

Measuring the Benefits of Delayed Price-Responsive Demand in Reducing Wind-Uncertainty Costs

Seyed Hossein Madaeni and Ramteen Sioshansi, *Senior Member, IEEE*

Abstract—Demand response has benefits in mitigating unit commitment and dispatch costs imposed on power systems by wind uncertainty and variability. We examine the effect of delays in consumers responding to price signals on the benefits of demand response in mitigating wind-uncertainty costs. Using a case study based on the ERCOT power system, we compare the cost of operating the system with forecasts of future wind availability to a best-case scenario with perfect foresight of wind. We demonstrate that wind uncertainty can impose substantive costs on the system and that demand response can eliminate more than 75% of these costs if loads respond to system conditions immediately. Otherwise, we find that with a 30-minute lag in the response, nearly 72% of the value of demand response is lost.

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

NOMENCLATURE

A. Model Sets and Parameters

- \mathbf{T} time index set,
- \mathbf{I} conventional generator index set,
- \mathbf{W} wind generator index set,
- $c_i^V(\cdot)$ generator i 's variable cost function,
- c_i^{NL} generator i 's no-load cost,
- c_i^{SU} 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,
- \bar{r}_i^{SP} generator i 's spinning reserve capacity,
- \bar{r}_i^{NS} generator i 's non-spinning reserve capacity,
- \bar{t}_i^- generator i 's minimum-down time,
- \bar{t}_i^+ generator i 's minimum-up time,
- $\bar{w}_{w,t}$ maximum generation available from wind generator \mathbf{W} in time period \mathbf{t} ,
- $\mathbf{p}_t(\cdot)$ inverse demand function in time period \mathbf{t} ,
- \bar{r}_t total reserve requirement in time period \mathbf{t} , and
- \bar{t}_t^{SP} spins51(f)-4C ene

Wind variability and uncertainty can also be accommodated using demand response. Having electricity demand follow wind output reduces the need for fast-responding generation. Papavasiliou and Oren [4] study the use of load control, wherein deferrable loads are directly controlled and scheduled to follow wind availability. They develop two methodologies for load scheduling and estimate the value of such a scheme. Klobasa [5] examines the effects of demand response in a future German power system with 48 GW of wind, showing that it reduces wind-uncertainty costs to less than €2/MWh. Sioshansi [6] studies the Texas (ERCOT) system with 14 GW of wind and real-time pricing (RTP). He shows that RTP can eliminate up to 93% of wind-uncertainty costs, depending on the price-responsiveness of the demand. Dietrich *et al.* [7] examine the effect of demand shifting and peak shaving on wind integration, showing that these programs can reduce wind-uncertainty costs by up to 30%.

These analyses implicitly assume that demand responds to real-time signals immediately, without any latency. While this assumption may be reasonable for some forms of direct load control, it can be more tenuous for indirect price-based mechanisms, such as RTP. This is because there may be a lag between price signals being sent, consumers observing them, and adjusting their behavior in response. Automated controls may alleviate such latency, however, since they reduce the need for consumers to exert real-time control. Such latency can reduce the value of RTP in mitigating wind-uncertainty costs, since its benefit arises from load quickly responding to wind availability and reducing the need for generators to provide balancing energy. Thus, a shortcoming of this literature is that it does not account for such latency in estimating the benefits of demand response in mitigating wind-uncertainty costs.

We address this shortcoming by studying the effect of consumer delays in responding to price signals on the benefits of RTP in reducing wind-uncertainty costs. This paper has

$$\text{s.t. } l_t = \sum_{i \in I} q_{i,t} + \sum_{w \in W} w_{i,t}, \quad \forall t \in T; \quad (2)$$

$$\sum_{i \in I} (\overset{\text{SP}}{i,t} + \overset{\text{NS}}{i,t}) \geq \bar{t}, \quad \forall t \in T; \quad (3)$$

$$\sum_{i \in I} \overset{\text{SP}}{i,t} \geq \overset{\text{SP}}{t} \cdot \bar{t}, \quad \forall t \in T; \quad (4)$$

$$\bar{t} = 0.03 \cdot l_t + 0.05 \cdot \sum_{w \in W} w_{i,t}, \quad \forall t \in T; \quad (5)$$

$$K_i^- u_{i,t} \leq q_{i,t}, \quad \forall i \in I, t \in T; \quad (6)$$

$$q_{i,t} + \overset{\text{SP}}{i,t} \leq K_i^+ u_{i,t}, \quad \forall i \in I, t \in T; \quad (7)$$

$$q_{i,t} + \overset{\text{SP}}{i,t} + \overset{\text{NS}}{i,t} \leq K_i^+, \quad \forall i \in I, t \in T; \quad (8)$$

$$0 \leq \overset{\text{SP}}{i,t} \leq$$

standard deviations, thus RTP should have similar effects if spatial correlation is explicitly modeled. On the other hand, better capturing spatial correlation should lead to a lag in the demand response having less of an effect on RTP's benefit in reducing wind-uncertainty costs. This is because discrepancies between time- t and $-(t$

TOTAL ANNUAL G

TABLE III

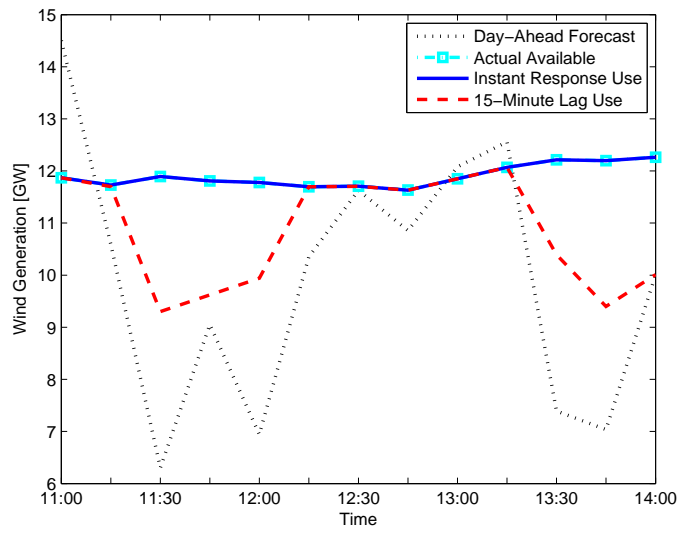


Fig. 5. Wind available and used from 11:00 to 14:00 on 1 January with immediate and lagged demand response.

interactions between these technologies.

ACKNOWLEDGMENT

The authors thank A. Sorooshian, the editors, and five anonymous reviewers for helpful discussions and suggestions.

REFERENCES

- [1] E. A. DeMeo, W. Grant, M. R. Milligan, and M. J. Schuerger, "Wind plant integration," *IEEE Power and Energy Magazine*, vol. 3, pp. 38–46, November–December 2005.
- [2] J. C. Smith, M. R. Milligan, E. A. DeMeo, and B. Parsons, "Utility wind integration and operating impact state of the art," *IEEE Transactions on Power Systems*, vol. 22, pp. 900–908, August 2007.
- [3] E. A. DeMeo, G. A. Jordan, C. Kalich, J. King, M. R. Milligan, C. Murley, B. Oakleaf, and M. J. Schuerger, "Accommodating wind's natural behavior," *IEEE Power and Energy Magazine*, vol. 5, pp. 59–67, November–December 2007.
- [4] A. Papavasiliou and S. S. Oren, "Coupling Wind Generators with Deferrable Loads," in *Energy 2030 Conference*. Atlanta, GA, USA: Institute of Electrical and Electronics Engineers, 17–18 November 2008.
- [5] M. Klobasa, "Analysis of demand response and wind integration in Germany's electricity market," *IET Renewable Power Generation*, vol. 4, pp. 55–63, January 2010.
- [6] R. Sioshansi, "Evaluating the Impacts of Real-Time Pricing on the Cost and Value of Wind Generation," *IEEE Transactions on Power Systems*, vol. 25, pp. 741–748, April 2010.
- [7] K. Dietrich, J. M. Latorre, L. Olmos, and A. Ramos, "Demand Response in an Isolated System With High Wind Integration," *IEEE Transactions on Power Systems*, vol. 27, pp. 20–29, February 2012.
- [8] C. De Jonghe, B. F. Hobbs, and R. Belmans, "Optimal Generation Mix With Short-Term Demand Response and Wind Penetration," *IEEE Transactions on Power Systems*, vol. 27, pp. 830–839, May 2012.
- [9] F. Bouffard and F. D. Galiana, "Stochastic Security for Operations Planning With Significant Wind Power Generation," *IEEE Transactions on Power Systems*, vol. 23, pp. 306–316, May 2008.
- [10] J. García-González, R. M. R. de la Muela, L. M. Santos, and A. M. González, "Stochastic Joint Optimization of Wind Generation and Pumped-Storage Units in an Electricity Market," *IEEE Transactions on Power Systems*, vol. 23, pp. 460–468, May 2008.
- [11] A. Tuohy, P. Meibom, E. Denny, and M. O'Malley, "Unit Commitment for Systems With Significant Wind Penetration," *IEEE Transactions on Power Systems*, vol. 24, pp. 592–601, May 2009.
- [12] S. H. Madaeni and R. Sioshansi, "The Impacts of Stochastic Programming and Demand Response on Wind Integration," *Energy Systems*, vol. 4, pp. 109–124, June 2013.
- [13] "Western wind and solar integration study," National Renewable Energy Laboratory, Tech. Rep. NREL/SR-550-47434, May 2010.
- [14] P. A. Ruiz, C. R. Philbrick, E. Zak, K. W. Cheung, and P. W. Sauer, "Uncertainty Management in the Unit Commitment Problem," *IEEE Transactions on Power Systems*, vol. 24, pp. 642–651, May 2009.
- [15] A. Papavasiliou, S. S. Oren, and R. P. O'Neill, "Reserve Requirements for Wind Power Integration: A Scenario-Based Stochastic Programming Framework," *IEEE Transactions on Power Systems*, vol. 26, pp. 2197–2206, November 2011.
- [16] R. P. O'Neill, P. M. Sotkiewicz, B. F. Hobbs, M. H. Rothkopf, and W. R. Stewart, "Efficient market-clearing prices in markets with nonconvexities," *European Journal of Operational Research*, vol. 164, pp. 269–285, 1 July 2005.
- [17] C. W. Potter, D. Lew, J. McCaa, S. Cheng, S. Eichelberger, and E. Gritmit, "Creating the Dataset for the Western Wind and Solar Integration Study (U.S.A.)," *Wind Engineering*, vol. 32, pp. 325–338, June 2008.
- [18] C. Loutan and D. Hawkins, "Integration of renewable resources," California Independent System Operator, Tech. Rep., November 2007.
- [19] Y. V. Makarov, P. V. Etingov, J. Ma, Z. Huang, and K. Subbarao, "Incorporating Uncertainty of Wind Power Generation Forecast Into Power System Operation, Dispatch, and Unit Commitment Procedures," *IEEE Transactions on Sustainable Energy*, vol. 2, pp. 433–442, October 2011.
- [20] S. Borenstein, J. B. Bushnell, and C. R. Knittel, "A Cournot-Nash Equilibrium Analysis of the New Jersey Electricity Market," New Jersey Board of Public Utilities, 5-648563(o)3.14438(c)7.3914(6.98(D)-0.699953(n)3.14438(d)-313.02)6.9x4438(f)7-1.0846(1545.674(r)1.764495.111367(p)3.1459156(a)7.3v