Unit Commitment and Operating Reserves with Probabilistic Wind Power Forecasts

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***Abstract*—In this paper we discuss how probabilistic wind power forecasts can serve as an important tool to efficiently address wind power uncertainty in power system operations. We compare different probabilistic forecasting and scenario reduction methods, and test the resulting forecasts on a stochastic unit commitment model. The results are compared to deterministic unit commitment, where dynamic operating reserve requirements can also be derived from the probabilistic forecasts. In both cases, the use of probabilistic forecasts contributes to improve the system performance in terms of cost and reliability.**

***Index Terms*—Wind power, probabilistic forecasts, scenario reduction, unit commitment, dispatch.**

I. Introduction

THE increasing penetration of wind power and other renewables are posing new challenges to power system operators in grid management and generation scheduling. The inherent uncertainty and variability from wind power calls for new approaches to the traditional unit commitment (UC) and economic dispatch (ED) problems. Stochastic UC has been proposed as one approach to better handle the wind power uncertainty in market operations [1]–[6]. Furthermore, new approaches to calculating operating reserve requirements under wind power uncertainty have also been proposed (e.g., based on assumed normal distributions of wind power forecasting errors [7][8], or on a probabilistic wind power forecast [9]). It is obvious that wind power forecasting (WPF) can provide important inputs to the operational decisions of the system operator. However, probabilistic WPF is still a relatively new area of research, and there is limited experience in the use of such forecasts in system operations so far.

In order to investigate the consequences of using different UC strategies and reserve requirements in the operation of the electricity market, we have developed a stochastic UC model [6][10]. The stochastic model determines the commitment of thermal generating units by minimizing the expected cost over a set of WPF scenarios. Alternatively, quantiles from probabilistic WPF can be used to determine operating reserve requirements in a deterministic UC. In either case, the quality of the probabilistic forecasts is clearly of major importance for the cost effectiveness and reliability of the resulting scheduling and dispatch.

In this paper, we use the model to analyze the scheduling of energy and operating reserves under wind power uncertainty. We compare different statistical methods for the generation of probabilistic forecasts and also compare two different scenario reduction approaches. Furthermore, we compare the use of stochastic and deterministic UC strategies and operating reserves requirements. The main contribution of the paper is in the systematic analysis of probabilistic WPF methods and their potential use in power system operations. The results and recommendations are highly relevant for ongoing efforts to improve the management of wind power uncertainty and variability in electricity markets.

The paper has the following structure: We provide a brief overview of the UC/ED model used in this paper in section II. In sections III. and IV. we describe different approaches to probabilistic WPF and scenario reduction. Then, in section V. we compare the use of different forecasts and operational strategies in a case study of a test system with wind power and thermal generation. Finally, we summarize our findings, draw conclusions, and point out directions for future work.

II. Scheduling of Energy and Operating Reserves

We use the model first proposed in [6] and later expanded in [10] to analyze the scheduling of energy and operating reserves in the electricity market.[1] The objective of the UC model can be expressed as:

$$Min\sum_{s} prob_s \cdot \left\{\sum_{t,i}\left[FC_{t,i}^{s} + C(RNS_t^s) + C(ENS_t^s)\right]\right\} + \sum_{t,i} SC_{t,i} \qquad (1)$$

The first component corresponds to minimizing the expected sum of fuel costs from thermal generators (*FC*), the cost of unserved reserve (*C(RNS)*), and the cost of unserved energy (*C(ENS)*) over a set of scenarios (*s*). The last part of

The authors acknowledge the U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy through its Wind and Water Power Program for funding the research presented in this paper.

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[1] Some changes have been made to the model to improve the run-time. First, an improved representation of the binary commitment variables for thermal units has been implemented based on [11]. Second, the model is now implemented in AMPL and uses the state-of-the-art solver CPLEX for the resulting mixed integer linear (MIP) and linear (LP) programming problems.

the objective function is the thermal generator start-up costs (*SC*). The problem is assumed to have an hourly time resolution and is solved for the next day. Two important constraints are to meet the demand for load and operating reserves (*OR*) in all time periods (*t*) and scenarios (*s*):

$$\sum_i gen^s_{thermal,i,t} + gen^s_{wind,t} = load_t - ENS^s_t,\ \ \forall\, t,s \qquad (2)$$

$$\sum_i or^s_{thermal,i,t} \geq OR_{reg,t} + OR^s_{wind,t} - RNS^s_t,\ \ \forall\, t,s \qquad (3)$$

Both thermal generation and wind power contributes to meet the load, but we assume that only thermal generation can meet the operating reserve. We only consider one type of operating reserves: spinning reserves, which are provided by committed thermal units.[2] However, we differentiate between reserve requirement to meet uncertainty in thermal generation and load (OR_{reg}) and wind power uncertainty (OR_{wind}). If there are scenarios with scarcity where operating reserves or load are not being served, this is penalized in the objective function. The traditional UC constraints are also included, such as ramping constraints and minimum-up and -down constraints. Note that the model becomes deterministic simply by assuming that there is only one scenario. For a complete formulation of the model, we refer to [6] and [10].

In this analysis, we focus on the impact of wind power uncertainty. We assume that commitment decisions are made based on a day-ahead wind power forecast. Then, we calculate the resulting real-time dispatch with the realized wind power generation.[3] The system's ability to handle real-time fluctuation in wind power will depend on both the UC strategy and the operating reserve policy. UC schedules the generating units over the next day, taking inter-temporal constraints into account. Operating reserves impose additional constraints on unit availability for each individual hour. The wind power uncertainty can be accommodated by using a stochastic UC, which considers a range of scenarios for wind power generation for the next day. The wind power scenarios can be generated from probabilistic WPF. If the scenarios give a good representation of the wind power uncertainty, it should not be necessary to impose an additional operating reserve for wind, OR_{wind}. Alternatively, a deterministic UC model could be used to handle the wind power uncertainty through the additional reserve requirement. In this case, OR_{wind} could be derived from probabilistic WPF. With the first approach, additional reserves are implicitly added through the stochastic UC, as opposed to the second approach, which uses an explicit reserve requirement for wind power. In either case, the performance of the scheduling decisions would depend on the quality of the probabilistic forecast. The different operating strategies are explored in the case study in section V.

[2] This assumption is obviously a simplification. For a discussion of different categories of operating reserve requirements, we refer to [12].

[3] Note that we do not consider the possibility of changing commitment decisions between day-ahead scheduling and real-time dispatch. Intra-day commitment would clearly add flexibility to operational decisions. However, we focus on the impact of different UC and operating reserve strategies and do not consider the additional flexibility from intra-day commitments.

III. Probabilistic Wind Power Forecasts

There are three main methods for estimating WPF uncertainty: (1) the *Numerical Weather Prediction (NWP) point forecast approach*, where the wind power uncertainty is directly computed from the NWP point forecast for weather; (2) the *power output point forecast approach*, which consists of forecasting uncertainty based on the historical WPF errors; and (3) the *NWP ensemble approach*, where NWP ensembles are used as input to the generation of probabilistic power forecasts. For a detailed discussion of state-of-the art in WPF and probabilistic forecasts, we refer to [13].

In our research, we are focusing on the statistical algorithms used in probabilistic WPF methods (1) and (2) above. A common approach is to use quantile regression (QR) to estimate the WPF uncertainty in terms of set of forecast quantiles [14]. We are currently also exploring novel statistical uncertainty forecasting approaches using kernel density forecasts (KDF). Two new KDF-based WPF methods based on the Nadaraya-Watson (NW) and Quantile-Copula (QC) estimators are proposed in [15] and [16].

KDF methods are based on conditional density estimation, which consists of estimating the density of a random variable, *Y*, knowing that the explanatory random variable, *X*, is equal to *x*. For the wind power problem, this consists of forecasting the wind power probability density function (pdf) at time step *t* for each look-ahead time step *t+k* of a given time-horizon when knowing a set of explanatory variables (e.g., NWP variables and measured wind power output). Mathematically, this set of conditions can be formulated as:

$$\hat{f}_P\left(p_{t+k} \mid X = x_{t+k|t}\right) = \frac{f_{P,X}\left(p_{t+k}, x_{t+k|t}\right)}{f_X\left(x_{t+k|t}\right)} \qquad (4)$$

where p_{t+k} is the wind power forecasted for look-ahead time $t+k$, $x_{t+k|t}$ are the explanatory variables forecasted for look-ahead time step $t+k$ and available at time step t, $f_{P,X}(p_{t+k}, x_{t+k|t})$ is the multivariate density function, and $f_X(x_{t+k|t})$ is the marginal density of *X*. The nonparametric conditional density estimation [17] for (4) is as follows:

$$\hat{f}(p \mid X = x) = \sum_{i=1}^{N} K_{h_p}(p - P_i) \cdot \frac{K_{h_x}(x - X_i)}{\sum_{i=1}^{N} K_{h_x}(x - X_i)} \qquad (5)$$

where the kernel bandwidth h_p controls the smoothness of each conditional density in the p direction, while h_x controls the smoothness between conditional densities in the x direction.

The output is a pdf for wind power generation for each look-ahead time step of a specific time horizon. The pdf is general, from which several uncertainty representations can be derived (e.g., standard deviation, quantiles). For details on the implementation of the KDF WPF methods, we refer to [15] and [16]. The forecasted pdfs for each look-ahead time step are the input of the scenario generation method described in section IV. In the case study in section V. we compare the use of probabilistic forecasts from splines QR and KDF based on the NW estimator.

IV. Scenario Generation and Reduction

The probabilistic forecasts described above express uncertainty information for specific points in time. However, in the unit commitment problem, it is important to take inter-temporal relationships in the forecast uncertainty into account. This makes scenarios a more appropriate representation of the uncertainty. We use the WPF scenario generation approach described in [18] to convert quantiles or pdfs to forecast scenarios. In this approach, scenario sampling is done using a Monte Carlo approach. A covariance matrix is estimated based on historical forecasting errors, and this is used to represent inter-temporal (hour-to-hour) correlations.

We can only use a limited number of scenarios as input to the stochastic UC model because of the computational complexity of the problem. In most cases, there will be a need for scenario reduction. In this paper, we are testing different methods to generate a reduced set of scenarios. One simple approach is to select a random subset of the original scenarios. In the case study below, this approach is referred to as scenario reduction method 1 (SR1). Within the power systems domain, it is common to use the scenario reduction method from [19], which we refer to as SR2. Here, a reduced scenario set is derived from the Kantorovich distance between the original and reduced set of scenarios, taking scenario probabilities and distances of scenario values into account.

We are also exploring alternative approaches to generate a reduced set of representative scenarios. The idea in [20] is to find the most attractive scenario that has a higher number of neighbors according to a flexible distance metric, which is selected to be compatible with the problem to be solved. For the stochastic unit commitment problem, we use the maximum absolute deviation distance:

$$d(i,j) = max \left\| X_t^{(i)} - X_t^{(j)} \right\|, \qquad t = 1, \ldots, T \tag{6}$$

where $X^{(i)}$ and $X^{(j)}$ are the two scenarios being compared, and T is their dimension. The two scenarios are considered to be "neighbors" if the distance between them is lower than the admissible tolerance, that is, $d(i,j) \leq \varepsilon$. When the more attractive scenario and all its "neighbors" are found, they are cut from the initial set of scenarios forming a cluster. The procedure is repeated until the attractive scenario cannot find a neighbor within the tolerance. The remaining scenarios without a neighbor are considered outliers. Starting from a small tolerance value, the total number of clusters may be higher than the desired number of scenarios set for the stochastic problem. The algorithm is then repeated with a lower ε in order to find the admissible tolerance that provides the desired number of clusters. Finally, each cluster is represented by its more representative scenario. Here, the scenario presenting the lower sum of distances, according to (6), with respect to all other members of the cluster has been used. The probability associated with each representative scenario is given by the sum of the probabilities of its cluster components. We refer to this method as SR3.

V. Case Study

The purpose of the case study is to test the different probabilistic WPF approaches, scenario reduction methods, and operating strategies on day-ahead UC decisions and the resulting real-time ED. Thermal units are committed based on a day-ahead wind power forecast by using stochastic or deterministic UC. The real-time ED is then solved with the realized availability of wind power. We focus solely on the impact of WPF uncertainty. Other uncertainties, like generator outages and load forecast errors, are therefore omitted. We first discuss the quality of the probabilistic wind power forecasts and resulting wind power scenarios. Then, we examine the impact on unit commitment and dispatch results in a simple case study with wind power and 10 thermal units.

A. Probabilistic Wind Power Forecasts

Time series of the day-ahead deterministic point forecasts and realized wind power output for 15 hypothetical locations in Illinois in 2006 were aggregated and used as the starting point for the probabilistic forecasts. The data were obtained from the National Renewable Energy Laboratory's Eastern Wind Integration and Transmission Study (EWITS) [21].

We use both QR and NW KDF to generate probabilistic wind power forecasts. The wind power point forecast is used as the only explanatory variable in both cases. The period from January to July is used to train the two statistical models, whereas the resulting forecast data for October to December are used in the analysis. An example of a quantile forecast is shown in Fig. 1.

In order to evaluate the outputs from the two different forecast uncertainty estimation procedures, we focused on the calibration forecasts. Calibration is a measure of how well the forecasted quantiles match the observed values [13]. Fig. 2 depicts the calibration diagram for the QR and NW methods. There is clearly a quite significant negative deviation (corresponding to an over-forecast) for both methods, with QR having the largest deviation.[4] We provide a more detailed comparison of different probabilistic WPF methods in [15] and [16]. The results indicate that KDF forecasts outperform QR in terms of calibration, whereas QR tends to perform better in terms of sharpness, which is a measure of the width of the forecast distribution.

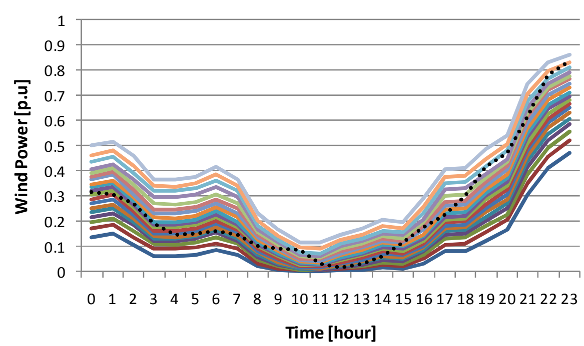

Fig. 1 Probabilistic forecasts of wind power quantiles (5%, 10%, ... 95%) based on QR and realized wind power generation (dotted line) for day 1.

[4] The large deviations may have to do with the short evaluation period.

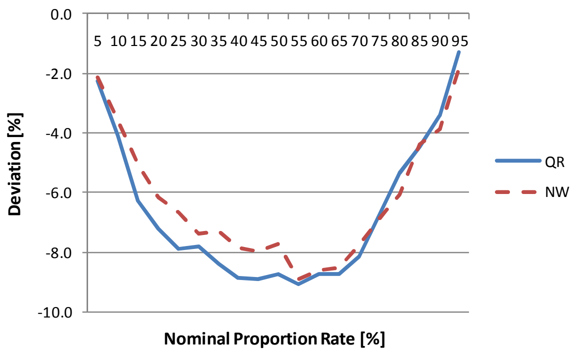

Fig. 2 Calibration diagram for QR and NW methods, Oct.–Dec. 2006.

Based on the probabilistic QR and NW forecasts, we generated 1,000 scenarios with the sampling method described in [18]. Scenario reduction is then used to reduce the full set to either 10 or 100 scenarios by using the three scenario reduction methods described in section IV. For SR2, we use the implementation in GAMS/SCENRED [22] with standard parameters. The SR3 method is implemented in Matlab.

Fig. 3 shows that the averages of the reduced scenarios are close to the average of the original 1,000 scenarios, although some deviations can be seen with random selection (SR1) and for the clustering-based scenario reduction method (SR3). Results in Fig. 4 and Fig. 5 show that the reduced scenarios based on SR2 and SR3 tend to have a significantly lower variance than the original 1,000 scenarios. The variance of the randomly selected scenarios (SR1) is higher on average than for SR2 and SR3, and with 100 scenarios, this method yields a closer match to the variance of the original scenarios.

Table I shows a comparison of the means and variances for the original and reduced scenarios. The statistics are calculated from the hourly forecasted scenario data over the full 3-month period. All the reduced sets are close to the original scenarios in terms of the overall average over the period. However, SR2 has a lower mean absolute error (MAE) than the other two methods. When it comes to variance, SR1 provides a closer fit than SR2 and SR3 do, both in terms of average and MAE. It is evident that both SR2 and SR3 result in a significant reduction in the scenario variance compared to the original scenario set. Still, the fit improves by increasing the size of the reduced scenario set from 10 to 100.

Further analysis of statistical properties could be performed by analyzing additional moments of the scenario distributions. A comparison of scenario reduction [19] and moment matching [23] approaches for scenario tree construction is conducted in [24]. The authors found that the moment matching approach yields a better fit compared to the original scenario set in terms of mean, variance, skewness, and kurtosis. However, the scenario reduction provides better correspondence in terms of autocorrelation. Scenario reduction is also considerably computationally faster than moment matching. The authors also tested the two approaches as input to a scheduling model for the electricity market within a region of Germany, and found that scenario trees derived from moment matching yields the lowest operational cost [24].

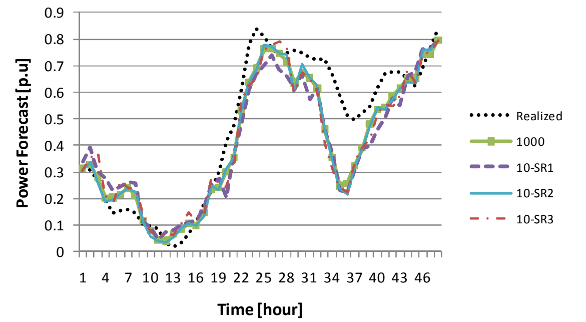

Fig. 3 Averages of 10 scenarios with reduction methods SR1, SR2, and SR3 as compared to the average of the original 1,000 scenarios, QR, days 1 and 2.

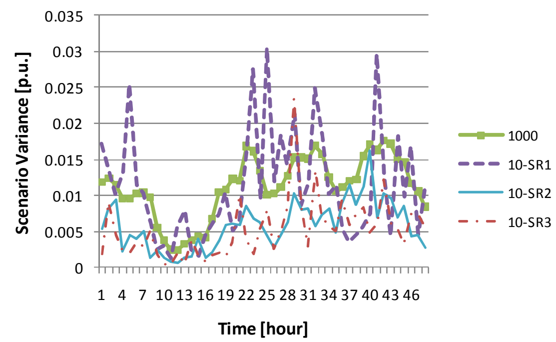

Fig. 4 Variances for 10 scenarios with reduction methods SR1, SR2, and SR3 as compared to the average of the original 1,000 scenarios, QR, days 1 and 2.

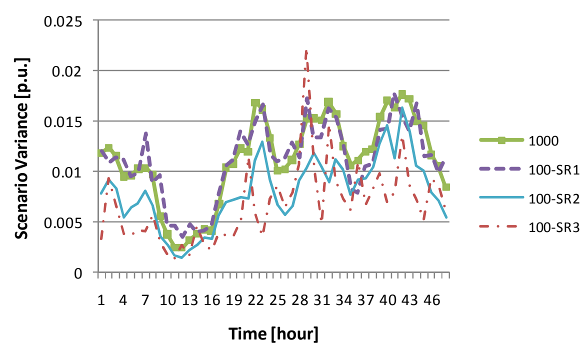

Fig. 5 Variances for 100 scenarios with reduction methods SR1, SR2, SR3 as compared to the average of the original 1000 scenarios, QR, days 1 and 2.

TABLE I
SUMMARY STATISTICS FOR SCENARIOS (QR) WITH DIFFERENT REDUCTION METHODS: AVERAGE (AVG), MEAN ABSOLUTE ERROR (MAE), OCT.–DEC.

	1,000	10-SR1	10-SR2	10-SR3	100-SR1	100-SR2	100-SR3
Mean (AVG)	0.419	0.417	0.418	0.417	0.418	0.418	0.417
Mean (MAE)	0	0.026	0.010	0.024	0.008	0.004	0.021
Variance (AVG)	0.011	0.011	0.006	0.005	0.011	0.008	0.007
Variance (MAE)	0	0.0041	0.0055	0.0060	0.0012	0.0027	0.0042

B. Overview of Simulated Cases

We use the same assumption for thermal generators, loads, and realized wind power availability as in [10]. The system consists of ten thermal generators with a mix of base, intermediate, and peak units. The characteristics of the units are shown in the Appendix. A time series with 91 days (October–December) of data for loads and wind power were simulated. The load data are based on scaled historical load profiles for Illinois from 2006 and therefore are synchronized with the wind power data. The total installed capacity is 1,662 MW of thermal power and 500 MW of wind power, and the peak load is 1,500 MW. The total wind energy amounts to 20% of the load within the 91-day simulation period. The costs of unserved reserve and load are assumed to be \$1,100/MWh and \$3,500/MWh. These costs are included in the objective function of the UC problem, as shown in (1).

An overview of the simulated cases is provided in Tables II and III. The cases differ in terms of which UC strategy, operating reserve requirements, wind power forecast, and scenario reduction method is employed. For the deterministic cases (Table II), the first case uses a perfect forecast and therefore serves as a benchmark for the analysis. The PF-QR and PF-NW cases use deterministic forecasts (i.e., the 50% quantile from either the QR or NW forecasts), without additional operating reserve for wind uncertainty, OR_{wind}. In RF-QR and RF-NW, we add a *fixed* OR_{wind} equal to the average difference of the 50% and 5% WPF quantiles. Finally, in the RD-QR and RD-NW cases, OR_{wind} is *dynamic*, updated each day, and set equal to the difference between the 50% and 5% quantiles. Because the 50% quantile is used as the point forecast, this should ensure that the demands for energy and regular operating reserves are met with a probability of 0.95. The optimal choice of quantile range for OR_{wind} generally depends on the cost of scheduling additional reserves compared to the cost of not meeting the regular reserve requirements. It should be noted that a more rigorous approach could be used to derive OR_{wind} (e.g., based on the ideas in [9]).

For the stochastic cases, we vary the probabilistic WPF approach, the scenario reduction method, and the number of scenarios, as shown in Table III. OR_{wind} is set to zero for the stochastic cases, with the assumption that the stochastic UC strategy internally addresses the wind power uncertainty.

TABLE II
SIMULATED CASES WITH DETERMINISTIC UC

Case	*Add'l Reserve: $OR_{wind,t}$**	*Forecast*
PERF	None	Perfect
PF-QR	None	QR: 50% quantile
PF-NW	None	NW: 50% quantile
RF-QR	Fixed: avg. 50–5% quantile	QR: 50% quantile
RF-NW	Fixed: avg. 50–5% quantile	NW: 50% quantile
RD-QR	Dynamic: 50–5% quantile	QR: 50% quantile
RD-NW	Dynamic: 50–5% quantile	NW: 50% quantile

* This reserve is applied at the UC stage only. All cases use a regular reserve, $OR_{reg,t}$, equal to 10% of hourly loads in both UC and ED.

TABLE III
SIMULATED CASES WITH STOCHASTIC UC

Case	*Forecast*	*Scenario Reduction**	*No. Scenarios*
S10-QR1	QR	SR1	10
S10-QR2	QR	SR2	10
S10-NW1	NW	SR1	10
S10-NW2	NW	SR2	10
S100-QR1	QR	SR1	100
S100-QR2	QR	SR2	100
S100-QR3	QR	SR3	100

*SR1-random, SR2-traditional scenario reduction, SR3-scenario clustering.

C. *UC and ED results*

The total operating costs for the different cases over the 91-day period are shown in Fig. 6 and Fig. 7. Additional results are summarized in Tables IV and V.

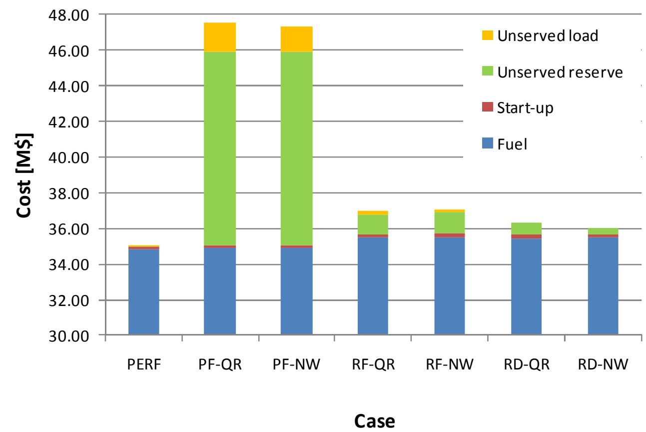

Fig. 6 Overview of simulated total costs for deterministic cases.

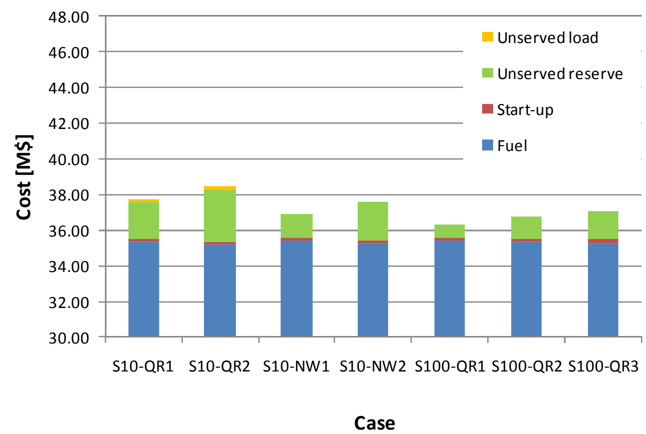

Fig. 7 Overview of simulated total costs for stochastic cases.

TABLE IV
SUMMARY OF OTHER RESULTS: DETERMINISTIC CASES

Case	No. of start-ups	Load curtailment [hours]	Reserve curtailment [hours]	Avg. Reserve [MW]
PERF	225	0	7	155.2
PF-QR	228	14	268	153.2
PF-NW	231	12	273	152.2
RF-QR	280	1	38	174.5
RF-NW	287	1	40	174.6
RD-QR	267	0	31	170.8
RD-NW	266	0	22	173.8

TABLE V
SUMMARY OF OTHER RESULTS: STOCHASTIC CASES

Case	No. of start-ups	Load curtailment [hours]	Reserve curtailment [hours]	Avg. Reserve [MW]
S10-QR1	278	1	71	169
S10-QR2	282	1	101	164
S10-NW1	267	0	49	171
S10-NW2	252	0	79	168
S100-QR1	234	0	35	175
S100-QR2	235	0	50	171
S100-QR3	234	0	68	170

The performance of the system clearly depends on the unit commitment and operating reserve strategy and on the WPF approach. We make the following main observations:

• Using a deterministic point forecast without additional reserve is too risky, and results in high levels of unserved load and reserve.
• For deterministic cases, a dynamic reserve requirement based on the probabilistic forecast performs better than a fixed additional reserve.
• A dynamic reserve based on a NW forecast performs better than a dynamic reserve based on QR forecast, possibly caused by the better calibration of the NW forecast (Fig. 2).
• With stochastic UC, scenarios based on NW forecasts perform better than scenarios from QR.
• Formal scenario reduction based on SR2 and SR3 does not improve the overall system performance under a stochastic UC strategy compared to a random selection of scenarios (SR1). This may have to do with the decrease in scenario variance under SR2 and SR3 (Table I), which may result in less hedging and more risky scheduling.
• Increasing the number of scenarios improves the performance of the stochastic UC strategy. However, the computational burden increases. In these cases, the run-time with 100 instead of 10 scenarios is 15 to 20 times longer.
• Some additional reserve is needed also in stochastic UC to cover wind power uncertainty not captured by the probabilistic forecasts and the limited number of scenarios. The best stochastic case (S100-QR1) yields a slightly higher total cost than that of the best deterministic case (RD-NW).
• The two best cases (S100-R1 and RD-NW) both make use of probabilistic WPF information.

VI. Conclusion

The results of our analysis clearly illustrate the potential value of probabilistic WPF in power system operations. Such forecasts can be incorporated into a deterministic UC through probabilistic reserve requirements or can provide scenarios as input to a stochastic UC. Some advantages of the deterministic approach with dynamic reserves includes that this is more aligned with current operating procedures. Furthermore, from a computational perspective, it is a simpler model with less computational burden. However, this approach does not capture the effect of inter-temporal ramping events. It also does not consider uncertainty and its cost in the objective function. In contrast, stochastic UC does address inter-temporal variability through the scenario representation of uncertainty. Moreover, the total cost, including the expected cost of scarcity, is explicitly taken into account in the objective function. However, the switch to stochastic UC involves a more radical departure from current practice, it may run into computational constraints in large systems, and the benefits in terms of cost savings may be limited.

More work is needed to improve the quality of probabilistic WPF, both in terms of pdf estimation and generation of adequate scenarios. However, there will always be inaccuracy in probabilistic forecasts, just as in point forecasts. This calls into question the overall risk paradigm under which scheduling decisions are made. In stochastic UC, with the minimization of expected cost one could adjust the risk level by changing the costs of unserved energy and reserves in the objective function. However, it may also be required to consider other approaches based on different decision paradigms, such as utility theory, value at risk, robust optimization, or regret. The optimal decision strategy does not only depend on the risk preferences of the system operator, but also on the quality of the probabilistic forecast.

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VIII. Appendix

Table AI shows the thermal generator data used in the case study. The data are based on [25], but with some adjustments in cost functions and introduction of ramp rates.

TABLE AI
GENERATOR DATA

Unit	P_{min} [MW]	P_{max} [MW]	Ramp limit [MW/h]	Min. up [h]	Min. dn. [h]	In. state [h]
1	455	150	200	8	8	8
2	455	150	200	8	8	8
3	130	20	100	5	5	−5
4	130	20	100	5	5	−5
5	162	25	100	6	6	−6
6	80	20	80	3	3	−3
7	85	25	85	3	3	−3
8	55	10	55	1	1	−1
9	55	10	55	1	1	−1
10	55	10	55	1	1	−1

Unit	Cost a [$/h]	Cost b [$/MWh]	Cost c [$/MW^{2}h]	Cold cost [$/h]	Warm cost [$/h]	Cold start time [h]
1	1,000	16	0.00048	9,000	4,500	5
2	970	17	0.00031	10,000	5,000	5
3	700	30	0.002	1,100	550	4
4	680	31	0.0021	1,120	560	4
5	450	32	0.004	1,800	900	4
6	370	40	0.0071	340	170	2
7	480	42	0.00079	520	260	2
8	660	60	0.0041	60	30	0
9	665	65	0.0022	60	30	0
10	670	70	0.0017	60	30	0

IX. Acknowledgment

The submitted manuscript has been created by UChicago Argonne, LLC, Operator of Argonne National Laboratory (‘‘Argonne’’). Argonne, a U.S. Department of Energy Office of Science laboratory, is operated under Contract No. DE-AC02-06CH11357. The U.S. Government retains for itself, and others acting on its behalf, a paid-up non-exclusive, irrevocable worldwide license in said article to reproduce, prepare derivative works, distribute copies to the public, and perform publicly and display publicly, by or on behalf of the Government.

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