The Use of Probabilistic Forecasts in Theory and Practice

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1. Introduction/Motivation

Much of the electric system is weather dependent; thus, our ability to forecast the weather contributes to efficient and economical operation of the electric system. Climatological forecasts of meteorological variables are used for long-term planning that captures changing frequencies of extreme events, like cold and hot periods, and to identify suitable locations for deploying new resources. Planning for fuel delivery and maintenance relies on sub-seasonal to seasonal forecasts. On shorter timescales of days, the weather affects both the energy demand and supply. Electrical load depends critically on weather because much electricity goes into heating and cooling. As more renewable energy is deployed, it becomes increasingly important to understand how those sources of energy vary with atmospheric conditions; thus predictions are necessary for planning unit commitments. On the scales of minutes to hours, short-term "nowcasts" aid in the real-time grid integration of these variable energy resources (VERs).

Meteorologists use the dynamical equations of fluid motion to forecast the weather by numerically integrating those equations forward in time in numerical weather prediction (NWP) models. The weather is both variable and uncertain. Because the equations are nonlinear, they are inherently chaotic. Thus, slight changes in initial or boundary conditions, or changes to the representation of physical processes, can lead to large changes in the forecasts. Meteorologists have learned to deal with the resulting uncertainty by providing probabilistic forecasts.

Varying degrees of uncertainty also exist in almost all other parts of the electric system's operation, including the load forecast, the dynamic capacity of transmission lines, and unscheduled outages of non-variable generators and transmission resources. Some of these are weather-dependent while others are associated with different uncertainty factors. Therefore, the entire system has uncertainties that are most effectively managed with a probabilistic approach.

Because both the atmosphere and the electrical system with significant amounts of VERS contain large uncertainties, a probabilistic approach to forecasting and planning becomes necessary to optimize the weather-dependent systems. Using probabilistic information provides knowledge that can be used to enhance situational awareness, assess multiple potential grid scenarios, optimize economical outcomes, leverage smart statistics, and improve plans. Probabilistic forecasts should not be understood as the only means to solve the problem of predictability of VER output, but rather a way forward to better deal with the many specific tasks in power system operations. These forecasts provide the possibility both to make decisions based on a "best guess" and to be able to prepare for the less likely (lower probability) scenarios or extremes that may cause security issues on the grid, such as too high costs for balancing services, or equipment misoperations or failures. We will describe some of the leading ways that probabilistic forecasts are currently being used and show how they might additionally be leveraged to enhance power system operation and planning.

2. Building Probabilistic Forecasts

Four primary methodologies are currently used to generate probabilistic forecasts for the power industry. These methods differ in their output and usage possibilities, their complexity, and computational resource requirements. Figure 1 summarizes these methodologies and their typical output types.

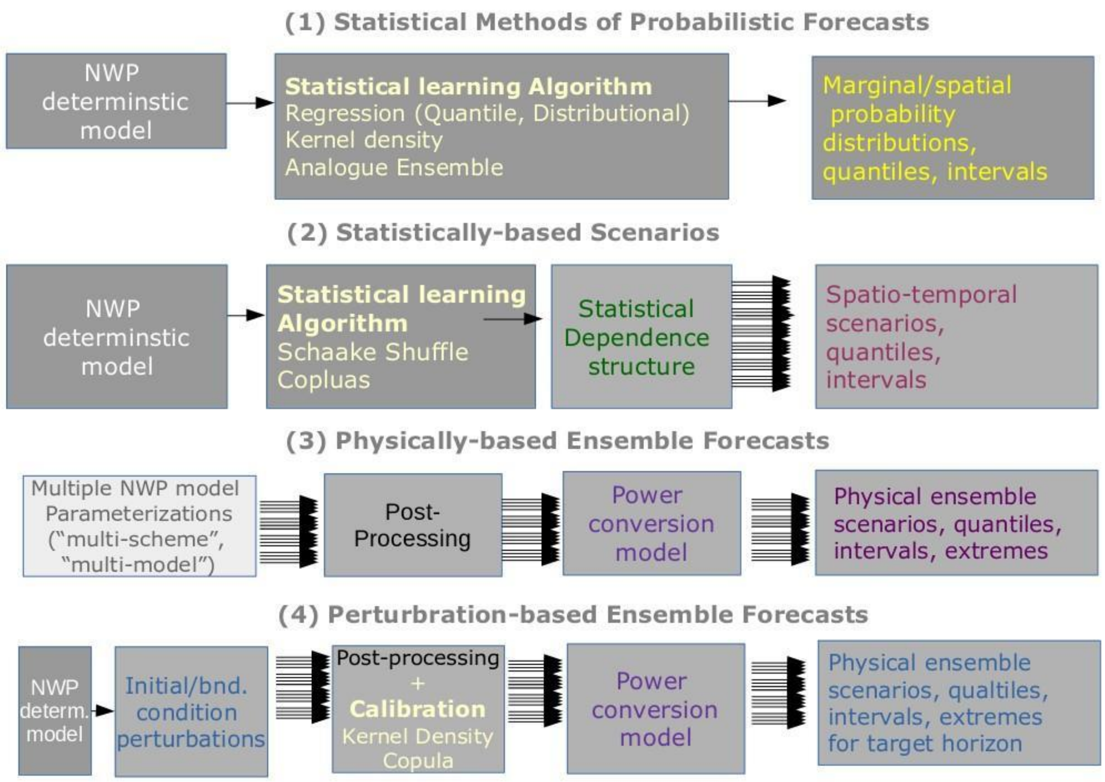

Figure 1: Overview of the four state-of-the-art forecast methodologies to generate probabilistic forecasts.

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The first two methodologies statistically generate a probability density function (pdf) from a deterministic NWP simulation, while the last two generate the pdf by employing different NWP models, model parameterization schemes, or perturbing the initial or boundary conditions. The disadvantage of running multiple ensemble members is the high computational cost in comparison to statistically based methodologies.

However, the user of such forecasts should be aware that each of these approaches conveys a different type of information about the forecast uncertainty. The statistical post-processing of a single NWP forecast represents the composite historical uncertainty (i.e. based on the statistical sample) whereas an NWP ensemble more explicitly characterizes the uncertainty of the current scenario. Figure 2 compares the difference of the uncertainty information as seen in the uncertainty bands for the wind power forecast for all German wind plants derived from a statistical Type 1 approach using a single NWP model and a multi-model approach. While the multi-model spread indicated a high risk of ramping up around noon, the single-model quantiles indicated a moderate potential error. This is because the statistical methods constructed a constant climatology band around a single forecast. Extremes and outliers in present weather situations are not well modeled by these methods.

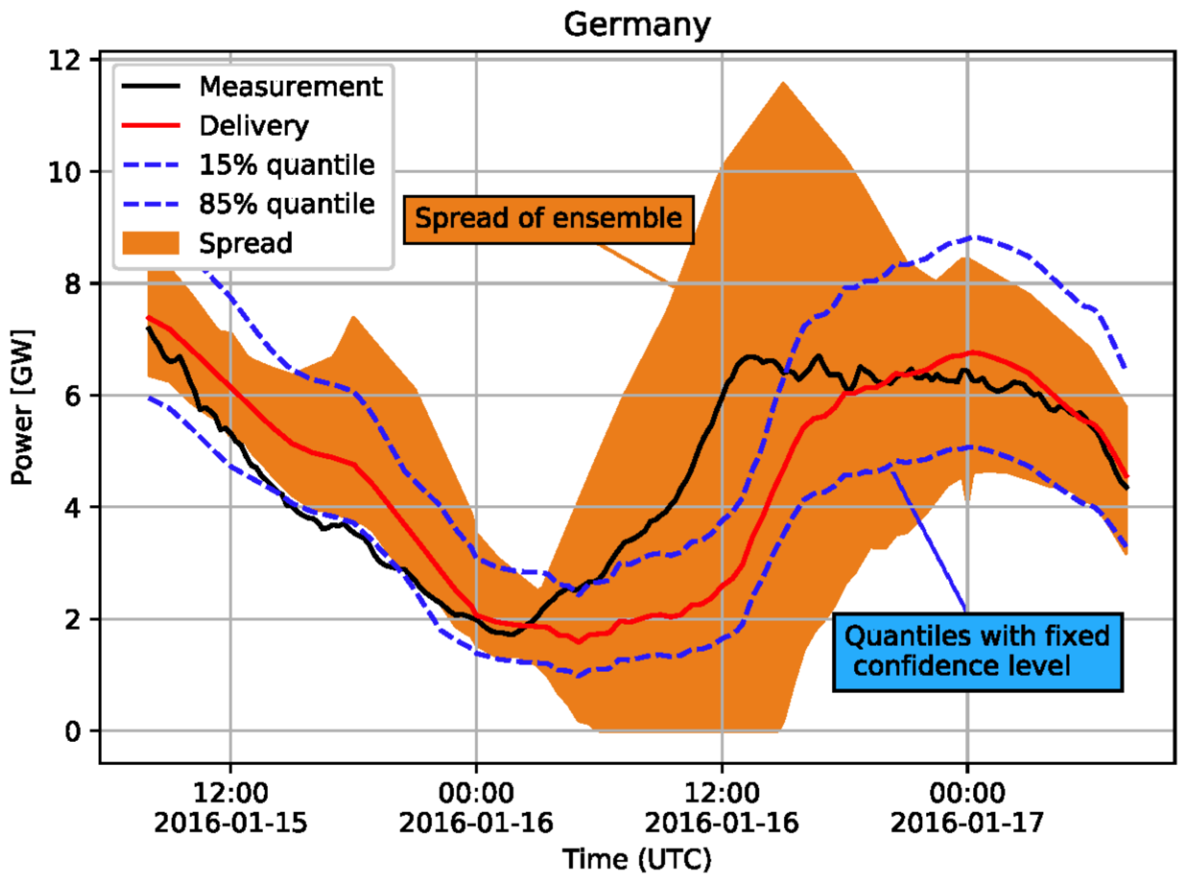

Figure 2: Comparison of uncertainty information between a statistical approach based on a single NWP (blue dashed lines) and spread (deviation) of multiple NWP forecasts (orange shading). (source: energy & meteo systems)

2. Evaluating Probabilistic Forecasts

The evaluation of the performance of probabilistic forecasts is unavoidably more complex than the assessment of deterministic forecasts because probabilistic predictions contain more information. There are three fundamental attributes that describe the performance of probabilistic forecasts: (1) reliability, (2) sharpness, and (3) resolution.

The "reliability" of a probabilistic forecast is the degree to which the frequency of the actual outcome matches the forecasted probability. For example, do events with a 60% probability occur in 60% of the cases? If the reliability is not high, the forecast presents a distorted view of the uncertainty and requires "calibration".

The "sharpness" attribute measures the spread of a pdf. The "sharpest" probability forecast is one in which one value of a forecast variable has a probability of 100% and all other values have a probability of 0%, which is essentially a deterministic forecast. A "sharper" forecast (i.e. closer to a deterministic forecast) is desirable, but only if reliability is high. If a set of forecasted pdfs typically displays less spread than the climatological frequencies, then the forecast is often considered to have meaningful sharpness.

The "resolution" attribute refers to the ability to distinguish among cases with different pdfs. A forecast method that produces the same probability distribution for all cases (e.g. every forecast cycle) shows zero resolution. An example of a zero resolution forecast is the climatological frequency distribution, which does not distinguish among forecast cases. However, such a forecast may be highly reliable (as in the case of a climatological distribution). A probabilistic forecast with high resolution enables the user to more effectively distinguish cases with low forecast uncertainty from those with high uncertainty, which may be the most valuable aspect of probabilistic forecasts for many applications.

Metrics have been constructed to individually measure each of these attributes. Reliability is most frequently evaluated. Although a high degree of reliability is necessary for a probabilistic forecast to have meaningful value, it is seldom sufficient. In practice, the sharpness and resolution distinguish among alternative probabilistic forecast solutions. Forecast providers often use composite scores that are implicitly sensitive to all three attributes.

3. How End-Users use Probabilistic Forecasts

Nearly all operators of grid systems with high shares of VERs use weather-dependent generation forecasts. Typically, they only use a "best," single (i.e. deterministic) forecast. The use of probabilistic forecasts by grid operators with heavy renewable penetrations is growing, leading to enhanced grid management decision-making. It is also providing market uncertainty products to enable automatic commitment of resources to assist with renewable uncertainty. The following subsections provide a range of examples of the current use of forecast uncertainty information in grid management processes.

a. Using Probabilistic Information as Input for Grid Security Calculations - A German Example

Several German TSOs and distribution system operators (DSOs) have recognized the importance of including VER predictions in load flow calculations to detect future grid congestion and identify counter-measures. In the German power system, most renewable generators are connected at the 110 kV or lower voltage level. This leads to an interest in the power flow through substations that connect different grid levels, referred to as "vertical grid load". The exchange of data between grid operators, especially between TSOs and DSOs, is traditionally quite tedious. Several recent initiatives to exchange data regarding grid topology, VER units connected to specific grid points, and actual output promises to optimize grid-related forecasts. Forecast vendors in Germany now provide forecasts of the vertical grid load to grid operators for a number of substations. Recent experience indicates that integrating generation, load, and price forecasts leads to a more accurate forecast of the vertical grid load. In addition, confidence bands indicate the uncertainty of the vertical grid load forecast as illustrated in Figure 3.

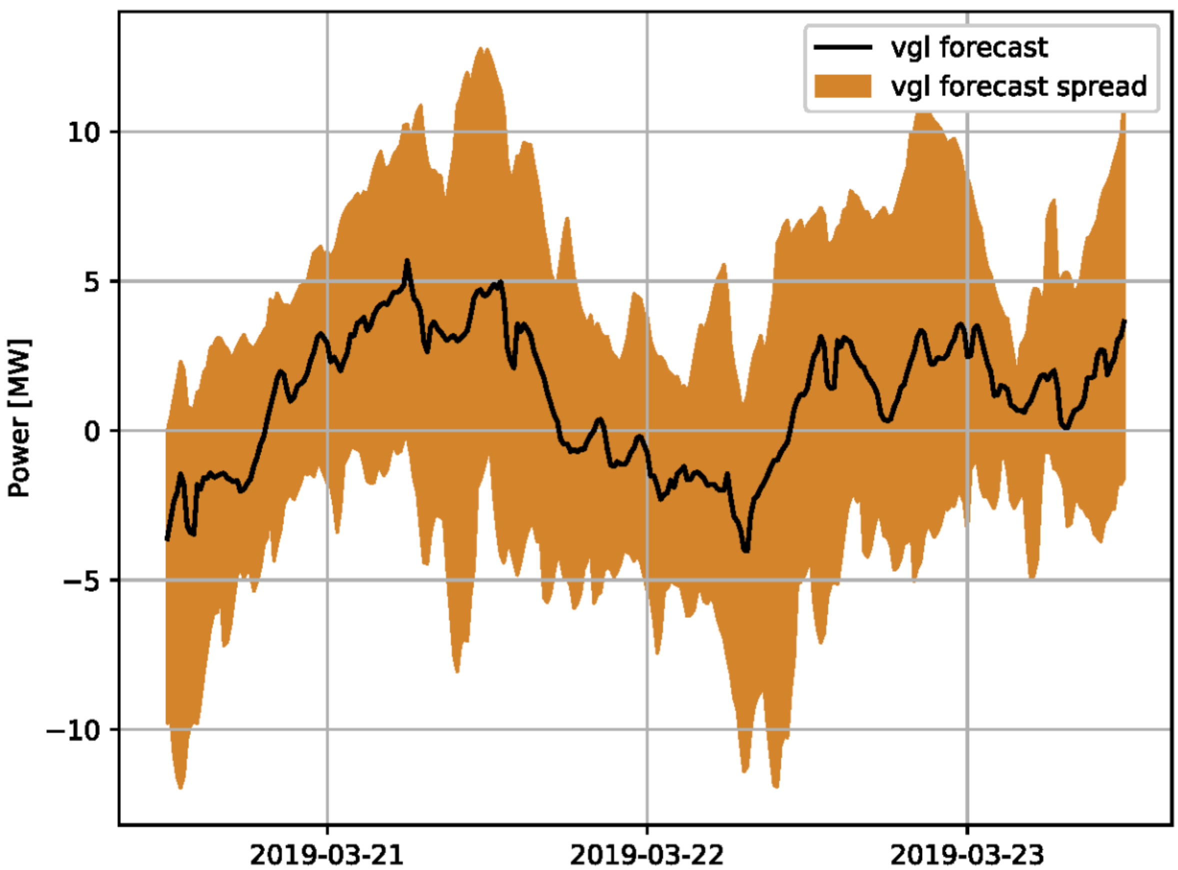

Figure 3. Forecast of vertical grid load (solid black line) for one substation between TSO and DSO grid with upper and lower band (dashed lines) indicating uncertainty. Negative values refer to transport to the lower voltage grid, positive toward the higher voltage grid.

German grid operators currently calculate congestion forecasts for a specific voltage level based on deterministic generation and load forecasts. Consequently, the resultant load flow forecasts and grid security measures do not incorporate any uncertainty information about volatile wind and PV generation. German TSOs plan to use probabilistic forecasts, i.e. scenario forecasts, as an input for grid congestion security calculations (e.g. congestion forecasts), to consider uncertainty in grid management processes.

Several methods are used for calculating forecast scenarios of the power production of spatially distributed wind plants and PV stations based on probabilistic forecasts. Using methods like ensemble copula-coupling approaches (method 2 in Figure 1), one can calibrate the scenario in time and space to obtain reliable wind and PV forecast scenarios with realistic weather-driven correlations among locations. Figure 4 displays an example of a vertical grid load measurement as well as probabilistic and deterministic forecasts of the wind power share at this transformer.

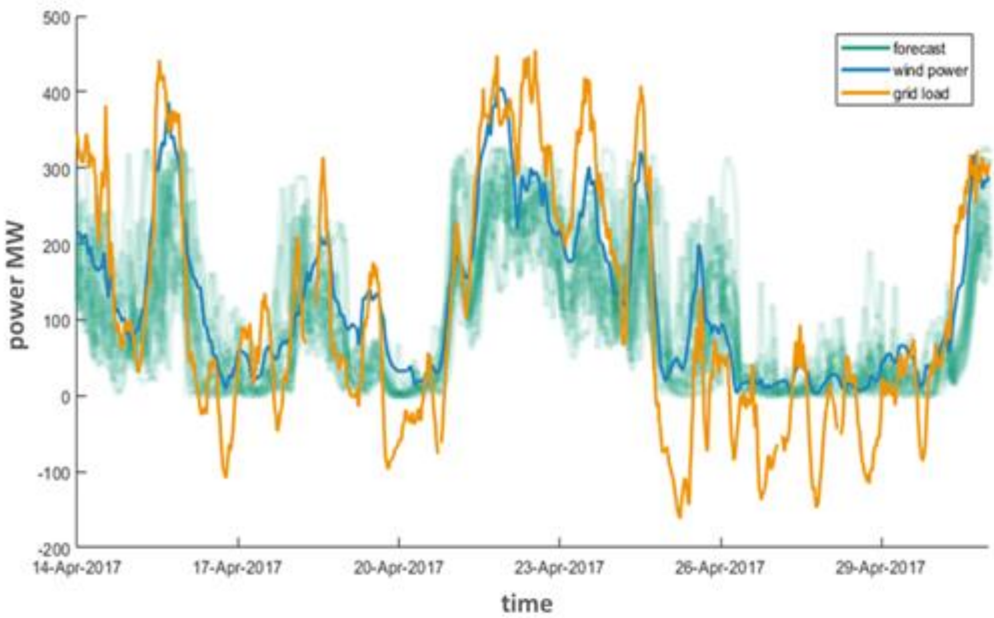

Figure 4. Example of a load flow measurement at a transformer between extra high and high voltage levels. The blue and green curves show deterministic and scenario-based forecasts of the wind power share at this transformer respectively.

Using a calibrated scenario forecast instead of a single "best" forecast for all points of common coupling (PCC) implies that the load flow calculation must be repeated for each scenario member. Besides the multiple load flow calculations, grid operators must interpret the characteristics of the resultant load flow for each grid state scenario. The resultant scenarios can be used to optimize redispatch and VER curtailment actions based on risk according to the probability of predefined critical grid states. Scenario forecasts can also be used to calculate a range of system services that a DSO could provide to a TSO at a single PCC. Figure 5 plots results from simulations using historical data from a German DSO. The plot demonstrates results for a use case concerning reactive power demand by the TSO. The system required that no reactive power exchange take place at this PCC. In the figure, the red triangles show the original expected interchange of reactive power flow at the PCC. The green triangles show the flow after optimization of the operation of the installed VER (none needed). The green regions represent the possible reactive power flexibility of the DER at each time step. The light red and yellow areas display a simulated forecast of reactive power at the beginning of the time series (6:00 am) and its uncertainty, respectively. In this case, the optimization did a good job of satisfying the criteria of meeting zero reactive power exchange at the PCC.

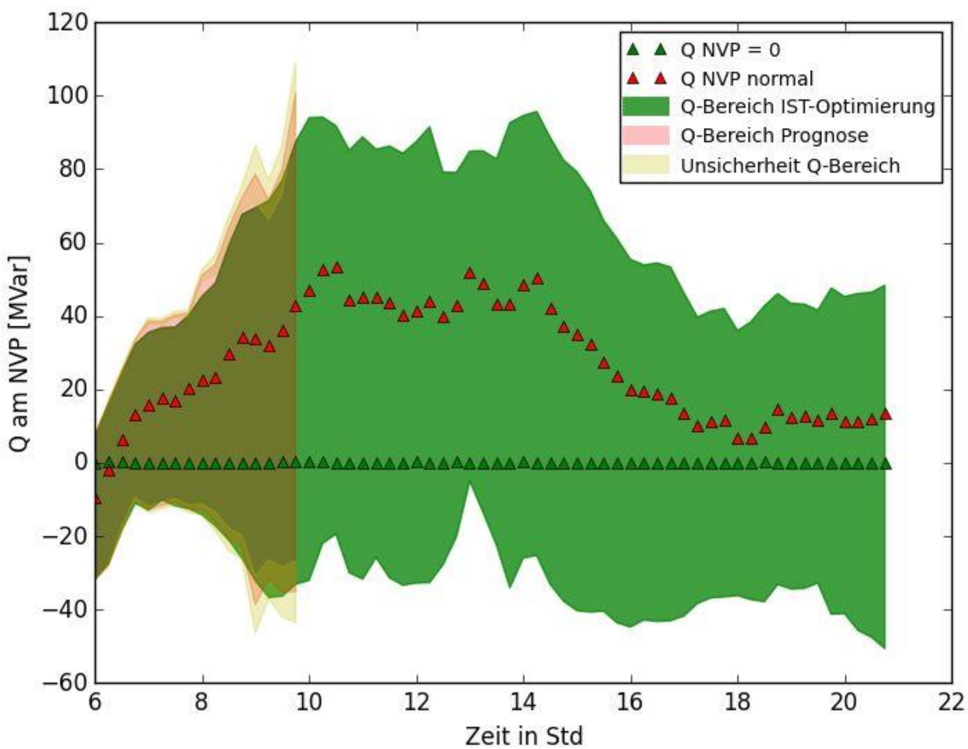

Figure 5 Simulation results for the use case concerning a reactive power (Q) demand on the part of the TSO with Q = 0 MVar at PCC (taken from Wende-von Berg et al. 2016).

b. Using Probabilistic Information to Fine-Tune Unit Commitment: A Lesson from SPP

The U.S. Southwest Power Pool (SPP) has incorporated more than 17 GW of wind resources into its generation fleet over the past decade. As of early 2019, SPP had a total wind capability of 21.5 GW. To date, SPP has seen upwards of 16.4 GW of instantaneous wind generation and has served an instantaneous 63.4% of system load with wind energy. These high levels of variable energy production make accurate and up-to-date resource forecasting critical for system reliability. As industry experts and vendors work to improve forecasts for end-user consumption, SPP is also taking steps to manage real-time, day-ahead, and multi-day forecast errors to better understand the potential impacts of forecast uncertainty. Thus, probabilistic forecasting is likely to provide value on these timeframes.

SPP has developed a process to maintain situational awareness of the impacts of potential forecast errors. Each day, staff run real-time studies which assume various forecast errors. These multi-day reliability studies help SPP ensure that, in the event forecast errors occur, it will still have sufficient energy capacity available to serve load. Currently, SPP runs four daily studies in which different levels of both error and resource flexibility are considered: two with an 85th-percentile of both load and variable resource forecast error applied and another two with 99th-percentile forecast errors. An advance notice interval of either 6 or 20 hours differentiates the two studies at each error percentile. The "advance notice interval" designates how far in advance of a particular target interval a resource can be called on to be available for that interval. This is particularly important because many resources have lengthy lead times and must be started far in advance to ensure that they are online and available to serve load. Staff use the results of these multi-day reliability studies to determine if additional generation needs to be started ahead of time to mitigate real-time forecast errors.

Currently, SPP takes into account up to ten unique NWP weather models and examines their potential spread to quantify the forecast's uncertainty level. If ensemble members are strongly clustered (i.e., spread is low), SPP treats the scenarios with higher certainty. But, if the ensemble spread is several GW, commensurate with lower overall capacity, SPP runs studies to account for higher forecast error to ensure reliability across the system. In cases where SPP commits additional units to mitigate the risk of forecast errors that do not materialize, the cost of system reliability due to incorrect interpretation of the forecast is equal to the make-whole payments of the generators committed.

In addition to multi-day reliability studies, SPP assesses probable forecast errors in the wind forecast during one-, four-, and eight-hour horizons across multiple days. For this uncertainty assessment, SPP applies probable errors and then evaluates available capacity during each of the horizons for sufficiency. The probable error is determined by correlating the forecasted weather with past 95th-percentile wind forecast errors. In cases where errors exceed available capacity for a particular horizon, actions may be taken to secure capacity beyond that horizon to ensure reliable system operations. An internal Uncertainty Response Team evaluates weather and other system conditions to identify high-risk timeframes during which SPP may face greater uncertainty in load and VER forecasts. The resulting heightened awareness of forecast uncertainty impacts has helped SPP maintain reliable operations during forecast excursions. SPP continues to work with forecast vendors to gain better visibility of high-uncertainty intervals.

Other operators are applying similar analyses or are considering whether to do so. For instance, the Portuguese TSO values the probabilistic forecast's ability to quantify the added reserves due to forecast errors of the renewable variable generation (wind, solar and hydro). The probabilistic information provides the confidence interval that the operator needs to manage the system.

c. Capturing Extreme Conditions: A Lesson from ERCOT

While renewable energy forecasting has advanced, it remains challenging to accurately predict the output from VERs. Figure 6 depicts histograms of system-wide wind generation forecast errors in 2018 at the Electric Reliability Council of Texas (ERCOT). Although the forecast errors are concentrated near zero, large forecast errors still occur. Probabilistic wind forecasting becomes particularly valuable for the large variations in wind generation that drive these large forecast errors. When these low-probability events are predicted within the distribution of the probabilistic forecast, their impact on the security and reliability of the grid can be assessed and a corresponding mitigation plan can be developed.

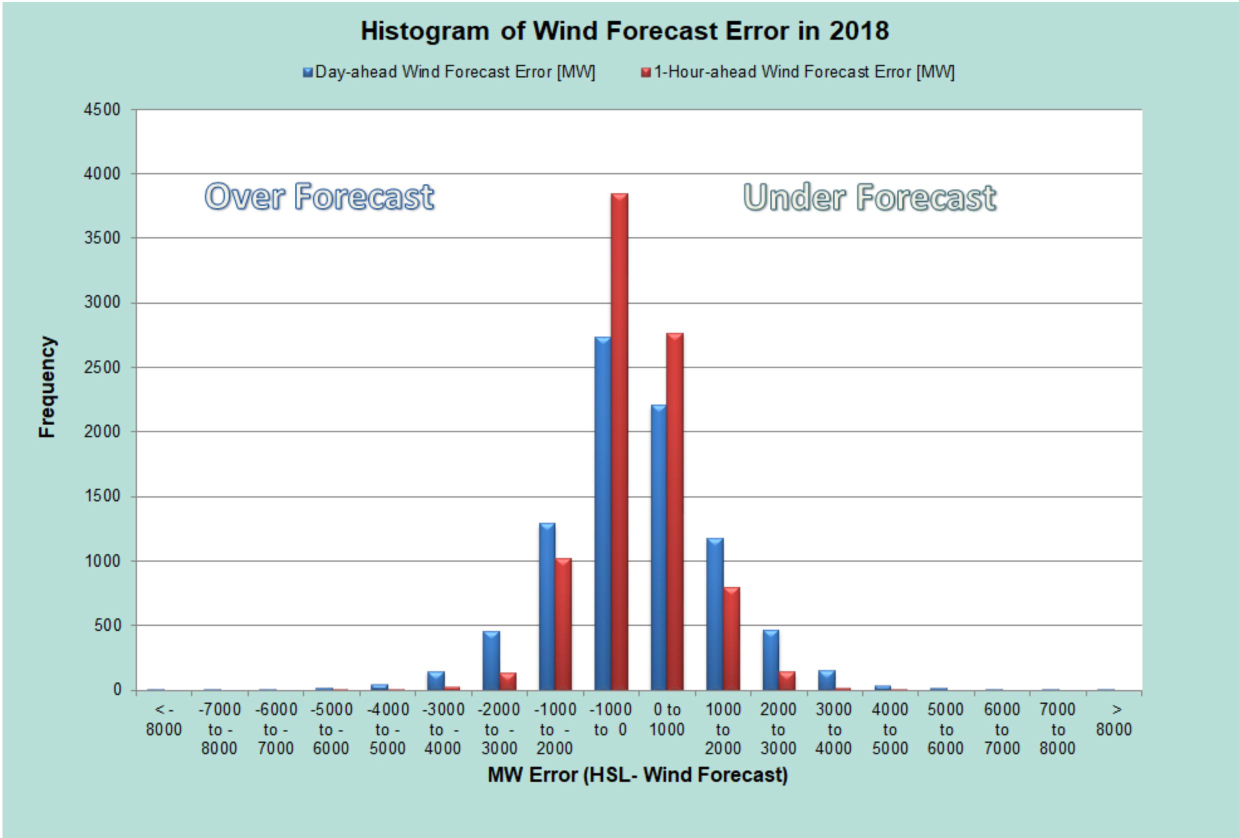

Figure 6. Histogram of system-wide wind generation forecast error at ERCOT in 2018

The fluctuations from VERs impose a challenge to the balancing services that operators perform to maintain satisfactory grid reliability. ERCOT utilizes a probabilistic forecast that is updated every 15 minutes to alert system operators of projections for large wind ramp rates during the next 6 hours. Figure 7 displays forecasts from ERCOT's Large Ramp Alert System (ELRAS). ELRAS provides estimates of the probability that wind ramp rates on the 15-min, 60-min and 180-min time scales will exceed a set of predefined thresholds. An early warning for a large wind ramp event will trigger an in-depth analysis to evaluate the system's robustness for accommodating this impending event.

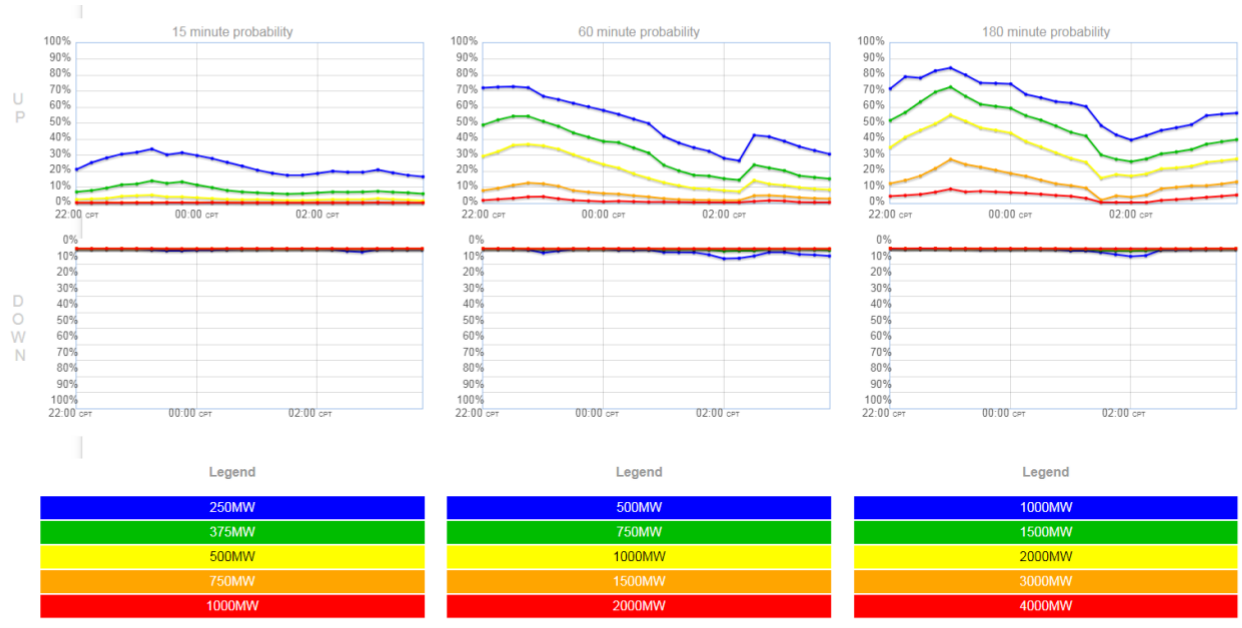

Figure 7. A display from the ERCOT Large Ramp Alert System (ELRAS)

A probabilistic forecast of Type 1 (see Statistical Methods of Probabilistic Forecasts in Figure 1) provides a range of values, characterized as percentiles or the probability of occurrence, which can help the operators gauge the need for reserves in each forecasted scenario. ERCOT has developed an online tool to incorporate probabilistic wind forecasts into the real-time decision process as shown in Figure 8. The probabilistic wind forecast is delivered for 50_{th}, 90_{th}, 95_{th} and 98_{th} percentiles for the next 6 hours. Operators can select one of these wind forecasts in the online tool. For example, the green line represents the load forecast while the blue line represents the online generation capacity when considering 50_{th} percentile wind forecast. The online generation capacity with a 90_{th} percentile wind forecast is given in red. The reserves (regulation-up [orange] and non-spinning [purple] reserves) are overlaid on the red line, which represents additional generation capacity to be deployed if needed. In this particular example, after 18:00, a greater than 10% chance exists for the forecasted load to be higher than the predicted online generation capacity. Because reserves are procured, the system maintains sufficient generation capacity to serve the load.

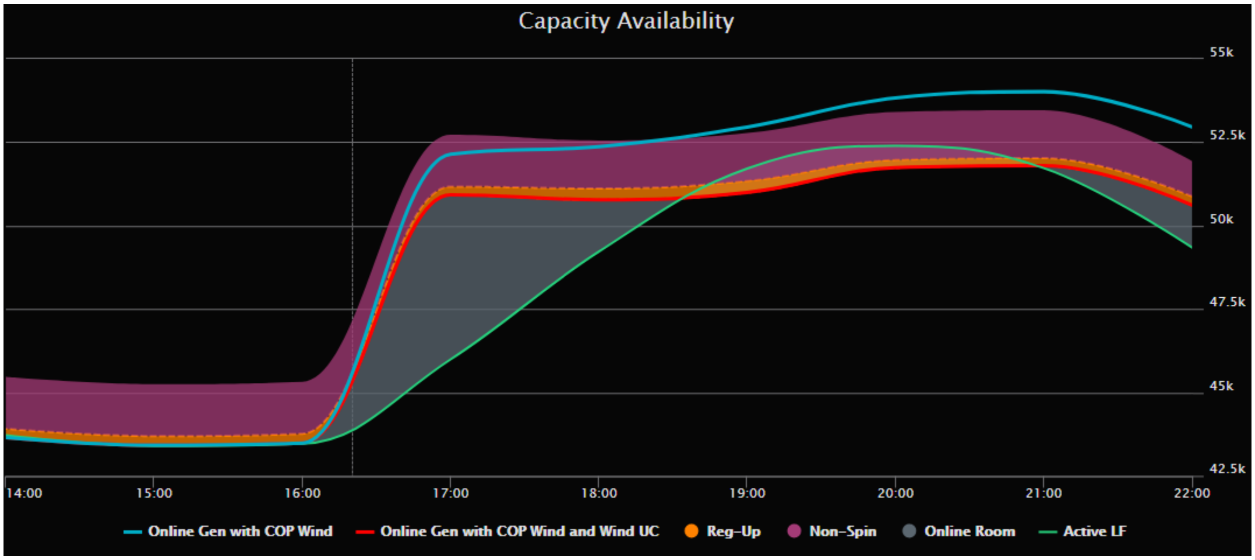

Figure 8. ERCOT online tool to use probabilistic wind forecast

d. Use of Probabilistic Forecasting for Extreme Events, such as High-speed-shut-down Risk Assessment - An Irish Case

High-speed shut-down (HSSD) events, caused by wind speeds near 25 m/s, occur predominantly in coastal or in mountainous areas, but seldom cover a large portion of a given jurisdiction. Nevertheless, in some regions the wind energy penetration has reached a level that, if wind power is producing at full capacity, can meet or exceed the local demand. In such areas, concurrent shutdown of multiple wind plants due to high wind speeds can indeed cause problems for the system.

Ireland is such an area, where practically all wind plants can produce full generation when wind speeds reach approximately 15 m/s and can continue until the plants reach their HSSD set point. The power measurements do not indicate when such set points are reached in the wind speed range below the HSSD, i.e. 20-25 m/s. Forecasting and signaling the high wind speed enables a system operator to prepare for large-scale HSSD events. Since missing power is more dangerous for power system reliability than surplus, which can always be curtailed, a need for action exists long before a deterministic forecast can provide accurate information.

A forecast of the probability of an HSSD event enables the system operator to verify system reliability and allocate reserves long in advance to keep costs at a minimum. At the Irish system operators EirGrid and SONI (System Operator for Northern Ireland), an HSSD warning system based on WEPROG's 75-member Multi-Scheme Ensemble Prediction System (MSEPS), a Type 3 method (see Statistical Methods of Probabilistic Forecasts in Figure 1), has been developed for this purpose. The HSSD warning system contains three components:

1) A probability indicator that a fraction of the HSSD will experience cut-off. In cooperation with the end user, the system critical part of the capacity is determined (e.g. 30% of the capacity).
2) An accumulated part of the expected cut-off capacity. This component provides the accumulated cut-off probability of the expected temporal shortage of capacity and ramps.
3) A table combining the information in (1) and (2) for more detailed analysis and action planning.

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Figure 9 displays the three components of the system. The first part shows the amplitude of the extreme wind speeds that cause a certain percentage of cut-off combined with strong down-ramps. This provides important knowledge to help determine 1) the maximum reserve required to maintain system balance, 2) the risk of a shortage that exceeds available up-ramp capacity, or 3) the risk for excess capacity and congestion in the power lines. After initial testing, EirGrid found that the amplitude of the events is useful for these considerations. However, a temporal accumulation of the capacity that is in shutdown risk (part 2) was required for the control room staff to be able to consider the total amount and length of reserve required and the associated down-ramps and up-ramp of prior down-ramped capacity. The table in Fig. 9 provides details for the control room staff's concrete planning.

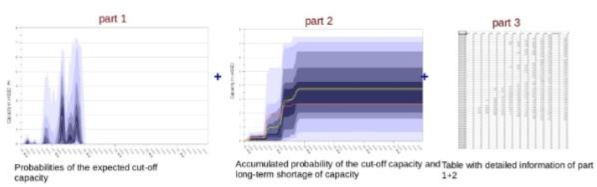

Figure 9. The three components of the HSSD warning system. Part 1 shows the probabilities of HSSD in terms of 9 percentiles P10 to P90, computed from WEPROG's 75-member MSEPS. The y-axis depicts the percentage of HSSD of total generating capacity. Part 2 is the accumulated probability over time and provides information about the required amount and length of reserve allocation with probabilities to be read from the 9 percentile bands. Part 3 presents the information in tabular format. (Figure courtesy of WEPROG)

Figure 10 shows a real-time example of two concurrent HSSD events in which the forecast system issued warnings when the probability for a high-speed shut down of more than 20% of the capacity exceeded 25%. The y-axis shows the probability of the percentage of capacity that will experience HSSD and the difference between the percentiles P10-P90 provides the probability for the event to occur. Due to the variability of forecasts in such situations, EirGrid decided that a warning would only be issued if these thresholds were exceeded a minimum of three consecutive forecast cycles. Thus, outliers are captured but not over-interpreted. In both cases, a warning was issued and in both cases, it was appropriate.

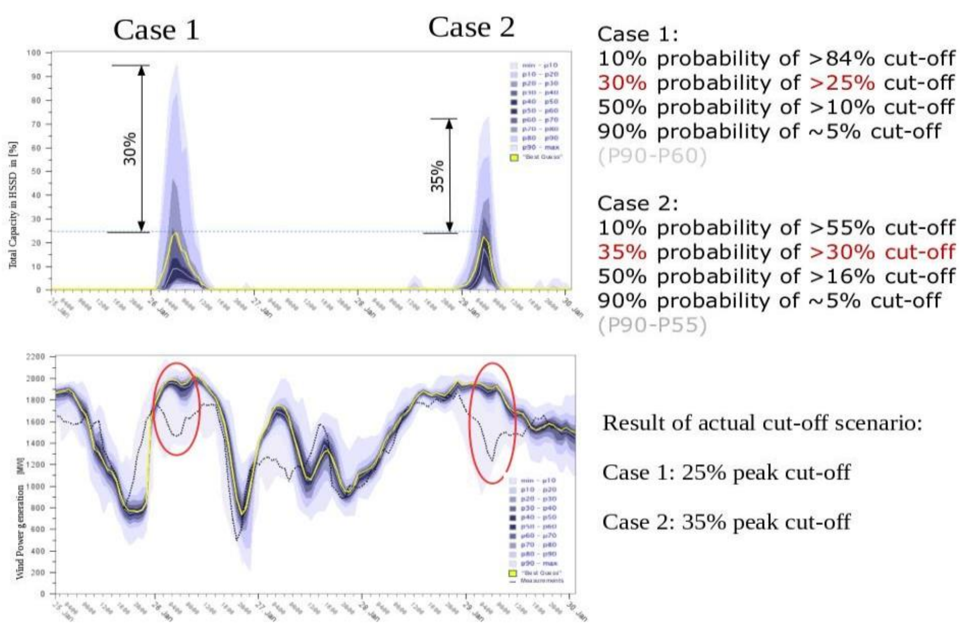

Figure 10: Example of a coupled extreme event that caused significant high-speed shutdown and how the HSSD warning system was applied. In this example the warning criteria were a minimum of 20% probability for 20% of capacity to experience HSSD in a minimum of three consecutive forecasts. (Courtesy: WEPROG)

One of the many challenges in developing the warning system was that the alert frequency must be carefully configured to assure that alerts are taken seriously when they contain a realistic security concern for the system. The main considerations for the adjustment of the alerts were lead time, change of severity level since previous alert, initial day of the week, valid day of the week, time of day, severity of the event computed from a ramp-rate, the actions required, and need and possibility to call back actions.

For the Irish case, the strategy for issuing an alert was found to work best after the following two points had been defined: 1) alerts are issued according to a simple scheme (e.g. probability of an HSSD of 20% capacity exceeding 25% probability for more than 3 subsequent forecasts), and 2) the number of alerts was reduced by issuing updates for changes in conditions once an initial alert is sent, thus preventing critical alerts from being overlooked.

This setup allows automatic filtering of unpredictable weather phenomena and reduces the risk for system shortages and unwanted volatility. Such probabilistic HSSD forecasts also allow the end user to strategically prepare for the increased risk of such events. With a suitable presentation and alert system strategy, the danger of HSSD conditions can be determined and respective actions taken in real time. By combining probabilistic forecasts and measurements in graphical and tabular formats, confidence in the forecasts increases and the operators become more likely to take the correct actions without wasting resources.

e. Use of probabilistic forecasts by the Transmission System Operator - A Spanish Case.

Red Eléctrica (REE), the Spanish TSO, is responsible for dealing with the imbalances between generation and consumption that take place in the electrical system; thus, it has generation reserves that provide frequency regulation. The physical value of these necessary reserves is determined by variables that have a stochastic behavior. The following stand out in the Spanish system:

- Deviation between market schedules and the wind forecast
- Forecast errors in other variables (demand, solar, cogeneration etc.)
- Unscheduled outages of the generation units

The large amount of wind generation (currently 23,070 MW) installed in the Spanish peninsular system has a significant impact on system balancing. Short-term (1-2 hour) fluctuations in wind energy on primary, secondary, and tertiary reserves remain less important because demand and sudden unscheduled outages of thermal units more significantly affect such reserves. However, the longer-term (8-12 hours) fluctuations of wind power have a primary impact on system reserves, especially on spinning reserves. The calculation of these reserves is the main role of probabilistic forecasts at REE. Both a probabilistic method and a deterministic method are used.

The probabilistic method assumes uncertainty as an independent probabilistic variable and calculates the combined probability of loss of reserve as the sum of a convolution of probability density functions calculated with the Type 1 probabilistic method (see Figure 1) and the additional reserve. The Type 1 method probabilistic reserve takes into account demand forecast errors, wind forecast errors, and unexpected outages of thermal units. The additional reserve takes into account possible uncertainties regarding deviations between forecast and market schedules and the management of international interconnections.

Peak-hour demand forecast errors for different horizons are fit to Gaussian distributions (Figure 11a) while the wind forecast errors (Figure 11b) are fit to a Weibull distribution. For the outages of thermal units, it is necessary to calculate the probability that a unit trips k-times in a period by using the Poisson distribution. Once the probabilities for all groups that are expected to run on the next day are calculated, a Monte Carlo simulation is performed, which provides the combined probability density function (Figure 11c).

The sum of the three previous stochastic variables results in another stochastic variable that indicates the necessary reserve to cover the demand (Figure 11d).

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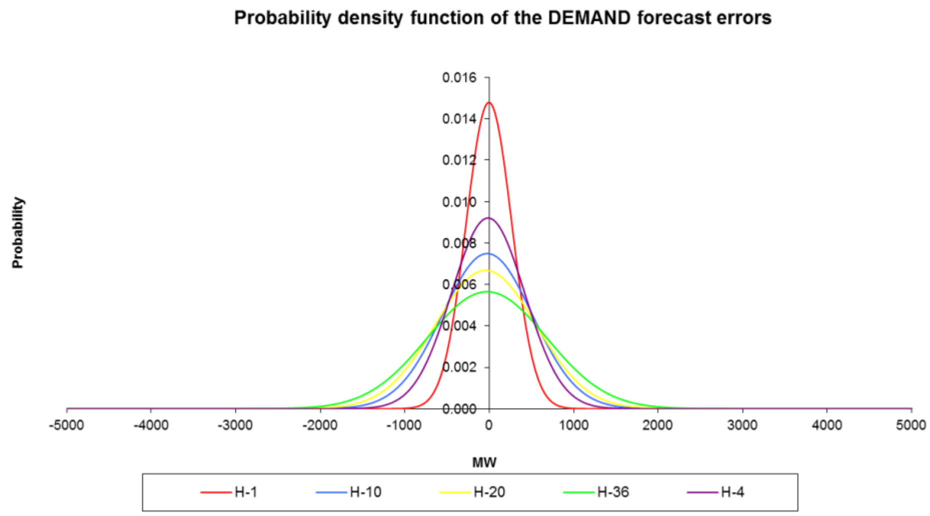
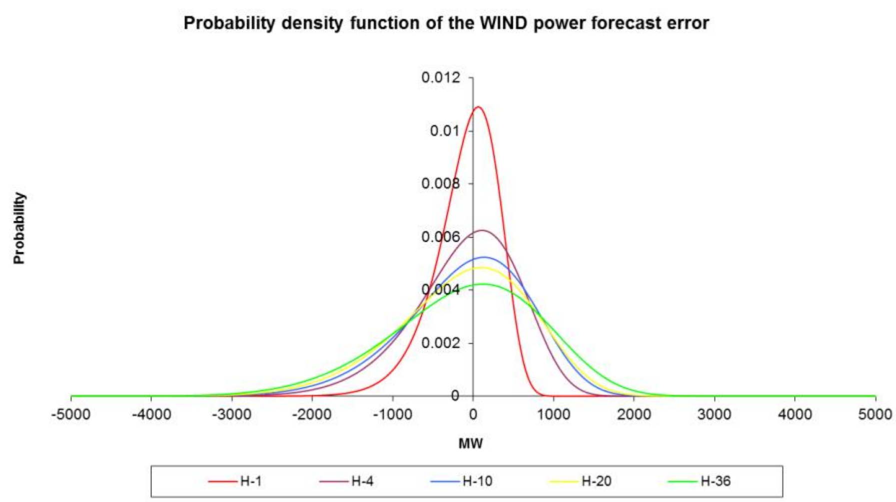


(a)



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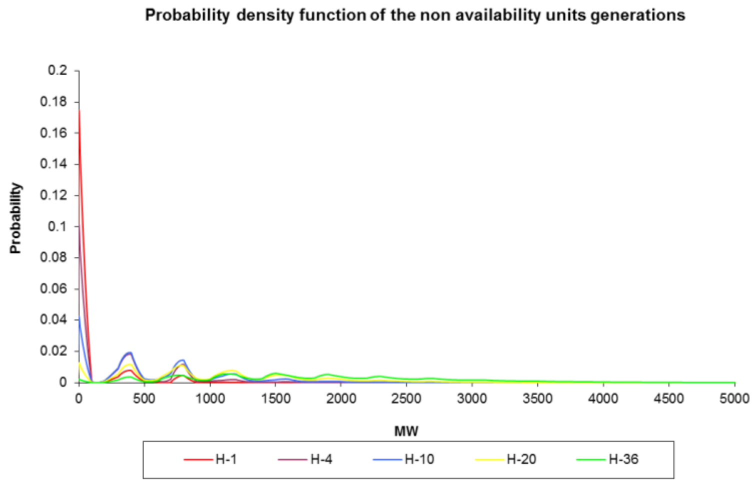
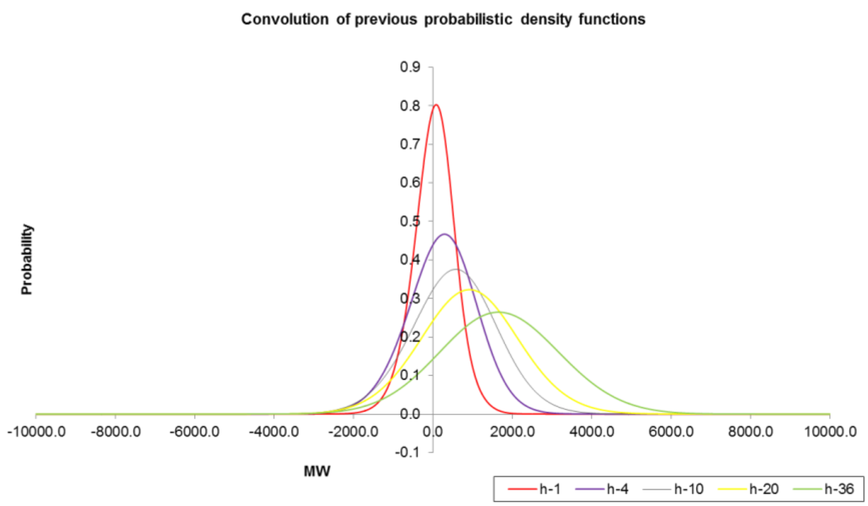


(c)



(d)

Figure 11. Convolution of probabilistic density functions for demand, wind, and outages. (a) Demand forecast error pdf, (b) wind forecast error pdf, (c) pdf of unscheduled outages of thermal units, and (d) convolution of demand, wind, and outage pdfs.

Figure 12 displays the amount of reserve required for each horizon with its margin of confidence. In this way, periodic runs of the probabilistic method determine a secure reserve level.

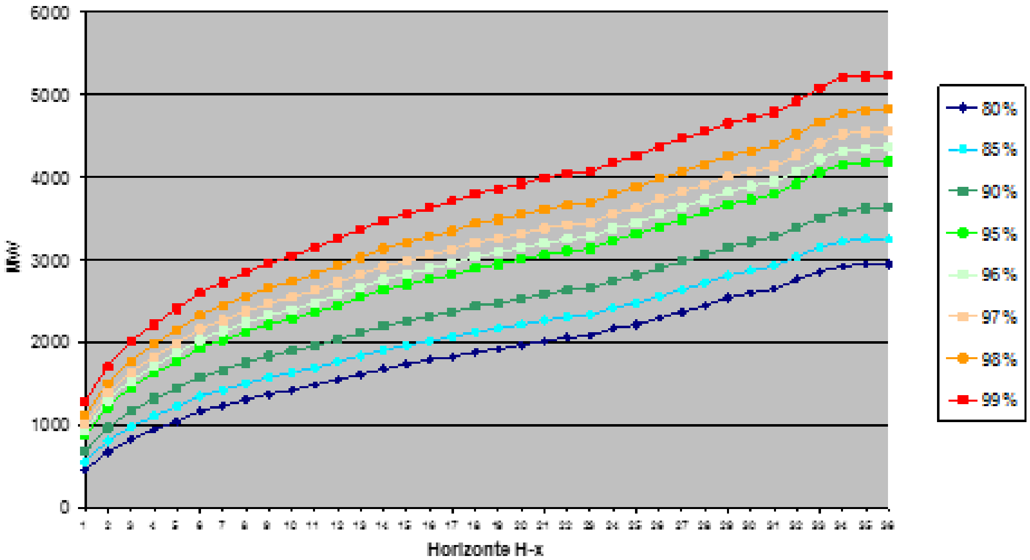


Figure 12. Probabilistic reserves at different time horizons and different confidence intervals.

REE also calculates reserve based on a deterministic method. This method uses the confidence intervals of the wind forecast (P50 and P85) calculated from meteorological ensembles of Type 4 (see Figure 1). In this way, the reserve is computed as the sum of the maximum loss of generation due to simple failure (1000 MW), demand deviation (2%), wind power deviation (difference between P50 and P85), and additional reserve.

The probabilistic method of sizing the reserves allows the system to carry less reserve without affecting the security of the supply, which is the highest priority for Red Eléctrica.

4. Experimental and Future Uses of Probabilistic Forecasts

Probabilistic forecasts can be used to enhance power system stability and to forecast future system conditions. As penetration of VER increases, reserve capacities decrease while ramping increases. Look-ahead system assessment tools will become more important to maintain an economic dispatch structure and unit commitment.

For instance, probabilistic forecasts are being designed for application in future CAISO (California ISO) Flexible Ramp Products (both day ahead and real time). Currently CAISO has deployed probabilistic method Type 1 (see Figure 1) for a Real-Time Flexible Ramp Product. This method leans heavily on a statistical histogram methodology that examines historic forecast movement between two periods of time and sets a requirement based on the uncertainty of net load. In the future, CAISO plans to expand this to include forecast information, either as regressors in the quantile regression technique (Type 2) or using the ensemble approach (Type 3 or 4). In addition, CAISO plans to include a new commitment called Day-Ahead Reliability and Deliverability Assessment (RDA) (replacing RUC) that will allow optimization of multiple scenarios beyond the meteorological information.

The Australian Energy Market Operator (AEMO) developed a Bayesian Belief Network to assess historic forecast performance then project forward, dynamically, using forecast conditions. This augments the reserve assessments based on the usual asset contingencies. This approach considers that weather forecast error (wind, solar and temperature) and contingent weather events show an increasing impact on their network, and at times present the largest contingency than historic rare largest asset contingencies.

5. Conclusions

Because the power system is sensitive to weather information, and because the atmosphere is inherently variable, it is prudent to quantify the uncertainty in weather forecasts and leverage that probabilistic information to the best advantage of system operators. Here we have listed current methods to provide probabilistic forecasts and how to judge whether the probabilistic forecast is sharp, resolves different distributions, and is statistically reliable. We have described some of the forefront and experimental applications of probabilistic forecasts, including as input for grid security assessment, to fine-tune unit commitment, to capture extreme conditions, to prepare for extreme events more effectively, to plan for reserves more efficiently, to better maintain system stability, and to design flexible ramping products.

One of the biggest hurdles for implementing probabilistic forecasting in industry is the lack of case studies, reference material in the form of documentation, standards, or guidelines for the industry. The IEA Wind Task 36 “Wind Energy Forecasting” is an international collaboration which has, as one of its tasks, to facilitate optimal use of forecasting solutions with a special focus on uncertainty/probabilistic forecasting for the power industry. The task concentrates on the use of forecast uncertainties for operation and management of the power system with substantial variable generation, for operation, trading and balancing in power markets. The task is to develop best practice guidelines for the implementation, measurement, and quantification of the value of probabilistic forecasts, based on experience from experts around the globe. Additional information can be found in For Further Reading below.

Many forecast users say that wind and solar forecasts would have more value in their decision-making processes if the forecasts were more accurate. We must recognize, however, that the atmosphere contains inherent variability that cannot be precisely predicted. A more realistic approach embraces that uncertainty, quantifies it, and uses that probabilistic information to optimize system operation. Probabilistic forecasts show promise for growth as a tool to manage the variability of wind and solar generation on electric systems. Decision-making processes that leverage forecast uncertainty information have almost always been demonstrated to produce consistently "better" decisions than those that don't use this information. Therefore, a near-term opportunity remains to glean more value from wind and solar forecasts through more effectively using the currently available uncertainty information without having to wait for future improvements in weather forecasting technology.

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