Reliability Assessment Unit Commitment with Uncertain Wind Power

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Abstract This book chapter reports a study on the importance of modeling wind power uncertainty in the reliability assessment commitment procedure. The study compares, in terms of economic and reliability benefits, the deterministic and stochastic approaches to modeling wind power. The report describes the mathematical formulation of both approaches and gives numerical results on a 10-unit test system. It is found that scenario representation of wind power uncertainty in conjunction with a proper reserve margin to accommodate for wind power uncertainty may provide higher benefits to market participants.

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, $l = 1..\ L$
m Index for reserve demand block, m = 1..M
s Index for scenario, $s = 1..\ S$

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Constants

a, b, c	Unit production cost function coefficients
$\alpha(s)$	Operating reserve percentage, scenario s
$WR(k)$	Additional wind reserve, period k
$D(k)$	Load, period k
C_{ens}	Cost of energy not served
$CR_{rns,m}$	Cost of reserve not served, block m
A_j	Operating cost at minimum 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
CC_j	Cold start cost, thermal unit j
HC_j	Hot start cost, thermal unit j
$\mathbf{G}(\cdot)$	Generalized network constraints
T_j^{cold}	Time for cold start cost (in addition to minimum 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 maximum 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
$ens^s(k)$	Energy not served, period k, scenario s
$rns_m^s(k)$	Reserve curtailed, period k, scenario s
$r^s(k)$	Reserve requirement (spinning), scenario s, period k

1 Introduction

In many electricity markets, power producers and buyers submit bids to an Independent System Operator (ISO/RTO) for an amount of energy and the price they are willing to offer or pay [1]. The electricity market is usually structured into day-ahead (DA) and real-time (RT) markets. In the DA, power producers submit generation offers, and consumers submit demand bids. The ISO/RTO computes market clearing prices for the next 24 h by using a least-cost security-constrained unit commitment (SCUC), and a security-constrained economic-dispatch (SCED) optimization model. The objective of ISO/RTO is to meet the demand at minimum cost while maintaining the reliability of the system.

However, high penetrating of wind power has caused great challenges to the ability of power system operators to reliably operating the system due to the uncertainty and variability from wind power, especially in the unit commitment stage. How to commit the generating units optimally to address the fluctuations of wind power becomes very critical. To account for load fluctuations, outages, and wind power output uncertainties, the unit commitment algorithms co-optimize energy and ancillary services. Most of current research is focused on how to integrate the wind power forecasts into the day-ahead SCUC only without simulating a complete market procedure. Barth et al. [2] presented the early stage of the Wind Power Integration in the Liberalised Electricity Markets (WILMAR) model in [3]. More recently, a more comprehensive UC algorithm based on Mixed Integer Linear Programming (MILP) has been introduced in WILMAR. However, the model is mainly a planning tool. 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 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, where the realized wind generation is likely to deviate from the forecast. 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. 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 system reserve requirements can be determined 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 wind power uncertainty is represented by scenarios, and Bender's decomposition is used to solve the problem.

In most of the existing markets, after the clearing of the DA market, the ISO/RTO performs a revised commitment procedure focusing on the reliability of the power system. This procedure is called Reliability Assessment Commitment (RAC). In this procedure, the demand bids are replaced with the forecasted load for the next day. Since this procedure is performed several hours after the DA market is cleared, the ISO/RTO may change the commitment schedule from the DA market clearing because of reliability issues. After the RAC procedure, the SCED is executed again every 5 min to economically dispatch the units. The 5-minute prices are integrated over the hour to obtain the real-time hourly prices. As in the DA market clearing, the RAC generates a new commitment schedule. In the real time, the SCED determines the hourly dispatch results and energy prices. The market settlement is based on real-time deviations from the DA transactions over the hour. A RT demand that exceeds its DA quantity pays a RT price for the shortage and a demand that is below its DA quantity is paid the RT price for the surplus. In the market procedure, wind power forecasting can play a role in several places as shown in Fig. 1. As can be seen in Fig. 1, the wind power forecast can help determine the operating reserve requirements, as a part of the required reserves may be used to accommodate the uncertainty and variability from wind power. Wind power bidding strategies should also be based on wind power forecasts to predict the actual wind power output in the real-time market. Furthermore, updated wind power forecasts can be used by the ISO/RTO in the RAC process to provide more accurate information. Moreover, wind power forecasts can be used in the operating day to guide the real-time system operations. The use of wind power forecasting in U.S. electricity markets is further discussed in [12].

Given that the day-ahead market is generally cleared as a financial market, we investigate the role of wind power forecasting in the reliability unit commitment by simulating the market procedure through a market simulation model in this book chapter. The model is used to investigate the effects of wind power uncertainty on unit commitment and dispatch decisions and to analyze its impact on reserve requirements for system operations. The purpose of this book chapter is to demonstrate that modeling wind power uncertainty properly can efficiently deal with the uncertainty and variability associated with high penetration of wind power generation in current markets. Also, a stochastic approach that utilizes a set of scenarios to represent the wind power uncertainty is developed and described in this book chapter. A deterministic approach that uses a wind power point forecast is implemented with the purpose to compare it to the stochastic approach.

The following sections give the mathematical formulation of both approaches and preliminary results are given for a 10-unit power system.

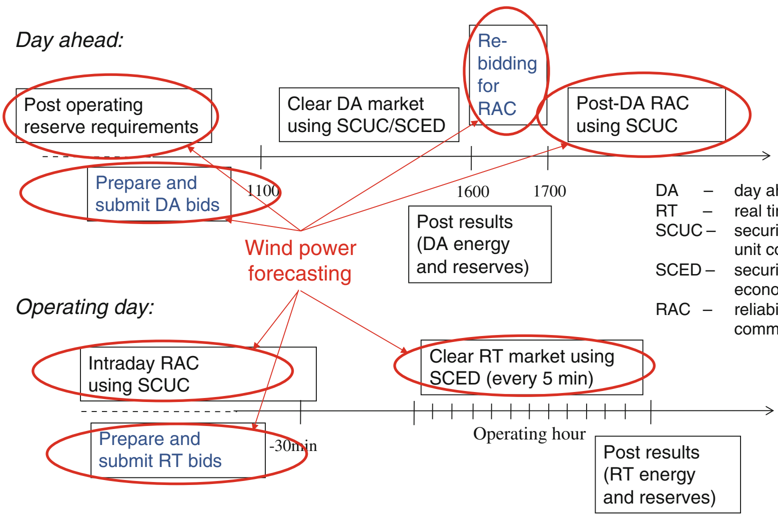

Fig. 1 Market operations timeline for midwest ISO, indicating where wind power forecasting could play an important role[1]

2 Unit Commitment and Dispatch Formulations

The general UC constraints follow the deterministic model in [13]. However, we make adjustments in this stochastic version based on the introduction of wind power and wind power forecasting uncertainty, which is represented in the form of scenarios. Our stochastic unit commitment model was first presented in [14]. We include the formulation here for completeness.

1. *Objective Function*

The objective is to minimize the sum of expected production costs, the expected cost of unserved energy and reserve curtailment, and start-up costs, as shown in (1). Constraints on load and operating reserves are represented in (2)–(3). We use a step-wise reserve demand curve to mimic the reserve requirement practiced by some system operators, such as MISO, as shown in (4). This formulation allows the reserve requirement, represented by a percentage of wind power, to be reduced at the reserve curtailment cost in some cases to avoid load curtailment. The idea is that this wind power reserve helps accommodate the uncertainty and variability from wind at the day-ahead UC stage since we do not simulate load forecasting errors and contingencies. Wind units may also be curtailed if necessary, as shown in (5). It is of note that the thermal dispatch, and therefore the production cost and the curtailed energy and reserve costs, all vary by wind scenario. The constraints

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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.

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 (6)–(9). The coefficients for the generation blocks are derived from the quadratic production cost function. 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 has been down. The mathematical formulation is shown in (10)–(12).

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 (13). The maximum power output of a unit, $\overline{pt}_j^s(k)$, is constrained by the generation limit of a unit in (14), limitations on start-up and ramp-up rates in (15) shut-down ramp rates in (16), and ramp-down limits in (17). The availability of spinning reserves is equal to the difference between the maximum potential generation and the actual generation, that is, $\overline{pt}_j^s(k) - pt_j^s$. Hence, the reserve requirement in (5) takes into account the constraints imposed by (13)–(17). The reserve requirement is maintained for each individual wind scenario.

The final constraints included are the minimum-up and -down time constraints. Minimum-up times are represented by (18)–(20), 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 (21)–(23). It is of note that the equations for generation and ramping limits, (13)–(17), must be included for all wind scenarios, because thermal dispatch depends on the wind generation. In contrast, the minimum-up and minimum-down time constraints, (18)–(23), are functions of commitment only and do not vary with wind scenarios. Generalized network constraints are represented in (24).

$$
\begin{aligned}
Min \sum_{s=1}^{S} prob_s \cdot \Bigg\{ & \sum_{k=1}^{K} \sum_{j=1}^{J} c_j^{p,s}(k) + \sum_{k=1}^{K} C_{ens} \times ens^s(k) \\
& + \sum_{k=1}^{K} \sum_{m=1}^{M} CR_{rns,m} \times rns_m^s(k) \Bigg\} + \sum_{k=1}^{K} \sum_{j=1}^{J} c_j^u(k)
\end{aligned}
\tag{1}
$$

s.t.

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

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

$$r^s(k) = WR(k) - \sum_{m=1}^{M} rns_m^s(k), \quad \forall k, \forall s \tag{4}$$

$$pw_i^s(k) + cw_i^s(k) = PW_i^{f,s}(k), \quad \forall i, \forall k, \forall s \tag{5}$$

$$c_j^{p,s}(k) = A_j v_j(k) + \sum_{l=1}^{L} MC_{l,j}(k) \cdot \delta_{l,j}^s(k), \quad \forall j, \forall k, \forall s \tag{6}$$

$$pt_j^s(k) = \underline{PT}_j \cdot v_j(k) + \sum_{l=1}^{L} \delta_{l,j}^s(k), \quad \forall j, \forall k, \forall s \tag{7}$$

$$\delta_{l,j}^s(k) \leq \overline{\Delta}_{\mathrm{l,j}}, \quad \forall l, \forall j, \forall k, \forall s \tag{8}$$

$$\delta_{l,j}^s(k) \geq 0, \quad \forall l, \forall j, \forall k, \forall s \tag{9}$$

$$\begin{gathered} c_j^u(k) \geq CC_j \cdot \left[v_j(k) - \sum_{n=1}^{N} v_j(k-n) \right], \quad \forall j, \forall k \\ where\ N = T_j^{dn} + T_j^{cold}. \end{gathered} \tag{10}$$

$$c_j^u(k) \geq HC_j \cdot \left[v_j(k) - v_j(k-1) \right], \quad \forall j, \forall k \tag{11}$$

$$c_j^u(k) \geq 0, \quad \forall j, \forall k \tag{12}$$

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

$$0 \leq \overline{pt}_j^s\ (k) \leq \overline{PT}_j \cdot v_j(k), \quad \forall j, \forall k, \forall s \tag{14}$$

$$\begin{aligned} \overline{pt}_j^s(k) \leq\ & pt_j^s(k-1) + RL_j \cdot v_j(k-1) \\ & + SU_j \cdot \left[v_j(k) - v_j(k-1) \right] \\ & + \overline{PT}_j \cdot \left[1 - v_j(k) \right], \quad \forall j, \forall k, \forall s \end{aligned} \tag{15}$$

$$\overline{pt}_j^s(k) \leq \overline{PT}_j \cdot v_j(k+1) + SD_j \cdot \left[v_j(k) - v_j(k+1) \right], \quad \forall j, \forall k = 1 \ldots 23, \forall s \tag{16}$$

$$\begin{aligned} pt_j^s(k-1) - pt_j^s(k) \le RL_j \cdot v_j(k) \\ + SD_j \cdot \left[v_j(k-1) - v_j(k)\right] \\ + \overline{PT}_j \cdot \left[1 - v_j(k-1)\right], \quad \forall j, \forall k, \forall s \end{aligned} \tag{17}$$

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

$$\begin{gathered} \sum_{n=k}^{k+T_j^{up}-1} v_j(n) \ge T_j^{up} \cdot \left[v_j(k) - v_j(k-1)\right], \\ \forall j, \forall k = T_j^{up,0} + 1, \ldots, T - T_j^{up} + 1 \end{gathered} \tag{19}$$

$$\sum_{n=k}^{T} \left\{v_j(n) - \left[v_j(k) - v_j(k-1)\right]\right\} \ge 0, \quad \forall j, \forall k = T - T_j^{up} + 2, \ldots, T \tag{20}$$

$$\sum_{k=1}^{T_j^{dn,0}} v_j(k) = 0, \quad \forall j \tag{21}$$

$$\begin{gathered} \sum_{n=k}^{k+T_j^{dn}-1} \left[1 - v_j(n)\right] \ge T_j^{dn} \cdot \left[v_j(k-1) - v_j(k)\right], \\ \forall j, \forall k = T_j^{dn,0} + 1, \ldots, T - T_j^{dn} + 1 \end{gathered} \tag{22}$$

$$\sum_{n=k}^{T} \left\{1 - v_j(n) - \left[v_j(k-1) - v_j(k)\right]\right\} \ge 0, \quad \forall j, \forall k = T - T_j^{dn} + 2, \ldots, T \tag{23}$$

$$\boldsymbol{G}\left(pw_i^s(k), pt_j^s(k)\right) \le 0 \tag{24}$$

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 UC problem. The selected scenario could be the expected wind power generation or point forecast or could also represent a certain quantile in the forecasting probability distribution.

4. *Economic Dispatch*

In order to assess the dispatch cost in real-time, we also develop an economic dispatch formulation. The commitment variables are now assumed to be fixed from the UC run. The representation of wind power generation by scenarios is replaced by the realized wind power output (without considering potential wind power curtailment). Hence, we formulate a deterministic economic dispatch problem consisting of Eqs. (1)–(9) and (13)–(17) 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 because of the fixed commitment. Ramping constraints are in (13)–(17), and the 24 h problem is solved simultaneously. It is of note that the operating reserve requirement in (3) is also imposed in the ED formulation.

3 Market Simulation

A market simulation set up has been put in place, which first clears the day-ahead market. This is done by first running UC and then ED on the basis of a day-ahead wind power forecast. Next, the RAC is performed with a new forecast, which could be a deterministic point forecast or a set of scenarios, as explained below. Finally, the real-time ED is run on the basis of the realized wind conditions. This action is performed 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 for the day-ahead and real-time market operations (UC, dispatch, available reserves, unserved load, curtailed reserve, prices, etc.) are calculated and stored after each simulation day.

Because the focus is the impact of wind power forecasts on system operation, the only uncertainty we consider is from wind generation. Other uncertainties, such as load or forced outage, are not directly considered. Hence, the additional amount of "wind power reserve" becomes critical to address the impact of uncertainty from use of wind power. With the stochastic UC formulation, the need for additional operating reserves is arguably already addressed because we include a representative set of wind power outcomes in the scenarios. However, because of the accuracy of the scenarios in capturing all of the possible wind power outputs, additional reserve may be needed even in the stochastic formulation to cover the extra uncertainty that the simulated scenarios are not able to capture. In the case study below, we run a number of different cases to investigate the impact of UC strategy and operating reserve policy on the system dispatch.

3.1 Deterministic Approach

In the deterministic approach, the DA market uses a wind power point forecast for the next 24 h of the operation day. Since the objective of the RAC procedure is to assure the reliability of the power system, a conservative estimate of the wind power, e.g. the 20th percentile, may be used in the procedure. After the units are

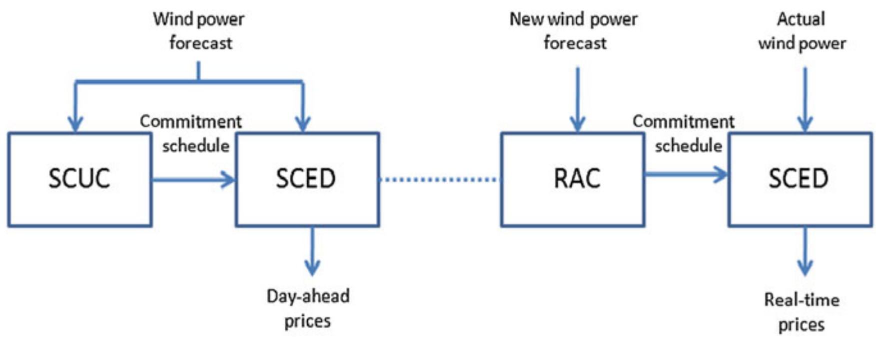

Fig. 2 Wind power forecast in the deterministic approach

committed in the RAC procedure, the units are economically dispatched by the SCED using the actual wind power. It is also assumed that there is no demand side bidding. Figure 1 illustrates the different stages of the market procedure and how the wind power data is used in the deterministic approach.

3.2 Stochastic Approach

In the stochastic approach, the DA market uses the same wind power forecast for the next 24 h of the operation day as in the deterministic approach. However, in comparison with the point forecast used in RAC in the deterministic approach, the RAC uses a set of wind power scenarios in the stochastic case. The scenarios are derived by using a combination of quantile regression and Monte-Carlo simulation [15, 16]. A comprehensive review of the state-of-the art in wind power forecasting, including uncertainty forecasts is provided in [17]. As in the deterministic approach, the dispatch of the units in the real-time market is completed by the SCED using the actual wind power. Again, we assume no uncertainty on the load and no generator outages. Figure 2 illustrates the use of the wind power data. It is also assumed that there is no demand side bidding in the stochastic approach.

4 Case Study

A test 10-unit power system is used to study the reliability unit commitment problem. Since we focus on the impact of different UC strategies and reserve requirement with wind power, we do not consider transmission constraints in this case study. Hence, the SCUC, SCED and RAC become UC and ED without transmission constraints and are solved in sequence as described in Figs. 2 and 3. The technical characteristics of the thermal units are given in Table 1. The values

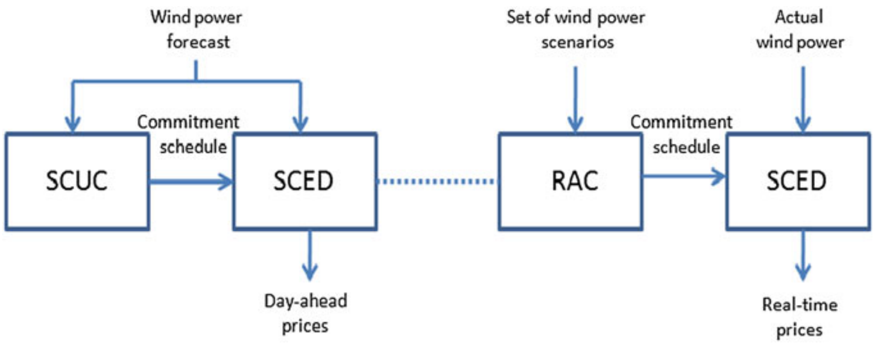

Fig. 3 Wind power forecast in the stochastic approach

Table 1 Generator data

Unit	$\overline{PT}_j$ (MW)	$\underline{PT}_j$ (MW)	RL_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
Unit	a_j ($/h)	b_j ($/MWh)	c_j ($/MW^{2}h)	CC_j ($/h)	HC_j ($/h)	T_j^{cold} (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

(*) Start-up and shut-down ramps, SU_j and SD_j, are equal to ramp rate RL_j

in this table are based on the case studies presented in [13, 18]. Ramp rates have been added to the table and the cost coefficients have been slightly modified. 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, with units 1 and 2 being the baseload plants.

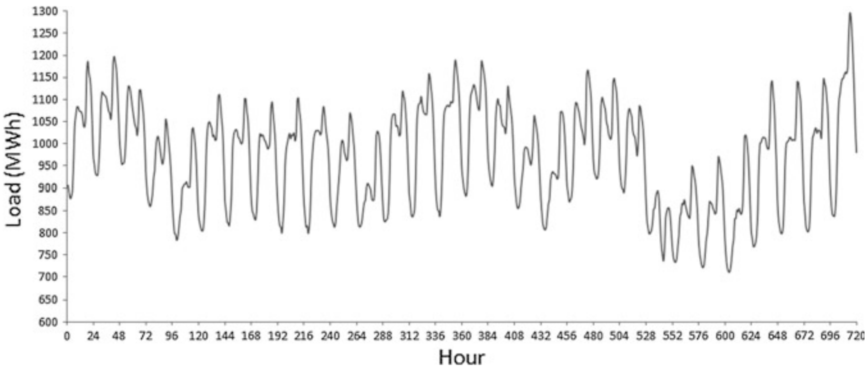

Fig. 4 Hourly load of November, 2006

The power system is simulated for 91 days. The hourly load profile corresponds to the historical data from two utilities in the state of Illinois for the months of October to December of 2006. The load has been scaled down to match the generation capacity of the test power system. Figure 4 shows the hourly load for the month of November. It is assumed perfect information about the load, i.e. the forecasted load is assumed to be equal to the actual load. Again, the reason for this assumption is to isolate the effects of wind power uncertainty from load uncertainty. Outages of thermal plants and wind farms are not simulated either. Thus, the results of the simulated cases show the effects of wind power uncertainty only. The cost of reserve curtailment is 1,100 ($/MWh) and the cost of unserved energy is 3,500 ($/MWh). The wind power plants do not provide reserves and therefore the operating reserve requirement is met by the thermal power plants .

The wind power data corresponds to wind power forecasts and realized wind power generation for 15 hypothetical locations in the state of Illinois for 2006. Time series of wind power generation for the 15 sites were obtained from NREL's EWITS study [19]. This data was produced by combining a weather model with a composite power curve for a number of potential sites for wind power farms. The forecasts were generated based on observed forecast errors from four real wind power plants. The wind power data for the 15 sites were aggregated into one time series. The accuracy of the day-ahead wind power forecast varies from day to day. For the forecast, the normalized mean average errors (NMAE) over a 91-day simulation period vary between 8.4 and 12.4 % for different hours of the day, with the highest forecast errors occurring in the afternoon between noon and 6 pm.

The total installed capacity of wind power is assumed to be 500 MW, and for simplicity it is modeled as one large wind power plant. For the simulated 91-day period, the wind power capacity factor is 40 %, and the wind power meets 20 % of the load (with no wind curtailment). Wind power and load are uncorrelated with a correlation coefficient of 0.01. With these assumptions, the total installed capacity of the thermal units is 10.8 % higher than the peak load. If we assign a capacity value of 20 % to the wind power capacity, the system reserve margin increases to 17.4 %.

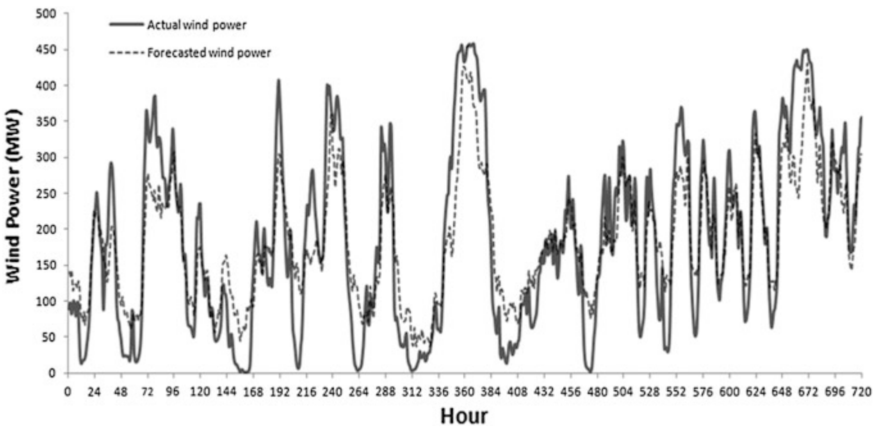

Fig. 5 Actual and forecasted hourly wind power of November, 2006

Table 2 Description of deterministic cases (10-unit system)

Case	UC and ED Reserve margin α (%)	RAC and ED Reserve margin α (%)
D0[a]	20	20
D1	20	20
D2	20	40
D3	40	20
D4	40	40
D5	No reserve	No reserve

[a] Case D0 uses a perfect forecast

Figure 5 shows the actual and forecasted hourly wind power for the month of November.

In the following sections, the results for the deterministic and stochastic approaches are compared. The purpose is to study how the use of wind power forecasts, reserve requirements, and unit commitment strategy influence cost, prices, and reliability in system operations.

1. *Deterministic Approach*

To study the impact of different reserve margins, five cases are developed. Their characteristics are shown in Table 2. All cases solve the UC and ED in the DA market using the same wind power forecast. The reason is to clear the DA market with the same amount of information on wind power in all cases. The RAC formulation uses an estimate of the 20th percentile of the wind power as a forecast. The 20th percentile is a conservative forecast of the actual wind power, which means that the actual wind power is expected to be higher than this forecast. In this way, the difference between the actual wind power and the 20th percentile acts as a natural reserve for the system. In order to clarify the structure of the cases, let us consider case D2 in Table 2. In case D2, the UC and ED use a forecast of wind power to commit and dispatch the thermal power plants in the day-ahead market. The reserve margin is set to 20 % of the wind power forecast to accommodate wind power variations. The RAC, on the other hand, commits the thermal units in the real-time market using a 20th percentile estimate of the wind power and a reserve margin equal to 40 % of the 20th percentile estimate. The thermal units are dispatched in the real-time market by ED using the actual wind power and with the same reserve margin as in the RAC procedure. Notice that all reserve requirements are functions of the wind power forecast. In addition, a hypothetical case D0 consisting of using a perfect wind power forecast (the forecast for the UC, ED, and RAC is the actual wind power) is also simulated. The fact that the forecast is a perfect prediction of the actual wind power is assumed to be unknown to the operator and a reserve of 20 % of the forecast is used to accommodate for the possible wind power variations.

A summary of the results for the six cases are provided in this section. The cases are solved using the mathematical programming formulation given in Sects. 2.1–2.4 and the commercial solver Lingo 12.0. A Lingo tolerance of 0.01 (1 % gap) is used in all cases for solving the integer programs. Microsoft Excel 2007 is used as the input and output interface. On average, it takes 12 s to simulate one day using a personal computer with 8 GB RAM and Intel(R) Core^{TM}2 Duo processor 3.33 GHz. Table 3 summarizes the overall performance during the real-time dispatch over the 91-day simulation.

As expected, D0 gives the best performance. It serves the load at all hours, and it has the lowest startup and production costs while maintaining the lowest percentage of units on-line. However, this case is unrealistic since the wind power cannot be predicted with absolute certainty. Case D5, on the other hand, is the worst case in terms of serving the load and total costs. 0.072 % (1,556.21 MWh over a total of 2161,989 MWh) of the total load is curtailed. The loss of load probability is equal to 0.0238 (52 h over a total of 2,184 h). It has also the higher total cost (startup + production + unserved load costs), a 16 % higher than the best case. Case D2 is the next best case in regard to serving the load. Under this case, 0.006 % of the total load is curtailed representing a 91 % improvement from the worst case D5. The loss of load probability is equal to 0.004, which represents

Table 3 10-unit system overall performance (91-day simulation of deterministic approach)

Case	Unserved load (MWh)	Unserved reserve (MWh)	Startup cost (M$)	Production cost (M$)	Unserved load cost (M$)
D0	0.00	5.5	100.70	34,357.24	0.00
D1	465.87	927.1	110.22	34,538.52	1,630.53
D2	137.37	1,678.6	110.70	34,676.18	480.80
D3	465.87	927.1	109.73	34,537.52	1,630.55
D4	137.37	1,678.6	110.49	34,676.46	480.80
D5	1,556.21	0.0	141.16	34,448.38	5,446.73

Table 4 10-unit system market prices (91-day simulation of deterministic approach)

Case	Average DA energy price ($/MWh)	Average RT energy price ($/MWh)	Load-weighted DA energy price ($/MWh)	Load-weighted RT energy price ($/MWh)
D0	26.91	26.91	27.60	27.60
D1	22.84	72.88	23.66	77.83
D2	22.76	64.64	23.56	68.88
D3	22.32	72.88	22.90	77.84
D4	22.76	64.64	23.50	68.89
D5	20.58	103.58	21.04	105.32

an 83 % improvement. This gain is at the cost of maintaining 5.4 % more units on-line than in the worst case. In addition to these improvements, case D2 reduces the total cost by 12.5 %. Case D4 performs similarly to case D2, except that the production cost is slightly higher. Cases D1 and D3 have similar performance but they do not provide better results than cases D2 and D4.

The six cases are also compared in terms of market prices. Table 4 summarizes the day-ahead and real-time prices over the 91-day simulation of each case.

In Table 4, Case D0 gives the lowest RT prices. There is no difference between the DA and RT prices because the actual wind power is used to clear both the DA and RT markets. The prices in the DA market are similar in all cases because the UC and ED in the DA market are solved using the same wind power forecast. However, the market prices in the RT market are much higher than those of the DA market. The reason is that the 20th percentile estimate of the wind power overestimates (27 % of the time) the actual wind power, which in turn increases the reserve requirements in the real-time market. In some hours, the reserve requirement causes the dispatch of more expensive thermal plants and sometimes the curtailment of the reserve or the load. For example, in case D2 the reserve is curtailed in 68 h and the load in 9 h. Case 5 produces the highest average RT price. The reason is that having no reserve requirements causes the ramp up of more expensive power plants to accommodate variations of the wind power. At the same time, the price goes up to the cost of unserved energy (3500 $/MWh) as soon as load curtailment occurs. The average DA price is the lowest because there is no cost attributed to reserve curtailment.

The results in Tables 3 and 4 demonstrate the importance of modeling the uncertainty of wind power and choosing an appropriate reserve margin to account for the wind power uncertainty.

2. *Stochastic Approach*

Three cases are developed to test the stochastic approach. Their characteristics are shown in Table 5. All cases solve the UC and ED in the DA market using the same wind power forecast as in the deterministic approach. In all cases, the RAC formulation uses a set of scenarios for representing the uncertainty of the wind power. For each scenario, a reserve margin is set to accommodate wind power uncertainty not captured by the scenarios. Within a case, the same percentage of reserve is

Table 5 10-unit system description of stochastic cases

Case	UC and ED Reserve margin α (%)	RAC and ED Reserve margin α(s)[a] (%)
S1	20	20
S2	40	20
S3	No reserve	No reserve

[a] The same percentage of reserve is used in all scenarios

Table 6 10-unit system overall performance (91-day simulation of stochastic approach)

Case	Unserved load (MWh)	Unserved reserve (MWh)	Startup cost (M$)	Production cost (M$)	Unserved load cost (M$)
D0	0.00	5.5	100.70	34,357.2	0.00
D2	137.37	1,678.6	110.70	34,676.2	480.8
S1	0.00	0.0	158.84	35,501.0	0.00
S2	0.00	0.0	160.92	35,511.5	0.00
S3	0.00	0.0	158.43	35,317.3	0.00

Table 7 10-unit system market prices (91-day simulation of stochastic approach)

Case	Average DA energy price ($/MWh)	Average RT energy price ($/MWh)	Load-weighted DA energy price ($/MWh)	Load-weighted RT energy price ($/MWh)
D0	26.91	26.91	27.60	27.60
D2	22.76	64.64	23.56	68.88
S1	22.78	19.97	23.58	20.33
S2	22.79	19.94	23.53	20.30
S3	20.42	20.03	20.90	20.39

used in all the scenarios. To produce the wind power scenarios for the months of October, November and December, data (forecasts and realized generation) for the period from January to July were used to train a quantile regression [20] and to estimate the co-variance matrix for the Monte-Carlo simulations. The months from August to December were used as a test dataset.

In this section, detailed results are provided for the three cases in Table 5. The cases are solved using the mathematical programming formulation given in Sects. 3.1–3.4 and the commercial solver Lingo 12.0. A Lingo tolerance of 0.01 (1 % gap) is used in all cases for solving the integer programs. On average, it takes 3 min to simulate one day. Table 6 summarizes the overall real-time performance over the 91-day simulation of each case. The results of cases D0 and D2 are shown again for comparison.

The cases are also compared in terms of market prices. Table 7 summarizes the day-ahead and real-time prices over the 91-day simulation of each case.

Except for case D0, all cases produce comparable total costs (startup + production + unserved load costs). However, they differ on the percentage of units that are kept online. The small dissimilarity observed in the DA average prices is due to the different reserve margins established in each case. As for the RT prices, a large difference between the stochastic approach cases and the deterministic case D2 exists. The three stochastic cases produce RT prices much lower than case D2. Moreover, the prices are lower than the prices produced by D0, which uses a perfect forecast of wind power. The reason is that more thermal plants are kept online in the stochastic cases than in the case D0, which in turn provides more flexibility in economically dispatching the thermal plants. Notice that case S3, which uses no reserve requirements, provides similar performance when it is compared to the other two stochastic cases. This fact implies that the wind power scenarios may be sufficient for dealing with the uncertainty of wind power.

5 Conclusion

In this book chapter, a market simulation model with reliability unit commitment is used to compare various unit commitment strategies to address the uncertainty from wind power. It is shown that the deterministic approach may not be suitable for coping with the complicating aspects of operations planning with large penetration of wind power. The deterministic approach intends to manage the uncertainty in wind power forecast through determining the commitments of thermal plants and scheduling sufficient levels of operating reserves to follow the rapid variations of the wind power. The stochastic approach, on the other hand, uses scenarios in modeling the uncertainty of wind power and determines an appropriate unit commitment by considering the dispatch of thermal plants across all the scenarios. Based on the simulation results, we conclude that the stochastic formulation is a promising alternative for coping with the uncertainty and variability of wind power and establishing an adequate reserve margin in the reliability unit commitment.

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