

How do Humans decide under Wind Power Forecast Uncertainty – an IEA Wind Task 36 *Probabilistic Forecast Games and Experiments* initiative

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Abstract. The need to take into account and explicitly model forecast uncertainty is today at the heart of many scientific and applied enterprises. For instance, the ever-increasing accuracy of weather forecasts has been driven by the development of ensemble forecasts, where a large number of forecasts are generated either by generating forecasts from different models or by repeatedly perturbing the initial conditions of a single forecast model. Importantly, this approach provides robust estimates of forecast uncertainty, which supports human judgement and decision-making. Although weather forecasts and their uncertainty are also crucial for the weather-to-power conversion for RES forecasting in system operation, power trading and balancing, the industry has been reluctant to adopt ensemble methods and other new technologies that can help manage highly variable and uncertain power feed-ins, especially under extreme weather conditions.

In order to support the energy industry in the adaptation of uncertainty forecasts into their business practices, the IEA Wind Task 36 has started an initiative in collaboration with the Max Planck Institute for Human Development and Hans-Ertel Center for Weather Research to investigate the existing barriers in the industry to the adoption of such forecasts into decision processes. In the first part of the initiative, a forecast game was designed as a demonstration of a typical decision-making task in the power industry. The game was introduced in an IEA Wind Task 36 workshop and thereafter released to the public. When closed, it had been played by 120 participants. We will discuss the results of our first experience with the experiment and introduce some new features of the second generation of experiments as a continuation of the initiative. We will also discuss specific questions that emerged when we started and after analysing the experiments. Lastly we will discuss the trends we found and how we will fit these into the overall objective of the initiative which is to provide training tools to demonstrate the use and benefit of uncertainty forecasts by simulating decision scenarios with feedback and allowing people to learn from experience, rather than reading articles, how to use such forecasts.

1. Introduction

The challenges of climate change require unprecedented investments in renewable energy sources (RES) and a fundamental transformation of existing infrastructures such as the power grid. A key challenge is that RES like wind and solar power are characterised by an inherent inter-

mittency and variability that is unknown to fossil fuels and other weather-independent energy sources. To deal with the inherent variability of RES and seamlessly integrate them into the power grid requires a combination of weather forecasts and weather-to-power conversion methods. However, current approaches are based on deterministic weather forecasts, which provide no means to explicitly represent the varying uncertainty of forecasts that can make it difficult and costly to integrate high amounts of such resources into the electric grid.

As the penetration levels of RES increase and extreme weather conditions rise with the observed climate change, current methods have reached their limit, because they neither model nor convey forecast uncertainties. Instead, new methods for power production forecasts are called for that explicitly model uncertainty in order to make robust predictions and allow communicating forecast uncertainty to market participants and system operators [1]. This has been confirmed by Sweeney et al. [2] in their review on the *Future of Forecasting for Renewable Energy*, where they conclude that “..future forecast products will need to include probabilistic information, but deliver it in a way tailored to the end user and their specific decision-making problems.

Integrating uncertainty into the decision process is also important, because RES can be used at much lower costs than traditional energy sources due to their high flexibility - although only one-sided for down-regulation and with limited capacity for balancing power at the grid level.

Another aspect is that trusting in deterministic forecasts alone means that one ignores the underlying uncertainty. The world meteorological organisation (WMO) argues that “...if a forecaster issues a deterministic forecast the underlying uncertainty is still there, and the forecaster has to make the 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” [3].

The WMO guide for communicating uncertainty also states that “..Uncertainty in the forecast can also arise from how the forecaster utilises the available information. Even if the model predictions are highly accurate, they must still be interpreted and translated by the forecaster into actual weather. This interpretation must then be rendered into a forecast, which in turn is received and interpreted by the user. Uncertainty can occur at each of these stages of the ‘information chain’.” [4]

2. Explaining the Need for the Initiative

The need to take into account and explicitly model forecast uncertainty is at the heart of many scientific and applied enterprises. For instance, the ever-increasing accuracy of weather forecasts has been driven by the development of *ensemble forecasts*, where a large number of forecasts are generated either by generating forecasts from different models or by repeatedly perturbing the initial conditions of a single forecast model. Importantly, this approach provides robust estimates of forecast uncertainty, which supports human judgment and decision-making (e.g.[5]). Although weather forecasts and their uncertainty are also crucial for the weather-to-power conversion for RES forecasting, the industry has been reluctant to adopt ensemble methods and other new technologies that can help manage highly variable and uncertain power feed-ins under different weather conditions. For instance, energy traders can use uncertainty forecasting to optimize the amount of power generation that they bid into the market, and transmission system operators can define the required reserve to account for the uncertainty in generation or be prepared for grid congestion much further in advance than with the currently used deterministic forecast. As a direct consequence of adopting these state-of-the art methods, the renewable energy sector forgoes critical potentials to reduce its vulnerabilities, build more robust prediction models, and improve judgment and decision-making of the involved parties.

There are two intertwined challenges responsible for the limited adoption of uncertainty forecasts in the renewable energy sector. First, current energy management systems (EMS) simply cannot operate with probabilistic forecasts. All processes in the EMS systems are designed as single value deterministic decision tools that are not capable of making simulation with ranges of possible outcomes or even different scenarios that reflect the uncertainty in the production of RES.

The second challenge is the human factor: New methods and approaches are bound to fail, if transmission system operators and other relevant agents do not know how to harness new forecast methods and systematically integrate uncertainty in their decision-making processes.

Probabilistic uncertainty forecasts have been shown to improve decisions in other weather related domains [6] and are likely to benefit power trading decisions as well. On the one hand, (a) probabilistic uncertainty forecasts contain information highly relevant to the decision [6]; on the other hand, (b) they make it easier for users to learn whether negative outcomes result from their decision strategy or the uncertainty of the forecasts compared to deterministic forecasts.

Our aim is to address these challenges in a unified and multi-disciplinary approach, bringing together hitherto separate fields (meteorology, behavioural insights, cognitive science, energy sector) and competencies. The overarching goal is to demonstrate the value of using ensemble forecasts in the RES sector.

3. The Games and Experiments

The objective of this initiative is to answer the most pressing questions that prevent the development and use of probabilistic forecast in the renewable energy sector by using behavioural decision experiments to simulate real-time problems for specific user groups using ensemble data and the corresponding power production forecasts.

The rationale behind the naming of “games & experiments” is that we design experiments in a game-like structure that is supposed to trigger some excitement in the participant’s experience in the race for the highest scores or money earned by taking the best decisions, applying the best strategy or by just being lucky.

The results and feedback from these experiments can then be used to formulate strategies for further research and how to overcome the barriers that prevent the use of such forecast information and the harvest of the associated benefits from the additional information.

3.1. Background and Setup

The goal of the first experiment was to simulate a decision-making task in the power market, where there is high uncertainty of the production forecasts and where wrong decisions directly could be related to costs. Uncertainty in weather and also power production forecasts is not a new topic (e.g. [1], [7], [8], [9]) and has been discussed in many workshops of industry groups such as the Energy Systems Integration Group (ESIG) in the USA or the German Forecasting Platform (IFP) run by the Fraunhofer Institute of Energy economy and energy systems technology (IEE) and the German Weather Service (DWD) over many years.

Today, such information is readily available and there seem to be obvious advantages of using such information. However, it is also known that a number of factors influence human responses and decisions under uncertainty that go beyond a “rational” calculation of costs and probabilities. In order to investigate the factors that may underlie the hesitant reaction to the use of probabilistic forecasts observed in industry, we designed the first experiment in such a way that the participants had a direct comparison of deterministic and probabilistic information as input to their decision-making task.

3.2. First Experiment: Wind Power Trading for an Offshore Wind Farm

For the first experiment, we chose a trading situation that provided different types of information for the decision-making:

- (i) deterministic forecasts of wind speed and wind power
- (ii) probabilistic ensemble forecasts of wind speed and wind power

In the experiment, we assumed that most traders and balance responsible parties would agree that over time, the success of trading wind and solar power in a power market situation is related to the costs of the balancing power that is required to level out forecast errors. The income or cost profile is relatively strongly correlated with these balancing costs and that few events with high forecast error would be the driver for the costs and reduction of the income. We assumed that approximately 5% of the time, where the forecasts are off track account for 95% of the costs over a longer period of time, e.g. some months or a year. The assumption here is that it is more beneficial to reduce the balancing costs for large errors than seeking for a general forecast improvement of 1-2%.

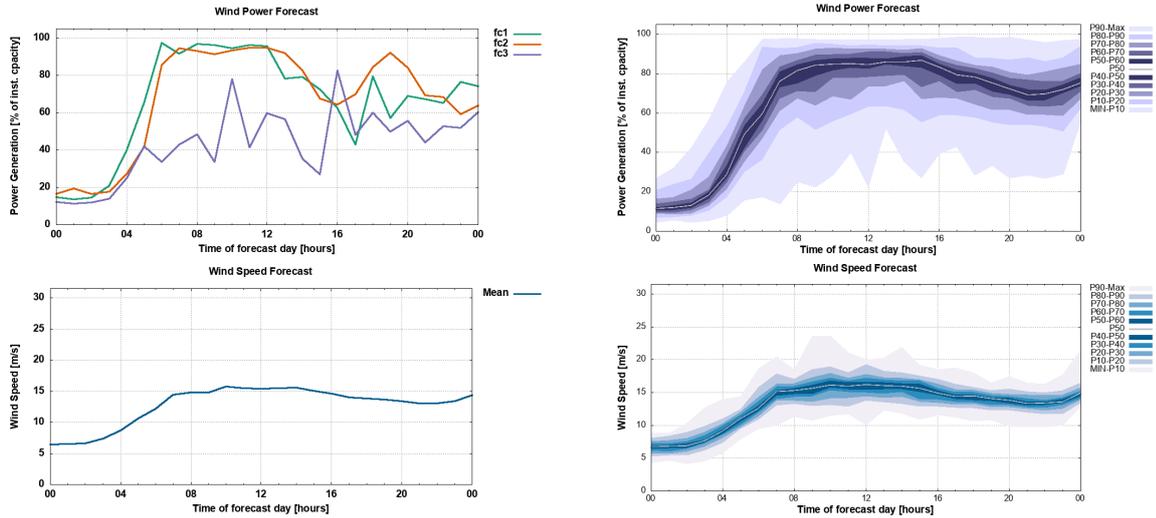


Figure 1. The deterministic forecasts (left) and the probabilistic forecast (right) as example of one of the chosen situations. For each type of forecast, the upper figure shows the wind power forecasts and the lower figure shows the wind speed forecast. The orange line in the wind speed forecasts marks the threshold (25 m/s) around which a high-speed shutdown can occur.

Fig. 1 shows one situation that was presented to the participants in the first example, where the deterministic forecast does not indicate or at least not clearly indicate the risk for a high-speed shutdown event, whereas the probabilistic forecast's upper percentiles P80-P90 and the maximum forecast in wind speed clearly indicated the risk, confirmed by the power forecast that shows the effect on the power generation with the percentiles P10-P40.

As shown in the example plot in Figure 1, we simplified the task by letting the users decide whether the generating power of an offshore wind park should be traded fully or partially given the possibility of a high-(wind)speed shutdown, where the wind park stops generating due to excessive wind conditions. Such so-called high-speed shutdown (HSSD) events occur in wind ranges between 21-27 m/s and are often referred to as cut-off wind threshold at 25 m/s. Because the wind turbines are not only calibrated to react on average wind speeds over a certain period of time, but also short-lasting wind gusts, there is considerable uncertainty on a wind farm to enter into high-speed shutdown (HSSD).

The cost function for the decisions to be taken in the experiment can be seen in Table 1. In the experiment, the participants had to decide, for each case, whether to trade 50% or 100%. The latter caused a penalty of 5.000 monetary units in case of the high-speed shutdown (HSSD) within the forecast period and a gain of 5.000 monetary units in case no HSSD occurred. When traded only 50%, the participants gained only 2.500 monetary units if no HSSD occurred, but did not lose any money, if a high-speed shutdown event occurred.

The rationale behind this cost-loss function was that in most applications, whether this is for trading purposes or balancing on system operation level, it is more expensive to buy balancing power than to have surplus generation. In the latter case, most units can be regulated down, which only causes a loss for not producing, but no extra cost. In the case of a lack of power in respect to the schedule, or bid in the market, due to a high-speed shutdown, the balancing power will be more expensive than the marginal costs for producing the power on the unit that shuts off. The simplification is therefore only on the timing, i.e. we do not request to ask for the specific hours in which the reduction takes place, but only whether any hour in the forecast time slot may experience a reduction. In other words, we look at the amplitude of the event, but ignore the phase.

All situations were real-world forecasts and reflect a decision that traders or operators are faced with in their daily work.

Trading amount	HSSD	No HSSD
100%	-5000	5000
50%	0	2500

Table 1. *Cost-Loss table for the “Offshore Wind Power Trading” experiment, where the participants are penalised when trading 100% and a high-speed shutdown (HSSD) event occurred and gain only 2500 monetary units, if they traded only 50% and no HSSD occurred.*

The first experiment showed us a number of interesting aspects, both from the participant’s reaction and the results of the experiment. These lessons learned can be summarised as follows:

- A significant amount of the participants would like to have both probabilistic wind speeds and wind power generation forecasts or a deterministic “best guess” inside the uncertainty bands
- The improvement in decisions with additional probabilistic information was not equally strong in all cases, which points to the importance to understand the indicators in the forecast and the strategies that people use to make their decisions
- A situation with low visible uncertainty caused participants to expect no HSSD and to take a false risky decision, which raises the questions how threshold values are intuitively or rationally evaluated for uncertainty bands

3.3. Second Experiment - Wind Power Trading for a Wind Farm in complex Terrain

In the first experiment, we used an experimental design, where participants made decision based on deterministic forecasts first and in a second step were shown probabilistic ensemble forecasts. Each decision had to be confirmed or reverted based on the probabilistic ensemble forecast. With this setup we investigated, whether participants benefitted from the additional information of the probabilistic forecasts and whether the risk strategy changed.

One disadvantage of this design with updates was, that it does not allow to quantify whether or not participants will make better decisions by using uncertainty or probabilistic ensemble

forecasts alone. Instead, the participants essentially decided whether to hold on to the previously made decision or change their mind. From a psychological perspective this is a critical aspect to consider when drawing conclusions from an experiment. For instance, often people do not update their beliefs sufficiently to change their minds. Thus, people may decide differently, independent of whether they were presented the probabilistic forecast or not.

For the second experiment, we instead used a design suited to evaluate the benefit of probabilistic forecasts independently (see Figure 2). The experiment has been setup in the following way:

- (i) Every participant makes all decisions based on deterministic as well as on probabilistic forecasts. For each forecast type, the situations are presented in blocks, randomized among each other.
- (ii) For every participant, the order of blocks is randomly chosen at the beginning.
- (iii) For each decision the participants have to indicate how confident they were with the decision in a scale from 50% to 100%.
- (iv) After each set of decisions, the participants are asked to describe the strategy and cues they have used in their decision-making.
- (v) A unique ID allows participants to play multiple times with different nicknames in order to try out different decision strategies.

As shown in the schematic graph in Figure 2, the forecast situations will be randomized in both runs so that participants are not getting the same sequence of forecasts to prevent that they remember the situations. In both runs, participants only take their decisions on the basis of either deterministic or probabilistic forecasts. The goal is to be able to identify the benefits, if any, by using the probabilistic forecasts and deterministic forecasts on their own and explore potential problems in the use of the probabilistic forecasts in more detail. The participants are additionally being asked after each decision how confident they are with the decision they made. With this, we want to investigate, whether there is a difference in confidence level between decisions taken on the basis of deterministic versus probabilistic forecasts. Another aspect that is going to be investigated is the way participants cope with failures or false alarms; that is, how participants react after taking a wrong decision and whether there is a difference when being presented deterministic or probabilistic forecasts. The use of forecasts from a real-time environment enables us to choose forecasts that seem to have clear indicators for a specific extreme event, but did not turn out to be one such event and vice versa. These so-called false alarm events and the reaction to such false alarms by the decision-makers are often highly underestimated in real-time environments to have impact on decision-making. The psychological effect of a false alarm can also turn out to be very different from person to person. By getting a better understanding of such reactions, we can find strategies how to adapt forecast presentations and train decision-makers, but also their managers and the forecast providers to better understand the difficulties coming along with such situations.

When decisions are made for all 40 cases, participants are asked a number of general questions; first they are asked about the cues or strategies that they used when making their decisions and how they found that this worked. Thereafter, the confidence level is requested once more, i.e. which type of forecasts the participants found useful in terms of deterministic forecasts and probabilistic forecasts and which of these forecasts they would want to have or consider irrelevant.

Lastly, the participants are asked about their background and the experience in the sense of time working in an area that is related to such decision-making, the age of the person and the gender. In that way, we can study various psychological aspects in the cognitive science area that may provide clues on how to best present the uncertainty of forecasts for decision-makers to benefit and to keep focus and confidence in their roles without becoming over-confident.

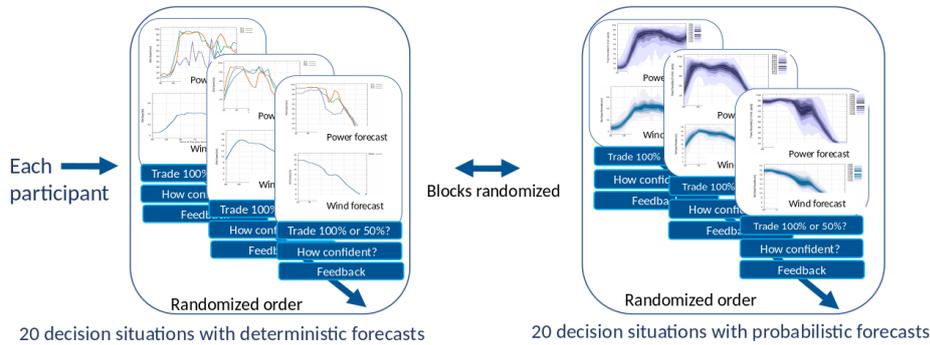


Figure 2. Setup of the second experiment, where the cases are separated between decisions made on the basis of deterministic forecasts (left side) and decisions made on the basis of probabilistic ensemble forecasts (right side).

4. Lessons learned and next Steps

The first experiment in the series has revealed a number of interesting aspects regarding decision-making with and without uncertainty information from probabilistic ensemble forecasts. Although we can conclude that there is a potential benefit, and most participants also confirmed in the follow-up questionnaires that they clearly prefer to have probabilistic forecasts at hand when making decisions on extreme events, there are still many open questions. Some of these will be answered in the second experiment, for instance, the impact on decisions, when presented by either probabilistic or deterministic forecasts on its own.

Nevertheless, when we closed the experiment, where 120 participants had gone through the 20 decision cases, there was a clear difference in the final balance scores and the distribution of these scores. Figure 3 shows the result of that final balance as whisker box plots and histogram of the income. The distance between the lower and upper limit of the boxes shows the interquartile range (IQR) of the distribution (distance between the 25th and 75th percentiles), where the median is represented by the horizontal line. The upper (lower) whisker extends from the box to the highest (lowest) value within $1.5 * \text{IQR}$. It can be seen in Figure 3, that the interquartile range for the probabilistic ensemble forecasts was with 33% significantly smaller than for the decisions based on deterministic forecasts. Also, the amount of participants that reached the highest scores, which corresponds to the generation of the highest income from the traded cases according to the applied cost function in Table 1, have all reached them when using the probabilistic ensemble forecasts for their decision.

The most obvious conclusion from the higher income generated with probabilistic forecasts suggests that there exists a benefit of using probabilistic ensemble forecasts for this type of application, i.e. trading, where such extreme weather events are responsible for the typical 5% of the largest error, leading to large balancing costs; it also indicates, seen in the smaller spread, that people tend to make more similar decisions when presented with probabilistic ensemble forecasts in their decision-making process. For many applications, where the final decisions are made by human decision-makers, this is an important aspect to consider, especially, if decisions are supposed to be fair, transparent or even just consistent.

One very interesting aspect of the latter observation is the phenomena of personal bias, well known from e.g. environmental assessment (e.g. [10]) or insurance case assessments (e.g. [11]). In other words, if the spread of the final balance decreases when using uncertainty forecasts, it would be a benefit for any organisation working with a group of decision-makers that work e.g. in shifts. Reduction of the so-called personal bias would be a benefit that goes beyond financial income. Once we have a large enough sample of participants in the second experience,

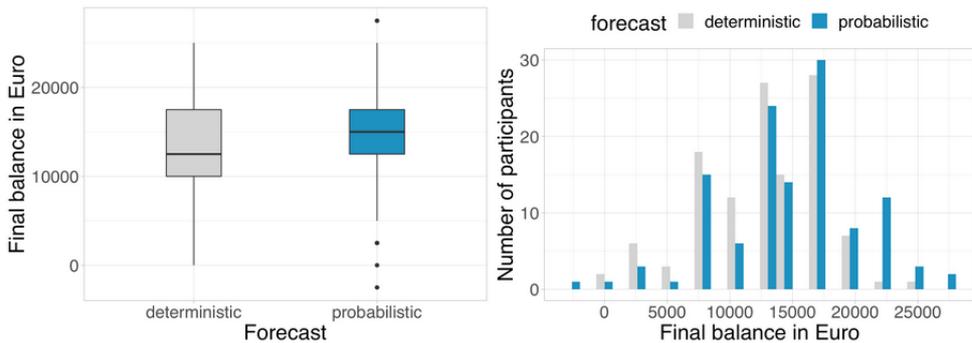


Figure 3. Final Balance of the first experiment, when closed, played by 120 participants; shown as whisker plot (left) with interquartile range, showing the result of 50% of the participants and as histogram (right).

this aspect will also be compared to the first experiment. Here, it will be interesting to explore the difference related to the decision-making process, i.e. when making all decisions based on deterministic or probabilistic forecasts. Especially in a transition phase, where the industry starts to use uncertainty forecasts, it could well be, that the benefit is stronger, if participants can change their mind when presented with uncertainty forecasts, i.e. reduce failure of the risky decisions.

4.1. Additional Forecast Information for the Decision-making Process

The first two experiments have been solely focusing on decision-making with the help of graphical time series forecasts for both, the deterministic and the probabilistic forecast types. However, we have not been investigating, as described e.g. in [12], whether the type of representation of the uncertainty also could have an impact on decisions, i.e. whether some or all end-users may be more likely to make better decisions, if they would get the probabilistic information additionally in a text or table format.

Or, if for example a graph or a series of graphs of the large-scale weather situation in a horizontal plot as shown in Fig. 4 could be useful for the decision-making process. The example shows the wind speed (colours), wind direction (arrows) and isobars, joining together places of equal atmospheric pressure, for the time of the highest probability of a high wind speed shutdown event from the example in Fig. 1 as mean (large left graph) of 75 forecasts and the minimum (upper right) and maximum (lower right) thereof, respectively.

5. Conclusion and Future Work

The results and reaction of participants from our first two experiments point towards an industry that has understood the need for uncertainty forecasting in the handling of renewable energy sources (RES). Nevertheless, the adaptation of uncertainty forecasts in the daily practices is still somewhat slow. One reason for this is the lack of knowledge about the different sources of uncertainty forecast products and their specific applicability, even though information is available in literature e.g. [1], [13]. The translation from research literature to industry guidelines together with the increasing need for uncertainty estimates in the power system operation may be necessary for the industry to make the leapfrog step into the probabilistic design of the underlying, e.g. EMS, software. The IEA Wind Task 36 has already started to incorporate uncertainty forecasts and currently applied probabilistic forecast in the recommended practice

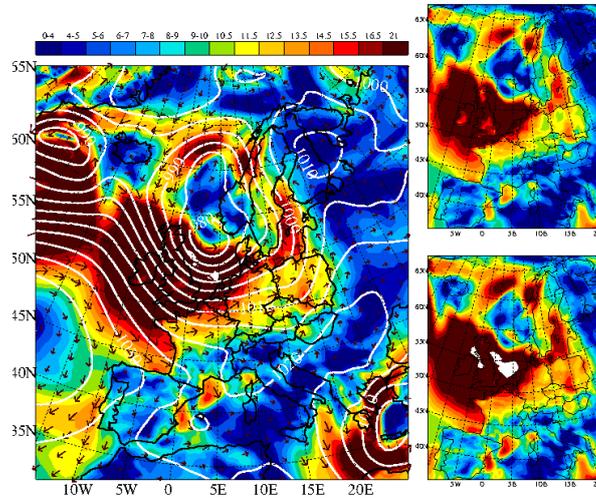


Figure 4. Weather maps of wind speed (colour scale), wind direction (arrows) and isobars. The large graph is the EPS Mean of 75 members, the upper right graph is the minimum and the lower right graph the maximum wind speed of the 75 members in each grid point.

guideline for forecast solution selection [14] in its updated version that is currently underway to support the industry in that process.

In our future work, we can with some certainties assume a general acceptance and request for probabilistic forecasts in energy related decision-making. Therefore, we will in the future focus more on low probability, but high-impact scenarios and which tools are most effective for the decision-making on the basis of probabilistic forecasts for typical decision problems. The following is a list of topics that we want to follow in the next period of the task 36:

- (i) Provision of other graphics, e.g. weather maps of large-scale weather or presenting percentiles versus all ensemble members to the decision-maker to investigate how decisions may change when more or less ensemble members are presented
- (ii) Provision of probabilities in form of text or combinations of graphics and text
- (iii) Study of false alarm situations, where the reaction of participants is specifically analysed in conjunction with the correctness of the decision
- (iv) Investigate whether decision-makers are more risk averse or prone given probabilistic forecasts and whether the amount of uncertainty makes a difference
- (v) Scenarios with extreme events, where different types of uncertainty forecasts are used and where some methods are not able to capture the event
- (vi) Scenarios with extreme balancing power prices (this sometimes occurs in the Nord Pool or EPEX market), where forecast errors in one direction can be highly penalized

Cases i and ii would be interesting to study, which tools are most useful for decision-making. Here, participants could for example be presented with different types of uncertainty forecasts, all ensemble members versus aggregated percentiles, as well as additional graphical or textual interpretations of the same event to make a decision.

Case iii and iv is an interesting investigation (1) when decision-making takes place on the basis of small or large probabilities and (2) how decision makers react, when they have taken a wrong decision. Part of the latter are we already investigating in the second experiment. What is

missing in that experiment is the discrete knowledge of the probability or a prior taken decision of the probability that leads to a certain event and the consequences thereof.

Case v are scenarios, where we investigate how difficult it is to evaluate, whether or not a certain methodology is suitable for an application with extremes with e.g. long return periods and where e.g. statistical methods fail, because (1) the event was never observed in historical data or (2) the temporal dependency structure is not modelled by the statistical approach used. Such an experiment would allow investigating how well different modelling approaches are understood and applied correctly when introduced to the industry. Since the science behind the probabilistic approaches are rather complicated, the IEA Wind Task 36 has started to establish documentation about different approaches broken down to a level that addresses the typical educated power engineers. However, it is unclear whether this type of scenario and its hidden uncertainty play a role in the currently observed barriers of implementing probabilistic applications. *Case vi* is more directed to specific user groups and applications. A good possibility could be to use the probabilistic game in a utility theory setup to study the choice between a feed-in tariff y (guaranteed income) or direct participation in the electricity market with probability p of earning less than y or $1 - p$ for winning more than y .

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