also seem to become larger at the end of the forecast horizon. This is due to a small number of scenarios in the beginning that cannot respect all moments and due to sequential optimization with fixed probabilities after the second branching.

If there are not enough scenarios the degrees of freedom do not suffice to respect all properties. As Høyland and Wallace (2001) point out counting degrees of freedom gives an indication for the necessary tree size. In the second stage five scenarios are generated. This gives 12*5 = 60 degrees of freedom plus 9 for the probabilities that must sum up to one. Due to the 66 spatial correlations in total 66 + 3*12 = 102 properties are to be matched. Consequently the tree cannot match all properties. After forecast hour five there are 10 scenarios and normally 129 degrees of freedom. As a matter of fact all properties are respected relatively well for forecast hour six. Besides tree generation is based on a non-linear optimization and it is not evident to find a global optimum.

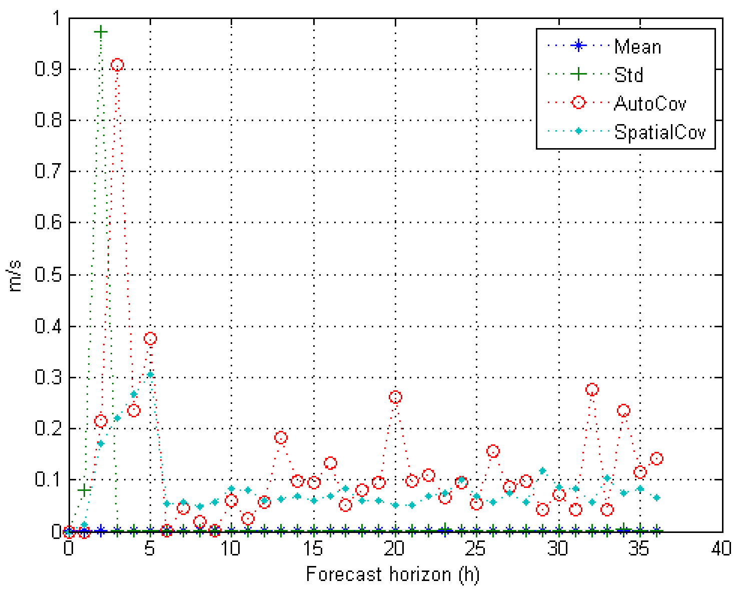

Figure 12: Mean deviations between simulated and defined moments

At every station speed forecast scenarios are transformed to power forecast scenarios. Each station represents a certain zone. To simulate the zone power output the installed wind capacity is taken into account and wind series are smoothed as the variability of wind power output decreases with region size (confer Norgaard and Holttinen (2004)). The applied model considers only three regions in Germany (see chapter 5) and each of them contains four of the twelve zones. Therefore, the corresponding power forecast scenarios are aggregated for each region. Finally, power forecast scenarios for each considered region are put into the market model.

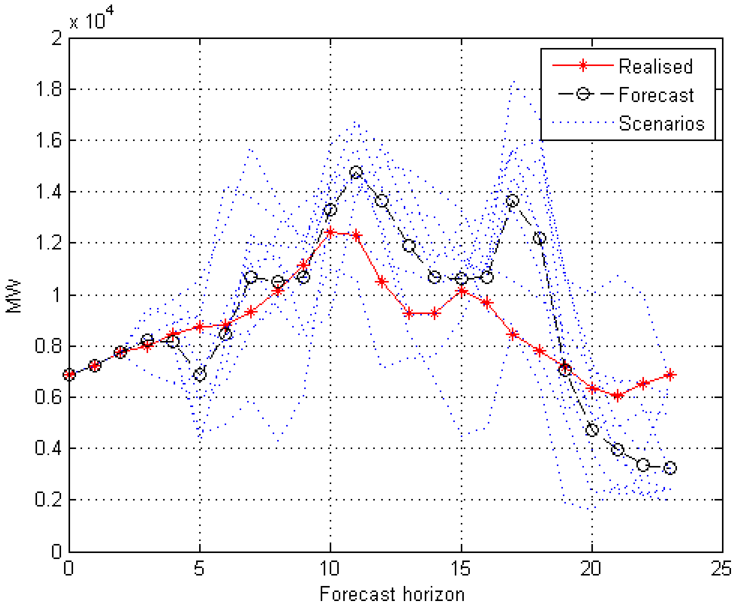

Figure 13: Input scenarios for market model (region north-west)

Figure 13 shows forecast scenarios for one optimization step in the applied model. The line with crosses indicates the real wind power input or a perfect forecast scenario. The line with circles indicates the forecast scenario or a forecast that does not take into account any forecast errors. The dotted lines indicate error scenarios or error probabilities that are taken into account during optimization to get a more robust operation. The last case stands for system operators who know that the incoming forecasts are never perfect and consider future errors.

5 Application

The described approach of scenario tree generation allows to explicitly define the assumed forecast quality in the model. Then the different yearly operational system costs including fuel, start up and other costs like emission taxes are calculated for the year 2020 assuming different forecast qualities.

In the model, Germany is divided into three regions: costal areas in the north-west and the north-east and a third, larger one for the central and southern part. This subdivision reflects the concentration of installed wind power capacities in the coastal areas where the demand is low in comparison to the central part. Furthermore, the borders of the model regions reflect the expected bottlenecks in the German power transmission grid from north to south. The installed wind power capacity in Germany for the year 2020 is based on the optimistic assumptions presented by Dena (2005). In total 48 GW wind power are installed whereof 5.6 GW are situated in the north-east and 23.1 GW in the northwest. The north-west region shows a very high wind power concentration due to off-shore wind power extensions. Also the assumed wind power capacity for the north-east region is not negligible compared to electricity demand in this model region. Transmission capacities are assumed to amount to 1.2 GW between north-east and north-west and 3 GW respectively 3.3 GW at the borders to the central region. Fuel prices are 8.1 €/MWh for coal, 3.8 €/MWh for lignite and 22.2 €/MWh for gas and fuel oil. The future capacities of thermal and hydro power plants have been derived applying a linear stochastic model with endogenous investments, confer Swider and Weber (2007). This model optimises endogenously the future power plant portfolio with respect to future wind power extensions. Figure 14 shows the resulting capacities differentiated by fuel in the individual regions.

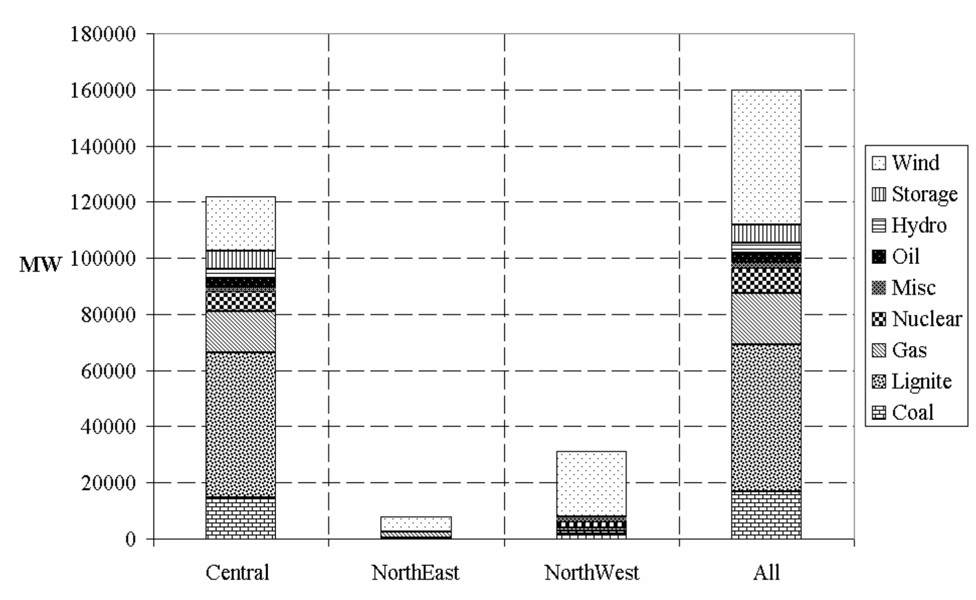

Figure 14: Installed capacities

The effects of different forecast qualities on costs in this system are analysed as follows. Forecast quality representing present forecasts is derived according to chapter 3 and 4. As mentioned in chapter 3 the standard deviation of forecast errors can be interpreted as index for forecast quality. To simulate improved forecast quality standard deviations of future forecast errors are assumed to be reduced by 20%, 40% and 50%. Correlations (spatial and auto) and mean values rest the same in all cases unlike covariances which depend on standard deviations.

There are two different optimization modes for every case. In one mode the system sees a normal forecast in every planning loop and knows the forecast error distribution. Error distributions are represented by the scenarios according to Figure 13. Consequently, the model executes a stochastic optimization. In the other mode the model only sees a normal single forecast. Power plant scheduling is optimized under assumption of the wind power output defined in this forecast. This case is referred to as normal optimization. It can be assumed that the market performs a mix of normal and stochastic optimization as risk hedging takes place. On the other hand error distributions are not known as far as that all market participants could perform something similar to a complete stochastic optimization. There is a common reference run for all cases. In the deterministic version, the model has perfect foresight and schedules unit operation according to the actual realised wind power, confer Figure 13.

Comparing the system costs in the three modes for each forecast quality two values can be calculated: the expected value of perfect information (VPI) and the value of stochastic solution (VSS), confer Birge and Louveaux (1997). The VSS indicates cost reduction that can be achieved by stochastic optimization compared to a normal optimization and the VPI measures the value of knowing future with certainty (compared to a stochastic optimization solution). As the optimization at the market will be something between stochastic and normal optimization VSS gives the minimum for the additional costs due to forecast errors and VPI plus VSS can be seen as an upper limit. So wind forecast errors cause additional costs in the system operation that lie between the VPI and VPI plus VSS.

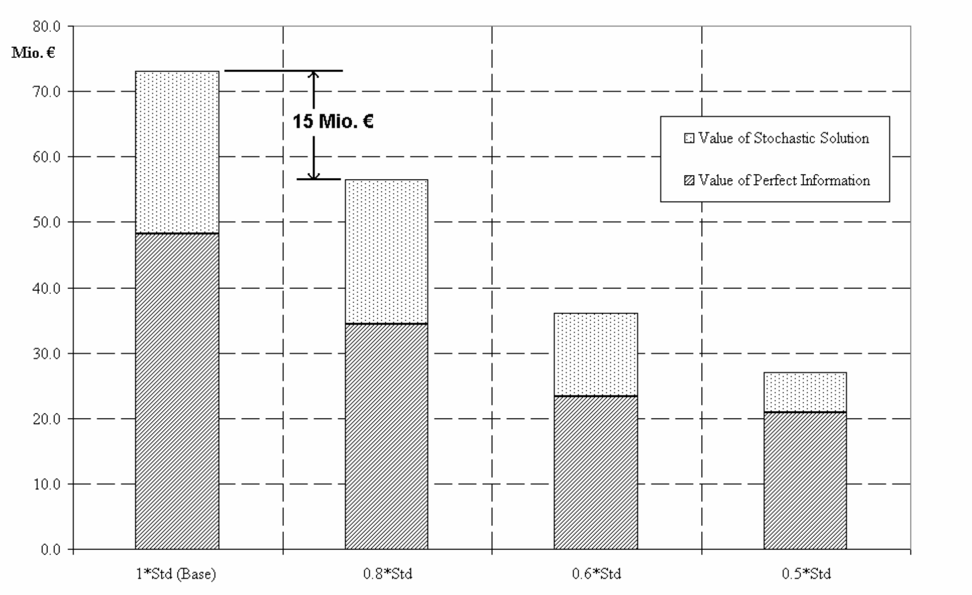

Figure 15: VSS and VPI

Figure 15 show these values for an operation over one year for different forecast quality cases. As expected, additional operation costs decrease with improved forecast quality. For the first three cases reduction of costs seems to be roughly linear over the rise in forecast quality. Interestingly, the values of stochastic solutions seem to decrease also in relation to the total additional costs. Thus for small forecast errors the share of the VSS in the total additional costs is reduced. Improving forecast quality by 20 percent reduces operational system costs by 15 million euros per year. Thus, improving forecast quality and corresponding research has a substantial value. It is also beneficial to know and use error distributions to the full extent. Stochastic optimization can reduce costs by up to 25 million euros per year. Remember, the models treats the first two forecast hours in a deterministic way due to computing reasons as explained in chapter 2. This means perfect forecast for the first two look-ahead hours which does not correspond with reality and reduces additional costs. In general, these and the following results represent ongoing research and have to be interpreted with care.

Additional costs due to forecast errors per MWh (integrated) wind power are presented in Figure 16. Again there are the following two cases: the model optimizes according to an incoming single forecast (normal optimization) or uses error distributions in optimization (stochastic optimization). Stochastic optimization and improved forecast quality lead to lower integration costs due to wind power forecast errors. Integrated wind energy is not the same in all cases as the system can cut wind power output if it is advantageous for system operation.

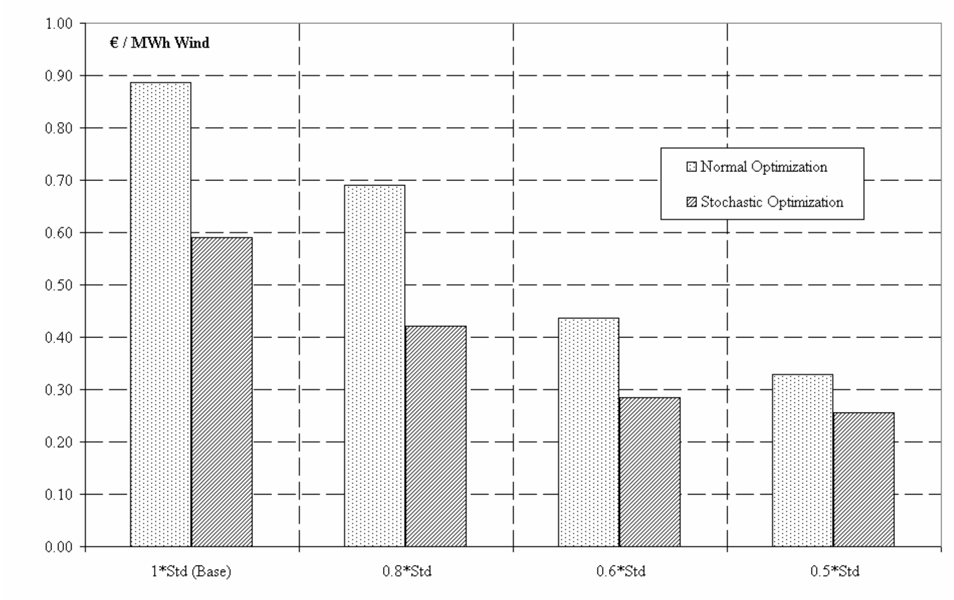

Figure 16: Additional costs per MWh wind due to wind forecast errors

6 Conclusion

Several topics were treated in this paper. A stochastic representation of wind forecast errors requires a statistical analysis of forecast errors. Consulting literature sources and analysing forecast data a broad statistical description of wind forecasting could be derived. The statistical description of forecast errors included mean values, standard deviations, autocorrelations and spatial correlations. The latter were described by a an empirical equation.

The presented parameters enabled a realistic simulation of wind speed forecast errors. As scenario tree generation method the chosen approach proved to be well adapted. Very small scenario trees can thus be generated that still respect important statistical properties. Besides, the applied approach allows also to emphasise certain statistical parameters. That way forecast error standard deviations representing forecast quality can be especially respected in the scenario tree. Further investigations would be necessary to find out which statistical properties of forecast errors affect the model results in particular.

Different scenario trees were formed according to different forecast qualities These scenario trees were applied in a German electricity market model. The values of perfect information and of stochastic optimization were calculated for different forecast qualities. Following conclusions can be drawn, even so the presented results derive from ongoing research and have to be interpreted with care. Operational costs due to forecast errors could be reduced by one third if an overall stochastic optimization were used in scheduling. For this purpose not only error distribution information has to be delivered by forecasters but also corresponding stochastic programming methods have to be used during unit-commitment. Naturally, improved forecast qualities reduce operation costs in any case. According to the results improving forecast quality by 20 percent leads to a minimal cost reduction of 15 million euros in Germany per year. Better forecast qualities and application of stochastic programming methods would also reduce the so-called integration costs of wind energy.

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