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The Impacts of Stochastic Programming and Demand Response on Wind Integration

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Abstract Wind imposes costs on power systems due to uncertainty and variability of real-time resource availability. Stochastic programming and demand response are offered as two possible solutions to mitigate these so-called wind-uncertainty costs. We examine the benefits of these two solutions, and show that although both will reduce wind-uncertainty costs, demand response is significantly more effective. We also examine the impacts of using demand response and stochastic optimization together. We show that most of the value of demand response in reducing wind-uncertainty costs remain if a stochastic optimization is used and that there are subadditive benefits from using the two together.

Keywords Wind power generation · unit commitment · wind-forecast error · real-time pricing · stochastic programming

1 Introduction

The past several years have seen increased interest in renewable energy. Much of this interest is driven by environmental, energy security, and other concerns surrounding fossil fuels and conventional generation technologies. This drive toward greater use of renewables has led to increases in installed wind capacity, due to the maturity and low cost of wind compared to most other renewable technologies. The integration of wind into power systems can, however, impose costs and present challenges for

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short-run system operations and planning, due to the variable and uncertain nature of real-time wind availability and the limited dispatchability of wind.

Wind variability may require more ancillary services (*e.g*. regulation, spinning, and non-spinning reserves) to be procured or more generating capacity to be committed to ensure system stability and reliability [22,33,14,23]. If wind resources are concentrated in a geographical region, bottlenecks may appear in the transmission network, requiring curtailment of wind generation [24,13,30]. Wind can also require more cycling and real-time redispatching of conventional generators. This increases unit commitment, dispatch, and maintenance costs. Moreover, because real-time wind availability is uncertain when commitment decisions are made, the set of generators that are committed may be suboptimal if poor forecasts are used when making operational decisions day- and hour-ahead. Several studies estimate the impact of these types of challenges with wind integration, showing that they can impose significant costs on the order of \$5/MWh of wind on the system [11,12,17,32].

Several solutions are offered to mitigate these cost impacts of wind. One is to use energy storage to reduce variability and uncertainty in the net output of the joint wind generator and storage device [34,8,9,24,25,10,1,3,20,36]. Although storage can mitigate costs related to wind and can have ancillary benefits, such as reducing the impacts of transmission constraints [24,13], the currently high capital cost of storage makes this an uneconomic solution. Another strategy is to better account for wind variability and uncertainty when making operational decisions by incorporating the distribution of wind availability in a stochastic unit commitment model [7,18,37]. A third suggestion is to leverage some form of demand response (DR) to make electricity loads more closely follow real-time wind availability. This could take the form of a direct mechanism, such as load control [26], or an indirect mechanism, which uses price or other signals to encourage customers to adjust their demand. Real-time pricing (RTP), which sets electricity prices dynamically based on the actual marginal cost of energy, can both increase wind use and reduce operational cost impacts of wind [29,31]. This is because real-time prices rise, reducing demand, during periods in which wind availability is overestimated and high-cost generation must be deployed in real-time and *vice versa*.

One limitation of existing analyses, however, is that they examine the value of DR if the system is operated using a deterministic model. This paper expands this line of research by examining the relative benefits of DR (specifically, RTP) and stochastic optimization in reducing the cost impacts of renewables (specifically, wind). We focus on the effect of wind uncertainty on the scheduling of conventional generators and the resulting cost impacts, which we henceforth refer to as the 'wind-uncertainty cost.' This is done by comparing cases in which the system is dispatched with uncertain future wind availability to a counterfactual best-case scenario with perfect foresight of wind. The difference in system operation costs between these cases represents the added costs imposed by wind uncertainty. We compare wind-uncertainty costs in cases with and without RTP and with and without the use of a stochastic planning model. Our results show that both RTP and stochastic optimization reduce wind-uncertainty costs, although RTP has a much greater benefit. We also find that most of the benefits of RTP in reducing wind-uncertainty costs remain if a stochastic optimization model is used. Nevertheless, there are incremental benefits to introducing both stochastic optimization and RTP together, as opposed to only RTP. We also explore the effect of varying the accuracy of the wind forecasts used to schedule generation. The remainder of the paper is organized as follows: section 2 describes the model and data underlying our analysis, section 3 summarizes our results, and section 4 concludes.

2 Model and Data

Our analysis uses a stochastic unit commitment model with RTP and our case study is based on the Electricity Reliability Council of Texas (ERCOT) system [29,37]. Since our focus is on the impact of wind variability and uncertainty on system costs, we assume wind availability to be the sole uncertain parameter. The model is divided into two main parts—a unit commitment model and a scenario tree. The scenario tree feeds different possible real-time wind availabilities to the commitment model, which optimizes generator commitments and dispatch. In the cases with RTP the price-responsiveness of the load is modeled using a price-sensitive inverse demand function. In the other cases the loads are assumed to be fixed. The model is used to simulate power system operations over a year with high wind penetrations. The models are formulated using `GAMS` and solved with `CPLEX` 9.0.

2.1 Unit Commitment and Dispatch Model

The unit commitment and dispatch is optimized using a mixed-integer linear stochastic programming model with recourse. The model assumes that conventional generators have a three-part cost structure, consisting of variable, spinning, and startup costs, and includes standard system and generator constraints. All commitment and dispatch decisions are modeled at hourly time intervals. The model neglects transmission constraints. This assumption can overstate the scale of wind-uncertainty costs, since transmission constraints can limit the amount of wind that can be feasibly used by the system [24,13,30]. To give the model formulation, we first define the following indices and parameters:

t: time index,
ξ: scenario index,
i: conventional generator index,
w: wind generator index,
π_ξ: probability of scenario ξ,
$\Xi_{\xi,t}$: set of scenarios that are indistinguishable from ξ at hour t,
$c_i^V(\cdot)$: generator i's variable cost,
c_i^N: generator i's spinning cost,
c_i^{SU}: generator i's startup cost,
K_i^-: generator i's minimum operating point when online,
K_i^+: generator i's maximum operating point when online,
R_i^-: generator i's rampdown limit,
R_i^+: generator i's rampup limit,

$\overline{\rho}_i^{sp}$: generator i's spinning reserve capacity,
$\overline{\rho}_i^{ns}$: generator i's non-spinning reserve capacity,
τ_i^-: generator i's minimum down-time,
τ_i^+: generator i's minimum up-time,
$\omega_{w,t,\xi}$: generation available from wind generator w in hour t under scenario ξ,
$p_t(\cdot)$: inverse demand function in hour t, and
η^{sp}: spinning reserve requirement as a fraction of total reserve.

We also define the following decision variables:

$q_{i,t,\xi}$: generation provided by generator i in hour t under scenario ξ,
$\rho_{i,t,\xi}^{sp}$: spinning reserves provided by generator i in hour t under scenario ξ,
$\rho_{i,t,\xi}^{ns}$: non-spinning reserves provided by generator i in hour t under scenario ξ,
$u_{i,t,\xi}$: binary variable indicating if unit i is online in hour t under scenario ξ,
$s_{i,t,\xi}$: binary variable indicating if unit i is started-up in hour t under scenario ξ,
$h_{i,t,\xi}$: binary variable indicating if unit i is shutdown in hour t under scenario ξ,
$g_{w,t,\xi}$: wind generation provided by wind generator w in hour t under scenario ξ,
$l_{t,\xi}$: load served in hour t under scenario ξ, and
$\eta_{t,\xi}^T$: total reserve requirement in hour t under scenario ξ.

The model is given by:

$$\max \sum_{\xi,t} \pi_\xi \left\{ \int_0^{l_{t,\xi}} p_t(x)dx - \sum_i [c_i^v(q_{i,t,\xi}) + c_i^N u_{i,t,\xi} + c_i^{SU} s_{i,t,\xi}] \right\}, \tag{1}$$

$$\text{s.t.} \quad l_{t,\xi} = \sum_i q_{i,t,\xi} + \sum_w g_{w,t,\xi}, \qquad \forall\, t,\xi; \tag{2}$$

$$\sum_i (\rho_{i,t,\xi}^{sp} + \rho_{i,t,\xi}^{ns}) \geq \eta_{t,\xi}^T, \qquad \forall\, t,\xi; \tag{3}$$

$$\sum_i \rho_{i,t,\xi}^{sp} \geq \eta^{sp} \eta_{t,\xi}^T, \qquad \forall\, t,\xi; \tag{4}$$

$$\eta_{t,\xi}^T = 0.03 \cdot l_{t,\xi} + 0.05 \cdot \sum_w g_{w,t,\xi}, \qquad \forall\, t,\xi; \tag{5}$$

$$K_i^- u_{i,t,\xi} \leq q_{i,t,\xi}, \qquad \forall\, i,t,\xi; \tag{6}$$

$$q_{i,t,\xi} + \rho_{i,t,\xi}^{sp} \leq K_i^+ u_{i,t,\xi}, \qquad \forall\, i,t,\xi; \tag{7}$$

$$q_{i,t,\xi} + \rho_{i,t,\xi}^{sp} + \rho_{i,t,\xi}^{ns} \leq K_i^+, \qquad \forall\, i,t,\xi; \tag{8}$$

$$0 \leq \rho_{i,t,\xi}^{sp} \leq \overline{\rho}_i^{sp} u_{i,t,\xi}, \qquad \forall\, i,t,\xi; \tag{9}$$

$$0 \leq \rho_{i,t,\xi}^{ns} \leq \overline{\rho}_i^{ns}, \qquad \forall\, i,t,\xi; \tag{10}$$

$$R_i^- \leq q_{i,t,\xi} - q_{i,t-1,\xi}, \qquad \forall\, i,t,\xi; \tag{11}$$

$$q_{i,t,\xi} - q_{i,t-1,\xi} + \rho_{i,t,\xi}^{sp} + \rho_{i,t,\xi}^{ns} \leq R_i^+, \qquad \forall\, i,t,\xi; \tag{12}$$

$$\sum_{y=t-\tau_i^+}^{t} s_{i,y,\xi} \leq u_{i,t,\xi}, \qquad \forall\, i,t,\xi; \tag{13}$$

$$\sum_{y=t-\tau_i^-}^{t} h_{i,y,\xi} \leq 1 - u_{i,t,\xi}, \qquad \forall\, i,t,\xi; \tag{14}$$

$$s_{i,t,\xi} - h_{i,t,\xi} = u_{i,t,\xi} - u_{i,t-1,\xi}, \qquad \forall\, i,t,\xi; \tag{15}$$

$$0 \le g_{w,t,\xi} \le \omega_{w,t,\xi}, \qquad \forall\, w,t,\xi; \tag{16}$$

$$l_{t,\xi} \ge 0, \qquad \forall\, t,\xi; \tag{17}$$

$$u_{i,t,\xi}, s_{i,t,\xi}, h_{i,t,\xi} \in \{0,1\}, \qquad \forall\, i,t,\xi; \tag{18}$$

$$q_{i,t,\xi} = q_{i,t,\xi'}, \qquad \forall\, i,t,\xi,\xi' \in \Xi_{\xi,t}; \tag{19}$$

$$\rho^{sp}_{i,t,\xi} = \rho^{sp}_{i,t,\xi'}, \qquad \forall\, i,t,\xi,\xi' \in \Xi_{\xi,t}; \tag{20}$$

$$\rho^{ns}_{i,t,\xi} = \rho^{ns}_{i,t,\xi'}, \qquad \forall\, i,t,\xi,\xi' \in \Xi_{\xi,t}; \tag{21}$$

$$u_{i,t,\xi} = u_{i,t,\xi'}, \qquad \forall\, i,t,\xi,\xi' \in \Xi_{\xi,t}; \tag{22}$$

$$s_{i,t,\xi} = s_{i,t,\xi'}, \qquad \forall\, i,t,\xi,\xi' \in \Xi_{\xi,t}; \tag{23}$$

$$h_{i,t,\xi} = h_{i,t,\xi'}, \qquad \forall\, i,t,\xi,\xi' \in \Xi_{\xi,t}; \tag{24}$$

$$g_{w,t,\xi} = g_{w,t,\xi'}, \qquad \forall\, i,t,\xi,\xi' \in \Xi_{\xi,t}; \tag{25}$$

$$l_{t,\xi} = l_{t,\xi'}, \qquad \forall\, i,t,\xi,\xi' \in \Xi_{\xi,t}. \tag{26}$$

Objective function (1) maximizes expected social welfare, which is defined as the difference between the integral (up to the amount of load served, $l_{t,\xi}$) of the inverse demand function and total generation costs. In cases without RTP, the load in each hour is fixed. Thus the integral term is fixed and maximizing expected social welfare is equivalent to minimizing expected cost. In cases with RTP, the inverse demand function is assumed to be a step function, and thus the integral term is piecewise-linear in $l_{t,\xi}$. The variable generation functions, $c_i^v(q_{i,t,\xi})$, are assumed to be piecewise-linear in $q_{i,t,\xi}$. These assumptions ensure that the mixed-integer program is linear in the decision variables.

Constraints (2) are load-balance restrictions, which ensure that the demand is served in each hour by conventional or wind generation. Constraints (3) through (5) impose the spinning and non-spinning reserve requirements. The total reserve requirement in each hour is determined using the so-called '$3+5$ rule' used in the National Renewable Laboratory's (NREL's) Western Wind and Solar Integration Study [19]. This rule sets the total reserve requirement in each hour to equal 3% of the system load plus 5% of forecasted wind generation, which is imposed by constraints (5). Note that this rule makes the reserve requirement scenario-dependent, since loads and wind generation will generally vary between the scenarios modeled, and reserve requirements will be greater in high-wind or -load scenarios. This is explicitly captured in our model since $\eta^T_{t,\xi}$ is indexed by scenario. We further assume that at least half of the total reserves must be spinning reserves (*i.e.* $\eta^{sp} = 0.5$).

Constraints (6) through (8) ensure that each conventional generator operates between its minimum and maximum generation point whenever online, and that it would not violate the upper-bound on its output if it has to provide additional energy due to reserves being required in real-time. Constraints (9) and (10) enforce each generator's ancillary service qualifications. Note that only generators with high ramping capabilities and no minimum up- and down-time restrictions (*e.g.* natural gas-fired combustion turbines) are qualified to provide non-spinning reserves. Constraints (11) and (12) enforce each generator's ramping limits. Constraints (13) and (14) impose each generator' minimum up- and down-times when they are started up and shutdown, respectively. Constraints (15) define the startup and shutdown state variables in terms of changes in the online state variables. Constraints (16) limit each wind generator's production based on wind availability under each scenario. Constraints (17) and (18) impose non-negativity and integrality restrictions.

Constraints (19) through (26) are nonanticipativity restrictions. These constraints ensure that the solution obtained by the model are implementable, meaning that they do not depend, at time t, on information that is not yet available at that time. The nonanticipativity constraints allow us to formulate our model in a compact manner, without having to explicitly specify the structure of the underlying scenario tree [16, 27].

2.2 Model Data

Our simulations are based on data from the ERCOT power system. We model all of the conventional generators that were in the ERCOT system in 2005. Nuclear generators are assumed to be must-run units that always run at maximum capacity. Costs of other conventional generators are estimated using heat rate and fuel and emission permit price data obtained from Platts Energy and Global Energy Decisions. Generator constraint data are also obtained from these sources. Table 1 summarizes technical characteristics of the conventional generators modeled, based on fuel type.

Table 1 Number of Units, Total Generating Capacity, and Average Heat Rate and Minimum Up- and Down-Time of Different Generator Types

Generator Type (Fuel)	Number of Units	Total Capacity (MW)	Heat Rate (GJ/MWh)	Minimum Up-Time (Hours)	Minimum Down-Time (Hours)
Coal	28	16081	11289	24	24
Natural Gas	320	59717	10439	8	11
Hydroelectric	20	529	N/A	0	0
Landfill Gas	7	44	10551	0	0

Hourly loads and the inverse demand functions in objective function (1) are based on historical load data from 2005, obtained from the Public Utility Commission of Texas (PUCT). In fixed-load cases, the $l_{t,\xi}$ variables model are fixed based on these historical data. Thus the integral term in objective function (1) is fixed and the objective is equivalent to expected cost minimization. In the cases with RTP, we use an assumed demand elasticity and calibrate the hourly inverse demand functions so the actual historical load in the hour corresponds to the historical average retail price of electricity in 2005 [5, 6, 31, 29]. Thus the hour-t demand function has the property that:

$$p_t(l_t) = p^{ret}, \tag{27}$$

where l_t is the actual historical load in hour t and p^{ret} is the average retail price of electricity in 2005. In doing so we only model own-price elasticities, assuming cross-price elasticities to be zero. This assumption can potentially understate the extent to which loads shift from on- to off-peak periods under RTP, since cross-price elasticities between such hours tend to be slightly negative [6,29,31]. This load shifting is somewhat captured by our model, however, because on-peak loads tend to decrease due to high real-time prices while off-peak loads increase because of relatively low prices.

We estimate the 2005 retail price of electricity, p^{ret}, using tariff filings with the PUCT. Because these retail prices include non energy-related charges (*e.g*. charges for distribution and end-user services), we subtract these from the tariff to yield a price per MWh of energy consumed. We consider cases with the own-price elasticity of demand ranging between -0.1 and -0.3, which is consistent with empirical estimates of short-term electricity demand elasticities [21].

We approximate the hourly inverse demand function as non-increasing step functions with 100 segments. Thus the integral term in objective function (1) is a concave piecewise-linear function of $l_{t,\xi}$. Figure 1 shows a representative inverse demand function, the function calibration condition in equation (27), and its piecewise-linear approximation. The hashed region in the figure also demonstrates how the integral term in objective function (1) is computed.

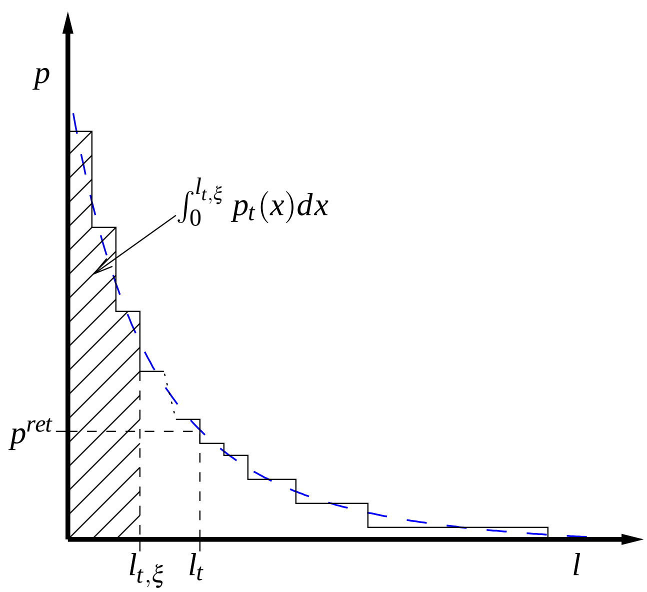

Fig. 1 Representative inverse demand function and its piecewise-linear approximation.

2.3 Wind Model

In order to analyze a high-wind penetration case, we model all wind plants that are planned to be installed in ERCOT by the end of 2011. This yields about 14 GW of nameplate wind capacity, or 18% of ERCOT's total generating capacity in 2005. We use mesocale modeled data available in NREL's Western Wind Resources Dataset (WWRD)[1] to model real-time availability of the wind generators. This dataset includes hourly output, as a percentage of nameplate capacity, at a number of locations in Texas for the year 2005. The modeled wind generators are associated with locations in the dataset based on geographic distance, and the data are used to determine the actual modeled energy available in each hour.[2] Thus if we let $\bar{\omega}_w$ represent the nameplate capacity of wind generator w, actual modeled wind availability in hour t is assumed to equal:

$$\phi_{w,t} \cdot \bar{\omega}_w, \tag{28}$$

where $\phi_{w,t}$ is a value between 0 and 1 taken from the WWRD.

The evolution of wind availability is modeled in the stochastic unit commitment using a scenario tree. In each hour, τ, our scenario tree has a three-stage structure [37]. The first stage, which covers the first three hours (τ through $\tau+2$), is assumed to be deterministic with wind availability perfectly known (and equal to the actual modeled wind availability, as defined by equation (28)). The second stage, which covers the following three hours ($\tau+3$ through $\tau+5$), has three possible wind availability realizations. The last stage, which covers the remaining hours, has six possible scenarios. Figure 2 is a schematic showing the assumed structure of the scenario tree.

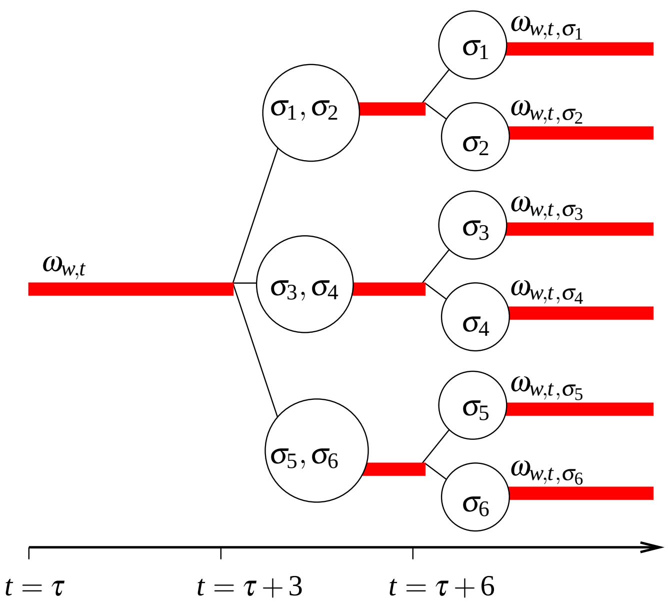

Fig. 2 Assumed structure of scenario tree.

[1] These data are publicly available at http://wind.nrel.gov/Web_nrel/.

[2] We caveat the word 'actual' with the word 'modeled' to stress that we use modeled data in our analysis. Thus these values may differ from actual weather conditions in 2005.

Power system operations over the year are modeled one day at a time using a rolling two-day planning horizon. The optimization starts at noon of each day and optimizes system operations over a 48-hour horizon, using the scenario tree structure shown in figure 2. The scenario tree then rolls forward three hours and the system is reoptimized over a 45-hour horizon starting from 3 pm. The starting state of the system (*i.e*. generator commitments and outputs) at 3 pm is fixed based on the solution for noon to 3 pm obtained from the first optimization. The scenario tree is also updated, reflecting the fact that wind availability between 3 pm and 6 pm is now deterministic and availability between 6 pm and 9 pm has three possible scenarios. This rolling process is repeated eight times to determine system operations over the day, at which point the process is repeated for the following day (*i.e*. the rolling process restarts by solving the model with a 48-hour optimization horizon). The second day is included in the optimization horizon to ensure that sufficient generating capacity remains committed at the end of each day to serve the following day's load [31, 29].

The scenario tree is generated by assuming that the system is committed and dispatched using imperfect wind forecasts. The forecasts are generated by adding a forecast error, $\varepsilon_{w,t}$, to the actual modeled wind availability. Thus the forecasted availability from wind generator w in hour t would be given by $(\varepsilon_{w,t} + \phi_{w,t}) \cdot \bar{\omega}_w$. Following the California ISO's renewable integration study, we assume that the forecast errors follow an unbiased first-order autocorrelated truncated normal distribution [23].[3] We assume an autocorrelation coefficient of 0.60 and standard deviations ranging between 0.05 and 0.15, which is consistent with forecast error studies [23].[4] The different standard deviations capture the effect of forecast quality, with a higher standard deviation corresponding to lower-quality forecasts. Monte Carlo simulation is used to generate 1000 different sample paths of the forecasts. The 1000 sample paths are reduced to the six scenarios and corresponding probabilities modeled in the stochastic unit commitment using the forward selection algorithm in the `SCENRED` scenario reduction tool [15].

In addition to modeling the operation of the system using the stochastic unit commitment model, we also consider deterministic and perfect-foresight cases. The deterministic case assumes that the system is committed and dispatched using a single point forecast of future wind availability. As in the stochastic unit commitment case, the system is optimized in a rolling fashion. In each hour wind availability is perfectly known in the first three hours whereas a single point forecast of wind availability is used in the subsequent hours. This point forecast is generated using the `SCENRED` scenario reduction tool to reduce the 1000 sample paths into a single scenario. The unit commitment model is solved, and the model then rolls forward three hours (updating the starting state of the system and forecasts) and reoptimizes for the remaining hours. This proceeds iteratively as in the stochastic unit commitment case. The perfect-foresight case is modeled by optimizing the system against actual modeled wind availability, as defined in equation (28). This is done one day at a time using a 48-hour optimization horizon.

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[3] Details of the wind forecast error model are given in appendix C of the California ISO's report.

[4] Section 2.4 of appendix B of the California ISO's report discusses empirical findings regarding the autocorrelation of wind forecast errors.

2.4 Cases

Table 2 summarizes the six different cases that we model, which vary in terms of whether demand is price-responsive or not and how wind uncertainty is handled. Typically differences in system operation costs between the different cases modeled are used to measure the wind-uncertainty cost [11, 12, 17, 32]. In our case, however, social welfare differences are more appropriate measures [29]. The reason is that we model cases in which demand responds to prices, which can result in consumer welfare changes that are not reflected by generation costs. Thus, letting W_α denote total annual social welfare in case α, differences in W_α between the cases modeled capture the added costs or benefits of wind uncertainty and price-responsive loads. Letting δ_α denote total wind annual generation used in case α, we divide these cost differences by δ_α to arrive at a wind-uncertainty cost per MWh of wind used. For instance, the quantity:

$$\frac{W_1 - W_3}{\delta_3},$$

represents the added costs imposed by wind uncertainty when a point forecast of wind is used to dispatch the system and loads are not price-responsive. Similarly:

$$\frac{W_5 - W_3}{\delta_5},$$

represents the cost savings from using stochastic programming to commit the system when loads are not price-responsive.

Table 2 Cases Modeled

Case	Optimization	Loads
1	Perfect foresight	Fixed
2	Perfect foresight	RTP
3	Deterministic	Fixed
4	Deterministic	RTP
5	Stochastic	Fixed
6	Stochastic	RTP

An issue raised in comparing social welfare between cases with and without RTP, however, is that demand response increases social welfare, independent of its effect on wind-uncertainty costs. This is because if consumers receive real-time price signals and make demand decisions based on these prices, energy is allocated more efficiently. Indeed, these efficiency gains are a primary reason that economists advocate the introduction of RTP or other DR programs with time-variant electricity pricing [4, 6]. The difference, $W_2 - W_1$, measures these allocative efficiency gains that result from introducing RTP in the absence of wind uncertainty. Thus the welfare differences between case 2 and cases with wind uncertainty and RTP measure wind-uncertainty costs with RTP (*i.e.* $(W_2 - W_4)/\delta_4$ measures wind-uncertainty costs when loads are price-responsive and a point forecast of wind is used to commit the system, while $(W_2 - W_6)/\delta_6$ measures these costs if stochastic programming is used).

3 Results

Table 3 summarizes annual wind-uncertainty costs in the base case in which loads are fixed and generation is scheduled using a deterministic planning model. This quantity is defined as $(W_1 - W_3)/\delta_3$, which gives the wind-uncertainty cost on a dollar per MWh of wind produced basis. The table shows that wind uncertainty can impose noticeable costs, which are increasing in the wind forecast error standard deviation. This is in keeping with the intuition that greater wind uncertainty will have greater impacts on the system. These results can also be used to estimate the value of increasing wind forecast accuracy, *e.g.* reducing the forecast error standard deviation from 0.15 to 0.05 reduces wind-uncertainty costs by more than 84%.

Table 3 Annual Wind-Uncertainty Cost ($/MWh of Wind) With Fixed Loads and Deterministic Programming

Wind Forecast Error Standard Deviation	Wind Uncertainty Cost ($/MWh of Wind)
0.05	0.60
0.1	1.95
0.15	3.94

Tables 4 and 5 summarize the value of RTP and stochastic programming, respectively, in mitigating wind-uncertainty costs when each is individually introduced to the system. The values in table 4 are computed as $(W_1 - W_3)/\delta_3 - (W_2 - W_4)/\delta_4$. The first term, $(W_1 - W_3)/\delta_3$, gives the wind-uncertainty cost with fixed loads and deterministic programming while the second term, $(W_2 - W_4)/\delta_4$, gives the wind-uncertainty cost with RTP and deterministic programming. Thus the difference between the two terms measures the value of RTP in reducing wind-uncertainty costs. As expected, RTP can yield significant wind-uncertainty cost reductions and this benefit is increasing in the price-responsiveness (elasticity) of the demand. This benefit of RTP is also reduced with less accurate wind forecasts. For instance, RTP eliminates 33–68% of wind-uncertainty costs when the most accurate wind forecasts are used, as opposed to only 20–58% with the least-accurate forecasts. The values in table 5 are similarly computed as $(W_1 - W_3)/\delta_3 - (W_1 - W_5)/\delta_5$. While stochastic programming also helps reduce wind-uncertainty costs, it gives smaller cost reductions of 6–7%, as opposed to the 20–68% reductions with RTP.

Table 4 Value ($/MWh of Wind) of RTP in Reducing Wind-Uncertainty Costs With Deterministic Programming

Wind Forecast Error	Demand Elasticity		
Standard Deviation	−0.1	−0.2	−0.3
0.05	0.20	0.30	0.41
0.1	0.70	1.01	1.24
0.15	0.80	1.76	2.27

Table 5 Value ($/MWh of Wind) of Stochastic Programming in Reducing Wind-Uncertainty Costs with Fixed Loads

Wind Forecast Error Standard Deviation	Value ($/MWh of wind)
0.05	0.04
0.1	0.12
0.15	0.25

Another question raised by this analysis is the effect of introducing stochastic programming and RTP together on wind-uncertainty costs. Since stochastic programming yields more robust commitment decisions, it is surmised that RTP has less of a cost mitigation impact when introduced on top of stochastic programming [29]. Tables 6 and 7 summarize these interaction effects. Table 6 shows the sum of the value of introducing RTP and stochastic programming individually on reducing wind-uncertainty costs. The values in this table are the sum of the values reported in table 4 and 5, or:

$$\left(\frac{W_1 - W_3}{\delta_3} - \frac{W_2 - W_4}{\delta_4}\right) + \left(\frac{W_1 - W_3}{\delta_3} - \frac{W_1 - W_5}{\delta_5}\right)$$
$$= 2 \cdot \frac{W_1 - W_3}{\delta_3} - \frac{W_2 - W_4}{\delta_4} - \frac{W_1 - W_5}{\delta_5}.$$

Table 7 summarizes the value of introducing RTP and stochastic programming together. This value is computed as $(W_1 - W_3)/\delta_3 - (W_2 - W_6)/\delta_6$, or as the difference between wind-uncertainty costs with fixed loads and deterministic programming, $(W_1 - W_3)/\delta_3$, and wind-uncertainty costs with RTP and stochastic programming, $(W_2 - W_6)/\delta_6$. The values in table 6 are all greater than those in table 7, showing that when RTP is introduced in conjunction with stochastic programming, the benefit of the two together will be less than the sum of the values of introducing the two separately. However, the difference in values between the two tables are between 3% and 12%, indicating that introducing both stochastic programming and RTP together provides non-trivial wind-uncertainty cost reductions, if these measures can both be feasibly implemented.

Table 6 Sum of Values of RTP and Stochastic Programming ($/MWh of wind) in Reducing Wind-Uncertainty Costs

Wind Forecast Error	Demand Elasticity		
Standard Deviation	−0.1	−0.2	−0.3
0.05	0.24	0.33	0.45
0.1	0.82	1.13	1.36
0.15	1.05	2.01	2.52

This effect of introducing RTP and stochastic programming together can also be viewed as reducing the incremental benefit of stochastic programming when a RTP

Table 7 Value of RTP and Stochastic Programming Together ($/MWh of Wind) in Reducing Wind-Uncertainty Costs

Wind Forecast Error	Demand Elasticity		
Standard Deviation	−0.1	−0.2	−0.3
0.05	0.23	0.32	0.42
0.1	0.75	1.05	1.26
0.15	0.92	1.86	2.33

program is in place. Table 8 shows the value of stochastic over deterministic programming when RTP is present. The values in the table are computed as the difference between the values in table 7 and 4 or as:

$$\left(\frac{W_1 - W_3}{\delta_3} - \frac{W_2 - W_6}{\delta_6}\right) - \left(\frac{W_1 - W_3}{\delta_3} - \frac{W_2 - W_4}{\delta_4}\right) = \frac{W_2 - W_4}{\delta_4} - \frac{W_2 - W_6}{\delta_6}.$$

Comparing tables 8 and 5 shows that when an RTP program is in place, stochastic programming only achieves 17–50% of the cost savings that would be realized with fixed loads. Moreover, the value of stochastic programming decreases as the elasticity of demand increases. This shows that more price-responsive loads reduce the incremental benefits of stochastic optimization in mitigating wind-uncertainty costs.

Table 8 Value ($/MWh) of Stochastic Programming over Deterministic Programming in Reducing Wind-Uncertainty Costs with RTP

Wind Forecast Error	Demand Elasticity		
Standard Deviation	−0.1	−0.2	−0.3
0.05	0.02	0.02	0.01
0.1	0.05	0.04	0.02
0.15	0.12	0.09	0.06

4 Conclusions

This paper analyzes the relative value of stochastic programming and DR (specifically, RTP) in reducing wind-uncertainty costs. We develop a stochastic unit commitment and dispatch model with RTP and a corresponding scenario tree to represent uncertain wind forecasts. Simulations are done for the ERCOT power system using conventional generation and load data from 2005 and a high wind penetration scenario that includes all wind generators that are planned to be installed by the end of 2011. Our results show that stochastic programming and RTP mitigate wind-uncertainty costs, but that RTP yields greater benefits compared to stochastic programming. For instance, with the lowest demand elasticity of −0.1 wind-uncertainty costs are much lower when introducing RTP than when introducing stochastic programming. Stochastic programming, by contrast, only yield cost reductions of less than 7% compared to deterministic programming. On the other hand, since electricity markets typically trade billions of dollars worth of energy annually, a 7% cost savings is significant in absolute terms. Moreover, since most of the value from introducing RTP and stochastic programming individually are derived from introducing the two together, there is incremental value in using stochastic programming and RTP together to reduce wind-uncertainty costs. Our results also show that RTP retains its value in mitigating wind-uncertainty costs, even if the system is operated using a stochastic planning model. Although our measure of wind-uncertainty costs is a standard metric used to evaluate the cost of integrating renewables in power systems, other metrics are available. This includes the value of stochastic solution and expected value of perfect information, which are commonly used in the stochastic optimization literature [2]. We opt to measure the benefits of stochastic optimization using wind-uncertainty costs, since it is the standard metric used by power system engineers.

While RTP has greater value in reducing wind-uncertainty costs, implementing a working program requires major communication, metering, and smart appliance investments. Thus stochastic programming may be a more implementable policy in the near term. On the other hand, stochastic programming imposes greater computational costs. Our relatively simple stochastic model with a six-leaf scenario tree takes an average of 1290 s of CPU time to determine unit commitments for a single day (all of the computations are done on a 2.7 GHz Pentium Core 2 processor). Conversely, the deterministic model only takes an average of 340 s to solve. System operators typically have very limited windows of time within which to determine day-ahead unit commitments [35]. Thus implementing stochastic programming may not be technically feasible with today's computational capabilities. We do not, however, use any decomposition schemes in solving our problems—rather we solve the deterministic equivalent problem using the nonanticipativity constraints. Such schemes may make larger stochastic unit commitment problems considerably more tractable. Moreover, improvements in linear and integer program solvers can further reduce optimization times for the stochastic model.

Further refinement of day-ahead, intraday, and real-time planning models can yield further cost reductions beyond our estimates here. For instance, our analysis uses a relatively simple heuristic rule to determine load- and wind-dependent spinning and non-spinning requirements. More sophisticated techniques, for instance incorporating seasonal and diurnal differences in wind profiles, may yield reserve requirements that result in more efficient system operations. This is an area of active research, since most system operators with high renewable penetrations still rely on deterministic models to schedule generation [14, 28]. Such refinements could yield different wind-uncertainty costs than those reported here, although we expect our general finding regarding the value of RTP to hold if such models are used.

It is important to note that our findings regarding the cost benefits of RTP are highly dependent on our assumption that price signals will have an immediate impact on electricity demand. If RTP is coupled with automated demand control technologies, such as smart thermostats, then such a response could be expected. If, however, the system is left to rely on consumers manually monitoring price signals and adjusting electricity demand, it is likely that the response would be less significant (*i.e.* the demand elasticity would be lower) and slower. In such a case, RTP may have a dramatically reduced effect in mitigating wind-uncertainty costs, although this is a topic that requires further investigation. Our results are also predicated on the assumption that loads exhibit the same price elasticity across all hours of the day. While empirical studies demonstrate that demand is price-responsive, price-sensitivity may differ between on- and off-peak periods. For instance, shifting activities overnight can increase off-peak loads, however this effect may be smaller than the decrease in on-peak loads. Further research is needed to understand how time-variant elasticities impact the benefits of RTP.

Our analysis is concerned solely with the benefits of RTP and stochastic optimization in mitigating wind-uncertainty costs. Clearly these must be weighed against the costs of implementing these programs. RTP can require major investments in infrastructure and consumer education. On the other hand, using a stochastic optimization model requires relatively small investments in model and algorithm development and testing. If these costs are accounted for, RTP may be a less economic means of integrating wind and other renewables into power systems.

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