Uncertainty forecasting in a nutshell

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A one-hundred percent faith in the weather forecast can lead to wet and cold hikers‘ feet. It is in the nature of chaotic atmospheric processes that weather forecasts will never be perfectly accurate. This natural fact poses not only challenges for private life, public safety and traffic, but also for electrical power systems with high shares of weather-dependent wind and solar power production.

To facilitate a secure and economic grid, and market integration of renewable energy sources (RES), grid operators and electricity traders must know how much power RES within their systems will produce in the next hours and days. That is why RES forecast models have grown over the past decade to be indispensable tools for many stakeholders in the energy economy. Driven by increased grid stability requirements and market forces, forecast systems have become specialized to the end-user's application and already perform reliably over long periods. Apart from a residually moderate forecast error, there are single extreme error events that not only lead to wet hikers‘ feet, but also to beads of sweat on the brows of grid operators.

Nevertheless, there are also forecast systems that provide additional information about the expected forecast uncertainty and estimations of both moderate and extreme errors besides the “best” single forecast. Such uncertainty forecasts warn the hiker in advance to pack new boots and the grid operator to prepare special actions to ensure grid stability.

Within this article we will start with a short overview about the state-of-the-art in RES forecast generation, followed by some examples about the present handling of forecast errors within the control rooms of different grid operators. Afterwards, we will define the terminology and methodology regarding forecast uncertainty. The article closes with an overview of the usage of forecast uncertainty in business practice and an explanation of how to assess the value of uncertainty forecasts.

State-of-the-art in forecast generation

Today, there are forecast systems especially developed to predict the power production of single wind and solar units, different sized portfolios, local transformer stations and sub-grids, distribution and transmission grids, and entire countries. Nearly all forecast systems have one thing in common: they rely on numerical weather predictions (NWPs) to be able to calculate the expected RES power production. The way to transform weather predictions into power forecasts depends crucially on the end-user's application and the available plant configuration and measurement data. If historical measurements are available, forecast model developers often use statistical and machine learning techniques to automatically find a relation between historical weather forecasts and simultaneously observed power measurements. If no historical measurement data are available, e.g. for new installations of RES units, the transformation of weather to power is often done by physically based models that consider the parameters of the unit in order to map the internal physical processes.

In the literature, hundreds of ways to improve forecast quality are described. One concept is based on the usage of different NWPs as well as different weather-to-power transformation models, and the subsequent combination of the resulting power forecasts. At time horizons up to about 5 hours, the assimilation of power measurements into the power forecast models leads to further significant reductions in the forecast errors. These strategies are well established within the model chains of forecast developers.

Most extreme forecast errors result from erroneous interpretation and propagation of atmospheric processes within the NWP models. To address such challenges, research projects focus on improving NWP quality specific to the RES forecasts. Within the publicly funded German project EWeLiNE (http://www.projekt-eweline.de/en/index.html) and the U. S. Department of Energy (DOE) sponsored Wind and Solar Forecast Improvement Projects (WFIP/SFIP https://www.esrl.noaa.gov/gsd/renewable/wind.html), researchers have already successfully shown the benefit of such focused research. Successful results include improved predictions of nightly low-level-jets and low-stratus cloud situations leading to better RES power forecasts.

However, most of the abovementioned improvements emphasized deterministic power forecasts tuned for the best average performance in terms of an expectation value. Today, such forecasts have undergone many improvements to achieve a high quality, but it is important that forecasts additionally quantify their uncertainty or warn of alternative weather conditions.

Interfacing forecast systems

Today operators are increasingly being faced with managing rapidly changing energy delivery conditions due to weather dependent RES with different uncertainty characteristics that depend on the weather, the time of day and season of the year. When you ask system operators what they would want from a forecasting system, the answer invariably is advanced warning of pertinent events and operating guidance so that network configuration and controllable generation resources can be efficiently managed and dispatched.

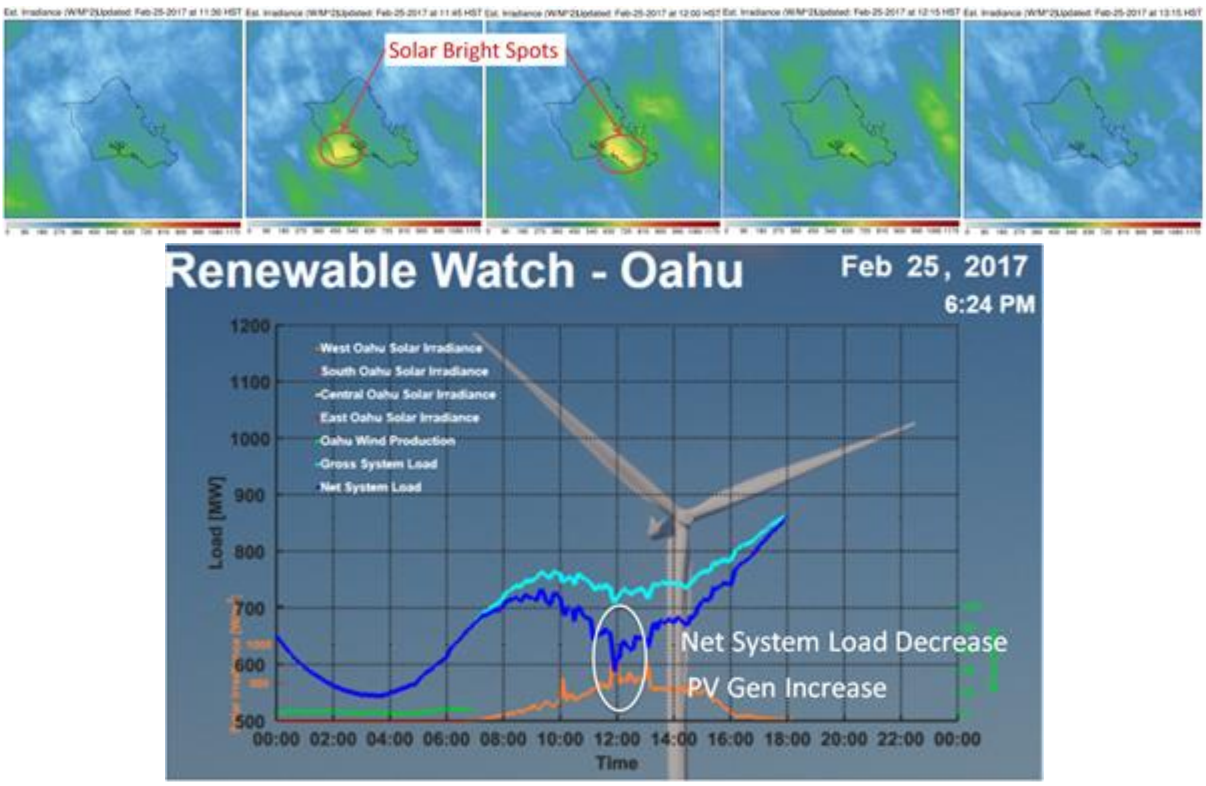
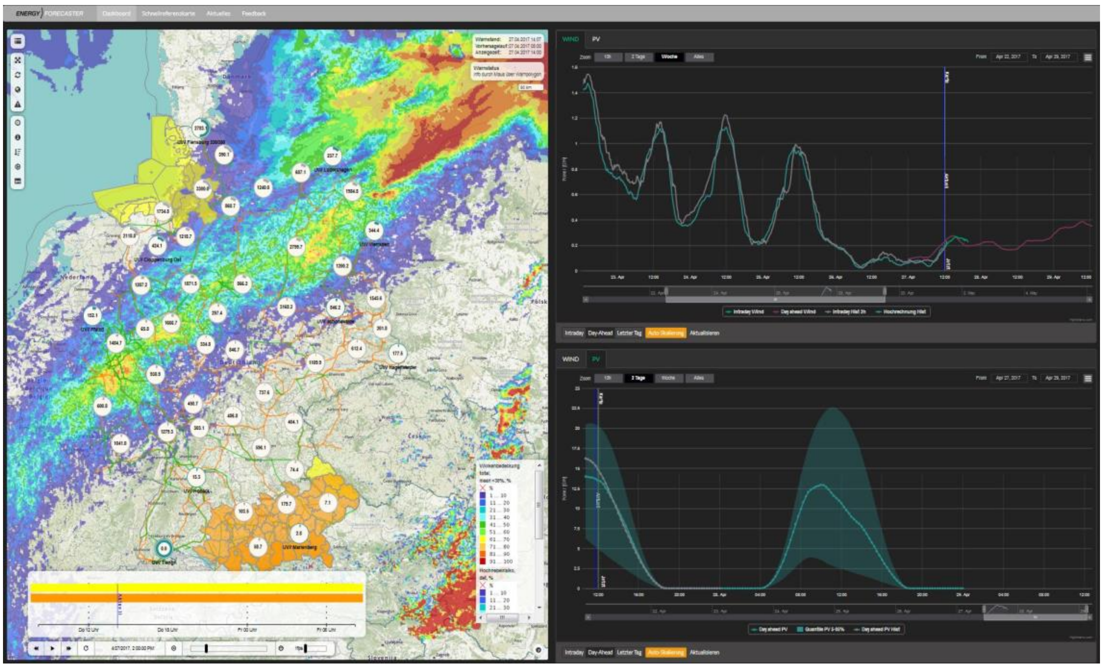


Figure 1: Example of a system ramping event due to weather impact on distributed resources from Hawaii's SWIFT forecast. Solar bright spot on the upper figure causes a PV (rooftop PV) ramp up resulting in a sudden system ramp down event and over frequency condition in the middle of the day (<15 min event).

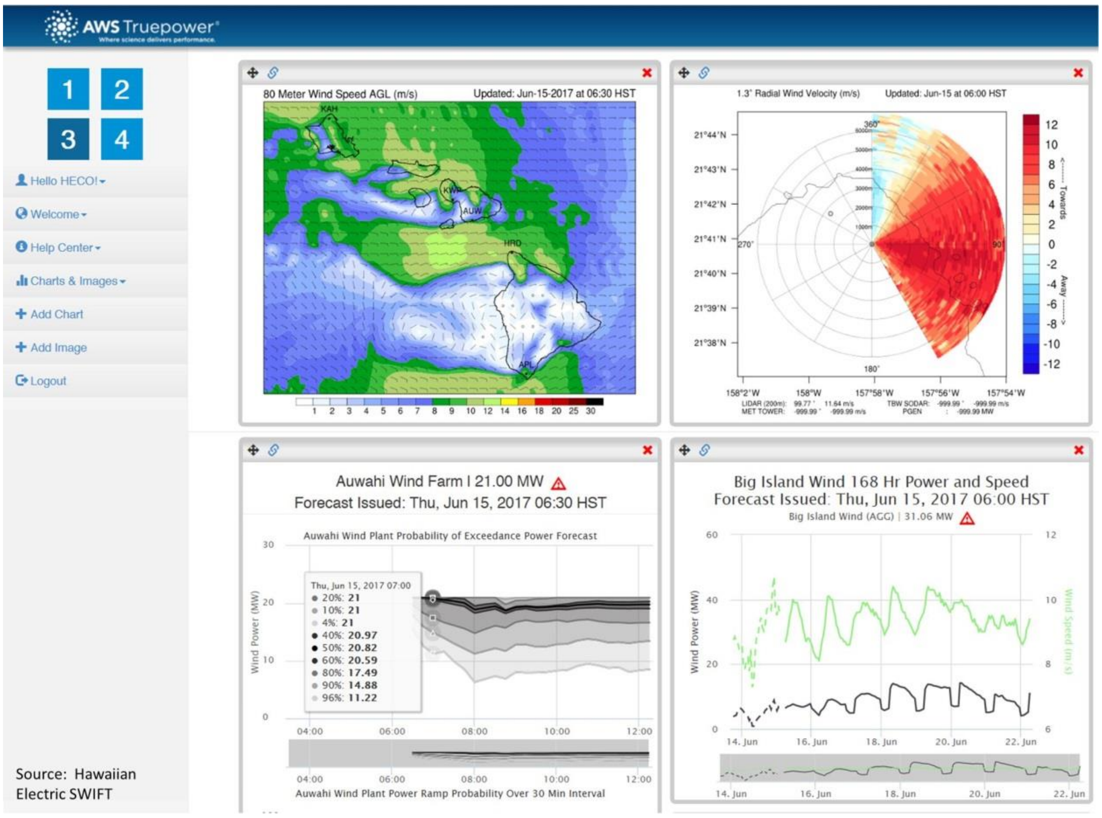
Recent events as shown in Figure 1 illustrate the types of short duration, difficult to predict weather conditions that challenge even the most sophisticated forecasting tools. These events represent the “tails” or extreme conditions where it is very difficult to forecast. But understanding limitations and coupling new visual capabilities that complement existing forecasts, provide enhanced situational awareness and a bird’s eye view of changing local and regional solar and wind conditions to support new operating response.

Working with state of the art forecasts, energy management system (EMS) providers are coupling solar and wind integrated forecast tools (SWIFT) and using a network of resource sensors for managing the island systems. Hawaii operators are routinely operating with 40% or more penetration of wind and solar resources on the grid. Efforts are underway to integrate system, regional and circuit level probabilistic forecasts from SWIFT into EMS and distribution management algorithms. Load estimation and state estimation algorithms require more intelligence and data from distributed energy resources with load and renewable forecasts to support dynamic dispatch needs, especially at high penetrations. Targeted and tailored forecasts that hone in on “event” driven conditions and EMS playback tools will help operators develop new strategies for handling uncertainty in forecasts, planning reserves, and contingencies that account for variability under related uncertainty conditions. Utilities and their suppliers are actively working together to refine and integrate these forecast capabilities to establish a more proactive and complete picture of predictable events, potential impacts, and mitigating actions to better manage the grid.

To relate weather and RES forecasts, geographic graphical user interface has been developed within both the EWeliNE and WFIP projects which enable synchronized display of spatial and temporal weather and power forecasts (Figure 2). Wind and solar power forecasts for the system, for an area, as well as for single transformer substations, can be visualized on a map together with selected meteorological parameters like wind speed, solar irradiance, resource variability and temperature. For some meteorological parameters, there are also probabilistic forecasts such as probability of exceedance of wind speed and cloudiness thresholds, as well as low stratus cloud risk levels, giving a first warning of weather situations that could have an impact on grid stability.



(a)



(b)

Figure 2: Geographic graphical user interfaces of forecast systems within a) EWeLiNE project and b) Hawaii SWIFT project showing wind and solar power forecasts over a region with single transformer stations forecasts, as well as forecasts of relevant meteorological parameters and exceeding probabilities of threshold values that are critical for grid security aspects.

How forecast quality impacts real-time operations

The prevailing practice in integrating RES is to procure a certain amount of reserve to compensate for the uncertainties of net-load, which is directly linked to RES forecast errors. Such reserves are mainly affected by demand, wind and solar forecasting errors and unplanned outages of thermal groups. In this sense, the quality of RES forecast has great influence on both the reliability and operation efficiency. To procure excessive reserve would lead to an inefficient operation while an inadequate amount of reserve could result in a potential reliability issue. However, as the RES forecast errors are time-varying, some judgment should be applied to determine an appropriate trade-off between the economics and the risk management. At the Electrical Reliability Council of Texas (ERCOT) for example, the volume of the reserve is sized based on the net-load forecast errors with a confidence level assigned as a function of the net-load ramp magnitude. Figure 3 depicts the 3-hour ahead load forecast error versus wind forecast error in 2016 at ERCOT. A large amount of wind generation greatly exaggerates the forecast error of net-load at ERCOT.

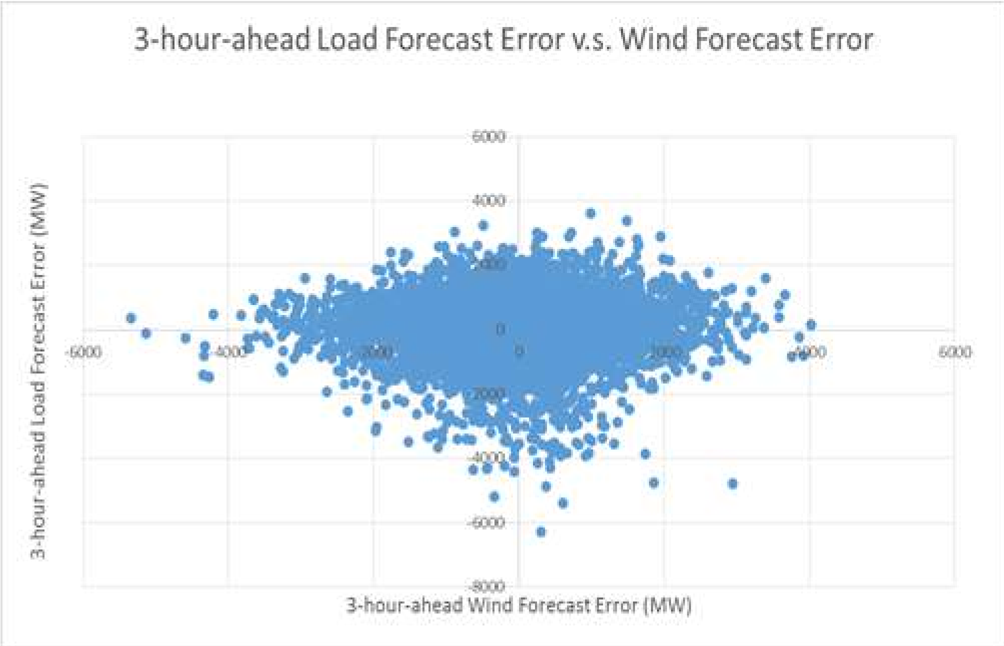


Figure 3: 3-hour ahead load forecast error versus 3-hour ahead wind forecast error and load forecast error in 2016 at ERCOT

Information about future forecast uncertainty already plays a crucial role in safeguarding the security of supply. For example, within the Spanish peninsular system, a task of the Transmission System Operator (TSO) Red Eléctrica de España (REE) is to assure that there is enough liquidity in the upward tertiary reserve market, as there is no specific capacity contracted from reserve providers and liquidity is assured by obligatory bidding. Therefore, it is of the utmost importance to guarantee that the system is operated with enough running reserves.
REE's uncertainty based approach uses different probability distributions depending on the RES production level. This probabilistic approach takes into account the historically observed errors of demand, wind and solar forecasts but not the uncertainty associated with the real meteorological situation predicted for the next hours. Even with some further improvement in the forecast quality, large deviations are still occasionally experienced, and are often referred to as outliers. These outliers are located on the flat, long tail of the probability distribution function of the forecast errors and clearly present a threat to the reliability and security of a power grid. The presence of those outliers also puts more burdens on the operators as manual actions may be required. Sometime, these outliers are driven by inclement weather conditions, for instance, icing conditions. One efficient way to mitigate these outliers is to provide an early situational awareness for the incoming events (e.g., large wind ramp-down events and volatile weather). In this way, operators can anticipate, detect and react to such events. Figure 4 shows an example of how such situations may be dealt with by uncertainty based reserve predictions. For that purpose, ERCOT implemented a reliability risk desk in Jan. 2017. One of its main tasks is to assess the risk of extreme errors and associated impact on the grid performance. If such large forecast errors could be detrimental to the grid, operators can purchase more reserves, bring

more generation units online or cancel a scheduled outage to mitigate the adverse effect.

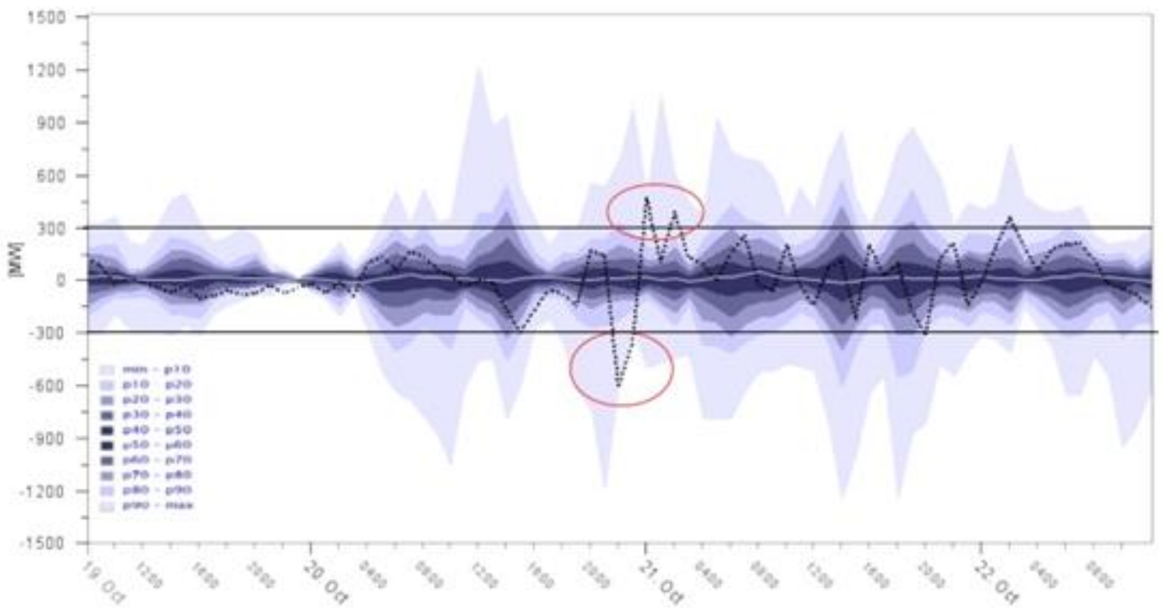


Figure 4: Example of a dynamic reserve prediction with percentile bands P10 to P90 (gray shading). The black lines at +/-300MW indicate a static reserve and show the spill that such static reserve allocation contains. The black dotted line is the allocated reserve and illustrates the issue of outliers that, if required to be captured, lead to over-allocation of reserves. Nevertheless, the p10/p90 band indicates the risk of outliers.

Better knowledge by considering the grid topology and ensemble forecasts

In energy systems with a high share of wind and solar power, it is crucial that the RES production can be curtailed or re-dispatched by different stakeholders of the energy system. In systems with established energy markets, as in many European countries, curtailments can be initiated either by traders selling RES energy to the market in order to maximize their income, or by Distribution System Operators (DSO) or TSOs in order to ensure grid stability and security of supply.

In some power systems, only a few very large wind farms and solar plants are directly connected to the transmission grid and, hence, visible to the TSO. Many RES units are located in DSO grids connected to medium voltage level. Large amounts of roof-top solar plant located in the low voltage level grid behind the meter (BTM) can cause issues for the TSOs, as well as for DSOs. In other power systems, either a larger proportion or RES is connected to the transmission grid or the TSO has some degree of observability of the production of DSO connected units, enabling it to generate and validate RES forecasts.

A power forecast of the aggregated production of each DSO area feeding into the TSO grid is a good start and is established in several European countries. In others, a more advanced approach is applied to consider the grid topology, i.e. taking into account the structure of the grid. Using this topology information can inform which RES units have an impact on critical parts of the grid, e.g. by dynamical load flow calculations. Although this topology information of the DSO as well as TSO grid is often not available to forecasters, many grid operators have started to enhance their power flow calculation tools to be able to accommodate forecast information. RES forecasts for individual sites or groups of plants with a common grid connection point can already

be used as input to power flow calculations on the DSO level and, in a second step, on the TSO level. If deterministic forecasts are used (Figure 5 top), the result is one scenario that provides information on areas where grid congestion is to be expected, e.g. overloads of lines or transformer stations. Depending on the computing resources, this can be repeated to cover all time scales, from two-days ahead down to minutes ahead.
The next step is then to estimate the forecast uncertainty in advance to become informed about the range of possible grid congestion areas. For this purpose ensemble forecasts are required as input (Figure 5 bottom), because they provide a range of different realistic scenarios consistent with the approaching weather situations. Though this is computationally expensive, it is considered necessary to include the correct spatio-temporal correlations, i.e. each ensemble member ensures a consistent behavior for each plant in the grid area for each point in time over the prediction horizon.

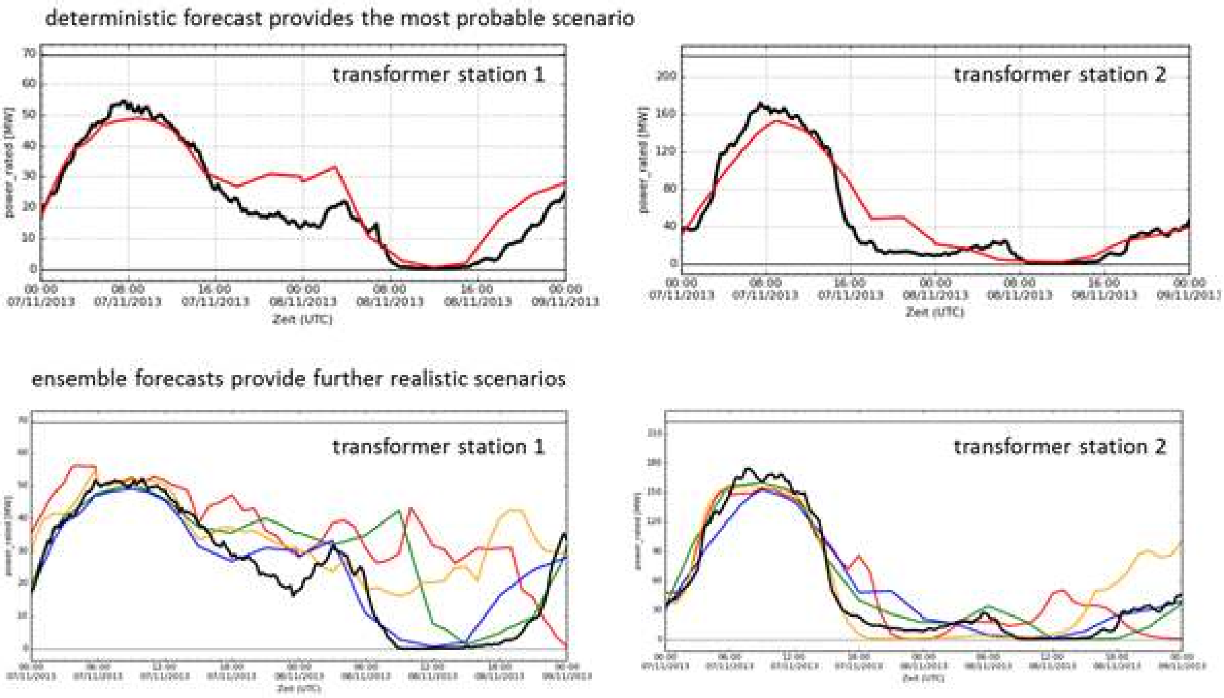


Figure 5: Wind power forecasts for two different transformer stations in the same DSO grid in Germany about 250 km apart. Top row: red line shows deterministic forecast indicating most probable scenario at both sides. Bottom row: colored lines show ensemble forecasts representing different scenarios, equal color belongs to an identical scenario at both sites. The black lines represent the measurement.

Terminology and methodology regarding forecast uncertainty

Where does uncertainty in the forecast of RES generation originate? To answer this question, it is necessary to separate weather forecast uncertainty and energy or power generation forecast uncertainty of RES. Weather forecast uncertainty stems in large from (1) observational limitations and (2) scientific limitations. The first category is a result of insufficient data, inconsistencies between instruments or simply incorrect measurements. These types of limitations lead to uncertainty in the initial or boundary conditions that are propagated into the future. The second category is a mixture of limitations caused by incomplete understanding of complex physical, chemical and dynamic processes and the need for approximations to model these complex atmospheric processes. In practice, it is a combination of both limitations that cause the overall weather forecast uncertainty.

The RES forecast uncertainty adds another dimension to the problem: uncertainty of measurements and calibration of the power generating units not related to weather. Even though there exists a physical description of the power output from wind turbines (or solar panels), there are differences in the hardware that cause uncertainty of the power output. The conversion to wind/solar power is not well-defined and is governed by nonlinear equations. Before discussing how forecast uncertainty can be produced in more detail, it is important to establish a standard terminology.

It is important to make the distinction between the concept of forecast interval and confidence interval as well as forecast error and forecast uncertainty. The confidence interval provides an interval of values and a respective confidence level that is likely to contain the population parameter of interest. Conversely, the forecast interval provides an interval of values and respective probability that is likely to contain the real value of the forecasted parameter. Forecast error is the actual deviation between forecasted and measured value at one point in time, while forecast uncertainty refers to a range of possible values in the future; forecast error can also refer to an error measure, e.g. mean absolute error. The uncertainty forecast should be conditional to a set of explanatory variables (flow dependent), like forecasted wind speed, expected value of generation levels, weather ensembles dispersion etc. The simple construction of empirical distributions from historical forecast error is not a true forecast uncertainty.

Forecast uncertainty can be estimated with three standard processes (Figure 6):

A. Statistical algorithms
B. Physically-based ensemble forecasts
C. Statistically-based ensemble forecasts

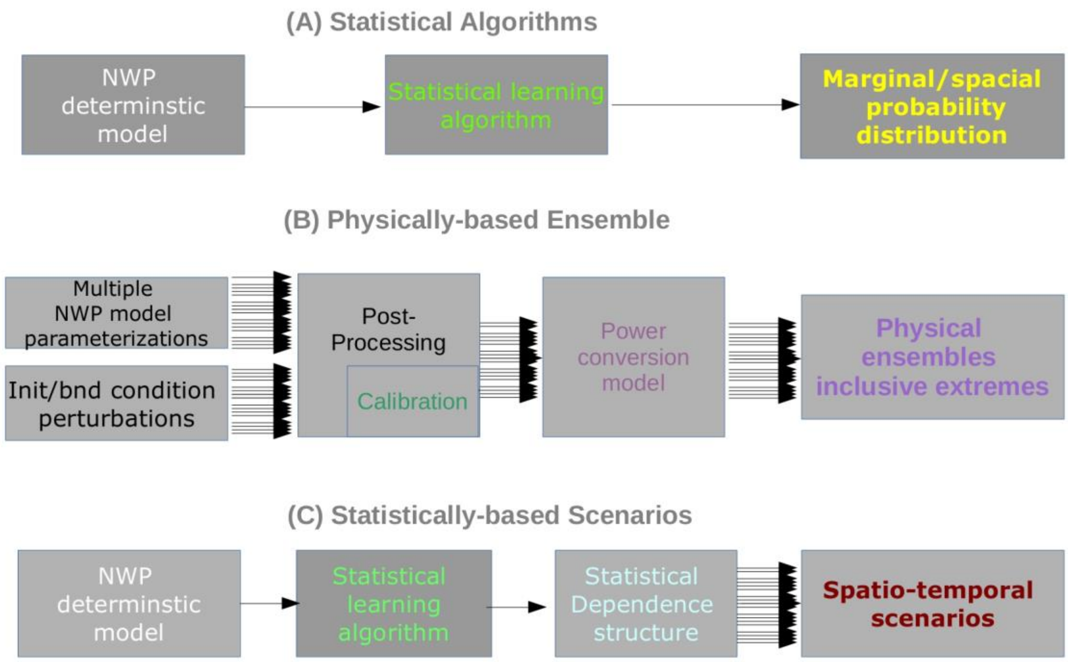


Figure 6: Standard procedures to generate uncertainty forecasts for renewable energy sources. Black arrows indicate where the generation of the so-called “ensemble members” take place.

In the first process (A), a statistical learning algorithm (e.g., machine learning) with an adequate loss function is fit to historical point NWP and power data, and generates uncertainty forecasts from an operational NWP. Other methods like the analog ensemble algorithm (AnEn) search through historical forecasts for those past forecasts that are most analogous to the current forecast. Those observations form the probability distribution of the forecast uncertainty. The integration of information from geographically distributed time series or from a grid of NWP is known to improve the uncertainty forecast accuracy and is the focus of recent research. The disadvantage is that this process does not produce a spatio-temporal representation of forecast uncertainty, nor is there a physical dependency on the results, as it is based on past climatology.
The second process (B) 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 or the result from different parameterization schemes of one NWP model ("multi-scheme" approach), converted in a subsequent phase into power with a curve fitting method. 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 with 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.
The statistically-based ensemble forecasts (C) result from statistical approaches based on copula theory applied to generate scenarios from the probability distributions produced by a statistical model. These scenarios have some similarity to the physically-based ensembles.

The uncertainty representation of both the physical and statistical ensembles are built to capture spatial and temporal variability, like ramps, and detect, with probability characterization, possible outliers like extreme events above cut-out wind speeds of wind turbines. The statistical scenarios, however, require an extreme event analysis for the latter.

Using forecast uncertainty in business practices

In the IEA Wind Task 36 "Wind Energy Forecasting" work package 3 (www.ieaforecasting.dk), the first overview about the current use of wind power uncertainty forecasts showed that there are many different levels of knowledge about the application of uncertainty forecasts in the power industry today. In some countries regulations lack transparency, and insecurity is spread among the market players and the investors, while in other countries the wind penetration is not high enough yet for uncertainty in production to become a bottleneck to efficient integration of renewables. It is therefore interesting to note that uncertainty forecasting has been mostly established where the penetration has exceeded a certain level (> 30% of gross annual energy supply) and where the cost of integration of RES has increased rapidly, such that a change of operating practice was required for the unit commitment and reserve allocation decisions, and for decision making in general.
Although it has been found in laboratory experiments by the University of Washington that decisions based on uncertainty are generally better, there is still insecurity in the industry regarding how to make use of uncertainty forecasts. Although risk assessment and reserve allocation are based on probabilities of exceedance of a pre-defined limit, there are many organizations that have difficulties establishing the tools and mechanisms to deal with uncertainties and use uncertainty forecasts for more efficient use of reserves.

One aspect that is gaining more attention recently is use of uncertainty forecasts for situational awareness in operations. Due to the variable output nature of RES, where small differences in wind speed can have a large impact on the power grid, operators in small island grids and those with high penetration levels request information about the probability that strong ramps could lead to congestion or shortage of power on the grid. This is especially important for high-speed cut-out events or at the peak load ramps in the morning and evening.
To summarize, uncertainty forecasts are today mostly used in industry for:

- Setting operating reserve requirements
- Unit commitment and economic dispatch
- Market bid optimization, e.g. minimize imbalance costs
- Virtual power plant operation
- Predictive grid management and flexibility allocation
- Maintenance scheduling
- Long-term commitment and portfolio planning

From the previous sections, it can be seen that TSOs are already starting the integration of, or using uncertainty forecasts in the aforementioned decision-making problems. Conversely, DSOs, with the advent of smart grid technology, are starting to explore renewable energy forecasts in the following use cases: a) forecast grid operating conditions for the next several hours; b) improved scheduling and technical assessment of transformer maintenance plans; or c) contract and activate flexibility from distributed energy resources to solve technical problems (e.g., congestion, voltage problems). For DSOs, the forecasting challenges are mainly related to scalability requirements associated with a high number of time series to forecast, and the need to have a spatio-temporal representation of forecast uncertainty because the technical problems are primarily local.

The value of forecasts

In the context of uncertainty forecasting, traditional metrics such as mean absolute or square errors only provide partial information about the forecasting skill (or quality). Uncertainty forecasts represented by probability distributions can be evaluated by matching empirical and nominal probabilities (called *calibration or reliability*), size of forecast intervals (called *sharpness*) and the ability to provide different conditional probability distributions, depending on the level of the predictand (called *resolution*). These properties are also used to evaluate forecasting skill of NWP ensembles and statistical scenarios. But new metrics with the ability to discriminate these properties are still needed to assess the modelling of the dependence structures. In the practice of the power industry, however, the more complicated metrics are often too time consuming for end-users to establish. Another aspect is that such metrics often do not measure the value of the forecast for the end-user. A cost function of how much reserve may be avoided by using probabilistic methods to identify reserve requirements with a longer time horizon would be more useful, for instance. Other applications, such as high-speed cut-out events, where the correct prediction of up-ramping or down-ramping and the probability of a shut-down of large parts of the wind generating units is essential to avoid grid stability issues, the value of such predictions lies in the avoidance of costs and maintaining grid security.
Another way to assign a cost value to forecasts is to apply full production cost modeling, both with and without forecasts. The difference provides the user with an estimate of the actual monetary cost difference of having the forecast. It is, however, difficult to distinguish between

employing only deterministic forecasts, versus also taking advantage of the probabilistic information from uncertainty forecasts.

Even traditionally deterministic tasks, like bidding into the power markets, are no longer captured by standard statistical metrics that measure the success or failure of a forecast. Probabilistic forecasts enable traders to make decisions based on the expected forecast accuracy and the expected imbalance costs and thereby avoid costs that reduce their overall income. So, even though single values are what a trader has to bid in with, the decision regarding which value to choose is today often the result of a probabilistic forecast. The correctness of the bid is not only the difference of the bid and the real production at that time, but also the cost at that time. For example, in some markets traders can earn on imbalances of their production, if the imbalance reduced the system imbalance.

The challenge therefore is to develop problem-specific metrics that link forecast quality with value. In other words, we need to understand how calibration and sharpness of uncertainty forecasts impact e.g. the market bidding strategies of a trader, and whether forecast quality improvements pay for the additional costs of such forecasts or forecast improvements. The integration of the decision-maker risk profile (e.g., risk averse, prone or neutral) in the evaluation of forecast value is indispensable to avoid incorrect assessments.

So, if the value of a forecast no longer has one specific measure or metric that is a sufficient means of evaluation, we may have to make a paradigm shift. We may need to consider the value more as an understanding of which approach to apply for a specific problem and how to optimally make use of the forecast type that best fits one's purpose. The evaluation can then look at costs impacted by a forecast. The forecast evaluation in itself is accomplished with a decision support tool that holistically examines whether the forecast fulfills certain criteria and supports the business processes. Figure 7 shows a possible decision support matrix that could be applied by a system operator evaluating forecasts for reserve allocation.

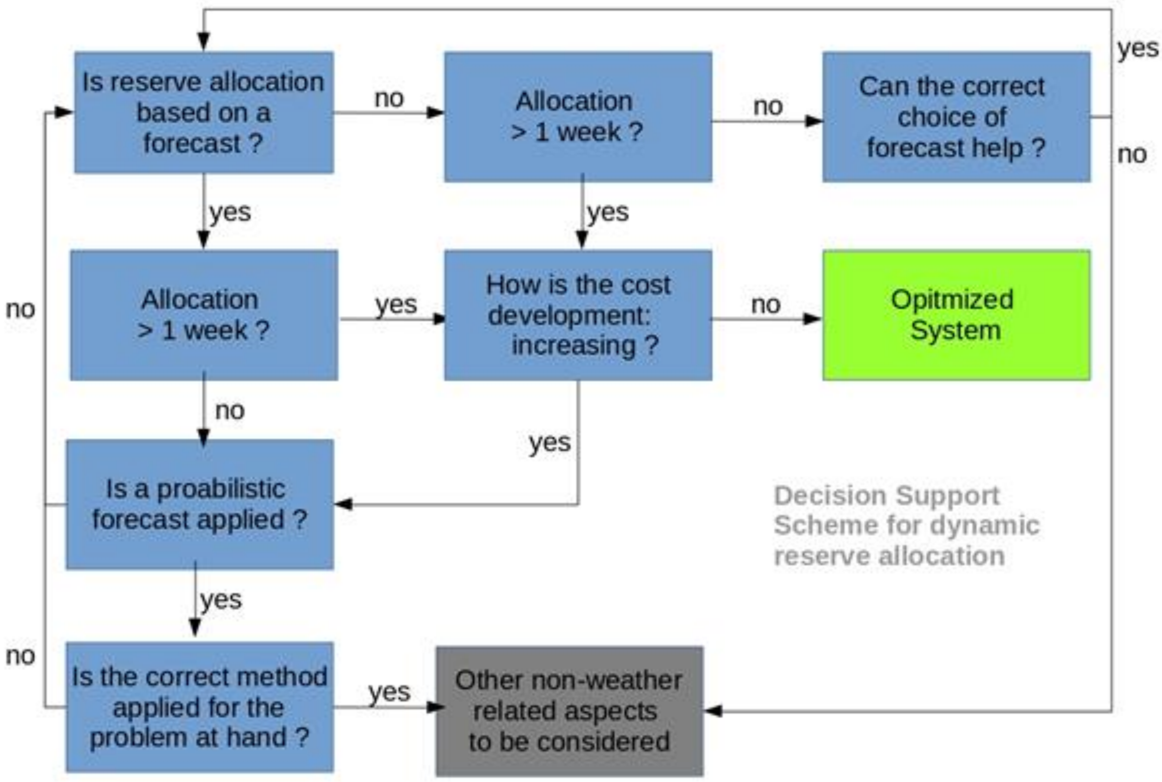


Figure 7: Example of a decision support scheme for dynamic reserve allocation at a system operator with the target requirements that allocation needs to be carried out at least 1 week ahead of time and the cost for allocated reserve is the optimization parameter.

Conclusion

Complex dynamic systems like the electrical power system require continuous scheduling of nearly all components. Without wind and solar forecasts, secure operation of a power system with high shares of RES and economically driven markets would not be possible. RES forecast models have been developed, improved and specially adapted to end-user's needs for more than 20 years. The forecast quality in terms of average errors has already leveled off.

New ground has to be broken to enable even larger shares of RES. Probabilistic forecasting constitutes such a ground by fostering a paradigm shift in the way forecasts have been used and evaluated so far, as well as new ways of handling uncertainties that are inherent in the generation of power from renewable sources. We are moving down a path from state-of-the-art deterministic approaches to the application of uncertainty forecasts in major parts of the power industry. New terminology and processes are being used to integrate uncertainty forecasts into forecasting systems to enhance TSO and DSO operations under high RES conditions, which increasingly depend on knowledge of the uncertainty of a forecast for better decision making.

The value of forecasts can no longer be reduced to simple statistical measures. Instead, a more holistic view on forecast skill and quality that looks at best-fit-for-purpose and the level of support of crucial business processes is required. In this way, future challenges towards more flexible, yet secure and economic, power systems can be tackled and further developed. Uncertainty forecasting can therefore be considered as a key element in developing the next generation power system. It is here to stay.

For Further Reading

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