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A Decision Framework for Optimal Pairing of Wind and Demand Response Resources

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***Abstract*—Day-ahead electricity markets do not readily accommodate power from intermittent resources such as wind because of the scheduling difficulties presented by the uncertainty and variability in these resources. Numerous entities have developed methods to improve wind forecasting and thereby reduce the uncertainty in a day-ahead schedule for wind power generation. This paper introduces a decision framework for addressing the inevitable remaining variability resulting from imperfect forecasts. The framework uses a paired resource, such as demand response, gas turbine, or storage, to mitigate the generation scheduling errors due to wind forecast error. The methodology determines the cost-effective percentage, or adjustment factor, of the forecast error to mitigate at each successive market stage, e.g., 1 h and 10 min ahead of dispatch. This framework is applicable to any wind farm in a region with available pairing resources, although the magnitude of adjustment factors will be specific to each region as the factors are related to the statistics of the wind resource and the forecast accuracy at each time period. Historical wind data from New England are used to illustrate and analyze this approach. Results indicate that such resource pairing via the proposed decision framework will significantly reduce the need for an independent system operator to procure additional balancing resources when wind power participates in the markets.**

***Index Terms*—Decision support, demand response, electricity markets, wind integration, wind power.**

I. Introduction

MANY states in the U.S. have passed either voluntary or mandatory requirements for a percentage of energy in their region to be served by renewable resources [1]. With hydro resources already exploited in most regions, it is assumed that wind power will be a main contributor in meeting these new standards. Although the energy generated by wind turbines is close to zero cost, nonzero costs are incurred when the power system as a whole responds to the uncertainty and variability associated with the wind resource itself. These costs arise from the need to dispatch other resources to ramp up or down to mitigate wind power deviating from its forecast output.

System analyses often focus on the costs of using the existing power system and, hence, conventional technologies, such as gas turbines, to mitigate wind [2], [3] and to increasingly include the option of storage as well. A third option is to use responsive demand to mitigate the variations in wind output that arise from forecasting errors. System operators are currently exploring the concept of using responsive demand to mitigate wind variability and for ancillary grid benefits. In particular, the California Independent System Operator (CAISO) is currently developing the *grid state indicators* to inform end-user response decisions [4], [5].

This paper presents a methodology to reduce the net variability of the wind power output and to therefore allow wind to participate more fully in forward markets. The proposed methodology uses power generation forecasts 1 h and 10 min ahead of dispatch. These forecasts are compared, successively, to the submitted day-ahead schedule to quantify the expected megawatt deviation in output (i.e., the variability) for the succeeding time period (1 h and 10 min). The proposed framework then schedules a dedicated paired resource, such as responsive load or storage, to mitigate the deviation from the day-ahead schedule. The optimal amount of the forecast error to be mitigated at 1 h and 10 min ahead of real time is determined through the proposed methodology.

Results demonstrate that the optimum level of mitigation with the paired resource is related to the relative costs of the resource, the accuracy of the wind forecast, and the penalty imposed for spilling wind energy. The capacity of a paired resource that would be required and the costs associated with the use of responsive load as the pairing resource are presented in a case study.

Section II discusses the government regulations and recent state-level developments related to the participation of wind generation in electricity markets. Section III describes the framework proposed for optimal pairing of resources with wind generation. The framework is tested using Nantucket sound region data, described in Section IV, and Section V quantifies the capacity that would be required from each of the paired resource options to maintain the net wind generation output to within acceptable deviation from the submitted day-ahead schedule. Section VI presents the conclusions and future work.

II. Wind Power Participation in Electricity Markets

Electricity market structures operated by independent system operators (ISOs) in the U.S. include day-ahead, hour-ahead, and real-time markets, as well as an increasing number of ancillary services markets. As investment in wind generation grows and regional expansion plans include possibilities for

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significant wind capacity, the uncertainty and variability in wind generation do impose real costs on system operation in terms of efficient unit commitment and through providing services such as balancing and regulation.

The characteristic of uncertainty in wind generation can be addressed to some extent by improving the accuracy of forecasting the wind resource. To this end, the Minnesota Public Utilities Commission ordered a study to investigate the impacts of incorporating wind generation at the level of 20% of retail electricity sales by the year 2020 [6]. For this study, sophisticated meteorological modeling was performed by WindLogics [7] for 2003, 2004, and 2005. The results of this study demonstrated that the day-ahead forecast errors were as low as 20%. In addition, the broader analysis, as performed by EnerNex, found that, as spatial and geographic diversity of the wind turbine sites increased, the error decreased by up to 43% [6].

A report conducted by GE Energy consulting on behalf of the CAISO [8], showed that the implications of ignoring forecasts were so significant that a central forecasting approach was implemented. A mechanism to facilitate the use of the state-of-the-art wind forecasting has been implemented in California through the Participating Intermittent Resource Program (PIRP) [9], [10]. If the participating resources submit schedules consistent with the ISO-approved forecasts, then they are not subject to penalties for deviations from the forecasts. The PIRP in California has been operating since August 2004, and achieved cumulative average deviation of the forecast close to 1% by 2005 and 2009 [11].

A recent study from the New York ISO (NYISO) provides a detailed analysis of the impacts of increasing wind penetration on power system operations and the need for transmission system expansion. The analysis is based upon serving "net load," determined by subtracting the variable wind generation from the variable load data series. As with many previous analyses, the NYSIO study assumes wind plants will operate in the markets as price takers, which allows this use of net load.

These state-level analyses and programs demonstrate that wind forecasting decreases the uncertainty in day-ahead schedules, and when combined with flexible market structures and settlements facilitate increased involvement of wind power generation in the day-ahead markets.

Although, some of the inherent variability in wind generation remains, even as the uncertainty is reduced. To address this variability, this paper investigates pairing wind output with responsive demand to reduce the variability in the net wind output. On the surface, this appears similar to using a net-load data stream as in the NYISO study. The difference is that, for the analysis presented in this paper, responsive load (not the entire system load) is actively paired with wind, and both are assumed to participate in the markets. Recent advances in demand response that would enable this pairing are discussed in earlier work from this project [12].

A contribution of the analysis presented in this paper is to advance the discussion of whether wind plants can and should participate fully in electricity markets. Such an assumption carries with it the need to demonstrate that such participation will not degrade the efficiency of the markets or harm system operations. This paper demonstrates the ability of wind to participate in electricity markets as facilitated by the proposed method for mitigating the day-ahead schedule deviations with optimized dispatch of demand response. This method addresses the issue of whether wind will or should always assume a passive price-taker role in electricity markets, or whether, as the presence of wind increases significantly, it should have active participation in more aspects of power systems and electricity market operations.

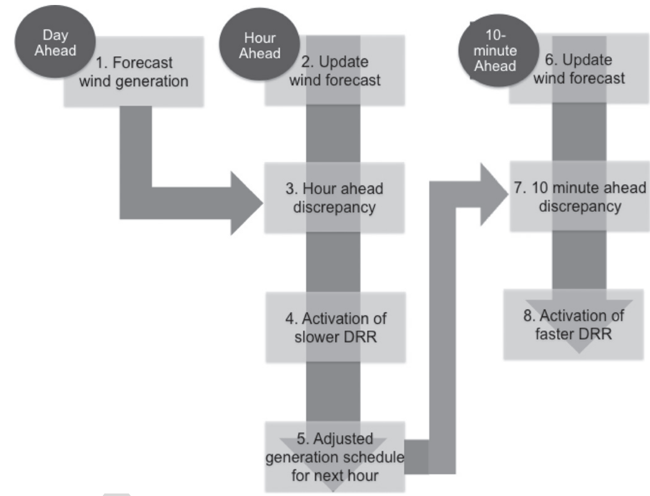

Fig. 1. Flowchart of decision structure for dispatch of paired (demand response) resource.

III. Framework for Pairing Wind and DRRs

The proposed framework, discussed here, determines the optimal amount of a paired resource to schedule to mitigate the variability in wind power generation. An important aspect of the proposed framework uses updated wind forecasts at each market stage to schedule the pairing resource as the time horizon approaches real-time dispatch. The amount of the paired resource scheduled at each time period is related to the magnitude of the discrepancy between the updated forecast and the day-ahead schedule.

At each time period considered, the shortfall or overshoot of forecast wind production is assessed, and the need for demand response or other paired resources is determined. The framework is shown in Fig. 1. As shown in this flowchart, the first step is to compare the day-ahead schedule to the hour-ahead schedule (both discussed in more detail in the following). The result of this comparison is a megawatt value of generation shortfall or excess expected between the day-ahead and hour-ahead schedules (see box 3 in Fig. 1). Based on the magnitude of this discrepancy, a decision will be made whether to activate the demand response resource (DRR) or not (see box 4 in Fig. 1). The purpose of this assessment one hour ahead of dispatch is to take advantage of the additional weather information available and to be able to utilize slower responding resources to mitigate some fraction of the expected scheduling deviation. However, as further deviations are expected between the hour-ahead schedule and real-time output, the paired DRR will never be dispatched to meet completely the deviation between the day-ahead and hour-ahead schedules. The framework

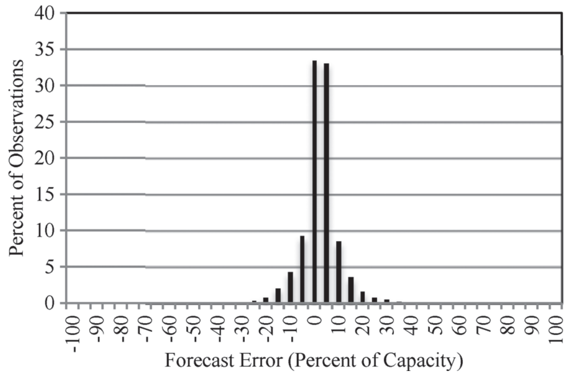

Fig. 2. Distribution of day-ahead forecast errors as percentage of capacity.

developed below is used to determine the optimal portion of the mismatch to mitigate at each time step. The remaining excess or shortfall in wind power output will be addressed with faster responding demand response alternatives, to be dispatched after each next-10-min forecast is made (see boxes 6–8 in Fig. 1).

Day-Ahead Forecast: At t_0, a day-ahead forecast determines a day-ahead schedule G_1 for the wind farm. For this project, an autoregressive (AR) persistence model is used for forecasting wind generation one day ahead, i.e.,

$$G_1 = \alpha_{24\mathrm{h}} + \beta_{24\mathrm{h}} P_{24\mathrm{h}}$$

where $\alpha_{24\mathrm{h}}$ and $\beta_{24\mathrm{h}}$ are regression parameters, and $P_{24\mathrm{h}}$ is the wind generation observed 24 h ahead.

Although more sophisticated forecasting algorithms are required for actual wind farm scheduling, for purposes of illustrating the proposed framework, the linear regression model is sufficient. Fig. 2 provides a sample histogram of forecast errors for one year (8760 observations) as a percentage of capacity for a single site in New England. The mean absolute error (MAE) corresponding to these data are approximately 5%. This corresponds well to the forecasting accuracy of the NYISO at 4.8% of the hour-ahead forecast [7].

Hour-Ahead Corrections: Although the day-ahead forecast is useful for initial scheduling, more accurate information about expected wind speed is available in the hour-ahead time frame. Although the most accurate wind speed data will not be available until 5–10 minutes ahead of actual dispatch, a first estimate of the discrepancy between the day-ahead forecast and real-time generation can be made 60–90 min ahead of real time. The correction at $t = t_0 + 23$ is determined by the discrepancy $\Delta_{1\mathrm{h}}$, between the day-ahead schedule and the updated hour-ahead forecast (determined 90 min in advance of dispatch).

Once again, an AR model is used for forecasting. At one hour ahead ($t = t_0 + 23$), the accuracy of a persistence model is significantly higher than it is day ahead, i.e.,

$$\Delta_{1\mathrm{h}} = G_1 - (\alpha_{1\mathrm{h}} + \beta_{1\mathrm{h}} P_{1\mathrm{h}})$$

$$\mathrm{DR}_{1\mathrm{h}} = \begin{cases} \Delta_{1\mathrm{h}}\gamma_{1\mathrm{h}}, & \text{if } \Delta_{1\mathrm{h}} > 0 \\ 0, & \text{otherwise} \end{cases}$$

where $\mathrm{DR}_{1\mathrm{h}}$ is the quantity of DRR to schedule one hour ahead of dispatch, calculated from $\gamma_{1\mathrm{h}}$, which is the fraction of forecast deviation to cover with the paired resource, one hour ahead.

A main contribution of the framework proposed here is to determine the value of $\gamma_{1\mathrm{h}}$ (and of $\gamma_{10\mathrm{min}}$, see the following) that will trade off between minimizing the deviation in wind generation in real time with minimizing the cost of dispatching the paired resource. The case study in Section V demonstrates the process for selecting $\gamma_{1\mathrm{h}}$ and $\gamma_{10\mathrm{min}}$.

Ten-Minute Ahead Corrections: Ten minutes before the real-time dispatch, a third forecast is determined. At this time, the discrepancy between the hour-ahead schedule and 10-min forecasts is estimated (see box 7 in Fig. 1), where this discrepancy, $\Delta_{10\mathrm{min}}$, is between the day-ahead schedule and the sum of the 10-min forecast and scheduled demand response resulting from the hour-ahead forecast $\mathrm{DR}_{1\mathrm{h}}$. This is described as follows:

$$\Delta_{10\mathrm{min}} = G_1 - \mathrm{DR}_{1\mathrm{h}} - (\alpha_{10\mathrm{min}} + \beta_{10\mathrm{min}} P_{10\mathrm{min}})$$

$$\mathrm{DR}_{10\mathrm{min}} = \begin{cases} \Delta_{10\mathrm{min}}\gamma_{10\mathrm{min}}, & \text{if } \Delta_{10\mathrm{min}} > 0 \\ 0, & \text{otherwise} \end{cases}$$

where $\gamma_{10\mathrm{min}}$ and $\mathrm{DR}_{10\mathrm{min}}$ are the fraction of forecast deviation to cover and the quantity of DRR to schedule 10 min ahead, respectively, (see box 8 in Fig. 1).

Minimizing Paired Resource Costs Associated With This Strategy: The final step in the proposed framework uses the cost of the DRRs that are utilized across all time scales. The fractions of the shortfall or overgeneration to mitigate at each decision point, i.e., $\gamma_{1\mathrm{h}}$ and $\gamma_{10\mathrm{min}}$, are estimated by minimizing the overall cost of paired resources in this strategy. This cost is given by

$$C_T = \Delta_{1\mathrm{h}}\gamma_{1\mathrm{h}}C_{1\mathrm{h}} + \Delta_{10\mathrm{min}}\gamma_{10\mathrm{min}}C_{10\mathrm{min}} + \Delta_{\mathrm{RT}}C_{\mathrm{RT}}.$$

The fractions to mitigate at both the 1-h- and 10-min-ahead time horizons are determined by selecting the mitigation fractions γ_i to minimize the overall cost of the strategy. To simplify notation, henceforth, the decision points will be denoted with numbers [1, 2, 3] representing hour ahead, 10 min ahead, and real time, respectively. Note that it is assumed that real-time shortfalls are covered through procurement in the real-time energy market or penalized at the real-time market price C_{RT}. This assumption is not critical to the formulation and can be altered to represent specific rules in any market under consideration.

The overall framework is presented mathematically as follows:

$$\begin{aligned}
&\underset{\gamma_i,\, i=1,\,2,\,3}{\arg\min} \left[C_T = \gamma_1\Delta_1^+ C_1 + \gamma_2\Delta_2^+ C_2 + \Delta_3^+ C_3 + \Delta_3^- C_P\right] \\
&\text{Subject to} \\
&C_{\mathrm{RT}} > C_{10\mathrm{min}} > C_{1\mathrm{h}} > 0 \\
&C_P \geq 0 \\
&0 \leq \gamma_i \leq 1, \text{ for } i = 1,\,2,\,3.
\end{aligned}$$

Note that it is assumed here that $C_{1\mathrm{h}} < C_{10\mathrm{min}} < C_{\mathrm{RT}}$. In fact, the actual costs are not important in determining the appropriate mitigation fractions γ as long as the relative costs can be estimated. Also note that overgeneration penalties can be also included in this framework by defining the penalty cost for overproduction as $C_P > 0$; otherwise, when $C_P = 0$, there is

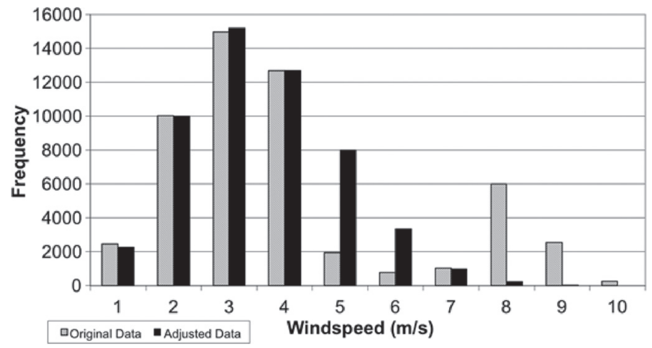

Fig. 3. Chart of time-series wind-speed data preaggregation and postaggregation algorithms.

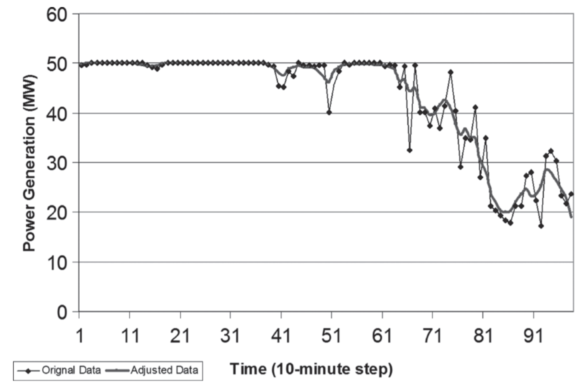

Fig. 4. Time series of wind power generation preaggregation and postaggregation algorithms.

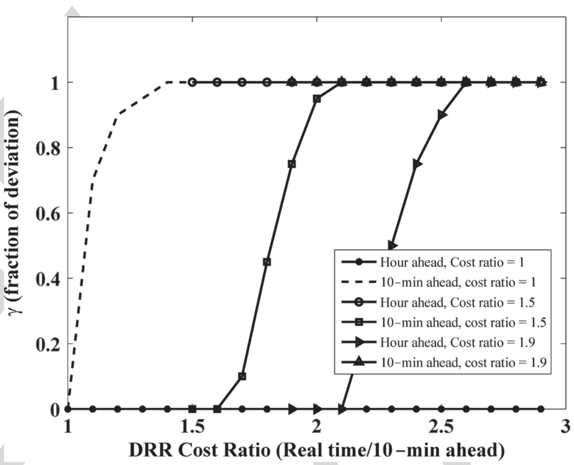

Fig. 5. γ values: DRR cost 10 min ahead/1 h ahead $= 1$.

no penalty for overgeneration, and the last term in the cost function C_T is zero.

The following step is application of this framework to a case study. For this purpose, offshore wind data from Nantucket Sound in Massachusetts is selected and discussed in Section IV.

IV. Case Study Region: Nantucket Sound

To test the feasibility of this decision framework, a case study of a hypothetical wind farm is presented. The wind farm is modeled using data for Nantucket Sound, obtained from [13] and [14] and includes wind speed measurements at 10-min intervals.

To represent the aggregate output of a wind farm instead of a single turbine, the effects of geographic diversity across the installation area are considered. These effects inherently decrease the variability of the wind generation and include two factors: the propagation of the wind and its associated dynamic events (e.g., wind gusts) through the wind farm, and the smoothing of the aggregate power curve due to multiple turbines. To model the decreased variability from the geographic diversity, the 10-min raw data are processed based on the algorithm presented in [13]. Samples of the results obtained from this process are presented in Figs. 3 and 4. Fig. 3 compares the distribution of wind speeds before and after adjustment, and shows significant smoothing effects for higher wind speeds, between 5 and 10 m/s. Fig. 4 shows the smoothing in the time series of wind power generation before and after applying the aggregation algorithm described in [12].This time series is used to represent the output from a hypothetical wind farm in Nantucket Sound.

These figures are one example of the decreased variability in wind power generation at any wind site as a result of geographic diversity.

V. Case Study Results

The decision framework in Section III is then applied using the data from Nantucket Sound discussed in Section IV. The steps required for this analysis are: determination of the optimal mitigation fractions $\gamma_{1\mathrm{h}}$ and $\gamma_{10\mathrm{min}}$, implementation of the framework using historical data and forecasts, and analysis of cost and variability outcomes.

Note that these results do not represent a 24-h time series simulation but rather are analyses of distinct snapshots at different time steps, gradually approaching real time, with the day-ahead schedule initiating the analysis, as shown in Fig. 1.

Determining the Mitigation Fractions, γ_T: In Section III, the proposed decision framework was discussed as a general approach. The objective of this framework is determining the magnitude of the forecast error to mitigate with the alternative resource at each step. These magnitudes are represented by the parameter γ_T, where T denotes the time remaining to real-time dispatch. As aforementioned, the value of γ_T must depend on the accuracy of the forecast and the cost of the pairing resource. The fact that forecast accuracy improves as T decreases (as the time to dispatch gets closer) means that each γ_T is likely to have a different value at each time horizon (T). However, faster ramping resources often have higher marginal costs; therefore, the cost of the pairing resource increases as T decreases.

Balancing these opposing factors is necessary to determine the optimal γ_T value for each T and can be quantified by optimization. To frame the optimization, it is not necessary to know the *actual* costs of the alternative resources at each T but only to know the *relative* costs. For illustration, we consider a range of DRR costs and the resulting γ_T values. The optimization is straightforward and solved in this case study using Solver tool in Microsoft Excel.

Representative results from applying the equations in Section III are provided in Fig. 5. This figure shows the optimal mitigation fractions for hour-ahead and 10-min-ahead DRRs given different ratios of real-time to hour-ahead resource costs. Note that each line on the figure includes information for the mitigation factor γ_T at both time steps, i.e., hour ahead and 10 min ahead, assuming any additional forecast error between the 10-min-ahead time frame and real time will be mitigated by the real-time resources. In Fig. 5, the x-axis represents an increasing *cost ratio* for real time to hour-ahead DRRs. Each line then graphs the optimal γ_T values for mitigating wind variability first with hour-ahead DRR γ_{1h} and then with 10-min-ahead DRR γ_{10min}. The lines differ in terms of the assumed fixed ratio of 10-min-ahead to hour-ahead resource costs.

The first two series (blue) in Fig. 5 depict a scenario in which the cost for DRRs is the same at 1 h and 10 min ahead of dispatch. In this case, the optimal γ values show that no DRRs should be used to cover deviations at an hour ahead, i.e., the line (with circles) for γ_{1h} is equal to zero for all real-time-to-hour-ahead DRR cost ratios. Since there is no additional cost incurred for waiting to mitigate the wind power forecast errors until 10 min ahead of the real-time dispatch, it is optimal to use the more accurate forecast at 10 min before dispatch to make decisions on mitigating the wind variability. It is also shown in Fig. 5 that γ_{10min} (shown with dashed line) varies with the ratio of real-time to hour-ahead DRR costs. For this scenario, in which the hour-ahead and 10-min-ahead DRRs have the same cost, the optimal fraction of the wind variability to mitigate in the 10-min-ahead time period increases to 100% for the situation in which real-time DRR costs are 150% or more of the cost of hour ahead.

The third and fourth series in Fig. 5 illustrate the case of a DRR that, at 10 min ahead of dispatch, demand response costs are 50% more than of the hour-ahead resources. This difference is significant enough to overcome the cost associated with the forecast inaccuracies at 1 h ahead. In this case, the expected deviation in wind generation at 1 h ahead should be mitigated by the cheaper hour-ahead DRR in entirety, even with the knowledge that the anticipated deviation is likely to change once the improved 10-min-ahead forecast is available.

Similar to the situation in the first series, the mitigation fraction at 10 min ahead γ_{10min} varies in a predictable way as a function of the cost of real-time DRR. Initially, none of the 10-min-ahead DRRs are cost effective. Once the real-time costs reach twice the cost of 10-min resources however, the 10-min mitigation factor γ_{10min} reaches 100%.

Finally, the fifth and sixth series (triangles) in Fig. 5 show similar results, but for the scenario in which the cost of 10-min-ahead DRR is nearly twice that of hour ahead resources. In this situation, it is also cost effective to mitigate the entire expected deviation with hour-ahead resources. In contrast to the smaller cost ratio series, in this case, it is not until the cost ratio for real-time to hour-ahead resources reaches 2.6 that it is optimal to mitigate the entire 10-min-ahead deviation with the 10-min DRR.

The results presented in Fig. 5 illustrate the optimal fraction of the wind scheduling error to be mitigated at each market stage, given different cost ratios for the DRRs that can respond in the different market time periods. These results are applicable when there is no financial penalty associated with scheduling errors.

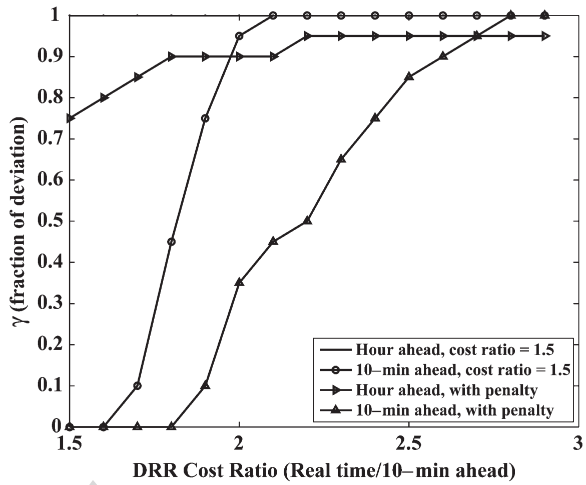

Fig. 6. Comparison with and without spillage penalty.

In general, electricity market design has imposed a penalty on generators that deviate more than 1.5%, for example, from their schedule. This financial incentive to meet a submitted schedule is consistent with the operation of dispatchable generators. However, it has been recognized that such penalties are not consistent with the operation of generators that rely on an intermittent resource such as wind since the operator of such a nondispatchable generator would rarely be responsible for schedule deviations. Therefore, the penalties for scheduling deviations included in Open Access Tariffs are routinely waived for wind farms, at least at the current level of low penetration.

The case study presented here recognizes that the schedule deviation penalties could be imposed on nondispatchable forms of generation as penetration of these resources increases. The case studies are not embedded in any specific market design but rather include the possibility of such penalties and analyze their effect.

Fig. 6 builds upon the scenario in Fig. 5 by analyzing the effect of a penalty for not meeting the submitted day-ahead schedule. If there were to be penalties imposed on wind generation for generation deviations in real time (based upon the day-ahead forecast), then there would be additional financial incentives to schedule a paired resource for mitigating the wind variability.

Fig. 6 compares the cost-effective mitigation fractions γ_{1h} and γ_{10min}, when there is a penalty associated with overgeneration, in comparison with the same scenarios without overgeneration penalty. Note that this penalty could be a direct financial penalty imposed by an ISO or could be the opportunity cost associated with unnecessarily spilling wind that appeared to be excess generation an hour or 10 min ahead of dispatch.

Fig. 6 shows that with a penalty for overgeneration, the hour-ahead mitigation fraction (γ_{1h}) does not ever reach unity, regardless of the fact that the resources that can respond 1 h ahead are assumed to be only half the cost of the faster resources that respond in the 10-min time frame. This result

TABLE I
ASSUMED DRR COSTS FOR NANTUCKET SOUND

Demand Response Resource	*Cost ($/MWh)*
Hour Ahead	$0.10/MWh
10 Minutes Ahead	$0.15/MWh
Real Time	$0.20/MWh

TABLE II
γ VALUES FOR THREE DIFFERENT MITIGATION STRATEGIES

γ_T	*Scenario 1*	*Scenario 2*	*Scenario 3:* γ_T from Figure 6
γ_{1h}	0	0.25	0.9
γ_{10M}	0	0.25	0.35

is consistent with the fact that if too much of the hour-ahead DRR is scheduled, there is significant risk of incurring an overgeneration penalty in real time.

Fig. 6 also shows that it only becomes cost effective to mitigate the entire forecast error at the 10-min time frame when the relative costs of real-time to hour-ahead resources reach a ratio of 2.8, when an overgeneration penalty is imposed.

It is cost effective to cover the entire deviation at lower cost ratios, for both the hour-ahead and 10-min-ahead time frames, only when the wind generator is not penalized for overgenerating.

The results for the particular γ_T shown here are specific to the data set from Nantucket Sound, the forecasting method used, and the scenarios defined in Figs. 5 and 6. The overall pattern of the results is useful for demonstrating implementation of the proposed decision framework for determining the amount of a paired resource to schedule for mitigating the uncertainty in wind power schedules.

In the following section, we consider the costs associated with the implementation of this strategy for the Nantucket Sound case study.

Cost Results for Nantucket Sound Case Study: In considering the benefit of using the proposed strategy for mitigating wind variability, it is important to consider the availability of the proposed pairing resources and the cost of implementation. To this end, we analyze the outcome of the decision framework using the Nantucket Sound site and DRR costs, as shown in Table I. These costs are consistent with Fig. 5, and assuming the real-time-to-hour-ahead cost ratio (x-axis) to be 2.0.

For comparing the use of the proposed decision framework to two somewhat naive approaches, three scenarios with different sets of gamma values are analyzed, shown in Table II.

The first scenario is the case in which no DRR used until real time and the simplest approach. The second scenario represents arbitrary values, as would likely be chosen if there were no guiding decision framework. For this example, these values are selected to bracket the gamma values that would result from applying the decision framework proposed here. Thus, the third set of gamma values are those obtained in Fig. 8, assuming a real-time-to-hour-ahead cost ratio of 1.5.

Using this strategy, the annual usage of DRR is summarized for the three scenarios (described in Table II) in Figs. 7–9. These figures compare the DRR usage for each time step prior to dispatch: hour ahead, ten minutes ahead, and real time.

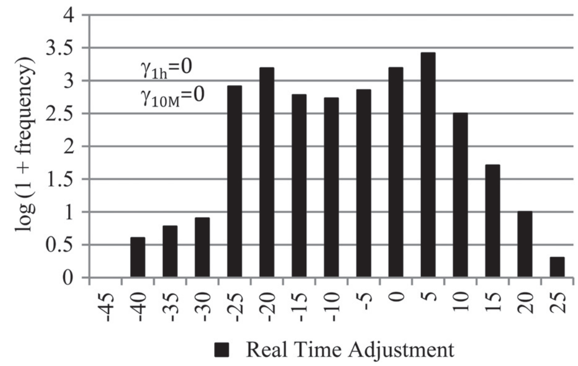

Fig. 7. Histogram of demand response usage, Scenario 1.

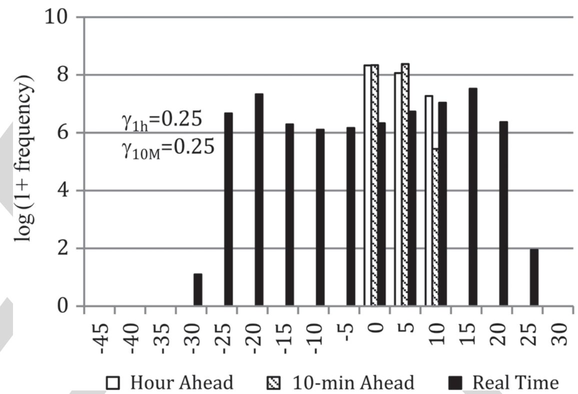

Fig. 8. Histogram of demand response usage, Scenario 2.

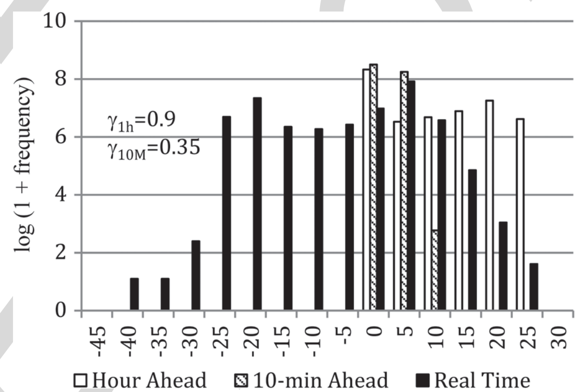

Fig. 9. Histogram of demand response usage, Scenario 3.

Fig. 10 shows a fourth scenario, when there is no penalty for overproduction at the wind farm. In this case, the optimal gamma variables are $\gamma_{1\mathrm{h}} = 1.0$ and $\gamma_{10\mathrm{min}} = 0.90$.

Figs. 7–9 show that the usage patterns of paired resources have an impact on cost. Of scenarios 1–3, where there is a minor penalty for overproduction, the optimal strategy (0.90, 0.35) is not intuitive but does produce lower overall costs for covering deviations. Table III summarizes the average nonzero use of DRRs (MW) at each decision point, and the cost savings associated with scenarios 2, 3, and 4 relative to scenario 1. It is interesting to note that, if overgeneration penalties are not imposed (scenario 4), the decision framework proposed here becomes even more beneficial, resulting in estimated savings

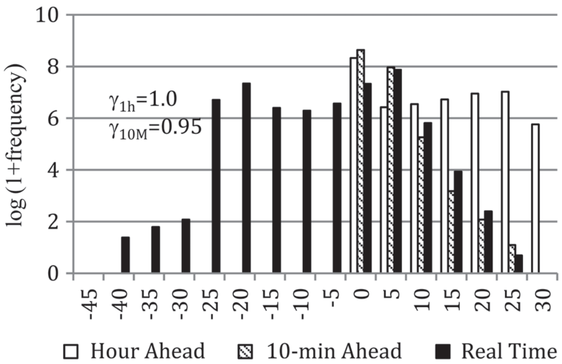

Fig. 10. Histogram of demand response usage, no overproduction penalty.

TABLE III
AVERAGE DRR USE AND SAVINGS FOR NANTUCKET SOUND CASE

Scenario	MW used (*10^3)				[1]Cost Savings (%)
	HA	10 M	Real Time		
			up	down	
1	0	0	2.5	-14	-
2	3.7	3.0	10	17	7%
3	13	1.0	3.9	16	15%
4	15	1.9	2.6	14	217%

[1] Savings are relative to naïve strategy of mitigating 100% of deviation at each time step.

TABLE IV
MAXIMUM SINGLE USE OF DRR BY SCENARIO

Scenario	Maximum Single Usage (MW)			
TTD	HA	10M	RT (up)	RT (down)
1	27	22	21	45
2	6.7	5.7	23	31
3	24	7.8	22	43
4	27	21	21	44

of 200% of the cost of a naïve strategy of mitigating the entire deviation in real time.

It is important to consider both the relative costs of these strategies and the availability of this level of DRR in the relevant region of New England. Therefore, in Table IV, we summarize the maximum single use of DRR usage for each scenario. In this table, TTD is the time to dispatch, for hour-ahead, 10-minute-ahead, and real-time market stages.

The size of the largest single use of DRRs at each decision point is important in assessing the resources necessary for implementation of such a strategy. It appears that scenario 2 uses the smallest amount of paired resource. However, comparing Table III and Fig. 9 shows that real-time DRR is used very frequently in this scenario. It is common in DRR contracts for the number of uses to be contractually limited; therefore, larger and less frequent uses might be more desirable. In the case without overgeneration penalties, the average magnitude of overproduction in real time is actually smaller than in other scenarios; however, data in Table IV shows that there are a small number of overgeneration events that are larger than in the other scenarios. The optimal balance depends on the specific DRR contracts of the region, and as a result, the optimal gamma values should be quantitatively determined on a case-by-case basis. It is also important to note that the error distributions can be nonstationary, particularly with a basic forecast model such as the one implemented here. The use of more sophisticated (and proprietary) forecasting models will result in more reliable error statistics and therefore more confidence in the optimal mitigation fractions estimated.

VI. CONCLUSION

In general, the uncertainty and variability in load is accepted as the basis for power system operations. These same characteristics in the wind resource raise significant obstacles for the integration of wind power generation into system and market operations. This paper introduces an analysis of pairing wind generation with DRRs to decrease the net variability of the wind generation.

Results from the application of this decision framework to a Nantucket Sound case study indicate that the balance between forecasting accuracy, availability, and cost of pairing resources (in this case demand response) is complex. Therefore, determination of the optimal level of mitigation of forecasting errors at each time step must be determined quantitatively on a site-by-site basis using specific forecasting methods, cost ratios, and wind data.

The results demonstrate that wind power can participate in day-ahead electricity markets through submitting schedules with price offers and do not need to be restricted to participating as price-takers. The analysis presented here also shows that the imposition of penalties for overgeneration at wind farms is the major contributor to the cost of the strategy. This highlights the importance of market policy and rules, as well as the importance of accurate forecasting techniques for the successful implementation of wind in existing power markets and systems.

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