Impact of Wind Power Forecasting on Unit Commitment and Dispatch

Jianhui Wang, Audun Botterud
Vladimiro Miranda, Cláudio Monteiro, Gerald Sheble

***Abstract*—The impact of wind power forecasting on unit commitment and dispatch is investigated in this paper. We present two unit commitment methods to address the variability and intermittency of wind power. The uncertainty in wind power forecasting is captured by a number of scenarios in the stochastic unit commitment approach, while a point forecast of wind power output is used in the deterministic alternative. Several cases with different wind power forecasts and reserve requirements are simulated. The preliminary results show that the quality of wind power forecasting has a great impact on unit commitment and dispatch. The stochastic method shows its value in terms of relatively lower dispatch cost. However, the dispatch results are also sensitive to the level of reserve requirement. Our results so far indicate that a deterministic method combined with an increased reserve requirement can produce results that are comparable to the stochastic case.**

***Index Terms*—Wind power, forecasting, electricity markets, unit commitment, dispatch, stochastic optimization.**

I. NOMENCLATURE

Indices

i	Index for wind unit, i = 1..*I*
j	Index for thermal unit, j = 1..*J*
k	Index for time period, k = 1..24
l	Index for generation block, thermal units, l = 1..*L*
s	Index for scenario, s = 1..*S*

Constants

a,b,c	Unit production cost function coefficients
$D(k)$	Load or demand, period *k*
$r(s)$	Op. reserve requirement (spinning), scenario *s*
C_{ens}	Cost of energy not served
A_j	Operating cost at min load, thermal unit *j*
$MC_{l,j}$	Marginal cost (or bid), block *l*, thermal unit *j*
$\overline{PT}_j$	Capacity, thermal unit *j*
$\underline{PT}_j$	Minimum output, thermal unit *j*
$\overline{\Delta}_{l,j}$	Capacity, block *l*, thermal unit *j*
CCj	Cold start cost, thermal unit *j*
HCj	Hot start cost, thermal unit *j*
DC_j	Shut-down cost, thermal unit *j*
T_j^{cold}	Time for cold start cost (in addition to min downtime), thermal unit *j*
T_j^{up}	Minimum up-time, thermal unit *j*
$T_j^{up,0}$	Minimum up-time, initial time step, thermal unit *j*
T_j^{dn}	Minimum down-time, thermal unit *j*
$T_j^{dn,0}$	Minimum down-time, initial time step, thermal unit *j*
SU_j	Start-up ramp limit, thermal unit *j*
SD_j	Shut-down ramp limit, thermal unit *j*
RL_j	Ramping limit (up/down), thermal unit *j*
$W_i(k)$	Actual maximum wind generation, wind unit *i*, period *k*
$PW_i^{f,s}(k)$	Forecasted max generation, wind unit *i*, period *k*, scenario *s*
$prob_s$	Probability of occurrence, wind scenario *s*

Variables

$c_j^p(k)$	Production cost, thermal unit *j*, period *k*
$c_j^u(k)$	Start-up cost, thermal unit *j*, period *k*
$pt_j(k)$	Generation, thermal unit *j*, period *k*
$\delta_{l,j}(k)$	Generation, block *l*, thermal unit *j*, period *k*
$\overline{pt}_j(k)$	Maximum feasible generation, thermal unit *j*, period *k*
$v_j(k)$	Binary on/off variable, thermal unit *j*, period *k*
$pw_i^s(k)$	Generation, wind unit *i*, period *k*, scenario *s*
$cw_i^s(k)$	Curtailed wind generation, wind unit *i*, period *k*, scenario *s*
$ens(k)$	Energy not served, period *k*

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J. Wang, A. Botterud, G. Conzelmann are with Argonne National Laboratory, USA (e-mails: jianhui.wang@anl.gov. abotterud@anl.gov, guenter@anl.gov).

V. Miranda, C. Monteiro, G. Sheble are with INESC Porto, Portugal (emails: vmiranda@inescporto.pt, cdm@fe.up.pt, gsheble@inescporto.pt).

II. INTRODUCTION

HIGH penetration of renewable generation such as wind has posed great challenges to power system operators in grid management and generation scheduling. The inherent intermittency and variability of renewable resources such as wind require that current industry practices, such as unit commitment (UC) and economic dispatch (ED), be altered to accommodate large amounts of renewable generation. While large amounts of research exists on how to formulate and improve the general UC algorithm [1] the unit commitment research that considers uncertain wind power is limited.

Unlike other conventional and controllable generation sources, wind power is unpredictable and intermittent. The impact of large amounts of wind has complicated implications to UC and ED. First of all, wind forecasting errors bring great uncertainty to the system operations, since the real-time wind power output may be very different from what is forecasted. The reliability of the system may be hampered in case of unforeseen decreases in wind power because the available ramping capability of on-line units in the system may not be sufficient to accommodate this change. Also, a large upward ramp in wind power may be unfavorable in a system in which sufficient downward reserves from other resources are not present. In this case, wind power may have to be curtailed, which leads to a waste of available resources. The same rationale applies to the wind power supply surplus that may happen at night, when the wind is usually the strongest but the system load is low. In this case, wind generation may also have to be spilled to maintain normal operation of other slow-start units, such as coal and nuclear, because of the physical and economic constraints of those units. Second, variability is also an issue to generation scheduling. Since wind power is normally assumed to have an operating cost of zero in the UC formulation, the system operator tries to utilize wind power as much as possible, with the objective of minimizing the supply cost to meet the system load. The system operator has to adjust other generation sources to address the variability of wind power. Accordingly, because wind power may vary to a great extent, the non-wind generation resources have to be scheduled skillfully through unit commitment and dispatch. Even though wind power might be forecasted perfectly, variability is still an important issue that has to be taken into consideration when the other resources are being scheduled. The physical constraints of other non-wind units, such as ramping up/down constraints, minimum-on and minimum-off time constraints, etc., are also influenced, which leads to the question of how to change the overall unit commitment and dispatch algorithms to accommodate wind power. Consequently, several areas for improving unit commitment and dispatch have been proposed to address the uncertainty and variability of wind power. Some researchers focus on revising the current security-constrained unit commitment (SCUC) formulation. Others aim at novel UC methods.

Barth et al. [1] presented the early stage of the Wind Power Integration in the Liberalised Electricity Markets (WILMAR) model [3]. More recently, a more comprehensive UC algorithm based on MILP has been introduced in WILMAR. However, the model is still mainly a planning tool and is not currently used for system operations. *Tuohy et al.* [4] extended their previous studies in [5] and [6] to examine the effects of stochastic wind and load on the unit commitment and dispatch of power systems with high levels of wind power by using the WILMAR model. The model used is in essence a planning model; as such, it builds on the assumptions needed for the hours-ahead or day-ahead system scheduling. The analysis compares only the scheduling alternatives at the scheduling stage. The effectiveness of the methods should be examined further by analyzing the operational impact in the real-time market.

Ummels et al. [7] analyzed the impacts of wind power on thermal generation unit commitment and dispatch in the Dutch system, which has a significant share of combined heat and power (CHP) units. A rolling commitment method is used to schedule the thermal units, where the common constraints (i.e., ramping constraints and minimum on/off time constraints) are considered. The wind power forecasting errors are captured by an autoregressive moving average (ARMA) process. *Bouffard* and *Galiana* [8] proposed a stochastic unit commitment model to integrate significant wind power generation while maintaining the security of the system. Rather than being pre-defined, the reserve requirements are determined by simulating the wind power realization in the scenarios. *Ruiz et al.* [9] proposed a stochastic formulation to manage uncertainty in the unit commitment problem. The stochastic alternative to the traditional deterministic approach can capture several sources of uncertainty and define the system reserve requirement for each scenario. In a related paper [10], the authors consider uncertainty and variability in wind power in the UC problem by using the same stochastic framework.

Wang et al. [11] presented a SCUC algorithm that takes into account the intermittency and variability of wind power generation. The uncertainty in wind power output is captured in a number of scenarios. To reduce the computational efforts, the original large-scale, mixed-integer problem is decomposed to a master problem and many subproblems by Bender's decomposition technique. Scenario reduction and variance reduction methods are applied to generate the scenarios and increase the accuracy of the Monte Carlo simulation. The algorithm is designed in a conservative way in that it does not allow for load curtailment in any scenario, and the objective is to accommodate the difference in wind power output between the real-time and the forecast by re-dispatching on-line generators while preserving the reserves for other possible contingencies in the system. The method can be improved by better modeling of wind forecasting errors and allowing wind spillage and load curtailment.

However, most of the models presented so far are used for planning purposes. There is very limited research on the impact of wind forecasting errors on the real-time dispatch in the market operation. The linkage between day-ahead unit commitment to real-time economic dispatch is largely missing. The forecasting errors, which are the mismatch between what is used in the unit commitment stage and the real-time dispatch, may cause great difficulty for system operators to balance the unexpected surplus or deficit of wind power. Hence, in this paper we focus on the impact of wind forecasting errors on power system operations. We propose two different unit commitment methods, that is, stochastic and deterministic — to analyze the possibility of using alternative scheduling methods to accommodate the uncertainty and variability of wind power. After the unit commitment solution is obtained from unit commitment runs with a wind power forecast, we run an economic dispatch model with the realized wind generation to investigate what impact the forecast errors can exert on the system. Several cases are simulated to analyze and compare the results in detail.

The rest of the paper is organized as follows: section III describes the wind power forecasting method. Section IV presents the problem formulation. Numerical examples are provided in Section V. Section VI concludes the discussion.

III. Wind Power Forecasting

Since this paper focuses on the UC and ED solution, only a brief description of how the wind power forecast scenarios are generated is given here. The point forecast is obtained directly from the wind power forecasting uncertainty distributions. While the scenario simulation uses the same origin for its distribution information, it is a stochastic representation. The scenarios are based on a stochastic process that uses the bi-dimensional discrete probability distribution associated with each time-interval transition in the scheduling period. The probabilistic information is different for each time-interval transition and for each day. The probability of a scenario is a normalized probability (relative probability of the 10 scenarios) derived from the product of probabilities along the transitions. The reason for generating relative probabilities is to attempt to reduce the inaccuracy of representing the reality with a limited number of scenarios. It is supposed that the weighted scenarios by probability produce an aggregate closer to the point forecast. It is of note that the point forecast and wind power output scenarios are used in the deterministic and stochastic unit commitments, respectively, while an actual wind power output curve is used in the economic dispatch process for both formulations. More details on wind power forecasts are provided in Section V.

IV. Unit Commitment and Dispatch Formulations

The formulation for the stochastic unit commitment is described in detail in this section. The general UC constraints follow [12]. However, we make adjustments in this stochastic version based on the introduction of wind power and wind power forecasting uncertainty, which is represented as scenarios with probabilities.

1) Objective Function

The objective is to minimize the sum of expected production costs, the expected cost of unserved energy, and start-up costs, as shown in (1). Constraints on load and operating reserves are represented in (2) and (3). We assume that all the operating reserves must be met by thermal units. Wind units may be curtailed if necessary, as shown in (4). Note that the thermal dispatch, and therefore the production cost and the cost of unserved energy, varies by wind scenario. Hence, the constraints for load, operating reserves, and wind curtailment must be met in all wind scenarios. In contrast, the start-up costs are independent of wind scenarios. This is because we assume that the commitment of thermal units has to be fixed at the day-ahead stage[1].

We assume that each thermal unit is offered into the market as a step-wise price-quantity offer function and that the offers can be derived by linearizing a standard quadratic production cost function. Hence, we can express the operating cost for one thermal unit with the equations in (5)-(8). The coefficients for the generation blocks are derived from a quadratic production cost function. Alternatively, the cost of each block could also reflect strategic bidding from the generators by introducing strategy multipliers to manipulate the original cost and quantity. It is of note that in this formulation, it is assumed that the system operator considers the thermal generators' operating cost at minimum load (A_j) and also the minimum generation level in the objective function through (5) and (6). This is not the case in all electricity markets.

[1] We may consider relaxing this assumption in the future, at least for flexible peaking plants with short start-up times and costs. In general, the frequency of unit commitment is one potential area for further analysis. Allowing wind power units to provide operating reserves by reducing the generation below their generation potential level is also an interesting and relevant extension.

The last part of the objective function is the start-up cost. This part is modeled by assuming that there is a cold start-up cost and a warm start-up cost, depending on the length of time that the unit is down. This treatment is a simplification compared to the formulation in [12], which assumes multiple steps in the start-up cost function. The mathematical formulation is shown in (9)-(11).

2) Thermal Unit Constraints

The constraints for the operation of thermal units include generation limits, ramping-up limits, ramping-down limits, minimum-up time, and minimum-down time. The upper and lower generation limits for the thermal plants are shown in (12). The maximum power output of a unit, $\overline{pt_j^s}(k)$, is constrained by the generation limit of a unit in (13), limitations on start-up and ramp-up rates in (14) shut-down ramp rates in (15), and ramp-down limits in (16). It is of importance to notice that the availability of spinning reserves is equal to the difference between the maximum potential generation and the actual generation, i.e. $\overline{pt_j^s}(k)$ - pt_j^s. Hence, the reserve requirement in (4) takes into account the constraints imposed by (12)-(16). The reserve requirement is maintained for each individual wind scenario.

The final constraints to include are the minimum-up and -down time constraints. Minimum-up times are represented by (17)-(19), which represent the initial status, the intermediate time periods, and the final time steps of the planning period, respectively. The minimum-down time constraints are represented analogously by (20)-(22).

Note that the equations for generation and ramping limits, i.e. (12)-(16), must be included for all wind scenarios, because thermal dispatch depends on the wind generation. In contrast, the minimum-up and -down time constraints, i.e. (17)-(22), are functions of commitment only and do not vary with wind scenario.

3) Deterministic formulation

In a simplified representation, the formulation above would consider only one scenario for forecasted wind generation. In this case, the formulation is equivalent to a deterministic version of the unit commitment problem. The selected scenario could be the expected wind power generation or could also represent a certain percentile in the forecasting probability distribution. The choice of representative scenario would depend on how conservatively the system operator wants to operate the system. When using multiple scenarios in the stochastic formulation, the challenge is to come up with a representative set of wind power scenarios, capturing both the magnitude and phase errors of the wind power forecast.

4) Economic Dispatch

In order to analyze the dispatch in real-time we also develop an economic dispatch formulation. The commitment variables are assumed to be fixed from the UC run. The maximum wind power generation in the scenarios is replaced with the realized maximum wind power output. Hence, we formulate a deterministic economic dispatch problem consisting of equations (1)-(8) and (12)-(16) with only one wind power scenario and fixed values for the thermal commitment variables, $v_j(k)$. The start-up cost and minimum-up and -down time constraints are not considered due to the fixed commitment. However, we still impose the ramping constraints in (12)-(16) and solve the 24-hour period in one shot. This is a simplification compared to real-world market operations, where the dispatch problem is solved frequently (usually every 5 minutes in U.S. markets), always using the latest available information. The resulting ED formulation becomes a linear optimization problem, and energy prices are easily derived from the dual variables of the energy balance in (2). Note that the operating reserve requirement in (3) is also imposed in the ED formulation. The dual variable of this constraint gives an indication of the marginal value of operating reserves, although we do not consider bids for operating reserves explicitly in the model.

To evaluate the performance of different unit commitment strategies over time we develop a market simulation set-up, which first solve the UC based on the wind power forecast, and then the ED based on the realized wind conditions. This is done in sequence for multiple days. An updated wind power forecast along with the unit status and generation output for the thermal units from the previous day are taken as initial conditions for the UC problem for the next day. The main results (unit commitment, dispatch, available reserves, unserved load, prices, etc.) are calculated and stored after each simulation day.

$$Min \sum_{s=1}^{S} prob_s \cdot \left\{ \sum_{k=1}^{K}\sum_{j=1}^{J} c_j^{p,s}(k) + \sum_{k=1}^{K} C_{ens} \times ens^s(k) \right\} + \sum_{k=1}^{K}\sum_{j=1}^{J} c_j^{u}(k) \tag{1}$$

s.t.

$$\sum_{i=1}^{I} pw_i^s(k) + \sum_{j=1}^{J} pt_j^s(k) = D(k) - ens^s(k) \quad , \quad \forall k, \forall s \tag{2}$$

$$\sum_{j=1}^{J}\left[\overline{pt}_j^s(k) - pt_j^s(k)\right] \geq D(k)\cdot r(s) \quad , \quad \forall k, \forall s \tag{3}$$

$$pw_i^s(k) + cw_i^s(k) = PW_i^{f,s}(k) \quad , \ \forall i, \forall k, \forall s \tag{4}$$

$$c_j^{p,s}(k) = A_j v_j + \sum_{l=1}^{L} MC_{l,j}(k)\cdot \delta_{l,j}^s(k), \quad \forall j, \forall k, \forall s \tag{5}$$

$$pt_j^s(k) = \underline{P}_j \cdot v_j(k) + \sum_{l=1}^{L} \delta_{l,j}^s(k) \quad , \quad \forall j, \forall k, \forall s \tag{6}$$

$$\delta_{l,j}^s(k) \leq \bar{\Delta}_{l,j} \quad , \quad \forall l, \forall j, \forall k, \forall s \tag{7}$$

$$\delta_{l,j}^s(k) \geq 0 \quad , \quad \forall l, \forall j, \forall k, \forall s \tag{8}$$

$$c_j^u(k) \geq CC_j \cdot \left[v_j(k) - \sum_{n=1}^{N} v_j(k-n) \right] \ , \ \forall j, \forall k \quad where\ N = T_j^{dn} + T_j^{cold} \tag{9}$$

$$c_j^u(k) \geq HC_j \cdot \left[v_j(k) - v_j(k-1) \right] \ , \quad \forall j, \forall k \tag{10}$$

$$c_j^u(k) \geq 0, \quad \forall j, \forall k \tag{11}$$

$$\underline{PT}_j \cdot v_j(k) \leq p_j^s(k) \leq \overline{pt}_j^s(k) \quad , \quad \forall j, \forall k, \forall s \tag{12}$$

$$0 \leq \overline{pt}_j^s(k) \leq \overline{PT}_j \cdot v_j(k) \quad , \quad \forall j, \forall k, \forall s \tag{13}$$

$$\overline{pt}_j^s(k) \leq pt_j^s(k-1) + RL_j \cdot v_j(k-1) + SU_j \cdot \left[v_j(k) - v_j(k-1)\right] + \overline{PT}_j \cdot \left[1 - v_j(k)\right] \quad , \quad \forall j, \forall k, \forall s \tag{14}$$

$$\overline{pt}_j^s(k) \leq \overline{PT}_j \cdot v_j(k+1) + SD_j \cdot \left[v_j(k) - v_j(k+1)\right], \ \forall j, \forall k = 1..23, \forall s \tag{15}$$

$$pt_j^s(k-1) - pt_j^s(k) \leq RL_j \cdot v_j(k) + SD_j \cdot \left[v_j(k-1) - v_j(k)\right] + \overline{PT}_j \cdot \left[1 - v_j(k-1)\right] \ , \ \forall j, \forall k, \forall s \tag{16}$$

$$\sum_{k=1}^{T_j^{up,0}} \left[1 - v_j(k)\right] = 0 \quad , \quad \forall j \tag{17}$$

$$\sum_{n=k}^{k+T_j^{up}-1} v_j(n) \geq T_j^{up} \cdot \left[v_j(k) - v_j(k-1)\right], \quad \forall j\ , \forall k = T_j^{up,0}+1, .., T - T_j^{up} + 1 \tag{18}$$

$$\sum_{n=k}^{T} \left\{ v_j(n) - \left[v_j(k) - v_j(k-1)\right] \right\} \geq 0\ , \quad \forall j\ , \forall k = T - T_j^{up} + 2, \ldots, T \tag{19}$$

$$\sum_{k=1}^{T_j^{dn,0}} v_j(k) = 0 \quad , \quad \forall j \tag{20}$$

$$\sum_{n=k}^{k+T_j^{dn}-1} \left[1 - v_j(n)\right] \geq T_j^{dn} \cdot \left[v_j(k-1) - v_j(k)\right], \quad \forall j\ , \forall k = T_j^{dn,0}+1, .., T - T_j^{dn} + 1 \tag{21}$$

$$\sum_{n=k}^{T} \left\{ 1 - v_j(n) - \left[v_j(k-1) - v_j(k)\right] \right\} \geq 0\ , \quad \forall j\ , \forall k = T - T_j^{dn} + 2, \ldots, T \tag{22}$$

5) Uncertainty and Operating Reserves

In this paper we focus on the impact of wind power on system operation and the only uncertainty we consider in the UC formulation is from the wind generation. Other uncertainties, such as load uncertainty and forced outages of generators and transmission lines are not directly considered. We assume that the operating reserves maintained in the real time dispatch are adequate to accommodate these uncertainties. One important question then becomes: what level of operating reserves should be imposed at the UC stage to take into account the additional uncertainty from wind? With the stochastic UC formulation, it may be argued that the need for additional operating reserves is already taken care of because we include a representative set of wind power outcomes in the scenarios. At the same time, the cost of unserved energy is included in the objective function. The outcome of the UC optimization should therefore give the optimal level of commitment. With a deterministic formulation, however, only one wind scenario is considered. In this case, the system operator could increase the amount of operating reserves at the UC stage to compensate for the wind uncertainty. Alternatively, a conservative deterministic wind forecast, would also result in more commitment of thermal units and therefore a higher level of reserves. In the case study below we run a few different scenarios to investigate the impact of UC strategy and operating reserve policy on the system performance. There is very limited research on these issues so far, but Ruiz et al. [10] find that a stochastic UC formulation combined with a reserve requirement give better results, measured in terms of economic metrics and curtailed wind power, than the traditional deterministic UC formulation with reserve requirements.

V. Case Study

A. Assumptions

In the case study we use a hypothetical power system to simulate the impact of using different wind power forecasts and operating reserve policies for the day-ahead unit commitment. The simulation period is 30 days, where UC and ED are run in sequence, as described above. The main assumptions for the case study are outlined below.

The hourly profile of the loads is taken from historical data from the state of Illinois for the month of January. However, the load level is scaled down to match the configuration of the generation capacity in the test power system. The peak load of 1,500 MW occurs on the second day of the simulation period, as can be seen from Fig. 1.

A time series of wind power generation is also obtained from historical data. The total installed capacity is assumed to be 400 MW, and for simplicity we represent this as one large wind power plant. For the simulated 30-day period, the wind power capacity factor is 40.1%, and the wind power meets 13.8% of the load (if there is no wind curtailment). The load and wind power data are both shown in Fig. 1. An example of a day-ahead wind power forecast and realized wind generation is shown in Fig. 2. In this example the forecast scenarios and point forecasts are all below the realized generation for the first part of the day. After hour 10 the realized generation lies within the scenarios of the forecast. The accuracy of the wind power forecast varies from day to day. For the point forecast, the normalized mean average errors (NMAE) over the 30–day period vary between 6.3% and 12.6% for different forecast hours.

The characteristics of the thermal power plants are based on the case studies presented in [12]and [13]. However, we have made some modifications to the cost coefficients and also introduced data for ramping constraints. The resulting input parameters are shown in Table 1 and Table 2. Each unit is assumed to have four blocks of equal size. The bid price of each block is based on the quadratic cost function. The production cost increases from unit 1 to unit 10.

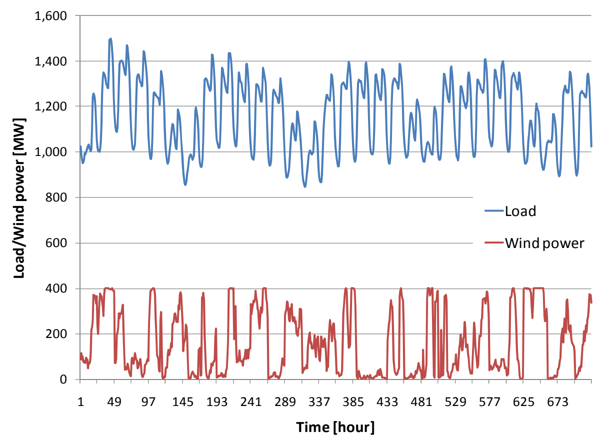

Fig. 1. Hourly loads and wind power in case study (30 days).

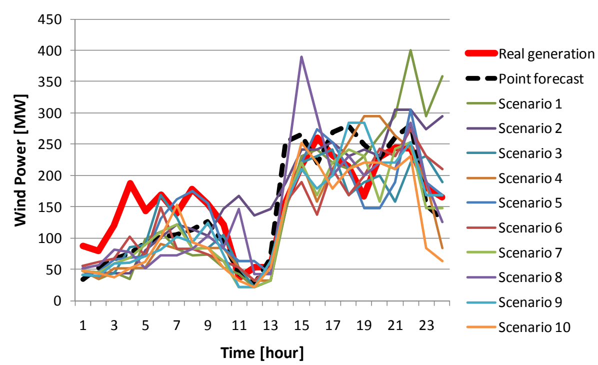

Fig. 2. Wind power forecast (deterministic point forecast and 10 stochastic scenarios) and realized wind generation for day 15.

Table 1. Assumptions for thermal power plants.

Unit	$\overline{PT}_j$ [MW]	$\underline{PT}_j$ [MW]	R_j [MW/h]	T_j^{up} [h]	T_j^{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

Note: Start-up and shut-down ramps, SU_j and SD_j, are equal to the ramp rate RL_j.

Table 2. Assumptions for thermal power plants.

Unit	a_j [$/h]	b_j [$/MWh]	c_j [$/MW^{2}h]	CC_j [$/h]	HC_j [$/h]	T_j^{cold} [h]
1	1000	16	0.00048	9000	4500	5
2	970	17	0.00031	10000	5000	5
3	700	30	0.002	1100	550	4
4	680	31	0.0021	1120	560	4
5	450	32	0.004	1800	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

With the current assumptions, the total installed capacity of the thermal units is 10.1% higher than the peak load. If we assign a capacity value of 20% to the wind power capacity, the system reserve margin increases to 16.1%, which is still relatively low.

The operating reserve (spinning) requirement in the UC formulation, $r(s)$, is assumed to be 10% as the default value. Note that the stochastic model allows the use of different reserve requirement in each scenario. However, in the case study we use the same value in all scenarios. We investigate the consequences of changing the reserve requirement in the UC, both with a deterministic and stochastic UC strategy. However, the reserve requirement is kept constant at 10% in the ED problem representing real-time operations.

B. *Simulated cases*

We focus on comparing the results of using different wind forecasts, and also on the differences between using a deterministic and stochastic unit commitment. The list of simulated cases is summarized in Table 3. The first case (D1) is a reference case with a perfect wind power forecast. Cases D2 and D3 use a deterministic point forecast, but with different reserve requirements at the UC stage. In case D4 the UC is performed without considering wind power at all. Finally, cases S1 and S2 use stochastic UC with regular and reduced UC reserve requirement.

Table 3. Simulated cases.

Case	*Description*	*UC*	*Forecast*	*Reserve*
D1	Det. UC w/perfect forecast	Det.	Perfect	10%
D2	Det. UC w/point forecast	Det.	Point	10%
D3	Det. UC w/additional reserve	Det.	Point	15%
D4	Det. UC w/no forecast	Det.	No	10%
S1	Stoch. UC w/regular reserve	Stoch.	Scenarios	10%
S2	Stoch. UC w/lower reserve	Stoch.	Scenarios	8%

Because we focus on the effect of wind power forecasting in the simulated cases, planned and forced outages are not included. It is assumed that the operating reserve in the economic dispatch is sufficient to handle these uncertainties. Furthermore, transmission constraints are currently not represented in the model.

C. *Results*

In this section, we provide detailed dispatch results for one selected day and the overall simulation results to show the short-term impact of different system scheduling methods and longer-term simulation statistics with different wind power forecasts.

1) *Results for one selected day*

We first present the dispatch results for a selected day, i.e. day 15. Fig. 3 shows the number of units on-line in cases D2, D3, and S1. These three cases are chosen since they are relevant candidates for how system operators may incorporate wind power forecast into their UC. In practice, a wind power point forecast is available in most areas with high penetration of wind, and the stochastic unit commitment approach has been shown to be an effective method to accommodate wind uncertainty in system operation. In the figure, we can see the number of on-line units in S1 and D3 is higher than in D2. This is because the stochastic approach in S1 considers multiple scenarios. More generating units are therefore scheduled on-line to provide sufficient ramping capability to handle the different wind power realizations represented by the scenarios (Fig. 2). A similar effect is obtained with the deterministic approach in D3 by imposing a higher reserve requirement[2]. This observation is supported by Fig. 4, which shows the higher level of available operating reserves in S1 and D3 compared to D2. In all cases the amount of available reserve is higher than reserve requirement in the real-time dispatch (10%), which is a fixed constraint. Note that the available capacity surplus is derived by subtracting the dispatch, $pt_j(k)$, from the sum of maximum feasible generation, $\overline{pt}_j(k)$, for each thermal unit and adding up the results. The units' commitment status and ramping constraints are therefore considered.

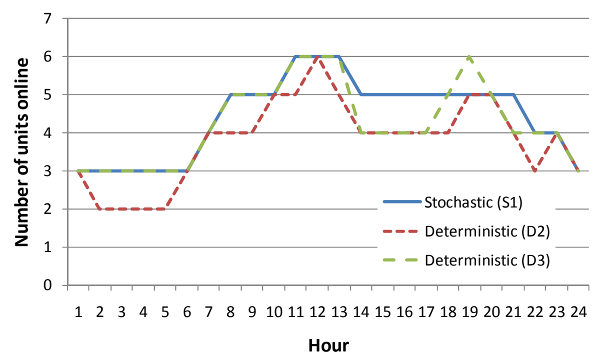

Fig. 3. Number of on-line units for day 15.

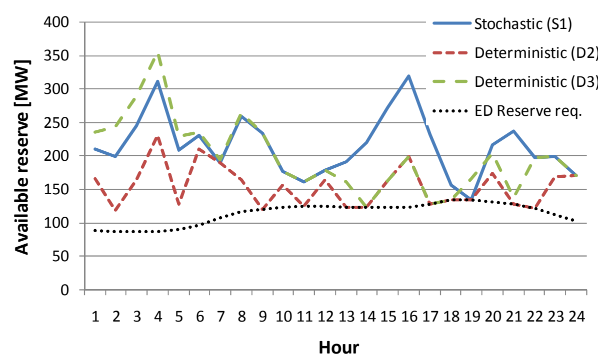

Fig. 4. Available operating reserves.

[2] We ran three deterministic UC cases with reserve requirements equal to 12, 15, and 18%. The 15% case gave the lowest total operating costs over the 30-day simulation period, and is included here. We are also investigating alternative reserve specifications, such as adding reserves in proportion to the wind power point forecast.

2) Results for 30-day simulation

Table 4 shows the total hours of commitment for the ten thermal units. The cheapest units (1 and 2) are committed throughout the simulation period in all of the six cases. Since the units are ranked by their production cost, unit 10 that is the most expensive unit is committed for only a limited number of hours in the cases. It is of note that unit 10 is on more frequently in S1 and S2 than in the deterministic cases. This is because unit 10 needs to be on to provide the additional ramping capacity to deal with the variability of wind power output in the scenarios in the stochastic approach. By comparing D1 and D2 we see that the commitment level is similar. This is because the only difference between those two cases is the substitution of point forecast and perfect forecast. In contrast, units 3-10 are dispatched more frequently in D3, due to the higher reserve requirement. The total hours of commitment is the highest in D4, since the wind power is not being taken into account in UC. More units are therefore needed to make up the wind power which is available in the other cases. This illustrates that if system operators are not using the information in wind power forecast it may easily lead to over commitment of thermal units. Finally, when comparing the two stochastic cases, we see that fewer units are committed in S2 than S1, since the reserve requirement is lower.

Table 4. Total hours of commitment for thermal units.

Unit	D1	D2	D3	D4	S1	S2
1	720	720	720	720	720	720
2	720	720	720	720	720	720
3	394	396	447	605	429	390
4	237	265	308	434	324	297
5	568	585	619	720	585	581
6	242	253	340	358	255	222
7	68	89	159	195	114	100
8	40	49	87	71	44	38
9	10	8	30	15	13	14
10	1	0	8	5	15	19

Table 5 shows the average dispatch of thermal units for all the cases. The results show that the differences in dispatch are much smaller than the differences in commitment. This is because the same realized wind generation output is used in the real-time dispatch in all the cases. The resulting average thermal dispatch therefore becomes quite similar in the six cases, despite the differences in commitment. For the peaking plants (units 8, 9, 10) it is worth noting that they are being dispatched at their minimum level most of the time. Hence, even if the commitment level varies considerably between the cases, the impact on the average dispatch is quite limited.

Table 5. Average dispatch for thermal units [MW].

Unit	D1	D2	D3	D4	S1	S2
1	453.2	453.2	453.2	451.7	453.2	453.2
2	404.1	402.5	400.8	390.3	401.5	401.5
3	58.5	57.9	59.2	62.7	58.8	55.8
4	35.1	35.9	37.8	40.8	39.8	36.6
5	38.3	37.6	31.4	35.8	33.6	39.9
6	7.0	7.3	9.6	10.0	7.3	6.5
7	2.4	3.1	5.5	6.8	4.0	3.5
8	0.6	0.7	1.2	1.0	0.6	0.5
9	0.1	0.1	0.4	0.2	0.2	0.2
10	0.0	0.0	0.1	0.1	0.2	0.3

Table 6 and Table 7 summarize operating costs and other main results. We can see, as expected, that D1 has the lowest total operating cost since it assumes a perfect wind power forecast is available. In other words, the dispatch from the unit commitment run does not need to change in the real-time economic dispatch. D2 has a higher cost, mainly due to more load curtailment cost, which is caused by wind power forecasting errors. In D3 the load curtailment is almost removed, since more units are online. The fuel cost is higher in D3 than in D2, but the total cost is considerably lower. This result shows that increasing the reserve requirements in the deterministic approach has the effect of better addressing wind variability and uncertainty because more units are required to be online to provide reserves. The resulting operating reserve is higher and the energy price is lower in D3 compared to D1 and D2 (Table 7). D4 can be regarded as the most conservative way to dispatch the units, ignoring the existence of wind power. The load curtailment is therefore completely removed and the level of realized operating reserves is much higher than in the other cases. However, D4 ends up with higher fuel cost than any of the other scenarios, because more high-cost generating units are being dispatched than what is needed. The total cost is also unfavorable in D4, a result that demonstrates the inefficiency of not considering the wind power forecast in unit commitment. However, due to the curtailed loads, the average energy prices are higher in all other scenarios than in D4. This shows the distinct implications of different system scheduling methods on system dispatch cost and energy prices.

For stochastic case S1, we see that it ends up with a total cost very close to deterministic case D3, which has additional operating reserves. This illustrates that both approaches are interesting alternatives for dealing with the uncertainty in the wind power generation. When comparing the two cases, we see that S1 has lower fuel cost, but higher curtailment cost than D3. Furthermore, S1 has a lower available reserve and higher price. In scenario S2, the reduction in operating reserve requirement results in a very low level of realized reserves. Hence, the curtailment cost, total cost, and average energy price all end up being higher than in the other cases. Finally, note that D3, S1, and S2 have more start-ups than the other cases. Still, there are only relatively small variations in start-up costs between the cases.

The results show that the unit commitment strategy and the reserve requirements have important implications for the cost and reliability of operating power systems with large amounts of wind power. The ramping capability and reserves provided by on-line units are to a large extent determined by these factors, which therefore influence the real-time dispatch results to a great degree.

Table 6. Summary of operating costs.

Scenario	Fuel cost [M$]	Start-up cost [M$]	Curt. cost [M$]	Total cost [M$]
D1	15.80	0.08	0.00	15.88
D2	15.85	0.08	0.84	16.76
D3	16.13	0.08	0.04	16.25
D4	16.50	0.06	0.00	16.56
S1	15.97	0.09	0.21	16.27
S2	15.88	0.08	0.99	16.96

Table 7. Summary of other results.

Scenario	No. of start-ups	Load Curtail-ment [MWh]	Avg. Avail. Reserve [MW]	Avg. Energy Price [$/MWh]
D1	165	0.8	162.5	30.5
D2	163	836.7	175.6	80.1
D3	197	0.1	214.3	29.5
D4	154	0.0	281.5	25.1
S1	190	210.3	191.0	43.5
S2	199	991.7	178.5	123.1

VI. Conclusions

This paper analyzes the impact of wind power forecasting on unit commitment and economic dispatch. Two unit commitment methods are tested in trying to address the uncertainty and variability inherent in the wind power output. The preliminary results show that wind power forecasting errors have great impact on the scheduling of generating units in the day-ahead market with implications for the real-time dispatch. Various wind forecast methods have distinct impacts on the market operations. The stochastic UC approach that models the wind forecasting errors by scenarios shows promising results, measured in terms of cost and reliability. However, the amount of reserve requirement imposed in the unit commitment also has an important impact on the results. A deterministic unit commitment strategy with increased reserve requirements shows similar results to the stochastic one. The value of wind power forecasting is confirmed by comparing the scenario with no wind forecast and the one with a perfect forecast. A better wind forecast can definitely lower the system dispatch cost as shown in the perfect forecast case.

It is important to notice that there is no wind curtailment observed in the case studies. One potential reason is that we do not consider transmission constraints in the model so far. Other future research topics include re-scheduling of fast-starting units such as combined-cycle gas units between day-ahead and real-time dispatch, reserve bidding and compensation for providing reserves, fixed vs. demand curve for operating reserves, price response of energy demand, and a more detailed financial settlement including day-ahead market clearing. These are issues we will continue investigating in the ongoing project.

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IX. Biographies

Jianhui Wang received his B.S. degree in management science and engineering and a Master’s degree in technical economics and management from North China Electric Power University, China, in 2001 and 2004, respectively, and his Ph.D. in electrical engineering from Illinois Institute of Technology, USA, in 2007. Presently, he is an Assistant Computational Engineer - Energy Systems with the Center for Energy, Environmental, and Economic Systems Analysis (CEEESA) at Argonne National Laboratory. His research interests include energy economics and policy, agent-based modeling and simulation, and electric power systems optimization and economics. He is chair of the IEEE PES power system operation methods subcommittee and co-chair of the task force on integration of wind and solar power into power system operations.

Audun Botterud is an Energy Systems Engineer in CEEESA at Argonne National Laboratory. He has a M.Sc. in Industrial Engineering (1997) and a Ph.D. in Electrical Power Engineering (2003), both from the Norwegian University of Science and Technology (NTNU). He was previously with SINTEF Energy Research in Trondheim, Norway, and has also spent 1 ½ years as a visitor at MIT Laboratory for Energy and the Environment in Cambridge, Massachusetts, USA. His research interests include power system planning and economics, renewable energy systems, wind power integration, stochastic optimization, and agent-based modeling.

Vladimiro Miranda received his Licenciado, Ph.D. and Agregado degrees from the Faculty of Engineering of the University of Porto, Portugal (FEUP) in 1977, 1982 and 1991, all in Electrical Engineering. In 1981 he joined FEUP and currently holds the position of Professor Catedrático. He is also currently a Director of INESC Porto, an advanced research institute in Portugal. He has authored many papers and been responsible for many projects in areas related with the application of Computational Intelligence to Power Systems.

Cláudio Monteiro was born in France, on March 14th, 1968. He received his Licenciado and MSc. and Ph.D degrees from FEUP in 1993, 1996 and 2003, in Electrical Engineering and Computers. In 1993 he joined INESC as a researcher in the Power System Unit.