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Temporal vs. Stochastic Granularity in Thermal Generation Capacity Planning with Wind Power

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Keywords

electricity markets, generationexpansion planning, stochastic programming, unit commitment, wind energy

Disciplines

Industrial Engineering | Systems Engineering

Comments

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Temporal vs. Stochastic Granularity in Thermal Generation Capacity Planning with Wind Power

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***Abstract*—We propose a stochastic generation expansion model, where we represent the long-term uncertainty in the availability and variability in the weekly wind pattern with multiple scenarios. Scenario reduction is conducted to select a representative set of scenarios for the long-term wind power uncertainty. We assume that the short-term wind forecast error induces an additional amount of operating reserves as a predefined fraction of the wind power forecast level. Unit commitment (UC) decisions and constraints for thermal units are incorporated into the expansion model to better capture the impact of wind variability on the operation of the system. To reduce computational complexity, we also consider a simplified economic dispatch (ED) based model with ramping constraints as an alternative to the UC formulation. We find that the differences in optimal expansion decisions between the UC and ED formulations are relatively small. We also conclude that the reduced set of scenarios can adequately represent the long-term wind power uncertainty in the expansion problem. The case studies are based on load and wind power data from the state of Illinois.**

***Index Terms*—Generation Expansion Planning, Wind Energy, Unit Commitment, Electricity Markets, Stochastic Programming.**

NOTATION

A. Sets

I	set of candidate thermal generators, indexed by *i*
L	set of load seasons, indexed by *l*
K	set of days in the study period, indexed by *k*
S^l	set of scenarios in load season *l*, indexed by *s*
T^l	set of hours in load season *l*, indexed by *t*

B. Binary Decision Variables

u_i	set to 1 if candidate thermal generator *i* is built or it is an existing thermal generator *i*, 0 otherwise
$z_{i,t,s}$	set to 1 if unit commitment decision for thermal generator *i* is on in hour *t*, under scenario *s*, 0 otherwise

C. Continuous Decision Variables

$y_{i,t,s}$	startup decision for generator *i*, in hour *t*, under scenario *s* (a relaxed binary variable enforced by startup constraints)
$x_{i,t,s}$	shutdown decision for generator *i*, in hour *t*, under scenario *s* (a relaxed binary variable enforced by shutdown constraints)
$g_{i,t,s}$	generation output of generator *i* in hour *t*, under scenario *s*, MWh
$r_{i,t,s}$	operating reserve provided by generator *i*, in hour *t*, under scenario *s*, MW
$ens_{t,s}$	energy not served, in hour *t*, under scenario *s*, MWh
$rns_{t,s}$	reserve not served, in hour *t*, under scenario *s*, MW
$wg_{t,s}$	wind output, in hour *t*, under scenario *s*, MWh
$wc_{t,s}$	wind curtailment, in hour *t*, under scenario *s*, MWh

D. Parameters

inv_i	annualized investment cost, for generator *i*, \$/MW/year
F_i	annual fixed O&M cost for generator *i*, \$/year
c_i	generation cost for generator *i*, \$/MWh
S_i	startup cost for generator *i*, \$
H_i	shutdown cost for generator *i*, \$
c^{ens}	energy not served cost, \$/MWh
c^{rns}	reserve not served cost, \$/MWh
$\bar{P}_i$	maximum power output for generator *i*, MW
$\underline{P_i}$	minimum power output for generator *i*, MW
P_s	probability of scenario *s*
θ_l	number of weeks in load season *l*
d_t	load in hour *t*, MW
RM	reserve margin for load and contingencies, MW
$WR_{t,s}$	reserve margin for wind, in hour *t*, under scenario *s*
$\overline{W}_{t,s}$	available wind power, in hour *t*, under scenario *s*, MW
$MxInc_i$	ramp up limit for generator *i*, MW/hr
$MxDec_i$	ramp down limit for generator *i*, MW/hr
$MAXSP_i$	maximum spinning reserve for generator *i* as a percentage of total capacity, MW

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I. Introduction

In recent years, considerable attention has been given to environmental concerns, clean energy and energy efficiency. Both the economic and environmental benefits of renewable energy resources make wind, solar, bio-mass, and hydro increasingly appealing. The US Department of Energy envisions that 20% of the nation's total energy consumption should come from wind energy by year 2030 [*1*]. However, different from the thermal generators, the variability of the wind power output from hour to hour, mainly affected by the weather conditions, adds an additional source of uncertainty to the power system. This temporal uncertainty in the wind power resource is important for long term thermal investment decisions to maintain an adequate level of installed generation capacity. Many recent studies (e.g., [*2*] [*3*] [*4*] [*5*] [*6*]) have investigated how the short term wind forecasting error, which is typically formulated as an uncertainty in a stochastic unit commitment (UC) model, affects the short term scheduling decisions. In contrast, the model in our paper is from a long term thermal expansion and portfolio planning perspective. With the increasing penetration of wind resources integrated into the power system, and the wind's intrinsic characteristics, we examine how the increasing wind capacity affects the optimal thermal generation expansion decisions. In particular, we analyze what is the optimal portfolio of thermal generating units to accommodate the variability and uncertainty from wind power outputs. Towards this end, we propose a centralized two-stage stochastic generation expansion planning model. The model considers the long term wind resource uncertainty by various weekly wind patterns with hourly time resolution and short term wind power forecast uncertainty in terms of increased operating reserve requirements.

The evolution of the hourly wind output within a given time period can be realized in various forms, which we formulate as a stochastic variable. More specifically, we treat a single weekly time series of hourly wind power outputs for a fixed wind penetration level as one scenario. A set of scenarios is then used to capture a variety of different realizations of the wind power as a long-term resource uncertainty, which could potentially impose additional physical constraints (ramp up/down limit for the thermal generators) on the generation portfolio planning problem. For example, in a week of less volatile wind, cheap and slowly responding coal-fired units might be preferred, while in a week with high variability in the wind output, quickly responsive gas-fired units might be more cost efficient.

These different weekly wind scenarios could also have an impact on the short-term UC decisions and the corresponding operating costs. Therefore, the UC constraints of the thermal generators are included in the optimization model, where thermal capacity investments are the first-stage decisions and the scenario-based commitment and dispatch are the second-stage decisions. Previous work in this area includes a generation expansion problem with wind integration investigated in [*7*], where a UC formulation is expanded to include binary decisions on existence of generators. Demand variability is simulated by optimizing over four typical weeks and an extreme winter week, while wind power patterns are assumed known but with normally distributed forecast error. Incorporation of UC constraints into a deterministic generation expansion model with wind power is discussed in [*8*]. A group commitment decision variable is proposed to reduce computation time and a numerical study for a full year (8760 hours) is conducted. In both [*7*] [*8*], the hourly wind profile is formulated as negative load, so renewable energy curtailment is therefore not considered. Generally speaking, traditional generation expansion planning models normally do not include UC constraints for the short term operational aspect (e.g. [*9*]). Such models are therefore capable of analyzing very long planning horizons. However, like the models in [*7*] [*8*] our generation expansion model with UC constraints integrated, is on an annual basis to avoid the prohibitive computational complexity caused by a longer planning horizon. We also employ scenario reduction to reduce the problem size.

With increasing renewable resources integrated into the power grid, additional operating reserve is required to cover the short-term wind power uncertainty that stems from the forecasting errors [*10*][*11*][*12*]. Comprehensive reviews of operating reserve definitions, standards, and practices from organizations in different regions in the United States and Europe are provided in [*13*] [*14*]. The operating reserve we consider in this paper consists of two parts: one is a traditional fixed fraction of the load to cover the load forecast error and generator contingencies; the other is an additional operating reserve to account for the day-ahead wind forecast error. The additional operating reserve for wind power is a dynamic percentage varied by different day-ahead wind power forecast levels and corresponding historical forecast errors. The increased need for operating reserves, as well as the scenario representation of wind resource uncertainty, will both influence the optimal expansion of thermal generation.

In this paper, we focus on the impacts of wind power on the optimal portfolio of thermal generators. We therefore formulate the problem as a centralized and static optimization problem, without considering the complex dynamics of decentralized and profit-driven investments in restructured electricity markets. Although investment timing and potential strategic interactions between market participants are not considered, the model can still be used to analyze future resource needs, both in competitive and regulated systems.

The contributions of this paper are: (1) We propose a stochastic generation expansion model with wind power uncertainty, and compare the results with a deterministic model. The results show the advantage of using the stochastic expansion model with multiple scenarios, and indicate that adopting a reduced set of scenarios is sufficient to generate the optimal expansion solution. (2) We compare two formulations of the expansion model: one with UC constraints and the other based on a simplified ED representation that includes ramping constraints. We find only small differences in the resulting expansion plans, and conclude that ED with ramping may be a satisfactory operational simplification for expansion planning

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purposes.

We present the model assumptions and the proposed expansion planning models in Section II and describe case study specifications of a wind-thermal test power system in Section III. Section IV presents numerical results and discusses detailed comparisons of the models. Finally, Section V summarizes conclusions and future work.

II. Models

In this section, we describe a stochastic expansion model with UC constraints and wind power uncertainty (StoExp UC), a simplified stochastic expansion model that relaxes UC constraints while retaining ramping constraints in an economic dispatch (StoExp ED), and an evaluation model that simulates operation under a given expansion plan with UC constraints in the stochastic environment (StoVal UC). Deterministic versions of the first two models are implemented by including only a single scenario having probability one.

We assume that the expansion decisions are evaluated on an annual basis. The model is static in the sense that all added thermal units are built at the same time and we analyze only one year of operations. The transmission network is not considered. The UC decisions [*15*] are based on typical weeks that represent distinct load seasons -- in the case studies we consider low, medium and high load seasons. In Section IV we compare the expansion results from the different models and, particularly, analyze the tradeoff between modeling accuracy and computational cost.

A. A stochastic generation expansion planning model with UC constraints (StoExp UC)

1) Objective function: The model minimizes total cost including investment, fixed operation and maintenance costs, expected commitment and dispatch costs, and expected penalties for unserved energy and unmet reserve.

$$min \sum_{i\in I} u_i\,(Inv_i + F_i)\bar{P}_i + \sum_{l\in L}\theta_l\{\sum_{s\in S^l} P_s[\sum_{t\in T^l}\big(\sum_{i\in I}\big(c_i g_{i,t,s} + S_i y_{i,t,s} + H_i x_{i,t,s}\big)\big) + c^{ens} ens_{t,s} + c^{rns} rns_{t,s})]\} \quad (1)$$

2) Load Balance and Reserve Requirement: Generation from all thermal units and wind plus unserved energy equals demand. In the reserve constraint, the parameter $WR_{t,s}$ is assumed to be a function of the wind power level $\overline{W}_{t,s}$, an assumption used in several recent wind integration studies [*14*], which will be elaborated in Section III.C. Note that the model assumes that all the operating reserves must be met by the thermal units; i.e., we do not consider the potential provision of reserves from demand and wind power.

$$\sum_{i\in I} g_{i,t,s} + wg_{t,s} + ens_{t,s} = d_t \quad \forall\, l, t\in T^l, s\in S^l \quad (2)$$

$$\sum_{i\in I} r_{i,t,s} + rns_{t,s} \ge d_t RM + \overline{W}_{t,s} WR_{t,s} \quad \forall\, l, t\in T^l, s\in S^l \quad (3)$$

3) Wind Generation: We assume that wind power can be curtailed when this is optimal from a cost perspective. Hence, wind generation and its curtailment should equal the available wind energy for each scenario.

$$wc_{t,s} + wg_{t,s} = \overline{W}_{t,s} \quad \forall\, l, t\in T^l, s\in S^l \quad (4)$$

To maintain focus on long-term planning study, for simplicity we use the same parameter $\overline{W}_{t,s}$ to represent the day-ahead (DA) wind power forecast in constraint (3) and the real time (RT) wind generation in (4). The model could be extended to a multi-stage version with two different parameters in constraints (3) and (4), and a stochastic description of the wind power forecast error. In our formulation, the forecast error is addressed through the wind reserve, $WR_{t,s}$.

4) UC Constraints: The UC constraints include minimum/maximum thermal unit output, maximum unit reserve, ramp up/down limits, and start up/shut down.

$$z_{i,t,s}\underline{P_i} \le g_{i,t,s} \quad \forall\, i, l, t\in T^l, s\in S^l \quad (5)$$

$$g_{i,t,s} + r_{i,t,s} \le z_{i,t,s}\bar{P}_i \quad \forall\, i, l, t\in T^l, s\in S^l \quad (6)$$

$$r_{i,t,s} \le \bar{P}_i MAXSP_i \quad \forall\, i, l, t\in T^l, s\in S^l \quad (7)$$

$$g_{i,t,s} \le g_{i,t-1,s} + MxInc_i \quad \forall\, i, l, t\in T^l, s\in S^l \quad (8)$$

$$g_{i,t,s} \ge g_{i,t-1,s} - MxDec_i \quad \forall\, i, l, t\in T^l, s\in S^l \quad (9)$$

$$z_{i,t,s} \le z_{i,t-1,s} + y_{i,t,s} \quad \forall\, i, l, t\in T^l, s\in S^l \quad (10)$$

$$z_{i,t,s} \ge z_{i,t-1,s} - x_{i,t,s} \quad \forall\, i, l, t\in T^l, s\in S^l \quad (11)$$

$$z_{i,t,s} \le u_i \quad \forall\, i, l, t\in T^l, s\in S^l \quad (12)$$

$$u_i \in \{0,1\} \quad \forall\, i \quad (13)$$

$$z_{i,t,s} \in \{0,1\}\ \forall\, i, l, t\in T^l, s\in S^l \quad (14)$$

$$x_{i,t,s}, y_{i,t,s} \ge 0 \quad \forall\, i, l, t\in T^l, s\in S^l \quad (15)$$

$$g_{i,t,s}, r_{i,t,s} \ge 0 \quad \forall\, i, l, t\in T^l, s\in S^l \quad (16)$$

$$wg_{t,s}, wc_{t,s}, ens_{t,s}, rns_{t,s} \ge 0 \quad \forall\, i, l, t\in T^l, s\in S^l \quad (17)$$

To reduce computational complexity, we omit minimum up/down time constraints in the models, since they are most likely satisfied by imposing the startup and shutdown costs.[1]

B. A reduced version based on ED (StoExp ED)

The full UC expansion model as outlined above can be computationally challenging because of the high number of binary variables for UC decisions. To examine the impact of modeling operational details on the expansion planning decisions, we also implemented a reduced version of the model based on an ED formulation with ramping constraints to capture the wind's impact on the system. This facilitates an analysis of the tradeoff between near-optimality of expansion decisions and computational complexity.

For the reduced expansion model, we eliminate the UC binary decision variables and their corresponding constraints. The objective function (1) changes to:

$$min \sum_{i\in I} u_i\,(Inv_i + F_i)\bar{P}_i + \sum_{l\in L}\theta_l\{\sum_{s\in S^l} P_s[\sum_{t\in T^l}\big(\sum_{i\in I}\big(c_i g_{i,t,s}\big)\big) + c^{ens} ens_{t,s} + c^{rns} rns_{t,s})]\} \quad (18)$$

Constraints (2)-(4), (7)-(9) remain the same, whereas (5)-(6), (10)-(12) and (14)-(15) are removed. An extra set of inequalities restricting the maximum power output is added:

$$g_{i,t,s} + r_{i,t,s} \le u_i\bar{P}_i \quad \forall\, i, l, t\in T^l, s\in S^l \quad (19)$$

C. An evaluation version (StoVal UC)

We use a stochastic commitment and dispatch model including all UC constraints and wind scenarios to evaluate the expansion decisions found by either *StoExp UC* or *StoExp ED* in terms of cost and robustness. This allows us to evaluate the expansion plans over a wider set of wind scenarios than what is used in the optimization. Once the expansion decisions are determined with either formulation, we can fix those

[1] In fact, after solving, we checked the UC decisions and find out that minimum up/down constraints actually are all satisfied for the thermal units in all the cases in the case study.

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expansion decisions, u_i, and then solve a complete UC problem to analyze the operational implications in detail. Because the expansion cost term, $\sum_{i\in I} u_i\,(Inv_i + F_i)\bar{P}_i$, is constant, the StoExp UC model, equations (1)-(17), can be decomposed by scenario into a set of deterministic UC models (DetExp UC). For each scenario s, objective function (20) is combined with equations (2)-(12) and (14)-(17) with $S^l = \{s\}$ and $P_s = 1$.

$$min \sum_{s\in S^l} P_s[\sum_{t\in T^l}(\sum_{i\in I}(c_i g_{i,t,s} + S_i y_{i,t,s} + H_i x_{i,t,s}) \\ c^{ens} ens_{t,s} + c^{rns} rns_{t,s})] \quad (20)$$

The relative simplicity of this model permits it to be solved with a significantly larger set of scenarios. The total expected cost can then be calculated as in equation (1) by combining the first-stage capacity costs with the second-stage operational costs for all scenarios, weighted by the scenario probabilities.

In all models, because the UC commitment decisions apply to three discontinuous weeks, the constraints (8)-(11) that connect at least 2 time periods are relaxed accordingly at both the beginning and the end of each load season.

III. Numerical Case Study

A. Load

The weekly load data are based on a real annual hourly load profile for the state of Illinois in the year 2006 and scaled proportionally to a new load profile with the peak load set to 2000 MW. We consider the load variability by selecting one week in April, August and December to represent low, high and medium load seasons, respectively. We define the weeks in March through June, July through October, and November through February, as the low, high, and medium load seasons, respectively. The scaling parameters θ_l are set to 52 (weeks) / 3 to scale the weekly loads to an annual basis.

B. Wind Profile and Uncertainty

Wind scenarios are assumed to be independent of load profiles. Given one weekly load profile for each season based on the 2006 load data, multiple wind scenarios are constructed based on the years 2004-2006 by aggregating the annual hourly wind profiles from 15 hypothetical sites in Illinois, using data from the EWITS study [*17*]. The 15 sites are from different locations in the state. Hence, the aggregate wind profile therefore reflects aggregation effects such as reduced variability and forecast uncertainty due to geographical diversity. Each wind scenario is represented by one weekly wind profile that falls in a particular load season, *l*. From the three years' worth of data, we extracted 51 independent wind scenarios with equal probability (1/51) to form each scenario set S^l. In our experiment, we varied the percentage of wind penetration to analyze the implications for the optimal expansion of thermal generators. We scaled the aggregate wind profile and let $\sum_{l\in L}\sum_{t\in T^l}\sum_{s\in S^l} P_s\overline{W}_{t,s}$ equal 0, 10%, 20% and 30% of the total demand $\sum_{l\in L}\sum_{t\in T^l} d_t$ with total wind capacity as 0, 380MW, 760MW and 1140MW, respectively.

We used GAMS/SCENRED scenario reduction to select three scenarios for each load season. The probabilities for scenarios in the reduced sets are shown in Table I [*18*] [*19*].

TABLE I
Scenario Probabilities By Different Load Seasons

Load Season	s, P_s	s, P_s	s, P_s
high load	1, 0.4706	2, 0.1765	3, 0.3529
medium load	4, 0.6078	5, 0.2549	6, 0.1373
low load	7, 0.1765	8, 0.1176	9, 0.7059

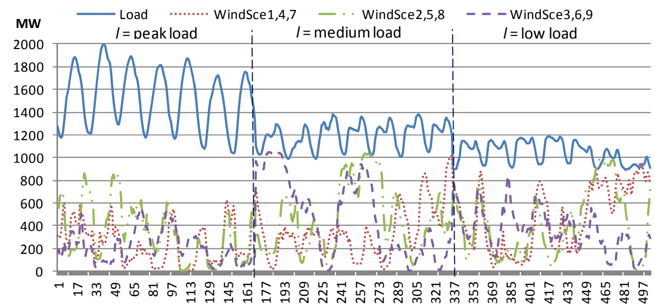

Fig. 1. Hourly load profile and reduced set of 3 wind scenarios corresponding to each load level *l* with 30% wind penetration levels.

The load profiles and wind scenarios for different load seasons at 30% wind penetration level are illustrated in Fig. 1.

C. Operating Reserves for Load and Wind

The operating reserves consist of two parts: a reserve margin, RM =10%, for load forecast error and generator contingencies, and a variable wind reserve, WR, to handle the short term forecasting error in wind.

To determine an adequate amount of WR, we conducted a statistical test of the 2006 EWITS hourly day-ahead (DA) forecast error data for selected sites in Illinois. We represent both DA and real-time (RT) wind generation as a percentage of the wind capacity. The data were first divided into several bins according to different forecast levels shown in Table II: less than 10% of the wind capacity (<10%), 10% to 20% (<20%), through 50% to 60% (<60%), and the last one, 60% to 100% (<1), due to the small size of the sample with such a high forecasting level. The percentage forecast error was then calculated as $(DA - RT)/DA$. Operating reserves for wind are intended to cover situations with insufficient RT wind generation due to over-forecasting. Thus, upper-tail percentiles of the percentage error were calculated as shown in Table II for the different forecast levels. We set the parameter $WR_{t,s}$ equal to the 95th percentile of the wind power forecast for hour *t* in scenario *s*, as further elaborated in [*20*].

TABLE II
Pencentiles for Percentage Difference of Forecasting Error by Forecasting Levels

Forecasting Level	<10%	<20%	<30%	<40%	<50%	<60%	<1
Sample Size	452	1987	2099	1473	1125	784	834
95th	0.964	0.933	0.764	0.528	0.378	0.226	0.093
90th	0.933	0.880	0.658	0.416	0.284	0.148	0.041
85th	0.911	0.811	0.581	0.334	0.189	0.088	-0.003
80th	0.875	0.755	0.525	0.277	0.132	0.029	-0.023
75th	0.849	0.699	0.478	0.226	0.087	-0.004	-0.044
70th	0.813	0.642	0.423	0.175	0.036	-0.042	-0.058
65th	0.766	0.589	0.378	0.126	0.005	-0.077	-0.078
60th	0.724	0.544	0.338	0.080	-0.035	-0.115	-0.097
55th	0.673	0.492	0.297	0.046	-0.071	-0.150	-0.118
50th	0.620	0.438	0.246	0.003	-0.106	-0.187	-0.138

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TABLE III
PARAMETERS FOR CANDIDATE UNITS IN 15 UNITS SYSTEM

Type	Base1	Base2	Medium1	Medium2	Peak1	Peak2
No. of Cand.	2	1	3	2	3	4
Inv_i	244600	219653	83923	86086	83579	57064
F_i	35970	29670	14390	14620	6980	6700
c_i	19.21	19.21	54.19	49.41	92.82	80.07
S_i	42900	87500	33900	21200	90	190
H_i	429	875	339	212	0.9	1.9
$\bar{P}_i$	325	650	270	200	42.5	105
$\underline{P}_i$	120	120	125	100	10	10
$MxInc_i$ $/MxDec_i$	170	250	150	100	42.5	105

The maximum spinning reserve parameter, MAXSP, is set to 30% for all the generators.

D. Candidate Units

We used two sets of candidate units. Parameters for the first set of 15 units, of which 3 were baseload, 5 were medium and 7 were peak units, are shown in Table III. In the first set of studies there were no existing units. For each technology, there were two different types of the units, based in part on [*21*]. We also considered a set of 40 units with all parameters except the fuel cost, c_i, the same as in Table IV. For the 40 unit system, we consider 20 existing units and 20 candidate units. For the larger set of units, the peak load was increased to 5000 MW, and the wind profiles were scaled up correspondingly to meet the same wind penetration levels. Besides, the generation costs, c_i, were updated based on more recent fuel prices [*22*] [*23*] with a significant reduction in natural gas prices caused by the recent increase in the shale gas production [*24*].

TABLE IV
PARAMETERS FOR GENERATING UNITS IN THE 40 UNIT SYSTEM

Type	Base1	Base2	Medium1	Medium2	Peak1	Peak2
No. Of Existing	2	1	4	3	5	5
No. Of Candidates.	2	1	4	3	5	5
c_i	23.97	23.97	24.58	22.40	47.25	39.12

E. Penalty Cost

The current practice at MISO [*25*] suggests the parameters c^{ens} and c^{rns}, the penalty costs for unserved energy and reserves, to be 3500 and 1100 $/MWh, respectively.

IV. RESULTS

In this section, the numerical results indicate how the temporal uncertainty in wind power affects the optimal generation portfolio decisions. We compare the results of models with different amounts of temporal and stochastic granularity according to solution accuracy and computation time.

A. Wind's Impact on Expansion and Dispatch Decisions

To examine the wind power's impact on the optimal portfolio of thermal generators, we vary the wind penetration levels from 0 to 30%. The model with UC constraints is a mixed integer programming (MIP) problem with 22,695 binary variables, 96,768 continuous variables and 231,336 constraints in total. We set the solver's relative MIP gap to 0.5%.

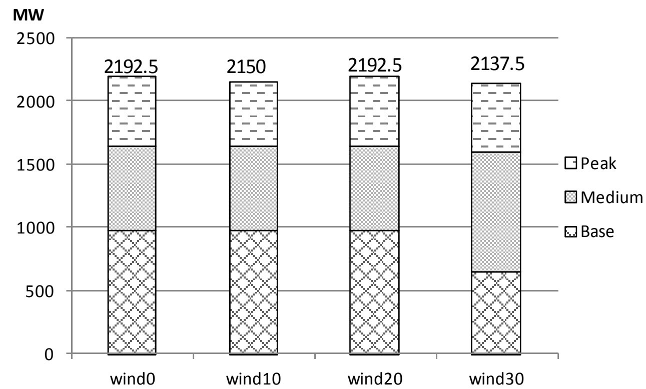

Fig. 2. Expansion capacity (MW) by unit technology at different wind penetration levels.

The total generation capacity at different wind penetration levels is shown in Fig. 2. At wind0, the optimal solution is to build one base 1, one base 2, one medium 1, two medium 2, three peak 1 and four peak 2 units. As the wind level increases, the total capacity remains at about the same level due to the increasing operating reserve requirements to prevent potential shortages resulting from the wind forecasting error. The wind20 case gives the same expansion plan as wind0, while the solution for wind10 is to build one fewer peak unit of 42.5 MW. Here, the solution found for the wind20 case is not strictly optimal, but rather a feasible solution having cost within the 0.5% optimality gap. In fact, we can find a better expansion plan for wind 20, the same as for wind10 in Fig.2, according to the numerical results presented in Table VII. The wind30 case indicates a major difference in generation mix with one medium unit replacing one base unit.

Since wind resources in Illinois tend to be more abundant during the night time when loads are lower, the net thermal load after wind reduction fluctuates more than the original load, as indicated in Fig. 3. The wind scenarios shown in Fig. 3 are those with the highest probability at each load level; i.e., scenarios 1, 4 and 9 (Table I). The higher net load fluctuations lead to difficulties in satisfying the UC constraints for the thermal units. Wind curtailment therefore occurs mostly during the valley hours to avoid the expensive start/stop costs of the base units.

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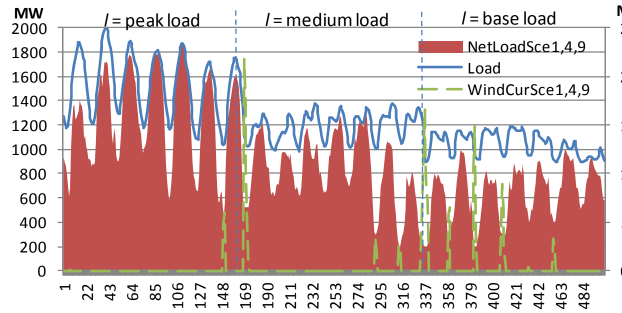

Fig. 3. Net thermal load and curtailment of wind power at 30% penetration level with the most likely wind scenario at each load level.

B. *Effect of Temporal Granularity*

The detailed UC constraints are relaxed in the StoExp ED model, as outlined above. StoExp ED therefore has many fewer binary variables than StoExp UC and can be solved more efficiently. We still set the relative MIP gap to 0.5% to compare the results to the StoExp UC model. There are 15 binary variables, 96,768 continuous variables and 117,936 constraints in total.

TABLE V
STOEXP ED MODEL COMPARED WITH STOEXP UC MODEL, 3 SCENARIOS

		Total Cost (Million $)	Eval. Cost (Million $)	Run Time (Sec)	Base (MW)	Medium (MW)	Peak (MW)
StoExp UC	wind0	666.618	665.072	2792	975	670	547.5
	wind10	629.665	625.803	4851	975	670	505
	wind20	598.346	596.184	14456	975	670	547.5
	wind30	573.454	569.359	9434	650	940	547.5
StoExp ED	wind0	650.616	665.072	16	975	670	547.5
	wind10	605.184	625.918	17	975	670	547.5
	wind20	574.332	596.184	21	975	670	547.5
	wind30	535.733	569.359	18	650	940	547.5

Because StoExp ED is a relaxation of StoExp UC, its optimal objective function value is lower, as shown in the first column of Table V. The computational time for StoExp ED is dramatically lower. Still, the expansion decision found by StoExp ED appears to be a fairly good approximation of that found by the full model according to the generation capacities from each type of technology as shown in Table V. The StoExp ED solutions for wind0, wind20 and wind30 are the same as the StoExp UC solutions. The only different case is wind10, in which the StoExp ED model builds one more peak unit compared to the StoExp UC model.

To further evaluate how well the ED model approximates the UC model in terms of generation expansion decisions in the wind10 case, we tested the expansion decisions u_i from both the UC and ED models, in the StoVal UC model using the entire scenario space; i.e., 153 scenarios in total with 51 scenarios at each load level. With all the scenarios included, the size of the extensive form of the StoExp UC problem would be extremely large, with 385,560 binary variables, 1,645,056 continuous variable and 3,161,592 constraints. However, each scenario subproblem has a more manageable 2,520 binary variables, 10,752 continuous variables and 20,664 constraints. When solving each one, we set the relative MIP gap to 0.05%.

The expected costs for the StoExp UC and StoExp ED optimal expansion plans in the Wind10 case are $625.803M and $625.918M respectively, as shown under "Eval. Cost" in Table IV. In other words, the relative cost difference is only 0.02%, which indicates that even though the expansion decisions from StoExp ED are not exactly the same as the ones from StoExp UC, the difference in the total expected cost over the entire scenario set is small.

From this result, we observe that in this instance StoExp ED, even without the detailed set of UC constraints, is able to capture the wind variability's impact on the generation expansion decision. The apparent accuracy of the approximation combined with the greatly improved computational time indicates that the StoExp ED may be an acceptable compromise for exploring effects of high wind penetration on the thermal generation requirements.

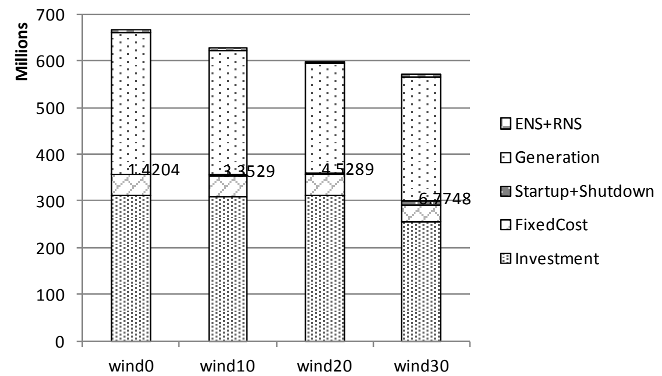

Fig. 4. Cost decomposition for thermal generation with the StoExp UC model

TABLE VI
STOEXP ED MODEL WITH 30 SCENARIOS

		Eval. Cost (Million $)	Run Time (Sec)	Base (MW)	Medium (MW)	Peak (MW)
StoExo ED (30 Sce)	wind0	665,072	2339.7	975	670	547.5
	wind10	625,918	2080.2	975	670	547.5
	wind20	598,851	1345.7	650	940	547.5
	wind30	569,359	1136.5	650	940	547.5

The StoExp ED model relaxes all the UC constraints that involve binary on/off variables; therefore, the unit startup and shutdown costs are excluded from the objective function (14) compared to equation (1) for the StoExp UC model. In Fig. 4, the total cost, which decreases as wind power penetration increases, is decomposed into five categories. The startup and shutdown costs are only a very small part of the total cost, ranging from 0.21% to 1.19% as wind penetration level increases from 0 to 30%. Thus, ignoring the startup and shutdown cost does not impose a big impact on the total cost, which is composed mainly of investment and generation costs. At the same time, the StoExp ED model does include the ramp up and down constraints (8)-(9), so that the wind variability can still be captured to some extent. These factors contribute to explain the solution accuracy resulting from the StoExp ED model.

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C. Effect of Stochastic Granularity

The computational savings of more than 99% in our case study (Table VII) could allow the incorporation in the StoExp ED model of a better uncertainty description, such as by including more wind power scenarios. Therefore, we further examine the StoExp ED model for the 15 unit system with 30 scenarios at each load level, in total 90 scenarios, selected by using GAMS/SCENRED.

TABLE VII
RESULTS FOR STOEXP AND DETEXP UC/ED MODELS

		Eval. Cost (Million $)	Cost Difference Compared to StoExp UC	Run Time (SEC)	Time Difference Compared to StoExp UC
StoExp UC (3 Sce)	wind0	665.072		2792.1	
	wind10	625.803		4851.7	
	wind20	596.184		14456.5	
	wind30	569.359		9434.1	
StoExp ED (3 Sce)	wind0	665.072	0.00%	16.5	-99.41%
	wind10	625.918	0.02%	17.8	-99.63%
	wind20	596.184	0.00%	21.7	-99.85%
	wind30	569.359	0.00%	18.3	-99.81%
StoExp ED (30 Sce)	wind0	665.072	0.00%	2339.7	-16.20%
	wind10	625.918	0.02%	2080.2	-57.13%
	wind20	598.851	0.45%	1345.7	-90.69%
	wind30	569.359	0.00%	1136.5	-87.95%
DetExp UC (1 most repre. Sce)	wind0	665.072	0.00%	3233.4	15.80%
	wind10	625.918	0.02%	2381.9	-50.91%
	wind20	594.900	-0.22%	2044.0	-85.86%
	wind30	573.586	0.74%	1920.5	-79.64%
DetExp ED (1 most repre. Sce)	wind0	665.072	0.00%	7.8	-99.72%
	wind10	625.918	0.02%	7.8	-99.84%
	wind20	594.900	-0.22%	14.6	-99.90%
	wind30	569.359	0.00%	8.5	-99.91%

The 30-scenario StoExp ED model takes a much longer time to solve than the 3-scenario one but still less time than the StoExp UC model (Table VII). The results indicate that expansion plans for wind0, wind10 and wind30 are all the same as the ones from the StoExp ED model with 3 scenarios. However, in the wind20 case one less base unit and one more medium unit are built compared to the results from the 3-scenario StoExp ED and UC models. According to StoVal UC, in the wind20 case the expected cost of the solution found using 30 scenarios is $598.851M; i.e., 0.45% more expensive than the solution found using 3 scenarios in the StoExp ED model.

We also investigate solution robustness by calculating the standard deviation and coefficient of variation across all the original 51 scenarios for the different expansion solutions (Table VIII). It turns out that the StoExp ED model with 3 scenarios also performs better than StoExp ED model with 30 scenarios in terms of robustness, i.e. with a smaller coefficient of variation in each load season in the wind20 case when the solutions differ.

All these results imply no marginal benefit resulting from the additional wind scenarios. Thus, we conclude that the 3 scenarios selected at each load level can well represent the wind uncertainties, and are sufficient to identify the optimal expansion decisions in this simplified case study. At the other extreme, we also investigated the deterministic expansion models with UC and ED representation, by including only one scenario at each load level. These 3 scenarios were also selected by the scenario reduction algorithm to be the most representative scenarios at the different load levels. The 3 scenarios happened to be scenario 1, 4 and 9, respectively; the most likely scenarios among three previously selected for each load level. The DetExp UC model has 7,575 binary variables, 32,256 continuous variables and 61,992 constraints while the DetExp ED model has 15 binary variables, 32,256 continuous variables and 39,312 constraints.

TABLE VIII
EXPECTED COST AND ROBUSTNESS EVALUATION OF STOEXP AND DETEXP UC/ED MODELS BY LOAD SEASON

Wind level	Model*	Load Season	Expected Cost (Mill. $)	Standard Deviation (Mill. $)	Coeff. of Variation
Wind 10	StoExp UC (3 Sce)	Low	173.268	3.315	1.91%
		Med	195.578	4.421	2.26%
		High	256.956	5.112	1.99%
	StoExp ED (3 Sce)	Low	174.499	3.324	1.91%
		Med	196.833	4.440	2.26%
		High	254.585	4.091	1.61%
Wind 20	StoExp UC (3Sce)	Low	165.881	5.386	3.25%
		Med	185.173	7.537	4.07%
		High	245.130	6.571	2.68%
	StoExp ED (30 Sce)	Low	160.851	7.896	4.91%
		Med	182.918	9.517	5.20%
		High	255.082	8.772	3.44%
	DetExp UC (1 most repre. Sce)	Low	163.920	8.544	5.21%
		Med	183.926	7.541	4.10%
		High	247.054	7.675	3.11%
Wind 30	StoExp UC (3Sce)	Low	152.873	9.237	6.04%
		Med	171.186	12.209	7.13%
		High	245.300	11.065	4.51%
	DetExp UC (1 most repre. Sce)	Low	158.778	6.245	3.93%
		Med	175.504	9.158	5.22%
		High	239.304	9.486	3.96%

*When several models give the same expansion result, we only list one model, i.e. the first one to occur with this result in Table VII.

In cases other than wind0, the DetExp UC solutions differ from the StoExp UC solutions. The total expected cost found in StoVal UC for deterministic wind10 and wind30 cases are 0.02% and 0.75% more expensive, respectively, than the corresponding stochastic solutions, while the deterministic wind20 solution is 0.22% less expensive than the stochastic solution. The better performance of wind20 resulting from the deterministic model may be caused by the 0.5% relative MIP gap assumed for all the models; i.e., some solutions may be closer to the global optimum than others. However, with respect to cost variance among all scenarios at each load level in Table VIII, StoExp UC with 3 scenarios has the smallest variation in the wind20 case.

Like the StoExp ED model, the DetExp ED model provides an acceptable approximation to the DetExp UC model with the same results for wind0, wind10 and wind20. The only difference in expansion results occur in wind30, where the results for DetExp ED are the same as in the StoExp UC and ED models and result in a better performance than the DetExp UC model by .74%. However, the robustness is less good with seasonal coefficients of variation 1 or 2 percentage points lower than for the DetExp UC model.

The computation times of different models and their expected costs evaluated by StoVal UC are summarized in

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Table VII. From all these computational results, we observe that, in this instance, 3 scenarios for each load level are sufficient to find near-optimal expansion plans in reasonable computational time. Even deterministic formulations with only one scenario perform relatively well in this small case. This somewhat surprising result may be attributed to the fact that each wind scenario covers a week, and exhibits in itself a variety of temporal patterns and levels of wind power, as can be seen in Fig. 1.

D. *Performance in a Larger System*

The computational benefit and approximation accuracy of the StoExp ED model enables the solution of a larger system, which would require prohibitive computation time by the StoExp UC model. We investigated the StoExp ED model with the three scenarios selected at each load level in Fig. 1. To have a reference case for comparison, we also solved a DetExp UC model with scenarios 1, 4 and 9 respectively at different load levels. The StoExp ED model has 20 binary variables, 82,656 continuous variables and 102,312 constraints, while the DetExp UC model has 6,740 binary variables, 27,552 continuous variables and 54,264 constraints. The computational efficiency also allows the StoExp ED model to be solved within a maximum MIP gap of 0.01%, compared to the DetExp UC model solved to its maximum accuracy within 0.5%.

The decrease in natural gas price reduces the production cost of medium and peak plants so that the coal fired base plants no longer have the distinct advantage of lower operational costs. Thus, no new coal plants are built. Increasing levels of wind power require more flexible peak units to accommodate the variable wind power (Fig. 5). The StoExp ED model generates the same expansion decision as the DetExp UC model for wind0 and wind10. StoExp ED suggests building one more peak unit and two more peak units compared to DetExp for UC wind20 and wind30, respectively.

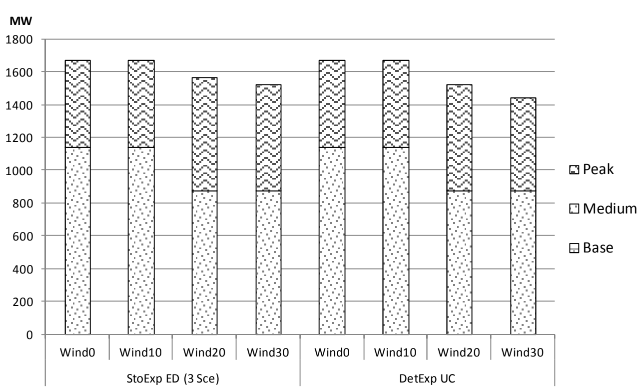

Fig. 5. Expansion capacity (MW) by unit technology at different wind penetration levels for the StoExp ED and DetExp UC models.

The computation times are presented in Table IX, which once again demonstrate the computational advantage of the StoExp ED model. The costs shown were computed by the StoVal UC model with the full set of 51 scenarios. Table VIII shows the relative cost difference of the StoExp ED model compared to the DetExp UC model as the reference case. The small differences, all falling within 0.09%, indicate an accurate approximation of ED model in making the expansion decisions. At wind30, the ED model even results in lower cost than the solution found by the UC model.

TABLE IX
RESULTS FOR STOEXP ED AND DETEXP UC MODELS

		Eval. Cost (Million $)	Cost Difference Compared to DetExp UC	Run Time (SEC)	Time Difference Compared to DetExp UC
StoExp ED (3 Sce)	wind0	806.746	0.00%	374.04	-52.13%
	wind10	737.392	0.00%	419.89	-65.18%
	wind20	674.227	0.09%	338.13	-46.97%
	wind30	623.008	-0.02%	363.32	-80.00%
DetExp UC (1 most repre. Sce)	wind0	806.746		781.38	
	wind10	737.392		1205.91	
	wind20	673.641		637.65	
	wind30	623.115		1816.76	

V. CONCLUSIONS

Wind power increases the variability and uncertainty in power system operations. The generation expansion planning problem with high wind penetration levels must consider these operational impacts as well as the overall wind resource uncertainty in the optimal generation expansion plan.

In this paper we presented a stochastic generation expansion model that includes UC constraints. Due to the high computational complexity of the model we also introduced a reduced version of the expansion model based on ED constraints and the continuous ramping constraints for all the thermal units, by relaxing all the UC constraints that involve the binary turn on/off variables. In two case studies with 15 and 40 units, respectively, we demonstrated the advantage of the StoExp ED model in terms of solution accuracy and computational efficiency. We find that the StoExp ED model reduces the computational time more than 99%, thereby allowing for the inclusion of more wind power scenarios in the model. However, our results also indicate that a reduced set of scenarios is sufficient to represent a variety of variability characteristics of the wind output between the consecutive hours and evaluate its impact on the optimal expansion plan. Finally, the inclusion of the continuous ramping constraints in the StoExp ED model appears sufficient to give an accurate expansion solution whereas the additional binary constraints in StoExp UC induce only small changes in the results.

The limited problem size these models can handle may contribute to the similarity in the solution results observed in this analysis. The somewhat simplistic treatment of short-term forecasting errors through additional operating reserves may also influence the results. In this paper we modeled wind variability by collecting sample paths from historical data. Alternatively, with additional data wind uncertainty itself could also be modeled as a stochastic process to generate different ramping up and down scenarios depending on the current output level. Developing this methodology is a topic for future research. Moreover, the expansion model can be extended to a three-stage stochastic model with a third stage explicitly addressing the short term wind forecasting uncertainty, the second stage dealing with the long term variability of the wind, and the first stage making the

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investment decision. More efficient formulations of the optimization problem, possibly through decomposition schemes, will also be required to solve larger and more realistic cases. Finally, consideration of investment timing and decentralized decision making dynamics in electricity markets also represent interesting directions for future work.

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