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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

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

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

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

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

$$u_{i,t,\xi}, s_{i,t,\xi}, h_{i,t,\xi} \quad \{0,1 \;, \qquad i,t,$$

each generator' minimum up- and down-times when they are started up and shut-down, 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:

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

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

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.

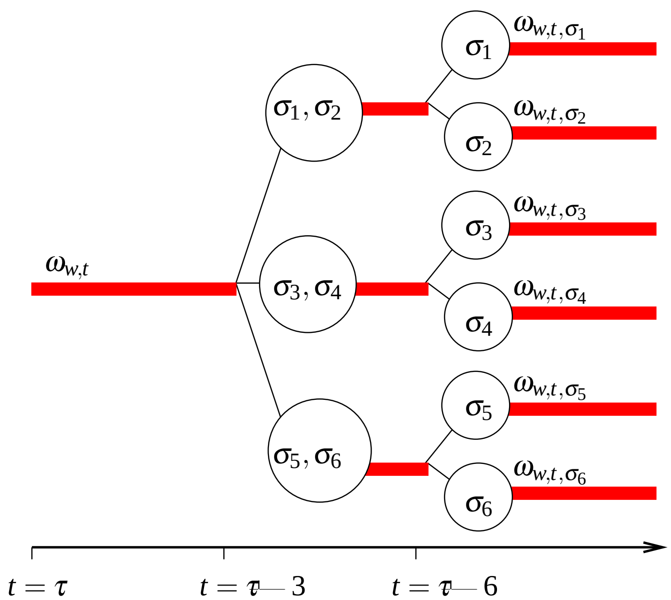

Fig. 2 Assumed structure of scenario tree.

[1] These dat-4.2603(n)-0.2 09 0.986341 2(l7)7.3689Td [(3)-3.691.986341 18s

Table 5

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

Wind Forecast Error Standard Deviation	Demand Elasticity −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 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 sys-