Evaluating the Impacts of Real-Time Pricing on the Cost and Value of Wind Generation

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***Abstract*—One of the costs associated with integrating wind generation into a power system is the cost of redispatching the system in real-time due to day-ahead wind resource forecast errors. One possible way of reducing these redispatch costs is to introduce demand response in the form of real-time pricing (RTP), which could allow electricity demand to respond to actual real-time wind resource availability using price signals. A day-ahead unit commitment model with day-ahead wind forecasts and a real-time dispatch model with actual wind resource availability is used to estimate system operations in a high wind penetration scenario. System operations are compared to a perfect foresight benchmark, in which actual wind resource availability is known day-ahead. The results show that wind integration costs with fixed demands can be high, both due to real-time redispatch costs and lost load. It is demonstrated that introducing RTP can reduce redispatch costs and eliminate loss of load events. Finally, social surplus with wind generation and RTP is compared to a system with neither and the results demonstrate that introducing wind and RTP into a market can result in superadditive surplus gains.**

***Index Terms*—Power system economics, wind power generation, wind forecast errors, real-time pricing, unit commitment**

I. NOMENCLATURE

T	number of periods
I	conventional generator index set
W	wind generator index set
$C_i(q)$	generator i's non-decreasing stepped variable generating cost function
N_i	generator i's no-load cost
SU_i	generator i's startup cost
K_i^-	generator i's minimum operating point
K_i^+	generator i's maximum operating point
R_i^-	generator i's rampdown limit
R_i^+	generator i's rampup limit
$\overline{SP}_i$	generator i's spinning reserve capacity
$\overline{NS}_i$	generator i's non-spinning reserve capacity
τ_i^-	generator i's minimum down-time
τ_i^+	generator i's minimum up-time
$\omega_{w,t}$	wind generation available from wind generator w in period t
$p_t(l)$	non-increasing stepped inverse demand function of energy in period t
η^s	spinning reserve requirement (as a fraction of load)
η^n	non-spinning reserve requirement (as a fraction of load)
$q_{i,t}$	generation provided by generator i in period t
$sp_{i,t}$	spinning reserves provided by generator i in period t
$ns_{i,t}$	non-spinning reserves provided by generator i in period t
$u_{i,t}$	binary variables indicating if unit i is up in period t
$s_{i,t}$	binary variables indicating if unit i is started-up in period t
$h_{i,t}$	binary variables indicating if unit i is shutdown in period t
$g_{w,t}$	wind generation provided by wind generator w in period t
l_t	load served in period t

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II. INTRODUCTION

ALTHOUGH wind generation is generally considered an energy source with zero marginal cost, it can impose costs on a power system. These costs typically stem from the limited-dispatchability of wind generation, the variability in wind resource availability, and errors in forecasting resource availability. For instance, day-ahead wind availability forecast errors can result in a suboptimal unit commitment if the system operator (SO) commits too many, too few, or the 'wrong set' of dispatchable generators. These forecasting errors can lead to high-cost ancillary services and replacement energy being used to cover a wind generation shortfall. Similarly, wind resource variability can require having more ramping capability available from dispatchable generators.

A series of studies have simulated and estimated these integration costs associated with wind generation. Reference [1] uses a probabilistic approach to estimate the energy redispatch costs associated with day- or hour-ahead wind forecast errors, and estimates that these costs can be as high as 10% of a wind generator's energy revenues. References [2], [3], [4] survey some techniques to study the impacts of wind generation on day-ahead unit commitment, real-time redispatch, and ancillary service requirements. Some of the estimates they report place these system integration costs as high as \$5/MWh of wind generation.

One way to reduce these wind integration costs is to introduce demand responsiveness by using a time-variant retail electricity rate, such as real-time pricing (RTP). RTP can potentially reduce wind integration and forecast error costs, since consumer demand could be made to follow the supply of wind generation by using a price signal. Under RTP, if available wind generation is less than forecast, the high cost of deploying ancillary services to cover the generation shortfall will reduce electricity demand and the cost of serving the load. Similarly, because wind generation has zero marginal cost, electricity demand will increase when there is more wind resource available than forecast, and wind generation may have to otherwise be curtailed due to constraints on the operation of conventional generators. Indeed, [5] demonstrates the effect RTP can have in reducing wind curtailment due to generator and power system constraints.

Besides reductions in wind integration costs, RTP has other economic benefits. Chief among them is increasing short-run efficiency by balancing consumers' willingness to pay for energy with production costs. Many economists have advocated RTP on the basis of economic efficiency gains. Reference [6] suggests that the demand elasticity from RTP could have reduced the severity of the California energy crisis in 2000 and 2001, and [7], [8], [9] analyze the long- and short-run efficiency gains from introducing RTP. In addition to these benefits, the fact that RTP makes electricity demand follow wind supply more closely suggests that the surplus gains from introducing RTP and wind generation together may be superadditive when compared to the surplus gains from introducing each individually.

This paper uses a unit commitment model to analyze the cost of day-ahead unit commitment errors and real-time redispatch associated with errors in day-ahead wind availability forecasts. The model is used to simulate a power system that is based on the ERCOT system with high wind penetration levels, both with fixed loads and RTP. The results show that with fixed loads wind forecast errors can result in high system redispatch costs—in some cases more than \$2/MWh of wind generation—and that RTP can reduce these costs significantly. System operations are also simulated with neither wind generation nor RTP and compared to a system in which each is introduced individually. The results show that while social surplus is increased by introducing wind generation or RTP individually, there are superadditive surplus gains from introducing both wind generation and RTP into the power system together. In addition to demonstrating these benefits of RTP in the test system considered here, this paper develops a modeling framework that can be applied to other power systems to determine the costs of wind forecasting errors and the impacts of RTP and other strategies in reducing these costs. The remainder of this paper is organized as follows: section III describes the model and the data underlying the simulations of the ERCOT system, the results are presented in section IV, and section V concludes.

III. Model and Data

The analysis is based on a series of unit commitment and dispatch models, which capture the fact that the day-ahead commitment must be done with forecasts of wind resource availability, which will typically have some forecasting error, and that the system must be subsequently redispatched in real-time in response to actual wind availability. Models with demand elasticity are formulated to maximize social welfare (the difference between consumer surplus and total generation costs), and as such demand is assumed to respond to electricity prices that are endogenously determined in the model. Models with fixed demands, on the other hand, are formulated to serve the fixed load at least cost. The formulation of the models is given in the appendix.

The first model is a unit commitment with a two-day planning horizon, which ensures that the commitment at the end of each day takes into account the need to serve the following day's load. In order to make this two-day unit commitment problem tractable, the commitment variables are modeled at three-hour long intervals. The second model is a unit commitment with a one-day planning horizon, which takes the starting and ending commitment of each generator as fixed, based upon the solution of the first unit commitment. This second unit commitment models all the commitment and dispatch variables at hourly intervals. These first two unit commitment models are solved using forecasts of wind resource availability, and are meant to represent a day-ahead commitment. Both unit commitment models include standard constraints, including hourly load-balance and spinning and non-spinning reserve requirements. In addition, unit operating constraints such as minimum and maximum operating points, minimum up and down times, ramp limits, ancillary service qualifications, and generator response times are modeled. It is important to note that this analysis uses a deterministic day-ahead unit commitment model. Some authors, such as [10], [11], have suggested that power systems with high wind penetrations could benefit from using a stochastic day-ahead unit commitment, which explicitly accounts for wind uncertainty. The implications of this assumption are discussed further in section V.

The results of these day-ahead unit commitments are then used, along with actual wind availability, to solve a real-time redispatch. The real-time dispatch problem takes generator commitments as fixed based upon the solution from the day-ahead unit commitment problems, with the exception of generators that are offline but providing non-spinning reserves and quick-start units, which are allowed to startup in real-time if needed. The committed generators are then redispatched to serve the load subject to the same unit operating constraints that are included in the day-ahead unit commitments. It bears mentioning that the day-ahead unit commitment and real-time redispatch models are meant to be illustrative of actual system operations in ERCOT (and many other power systems), but are not an exact representation of their protocols.

This analysis simulates one year's operation of the ERCOT system with the conventional generator set, generation costs, and loads taken from 2005. In order to simulate a power system with very high wind penetration, all wind farms that are proposed to be built and in operation by 2011 are included—which consists of more than 14 GW of nameplate wind capacity or more than 18% of the system's generating capacity.

The hourly demand functions for scenarios with RTP are calibrated based on actual load data for 2005, which is reported by ERCOT, and an assumed demand elasticity. Following [12], the hourly demand functions are calibrated to intersect the point defined by the actual load in that hour and the retail price of electricity. Retail electricity price data is based upon average rates in Texas for the year 2005, which are reported by the US Department of Energy's Energy Information Administration. This retail rate data is combined with tariff data for 2005 from the Public Utility Commission of Texas to remove non-energy charges (such as metering and billing) to arrive at the retail rate of energy. A set of scenarios with own-price demand elasticities ranging between -0.1 and -0.3 are simulated, which is consistent with the estimates of short-term electricity elasticities reported in [13]. Following [8], cross-price elasticities are assumed to be zero. The implications of this assumption and its potential for underestimating the effects of RTP are discussed in section V. In order for the objective functions of the models to be linear, the hourly demand functions are approximated by non-increasing step functions. The day-ahead unit commitment models include hourly load-based ancillary service constraints, which consist of a 4.5% spinning reserve and an additional 4.5% non-spinning reserve requirement.

Conventional generators are modeled as having a standard three-part cost structure, which consists of a startup cost that is incurred whenever a generator is brought online; a spinning no-load cost that is incurred in any hour a generator is online, regardless of generating output; and a non-decreasing stepped variable generation cost. Generation costs are calculated from tested heat rate and fuel and emission permit price data reported by Ventyx and Platts. Ventyx and Platts also provided data on generator constraints and capabilities, including minimum and maximum generation levels, ramp limits, minimum up and down times, must-run requirements, qualifications to provide spinning and non-spinning reserves, and which units are quick-start. The entire set of 375 dispatchable generators, which were interconnected with the ERCOT system in 2005, is included in the analysis, except for the Comanche Peak and South Texas nuclear power stations, which are assumed to always run at capacity.

Actual availability of wind generation is based on a mesoscale model of historical wind data by 3TIER. The 3TIER data models hourly generation available from hypothetical wind farms at 659 locations in Texas. This hourly wind resource data is translated into the fraction of the nameplate capacity of the wind farm:

$$f_{w,t} = \frac{g_{w,t}}{K_w},$$

where $g_{w,t}$ is the available generation and K_w the nameplate capacity of wind farm w in hour t. The wind farms in the model are associated to locations in the 3TIER data based on geographical location and the model assumes that the available generation of the modeled wind farms will scale linearly based on the fraction of nameplate capacity, $f_{w,t}$.

The day-ahead forecast of wind resource availability is assumed to be given by:

$$\tilde{f}_{w,t} = f_{w,t} + \eta_{w,t},$$

where $\eta_{w,t}$ is the forecast error. Following the statistical analysis of wind forecast errors in [14], the forecast error is assumed to have an unbiased first-order autocorrelated truncated normal distribution. A set of scenarios with the forecast error's variance ranging between 0.0049 and 0.0121 and an autocorrelation coefficient of 0.6 are used in the simulations, which are in line with the parameters estimated in [14].

IV. Results

The day-ahead and real-time commitment and dispatch of the ERCOT system are simulated under the various scenarios with different forecast error variances and demand elasticities. The analysis compares the cost and social surplus from system operations with day-ahead wind forecasting errors to that with perfect foresight of wind availability (*i.e.* assuming actual real-time wind resource availability is known day-ahead).

A. Cost of Wind Forecast Errors With Fixed Loads

Table I compares total annual system operation costs with day-ahead wind forecast errors to operation costs with perfect foresight of wind resource availability. The system operation costs consist of the three-part generation cost structure described in section III. The increased generation costs with wind forecast errors stems from suboptimal generator commitments made day-ahead and costly redispatch in real-time. The increase in system operation costs is divided by total wind generation, which gives the wind integration cost in \$/MWh of wind generation. The results in table I show that increased wind forecast errors, which are characterized by a higher forecast error variance, result in higher integration costs.

TABLE I
ADDITIONAL ANNUAL SYSTEM OPERATION COSTS DUE TO WIND FORECAST ERRORS WITHOUT RTP (\$/MWH OF WIND GENERATION)

Forecast Error Variance	Forecast Error Cost (\$/MWh Wind Generation)
0.0049	0.868
0.0064	1.109
0.0081	1.385
0.0100	1.744
0.0121	2.172

One of the costs of wind forecast errors that is not included in table I is the value of lost load (VOLL). Lost load events occur when forecasts of wind availability are much higher than actual resource availability and result in insufficient conventional generating capacity being committed and available to serve the load in real-time. Figure 1 shows the annual wind integration cost, again normalized by the amount of wind energy generated, when the VOLL over the year is included in the cost calculation. Figure 1 uses a range of VOLL which is in line with the price paid to curtailed loads under utility interruptible load programs. Figure 1 shows that wind forecasting errors can potentially result in many loss of load events if the forecast error variance is sufficiently high. Forecast error variances of below 0.0081 result in reasonable wind integration costs of below \$4/MWh of wind generation even with a VOLL of \$10000/MWh. Higher forecast error variances result in much higher integration costs of up to \$12/MWh of wind generation due to the greater amount of lost load.

B. Cost of Wind Forecast Errors with RTP

When analyzing wind integration and forecast error costs with RTP, the change in social welfare is the more appropriate metric to use as opposed to changes in operation costs. This

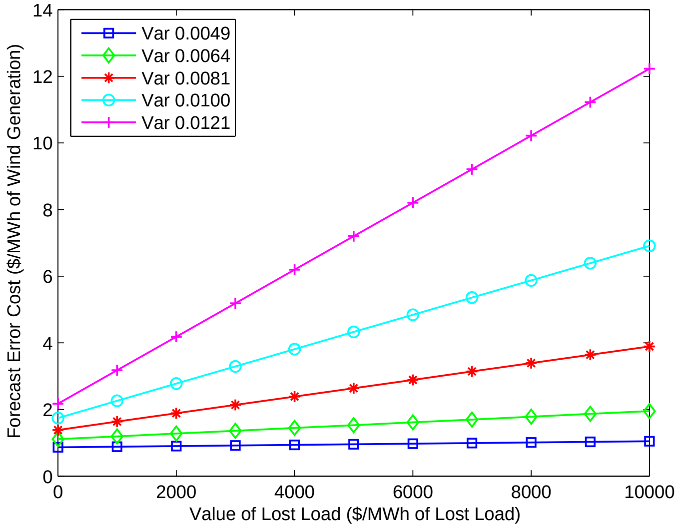

Fig. 1. Annual forecast error cost including cost of lost load as a function of the value of lost load ($/MWh of Wind Generation).

TABLE III
ANNUAL SOCIAL SURPLUS LOSS DUE TO WIND FORECAST ERRORS ($/MWH OF WIND GENERATION) WITH DEMAND ELASTICITY OF −0.2

Forecast Error Variance	Without RTP	With RTP
0.0049	0.879	0.133
0.0064	1.162	0.166
0.0081	1.543	0.212
0.0100	2.068	0.252
0.0121	2.804	0.302

TABLE IV
ANNUAL SOCIAL SURPLUS LOSS DUE TO WIND FORECAST ERRORS ($/MWH OF WIND GENERATION) WITH DEMAND ELASTICITY OF −0.3

Forecast Error Variance	Without RTP	With RTP
0.0049	0.875	0.081
0.0064	1.146	0.116
0.0081	1.497	0.134
0.0100	1.973	0.152
0.0121	2.618	0.171

is because social welfare captures the changes in consumer surplus from increases or decreases in demand due to wind forecast errors. When wind forecasts are less than actual available wind generation, demand may increase since there is excess costless generation. Similarly, when wind forecasts are greater than actual wind resource, demand can decrease since the cost of replacement energy may be greater than the value of the load to consumers.

Tables II through IV summarize the annual social surplus loss due to wind forecast errors, in $/MWh of wind generation. The surplus values reported in the cases without RTP use consumer surplus losses to quantify the value of lost load, assuming that retail electric customers are heterogeneous with different willingness to pay for energy given by the same price-elastic demand function used in the cases with RTP. The calculation of surplus losses further assumes that load curtailments will be randomly allotted to customers, since loads would presumably be curtailed using rolling blackouts or some other administrative measure, without consideration of willingness to pay. This computation assumes that in cases without RTP consumers have an underlying price-elastic demand for electricity, but that these preferences are not expressed and the load is fixed because customers face a fixed retail electricity rate. Comparing these surplus loss values with figure 1 also provides another way of quantifying the cost of lost load without RTP.

TABLE II
ANNUAL SOCIAL SURPLUS LOSS DUE TO WIND FORECAST ERRORS ($/MWH OF WIND GENERATION) WITH DEMAND ELASTICITY OF −0.1

Forecast Error Variance	Without RTP	With RTP
0.0049	0.889	0.310
0.0064	1.209	0.380
0.0081	1.682	0.477
0.0100	2.355	0.539
0.0121	3.361	0.661

Tables II through IV show that introducing demand response through RTP can have significant impacts in reducing the cost of wind forecasting errors. It is also worth noting that the demand flexibility from RTP eliminates lost load events, since the high real-time price of dispatching replacement energy will reduce energy demand when wind forecasts are much higher than actual resource availability. It is also important to note that if retail electric customers are heterogeneous, with different values of electricity consumption, because the demand curtailment with RTP is done on the basis of willingness to pay, the 'load rationing' is efficient with RTP. Without RTP, load rationing is often done using inefficient arbitrary and administrative means such as rolling blackouts. Even curtailable and interruptible load contracts may result in inefficiencies since load-serving entities typically choose which customers to interrupt without regard to their real-time willingness to pay for energy. Given the fact that retail electricity customers encompass a wide range of consumer types such as commercial, industrial, and residential, and the differences in wealth and income amongst these customers, it is likely that the willingness to pay and value of electricity demand will be heterogeneous amongst different customers and these efficiency gains over a fixed demand regime could be considerable.

Table V summarizes the efficiency losses that would result if the load curtailments that occur without RTP are uniformly distributed among customers with different willingness to pay for energy. As in tables II through IV, customers' willingness to pay for energy is computed from the demand function. The consumer surplus loss with random curtailment is compared to that if loads are curtailed based on willingness to pay, and normalized to give consumer surplus losses in $/MWh of curtailed load. Table V shows that the surplus losses are similar for different forecast error variances, but are quite sensitive to demand elasticity, since a more inelastic demand function will have more customer heterogeneity with a wider range of willingness to pay and more efficiency losses from random curtailment.

TABLE V
CONSUMER SURPLUS LOSS FROM RANDOM LOAD CURTAILMENT ($/MWH OF CURTAILED LOAD)

Forecast Error Variance	Demand Elasticity -0.1	-0.2	-0.3
0.0049	995.59	497.80	331.86
0.0064	1038.13	519.07	346.04
0.0081	979.91	489.95	326.64
0.0100	1006.80	503.40	335.60
0.0121	976.31	488.15	325.44

C. Superadditive Surplus Gains From Wind Generation and RTP

Many analyses of RTP have focused on the social welfare gains from having electricity demand react to real-time variation in marginal generation costs. In addition to these welfare improvements, the results thus far have demonstrated that introducing RTP in a market with supply uncertainty will increase social welfare by allowing demand to react to changes in actual real-time supply. At the same time, wind generation can increase short-run social welfare by providing a costless source of energy.[1] An interesting question is whether there would be an interaction between introducing RTP and adding wind generation, which would result in superadditive social surplus gains, compared to introducing each to an electricity market in isolation.

These social surplus improvements are examined by comparing a set of scenarios in which there is:

1) no RTP, no wind generators;
2) no RTP, wind generators;
3) RTP, no wind generators; and
4) RTP, wind generators.

Defining σ_x to be the social surplus under scenario x, this analysis compares the increase in welfare from introducing both RTP and wind generation together ($\sigma_4-\sigma_1$) to the sum of the welfare increases from introducing each of RTP and wind generation individually ($\sigma_3+\sigma_2-2\sigma_1$). If $\sigma_4-\sigma_1 > \sigma_3+\sigma_2-2\sigma_1$ this implies that the combination of RTP and wind result in superadditive surplus gains, or that RTP increases the social value of wind generators. Scenarios 1 and 3, which assume that there are no wind generators, use only the conventional generator set in ERCOT in 2005 to serve the load. Moreover, because there is no wind generation, these scenarios will not have any added redispatch costs due to wind forecast errors. The surplus values for scenarios 2 and 4, on the other hand, do include real-time redispatch costs and the value of lost load is computed as done in tables II through IV. Similarly, because scenarios 1 and 2 assume no RTP, electricity demand is assumed to be fixed in these scenarios.

Table VI presents, as an illustrative example, the annual surplus gains from each of introducing wind, RTP, and wind and RTP. The example assumes the lower wind forecast error variance of 0.0049 for scenarios with wind generators (scenarios 2 and 4). The example shows that on an annual basis, adding wind generation to the market can result in large social surplus gains, and that RTP can also increase social surplus through more efficient real-time energy use. Comparing the last two rows of the table shows that introducing wind generation and RTP together does indeed result in superadditive surplus gains, and that RTP enhances the social value of wind generation.

[1] Wind generation is costless insomuch as it does not incur any fuel cost. Many countries, including the United States, provide wind generators with generation-based subsidies or tax incentives to spur wind investment. These subsidies can be considered a cost in that society bears a tax burden to pay for them, however this is a wealth transfer between taxpayers and wind generators and as such there are no social welfare losses from such a subsidy, with the exception of some deadweight losses from taxation.

TABLE VI
ANNUAL SOCIAL SURPLUS GAINS FROM WIND, RTP, AND WIND AND RTP TOGETHER WITH A FORECAST ERROR VARIANCE OF 0.0049 ($ MILLION)

	Demand Elasticity -0.1	-0.2	-0.3
$\sigma_2-\sigma_1$	2,658	2,658	2,658
$\sigma_3-\sigma_1$	190	355	489
$\sigma_3+\sigma_2-2\sigma_1$	2,848	3,013	3,147
$\sigma_4-\sigma_1$	2,924	3,131	3,298

Table VII summarizes these superadditive surplus gains for all of the forecast error variances and demand elasticities considered in section IV-B. The table reports the increase in social welfare from introducing both wind generators and RTP together, as a percentage of the sum of the increase in social welfare from introducing each of wind generators and RTP separately, or

$$\frac{\sigma_4-\sigma_1}{\sigma_3+\sigma_2-2\sigma_1}-1.$$

Table VII shows that introducing both wind generators and RTP together can result in noticeable social welfare gains of between 2.7% and 6.6%, depending upon the forecast error variance and demand elasticity. The combination of wind and RTP is more valuable with higher forecast error variances, because the demand flexibility from RTP reduces real-time redispatch costs and surplus losses from wind forecast errors.

TABLE VII
INCREASE IN SOCIAL SURPLUS FROM INTRODUCING BOTH WIND GENERATORS AND RTP TOGETHER (% OF SUM OF SURPLUS INCREASE FROM INTRODUCING EACH OF WIND GENERATORS AND RTP INDIVIDUALLY)

Forecast Error Variance	Demand Elasticity -0.1	-0.2	-0.3
0.0049	2.7	3.9	4.8
0.0064	2.9	4.3	5.1
0.0081	3.2	4.6	5.5
0.0100	3.7	5.1	6.0
0.0121	4.2	5.7	6.6

V. DISCUSSION AND CONCLUSIONS

This paper developed and discussed a model to simulate power system operations under high wind penetration scenarios, which can be used to assess the cost of wind resource forecast errors. The simulations have shown that wind forecast errors can increase system costs through suboptimal unit commitments day-ahead, the subsequent redispatch of the system in real-time, and the potential for lost load due to insufficient generating capacity being committed and available in real-time. These costs can range up to $2.18/MWh of wind generation without the VOLL and can be much higher when lost load is considered. The results demonstrate that introducing demand flexibility in the form of RTP can reduce these integration costs, by allowing electric loads to respond to actual resource availability. RTP not only decreases the cost of redispatching the system in real-time, but also eliminates loss of load events.

Social surplus with both wind generation and RTP was compared to cases without wind or RTP to determine the surplus gains from introducing the two together. The results show that introducing wind and RTP together would result in superadditive surplus gains, which can increase total surplus by between 2.2% and 6.6% above the sum of the surplus increases from introducing each of wind and RTP individually. These superadditive surplus gains can be thought of as increasing the social value of wind generation to the system. In interpreting these result, it is important to note that so long as consumer bids are within an appropriate range, RTP will tend to reduce costs, increase surplus, and improve reliability in power systems regardless of whether wind is in the system. Our results suggest that wind and RTP are particularly well suited to one another and that they enhance the benefits borne by one another. As discussed above, the reason RTP and wind behave in this way is because RTP causes the load profile to more closely follow the available supply of wind. Because the availability of wind tends to suppress the real-time price, RTP will cause customer loads to shift towards periods in which wind generation is available. Conversely, hours in which wind is not available (and periods in which wind availability has been overforecast) will have comparably higher energy prices, which will tend to shift loads away from those periods.

It bears mentioning, however, that there will be some social welfare losses from increased use of wind. Taxes that are levied to fund production tax credits and other subsidies for wind generation will generally lead to some deadweight losses, as will sunk costs borne by conventional generators that are displaced from the market by wind generators. While it can be expected that these surplus losses would be small relative to the surplus gains from RTP, it is nonetheless important to note them in evaluating the net surplus effect of RTP and wind. It is also important to note that the model developed here is illustrative to the extent that it does not exactly represent system operations in ERCOT, but the results are nonetheless useful for quantifying the extent to which RTP can reduce wind integration costs. Furthermore, the modeling framework developed here can easily be adapted to studying wind integration in other power systems and the effect of RTP and other policies in reducing the cost of wind forecasting errors.

This analysis assumes the cross-price elasticity of electricity demand to be zero and models only own-price elasticities. As discussed in [5], this assumption may be understating the effect of RTP, since it does not account for the cross-hour load shifting that would occur if cross-price elasticities are non-zero. If own-price elasticities remain the same and cross-price elasticities are non-zero, then when actual wind resource availability in a given hour is less than expected day-ahead, electricity demand in that hour will likely be reduced both due to the high price of generation in that hour and the comparably lower price of energy in other hours. This load shifting between hours would tend to further decrease wind integration costs below the estimates given here, which only account for demand reductions in an hour due to a high energy price in that hour. This effect of cross-price elasticities is obviously dependent upon the assumption that own-price elasticities remain the same. If some of the impacts of load-shifting are captured in own-price elasticity estimates, then a proper model with cross-price elasticities would have to include lower own-price elasticities, and the effects of changing the two elasticities may cancel each other out.

Another assumption in this analysis is that loads are able to respond to price signals in a symmetric and predictable manner, which may be tenuous in practice. The value of RTP is that it allows loads to respond to wind resource availability. In reality, electricity demand may not respond to price signals symmetrically, since customers may respond more to increases in electricity prices than to decreases. For instance, a consumer may turn off an air conditioner or other appliance when electricity prices are high, but may not turn on an air conditioner when it is not needed simply because the price of electricity is low. While this type of asymmetric demand response may reduce some of the surplus gains from providing consumers with additional energy when actual wind availability is greater than forecast, much of the benefits of RTP stem from demand reductions when wind forecasts are too high. Thus, most of the benefits estimated here would be captured even with asymmetric demand response.

Similarly, this analysis assumes that loads and their response to prices are known by the SO. This assumption can also be problematic since day-ahead load forecasts typically have some errors, and loads may not respond to prices in an entirely predictable fashion. In practice, it may take consumers time to process updated price information and adjust their energy use. The assumption that there are no day-ahead load forecast errors is made to isolate the effect of wind forecasting errors on redispatch costs and loss of load events—without including the effect of load forecasting errors. The assumption regarding the ability of loads to respond to prices immediately warrants further investigation, since demand response may lag electricity price changes in practice. This analysis would raise important issues regarding the timing of when wind forecasts and prices are updated. This paper implicitly assumes that consumers employ some type of automated control that can immediately adjust energy use in response to price signals and user inputs regarding willingness to pay and demand elasticity.

This analysis also assumes that ancillary service requirements would remain the same, regardless of expected or scheduled wind generation day-ahead. This assumption results in loss of load events with fixed demands when there is insufficient conventional generating capacity available in real-time to meet a wind generation shortfall. Previous studies, such as [3], [14], [15], [16], [17], [18], have estimated the amount of regulation, spinning, and non-spinning capacity which would be required to maintain reliability standards under high wind penetration scenarios due to resource forecasting errors and transience issues. Some markets schedule wind generators based on a probabilistic assessment of resource availability. Under the proposed nodal market redesign, ERCOT will use a wind resource forecast with an 80% probability of exceedance in its reliability unit commitments. This analysis shows that with fixed loads, except in cases in which forecast error variances are small, lost load events can be costly and increase wind integration costs. This suggests that it may be prudent for ancillary service requirements to be dependent on wind schedules or for an SO to use an approach similar to the one proposed by ERCOT to ensure system reliability. Despite this, some SOs do not explicitly consider wind schedules in determining ancillary service requirements. The current market design in ERCOT, for example, does not adjust ancillary services based on wind schedules. The results of this analysis show, however, that introducing RTP can eliminate (or reduce) the need for additional ancillary service capacity, which can further reduce system operation and wind integration costs.

Other authors, such as [10], [11], have advocated using a stochastic day-ahead unit commitment to explicitly deal with resource forecasting errors. These approaches will reduce the cost of forecast errors without demand response, since the day-ahead unit commitment would be optimized to take account of wind uncertainty. As such some of the surplus gains and redispatch cost savings from introducing RTP would be reduced. Nevertheless, RTP would likely still be a valuable tool for managing wind uncertainty, since load shifting and demand response expected in real-time could reduce the need to change the day-ahead commitment to account for uncertainty. This interaction between RTP and these other means of addressing wind uncertainty is an area of future research that we plan to pursue.

APPENDIX
MODEL FORMULATION

The formulation of the unit commitment model used in the simulations is presented. The AS constraints are only enforced for the day-ahead commitment models, not for the real-time dispatch models. Moreover, the binary commitment variables of all conventional generators, except fast response units and those that provide non-spinning reserves while offline, are fixed in each real-time dispatch model based on the day-ahead unit commitment solution. Finally, the unit commitments with price inelastic demand are formulated with a fixed load, which could be equivalently represented within this formulation as a single-step demand function with an extremely high price. The models are all formulated using GAMS and solved with CPLEX 9.0.

The problem is formulated as maximizing social surplus:

$$\max \sum_{t \in T} \int_0^{l_t} p_t(x)dx - \left(\sum_{i \in I, t \in T} C_i(q_{i,t}) + N_i u_{i,t} + SU_i s_{i,t} \right);$$

subject to the following constraints:

- load-balance ($\forall\ t \in T$):
$$l_t = \sum_{i \in I} q_{i,t} + \sum_{w \in W} g_{w,t};$$
- total and spinning reserve requirements ($\forall\ t \in T$):
$$\sum_{i \in I} (sp_{i,t} + ns_{i,t}) \geq \eta^n l_t$$
$$\sum_{i \in I} sp_{i,t} \geq \eta^s l_t;$$
- conventional generator minimum and maximum generation bounds ($\forall\ i \in I, t \in T$):
$$K_i^- u_{i,t} \leq q_{i,t}$$
$$q_{i,t} + sp_{i,t} \leq K_i^+ u_{i,t}$$
$$q_{i,t} + sp_{i,t} + ns_{i,t} \leq K_i^+;$$
- conventional generator AS bounds ($\forall\ i \in I, t \in T$):
$$0 \leq sp_{i,t} \leq \overline{SP}_i u_{i,t}$$
$$0 \leq ns_{i,t} \leq \overline{NS}_i;$$
- conventional generator ramping limits ($\forall\ i \in I, t \in T$):
$$R_i^- \leq q_{i,t} - q_{i,t-1}$$
$$q_{i,t} - q_{i,t-1} + sp_{i,t} + ns_{i,t} \leq R_i^+;$$
- conventional generator minimum up- and down-times ($\forall\ i \in I, t \in T$):
$$\sum_{y=t-\tau_i^+}^{t} s_{i,y} \leq u_{i,t}$$
$$\sum_{y=t-\tau_i^-}^{t} h_{i,y} \leq 1 - u_{i,t};$$
- conventional generator startup and shutdown state transitions ($\forall\ i \in I, t \in T$):
$$s_{i,t} \geq u_{i,t} - u_{i,t-1}$$
$$h_{i,t} \geq u_{i,t-1} - u_{i,t};$$
- wind generation bounds ($\forall\ w \in W, t \in T$):
$$0 \leq g_{w,t} \leq \omega_{w,t};$$
- non-negativity ($\forall\ t \in T$):
$$l_t \geq 0; \text{ and}$$
- integrality of variables ($\forall\ i \in I, t \in T$):
$$u_{i,t}, s_{i,t}, h_{i,t} \in \{0, 1\}.$$

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