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An integrated reservoir-power system model for evaluating the impacts of wind integration on hydropower resources☆

Jordan D. Kern [a,*], Dalia Patino-Echeverri [b], Gregory W. Characklis [a]

[a] University of North Carolina at Chapel Hill, Department of Environmental Sciences and Engineering, Rosenau Hall CB #7431, Chapel Hill, NC 27599-7431, United States

[b] Duke University, Nicholas School of the Environment A150 LSRC, Box 90328, Durham, NC 27708, United States

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ABSTRACT

Despite the potential for hydroelectric dams to help address challenges related to the variability and unpredictability of wind energy, at present there are few systems-based wind-hydro studies available in the scientific literature. This work represents an attempt to begin filling this gap through the development of a systems-based modeling framework for analysis of wind power integration and its impacts on hydropower resources. The model, which relies entirely on publicly available information, was developed to assess the effects of wind energy on hydroelectric dams in a power system typical of the Southeastern US (i.e., one in which hydropower makes up <10% of total system capacity). However, the model can easily reflect different power mixes; it can also be used to simulate reservoir releases at self-scheduled (profit maximizing) dams or ones operated in coordination with other generators to minimize total system costs. The modeling framework offers flexibility in setting: the level and geographical distribution of installed wind power capacity; reservoir management rules, and static or dynamic fuel prices for power plants. In addition, the model also includes an hourly 'natural' flow component designed expressly for the purpose of assessing changes in hourly river flow patterns that may occur as a consequence of wind power integration. Validation of the model shows it can accurately reproduce market price dynamics and dam storage and release patterns under current conditions. We also demonstrate the model's capability in assessing the impact of increased wind market penetration on the volumes of reserves and electricity sold by a hydroelectric dam.

1. Introduction

The extent to which large scale integration of wind energy in electric power systems will impact market prices, system costs and reliability may depend greatly on the availability of sources that can quickly change (or 'ramp') electricity output [1–3]. Due to their capacity for energy storage, low marginal costs, and fast ramp rates, hydroelectric dams are often regarded as an ideal resource for mitigating problematic issues related to wind's intermittency and unpredictability [4]. In recent years, researchers have investigated a wide range of topics concerning the coordinated use of wind and hydropower. However, few studies to date have made use of comprehensive reservoir and power system models in assessing the costs and benefits of wind-hydro projects, and the development of such models remains a limiting factor in addressing a number of unanswered questions in this area.

Previous studies of wind-hydro projects can be separated conceptually into two categories of analysis: 'pairwise' and 'system-based' [4]. Pairwise analyses evaluate the costs and benefits of wind-hydro projects operated in isolation (i.e., somewhat disconnected from other elements of a larger electric power system). Simpler examples include investigations of the capacity value [5] and firm energy costs [6,7] of wind-hydro projects. More sophisticated pairwise studies have used historical market prices to represent wind-hydro projects' connection to larger electric power systems. Examples include previous research on: the value of energy storage in wind-hydro systems [8,9]; the financial and environmental costs of dams' providing a 'wind firming' service [10]; project optimization [11]; the use of dams to increase wind market penetration [12]; and the use of multipurpose dams to integrate wind energy [13]. Pairwise wind-hydro studies, particularly those

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* Corresponding author. Tel.: +1 2023650095.
E-mail addresses: jdkern@live.unc.edu (J.D. Kern), dalia.patino@duke.edu (D. Patino-Echeverri), charack@email.unc.edu (G.W. Characklis).

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that include some consideration of a project's system context, can offer valuable insights. However, they are generally less capable of capturing the more complex, endogenous economic and operational consequences of large scale wind integration for generators and consumers [4].

More comprehensive 'system-based' models simulate the effect of wind power integration on the workings of entire electric power systems made up of many different sizes and types of generators. As such, they offer the significant advantage of being able to simulate changes in market prices and system costs that may occur as a result of wind power integration, and then evaluate how these changes could impact the use of hydroelectric dams. However, most previous system-based wind-hydro studies have been conducted by electric power utilities, and detailed modeling information (and even results) from these studies is generally considered proprietary [4]. Examples of system-based studies from academic literature include investigations of the impacts of wind-hydro projects on: the value of wind energy [14]; and the cost of reducing CO_2 emissions [15].

Few wind-hydro studies to date have taken a system-based approach. As a consequence, significant gaps in knowledge remain as to how wind power integration may impact hydropower resources. For example: in all but a few US states, hydropower meets less than 10% of total annual electricity demand; but most (if not all) system-based wind-hydro studies have focused on 'hydro dominant' systems, in which hydropower makes up a much larger percentage of total system generation. The effects of wind power integration on dam operations may be much different in a system with relatively little hydropower capacity. There has likewise been little consideration in previous studies given to the role of market type (i.e., regulated versus competitive) in framing the incentive structure for hydroelectric dams to help integrate intermittent wind energy. In addition, no system-based study has addressed the potential for wind energy to impact environmental flows downstream of hydroelectric dams. Investigation of these topics requires models that can simulate the effects of wind power integration on hydroelectric dams under a variety of structural, economic, and hydrological conditions, while also maintaining the operational complexity of interconnected reservoir and electric power systems.

At present, there are few systems-based wind-hydro studies available in the scientific literature. This work represents an attempt to begin filling this gap through the development of a systems-based modeling framework for analysis of wind power integration and its impacts on hydropower resources. The model, which relies entirely on publically available information, was developed to assess the effects of wind energy on hydroelectric dams in a power system typical of the Southeastern US (i.e., one in which hydropower makes up <10% of total system capacity). However, the model can easily reflect different power mixes; it can also be used to simulate reservoir releases at self-scheduled (profit maximizing) dams or ones operated in coordination with other generators to minimize total system costs. The modeling framework offers flexibility in setting: the level and geographical distribution of installed wind power capacity; reservoir management rules, and static or dynamic fuel prices for power plants. In addition, the model also includes an hourly 'natural' flow component designed expressly for the purpose of assessing changes in hourly flow patterns that may occur as a consequence of wind power integration.

2. Methods

The reservoir-power system model consists of: 1) an electricity market (EM) model; and 2) a reservoir system model. The EM model iteratively solves two linked mixed integer optimization programs, a unit commitment and economic dispatch problem, to allow a power system operator to meet fluctuating hourly electricity demand. A single iteration of the EM model and its two sub problems yields hourly market prices for a single 24 h period.

The reservoir system model consists of: 1) an hourly natural flow model that simulates 'natural' (pre-dam) flows at dam sites; 2) a daily reservoir operations model that determines available reservoir storage for hydropower production; and 3) a hydropower dispatch model that schedules hourly reservoir releases in order to maximize dam profits. Fig. 1 shows a schematic of the integrated reservoir (components shown in dark grey) and EM (components shown in light grey) model.

2.1. Electricity market model

The EM model was developed in order to simulate the operation of a large power system based on the Dominion Zone of PJM Interconnection (a wholesale electricity market located in the Mid-Atlantic region of the U.S). Dominion's total generation capacity is approximately 23 GW, with a peak annual electricity demand of roughly 19 GW. Using the Environmental Protection Agency's (EPA) 2010 eGrid database, each generator in the utility's footprint was cataloged by generating capacity (MW), age, fuel type, prime mover and average heat rate (MMBtu/MWh). Specific operating constraints parameters were estimated for each size and type of plant using industry, governmental and academic sources. To reduce the computational complexity of the EM model (i.e., maintain reasonable solution times) units from each plant type were clustered by fixed and variable costs of electricity and reserves, with each cluster of similar generators forming a 'composite' plant. The total number of power plants represented in the model was reduced from 68 to a more manageable, yet representative, quantity (24)—with total system wide capacity remaining the same. Each generator in the modeled system belongs to one of eight different power plant types: conventional hydropower, pumped storage hydropower, coal, combined cycle natural gas (NGCC), combustion turbine natural gas (NGCT), oil, nuclear or biomass. Table 2 of supplemental materials section shows detailed operating characteristics of each plant in the modeled generation portfolio.

The EM model has two main components: 1) a unit commitment (UC) problem that represents both 'day ahead' electricity and 'reserves' markets; and 2) an economic dispatch (ED) problem that represents a 'real time' electricity market [16].

2.1.1. Unit commitment problem

The UC problem uses information regarding the costs (variable, fixed, and start) of participating power plants to schedule the status (on/off) and generation (MWh) at each plant in the system 24 h in advance. The UC problem is responsible for meeting forecast 'day ahead' (DA) electricity demand and satisfying system wide requirements for the provision of spinning and non spinning 'reserves' (unscheduled generating capacity that is set aside for the next day as 'back up'). The objective function of the UC problem is to minimize the cost of meeting forecast electricity demand and reserve requirements over a 96 h planning horizon, given a diverse generation portfolio:

$$\begin{aligned}\text{Minimize } Z_{\text{UC}} \sum_{t=1}^{96}\sum_{j}^{J}\big[&(\text{DA\_MWh}_{t,j}*\text{VC}_j) + (\text{ON}_{t,j}*\text{FC}_j)\\ &+ (\text{SRV\_MW}_{t,j}*\text{VC\_SR}_j) + (\text{SRV\_ON}_{t,j}*\text{FC\_SR}_j)\\ &+ (\text{NRV\_MW}_{t,j}*\text{VC\_NR}_j) + (\text{START}_{t,j}*\text{SC}_j)\big]\end{aligned} \tag{1}$$

where, t = hour in planning horizon $\in\{1,2,\ldots 96\}$, j = generator in system portfolio.

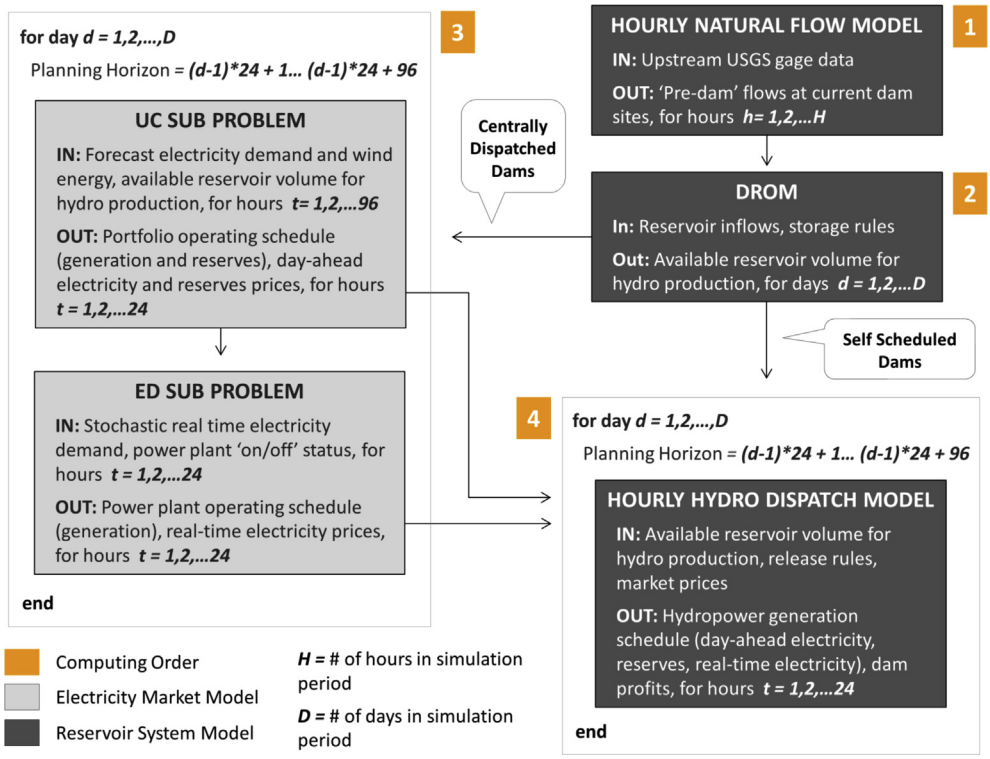

Fig. 1. Conceptual framework of integrated reservoir-power system model. Orange boxes denote computing order; light grey boxes denote components of the electricity market (EM) model; and dark grey boxes denote components of the reservoir system model. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Decision variables

- $DA\_MWh_{t,j}$ = DA electricity scheduled in hour t at generator j (MWh).
- $ON_{t,j}$ = Binary 'on/off' variable indicating DA electricity production.
- $SRV\_MW_{t,j}$ = Spinning reserve capacity scheduled in hour t at generator j (MW).
  $SRV\_ON_{t,j}$ = Binary 'on/off' variable indicating spinning reserve provision.
- $NRV\_MW_{t,j}$ = Non spinning reserve capacity scheduled in hour t at generator j (MW).
- $START_{t,j}$ = Binary 'on/off' variable indicating plant start.

Parameters

- VC_j = Variable cost of DA electricity production at generator j ($/MWh).
- FC_j = Fixed cost of DA electricity production at generator j ($).
- VC_SR_j = Variable cost of spinning reserve at generator j ($/MWh).
- FC_SR_j = Fixed cost of spinning reserve provision at generator j ($).
- VC_NR_j = Variable cost of non spinning reserve at generator j ($/MW).
- SC_j = Start cost of generator j.

Solution of the UC problem yields a preliminary hourly schedule of DA electricity generation and provision of reserves for each plant in the system over the entire planning horizon (t = 1,2,…96). However, only the first 24 h of the calculated operating schedule is considered 'locked in'—scheduled generation and reserves for later hours, i.e., t = 25, 26,… 96, are immediately discarded. This strategy ensures that plant operating schedules are conditioned on multi-day forecast information for electricity demand, wind availability, and hydropower capacity, but it also makes sure plant operations are formally scheduled no more than 24 h in advance. Market prices for both DA electricity and reserves for hours t = 1,2,…24 are then determined by the variable cost of the most expensive plant used to meet demand in each market, respectively.

2.1.2. Economic dispatch problem

After the UC problem is solved, the model adjusts in real time via the economic dispatch (ED) problem. The ED problem represents the operation of a 'real time' (RT) electricity market that compensates for demand forecast error, forced reductions in power plant output, and/or wind forecast errors by scheduling generation from system reserves. The objective function for the ED problem is to minimize the cost of meeting RT electricity demand over a 24 h planning horizon (t = 1,2,…24) using generation capacity that was designated one day prior as reserves by the UC problem:

$$\text{Minimize } Z_{\text{ED}} : \sum_{t=1}^{24}\sum_{p}^{P}(\text{RT\_MWh}_{t,p}*\text{VC}_p) + \sum_{t=1}^{24}\sum_{n}^{N}\left[(\text{RT\_MWh}_{t,n}*\text{VC}_n) + (\text{RT\_ON}_{t,n}*\text{FC}_n) + (\text{START}_{t,n}*\text{SC}_n)\right] \tag{2}$$

where, t = hour in planning horizon $\in\{1,2,\ldots 24\}$.

p = generator in spinning reserves portfolio n = generator in non spinning reserves portfolio.

Decision variables

- $RT\_MWh_{t,p}$ = RT electricity produced in hour t using spinning reserves from generator s (MWh).
- $RT\_MWh_{t,n}$ = RT electricity produced in hour t using non spinning reserves from generator n (MWh).
- $RT\_ON_{t,n}$ = Binary 'on/off' variable indicating real time electricity production from non spinning reserves at generator n.
- $START_{t,n}$ = Binary 'on/off' variable indicating plant start (Non-spinning generator).

Parameters

- VC_p = Variable cost of RT electricity production at generator p ($/MWh).
- VC_n = Variable cost of RT electricity production at generator n ($/MWh).
- FC_n = Fixed cost of electricity production at generator n ($).
- SC_n = Start cost of generator n.

Solution of the ED problem yields an hourly schedule of RT electricity generation from each plant in the system's combined spinning and non-spinning reserves portfolio over the planning horizon (t = 1,2,…24). RT electricity prices are then set by the variable cost of the most expensive generator used to meet demand in each hour. After the ED problem is solved, the larger electricity market (EM) model shifts 24 h into the future and begins its two stage process again.

Both the UC and ED problems are subject to a number of constraints, which can be separated conceptually into two classes: 1) constraints that enforce adherence to plant specific operating characteristics (e.g., minimum/maximum generating capacities, maximum ramp rates, minimum up/down times, etc.); and 2) constraints that apply to overall system operation (e.g., the system must always meet hourly demand for electricity and reserves). It is important to note that the EM model does not include consideration of transmission constraints and therefore assumes infinite transmission capacity on all lines. Further details regarding the EM model, including plant specific operating parameters for the modeled generation portfolio, problem constraints, and modeling assumptions, and full mathematical formulations can be found in supplemental materials Section 6.1.

2.1.3. Wind development scenarios

The EM model can represent a wide array of potential wind development pathways using hourly wind data from the Eastern Wind Integration and Transmission Study (EWITS) dataset [17]. Wind development scenarios are developed for testing by specifying a desired: 1) geographical source region(s) (e.g., Mid West, Offshore Atlantic coast, etc.); 2) wind site distribution (i.e., single or multi region); and 3) average annual wind penetration (wind energy as a fraction of total electricity demand— e.g., 5%, 15%, or 25%). After these three parameters have been specified, the EWITS database is filtered to remove wind sites outside the desired geographical region(s); then the remaining wind sites are sorted by capacity factor (CF) and selected one at a time (highest CF value first) until the product of cumulative installed wind capacity (MW) and average wind site CF (%) is equivalent to the product of target wind market penetration (%) and average annual DA electricity demand (MWh). This wind site selection algorithm inherently assumes that in order to maximize return on investment, wind power developers will first exhaust sites with higher capacity factors before installing wind turbines in areas where wind is less active. This assumption does not, however, account for the cost of transmission infrastructure, which may make the distance between wind sites and demand centers a more important concern than capacity factor [18].

The wind site selection algorithm yields an assembly of individually modeled wind sites, each of which is associated with two unique time series: 1) a vector of hourly DA wind energy forecasts (MWh); and 2) a vector of hourly wind forecast errors, i.e., actual minus forecast wind energy output (MWh). For a given wind development scenario, time series data are summed across all individually selected sites, yielding a pair of composite wind data vectors—the first describing total DA forecast wind energy across all selected wind sites, and the second describing total wind energy forecast error across the same collection of wind sites.

2.1.4. Day ahead and real time electricity demand

Forecast wind energy is incorporated into the DA electricity market as 'demand reduction' by estimating hourly net demand as equal to forecast DA electricity demand (taken from historical databases maintained by PJM Interconnection) [19] minus forecast wind energy (taken from the EWITS database) (Equation (3)). RT electricity demand in each hour is simulated stochastically as the sum of three different factors: 1) forced reductions in plant output; 2) demand forecast errors in the DA electricity market; and 3) wind forecast errors:

$$\text{Net\_DA\_Demand}_{s,t} = \text{DA\_Demand}_t - \text{Wind\_For}_{s,t} \tag{3}$$

$$\text{RT.Demand}_{s,t} = \max\left(\text{Dem.Err}_t + \sum_j^J \text{Out.Gen}_{t,j} - \text{Wind.Err}_{s,t}, 0\right) \tag{4}$$

where, $\text{DA\_Demand}_{s,t}$ = forecast DA electricity demand in hour t (MWh).

$\text{Wind\_For}_{s,t}$ = forecast wind energy supply for scenario s in hour t (MWh).

Dem_Err_t = DA electricity demand forecast error (actual minus forecast) in hour t (MWh).

$\text{Out\_Gen}_{t,j}$ = Forced reduction in electricity output at generator j in hour t (MW).

$\text{Wind\_Err}_{s,t}$ = DA wind error (actual minus forecast)in hour t in scenario s (MWh).

s = wind scenario.

t = hour in simulation period.

j = generator in system portfolio.

The *max* operator in Equation (4) ensures that RT electricity demand is always greater than or equal to zero, thereby disregarding cases when forecast errors can lead to negative demand. Details regarding the stochastic model used to simulate RT electricity demand are described in Section 6.1.3 of supplemental materials.

2.1.5. Reserve requirements

Each wind scenario tested assumes a static, baseline reserve requirement consistent with an N minus 1 criterion (i.e., the system operator must always have enough reserves to be able to compensate for the loss of its single largest generator). In addition, each scenario includes an additional dynamic reserve component set as a fixed percentage of forecast wind energy in each hour. The total hourly system reserve requirement for each scenario is then calculated as:

$$\text{Reserve}_{s,t} = \text{NM1} + \alpha_s * \text{WindFor}_{s,t} \tag{5}$$

where, s = a given wind scenario.

t = hour in simulation run.

$NM1$ = static N minus 1 reserve requirement (MWh) α_s =fixed percentage specified for wind scenario s.

An approach similar to those described in Refs. [20,21] is used to determine values ofα_s. Values of α_s are selected for each scenario such that loss of load probability is equivalent to baseline conditions (i.e., system reliability is equivalent to that of a system with 0% wind market penetration). Detailed discussion of the reserve requirement calculation process, along with typical values of α_s found for different wind levels, can be found in Section 6.4.1 of the supplemental materials.

2.2. Reservoir system model

The reservoir system model is based on a three dam cascade in the Roanoke River basin, which spans both North Carolina and Virginia (Fig. 2). The reservoir system model comprises: 1) an hourly natural flow model that simulates reservoir inflows into the furthest upstream reservoir (John H. Kerr Dam), as well as natural flows at the present day site of the furthest downstream dam in the basin (Roanoke Rapids Dam); 2) a daily reservoir operations model that outputs daily volumes of reservoir storage available for hydropower production at each dam; and 3) a hydropower dispatch model that optimizes hourly reservoir releases. The hydropower dispatch model is only used to schedule releases (maximize hydropower profits) at dams that are assumed to be self-scheduled. If dams are assumed to be controlled by a central operator, they are included as generators in the EM model and scheduled in a manner consistent with the system's minimum cost objectives.

2.2.1. Hourly natural flow model

In many regions, there is considerable interest in how flow patterns below hydroelectric dams influenced by wind development would compare to flows under both baseline (0% wind) and 'natural' (pre-dam) conditions. However, despite widespread availability of historical daily flow data, no records of hourly, pre-dam flows exist for many present day dam sites. In order to simulate natural hourly flow dynamics at the sites of present day hydroelectric dams, an hourly river flow model was developed using a signal processing technique similar to that used by Knapp [22]. Details on model construction and validation can be found in supplemental materials Section 6.2.1.

2.2.2. Daily reservoir operations model

Reservoir inflows to the furthest upstream dam in the system (John H. Kerr Dam) simulated by the hourly natural flow model are fed directly to a daily reservoir operations model (DROM), which uses time series inputs of inflows, precipitation, and evaporation to drive water balance equations at all three reservoirs. The DROM calculates available storage for hydropower generation at each dam on a daily basis as a function of: reservoir guide curves (schedules of target lake elevation for each day of the calendar year); beginning of period reservoir storage values; hydropower turbine capacities; minimum flow requirements, and water supply contracts. Output from the DROM (in the form of daily volumes of water for release) is then fed to the EM model (for centrally controlled dams) or the hourly hydropower dispatch model (for self-scheduled dams) for more detailed hourly scheduling. For more information on the daily reservoir operations model (data sources, reservoir operating parameters, and model validation), please refer to Kern et al. [23].

2.2.3. Hourly hydropower dispatch model

Any dam assumed to be controlled by a central system operator is scheduled by the EM model, consistent with the objective of minimizing system cost. For self-scheduled dams, however, an hourly hydropower dispatch model is used to maximize profits from the sale of DA electricity, reserves and RT electricity. The hydropower dispatch model works by iteratively solving a deterministic optimization program with the following objective function:

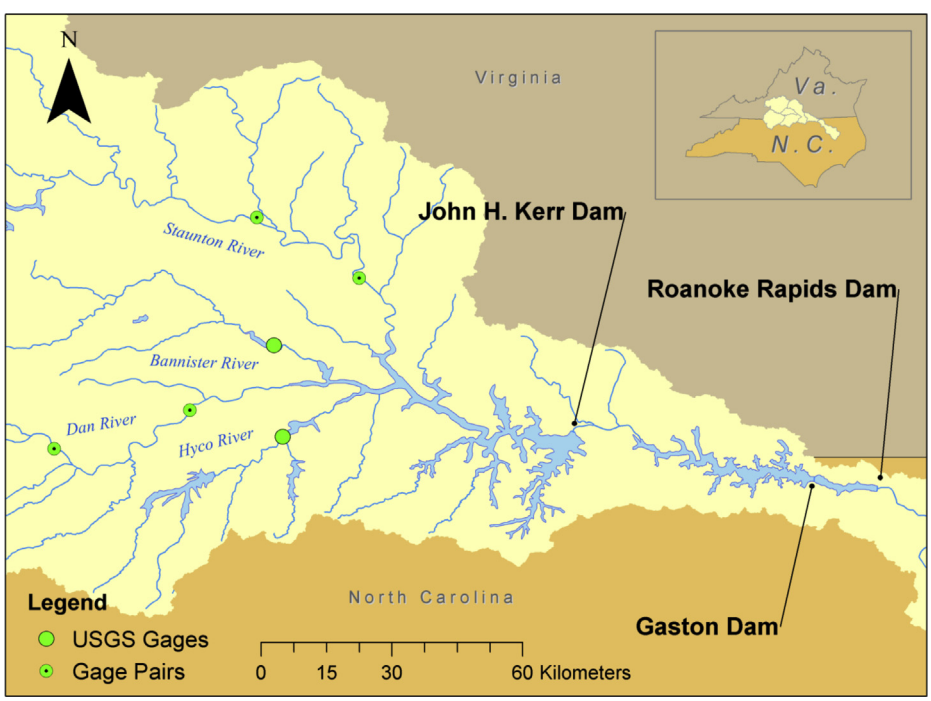

Fig. 2. Three dam cascade in Roanoke River basin. USGS gages used to calculate hourly inflows at John H. Kerr reservoir and at the present day site of Roanoke Rapids Dam are shown in green. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

$$\text{Maximize Profits}: \sum_{t=1}^{96}(\text{DA\_MWh}_t*\text{DA\_P}_t) + (\text{RV\_MW}_t*\text{RV\_P}_t) + (\text{RT\_MWh}_t*\text{RT\_P}_t) - (\text{ON}_t*\text{Fixed Cost}) - (\text{START}_t*\text{Start Cost}) \quad (6)$$

where, t = hour of planning horizon, $\in\{1,2,\ldots 96\}$.

Decision variables

- DA_MWh $_t$= Electricity (MWh) sold in DA market in hour t.
- RV_MW$_t$ = Capacity (MW) sold in reserves market in hour t.
- RT_MWh$_t$ = Electricity (MWh) sold in RT market in hour t.
- ON$_t$ = Binary 'on/off' variable indicating electricity production.
- START$_t$ = Binary 'on/off' variable indicating plant start.

Time series parameters

- DA_P$_t$ = DA electricity price in hour t ($/MWh).
- RV_P$_t$ = reserves price in hour t ($/MWh).
- RT_P$_t$ = RT electricity price in hour t ($/MWh).

A single iteration of the hydropower dispatch model's core optimization program yields an hourly schedule of hydropower production in each market (i.e., DA electricity, reserves, and RT electricity) for hours t = 1,2,…96. However, only the first 24 h of the proposed hydropower schedule are considered 'locked in'. Sales of electricity and reserves in other hours (t = 25,26,…96) are discarded immediately, and water associated with these discarded sales are retained as available storage. This strategy ensures that reservoir releases are conditioned on expectations of future water availability and market prices, but also makes sure that releases are formally scheduled no more than 24 h in advance. After the hydropower dispatch model schedules reservoir releases for a single 24 h period, the planning horizon is shifted one day into the future. The model gives the dam operator some degree of perfect foresight for future day-ahead, reserves and real time prices. Thus, the solutions obtained are considered an upper bound to the profits a dam would make in reality by responding to market prices. Further discussion of the hydropower dispatch model for self-scheduled hydroelectric dams (including a complete mathematical formulation) is presented in Section 6.2.2 of supplemental materials.

3. Results and discussion

In the following section, we present results on computational performance and discuss model validation of the reservoir and EM models. In addition, results from three yearlong wind development scenarios are presented in order to demonstrate the capabilities of the integrated modeling framework in evaluating the impact of wind power integration on hydropower resources.

3.1. Computing environment and solver algorithm performance

The hourly natural flow model and daily reservoir operations model were implemented in MATLAB. All optimization problems (the EM and hydropower dispatch models) were formulated using the AMPL language and solved using CPLEX.

By far, the most computationally intensive component of the integrated model is the UC problem of the EM model, due to the large number of binary variables involved in its mathematical structure (three binary variables per generation unit (24), per hour (96), for a total of 6912). As such, efforts to shorten the average simulation time of the larger integrated model focused on limiting the UC model's role as a performance bottleneck. Solution times for a single iteration of the UC problem—a single iteration simulates hourly prices in the DA electricity and reserves markets for one day—were restricted to 4 min. This time restriction, which ensures that a yearlong modeling run requires roughly 24 h of computing time (or less), was selected heuristically based on tradeoffs between model detail and solution optimality.

The solver CPLEX works by first identifying the non integer based solution of a linear program; then it employs branch and bound and simplex algorithms to identify integer based solutions whose objective function values approximate that of the non integer solution. The relative degree of separation between the objective functions of integer and non integer solutions (Equation (7)) can be viewed as a measure of solution optimality, and is calculated as:

$$\text{Relative MIP Gap} = \frac{\text{OBJ}_n - \text{OBJ}_i}{\text{OBJ}_n} \quad (7)$$

where, OBJ$_n$ = objective function value for non integer solution.

OBJ$_i$ = objective function value for integer solution.

The effect of a 4 min time restriction on the solver's ability to achieve optimal solutions is explored in Fig. 3. A cumulative probability distribution function (CDF) was derived from relative MIP gap values observed in 19 separate yearlong simulation runs of the UC problem (each representing a different wind development scenario). Fig. 3 shows that roughly 83% of all UC problem iterations were within 1% of the non integer objective function value (i.e., total system costs in $US), and 99.4% of all solutions were within 10% of the non integer objective function value. Thus, even with a time restriction of 4 min, the solver is able to closely approximate the optimal non integer solutions to the UC problem over a range of wind development scenarios.

3.2. Model validation

3.2.1. Electricity market model

Fig. 4 compares historical mean daily prices for DA electricity in the Dominion Zone of PJM alongside prices simulated by the UC problem of the EM model for the year 2006. Panel A, which shows

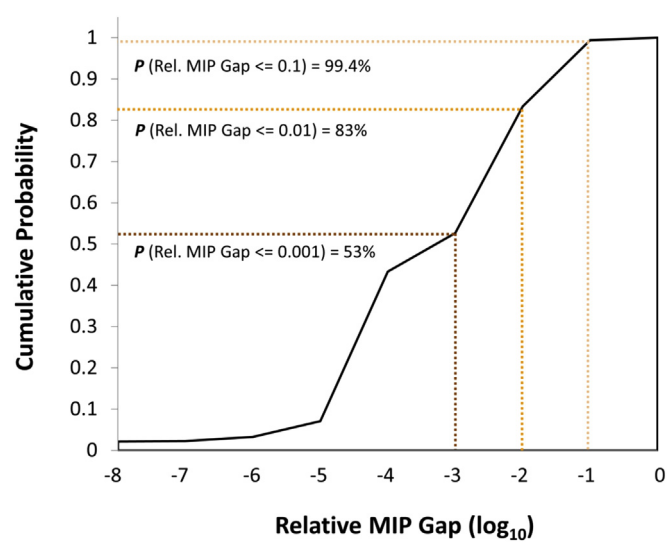

Fig. 3. Cumulative probability distribution function of relative MIP gap values for the UC problem from 19 yearlong simulation runs (6935 model solutions), using a 4-min restriction on solution time by CPLEX. 83% of all individual solutions are within 1% of the optimal non-integer objective function value.

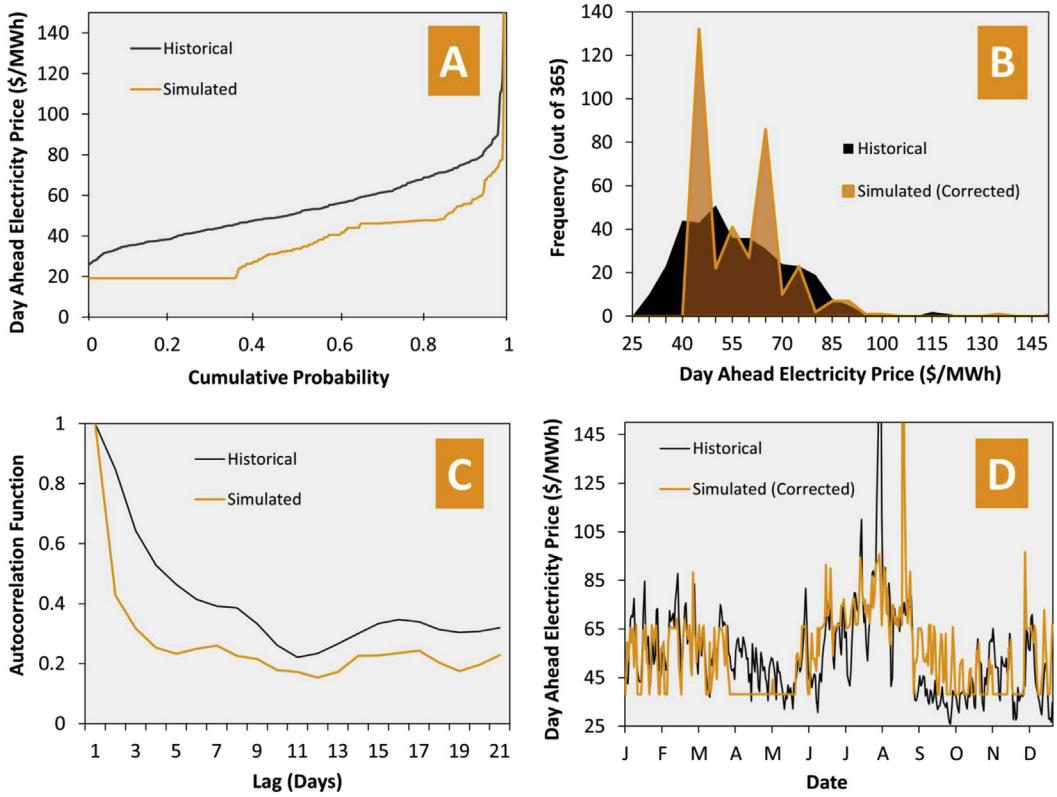

Fig. 4. Validation of unit commitment problem of electricity market model. A) Cumulative probability distribution functions for simulated and historical mean daily day-ahead electricity prices; B) Histogram of corrected (simulated + $19/MWh) and historical mean daily day-ahead electricity prices; C) Daily autocorrelation functions for simulated and historical electricity prices; D) Time series of corrected and historical mean day-ahead electricity prices.

CDFs for both historical and simulated DA prices, suggests that the simulation underestimates most prices by between $15 and $25/MWh. This error may be due to underestimated fuel prices and plant heat rates; is also likely due to generators in Dominion's actual portfolio submitting bids to provide electricity at rates higher than their marginal costs to recoup fixed operational and start costs (or, possibly, take advantage of market power). In panel B of Fig. 4, frequency histograms are shown for historical DA electricity prices and 'corrected' prices simulated by the UC problem (i.e., simulated prices + $19/MWh). Histograms for both historical and corrected prices are mean centered on $55/MWh, but the distribution of corrected prices shows significantly more kurtosis, due to the smaller number of generating units and corresponding unique prices possible in the EM model. Nonetheless, panels B and C of Fig. 4 demonstrate that the UC problem is able to accurately reproduce historical dynamics in DA electricity prices over different timescales.

The UC model also demonstrates a high degree of success in replicating the time series characteristics and statistical moments of historical reserves prices, which, compared to electricity prices, tend to be significantly much lower and less volatile (typically fluctuating between $5 and $15/MW).

RT electricity demand in the ED component of the EM model is driven by stochastic models for demand forecast error and forced unit outages; as such, no effort was made to reproduce the exact historical sequence of RT electricity prices in the Dominion Zone of PJM. However, it is worth nothing that, like historical RT electricity prices, those simulated by the ED problem tend to be lower on average (but more volatile) than DA prices. The main discrepancy between historical and simulated RT electricity prices is a higher frequency of simulated prices with a value of $0/MWh; this is due to the EM model's hourly temporal resolution, which precludes it from considering minute to minute markets for load following electricity or frequency regulation.

3.2.2. Reservoir system model

The hourly natural flow model developed in order to simulate 'pre-dam' river flows and current dam sites was able to closely reproduce hourly time series characteristics of natural river flows; however, the model does underestimate total annual inflows to the three dam system by roughly 11%, because it does not account for runoff from floodplains adjacent to the river. A detailed validation of the hourly natural flow model can be found in supplemental materials, Section 6.2.1. The DROM, which calculates available storage for hydropower generation at each dam on a daily basis, was fully developed as part of a previous study. For details on the DROM (including data sources, reservoir operating parameters, and model validation), please refer to Kern et al. [23].

Output from the DROM (daily volumes of reservoir storage available for hydropower production) is fed to the EM model (for centrally controlled dams) or the hourly hydropower dispatch model (for self-scheduled dams) for hourly scheduling. Fig. 5 compares historical hourly reservoir releases at Roanoke Rapids Dam for the year 2006 alongside releases simulated by the EM model (i.e., Roanoke Rapids Dam is assumed to be controlled by the centralized system operator). Panel A of Fig. 5 shows a count of simulated and historical hourly flows compartmentalized into four quadrants: i) hours of historical 'peak' releases (i.e., reservoir discharges $\geq$ 280 kL/s) that were correctly simulated as such; ii) hours of historical minimum flow releases (i.e., flows < 280 kL/s) that were simulated as peak releases; iii) hours of minimum flow releases that were correctly simulated as such; and iv) hours of

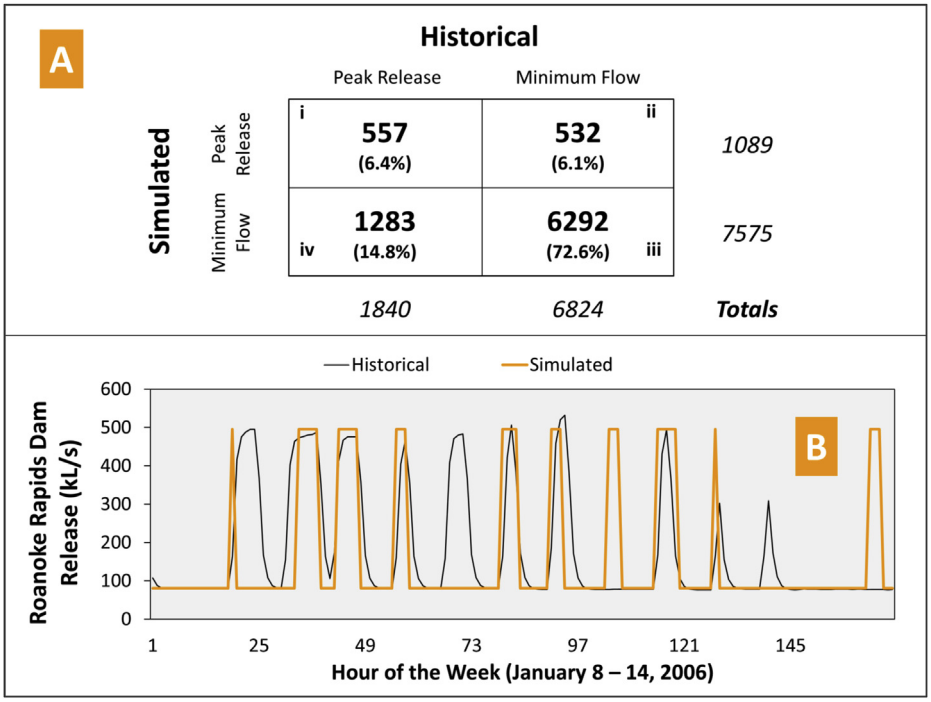

Fig. 5. Comparison of historical and simulated hourly hydropower releases at Roanoke Rapids Dam. A) Historical and simulated flows presented in tabular form show the model correctly predicts hourly flows 80% of the time; B) Time series of historical and simulated reservoir releases.

historical peak releases that were simulated as minimum flow releases. Approximately 80% of all simulated flows are located in quadrant (i) or (iii), i.e., they are correctly matched to historical reservoir releases. The largest source of error (accounting for roughly 15% of simulated hourly flows) is the EM model scheduling minimum flows at Roanoke Rapids Dam during hours of historical peak flow. The primary source of this error is the hourly natural flow model, which underestimates inflows to the reservoir system (and thereby reduces reservoir storage available for peak hydropower releases. Panel C of Fig. 5 shows that overall, however, the reservoir system model does well at replicating typical reservoir release schedules.

3.3. Wind integration case study

The EM model was used to simulate market prices for DA and RT electricity and reserves under three different levels (0%, 5% and 25%) of average daily wind market penetration (i.e., wind energy consumed as a fraction of total electricity demand) using land based wind sites located in the Mid-Atlantic region of the US.

Fig. 6 shows CDFs of mean daily prices for DA (panel A) and RT electricity (panel B), estimated from the results of a yearlong simulation that assumed average 2010 fuel prices for coal and natural gas power plants (of about $1.62/MMBtu, and $4.86/MMBtu respectively) [24]. Each panel also indicates the plant type that is dominant in setting the hourly market clearing price for each section of the CDF. Panel A shows that a modest amount (i.e., 5% market penetration) of low cost wind energy reduces the market share of combined cycle natural gas (NGCC) generators in the DA electricity market, which results in less expensive coal generators setting the market clearing price more often. At 25% wind penetration, however, the system relies much more on NGCC generators in order to accommodate lower, more volatile net electricity demand patterns and increased demand for spinning reserves; as a result, NGCC units more frequently set the market clearing price and the bottom 2/3 of the cumulative probability distribution increases in value. At the same time, 25% wind market penetration reduces the frequency of DA price spikes (e.g., especially those caused by periods of peak summer demand) associated with the use of more expensive oil and combustion turbine natural gas generators. Thus, panel A shows that the upper quartile of the DA price distribution is reduced at 25% wind penetration.

In the RT electricity market (Fig. 6, panel B) wind energy has two main effects on prices: 1) positive wind forecast errors offset other sources of RT electricity demand and result in more frequent hours with an RT price of $0/MWh; and 2) negative wind forecast errors increase RT electricity demand and cause more frequent occurrences of high RT prices. Particularly at 25% market penetration, wind energy causes the bottom portion of the cumulative probability distribution function for RT prices to decrease, while the top half increases.

In order to illustrate the ability of the integrated model to capture changes in dam operations and revenues as a consequence of wind power integration, results are also presented from the hydropower dispatch model under 0%, 5%, and 25% average daily wind market penetration (i.e., here Roanoke Rapids Dam is assumed to be a self-scheduled, profit maximizing entity). Fig. 7 shows that at 0% wind market penetration, the ratio of total annual DA electricity to reserves sold is roughly 8:5 in favor of the DA market. At 5% wind market penetration, Roanoke Rapids Dam sells slightly more reserves and RT electricity and less DA electricity. Average prices in each market decrease due to wind energy's effect on the market share of NGCC plants, and annual profits at the dam decrease from $US 8.13 million at baseline to $US 7.81 million at 5% wind penetration.

At 25% wind market penetration, average prices in each market increase due to increased market share of NGCC plants—and profits at the dam increase to $US 9.44 million. More severe negative wind forecast errors entice the dam to significantly increase its sale of reserves and RT electricity on an annual basis, resulting in a sales

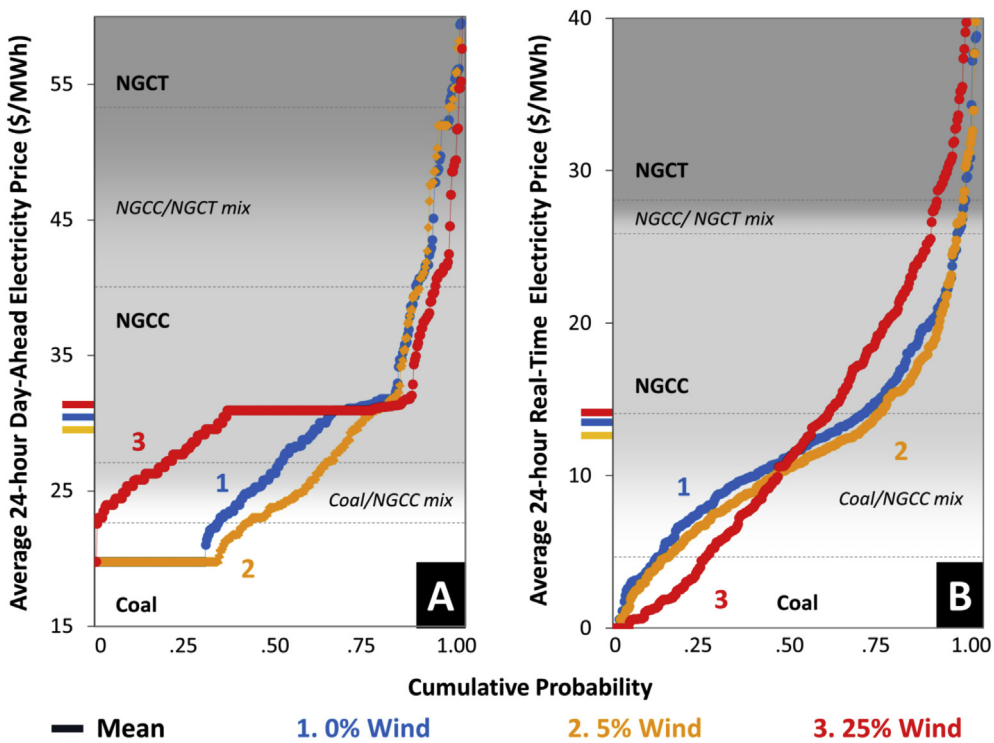

Fig. 6. Cumulative probability distribution functions of DA (panel A) and real time (panel B) electricity prices at baseline (0%), 5% and 25% average daily wind market penetration. Market clearing plant types are noted at each price level.

volume ratio of roughly 1:1 (DA electricity to reserves). This considerable increase in the Dam's sale of reserves may entail more 'stop/start' reservoir releases, which could negatively impact the operational efficiency and longevity of power equipment, and river flows downstream. However, further investigation is needed to develop a robust understanding of these effects on the dam from wind energy.

4. Conclusions

Building a more complete understanding of the costs and benefits of incorporating intermittent energy resources will require comprehensive, yet transferable, modeling approaches that can be adapted to different circumstances. This paper presents an integrated reservoir-power system model specifically designed for system-based analysis of the effects of wind power integration on hydropower resources. The model relies only on publically available information from government, industry and academic sources, and model detail can be tailored to a desired solution time to accommodate available computing resources. It can incorporate a large number of assumptions regarding power system makeup and fuel prices, wind development pathways, and reservoir management strategies. As such, it is capable of addressing many unanswered questions concerning the use of hydroelectric dams as a complement to wind energy.

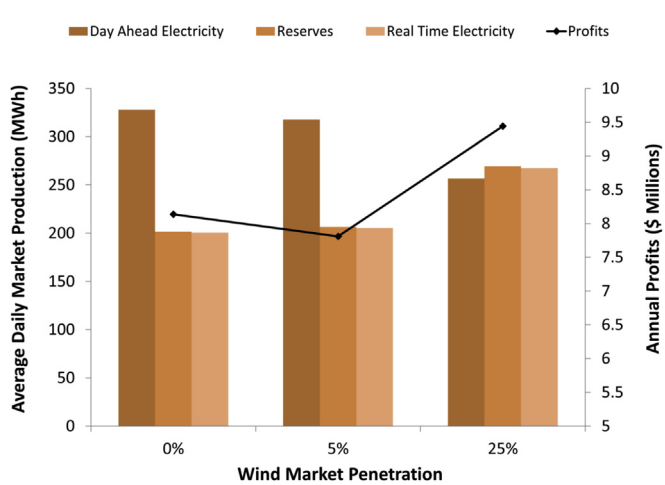

Fig. 7. Impact of wind market penetration on market production (primary *y*-axis) and annual profits (secondary *y*-axis) at Roanoke Rapids Dam. Results show the dam selling significantly more reserves (and less DA electricity) at 25% wind market penetration.

Appendix A. Supplementary data

Supplementary data related to this article can be found online at http://dx.doi.org/10.1016/j.renene.2014.06.014.

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