Understanding Uncertainty: the difficult move from a deterministic to a probabilistic world

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Abstract—**Forecast methodologies have advanced over the past 20 years along side the needs of system operation and trading of energy at the power exchange markets. Like every discipline in development, also forecasting of renewable generation has evolved disruptive and chaotic at times when new ways to handle these variable sources were sought. The forecasts of these sources inherit an uncertainty in their operation due to the uncertainty of the underlying weather forecast. Once these uncertainties are understood the future outcome at the time scale required to operate our electric grids and trade the energy on our power exchanges can be forecasted much more efficient than with deterministic methods. Uncertainty forecasts are filling a gap of information missing in deterministic approaches and are gradually moving into the control rooms and trading floors. Nevertheless, there are a number of barriers in the industrial adaptation of uncertainty forecasts that have their root in a lack of understanding of the methodologies and their respective applicability. There is a complication level that needs to be overcome in order to move forward. The IEA Wind Task 36 has been carrying out a number of expert round discussions picking up a number of the loose ends of integration and application issues. The applications presently used in industry, suggestions how to apply and integrate uncertainty forecasts into operation and an outlook from this discussion are presented and discussed hereafter.**

I. Introduction

Until now, most wind power forecasting solutions are deterministic, ignoring the uncertainty of the forecast, both in terms of the weather forecast uncertainty, but also of non-weather related power generation conversion uncertainty.

Probabilistic forecasts draw a much better picture of the forecast process and enable the user to understand the underlying uncertainty inherent in any forecast. But from where does the uncertainty in wind power generation arise? How are wind power forecasts produced? How can the uncertainty in a wind power forecast be communicated? What are some of the ways that probabilistic forecasts are currently used in practice, and how might they be used in the future? We will in the next sections shed light into these questions and provide a practical guide to the use and examples of applications of uncertainty forecasts and their relationship to defining and making use of the knowledge when dealing with weather dependent power resources.

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II. Methods for generating uncertainty forecasts

The methodology with which uncertainty forecasts are generated is a crucial parameter for the success of an application for a specific purpose. There are simple statistical methods that are almost cost neutral, once a deterministic model result is available and there are methods that bare significant costs and in order to achieve a consistent and weather dependent real-time result. Some methods rely solely on historical and climatological information and do not contain any information about the current weather conditions and no time dependence. Such methodologies are limited in their applicability. This is an important aspect that is often neglected, especially in public procurements, where cost has highest weight. If the requirements for the methodology are not set correct, the end-user risks to buy a product that does not fit purpose. In Bessa et al. [1], all common methodologies for uncertainty forecasts have been reviewed and described in detail. We therefore only name the relevant approaches here to be able to refer to them in the discussion of the applications.

There are two ways of determining uncertainty:

(A) Statistical methods
(B) Statistical Scenarios
(C) NWP Ensemble forecasts based on parameterization differences
(D) NWP Ensemble forecasts from perturbed deterministic models

The four main methodologies will be used in the following description of applications for uncertainty forecasts with their letters.

III. Applications for uncertainty forecasts

In this section we will concentrate on describing applications of uncertainty forecasts in the operations of system operators, utilities, market management organisations or traders in the power sector. Some of the applications may be described for one specific purpose. In that case, it should be considered an example or an inspiration source for the application rather than a recommendation for use in only that specific case. The list is not exhaustive and covers only parts of possible applications. The authors have tried to focused on the most relevant applications for current development level and trends in the power industry. For example, "Using uncertainty forecasts for risk evaluation in the control room" and "Dynamic Reserve Prediction" have been discussed in more detail already in [1], [2] and [3].

A. Using uncertainty forecasts for situational awareness in the control room

Situational awareness has been a topic so far mostly at system operator level as a tool to take the "uncomfortable" surprises with high costs in the electric grid out of the control rooms and to help the operators be better prepared for "unforeseen" imbalances. In many cases, the managers are afraid that there is too much information available to the operators and think an overload of information takes the focus from concentrated work. Unfortunately, this has been and is exactly the wrong strategy in this case. It has been investigated thoroughly with lab experiments [4] that operators get more confused by not knowing when they can trust a forecast and when they have to expect that a forecast can be way off. The issue here is that forecast uncertainty is not something that can be ignored. Especially, because the industry has developed in a way that quality and performance is measured with standard statistical methods, which in fact dampens all extremes and hence "confuse" exactly when it is most critical.

Making the uncertainty of forecasts visible is therefore an empowering method for the operators and should not be seen as a complication. Providing information to the operator about the trustworthiness of a forecast and possible outliers is exactly what is required to be prepared and be able to act in good time, making operations more smooth, less expensive and after all much less stressful.

The two most important requirements in the development of situational awareness in the control room are associated with:

(1) method being used to provide uncertainty indicators
(2) communication of the uncertainty

The pitfalls are that these two aspects are not taken serious enough in the planning and design phase. It is not so much the design of any type of graphics, but more the availability of the correct methodology for the task at hand and the way the uncertainty is provided in order for the operators to be able to best handle and absorb the information. Some people prefer graphical solutions and others text that is added to the the interfaces. Nevertheless, it is crucial that this is taken into account in the design phase. Interviews with system operators within the IEA Wind Task 36 have shown that the relevant information often needs to come as raw information not as pre-fabricated, as is possible with deterministic forecasts. For example, if ensemble forecasts are used to estimate the uncertainty of the power in-feed, the forecasts of the individual ensemble members need to be supplied as raw input, i.e. not calibrated to a specific time horizon, as these information has to propagate also into the load forecasts. In such a case, there is only two methodologies available, namely physical ensembles of type multi-scheme or multi-model, as they need no time horizon calibration or statistical scenarios with time-dependency. If other methods are applied, the end-user will become disappointed and think that the development is not far enough established.

B. Using uncertainty forecasts for trading and balancing

It is part of the DNA of traders to look for profits. But, what do you do, if you cant earn money, where you should. Usually, if classical trading does not bring profits, the traders look for areas, where they can take risks and get rewarded. In other words, the trader starts to speculate. In some markets, where forecasting is done on a per wind farm basis, the risk for speculation is higher. Especially, if there are few forecast providers or a monopoly that provides forecasts to more than 40% of the market participants. In this case, the risk for speculation increases. The following points are critical points for such situations:

- if the entire market uses the same procedures, its easy to speculate against system imbalance
- if there is no real competition and the same tools are used to balance and to trade, its easy to manipulate
- if curtailment increases, its easy to cheat wind farm owners

The result of such situations usually are higher balancing costs on the system leading to more expensive reserve, lower system security, due to missing reserve in extreme events and ultimately higher costs for consumers, when market prices fall and reserve costs increase. The way such situations can be avoided and "the cancer in the syste" healed is by applying uncertainty forecasts. By doing so, the traders become price makers and reduce system imbalance by bidding the "secure" part of the forecast unlimited and the uncertain part with higher prices. On the other side of the equation, the system operator should be prepared for outliers and extremes, allocate dynamic reserve and be more confident and "aware of the situation", i.e. knowing the risk for fast ramps, large errors due to uncertain weather conditions etc.

The strategy for a trader would be to:

(1) Split your pool into portions and become price maker
(2) Optimize your trading volume with intra-day balancing
(3) Base your bids on a preliminary plan for the balance process
(4) Make sure you help to avoid negative prices

Using this strategy, the trader will experience the following advantages:

- Reduced day-ahead schedule error with approx. 50%
- Reduced need for peak reserve
- Reduced volatility of balancing costs
- More volume in the market
- Small pools may not need to be 24x7 in the market

The most simple way to apply uncertainty forecasts for traders has been described in detail by Moehrlen et al. [5] already in 2012 and again in 2017 in Du et al. [2]. With such a method a realistic uncertainty band is employed to a day-ahead forecast and then used in combination with a short-term forecast to decide within the intra-day how to bring units into balance. It is of advantage, but not necessary, to use a short-term forecast that is adopted to measurements.

Such trading strategies can of course also be automated by simply letting a program decide upon threshold values and limits, when and how much volume should be traded. Once such trading strategies have been established, i.e. point 1-3 in the list above is implemented, it is possible to think of how to avoid negative prices, or in more general terms, how to trade some of your energy with higher costs in order to maintain a market price that reflects the real production costs. Let's have a look at an example how to establish this. In the example, we assume that a risk of negative prices has been discovered. Our example pool size is 2000 MW, where there are 200MW of controllable wind power. The forecast shows an uncertainty (defined as MAX-MIN of 450MW. The "best guess" forecast says production lies at 1200MW and the overall trading strategy says: "bid safe and work with a risk volume of 10% as maximum trading volume above the unlimited cost price to increase profit and increase pool balance". In this case, the first step is to decide hour for hour how much volume we trade at higher costs. For simplicity, we regard here just one hour. At hour 1 we take the following bids under the respective assumption:

Bid unlimited: 1200MW $->$ market price
Bid price 1 (=0): 80MW $->$ prevent negative prices
Bid price 2 (>0): 60MW $->$ help to increase market price
Bid price 3 (>>0): 40MW $->$ increase income
Bid price 4 (>>>0): 20MW $->$ increase income further

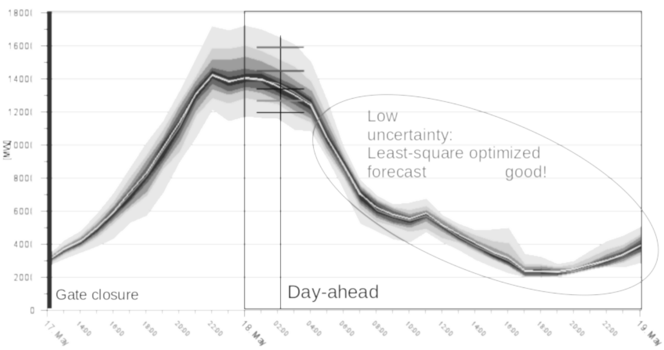

Fig. 1. Example of a forecast with areas of high uncertainty (ca. 00:00-06:00), which opens possibilities for trading parts of the pool at other volumes and price levels.

Fig.1 shows the way a trading strategy can be built up, i.e. once the hours of high uncertainty that contain an "opportunity" are identified, different percentile values are picked for each hour. This is done in a table. The table in Fig.2 shows the way the trading strategy can be managed manually or by an automatic algorithm, once the threshold limits and the strategy is set. In each hour there is a value for the minimum, P10...P90 and the maximum. An automatic algorithm can now start evaluating in which hour the spread is over the threshold value. Then compare the differences between the percentiles and e.g. searches in the database for similar events. On a manual basis, the trader can use his expertise to adjust some volume to what is expected to happen due to the weather situation and/or the way the market reacts upon certain weather situations.

Date Hour	18. May 00:00	18. May 01:00	18. May 02:00	18. May 03:00	18. May 04:00	18. May 05:00	18. May 06:00	18. May 07:00	18. May 08:00	18. May 09:00	18. May 10:00
Min [MW]	1167	1158	1154	1086	1079	911	726	523	475	427	406
p10 [MW]	1281	1262	1245	1178	1137	948	802	617	538	506	472
p20 [MW]	1330	1310	1271	1205	1160	975	817	639	561	521	498
p30 [MW]	1350	1334	1295	1245	1184	1002	843	657	572	532	514
p40 [MW]	1376	1378	1316	1269	1211	1014	868	671	586	552	525
p50 [MW]	1398	1390	1367	1317	1248	1040	881	707	604	564	540
p60 [MW]	1426	1427	1379	1334	1270	1058	896	721	629	573	555
p70 [MW]	1459	1442	1403	1354	1286	1086	903	732	648	596	565
p80 [MW]	1531	1503	1457	1389	1324	1126	918	743	659	612	578
p90 [MW]	1598	1562	1517	1470	1379	1164	939	756	671	622	603
Max [MW]	1721	1699	1657	1607	1502	1267	985	788	691	640	651
DA-FC [MW]	1403	1391	1350	1296	1238	1039	873	699	618	574	552
Measurement	1596	1558	1473	1355	1284	1113	886	691	591	548	537

Fig. 2. Example of a trading strategy, where parts of the pool is traded within the uncertainty of the forecast with different price and volume levels.

A typical example could be a low pressure system that travels in a known path, where it is known that a small difference in the center of the low pressure system can cause a very different power generation pattern. If in such cases, the market usually bids over, the trader now has the opportunity to do the opposite to what he expects the market will do when using a general average forecast. To not do this purely subjectively, the trader stays within the uncertainty of the forecast. That means, that he will not bid in with a forecast below or above the minimum or maximum. That is an essential and crucial feature of the application.

The step by step recipe to built up a trading strategy as a guideline for the traders or the programmers, if an automatic solution is chosen is summarized in the following. The four main steps are:

(1) Know your pools controllable and non-controllable generation
(2) Use appropriate uncertainty forecast intervals to:
    - trade the safe part with a mean or deterministic day-ahead forecast
    - trade uncertain parts with higher prices and control curtailment yourself
    - trade in the intra-day market only difference outside uncertainty band
(3) Design price levels considering
    - time of the day
    - current weather situation
    - liquidity in the market
    - expected load
    - risk for negative prices
    - risk for curtailment
(4) Choose an appropriate method

Note that the last item in this list (4) is a crucial one. For trading purposes you need an hour-to-hour uncertainty method, which means that you need to ensure that the method that is used is one of type B or C (see section II). Method A and D are not suitable for this type of application and will not provide the features that are needed to generate an objective and weather dependent strategy. Method A is generating only a spacial probability distribution and hence lacks the time dimension. Method D needs calibration for the time component and becomes computationally impossible to handle in real-time, as an ensemble method of that type required calibrated for each target horizons, if it is not that of the raw ensemble output. This is seldom the case, due to the various different obligations met services have to serve the public. In the case of an intra-day trading a minimum of 24 calibrations would be required which is technically not possible.

The main learning to take away from this is that "METOHD IS IMPORTANT". In the selection of vendors this is the most crucial point and should not be underestimated. It is important to understand the impacts of the chosen method and be sure the method is suitable for the application at hand.

1) Critical Ramp Events: In our discussion with end-users, one end-user mentioned that ”Communication of uncertainty in timing of ramp events is the most challenging. It is not so much the uncertainty of the amplitude. Getting the shape right would already help, even if the timing is off”. If this would be the objective of a ramp forecast, then the forecast provider would have to work on the shape, i.e. allowing all extremes to develop and then generating a probability function for it. The resulting ramp forecast would have steep ramps, often with a time lag of a few hours. If another forecast provider would consider how the forecasts are evaluated by the customer, the strategy would be to suppress the outliers and get less extreme ramps with a timing that spans longer and generates less error in average. Subjectively, the first provider does what the customer asks for and what would provide most value for the end-user. However, if the evaluation of the forecasts is carried out with standard statistical metrics, e.g. root mean square (RMSE) or mean absolute error (MAE), the timing will be punished more than the lack of steepness (amplitude). This is commonly called “double punishment”, as the forecast is punished twice in the case of bad timing, once for not having the peak at the right time and once for having it where it did not happen. Figure 3 illustrates this situation and the inherent misunderstandings between value of a forecast and the evaluation of a forecast with standard and average statistical verification methods. The forecast vendor is put into the dilemma of fulfilling the customers request or risking to loose a contract due to “insufficient” forecast performance.

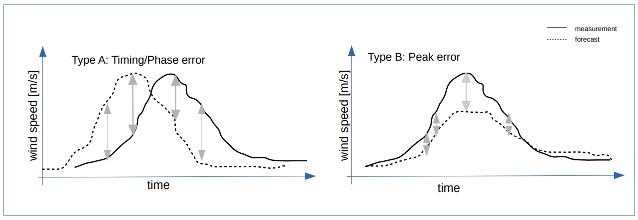

Fig. 3. Illustration of typical phase errors (left fig.) and amplitude errors (right figure). The phase error causes a a so-called “double punishment” in a statistical averaging metric due to large amplitude errors prior to the peak and past the peak.

Figure 4 shows a real ramp forecast inclusive the P10 to P90 uncertainty bands from 75 ensemble forecasts. The risk tuned prediction is the dark gray line and a least square error optimized ramp prediction is shown in white, the observations are the black line. The more realistic “looking” ramp rate prediction (gray) has subjectively a much better fit than the white line. However, with objective verification the white “conservative” line gets a better score with a statistical standard metric, because the more realistically behaving forecast gets punished harder for the phase errors than the other one for the missing peaks.

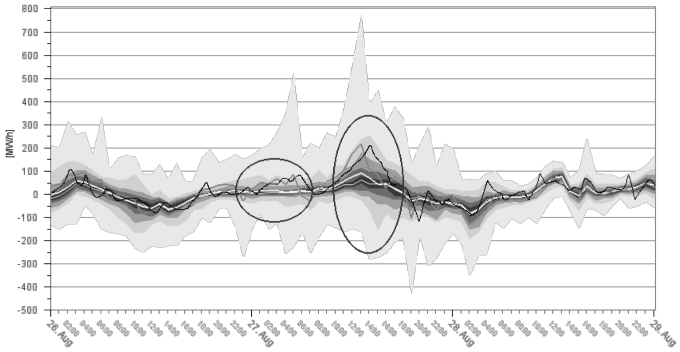

Fig. 4. A typical ramp example with uncertainty bands from an ensemble prediction system of type (C) with phase errors marked in circles.

What should also be noted in figure 4 are the uncertainty bands. Such bands provide a lot of value to the operator, also if the end-users strategy is to employ more than one forecaster for ramp events. Having a realistic uncertainty distribution in every time step of the forecast, an operator can much better evaluate the risk of a critical event, if this can be expressed in probabilities such as quantile or percentile bands.

As an example, an operator may have enough cheap or unavoidable reserve for 200MW per 15min. If the risk of a ramp exceeding this threshold goes beyond 25% probability, the operator needs to act. In figure 4 we can spot about 6 peaks that reach above the 200MW limit. However, there is only one with a probability exceeding 25%. At that stage, there is a small risk (10%) of a peak that exceeds 200MW by far and could reach up to 750MW in 15 min. Knowing this one day in advance, or even 12 hours in advance will make operations much easier and more efficient. The drawback: there need to be established rules, thresholds, limits and a communication layer. Without that, a forecaster cannot provide the necessary information to make such a risk index automatic and reliable.

2) High-speed shut down events: As mentioned already in the last section, communication is crucial for the interpretation of probabilities for a certain event to take place. The information needs not always to be visually accessible, but easy to interpret. This means that the operators need to be able to understand the way probabilities are communicated to them. As an example, Warnings that tell the operator that e.g. there is a 10% probability of a 50% high-speed shut-down, or a 5% probability of 90% shutdown, or a 90% probability of a 10% shutdown have very different impact on the operation and security requirements of the grid operation. In that sense, choosing the appropriate method to discover events that are critical for the system operation or establish procedures that enable more cost efficient operation, is the starting point. However, unless there is a structure of the thresholds, the best method cannot deliver a useful product.

A warning system can be established in the form of graphics or text. The underlying instruments however should contain two components:

- Probability computation of the expected cut-off capacity In cooperation with the end-user the system critical part of the capacity will be determined (e.g. 30% of the

TABLE I
EXAMPLE OF AN ALERT SYSTEM EVALUATION FOR TWO CASES.

Probability [%]	Threshold capacity [%]	case 1 [%]	case 2 [%]
10%	>90	84	55
30%	>25	*25*	**30**
50%	>15	10	16
90%	10	7	5

capacity)

- Accumulation of the expected cut-off capacity
  This component provides the accumulated cut-off probability of the expected temporal shortage of capacity and ramps

In a graphical setup, where the end-user has access to the graphics, receives a combination of text and graphics, or an automatic solution is established, a table of the probabilities with the information of (1) and (2) from above is useful, as this allows the user to do a more detailed analysis and action planning. Dependent on the time of issue of warnings, this can be an extremely efficient planning tool.

To illustrate the difficulty and the importance of defining what a critical event is for the end-user the example in figure 5 shows an example of a graphical tool to interpret a warning that has been generated by an automatic system. The example shows two subsequent alerts.

Table I shows the raw values from the alert generation. It is quite obvious that without an operating rule, the information is not worth much, as an operator would not have the time to figure out how much probability would be enough to start acting upon a high-speed shutdown capacity percentage. The threshold values in the above system can be seen in row 2 of table I.

In this case we can see that only the second threshold in case 2 is fulfilled. If this is would be in 2 subsequent forecast cycles, the warning would have been issued, but only for case 2. The result of the actual cut-off scenario in this example was consistent with the warning system. The result of the peak cut-off capacities shown in the lower graph of figure 5 were as follows:

Case 1: 25% peak cut-off
Case 2: 35% peak cut-off

In case 1, the cut-off was just on the edge of being critical and in case 2 the warning was important, as the threshold was exceeded by 5%. The lack of warning for case 1 shows how important it is that such rules are defined with care and assessed regularly.

The next step in the development of such a warning system is to add the time aspect to the warning, i.e. to compute the accumulated effect of high-speed shutdown events in space and time. Only when the probabilities are accumulated, the operators have the correct information about the required reserve for such events, as it is often the area or time aspect that is causing the problem in the operation of the grid.

Besides this, the communication layer of the alerts is imperative in the development of the alarm system. The communication frequency of the generated alerts need to be handled with care. If too many alarms are send out, the receiver do not take alerts serious when they may be. The following list can assist in taking the most important time coordinates into account:

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

A thumb rule for a strategy of issuing alerts is to (1) issue every alert according to a simple scheme, e.g. a probability exceeding 10% for more than 2 subsequent forecasts rounds, and (2) reduce the amount of alerts to a minimum in order to prevent that critical alerts are not accidentally overlooked. It is wise to observe the situation before an alarm is issued. In that sense, this type of service is partially automatic and partially manual interpretation. As more such systems will be developed, there will be more experience with the types of alters and automation of the process can be expected.

Lastly, it is imperative that there are established procedures for:

- Training, analysis of effective information handling
- Guide lines on action upon presented alert probabilities

C. Grid Technical Constraints Management

System operators of transmission and distribution systems are exploring the predictive grid management paradigm, divided in two phases: (i) anticipate technical problems such

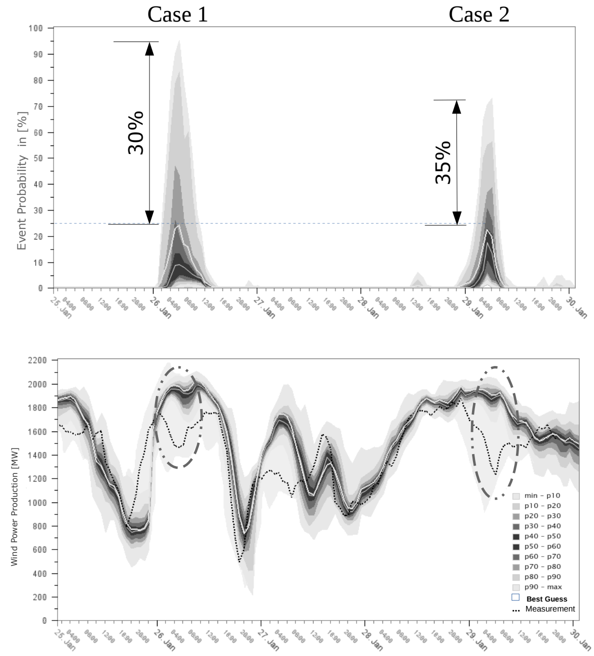

Fig. 5. Example of a probabilistic type (C) method high-speed shut down forecast of 2 concurrent events (upper fig.) and the corresponding power production (lower fig) forecast shown with uncertainty bands P10..P90 and measurements (dotted black line).

as congestion and voltage limits violation in the electrical grid in advance; ii) define remedial actions (e.g. grid reconfiguration, demand response, re-dispatch) to solve the potential technical problems.

However, the information that is being included, for instance in the Day Ahead Congestion Forecasting (DACF) [6], consists of deterministic forecasts for both load and renewable energy. The main barriers for the integration of renewable energy forecast uncertainty in network operational management are the following:

- The uncertainty representation should fully capture at least the spatial dependence structure (and the temporal structure in case of multi-period constraints), which can be met by using calibrated meteorological ensembles for grid nodes. However, this requires the implementation of stochastic optimization methods [7] that exhibit high computational times and human operators are used to receive fast (and simple) advices for remedial actions.
- Integration of uncertainty will increase the operational cost due to a trade-off between cost and exposed risk. In the state of the art there is a lack of business cases that perform cost-benefit analysis of stochastic approaches for grid management. This gap is not contributing to a wide adoption of these techniques by the industry.
- Cognitive load of human operators in the presence of probabilistic information for a large electrical network. Similarly to human traders (see section III-B), human operators in control rooms also like to use their expertise to define remedial actions based on what is expected to happen and search "mentally" for similar situations.

Potential solutions to facilitate the integration of forecast uncertainty in network analysis can be summarized to the following:

- Integrate forecast uncertainty in "imitation learning" methodologies, i.e. automatic procedure that imitate decisions made by experts [8]. This will ease the acceptance of the information about uncertainty by the human operator.
- Design local (or segmented) stochastic optimization methods, instead of applying large-scale stochastic optimization tools for the full network. This approach will decrease the computational time, as well as the complexity in visualizing the forecasted information and remedial actions definition.
- Invest in new visualization techniques, e.g. hypervision to reduce number of informations into a manageable amount of data and alarms [9].

IV. Summary and Outlook

The integration of uncertainty forecasts into grid control, grid management and trading strategies is not a fast roll-out into the industry due to an increased level of complexity and computational requirements, different approaches and methodologies, some with limitations that have caused distrust to the overall concepts, and finally the paradigm shift required to accept uncertainty as a parameter that needs to be dealt with. It's not that operators did not deal with uncertainty before, the N-1 criteria is the counterpart of dealing with uncertainty in the grid. Nevertheless, dealing with new technologies, where the uncertainty needs to be considered constantly, not only as single events, requires a mind shift and new tools in the control and trading rooms in order to be accepted.

As penetration of wind and solar power increases, this step will naturally be taken due to the increases in uncertainty and grid constraints. Once a threshold of renewables feeding into the grid is reached, probabilistic methods seem to be required in order to manage the large ramps associated with wind changes or strong cloud activity. Societal changes also increase the variability in the load pattern, which needs to be incorporated into the grid management.

For this reason, part of the IEA Task 36 is dedicated to translate academic knowledge into industry applications to increase this acceptance and provide objective information about existing methods to deal with uncertainty, how, when and which method to apply to typical or specific challenges and publish freely accessible information for the industry and interested individuals through the website ieawindforecasting.dk and open access publications.

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