A Review of Probabilistic Methods for Defining Reserve Requirements

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***Abstract*—In this paper we examine potential improvements in how load and generation forecast uncertainty is captured when setting reserve levels in power systems with significant renewable generation penetration and discuss the merit of proposed new methods in this area. One important difference between methods is whether reserves are defined based on the marginal distribution of forecast errors, as calculated from historic data, or whether the conditional distribution, specific to the time at which reserves are being scheduled, is used. This paper is a review of published current practice in markets which are at the leading edge of this problem, summarizing their experiences, and aligning it with academic modeling work. We conclude that the ultimate goal for all markets expected to manage high levels of renewable generation should be a reserve setting mechanism which utilizes the best understanding of meteorological uncertainties combined with traditional models of uncertainty arising from forced outages.**

I. Introduction

The increasing penetration of highly variable renewable generation poses a number challenges for power transmission system operators (TSOs), not least of which is the task of determining the amount of reserve to schedule in order to maintain a specified level of system security. Loosely, this means holding enough reserve to restore the balance of generation and consumption in the event of unplanned deviations from the forecast system operation state, keeping electrical parameters within statutory limits, and without having to resort to any authorized or un-contracted reduction or disconnection of demand.

In practice, in many markets there are different categories of reserve, defined to address uncertainties arising in different time-scales, the different sources of energy that might be available to manage the impact of imbalance, and the vulnerability of a particular synchronous area to frequency variation [1, 2]. In principle the arguments and methods discussed in this paper could be applied to any type of reserve but are most relevant to balancing services being procured on intra-day and day-ahead time-scales and operated on sub-hour time-scales to respond to load and generation forecast errors [3].

Increasing the level of stochastic generation in the system increases the impact that external, non-controllable variables (such as instantaneous wind speed) have on the reserve-setting problem. Defining reserve requirements in this context to meet a defined level of system security remains an open question. Decisions made under uncertainty must be informed by probabilistic information in order to correctly quantify the risk the decision maker is exposed to [4]. Due to the complexity and difficulty of managing probabilistic information these decisions are typically informed by heuristic rules based on past experience, but as the number and size of uncertainties increases it is likely to be worth employing more sophisticated approaches in order to achieve cost savings. Additionally, heuristics may be defined by analysis of past system states which do not adequately represent the expected states of that same system under future conditions with a different generation mix and geographic distribution of generators. For example, in Great Britain wind generation has historically been located towards the northern extent of the network, distant from the main load centers, where the future development of offshore wind may shift the distribution this generation towards the south-east of the network, requiring uncertainties in wind output to be captured for a very different set of possible network flows [5].

The optimum reserve level is found by balancing the cost of procuring reserve capacity against the cost of failing to supply energy in the event of a shortfall. Historically, the two main sources of uncertainty were significant but well defined: the possibility of multiple large generators failing has low probability but high impact if reserves are inadequate, and load forecast errors are common but usually relatively small. This allowed reserve levels to be set using simple rules based on the size of largest generator and/or some fraction of the total load [6]. Today, the output of variable generation in the near future is uncertain and must be forecast. Managing power systems against this new characteristic has been the focus of much research.

Over the past decade many industry and academic studies have been carried out to assess the impact of integrating variable renewable generation into the world's power systems, and many have been compared and reviewed as in [2, 7, 8], for example. A critical finding of recent studies is that operating reserve requirements need to be more dynamic [8]. In order to maintain a constant level of risk, TSOs use both analytic methods and their experience to assess the uncertainty in near-future load and generation, and schedule reserves accordingly [8]. The methods used to quantify uncertainty varies significantly between operators, and in this paper we attempt to present representative examples of the variety of different approaches.

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In Section II we describe the reserve scheduling problem, followed in Section III by a discussion of current practice as documented by several TSOs. In Section IV we discuss two proposed solutions based on probabilistic forecasts: the first makes use of density forecast and the second uses scenario forecasts. Finally we present a discussion and some conclusions in Section V.

II. Problem Description

Reserves are required to maintain system security and ultimately the goal is to maintain the supply of electricity to consumers within appropriate cost constraints in response to unscheduled deviations in generation and demand. In order to define an appropriate level of reserves, it is necessary to identify risk indices that quantify the desired level of system security. The three most common examples are listed here:

- Loss of Load Probability (LOLP), which is the probability that generation will be insufficient to meet demand during a given period.
- Loss of Load Expectation (LOLE) is defined as the portion of time, over the long-term, that it is expected that supply will not meet demand, as used in the capacity markets recently introduced in Great Britain and France.
- Expected Energy Not Served (EENS) gives a measure of the total energy not delivered due insufficient supply.

Given a probability density function of load and generation forecast error (including the chance of plant of interconnector failure), the level of reserves required can be calculated for a chosen value of one of these indices.

For any given index, the target value chosen depends on how risk-averse the TSO is. The European Network of Transmission System Operators for Electricity (ENTSO-E) includes recommendations in its policy on load-frequency control [1] for a 'probabilistic risk management sizing approach': holding enough reserve to meet requirements, for example, during 99.9% of hours based on the individual distribution curve of the power imbalance of the control area in question.

There is also an economic case to be made. Scheduling and operating reserves comes at some financial cost, and there is an economic cost associated with disconnecting customers. Often, the latter is termed the value of lost load (VoLL). It should be noted that calculating VoLL is problematic as the nature of the load not supplied can have a large impact on the associated economic cost [9], and many of the non-financial impacts are difficult to quantify. For example, VoLL will vary depending on the time of day and year, and the type of customer, and the economic cost of failure to supply energy may have significant knock-on and distributional effects.

However, once a VoLL is defined in some manner, combining it with the LOLP, LOLE or EENS allows the decision maker to choose a level of reserve that returns an acceptable level of financial risk. For example, reserves could be scheduled up until the point that the marginal cost of increasing the reserve level exceeds the cost of not delivering energy to customers multiplied by the LOLP. Another approach would be to minimize the conditional value at risk (CVaR), which is the expected total cost of a reserve schedule, including the cost of lost load.

Whether considering the risk of lost load or economic risk, having representative probabilistic information as an input is crucial. As discussed in the next section, uncertainties in load and generation forecasts are commonly treated independently and calculated on basis of historic forecast error; however, these are both weather-dependent quantities and therefore not independent.

Importantly, the uncertainty associated with a given weather forecast depends on the how well the present state of the atmosphere is estimated and the sensitivity of the forecast to this estimate [10]. This means that the distribution of historic forecast errors is a measure of *'average'* uncertainty and is not representative of uncertainty for specific forecasts. This poses a problem for decision makers, for example: if conditions are such that uncertainty is relatively low, present practice may prescribe more reserve than is necessary and incur associated additional costs; likewise, if the weather forecast is highly uncertain present practice may not prescribe sufficient reserves to meet the desired level of system security. Furthermore, as the penetration of weather-dependent generation increases, the impact of this mismatch will become more severe.

A number of academic studies have investigated the impact of load and generation uncertainty on power system operating costs using stochastic programming [11–14]; however, they model specific generation and reserve markets, often cleared simultaneously which is not the case in many energy markets. In addition, they do not provide the decision maker with information about the risk associated with the dispatch solution. That said, the result that treatment of actual forecast uncertainty offers a saving over heuristic approaches is still relevant. What is not known is how much of these savings can be realized in reality and in different market structures, or at what level of renewable penetration it becomes economic to invest in implementing new systems.

III. Uncertainty Defined by Historic Forecast Error

At the time of writing, a heuristic approach is taken by many TSOs. It should be noted that these approaches are meant as decision aids and that reserves scheduled in real time will vary depending on conditions at that time, including time of day, market conditions and any special circumstance, at the operator's discretion. These examples share a common assumption that the distribution of forecast errors depends only on historic forecast performance scaled by the installed capacity and spatial dispersion of variable generation, not on the uncertainty associated with specific weather forecasts.

In Texas, where in 2014 10.6% of the demand for electricity was met by wind power, the Electric Reliability Council of Texas (ERCOT) determines the reserve requirements for each hour of the coming month before the 20^{th} day of the current month. The total amount of available reserve to be procured a month ahead is a combination of the Regulation Service Requirement (deployed to maintain target frequency), a Non-spinning Reserve Service (to replace lost generation and compensate for load/generation forecast errors, with a 30 minute response time), and a Responsive Reserve Service (responding to events that cause significant deviation from system frequency) [15].

The Regulation Service Requirement is derived from the 98.8$^{\text{th}}$ percentile of net load (load and wind) and the 98.8$^{\text{th}}$ percentile of reserves deployed for the 30 days prior to the period of interest and from the same month in the previous year, with an adjustment for new wind capacity. Enough non-spinning reserve is then scheduled such that it plus the average Up Regulation (equivalent to primary response in ENSTO-E and frequency response in GB) procured meets or exceeds 95% of the net load uncertainty. Finally, the Responsive Reserve Service requirement is set based on historic diurnal load and wind trends.

In Great Britain, where 9.3% for demand for electricity was met by wind power in 2014, the TSO calculates its short-term reserve requirements for each half-hour settlement period four hours ahead of time in order to contract balancing services which are required to be operational within that time frame [16, 17]. The final measure of uncertainty to be catered for is a combination of the Upward Reserve Error (conceptually the amount of conventional plant failure), historic demand forecast error and historic wind forecast error, for the respective four-hour-ahead forecasts. A reserve level is then chosen such that in a given half-hour there is sufficient reserve to cater for forecast errors on all but one day a year, with an adjustment made depending on the geographic dispersion of operational wind farms. Finally, a layer of Reserve for Response is added which comprises part-loaded units to provide frequency response. This approach is in line with ENTSO-E's guide lines; similar approaches are employed in other European TSOs, such as the French TSO, RTE [18].

IV. Forecasting Uncertainty

When making a forecast, the goal is to predict the outcome of some future observation. A probabilistic forecast attempts to describe the likelihood of all possible outcomes and can take a number of forms. The two most relevant to this discussion are density forecasts and scenario forecasts. Both types of forecast provide information pertaining to uncertainty by describing the spread of possible outcomes and their relative likelihood.

A density forecast is an estimate of the probability distribution of the future observation. Both parametric probability distributions, such as the familiar Normal distribution, and non-parametric, typically expressed as quantiles, can be used [19]. Density forecasts are popular because they are familiar and simple to work with, though combining forecasts, of wind and solar power generation for example, must be done with care and account for any correlation between variables [20].

A scenario forecast comprises a set of possible futures outcomes, each with an equal chance of being realized [21]. Scenarios have the advantage of being able capture the temporal evolution of variables — which is necessary for multi-stage decision making — and the dependency between different variables. Each scenario member includes the realization of multiple variables, e.g. wind and solar generation.

In this section we will review two examples of decision tools for setting reserve levels, one based on density forecasts and one based on scenarios.

A. Density Forecast

The work of Matos, Bessa *et al.* follows a similar risk-based methodology to that discussed in the previous section but using wind power density forecasts, rather than historic error statistics [22, 23]. They produce a decision tool to aid the day-ahead setting of operating reserves for a given generation schedule. As inputs, the approach requires probabilistic load and wind power forecasts in the form of density forecasts, plus a capacity outage probability table (COPT) and an outage replacement rate. The output is a risk/reserve curve and a risk/reserve cost curve which together act as a decision aid to be combined with the decision maker's preferences to set the level of reserve.

This tool is installed and operational at the Portuguese TSO (REN, Portugal) providing suggested reserve allocations during day-ahead and intra-day market sessions [23]. In 2014, approximately 20% of Portugal's electricity demand was met by wind power.

The methodology used by Matos, Bessa *et al.* to calculate risk from a measure of uncertainty is very similar to that of the heuristic approaches described in Section III, with the significant difference being the use of probabilistic forecasts, rather than historic forecast error, to give a more representative evaluation of uncertainty. In a case study [22], this approach is compared to a method using a simple probabilistic wind power forecast where the density forecast is a normal distribution with variance estimated from historic point forecast error. It is noted that the normal distribution is inadequate and resulted in a higher than acceptable loss of load expectation due to the mismatch between the modeled uncertainty and the observed outcomes.

The authors go on to discus how risk/cost based decisions can be made but depend on the decision maker's preference regarding exposure to either higher reserve costs or higher levels of EENS. In [23] examples are given of days when deterministic rules fail to recommend sufficient reserve and provide no indication of the risk the system is exposed to. The proposed approach captures this risk and recommends appropriate reserve levels. A drawback of this analysis is the lack of consideration for differing economic impacts of EENS.

A similar example applied to solar power can be found in [24]. In principle the methodology can be applied to a power system with significant penetration of both wind and solar power however the correlation between wind, solar and demand would have to be appropriately modeled [20].

B. Scenarios

The approach described in [25] addresses the problem of capturing the actual uncertainty of wind and load forecasts with a scenario forecasting approach. Wind power and load scenario forecasts are produced together to capture the correlation between the two and included a model of plant failure based on the frequency of historic failures as a proportion load.

A case study in the DK1 area of Nord Pool is used where the reserve market is cleared before the generation market. This is important since it rules out many other approaches including the stochastic programs of [11, 12] which clear generation and reserves simultaneously, and the approach of [22, 23] which requires knowledge of the generation schedule in order to form the COPT.

Two methods of determining a day-ahead reserve schedule are presented: the first for a chosen value of the LOLP and the second based on the CVaR. The solution controlled by LOLP optimizes the reserve schedule to deliver a set level of security, in terms of reserve adequacy, regardless of cost. The CVaR approach on the other hand optimizes the schedule in terms of both risk (in this cases expected LOLP) and associated cost, similar to [22]. The challenge for the user is to determine the risk-aversion parameter (which has no physical interpretation) and the VOLL.

The schedules produced by both approaches are compared to the actual reserves scheduled by the Danish TSO during four one-week test periods. The method based on LOLP is shown to be reliable, with the method able to produce the desired level of security set by the user, but the resulting schedule is more expensive than the TSO's simple schedule. The CVaR method with a high risk-aversion setting is found to produce a less expensive schedule with greater savings for higher VOLL.

V. Discussion and Conclusion

We have described a range of techniques from both industry and academia that aid and inform TSOs when defining reserve levels under uncertainty due to variable load and generation. While all the examples we present are probabilistic — they quantify uncertainty in order to produce risk-based results — they fall into two main groups: heuristic methods based on statistics derived from historic point forecast error, and those that employ probabilistic forecasts of load and generation. This distinction is important since the uncertainty associated with weather-dependent forecasts is complex and variable, and not well represented by historic error statistics.

The heuristic methods examined determine reserve requirements based on security criterion such as LOLP that do not account for the economic impact of lost load; however, there is significant scope for operator discretion and economic analysis will certainly be undertaken by TSOs although the specific methodology is not detailed in publicly available documentation. The methods that derive reserve levels from probabilistic forecasts present results using both security and economic metrics. Economic metrics are required to compute the cost-optimal reserve schedule, as demonstrated by [25].

The tool discussed in Section IV-A and [22, 23] is "considered to be very useful by the end user, in particular for situations with high forecast error," although the economic benefit is not quantified. The example discussed in Section IV-B and [25] compares the cost of the proposed model's reserve schedule to actual schedule used by the TSO during a test period to evaluate the method's performance and reports significant savings although the suitability of the schedule with respect to network constraints is not considered.

While there are potential advantages in using sophisticated decision making tools, incorporating them into complex and risk-averse power system control rooms may not be economic for many TSOs until renewable penetration exceeds a certain level. More work is required to determine what this level is and results will undoubtedly depend on the power system being studied. At present, it my be more appealing for TSOs to focus investment on improving point forecast accuracy since the value in this is easily realized and well studied (see [14], for example), and does not require adoption of new decision making procedures.

However, while there is clearly value in improving the way uncertainty is modeled decision aids based on power balance alone are limited. Other system constraints are important, such as zonal balancing, transmission constraints and system inertia, especially since care must be taken with respect to the spatial correlation between zones. These related problems have also received attention from the research community but are beyond the scope of this review, for example: stochastic dispatch models have demonstrated economic value in using probabilistic forecasts over heuristic rules, such as [12]; and the multi-stage aspect of reserve scheduling has been examined in [26]; and optimal power flow constrained by the chance of transmission line ratings being exceeded in [27].

There are also further considerations for TSOs that are having to adapt to increasing penetration of renewable generation: smart grid concepts, increased demand-side management and electric vehicles, plus developments in the capability of wind, solar and storage devices offering ancillary services, could all play a part in mitigating the variability of renewables [28–30]. These technologies will likely have a profound effect on the way our power systems are operated, but while the future is unknown in many respects, one thing we can be sure of is that the wind and solar resource will remain variable and uncertain; understanding that uncertainty and how to utilize this information in decision-making is critical.

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