Uncertainty Forecasting Practices for the Next Generation Power System

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Abstract—**Probabilistic forecasts in general and ensemble forecasting in particular may contain a paradigm shift in the way renewable energy forecasts have been used and evaluated in the past 20 years, where deterministic forecasting has been established and been practiced in all power markets, where the level of wind power penetration increased over a few percent of total energy consumption. In the next generation power system with large amounts of intermittent and renewable energy sources (RES), where more than a quarter of the energy is delivered by RES, deterministic methods are no longer sufficient. Handling the uncertainties that come with the variable weather driven generation from RES is a key requirement for forecasting tools. Probabilistic forecasting methods offer such new ways of handling uncertainties that are inherent in the generation of power from renewable sources. In this paper we demystify the use of uncertainty forecasts by providing some important definitions, showing a number of applications with best practices cases and pitfalls when choosing a solution that fits the current and future development of an end-user.**

I. Introduction

Although uncertainty terms are part of our day-to-day communication and language, communication and application of uncertainty in weather forecasting and the power industry's decision making is still in its infancy on many levels. Research in psychology and cognitive decision-making has proven over the past decade that uncertainty information not only helps decision making, it also reduces the distrust in forecasts when they fail from time to time.

In the world meteorological organization's (WMO) guidelines on ensemble prediction [1], the WMO actually warns about ignoring uncertainty in forecasts, even if an end-user receives a deterministic forecasts. The WMO argues that *if a forecaster issues a deterministic forecast the underlying uncertainty is still there, and the forecaster has to make a best guess at the likely outcome. Unless the forecaster fully understands the decision that the user is going to make based on the forecast, and the impact of different outcomes, the forecaster's best guess may not be well tuned to the real needs of the user*.

It is this gap in the basic understanding of uncertainty inherent in forecasts that lead to wrong assumptions among end-users with little or no experience in basic meteorology or atmospheric science. Mistrust in forecasts and forecasting methods including uncertainty methodologies often stem from a wrong expectation on the quality of forecasts for a specific problem.

If uncertainty forecasts should find their way into the power industry's weather related decision making, a deeper understanding of weather uncertainty, the way weather services produce uncertainty of weather forecasts, and how such forecasts are to be translated into end-user applications is required [2]. In the following sections, we try to shed some light into the gaps and pitfalls and highlight some of the many advantages of applying uncertainty forecasts in power system applications.

II. Uncertainty forecasts: a brief review

One of the gaps of understanding uncertainty in the power industry and among those end-users with an interest in uncertainty forecasts due to higher wind power and solar power penetration levels is the definition of uncertainty and the corresponding methodologies that provide forecast uncertainty. In the IEA Wind Task 36 "Wind Power Forecasting"[1] interview analysis it was found that many people had difficulties distinguishing:

1) forecast error spread
2) confidence interval
3) forecast uncertainty
4) forecast interval

The *forecast error spread* is defined as the historically observed deviation of a forecast to its corresponding observation at a specific time. It can also refer to an average error provided by an error metric, e.g. variance or standard deviation. One of the common misunderstandings is that a *confidence interval* is showing the uncertainty of a forecast. This is not the case. By adding and subtracting for example one standard deviation to the deterministic forecast of wind speed and converting it to wind power, such intervals represent a measure of the deviation to climatology and do not represent current or geographically distributed uncertainty.

The *forecast uncertainty* on the other hand is defined as a possible range of forecast values in the future. In meteorology this range is defined by the uncertainty of the atmospheric development in the future and represented in ensemble forecasts by applying perturbations to inital and boundary conditions and expressing model physics differences. When represented in *forecast intervals* the so-determined uncertainty band represents *forecast uncertainty* containing the respective probability of the real value being contained in the range of forecasted values, which will only be observed in the future.

[1] see http://ieawindforecasting.dk

Forecast intervals can be derived from parametric (e.g. Gaussian distribution) or non-parametric (e.g. empirical distribution functions, kernel density estimation) representations of uncertainty or from a larger number of NWP forecasts in an ensemble forecasting system that represent the forecast uncertainty of the target variable.

From these probability density functions (PDFs) quantiles or percentiles[2] can be extracted and higher-order statistics such as skewness and kurtosis can be calculated. This is where the distinction is most pronounced: from a statistical error measure like standard deviation, it is not possible to derive quantiles or percentiles.

Especially in applications like reserve predictions, ramp constraints or optimization tasks for storage applications, this distinction is imperative. Such applications also require that the geographical distribution of the variables are captured by scenarios of ensembles of possible outcomes of a pre-defined value.

In that sense, it is important to have an understanding about which types of uncertainty representation the various methods present and how they are built.

Wind power output can be regarded as a stochastic variable when representing it as a probabilistic function. Its properties can for example be represented by quantiles, moments of the probability distribution (e.g. mean and variance) or the full PDF, from which quantiles and moments can be derived. The "fan chart" is a quite common way of visualization of a set of *forecast intervals* that are aggregated in one plot. Visualizations as shown in Figure 1 may however provide misleading information to a decision-maker. For example, if the decision-maker interprets each one of the quantiles as a possible evolution of wind power production in time, he needs to be sure that the visualization tool uses the data that he expects to interpret the information correct.

Let's look upon an example. A fan chart generated with a statistical method visualizes the marginal forecast intervals. The term "marginal forecast interval" is used here since each interval is only confined to separated forecast lead-times and does not have information about the joint probability distribution across the full set of lead times, or in other words, these intervals are not modeling the inter-temporal dependency structure of forecast uncertainty. These intervals are different for each lead-time. Figure 1 shows an example of a fan chart where the intervals were generated with a statistical model. The lead-time dependence is visible through the relatively equal intervals in size over the entire forecast. The observations (black solid line) are covered, except for a short period around midnight of the first day. In that hour there is a probability of around $\alpha = 90\%$ (limited by quantiles 95% and 5%) that the observed value is within approximately $P^{\tau^L}_{t+k} = 0.18$ and $P^{\tau^H}_{t+k} = 0.65$. This is the typical interpretation. Looking at the observations, another way to interpret is that there is a 5% likelihood that the observations are within $P^{\tau^L}_{t+k} = 0.63$ and $P^{\tau^H}_{t+k} = 0.65$

In Figure 2 we also see forecast intervals for the same wind farm and day. This time, the intervals were formed of

[2]In statistics and the theory of probability, quantiles are cut points dividing the range of a probability distribution into contiguous intervals with equal probabilities. The 100-quantiles are called percentiles.

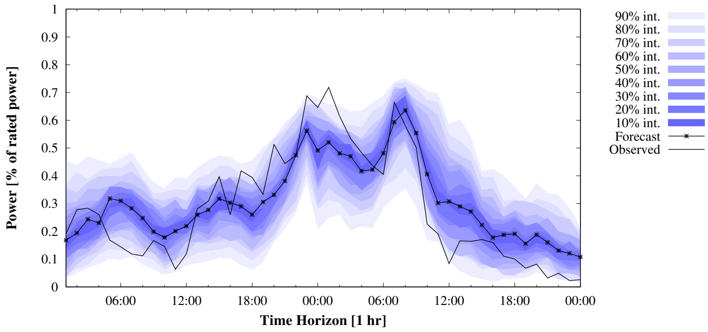

Fig. 1. Example of a "Fan chart" of wind power production at a single wind farm built marginal forecast intervals of a statistical method.

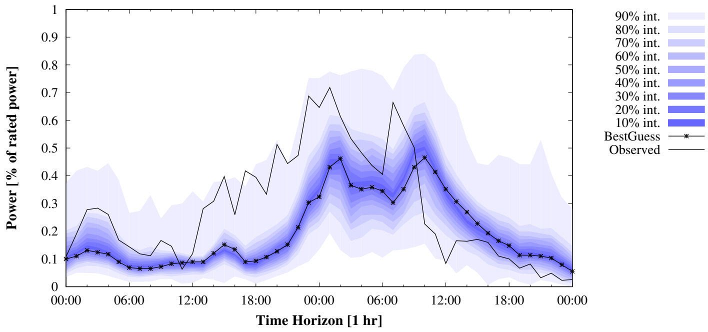

Fig. 2. Example of a "Fan chart" of wind power forecasts at the same time and wind farm as in 1, built by a 75 member multi-scheme NWP ensemble system (MSEPS).

300 wind speeds in 4 different heights by a 75 member multi-scheme NWP based ensemble (MSEPS). These intervals look very different from the statistically generated intervals. Even though the 90% probability is within approximately $P^{\tau^L}_{t+k} = 0.21$ and $P^{\tau^H}_{t+k} = 0.75$, the 5% probability that the observations is found within the upper quantile has an interval size of 0.25 (range $P^{\tau^L}_{t+k} = 0.50$ and $P^{\tau^H}_{t+k} = 0.75$). That means the interval size is larger by a factor of 10. Compared to the statistical method, this result indicates that the current weather development contains a low probability for a high uncertainty range towards increased production.

Figure 3 shows the same wind farm, forecast days and method as in Figure 2, but as individual forecasts in a so-called spaghetti-plot where each of the 300 wind power forecasts are one line. In this way, it becomes apparent, how individual ensemble forecast "members" generated outliers.

In comparison to the lead-time dependent approach, the physical approach forms a large outer quantile band and a more condensed inner part, indicating that many of the 75 forecasts are aligned in their atmospheric development, while there are a small number of forecasts that result in higher power generation. The difference here is that the intervals are a result of the NWP ensembles reproducing the physical uncertainty of the current atmospheric processes that generate the power and are fully independent of the lead-time. Here, a large spread can be generated based on a very low likelihood or probability, also if such events have not been observed before.

An operator or trader has a number of ways to interpret such a forecast. Two likely scenarios could be: (1) ignoring

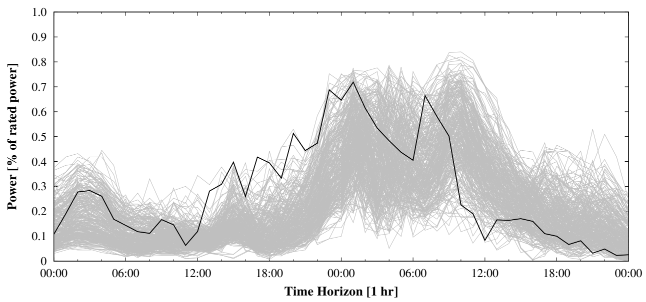

Fig. 3. Example of a spaghetti plot of 300 wind power forecasts at the same time and wind farm and method as in 2.

the outer interval and acting upon the highest probability ranges; (2) verifying the system upon issues or the market price that could arise, if the low probability of high generation would become reality. Whether the operator or trader acts upon such a forecast depends on their business practices. Nevertheless, it shows that the information contained in the forecast intervals have a direct practical application.

The different results also illustrate that the successful interpretation of such information depends on the algorithm used to generate these intervals and an understanding of the methods with which such intervals have been created. The major difference here is that one method is based on current atmospheric conditions (NWP ensemble) and the other relies on historical documentation of the atmospheric conditions. Here, the intervals of extremes are usually smaller and less pronounced unless there are long time series available that contain a significant number of such extremes to impact the spread in given weather conditions.

In order to deepen that understanding, we will go into more detail on how the methods that are today available as industry standards are formed and explain their main characteristics in the next section. A more profound review can be found in Bessa et al. [2].

III. Uncertainty Forecast Methodologies

Forecast uncertainty for application in the power industry are today based on three main processes and procedures (fig. 4):

1) Statistical methods of probabilistic forecasts
2) Statistically-based ensemble scenarios
3) Physically based ensemble forecasts

The first type of methods "Statistical methods of probabilistic forecasts" are based on statistical processing of past (historic) data in order to derive a probability density function of the possible forecasting spread. The advantage of such methods are that they are computationally extremely cheap and simple to apply. The disadvantage is that none of these methods produce a realistic representation of the forecast uncertainty in a spatial and temporal manner. There is also no physical dependency on the forward results, as the spread is based on past climatology. Typically, statistical learning algorithms (e.g., neural networks, machine learning) are used to fit historical time series of weather parameters from a NWP model to their corresponding power generation data. From the fitting process, a PDF can be derived and used forward in time. A newer, more intelligent method is

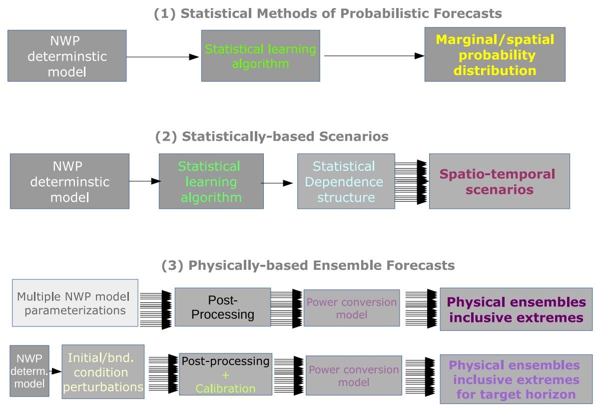

Fig. 4. Standard methods of uncertainty forecast generation to be used in wind power and PV forecasting. The black arrows indicate whether the so-called ensemble members stem from a statistical procedure or are individual scenarios.

the analog ensemble method (AnEn) that searches through historical forecasts for those past events that are most similar or "analogous" to the current forecast. The observations with the best fit form the probability distribution of the forecast uncertainty. So far the method is one-dimensional and hence does not take geographical or temporal aspects of uncertainty into account. To be able to benefit from integration of information from geographically distributed time series or from a grid of NWP the methods needs to add a second dimension. This is in the focus of some recent research [3], where each grid point in an area, where wind farms are located, is treated independently, using meteorological analysis instead of observations.

The second type of methods "Statistically-based scenarios" produce statistically-based scenarios that are a result of statistical generation of scenarios from the probability distributions produced by statistical models based on the copula theory. We define them as scenarios, as the further processing of the approach contains x independent results in contrast to the statistical method, producing a PDF function. Such scenarios are quite similar to the third methods, the physically-based ensembles. However, the uncertainty representation of the statistical scenarios today only capture the spatial variability of the forecast, like ramps. We therefore distinguish them here as scenarios rather then ensembles. Outliers that indicate extreme events, for example above cut-out wind speeds of wind turbines can only be detected with probability characterization and require an extreme event analysis. This is due to the conversion to power taking place in the first step of the statistical training in the same way as for deterministic forecasts. Extremes in wind power are in that way difficult to detect, because the flat part of the power curve prevents extremes that would be visible in the wind speeds to show up in the power scenarios. The clear advantage of the statistically based scenarios is that they are computationally much cheaper than physical ensembles as they are built from a deterministic weather forecast. They also generate a much more realistic uncertainty representation than the pure statistical approach, while only being slightly more computationally costly.

The third type of methodologies, the "physically based ensembles" can be considered a post-processing of a set of NWP ensemble members, which are a set of NWP forecasts produced by perturbing the initial or boundary conditions and/or model physics perturbation, the result from different parameterization schemes of one NWP model "multi-schem" approach) or complete different NWP models "multi model" approach), converted in a subsequent phase into power with a curve fitting method (see e.g. [2]). The NWP ensemble is configured to represent the physical uncertainty of the weather ahead of time rather than uncertainty as a function of past experience. In practice, this means that the NWP ensembles, especially the multi-scheme approach, are event driven, produce outliers and also catch extremes, even those with a return periods of 50 years. This is a clear distinction from statistical methods, because even long time-series of historic data contain too few extreme events to have impact in the learning algorithms. Often ensemble prediction systems (EPS) are found "under-dispersive", i.e. the uncertainty spread does not cover or represent the uncertainty of the target variables. This can have many reasons, some often found reasons being that (1) the ensemble is not targeted to the variable of interest of the end-user, (2) the time or spatial resolution is too coarse to capture the small scale phenomena of the target variable, (3) insufficient information is extracted or used in the conversion to wind power to represent a realistic uncertainty. Mostly such deficiencies can be mitigated by calibration methods ((see e.g. [2]).

IV. Applications of Uncertainty Forecasts in the Power Industry

Some of the most used applications in the power industry today are:

1) Balancing/trading of wind/solar power
2) Probabilistic reserve setting
3) Situational awareness
4) Flexibility management in smart power grids
5) High-Speed shut down warning system

In the following we will show how such applications can be implemented and which consideration are required to do so.

Balancing/trading of wind/solar power

The majority of the renewable energy trading companies solely use point forecasts, despite the availability of forecast uncertainty products from the service providers, and apply expert knowledge for scaling these point forecasts (in some cases based on the level of uncertainty provided by the 10% and 90% percentiles) in order to minimize the imbalance costs.

It is known from the literature that the optimal bid, from the expected value decision paradigm, consists in a quantile calculated from the forecasted imbalance costs [4]. Therefore, the calibration of uncertainty is a critical requirement for the end-user and has a non-marginal economic impact. Moreover, in electricity markets with high integration levels of wind/solar power, the combination of extreme forecast errors and high imbalance prices is critical and demands for risk modeling techniques and uncertainty forecasts with high accuracy in detecting extreme events (e.g., cut-out wind speed, ramps) ([2]).

If the portfolio includes energy storage units, the temporal dependency of forecast uncertainty is a primary requirement [5]. For this use case, the end-user should request ensemble forecasts, either from physical or statistical models.

Dynamic reserve setting with probabilistic forecasts

The use of uncertainty forecasts for setting the power system reserve requirements is probably the most well-accepted business case for the energy industry. For example, the Electric Reliability Council of Texas (ERCOT) uses a probabilistic rule based on data of forecast errors for setting the non-spinning reserve requirements. Similar concepts are being explored by European TSOs [6]. A critical requirement is minimum deviation from perfect calibration to avoid under- and over-estimation of the risk (i.e., loss of load probability, probability of curtailing renewable energy) [7].

In this sense, allocating reserve dynamically requires probabilistic forecasts and the value for the TSO is well defined. Yet, the following challenges remain to be addressed: i) communication and visualization of forecast uncertainty and extreme events in TSO dispatch centers; ii) training of human operators to understand and exploit the probabilistic information, i.e. move from a deterministic/ real-time paradigm to a probabilistic/predictive operation paradigm.

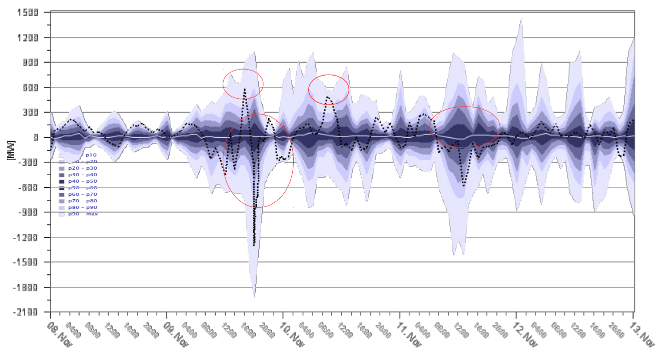

Fig. 5. Example of the graphical visualization an operational dynamic reserve prediction at a system operator. The reserve requirement with the

Figure 5 shows an example of the graphical visualization of an operational dynamic reserve prediction system at a system operator, where operators requested to have various intervals in order to evaluate which of the intervals was economically or from a system security aspect the better choice in a given situation. The reserve requirement is built with a NWP ensemble approach where the ensemble spread is related and calibrated to the expected forecast error of wind power, demand and an estimated cross-border exchange requirement. The mean of the computed reserve requirement is scaled to zero and the possible positive and negative requirement intervals are plotted in form of 4 percentiles up and down, respectively. The red circles indicate areas, where the requirements would have been higher than what e.g. a P20-P80 interval would have covered, if this was the uncertainty range the operators would have requested. It also illustrates why the operators wanted to be "aware" of such outliers, even if they may not have pre-allocated according to the outer ranges or boundaries.

Situational awareness

For system operators, information from uncertainty forecasts can be integrated at two levels:

1) *Visualization and cognition*: generate alarms and early warnings to human operators about predefined events with impact in the frequency control tasks, e.g. large ramps, wind turbines tripping, large forecast errors. With this information, the human operator can use his/her "natural" neural network to derive a set of control actions (e.g., change current dispatch, activate reserve) that mitigate the effects of renewable energy uncertainty and variability in the system's frequency.
2) *Technical evaluation of network constraints*: uncertainty forecasts can be integrated in a power flow module, available in commercial energy management systems (EMS), to detect voltage and congestion problems with a certain probability threshold [8]. With this information the human operator can plan preventive actions in advance, e.g. change the market dispatch, define a cape for market offers in a specific network area/node.

The following requirements should be requested by the end-user for the forecasting provider: a) high accuracy in detecting extreme events related to RES uncertainty and variability; b) capacity to capture the temporal and spatial dependency of forecast errors.

Flexibility management in smart power grids

The deployment of smart grid technology enables the control of distributed energy resources (DER), e.g. storage and demand response, which flexibility can contribute to increase the RES hosting capacity while maintaining the standard quality of supply levels. The combination of forecasting systems and optimal power flow tools can be used by transmissions and distribution system operators to pre-book flexibility for the next hours in order to handle the technical constraints of their electrical network [9].

Presently, distribution system operators are starting to explore RES forecasts in the following use cases: a) forecast grid operating conditions for the next hours; b) improved scheduling and technical assessment of transformer maintenance plans; c) contract and activate flexibility from DER to solve technical problems.

In all these cases, a primary requirement is the need to have a spatial-temporal representation of forecast uncertainty, where the temporal component is only relevant, if inter-temporal constraints are required (e.g., operation of storage devices, control of capacitor banks and on load tap changers).

Finally, a current topic of interest is the coordination between the transmission and distribution systems. Different frameworks for information management and exchange are under discussion [10]. It is clear that uncertainty forecasts can be used to provide future information about nodal consumption/injection in the interface between the two networks. For example, the German gridcast research project (2017-2021) will develop a nodal forecasting system for the TSO-DSO interface and the FP7 European Project evolvDSO developed the concept of flexibility maps where RES forecasts are used to quantify the operating point and flexibility range in the TSO-DSO interface [11]. This paves the way to combine information about forecast uncertainty and flexibility, as proposed in [12].

High-Speed shut down warning system: In a typical area where high-speed shut down is a challenge for the grid security, the development of low pressure systems are frequent and the variability of the wind resources are relatively high. Thus, an alert system concerning high-speed shutdown of wind power must be established based on probabilities computed from a probabilistic prediction system that can take the spatial and temporal scales into consideration in order to capture the temporal evolution and spatial scale of such low pressure systems that contain wind speeds leading to large scale shut-down of wind farms.

This can for example be provided by a physical approach based on a NWP ensemble that ideally contains all extreme values inherent in the approach without the requirement of statistical training. Alternative solutions may exist from statistical approaches (see III by employing an extreme event analysis to a statistical ensemble of type 2. This is due to the requirement that such forecasts must be able to provide probabilities of extreme events, where each "forecast member" provides a valid and consistent scenario of the event. The probabilities need to be suitable solutions for a decision process. They can be computed for very critical and less critical events, dependent on the end-users requirements.

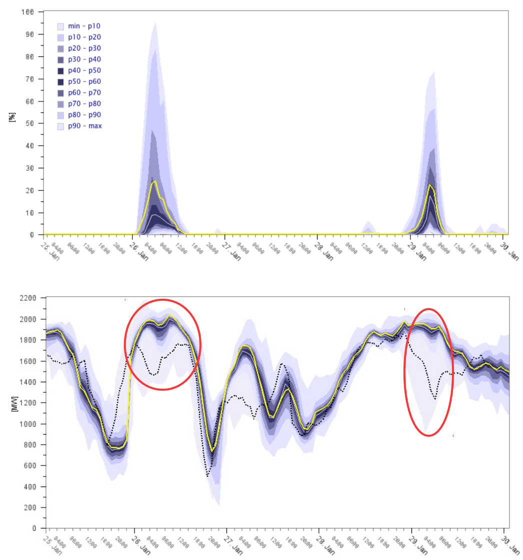

Fig. 6. Example of a high-speed shut-down example, where within 5 days 2 extreme events showed up in the risk index of the system (upper graph), showing the probability of occurrence in terms of probability ranges as percentiles P10...P90 of a high speed-speed shutdown. The second graph shows the 5-day wind power forecast inclusive uncertainty intervals as percentile bands P10...P90 and the observations (black dotted line). The red circles indicate the time frame in which the alarms were relevant.

Figure 6 shows an example of a real-time setup of such a high speed shut down warning system. The example exhibits 2 events. The first graph shows the risk index in probability space of a high-speed shutdown event to occur. The second graph shows the wind power forecast with uncertainties inclusive the observations (black dotted line) of what happened. From the upper graph, the operator can

TABLE I
DEFINITIONS OF A HIGH-SPEED SHUT DOWN INDEX FOR A CONTROL AREA WITH A HIGH PENETRATION LEVEL OF WIND POWER AND A WIND RESOURCE WITH A HIGH VARIABILITY AND WIND SPEEDS OFTEN EXCEEDING 25M/S.

wind speed in 100m	index value
0 - 22.5 m/s	0.00%
22.5 - 24.5 m/s	0 -¿ 100%
24.5 m/s	100.00%

directly read out the following:

- Case 1 at 26. January:
  - 10% probability of 50- 8% probability of 90- 90% probability of 5
- Case 2 on 31. January:
  - 10% probability of 50- 15% probability of 90- 90% probability of 10

The reality is shown by the observations in the lower graph of figure 6, where it an be seen that the first case's peak value was 35% high-speed shut-down and the second case exhibited a peak value of 45% of high-speed shut-down.

Practical experience from evaluating high-speed shutdown events and discussing the alert system with the operators, showed that it is absolutely crucial that the operators understand the alerts and are capable of checking and verifying themselves in a graphical way, what they may receive as written alert. Therefore, the impact of a false alarm needs to be evaluated, decided upon and documented in the design phase, so that the operators have a clear reference system to relate an alert to. Technically, the frequency of the alert generation should be adjusted to:

a lead time of the alert
b change of severity level since previous alert
c initial and valid week day and time of the day
d severity of the event computed from a ramp-rate perspective and actions required
e the need and possibility to call back and/or revert actions

The strategy of issuing an alert should include (1) issuing of every alert according to a simple scheme and (2) reduction of the amount of alerts to a level that prevents that critical alerts are not accidentally overlooked.

It was also found that the Use of sliding interval from 23-25m/s was an important introduction into the design to ensure that tje warning is issued **before** the event.

An "high-speed event" can be defined as active, if the hub height wind speed is above 24.5m/s, while there is no event, if the wind speed is below 22.5m/s. Table IV shows how such an index may be defined.

As briefly discussed in under IV, if a major fraction of the power generation is wind dependent, it would be considered best practice, if the operator is aware of the risk of high-speed shutdown, even if the likelihood is low, but still justifiable.

V. WRAP UP

We have been providing a short, but comprehensive review of currently used methodologies of generating uncertainty forecasts for the power industry and described a number of applications, where the value of uncertainty forecasts have proven concepts and are integrated in today's business practices. Looking into these applications, it becomes apparent that uncertainty forecasts have found their place in the power industry, but are on the other hand far from being exploited to a level that could be expected and may be necessary in the future, considering the value that uncertainty forecasts already today can provide to many processes and applications. The IEA Wind 36 Task on wind power forecasting has dedicated a work package to promote and communicate the advantages of uncertainty forecasts for the power industry and shed light into the gaps of understanding how and where to best make use of such forecasts.

ACKNOWLEDGMENT

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