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The Impacts of Wind Power Integration on Sub-Daily Variation in River Flows Downstream of Hydroelectric Dams

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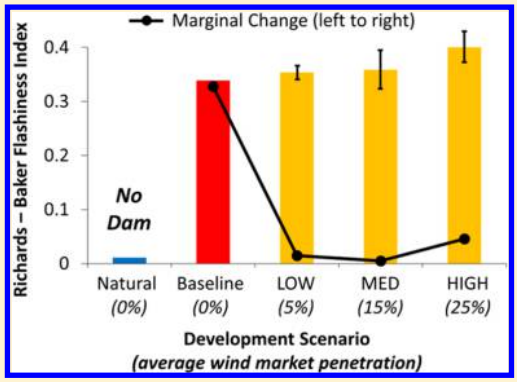
Supporting Information

ABSTRACT: Due to their operational flexibility, hydroelectric dams are ideal candidates to compensate for the intermittency and unpredictability of wind energy production. However, more coordinated use of wind and hydropower resources may exacerbate the impacts dams have on downstream environmental flows, that is, the timing and magnitude of water flows needed to sustain river ecosystems. In this paper, we examine the effects of increased (i.e., 5%, 15%, and 25%) wind market penetration on prices for electricity and reserves, and assess the potential for altered price dynamics to disrupt reservoir release schedules at a hydroelectric dam and cause more variable and unpredictable hourly flow patterns (measured in terms of the Richards-Baker Flashiness (RBF) index). Results show that the greatest potential for wind energy to impact downstream flows occurs at high (~25%) wind market penetration, when the dam sells more reserves in order to exploit spikes in real-time electricity prices caused by negative wind forecast errors. Nonetheless, compared to the initial impacts of dam construction (and the dam's subsequent operation as a peaking resource under baseline conditions) the marginal effects of any increased wind market penetration on downstream flows are found to be relatively minor.



INTRODUCTION

An increased reliance on intermittent wind energy by the electric power industry has augmented the need for sources of generation that can rapidly change power output.[1] Hydroelectric dams can do this more quickly and less expensively than thermal power plants (i.e., coal, natural gas, nuclear, or oil)—as such, they are ideally suited to compensate for the variability and unpredictability of wind energy production. The operational flexibility of dams allows them to start and rapidly increase electricity production when wind is unavailable, and/or curb output when wind is plentiful;[2] and unlike thermal power plants, operating hydroelectric dams in this manner does not entail significant sacrifices in plant efficiency or additional contributions to CO_2 emissions.[3] Nonetheless, the coordinated use of wind and hydropower may exacerbate dams' current impacts on downstream environmental flows, that is, the magnitude and timing of water flows needed to sustain river ecosystems.

Due to their operational flexibility and low variable costs, hydroelectric dams are often used as "peaking" resources; that is, they generate electricity at maximum turbine capacity during a few high demand periods per day and release much less water during other, less valuable hours. This practice triggers large, abrupt changes in flows that have been linked to numerous negative consequences for river ecosystems, including habitat loss, altered temperature, and sediment dynamics, stranding of fish and other organisms, and/or the disruption of life cycle processes.[4−8] However, results from previous studies on the ecosystem impacts of hydropower peaking are predicated on traditional market dynamics, that is, predictable fluctuations in electricity demand and prices that yield 1−2 peak periods (sustained reservoir releases) per day. More recently, research has investigated the effects of altered price dynamics caused by electricity market deregulation on flow patterns below dams.[9] Nonetheless, very little consideration has been given to the potential impacts of hydroelectric dams on environmental flows in systems with higher levels of intermittent wind power penetrating the market.

Two previous studies have suggested that providing an exclusive "back-up" service to wind farms could compromise a hydroelectric dam's ability to meet instantaneous minimum flow targets;[10,11] as well as increase the intensity of short-term flow fluctuations.[10] But, these studies give little attention to the

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larger system context in which wind and hydropower resources operate. As a result, they do not capture the effect wind power integration could have on market prices for electricity and reserves. Market prices, along with reservoir inflows, are often the primary drivers of short-term reservoir release scheduling. These previous studies also omit consideration of coal and natural gas-fired power plants, which will help bear the brunt of wind power integration in regions with limited hydropower capacity;[3] as well as the level and geographical location of wind energy production, two factors that may be critical in determining how power systems accommodate a significant influx of new wind energy.[12]

This study represents an effort to more fully understand the implications of wind power integration for river ecosystems using a system-based approach. An integrated reservoir-power system modeling framework is used to (1) explore the effects of wind energy on market prices for electricity and reserves in a system with limited (<10%) hydropower capacity under different levels of wind market penetration; and (2) show how shifting financial incentives for hydropower producers could affect reservoir release schedules and impact subdaily flow patterns below dams.

■ MATERIALS AND METHODS

Incorporating Wind Energy in Electric Power Systems. Wholesale electricity markets generally rely on three different mechanisms to meet demand on an hourly basis: (1) a "day-ahead" electricity market; (2) a "real-time" electricity market; and (3) a "reserves" market.[13] The vast majority of electricity produced and consumed in wholesale markets is bought and sold via day-ahead markets,[14,15] in which participating power plants submit "bids" (an amount of electricity in megawatt-hours (MWh)) to provide electricity 24 h in advance. Bids are collected by a system operator, who uses them to meet forecast electricity demand (schedule generation) for the next day at the lowest possible cost.

In real-time electricity markets, system operators schedule smaller amounts of generation in order to compensate for real-time electricity demand (eq 1), calculated as the sum of positive day-ahead demand forecast errors (eq 2), which typically range from 1 to 3%,[16] and forced reductions in power plant output.

$$\text{real time demand}_t = (\text{ED}_t - \text{f\_ED}_t) + \text{outage}_t \tag{1}$$

$$\text{demand forecast error}_t = \frac{(\text{ED}_t - \text{f\_ED}_t)}{\text{ED}_t} \times 100 \tag{2}$$

where, t = hour of the day; ED_t = actual electricity demand in hour t (MWh); f_ED_t = day-ahead forecast electricity demand for hour t (MWh); outage_t = forced reduction in output at power plants in hour t (MWh)

In order to ensure that adequate generation capacity is always available to meet potential real-time electricity demand, system operators also manage markets for reserves, or unscheduled power capacity (MW). In reserves markets, providers are paid for each unit of capacity they leave unscheduled (with the understanding that, should the system have a need for real-time electricity, reserved capacity may be called upon to provide it). Reserves can be provided by power plants that are already online and synchronized to the grid (i.e., "spinning"), provided these plants are operating below their maximum generating capacity, and by units that are offline and/or not synchronized (i.e., "non-spinning"), assuming these plants are able to start and increase production quickly.

Each type of market (i.e., day-ahead electricity, real-time electricity, and reserves) is associated with a separate hourly price generally set by the variable cost of the most expensive resource used to meet demand. Price dynamics in these three markets, which constitute a critical driver of hourly reservoir release schedules at hydroelectric dams, may be significantly affected by large-scale wind integration. Due to the extremely low variable costs of wind energy, forecast wind energy is generally incorporated into day-ahead electricity markets as "demand reduction"; that is, each unit (MWh) of forecast wind energy results in a commensurate reduction in "net" day-ahead electricity demand (eq 3). Wind energy thus yields lower (but sometimes more volatile) demand patterns for day-ahead electricity.

$$\text{net day ahead demand}_t = \text{f\_ED}_t - \text{f\_WE}_t \tag{3}$$

where, f_WE_t = day-ahead forecast wind energy in hour t (MWh)

The effect of wind energy on demand for real-time electricity depends largely on wind forecasting skill (i.e., the magnitude and sign of wind forecast errors in each hour (eq 4)), with positive errors serving to reduce real-time electricity demand, and negative errors increasing it (eq 5).

$$\text{winderr}_t = \text{WE}_t - f\_\text{WE}_t \tag{4}$$

$$\text{real time demand}_t = (\text{ED}_t - f\_\text{ED}_t) + \text{outage}_t - \text{wind err}_t \tag{5}$$

where, WE_t = actual wind energy in hour t (MWh)

Wind power integration also increases demand in reserves markets, with the extent of this increase dependent on the amount of installed wind capacity and the accuracy of wind energy forecasting.[17,18] In this study we employ methods similar to those used in previous studies[3,19,20] to model hourly demand for reserves dynamically as a function of forecast wind energy (eq 6) using proportionality constants (α) calculated based on the level of installed wind power capacity (MW) in the system, as well as the accuracy of wind forecasting at modeled wind sites. For the system presented in this paper, values of α range from 7.7% at lower levels of wind capacity up to 29% at higher levels of wind capacity (see Table S12 in the Supporting Information (SI) section for α-values used in this study).

$$\text{reserve requirement}_t = \text{NM1} + \alpha \times f\_\text{WE}_t \tag{6}$$

where, t = hour in simulation run; NM1 = fixed "N minus 1" reserve requirement (i.e., contingency against loss of largest power plant in the system; α = value between 0 and 1.

Implications for Hydroelectric Dams. In its simplest form, the problem of maximizing profits at a hydroelectric dam can be viewed as a choice (made in each hour) between (1) producing day-ahead electricity; and (2) offering reserves and selling real-time electricity (alternatively, dam operators can choose to do neither and instead retain reservoir storage until a later, more valuable time).

Based on the effects of wind power integration outlined above, we hypothesize that wind power integration will decrease prices for day-ahead electricity and increase prices for reserves, and that a profit maximizing dam will respond accordingly by selling less day-ahead electricity and selling more

reserves and real-time electricity. In line with this shift in strategy, we also expect that such a dam will make more frequent and shorter duration reservoir releases as power production at the dam is increasingly used to compensate for negative wind forecast errors, and that this change in behavior will drive "flashier" river flows downstream.

Modeling Framework. An electricity market (EM) model is used to represent the operation of the Dominion Zone of PJM Interconnection, a 23 gigawatt (GW) electric power system in the Mid-Atlantic region of the U.S. The EM model has two main components: a unit commitment problem, which is used to conduct separate hourly markets for day-ahead electricity and reserves, and an economic dispatch problem, which is used to conduct an hourly market for real-time electricity. Each generator in the system belongs to one of eight different power plant types. Listed by fraction of total system capacity, they are coal (34.4%), natural gas combustion turbine (NGCT) (24.3%), nuclear (15.5%), natural gas combined cycle (NGCC) (13.4%), pumped storage hydropower (6.9%), biomass (1.9%), conventional hydropower (2.1%), and oil (1.5%). The exact system of generators used by the EM model is listed in Table S2 of the SI. The EM model is used to simulate hourly market prices for day-ahead electricity, reserves, and real-time electricity over a 1-year period (2006), under baseline conditions (0 MW wind power capacity) and under 15 different wind scenarios (varying the amount and geographical source of installed wind power capacity in the system).

Simulated market prices for each scenario are then sent to a reservoir system model representing the Lower Roanoke River basin (Virginia and North Carolina, U.S.). Using market price inputs from the EM model, the reservoir system model schedules profit-maximizing, hourly reservoir releases at Roanoke Rapids Dam (100 MW), the furthest downstream dam in the basin. The hydropower scheduling component of the reservoir system model employs an optimization program with a rolling, 96 h planning horizon to schedule hourly reservoir releases. This optimization program is subject to several operational constraints at the dam: a maximum turbine capacity of 20 000 cubic feet per second (cfs); an instantaneous minimum flow requirement of 325 cfs; and a "run-of-river" designation, that is, reservoir outflows = inflows on a rolling 4-day basis. The resultant river flows simulated under baseline conditions and under the 15 wind scenarios are then compared alongside simulated "natural" (predam) flows in terms of an ecologically relevant flow metric, the Richards-Baker Flashiness index,[21] to estimate the impacts of wind energy on subdaily flow patterns.

Additional modeling information for both the EM and reservoir system models can be found in the SI. For a complete description of the modeling framework used in this study, including model validation and data sources, please refer to.[22]

Wind Scenarios. The 15 wind scenarios explored in this study represent a range of potential development pathways by considering five different geographical sources of wind energy production (Southern Plains, Northern Plains, Midwest, Mid-Atlantic, and offshore Atlantic Coast) and three different levels of installed wind power capacity (LOW, MED, and HIGH, corresponding to *average annual* wind market penetrations (a_WMP) (eq 7) of 5%, 15%, and 25%, respectively). A range of wind source regions is considered in order to determine whether geographical differences in wind variability and forecasting skill could be important factors in shaping any potential impacts of wind power development on the operations of hydroelectric dams. It is important to note the difference between a_WMP and *daily* wind market penetration (d_WMP) (eq 8), which is a dynamic value that fluctuates depending on wind availability and electricity demand.

$$\text{a\_WMP} = \frac{1}{365}\sum_{1}^{365} \text{d\_WMP}_d \tag{7}$$

$$\text{d\_WMP}_d = \frac{1}{24} \times \sum_{1}^{24} \frac{f\_\text{WE}_t}{\text{f\_ED}_t} \tag{8}$$

where d = day of simulation year; t = hour of day d.

Hourly wind data (day-ahead wind energy forecasts and forecast errors) were taken from the updated Eastern Wind Integration and Transmission Study (EWITS) data set made publicly available by the National Renewable Energy Laboratory.[23] Details regarding contributing U.S. states, total installed wind capacity (GW), and average capacity factors for the 15 wind scenarios can be found in Table S11 of the SI. The algorithm used to select individual wind sites for each scenario is explored in detail in ref 22.

River Flow Analysis. The use of flow metrics that describe one or more general characteristics of river flows (i.e., magnitude, duration, frequency, rate-of-change, and timing) is common in efforts to quantify the impact of hydroelectric dams on the downstream environment.[9,24−27] In this study, the Richards-Baker flashiness (RBF) index (eq 9), which has been used in previous efforts to characterize changes in subdaily flows due to human influences like dams,[21,27] is employed to quantify the impacts of wind power integration on downstream flows.

$$\text{RBF}_d = \frac{\sum_{24}^{i=2} 0.5(|q_{i+1} - q_i| + |q_i - q_{i-1}|)}{\sum_{24}^{i=1} q_i} \tag{9}$$

where, q_i = average river flow in hour i (kilo liters per second)

The RBF index is a value assigned to each calendar day that approximates the length of a river's hydrograph within a 24 h period, weighted inversely by total daily discharge. As such, the RBF index is a visually intuitive measure of the frequency and magnitude of fluctuations in hourly flows, with high RBF values indicating frequent, large flow fluctuations, and low RBF values denoting relatively static flows. The RBF index is also (in hydropower systems) highly correlated with metrics used in previous studies to address the response of fish populations to changes in hourly flows, such as coefficient of variation[28] and percentage of total flow;[6] it is also moderately correlated with the number of "flow reversals", or successive periods of increasing and decreasing flow often produced from dams' practice of hydropower peaking.[29] It is important to note, however, that while the RBF index is useful for describing changes in hourly flow patterns (some of which may be associated with direct or indirect impacts to riparian ecosystems), results presented in terms of this flow metric cannot be viewed explicitly as measures of ecological damage—only the potential for it to occur.

RESULTS

Impacts of Wind Energy on Market Prices. Figure 1 shows expected changes in mean daily prices, relative to baseline conditions, as a function of daily wind market penetration (d_WMP), using results from all 15 wind

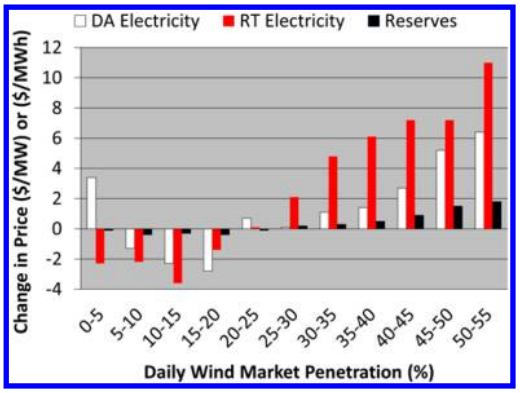

Figure 1. Expected changes in mean daily price at different levels of daily wind market penetration. Wind energy generally causes prices in all three markets to decrease at daily wind market penetration <20%. Above this level, wind energy causes increases in prices.

scenarios. In general, we find that prices in all three markets move in the same direction in response to increased wind market penetration, with prices decreasing at d_WMP less than 20% and increasing at d_WMP greater than 20%. This finding does not support the hypothesis that increased wind market penetration will have opposite effects on prices for day-ahead electricity and reserves. Nonetheless, increases in real-time electricity prices at d_WMP greater than 25% are found to be considerably larger than corresponding increases in day-ahead electricity prices or reserves (see Figure 1). These large increases in real-time electricity prices are caused by more severe negative wind forecast errors, and they represent the strongest potential for wind energy to financially incentivize a change in behavior at Roanoke Rapids Dam. The following two sections give more details about how wind energy causes price changes in each market.

Day-Ahead Electricity and Reserves. Figure 2 shows the modeled system's marginal cost curve for production of

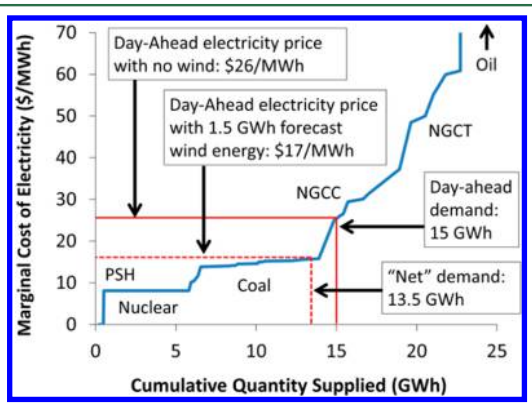

Figure 2. Effect of low-to-moderate forecast wind energy on the day-ahead electricity price. Figure shows 1.5GWh of forecast wind energy reducing "net" day-ahead electricity demand from 15 GWh to 13.5 GWh (10%) and the price decreasing from $26/MWh (marginal cost of electricity from a NGCC unit) to $17/MWh (marginal cost of electricity from a coal plant).

electricity. Under baseline conditions, market prices for both day-ahead electricity and reserves are set by either coal or natural gas combined cycle (NGCC) plants for a combined 90% of the simulation year (prices in the remaining 10% of the year set by more expensive natural gas combustion turbines or oil generators). The model assumes 2010 fuel prices for coal ($1.62/MMBtu) and natural gas ($4.86/MMBtu).[30] With these fuel prices, NGCC plants have higher variable costs of electricity generation ($29−35/MWh) than coal plants ($14−20/MWh) (see Figure 2). NGCC plants also have more convex heat rate curves than coal plants, which cause them to experience larger losses in efficiency when providing spinning reserves. As a result, the variable cost of spinning reserves from modeled NGCC plants ($7−9/MW) is also higher than that of coal plants ($4−6/MW).

At levels of d_WMP *below* 20%, forecast wind energy incorporated as "demand reduction" often displaces NGCC plants completely from the day-ahead electricity market (these NGCC plants would otherwise be turned on under baseline conditions). Less expensive coal plants become the marginal system generator and day-ahead prices decrease. Figure 2 shows a hypothetical example of how forecast wind energy can decrease day-ahead electricity prices by reducing net demand and allowing coal plants to set the market price. In the example shown, 1.5 GWh of forecast wind energy reduces net demand by 10%, and the price of day-ahead electricity decreases from $26/MWh (the marginal cost of electricity from a NGCC plant) to $17/MWh (the marginal cost of electricity from a coal plant). Since demand for reserves increases as a function of forecast wind energy (see eq 6) lower levels of d_WMP result in only modest increases in demand for reserves. If NGCC plants are displaced from the day-ahead electricity market by wind energy (as shown in Figure 2), the system operator may also have to compensate for the loss of spinning reserves from NGCC plants, which cannot provide spinning reserves if they are offline. But, at lower wind market penetration the system is generally able to meet increased demand for spinning reserves and absorb the loss of NGCC plants using less expensive coal plants and pumped storage. As a result, prices for reserves typically decrease alongside prices for day-ahead electricity.

At levels of d_WMP *above* 20%, prices for reserves and day-ahead electricity typically increase, relative to baseline conditions. High levels of d_WMP cause the system to experience very low net demand for day-ahead electricity and, simultaneously, high demand for spinning reserves. Under these circumstances, the system operator is forced to rely much more on NGCC plants. Compared to coal plants, NGCC plants have higher maximum "ramp rates", lower minimum output requirements, and lower start costs. As such, they can physically provide more reserves and are better suited to be turned on and off in response to changes in forecast wind energy under low net demand conditions. But, because NGCC plants also have higher variable costs than coal plants, increased usage of NGCC plants at high levels of d_WMP often leads to higher prices for reserves and day-ahead electricity.

Real-Time Electricity. Real-time electricity prices are similarly affected by increases and decreases in the system's usage of NGCC plants. But the effect of wind energy on real-time electricity prices also depends strongly on the magnitude and sign of wind forecast errors. Panel A of Figure 3 shows the median and interquartile range (IQR) of wind forecast errors as a function of forecast wind energy (f_WE) for all 15 wind scenarios tested. This graph shows that at high levels of f_WE negative wind forecast errors (increases in real-time electricity demand) are much more likely to occur than positive wind forecast errors (reductions in real-time demand). Figure 3 also shows that the magnitude (absolute value) of negative wind forecast errors generally increases as a function of f_WE.

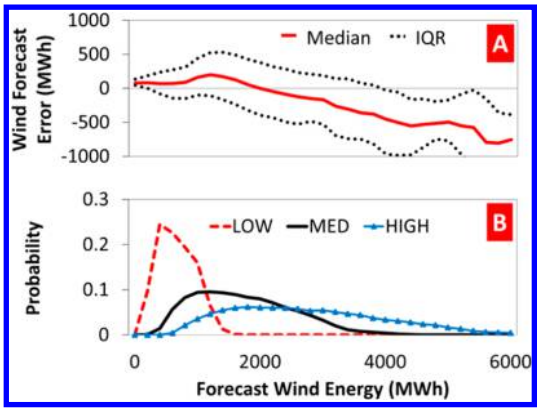

Figure 3. Wind forecast errors as a function of forecast wind energy (panel A) and probability distribution functions of forecast wind energy for each level of installed wind power capacity (panel B). Panel A shows median and IQR wind forecast errors for the 15 wind scenarios considered. Negative wind forecast errors (increases in real-time electricity demand) are much more likely to occur at HIGH wind capacity.

These two trends are due in part to the logical upper and lower bounds on the value of wind forecast errors. Panel A of Figure 3 may also reflect systematic errors in the forecasting technique used in the EWITS. Regardless, the positive relationship observed between f_WE and the frequency and severity of negative wind forecast errors has important implications for the effects of wind energy on the real-time electricity market. Panel B of Figure 3 shows probability distributions of hourly f_WE at LOW, MED and HIGH installed wind power capacity. HIGH wind capacity is much more likely to experience very large negative wind forecast errors (spikes in real-time electricity demand) than LOW and MED wind capacity. This trend explains the significant increases in real-time electricity prices observed at high levels of dWMP (see Figure 1) and likewise plays an important role in incentivizing changes in hydropower operations.

Impact of Market Price Changes on Dam Operations. Table 1 shows annual volumes of day-ahead electricity, reserves, and real-time electricity sold by Roanoke Rapids Dam (hereafter "the Dam") at different levels of installed wind power capacity. Data for the wind scenarios (i.e., LOW, MED, and HIGH wind capacity) are shown in terms of the average values and standard errors (in italics) for the five geographical regions tested. Tables S1 and S2 in the SI section list additional results for each of the 15 individual scenarios considered.

Table 1. Impacts of Wind Energy on Dam Operations and Downstream Flows[a]

		installed wind capacity [average wind market penetration %]		
	baseline [0%]	LOW [5%]	MED [15%]	HIGH [25%]
day ahead electricity (GWh)	118.64	118.38 *(1.41)*	111.83 *(1.65)*	93.55 *(3.75)*
reserves (GW)	72.90	71.50 *(1.53)*	78.72 *(1.59)*	96.94 *(3.83)*
real time electricity (GWh)	72.57	71.00 *(1.53)*	78.11 *(1.63)*	96.39 *(3.88)*
mean reservoir release duration (hrs)	7.08	6.82 *(0.1)*	6.46 *(0.19)*	5.81 *(0.2)*
static minimum flow days (out of 365)	148	149.6 *(3.17)*	142.4 *(5.03)*	129 *(9.84)*
richards baker flashiness (RBF) index	0.339	0.354 *(0.006)*	0.359 *(0.018)*	0.404 *(0.015)*

[a]For the wind scenarios (i.e., LOW, MED, and HIGH installed wind capacity) data are presented in terms of the means and standard errors (italics) across each of the five geographical regions considered.

We find little potential for wind power to impact the volumes of electricity and reserves sold at LOW and MED installed power capacity, due in large part to the similar manner in which prices in each market respond to increased wind market penetration. Table 1 shows that the Dam sells equivalent amounts of day-ahead electricity and reserves at baseline conditions and LOW installed wind capacity, and only slightly less day-ahead electricity (more reserves) at MED wind capacity.

The strongest potential for wind energy to cause changes in hydropower operations occurs at HIGH wind capacity. At HIGH wind capacity the Dam sells significantly more reserves and less day-ahead electricity, relative to baseline conditions. This shift in strategy is not, however, due to any observed effects of wind energy on prices for day-ahead electricity and reserves. Rather, it reflects the increased likelihood of large negative wind forecast errors at higher levels of daily wind market penetration (see Figure 3). We find that real-time electricity price spikes caused by large negative wind forecast errors are the critical factor in incentivizing the Dam to shift capacity away from the day-ahead electricity market to reserves at HIGH wind capacity.

The Dam's decision to sell more reserves at HIGH capacity also has implications for reservoir release schedules. Table 1 shows that the expected duration of reservoir releases made at maximum turbine capacity decreases by 1.3 h, relative to baseline conditions. Since the total volume of water passing through the dam on an annual basis is equal for each scenario, this likewise translates to more frequent reservoir releases made at turbine capacity. We also find that at HIGH wind capacity the frequency of days in which the Dam releases only static minimum flows decreases by 19, relative to baseline conditions. Collectively, these changes indicate that dam operators are scheduling hydropower production in smaller discretized amounts and spreading this production more evenly throughout the day and week, as opposed to simply concentrating production around traditional peak demand periods. This result is consistent with the Dam being used more frequently to compensate for brief periods of negative wind forecast errors, which occur somewhat randomly and are not tied to regular changes in electricity demand.

Impacts of Wind Energy on Richards-Baker Flashiness (RBF) Index. Table 1 shows that statistically significant increases (relative to baseline conditions) in the expected value of the Richards-Baker Flashiness (RBF) index occur at LOW and HIGH installed wind power capacity. The increase in the RBF index at LOW capacity occurs despite no significant difference in the volume of reserves sold by the Dam, indicating that other consequences of wind power integration (in particular, increased volatility of day-ahead electricity prices) are capable of exerting modest impacts on downstream flows, even if the Dam's annual production of day-ahead electricity and reserves remains the same. Nonetheless, the largest change in the RBF index occurs at HIGH wind capacity and is directly attributable to the Dam selling more reserves.

Figure 4 explores the link (at HIGH wind capacity) between wind market penetration, changes in the amount of reserves sold by the Dam, and changes in the RBF index. Daily RBF

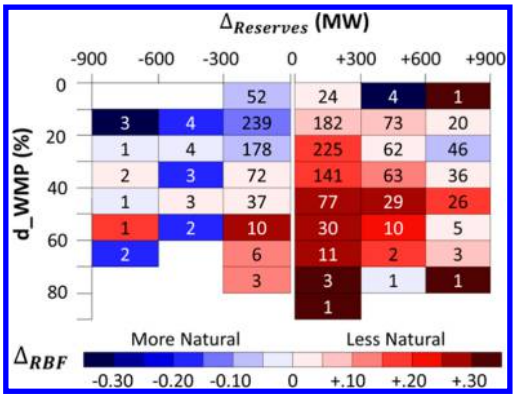

Figure 4. Relationship at HIGH installed wind capacity between wind market penetration (d_WMP), changes in the amount of reserves sold by the Dam ($\Delta_{reserves}$), and changes in the Richards-Baker Flashiness (Δ_{RBF}) index. Cell numbers denote the frequency of simulated days contained in each bivariate bin. Those days in which the dam sells more reserves ($\Delta_{reserves} > 0$) are strongly associated with an expected increase in the RBF index (red cells, less natural flows).

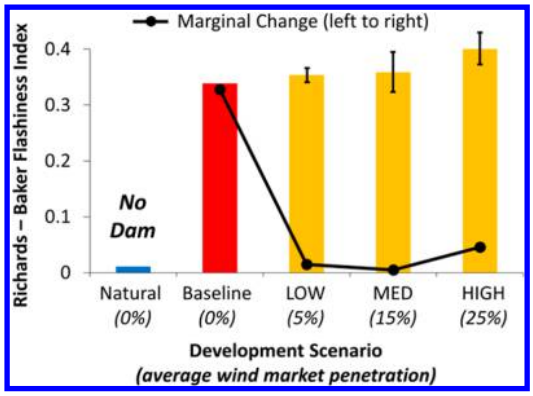

Figure 5. Impacts of wind power integration on values of the Richards–Baker Flashiness (RBF) index. Marginal changes (dotted line) are calculated as the difference between a given scenario and its neighbor to the left. Statistically significant increases in RBF index values occur at LOW and HIGH installed wind capacity, but the marginal impacts of wind energy on downstream flows are considerably lower than the impact of initial dam construction (baseline conditions).

index values simulated under baseline conditions were subtracted from those simulated at HIGH wind capacity (eq 10) for each of the five geographical regions considered, yielding a total of 1790 time-series data points (5 simulation runs × 358 days). These RBF index differentials ($\Delta_{RBF,d}$) were then sorted into bivariate bins according to daily wind market penetration (d_WMP) and reserve differentials (eq 11).

$$\Delta_{RBF,d} = RBF_{HIGH,d} - RBF_{baseline,d} \quad (10)$$

$$\Delta_{reserves,d} = reserves_{HIGH,d} - reserves_{baseline,d} \quad (11)$$

where, d = day of simulation year

$RBF_{HIGH,d}$ = RBF index value at HIGH wind capacity in day d; $RBF_{baseline,d}$ = RBF index value under baseline conditions in day d; $Reserves_{HIGH,d}$ = reserves sold by dam under HIGH wind capacity in day d (MW); $reserves_{baseline,d}$ = reserves sold by dam under baseline conditions in day d (MW).

Figure 4 shows a histogram of $\Delta_{RBF,d}$ values sorted by d_WMP and reserve differentials ($\Delta_{reserves,d}$). Cell numbers denote the frequency of simulated days (out of 1790) contained in each bivariate bin (empty cells have a frequency of zero), and cell coloration indicates the expected value of $\Delta_{RBF,d}$ for each bin. Red cells, which indicate an expected increase in the RBF index ($E[\Delta_{RBF,d}] > 0$), account for 89% of the days in which the Dam sells more reserves ($\Delta_{reserves,d} > 0$); conversely, blue cells, which indicate an expected decrease in the RBF index ($E[\Delta_{RBF,d}] < 0$), account for 78% of the days in which the Dam sells less reserves ($\Delta_{reserves,d} < 0$). We thus fund that, on average, increases in the Dam's daily provision of reserves *exacerbate* subdaily variation in river flows, while decreases in reserves sold *reduce* this variation.

Another important question is how changes in wind market penetration impact flow patterns relative to the current impacts of the dam. Figure 5 shows a bar graph of annual expected values of the RBF index for "natural" (predam) flows, baseline conditions, and the three levels of installed wind capacity tested. Figure 5 also shows the marginal impact of each scenario on the expected value of the RBF index, calculated as the difference between a given scenario and its neighbor to the left (e.g., baseline conditions minus natural flows, LOW wind capacity minus baseline conditions, etc.). Despite the potential for wind power integration (in particular, HIGH wind power capacity) to increase values of the RBF index, Figure 5 nonetheless shows that the marginal impacts of the wind scenarios are considerably smaller than the initial change exerted on natural flows by dam construction (and the Dam's subsequent use as a peaking resource under baseline conditions). The largest impact from wind energy occurs at HIGH wind capacity, when the expected value of the RBF index increases by +0.065, relative to baseline conditions. But, this change is equivalent to a relatively small fraction of the increase in the RBF index that occurs moving from natural flows to baseline conditions (+0.328).

■ DISCUSSION

Increased wind market penetration was expected to decrease prices for day-ahead electricity and increase prices for reserves, and incentivize a profit-maximizing hydroelectric dam to sell more reserves and less day-ahead electricity on an annual basis. We hypothesized that greater participation by dam operators in the reserves market would more directly link reservoir releases to spikes in real-time electricity prices caused by negative wind forecast errors, and that this would exacerbate existing levels of subdaily variation in downstream flows (increase RBF index values).

Our results, however, indicate that in a power system dominated by coal and natural gas plants (assuming 2010 fuel costs), prices for day-ahead electricity and reserves decrease and increase together as a function of daily wind market penetration. Accordingly, we find limited potential for wind power integration to financially incentivize dams to sell more reserves except at HIGH wind capacity (an average annual market penetration of 25%), when large negative wind forecast errors (i.e., spikes in real-time electricity demand) are more prevalent. At HIGH wind capacity the Dam is found to sell significantly more reserves in order to exploit substantial increases in real-time electricity prices, and reservoir releases made at turbine capacity become shorter and more frequent. This, in turn, yields increased subdaily variation in downstream flows.

It is important to note that the deterministic optimization framework used to schedule hydropower releases at the Dam gives operators perfect foresight regarding market prices,

including increases in real-time prices caused by negative wind forecast errors. Although wind data used in this study (taken from the EWITS) indicate that large negative wind forecast errors are much more likely to occur at higher forecast wind energy levels, results presented in this paper should be viewed as an upper bound on the Dam's ability to take advantage of changes in market prices. Even with a heightened ability to predict real-time prices, however, we do not find that the Dam uses its capacity exclusively to provide reserves under any wind scenario (even at HIGH wind capacity, roughly half of the Dam's capacity remains in the day-ahead electricity market).

Thus, although our results confirm some potential for wind power integration to increase RBF index values (in particular, at HIGH wind capacity), the greatest marginal impacts to hourly flow patterns are shown to occur as a result of initial dam construction (and the Dam's subsequent use as a peaking resource under baseline conditions). The additional effects of wind energy on downstream flows are relatively minor, due in part to the significant degree of flow impairment that exists below the Dam under baseline conditions. Moreover, the critical role of wind forecast errors in pushing the dam to sell more reserves suggests that improvements in forecasting methods would eliminate most of the potential that does exist for wind energy to exacerbate subdaily variation in river flows below the Dam.

A number of results from this study may be transferrable to other systems—in particular, the impacts of wind energy on market prices in fossil-fuel based systems, and the limited ability of wind energy to exacerbate dams' current impacts on hourly flows. It is likely, however, that the findings of this paper are most applicable in systems similar to the one presented in this paper. The effects of increased wind market penetration on dams in different systems, for example, ones with significantly different generation mixes or systems in which dams are centrally controlled (scheduled to help minimize total system costs, rather than maximize hydropower revenues), could vary from the results presented in this paper. Future research should address these and other important factors that could influence the effects of wind energy on dam operations and downstream flows, such as seasonal reservoir storage strategies and watershed type.

■ ASSOCIATED CONTENT

Ⓢ Supporting Information

Additional information as noted in the text. This material is available free of charge via the Internet at http://pubs.acs.org/.

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Notes

The authors declare no competing financial interest.

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