Benefits of Strategically Sizing Wind-Integrated Energy Storage and Transmission

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Abstract—We examine the behavior of a strategic firm that invests-in and operates wind, energy storage, and transmission. The capacity of the energy storage and transmission are cooptimized with the firm's wind-supply and energy-storage offers into a centrally dispatched electricity market. We employ a bilevel stochastic optimization model. The upper level determines the capacities and offering strategies to maximize the firm's expected profits. Multiple lower-level problems represent market clearing under different operating conditions, which capture uncertainties. The resulting large-scale optimization model is solved using multi-cut Benders's decomposition. The model is applied to a case study that is based on Alberta's electricity market.

Index Terms—Power system markets, decomposition, energy storage, wind generation, transmission, power system planning

NOMENCLATURE

| Indices an | d Sets |
|------------|--|
| d | index of demands in set, D |
| g | index of generators in set, G |
| h | index of hours in set, H |
| ι, i | indices of Benders's-decomposition iterations in |
| | set, \mathcal{I} |
| s | index of scenarios in set, S |
| w | index of weeks in set, W |
| au | index of transmission types in set, T |
| D | |
| / | |

Parameters and Constants

- C^{ch} annualized capital cost of charging power capacity of energy storage (\$/MW-yr)
- C^{dis} annualized capital cost of discharging power capacity of energy storage (\$/MW-yr)
- C^E annualized capital cost of energy-carrying capacity of energy storage (MWh-yr)
- C_{τ}^{tr} annualized capital cost of type- τ transmission line (\$/yr)
- e_0 initial state of energy (SOE) of energy storage at the beginning of each week (MWh)
- \bar{E}^{ch} maximum possible charging power capacity of energy storage (MW)

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| \bar{E}^{dis} | maximum possible discharging power capacity of |
|--------------------------------|--|
| | energy storage (MW) |
| \bar{E}^E | maximum possible energy-carrying capacity of en- |
| | ergy storage (MWh) |
| $O_{g,w,h,s}$ | scenario- s offer price of generator g during hour h |
| | of week w (\$/MWh) |
| $\bar{P}_{d,w,h,s}$ | maximum scenario- s consumption of demand d |
| | during hour h of week w (MW) |
| \bar{P}_{q} | generating capacity of generator g (MW) |
| $P_{w,h,s}^{wind}$ | scenario- s wind power available during hour h of |
| <i>a</i> , <i>n</i> , <i>o</i> | week w (MW) |
| $U_{d,w,h}$ | bid price of demand d during hour h of week w |
| | (\$/MWh) |
| β | round-trip efficiency of energy storage (p.u.) |
| γ | required SOE of energy storage at the end of each |
| | week (p.u.) |
| $\theta_{	au}$ | capacity of type- τ transmission line (MW) |
| $ ho^{ m max}$ | maximum power-to-energy ratio of the energy stor- |
| | age (h^{-1}) |
| $ ho^{\min}$ | minimum power-to-energy ratio of the energy stor- |
| | age (h^{-1}) |
| ϕ_s | probability of scenario s occurring |
| χ^{ch} | cost of operating energy storage in charging mode |
| | (\$/MWh) |
| $\chi^{ m dis}$ | cost of operating energy storage in discharging |
| | mode (\$/MWh) |
| χ^{wind} | cost of wind production (\$/MWh) |

Upper-Level Variables

| b_{τ} | binary variable that equals 1 if type- τ transmission |
|--------------------------------|--|
| | line is built and equals 0 otherwise |
| E^{ch} | installed charging power capacity of energy storage |
| | (MW) |
| E^{dis} | installed discharging power capacity of energy stor- |
| | age (MW) |
| E^E | installed energy capacity of energy storage (MWh) |
| $e_{w,h,s}$ | ending hour- h SOE of energy storage in week w |
| | of scenario s (MWh) |
| $o_{w,h,s}^{\text{dis}}$ | scenario-s offer price of discharging energy storage |
| , , | during hour h of week w (\$/MWh) |
| $o_{w,h,s}^{\text{grid,ch}}$ | scenario-s offer price of charging energy storage |
| <i>w</i> , <i>n</i> , <i>o</i> | during hour h of week w (\$/MWh) |
| $o_{w,h,s}^{\text{wind}}$ | scenario-s offer price of wind generator during |
| ,,- | hour h of week w (\$/MWh) |
| $p_{w,h,s}^{ch}$ | scenario- s curtailed wind production that is stored |
| , ,= | during hour h of week w (MW) |
| | |

| $\bar{p}_{w,h,s}^{\text{dis}}$ | scenario-s discharging capacity of energy storage | | | | |
|--------------------------------|---|--|--|--|--|
|)) | that is offered during hour h of week w (MW) | | | | |
| orid ch | | | | | |

| $p_{w,h,s}$ | scenario-s charging capacity of energy storage that | | | | |
|-------------|--|--|--|--|--|
| , , | is offered during hour h of week w (MW) | | | | |
| wind | approximate a grantity of wind conception that is of | | | | |

scenario-s quantity of wind generation that is of $p_{w,h,s}$ fered during hour h of week w (MW)

Lower-Level Variables

| $p_{d,w,h,s}$ | scenario-s consumption by demand d during hour h | | | |
|--------------------------------|---|--|--|--|
| | of week w that clears the market (MW) | | | |
| $p_{g,w,h,s}$ | scenario- s production from generator g during | | | |
| | hour h of week w that clears the market (MW) | | | |
| $p_{w,h,s}^{\text{dis}}$ | scenario-s energy-storage discharging during | | | |
| ,- ,- ,- | hour h of week w that clears the market (MW) | | | |
| $p^{\rm grid, ch}_{w,h,s}$ | scenario- s energy-storage charging during hour h | | | |
| | of week w that clears the market (MW) | | | |
| $p_{w,h,s}^{\text{wind,clrd}}$ | scenario- s wind production during hour h of | | | |
| , ,- | week w that clears the market (MW) | | | |

I. INTRODUCTION

AVORABLE regulatory policies and technology-cost reductions are giving rise to increased wind-generation penetrations [1]-[3]. Increased wind penetrations can impose pecuniary externalities, because wind generation can suppress wholesale electricity prices. Moreover, wind's pricesuppression effect is concentrated during periods of high wind availability [4]. Coupling energy storage with wind can help to mitigate this price suppression [5] and can reduce the need for transmission capacity to deliver wind generation to load [6]. However, energy storage is costly, meaning that investments must be co-optimized with transmission sizing and how wind and energy storage are offered into the market to maximize return on investments [7].

Most works that examine the coupling of wind and energy storage assume price-taking behavior. Dicarto et al. [8] use a dynamic-optimization approach to size and dispatch windintegrated batteries. Their approach utilizes wind forecasts to match generation profiles and energy storage better. They show that high-capacity energy storage allows improved market performance while complying with the dispatch schedule. However, they do not investigate strategic behavior on the part of the hybrid wind/battery firm. Moreover, they do not examine the benefits of sizing strategically the transmission interconnector for the hybrid facility. Bludszuweit et al. [9] develop a probabilistic method to determine the power and energy capacity of a hybrid system consisting of wind and energy storage. They assume price-taking behavior by the firm and focus on the role of energy storage in reducing wind-forecast errors. Wang et al. [10] develop a model to optimize the size of batteries that are used to buffer the output of wind generators. Their model determines the size of a battery system for a given wind profile, as opposed to taking more explicit account of stochastic wind-availability profiles. Yao et al. [11] develop control strategies to size batteries to improve the dispatchability of wind generators. Their method uses long-term historical wind data. Li et al. [12] develop a performance matrix that determines the size of a battery to optimize the dispatch schedule of a hybrid system consisting

of the battery and wind generators. Their methodology takes account of battery cost, life, and degradation and long-term historical wind-condition data. Luo et al. [13] consider errors in forecasting wind availability to size energy storage. Haessig et al. [14] account for auto-correlated errors in day-ahead forecasts of wind availability using a data-fitted auto-regressive model. Zhang et al. [15] use a unit-commitment model to determine how to size energy storage that is coupled with wind. Generation costs and wind curtailment are evaluated for different energy-storage capacities. Le et al. [16] solve an optimization problem to determine the size of wind-coupled energy storage while considering social welfare, voltage stability and total cost of grid-supplied energy. Brekken et al. [17] examine the impacts of control schemes on the optimal sizing of energy storage that is coupled with wind generation.

A gap in these works is that they do not allow energy storage to behave strategically to influence market price. This can be contrasted with price-making models, wherein agents are assumed to behave strategically. There are a few pricemaking models in the existing literature that are applied to the operation and planning of wind and energy storage. Wogrin et al. [18] investigate strategic generation investment of conventional generation technology using a bi-level model. They show that strategic behavior can influence investment of one technology over another. Bludszuweit et al. [19] use a probabilistic method to size energy storage that is coupled with wind generation for a price-making entity. Sioshansi [5], [20] investigates the interplay of strategic wind and energy storage in a market environment, but does not consider planning. Zugno *et al.* [21] model the participation of a strategic wind generator in a two-settlement market. However, they do not propose a framework to optimize investments in energy storage and transmission for the wind generator. Nasrolahpour et al. [22] propose a bi-level model to determine the size of standalone energy storage assuming strategic behavior.

To our knowledge there are no works that examine investment and operation of price-making wind, transmission, and energy storage in a co-optimized fashion. We fill this gap by proposing a stochastic bi-level model of such a problem. Specifically, the lower level represents the clearing of the electricity market under different scenarios that represent uncertainties (e.g., wind and load patterns, load growth, or the offers of rival generators). The upper level represents the three sets of strategic decisions for the owner of the wind, transmission, and energy storage. The firm decides how to size the energy storage that is co-located with its wind generator and the radial transmission line that connects the wind and energy storage to the power system. Moreover, the firm decides how to offer its wind generation and energy storage into the market (which clears in the lower level). Finally, the firm decides whether to store any curtailed wind energy. Due to the potentially large number of scenarios, our model can be large and computationally intractable. We address this using multi-cut Benders's decomposition [23]. Such a decomposition algorithm is not applied in related works that are in the extant literature. We apply our model to an example and a case study. We derive insights regarding the impact of market power and strategic price-making behavior on investment decisions in

energy storage and transmission.

Thus, our work makes three major contributions to the existing literature. First, we propose a co-optimization framework to determine the size of energy storage that is coupled with a wind generator and the capacity of the transmission connector that connects the hybrid wind/energy-storage facility to the electricity grid. The proposed optimization is carried out from the perspective of a private investor. One important contribution of our model is that we take a price-making perspective, which allows strategic behavior by the private investor, unlike other works that assume price-taking behavior [8]–[17], [19]. Second, unlike other works that consider strategic price-making behavior of stand-alone wind generation or energy storage [5], [18], [20]-[22], we consider strategic behavior on the part of a hybrid resource that must size energy storage and a transmission interconnector with the grid. Third, we take explicit account of uncertainty in our model, unlike other works that employ deterministic approaches [8]–[17], [19].

The remainder of this paper is organized as follows. Sections II and III provide model formulations and our solution algorithm, respectively. Sections IV and V provide example and case-study results, respectively. Section VI concludes.

II. MODEL FORMULATION

We model the case of an existing wind generator (*i.e.*, the capital cost of the generator is sunk) that connects to the power system using a radial transmission line that must be built. The firm can build energy storage that is co-located with the wind plant. After these investments are decided, the firm determines price/quantity offers for its wind production and energy storage into a market that is cleared by a market operator in different time periods and scenarios. The firm can submit scenario-dependent offers, whereas the investment decisions are scenario-invariant and made under uncertainty.

The market operator's problem is the lower-level model that is embedded within the firm's optimization. We assume strategic price-making behavior on the part of the firm that is being modeled. Thus, the market operator's problem is integrated as the lower level of the bi-level formulation. This lower-level model is incorporated so that the impact of the firm's behavior on market prices can be captured endogenously, taking into account load and wind-production data and supply offers and demand bids from other market participants. In principle, load and wind-production data and offers and bids can be estimated in any way. In our case study, we use historical data to calibrate these. After the market clears in each scenario, the firm has the option to store curtailed wind energy that does not clear the market (subject to the capacity of its energy storage), in addition to energy-storage charging that clears the market.

We proceed in this section by providing the formulation and optimality conditions of the lower-level market operator's problem and the formulation of the wind generator's problem.

A. Market Operator's Model

The market operator clears each hour of each scenario independently. Thus, we assume that the wind generator must

manage the SOE of its energy storage. The market operator's model in hour h of week w of scenario s is formulated as:

$$\min_{\Omega_{w,h,s}^{L}} \sum_{g \in G} O_{g,w,h,s} p_{g,w,h,s} - o_{w,h,s}^{\text{grid,ch}} p_{w,h,s}^{\text{grid,ch}} + o_{w,h,s}^{\text{dis}} p_{w,h,s}^{\text{dis}} + o_{w,h,s}^{\text{wind}} p_{w,h,s}^{\text{wind,clrd}} - \sum_{d \in D} U_{d,w,h} p_{d,w,h,s} \tag{1}$$

s.t.
$$p_{w,h,s}^{\text{dis}} - p_{w,h,s}^{\text{grid},\text{ch}} + p_{w,h,s}^{\text{wind,clrd}} + \sum_{g \in G} p_{g,w,h,s}$$
 (2)

$$= \sum_{d \in D} p_{d,w,h,s}; \quad (\lambda_{w,h,s})$$

$$0 \le p_{g,w,h,s} \le \bar{P}_g; \forall g \in G \quad (\mu_{q,w,h,s}^{1,\min}, \mu_{q,w,h,s}^{1,\max}) \quad (3)$$

$$0 \le p_{d,w,h,s} \le \bar{P}_{d,w,h,s}; \forall d \in D$$
(4)

$$(\mu_{d,w,h,s}^{2,\min}, \mu_{d,w,h,s}^{2,\max})$$
wind cfrd ..., wind ..., (3 min ..., 3 max)

$$0 \le p_{w,h,s}^{\text{wind,cind}} \le \bar{p}_{w,h,s}^{\text{wind}}; \quad (\mu_{w,h,s}^{\circ,\text{min}}, \mu_{w,h,s}^{\circ,\text{max}}) \tag{5}$$

$$0 \le p_{w,h,s}^{\infty} \le p_{w,h,s}^{\infty}; \quad (\mu_{w,h,s}, \mu_{w,h,s})$$

$$0 \le \text{grid.ch} \le -\text{grid.ch} \qquad (5,\min 5,\max)$$

$$(7)$$

$$0 \le p_{w,h,s}^{\circ} \le p_{w,h,s}^{\circ}; \quad (\mu_{w,h,s}, \mu_{w,h,s}^{\circ}) \tag{7}$$

$$-\sum_{\tau \in T} \theta_{\tau} b_{\tau} \le p_{w,h,s}^{\text{minicular}} + p_{w,h,s}^{\text{minicular}} - p_{w,h,s}^{\text{solution}}$$
(8)

$$\leq \sum_{\tau \in T} \theta_{\tau} b_{\tau}; \quad (\mu_{w,h,s}^{6,\min}, \mu_{w,h,s}^{6,\max})$$

where the Lagrange multiplier that is associated with each constraint appears in parentheses to its right, we have:

$$\begin{split} \Omega^L_{w,h,s} &= \left\{ p_{d,w,h,s}, \forall d \in D; p_{g,w,h,s}, \forall g \in G; \\ p^{\mathrm{dis}}_{w,h,s}; p^{\mathrm{grid},\mathrm{ch}}_{w,h,s}; p^{\mathrm{wind},\mathrm{clrd}}_{w,h,s} \right\}; \end{split}$$

and the Lagrange multiplier set is:

$$\begin{split} \Xi_{w,h,s} &= \left\{ \lambda_{w,h,s}; \mu_{g,w,h,s}^{1,\min}, \mu_{g,w,h,s}^{1,\max}, \forall g \in G; \mu_{d,w,h,s}^{2,\min}, \\ & \mu_{d,w,h,s}^{2,\max}, \forall d \in D; \mu_{w,h,s}^{3,\min}; \mu_{w,h,s}^{3,\max}; \mu_{w,h,s}^{4,\min}; \mu_{w,h,s}^{4,\max}; \\ & \mu_{w,h,s}^{5,\min}; \mu_{w,h,s}^{5,\max}; \mu_{w,h,s}^{6,\min}; \mu_{w,h,s}^{6,\max} \right\}. \end{split}$$

Objective function (1) maximizes the social welfare that is engendered by the market. Constraint (2) enforces load balance, by ensuring that demand and supply are equal exactly. Constraint sets (3)–(8) enforce capacity constraints on the dispatch of generators, loads, wind, discharging and charging of energy storage, and transmission, respectively. The model captures only the capacity of the radial transmission line that connects the wind generator to the power system. The remaining balance of the system is modeled as a market pool, with no transmission constraints. This dichotomy in the treatment of transmission constraints is due to the focus of our work, which is (in part) to examine the tradeoff between building transmission and energy storage for purposes of wind integration. Other transmission constraints could be added to our model, but would not have salient impacts on our analysis.

B. Optimality Conditions of Market Operator's Model

The market operator's model is linear and its constraints satisfy the Slater condition. As such, an optimal solution to the market operator's model can be characterized by its necessary and sufficient Karush-Kuhn-Tucker (KKT) conditions [24], [25]. The KKT conditions of the market operator's model in hour h of week w of scenario s are (2) and:

$$O_{g,w,h,s} - \lambda_{w,h,s} + \mu_{g,w,h,s}^{1,\max} - \mu_{g,w,h,s}^{1,\min} = 0; \forall g \in G$$
(9)

$$-U_{d,w,h} + \lambda_{w,h,s} + \mu_{d,w,h,s}^{2,\min} - \mu_{d,w,h,s}^{2,\min} = 0; \forall d \in D \quad (10)$$

$$o_{w,h,s}^{\text{dis}} - \lambda_{w,h,s} + \mu_{w,h,s}^{4,\max} - \mu_{w,h,s}^{4,\min} + \mu_{w,h,s}^{6,\max}$$
(12)

$$-\mu_{w,h,s}^{\text{grid,ch}} = 0;$$

- $o_{w,h,s}^{\text{grid,ch}} + \lambda_{w,h,s} + \mu_{w,h,s}^{5,\max} - \mu_{w,h,s}^{5,\min} - \mu_{w,h,s}^{6,\max}$ (13)

$$+\mu^{6,\min}_{w,h,s}=0$$

$$0 \le p_{g,w,h,s} \perp \mu_{g,w,h,s}^{1,\min} \ge 0; \forall g \in G$$

$$(14)$$

$$p_{g,w,h,s} \le P_g \perp \mu_{g,w,h,s}^{\text{1,max}} \ge 0; \forall g \in G$$
(15)

$$0 \le p_{d,w,h,s} \perp \mu_{d,w,h,s}^{2,\min} \ge 0; \forall d \in D$$
(16)

$$p_{d,w,h,s} \le \bar{P}_{d,w,h,s} \perp \mu_{d,w,h,s}^{2,\max} \ge 0; \forall d \in D$$

$$(17)$$

$$0 \le p_{w,h,s}^{\text{wind,clrd}} \perp \mu_{w,h,s}^{3,\min} \ge 0;$$
(18)

$$p_{w,h,s}^{\text{wind,clrd}} \le \bar{p}_{w,h,s}^{\text{wind}} \perp \mu_{w,h,s}^{3,\max} \ge 0;$$
(19)

$$0 \le p_{w,h,s}^{\text{dis}} \perp \mu_{w,h,s}^{4,\min} \ge 0;$$
(20)

$$p_{w,h,s}^{\text{dis}} \le \bar{p}_{w,h,s}^{\text{dis}} \perp \mu_{w,h,s}^{\text{s},\max} \ge 0;$$
(21)

$$0 \le p_{w,h,s}^{\text{enden}} \perp \mu_{w,h,s}^{\text{o,min}} \ge 0; \tag{22}$$

$$p_{w,h,s}^{\text{grid},\text{ch}} \leq \bar{p}_{w,h,s}^{\text{grid},\text{ch}} \perp \mu_{w,h,s}^{\text{s,max}} \geq 0;$$

$$\sum_{k=1}^{\infty} 0 \quad k \in \mathbb{R}^{\text{wind},\text{ch}} \quad \text{(23)}$$

$$-\sum_{\tau \in T} \theta_{\tau} b_{\tau} \leq p_{w,h,s}^{\text{wind, rid}} + p_{w,h,s}^{\text{uis}} - p_{w,h,s}^{\text{pind, rid}}$$

$$\perp \mu_{w,h,s}^{6,\min} \geq 0;$$

$$(24)$$

$$p_{w,h,s}^{\text{wind,clrd}} + p_{w,h,s}^{\text{dis}} - p_{w,h,s}^{\text{grid,ch}} \le \sum_{\tau \in T} \theta_{\tau} b_{\tau} \perp \mu_{w,h,s}^{6,\max} \ge 0.$$
(25)

Conditions (9)–(13) and (14)–(25) are stationarity and complementary-slackness requirements, respectively.

C. Wind Generator's Problem

The wind generator's problem is:

$$\max_{\Omega^{U}\cup\Omega^{L}} \sum_{s\in S, w\in W, h\in H} \left[\left(p_{w,h,s}^{\text{wind,clrd}} + p_{w,h,s}^{\text{dis}} - p_{w,h,s}^{\text{grid,ch}} \right) \lambda_{w,h,s} - \chi^{\text{wind}} p_{w,h,s}^{\text{wind,clrd}} - \left(p_{w,h,s}^{\text{ch}} + p_{w,h,s}^{\text{grid,ch}} \right) \chi^{\text{ch}} - \chi^{\text{dis}} p_{w,h,s}^{\text{dis}} \right] \phi_{s} - \sum_{\tau\in T} C_{\tau}^{\text{tr}} b_{\tau} - C^{E} E^{E} - C^{\text{ch}} E^{\text{ch}} - C^{\text{dis}} E^{\text{dis}} \tag{26}$$

s.t.
$$\sum_{\tau \in T} b_{\tau} = 1 \tag{27}$$

$$b_{\tau} \in \{0, 1\}; \forall \tau \in T \tag{28}$$

$$0 \le E^{\rm dis} \le \bar{E}^{\rm dis};\tag{29}$$

$$0 \le E^{\rm ch} \le \bar{E}^{\rm ch};\tag{30}$$

$$0 \le E^E \le \bar{E}^E; \tag{31}$$

$$\rho^{\min} E^E \le E^{\operatorname{ch}} \le \rho^{\max} E^E; \tag{32}$$

$$\rho^{\min} E^E \le E^{\dim} \le \rho^{\max} E^E; \tag{33}$$

$$0 \le \bar{p}_{w,h,s}^{\text{dis}} \le E^{\text{dis}}; \forall s \in S, w \in W, h \in H$$
(34)

$$0 \le p_{w,h,s}^{\text{ch}} + \bar{p}_{w,h,s}^{\text{grid,ch}} \le E^{\text{ch}};$$

$$\forall a \in S \text{ av } \in W \text{ } b \in H$$
(35)

$$0 \le \bar{p}_{w,h,s}^{\text{wind}} \le P_{w,h,s}^{\text{wind}}; \forall s \in S, w \in W, h \in H$$
(36)

$$\sum_{w,h,s}^{\text{is}}, o_{w,h,s}^{\text{grid,ch}}, o_{w,h,s}^{\text{wind}} \ge 0;$$

$$(37)$$

$$\forall s \in S, w \in W, h \in H$$

$$p_{w,h,s}^{cn} \le P_{w,h,s}^{wind} - p_{w,h,s}^{wind,cnd};$$

$$\forall s \in S, w \in W, h \in H$$

$$(38)$$

$$e_{w,1,s} = e_0 + \beta \cdot (p_{w,1,s}^{ch} + p_{w,1,s}^{grid,ch}) - p_{w,1,s}^{dis}; \qquad (39)$$

$$\forall s \in S, w \in W$$

$$e_{w,h,s} = e_{w,t-1,s} + \beta \cdot (p_{w,h,s}^{ch} + p_{w,h,s}^{grid,ch})$$

$$- p_{w,h,s}^{dis} : \forall s \in S, w \in W, h \in H, h > 1$$

$$(40)$$

$$e_{w \mid H \mid s} = \gamma e_0; \forall s \in S, w \in W$$

$$(41)$$

$$0 \le e_{w,h,s} \le E^E; \forall s \in S, w \in W, h \in H$$

$$(42)$$

$$(1)-(8); \forall s \in S, w \in W, h \in H$$
(43)

where:

 o_i^d

$$\begin{split} \Omega^U &= \left\{ b_1, \dots, b_{|T|}, E^{\mathrm{ch}}, E^{\mathrm{dis}}, E^E \right\} \cup \left\{ e_{w,h,s}, o_{w,h,s}^{\mathrm{dis}}, \\ o_{w,h,s}^{\mathrm{grid},\mathrm{ch}}, o_{w,h,s}^{\mathrm{wind}}, p_{w,h,s}^{\mathrm{ch}}, \bar{p}_{w,h,s}^{\mathrm{grid},\mathrm{ch}}, \bar{p}_{w,h,s}^{\mathrm{wind}}, \\ \forall s \in S, w \in W, h \in H \right\}; \end{split}$$

and:

$$\Omega^L = \bigcup_{s \in S, w \in W, h \in H} \Omega^L_{w,h,s}$$

Objective function (26) computes the expected annualized profit of the wind generator. The final four terms in (26) give the cost of building the radial transmission line and energy storage. The remaining terms give the expected operating profit. The Lagrange multiplier, $\lambda_{w,h,s}$, that is associated with (2) is used as the market-clearing price for settling energy transactions between the wind generator and market operator.

The model has four sets of constraints. The first, (27)–(33), imposes restrictions on the capacity investments. Constraints (27) and (28) force the wind generator to select exactly one type for the radial transmission line. The remainder of (29)–(33) impose resource and power-to-energy-ratio limits on the size of the energy storage.

The second set of constraints imposes physical and marketrule restrictions on the offers. Specifically, (34)–(36) impose the corresponding component capacities on the amount of discharging and charging power from the energy storage and the amount of wind power that are offered into the market. Constraints (37) require non-negative offer prices.

The third set of constraints imposes physical limits on the operation of the wind and energy storage. Constraints (38) limit the amount of additional energy-storage charging (beyond the amount that clears in the market) to be no greater than curtailed wind production. This additional charging is a 'private transaction' between the wind generator and its own energy storage. Thus, the market-clearing price ($\lambda_{w,h,s}$) does not accrue to this charging in (26). Constraints (39)–(41) define the evolution of the SOE of the energy storage over the hours of each week and (42) ensure that the SOE does not exceed the energy-carrying capability of the energy storage.

Finally, (43) embeds the market operator's problems as lower-level problems within the wind generator's optimization.

III. SOLUTION METHOD

We address the computational intractability of bi-level stochastic mixed-integer optimization problem (26)-(43) in two ways. First, we replace the lower-level problems in (43) with their necessary and sufficient KKT conditions, which yields a single-level stochastic mathematical program with equilibrium conditions (MPEC). Then, we apply multi-cut Benders's decomposition.

A. Conversion From Bi-Level to Single-Level Problem

Because the Slater condition applies to (1)–(8), (43) can be replaced in the wind generator's problem with (2), (9)-(25), $\forall s \in S, w \in W, h \in H$. This yields a single-level stochastic MPEC [26].

B. Multi-Cut Benders's Decomposition

We employ multi-cut Benders's decomposition to solve the simplified problem that is obtained in Section III-A. In doing so, we treat the investment decisions (*i.e.*, $b_1, \ldots, b_{|T|}$, E^{ch} , E^{dis} , and E^{E}) as the complicating variables that are optimized in the master problem. A set of sub problems, each of which corresponds to a second-stage scenario, are obtained by fixing the investment variables and optimizing with respect to the remaining variables. Each sub problem provides an optimality cut to add to the master problem (feasibility cuts do not need to be added, as it is feasible to set the offer quantities and dispatch of the wind and energy storage to zero for any set of investments), which gives us multiple cuts per iteration of the algorithm and speeds convergence [27].

We proceed by providing formulations of the sub and master problems. Then we discuss some technical issues related to simplifying the sub problems and separating optimality cuts. Finally, we provide pseudocode of the solution algorithm.

1) Sub Problems: The scenario-s sub problem is:

$$\max_{\Omega_s} \sum_{w \in W, h \in H} \left[\left(p_{w,h,s}^{\text{wind,clrd}} + p_{w,h,s}^{\text{dis}} - p_{w,h,s}^{\text{grid,ch}} \right) \lambda_{w,h,s} \right]$$
(44)

$$-\chi^{\text{wind}} p_{w,h,s}^{\text{wind,clrd}} - \left(p_{w,h,s}^{\text{ch}} + p_{w,h,s}^{\text{grid,ch}} \right) \chi^{\text{ch}} - \chi^{\text{dis}} p_{w,h,s}^{\text{dis}} \right]$$
(2), (9)–(25); $\forall w \in W, h \in H$
(45)

s.t. (2), (9)–(25);
$$\forall w \in W, h \in H$$
 (4)

$$0 \le \bar{p}_{w,h,s}^{\text{dis}} \le E^{\text{dis}}; \forall w \in W, h \in H$$
(46)

$$0 \le p_{w,h,s}^{\text{ch}} + \bar{p}_{w,h,s}^{\text{grid,ch}} \le E^{\text{ch}}; \forall w \in W, h \in H$$
(47)

$$0 \le \bar{p}_{w,h,s}^{\text{wind}} \le P_{w,h,s}^{\text{wind}}; \forall w \in W, h \in H$$
(48)

$$o_{w,h,s}^{\text{dis}}, o_{w,h,s}^{\text{grad,ch}}, o_{w,h,s}^{\text{wind}} \ge 0; \forall w \in W, h \in H$$

$$(49)$$

$$p_{w,h,s}^{\text{ch}} \le P_{w,h,s}^{\text{wind}} - p_{w,h,s}^{\text{wind,clrd}}; \forall w \in W, h \in H$$
(50)

$$e_{w,1,s} = e_0 + \beta \cdot (p_{w,1,s}^{ch} + p_{w,1,s}^{gnd,ch}) - p_{w,1,s}^{dis};$$
(51)
$$\forall w \in W$$

$$e_{w,h,s} = e_{w,t-1,s} + \beta \cdot (p_{w,h,s}^{ch} + p_{w,h,s}^{grid,ch})$$

$$- p_{w,h,s}^{dis}; \forall w \in W, h \in H, h > 1$$

$$(52)$$

$$e_{w,|H|,s} = \gamma e_0; \forall w \in W$$
(53)

$$0 \le e_{w,h,s} \le E^E; \forall w \in W, h \in H$$
(54)

$$b_{\tau} = \tilde{b}_{\tau}; \forall \tau \in T \quad (\sigma_{s,\tau}) \tag{55}$$

$$E_{\ell}^{\rm ch} = \tilde{E}_{\ell}^{\rm ch}; \quad (\sigma^{\rm ch}) \tag{56}$$

$$E_{\rm dis}^{\rm dis} = \tilde{E}_{\rm dis}^{\rm dis}; \quad (\sigma^{\rm dis}) \tag{57}$$

$$E^E = \tilde{E}^E; \quad (\sigma_s^E) \tag{58}$$

where:

$$\Omega_s = \bigcup_{w \in W, h \in H} \Xi_{w,h,s} \cup \left\{ e_{w,h,s}, o_{w,h,s}^{\text{dis}}, o_{w,h,s}^{\text{grid,ch}}, o_{w,h,s}^{\text{wind}}, p_{w,h,s}^{\text{ch}}, \bar{p}_{w,h,s}^{\text{dis}}, \bar{p}_{w,h,s}^{\text{grid,ch}}, \bar{p}_{w,h,s}^{\text{wind}}, \forall w \in W, h \in H; \right\}$$

Objective function (44) computes the scenario-s operating profit of the wind generator. Constraints (45) impose the KKT conditions of the market operator's scenario-s problems. Constraints (46)–(54) impose the wind firm's scenario-s operatingstage constraints. Finally, (55)-(58) fix the investment decisions based on values that are obtained from solving the master problem. The terms with tildes on the right-hand sides of (55)–(58) denote parameters that hold these fixed values. Dual variables that are associated with (55)–(58), and which are used to separate optimality cuts, appear in parentheses to the right of these constraints.

2) Master Problem: The master problem is formulated as:

$$\max_{\Omega_M} - \sum_{\tau \in T} C_{\tau}^{\text{tr}} b_{\tau} - C^E E^E - C^{\text{ch}} E^{\text{ch}} - C^{\text{dis}} E^{\text{dis}}$$
(59)
+
$$\sum_{s \in S} \phi_s \alpha_s$$

s.t. (27)–(33) (60)

$$\alpha_{s} \geq \phi_{s} \cdot \left\{ \sum_{w \in W, h \in H} \left[\left(\tilde{p}_{w,h,s}^{\text{wind},\text{clrd},(\iota)} + \tilde{p}_{w,h,s}^{\text{dis},(\iota)} - \tilde{p}_{w,h,s}^{\text{grid},\text{ch},(\iota)} \right) \tilde{\lambda}_{w,h,s}^{(\iota)} - \chi^{\text{wind}} \tilde{p}_{w,h,s}^{\text{wind},\text{clrd},(\iota)} \right] \right\}$$

$$(61)$$

$$-\left(\tilde{p}_{w,h,s}^{\mathrm{ch},(\iota)} + \tilde{p}_{w,h,s}^{\mathrm{grid},\mathrm{ch},(\iota)}\right)\chi^{\mathrm{ch}} - \chi^{\mathrm{dis}}\tilde{p}_{w,h,s}^{\mathrm{dis},(\iota)}\right] \\ + \sum_{\tau \in T} \left(b_{\tau} - \tilde{b}_{\tau}^{(\iota)}\right)\tilde{\sigma}_{s,\tau}^{(\iota)} + \left(E^{\mathrm{ch}} - \tilde{E}^{\mathrm{ch},(\iota)}\right)\tilde{\sigma}_{s}^{\mathrm{ch},(\iota)} \\ + \left(E^{\mathrm{dis}} - \tilde{E}^{\mathrm{dis},(\iota)}\right)\tilde{\sigma}_{s}^{\mathrm{dis},(\iota)} \\ + \left(E^{E} - \tilde{E}^{E,(\iota)}\right)\tilde{\sigma}_{s}^{E,(\iota)}\right\}; \forall \iota \in \mathcal{I}$$

where:

$$\Omega_M = \left\{ b_1, \dots, b_{|T|}, E^{\mathsf{ch}}, E^{\mathsf{dis}}, E^E, \alpha_1, \dots, \alpha_{|S|} \right\}$$

The first four terms in (59) compute the direct cost of the investment decisions. The final term represents the resultant operating profit that is estimated in the master problem. More specifically, α_s represents the estimated scenario-s operating profit. Constraint (60) imposes the constraints in (26)-(43) that pertain directly to the investments. Finally, (61) are optimality cuts, which are added at each iteration of the algorithm. Terms in these constraints with tildes and the superscript, (ι) ,

denote fixed parameters that are obtained from solving the corresponding sub or master problems in iteration ι of the algorithm. Thus, for instance, $\tilde{p}_{w,h,s}^{\mathrm{dis},(\iota)}$ and $\tilde{E}^{E,(\iota)}$ denote the optimized values of $p_{w,h,s}^{\mathrm{dis}}$ and E^{E} that are obtained from solving the scenario-s sub and master problem, respectively, in iteration i.

Hereafter, we define \mathcal{M} as the master problem and let ω_M denote its decision-variable vector.

3) Linearizing Sub Problems: The sub problems have two types of non-linearities, which we linearize as follows [28].

a) Complementarity Conditions: Constraints (14)–(25), which are in (45), are nonlinear, because the condition:

$$0 \ge g(x) \perp \mu \ge 0,$$

is equivalent to:

$$0 \ge g(x)$$

$$0 \ge \mu$$

$$g(x) \cdot \mu = 0$$

We linearize (14)–(25) using the technique that is outlined by Fortuny-Amat and McCarl [29], which requires the use of binary variables.

b) Objective Function: Objective function (44) contains bilinear terms in which $\lambda_{w,h,s}$ multiplies $p_{w,h,s}^{\text{wind,clrd}}$, $p_{w,h,s}^{\text{dis}}$, and $p_{w,h,s}^{\text{grid,ch}}$. We can linearize this using the strong-duality equality of the market operator's problem, which is:

$$\sum_{q \in G} O_{g,w,h,s} p_{g,w,h,s} - o_{w,h,s}^{\text{grid,ch}} p_{w,h,s}^{\text{grid,ch}} + o_{w,h,s}^{\text{dis}} p_{w,h,s}^{\text{dis}}$$
(62)

$$+ o_{w,h,s}^{\text{wind}} p_{w,h,s}^{\text{wind,clrd}} - \sum_{d \in D} U_{d,w,h} p_{d,w,h,s} = -\sum_{g \in G} \bar{P}_g \mu_{g,w,h,s}^{1,\max}$$
$$- \sum_{d \in D} \bar{P}_{d,w,h,s} \mu_{d,w,h,s}^{2,\max} - \bar{p}_{w,h,s}^{\text{wind}} \mu_{w,h,s}^{3,\max} - \bar{p}_{w,h,s}^{\text{dis}} \mu_{w,h,s}^{4,\max}$$
$$- \bar{p}_{w,h,s}^{\text{grid,ch}} \mu_{w,h,s}^{5,\max} - \left(\mu_{w,h,s}^{6,\min} + \mu_{w,h,s}^{6,\max}\right) \sum_{\tau \in T} \theta_{\tau} b_{\tau}.$$

Multiplying each of (11)–(13) by $p_{w,h,s}^{\text{wind,clrd}}$, $p_{w,h,s}^{\text{dis}}$, and $p_{w,h,s}^{\text{grid,ch}}$, respectively, using complementary-slackness conditions (18)–(25), and substituting the resulting terms into (62), gives:

$$\sum_{w \in W, h \in H} \left| \sum_{d \in D} \left(U_{d,w,h} p_{d,w,h,s} - \bar{P}_{d,w,h,s} \mu_{d,w,h,s}^{2,\max} \right)$$
(63)
$$- \sum_{g \in G} \left(O_{g,w,h,s} p_{g,w,h,s} + \bar{P}_{g} \mu_{g,w,h,s}^{1,\max} \right)$$
$$- \chi^{\text{wind}} p_{w,h,s}^{\text{wind,clrd}} - \left(p_{w,h,s}^{\text{ch}} + p_{w,h,s}^{\text{grid,ch}} \right) \chi^{\text{ch}} - \chi^{\text{dis}} p_{w,h,s}^{\text{dis}} \right];$$

as a linearized objective function that is equivalent to (44).

4) Separating Optimality Cuts: We let S_s denote the linearized scenario-s sub problem, which consists of Objective function (63) and Constraints (45)–(58), where Conditions (14)–(25) in (45) are linearized using binary variables. We let Ω'_s denote the decision-variable set of S_s and f_s its objective-function value. S_s is a mixed-integer linear optimization problem. Due to the presence of binary variables in S_s , the values of the dual variables, $\sigma_{s,1}, \ldots, \sigma_{s,|T|}$, $\sigma_s^{ch}, \sigma_s^{dis}$, and σ_s^E , which are used to separate optimality cuts, can be distorted [30].

We address this by solving the sub problems and generating optimality cuts in two steps. In the first step, we solve S_s to obtain ω_s^* , which denotes an optimal-variable vector. Next, we solve an auxiliary problem, which we denote as \mathcal{A}_s . \mathcal{A}_s is identical to S_s , with two differences. First, (45), which characterize an optimal solution to the market operator's problem, are replaced with (2)–(13), $\forall w \in W, h \in H$ and (62), which characterize equivalently an optimal solution to the market operator's problem. This equivalence is because (2)–(13), $\forall w \in W, h \in H$ are primal and dual constraints for the market operator's problem, while (62) is its strong-duality equality. The other difference between \mathcal{A}_s and \mathcal{S}_s is that the values of $\sigma_{w,h,s}^{\text{dis}}$, $\sigma_{w,h,s}^{\text{grid,ch}}$, $\sigma_{w,h,s}^{\text{wind}}$, $\mu_{w,h,s}^{3,\max}$, $\mu_{w,h,s}^{4,\max}$, $\mu_{w,h,s}^{5,\max}$, $\forall s \in S, w \in W, h \in H$ are fixed equal to the corresponding optimal values that are in ω_s^* . In doing so, (62) is linear. We let Ψ_s denote the decision-variable set and ψ_s^* an optimal decision-variable vector of \mathcal{A}_s .

5) Algorithm Pseudocode: Algorithm 1 provides pseudocode of our solution algorithm. Lines 1 and 2 input a convergence tolerance, ϵ , and initialize the starting set of optimality cuts to be empty and the iteration counter to one. The remaining lines are the main iterative loop. In Line 4 the master problem is solved to obtain optimal investments, which we denote as $b_1^*, \ldots, b_{|T|}^*$, $E^{ch,*}$, $E^{dis,*}$, and $E^{E,*}$. These values are fixed in the sub problems in Line 5.

| Alg | Algorithm 1 Multi-Cut Benders's Decomposition | | | |
|-----|--|--|--|--|
| 1: | input: ϵ | | | |
| 2: | initialize: $\mathcal{I} \leftarrow \emptyset, i \leftarrow 1$ | | | |
| 3: | repeat | | | |
| 4: | $\omega_M^* \leftarrow \arg \max_{\Omega_M} \mathcal{M}$ | | | |
| 5: | $b_{\tau} \leftarrow b_{\tau}^*, \forall \tau \in T; E^{ch} \leftarrow E^{ch,*}; E^{dis} \leftarrow E^{dis,*}; E^E \leftarrow E^{dis,*}; E^{dis} \leftarrow E^{dis,*}; E^{$ | | | |
| | $E^{E,*}$ | | | |
| 6: | for $s \in S$ do | | | |
| 7: | $\omega_s^* \leftarrow rg \max_{\Omega_s'} \mathcal{S}_s$ | | | |
| 8: | if $\alpha_s < f_s$ then | | | |
| 9: | $\psi_s^* \leftarrow rg\max_{\Psi_s} \mathcal{A}_s$ | | | |
| 10: | $\widetilde{p}_{w,h,s}^{\text{wind,clrd},(i)} \leftarrow p_{w,h,s}^{\text{wind,clrd},*}, \ \widetilde{p}_{w,h,s}^{\text{dis},(i)} \leftarrow p_{w,h,s}^{\text{dis},*},$ | | | |
| | $\tilde{p}_{u}^{\text{grid},\text{ch},(i)} \leftarrow p_{u}^{\text{grid},\text{ch},*}, \ \tilde{\lambda}_{u}^{(i)} \leftarrow \lambda_{u}^{*} \leftarrow \lambda_{u}^{*} \leftarrow \tilde{p}_{u}^{\text{wid},\text{clrd},(i)} \leftarrow$ | | | |
| | $p^{\text{wind,clrd},*}$ $\tilde{p}^{\text{ch},(i)} \leftarrow p^{\text{ch},*} \tilde{p}^{\text{grid,ch},(i)} \leftarrow p^{\text{grid,ch},*}$ | | | |
| | $P_{w,h,s}$, $P_{w,h,s}$, $P_{w,h,s}$, $P_{w,h,s}$, $P_{w,h,s}$, $\sim \operatorname{dis}_{(i)}$, $\operatorname{dis}_{*}^{*}$, $Q_{w,h,s}$, $P_{w,h,s}$, $P_{w,$ | | | |
| | $p_{w,h,s} \leftarrow p_{w,h,s}, \forall s \in S, w \in W, h \in H; b_{\tau}^{-} \leftarrow b_{\tau}^{-},$ | | | |
| | $\tilde{\sigma}_{s,\tau}^{(\iota)} \leftarrow \sigma_{s,\tau}^*, \forall \tau \in T; E^{\mathrm{ch},(\iota)} \leftarrow E^{\mathrm{ch},*}, \tilde{\sigma}_s^{\mathrm{ch},(\iota)} \leftarrow \sigma_s^{\mathrm{ch},*},$ | | | |
| | $\tilde{E}^{\mathrm{dis},(i)} \leftarrow E^{\mathrm{dis},*}, \ \tilde{\sigma}_s^{\mathrm{dis},(i)} \leftarrow \sigma_s^{\mathrm{dis},*}, \ \tilde{E}^{E,(i)} \leftarrow E^{E,*},$ | | | |
| | $\tilde{\sigma}_s^{E,(i)} \leftarrow \sigma_s^{E,*}$ | | | |
| 11: | end if | | | |
| 12: | end for | | | |
| 13: | $\mathcal{I} \leftarrow \mathcal{I} \cup i$ | | | |
| 14: | $i \leftarrow i + 1$ | | | |
| 15: | until $\sum_{s \in S} \phi_s \cdot \alpha_s - f_s \le \epsilon$ | | | |

Lines 6–12 loop through the sub problems and add optimality cuts, as needed. Specifically, in Line 7 the scenario-s sub problem is solved. If α_s underestimates the true scenario-s operating profit, which is given by f_s , the scenario-s auxiliary problem is solved in Lines 8 and 9 to obtain undistorted dualvariable values. The primal- and dual-variable values that are obtained from the auxiliary problem are used in Line 10 to add a new optimality cut. Lines 13 and 14 update the cut set and iteration counter, respectively. Line 15 gives the termination criterion, which is that the expected operating profit that is estimated in the master problem be sufficiently close to the true operating profit that is given by the sub problems.

IV. EXAMPLE

This section summarizes the results of a simple illustrative example, which demonstrates the differences in investments, offers, and operations between our proposed price-making model and a price-taking wind firm. We assume three hourlong operating periods with 10-GW, 9-GW, and 8-GW loads and 150 MW, 0 MW, and 0 MW of wind available, respectively. We relax (32) and (33), thereby removing constraints on the power-to-energy ratio of energy storage, and assume energy storage to have a round-trip efficiency of $\beta = 0.85$. We neglect uncertainty. The model is implemented and solved using GAMS version 24.5 and cplex version 12.6.2 on a workstation with an Intel Core i7 CPU with eight 3.4-GHz processing cores and 32 GB of memory.

We contrast the decisions of the wind firm under two behavioral assumptions. The first assumes a perfectly competitive wind firm. In this case, the wind firm offers the full 150 MW of wind that is available in hour 1 at its assumed marginal production cost of \$0/MWh. Under this behavioral assumption, all 150 MW of wind that is available in hour 1 is dispatched. As such, the wind generator builds a 150-MW transmission interconnector. Moreover, because there is no curtailed wind and limited opportunity for energy arbitrage (which stems from our assumption of loads decreasing over the three hours), the wind generator does not invest in energy storage.

Our second behavioral case assumes that the wind firm can behave strategically by offering wind and energy storage at prices that differ from their marginal operating costs. In this case, the wind firm withholds economically 25 MW of wind energy during hour 1. This withholding is done by offering 25 MW of wind at a sufficiently high price that a conventional generator is dispatched to replace that wind production, which is curtailed by the market operator. In doing so, the market price during hour 1 increases by 66.7% relative to the perfectly competitive case. As a result of this behavior, the wind generator downsizes the capacity of the transmission line to 125 MW (saving on its investment cost) and builds energy storage with 25-MW and 21.25-MWh power and energy capacities, respectively. This energy storage allows the wind energy that is curtailed during hour 1 to be stored and sold during hour 2. This strategic behavior results in 42.7% higher profits compared to the perfectly competitive case.

We verify the accuracy and performance of the proposed multi-cut Benders's algorithm by comparing the results of the decomposed and undecomposed models. The undecomposed model replaces (43) in the wind generator's problem with (9)–(25), $\forall s \in S, w \in W, h \in H$ to convert the bi-level problem into a single-level problem. Moreover, the linearization techniques that are described in Section III-B3 are used to convert the nonlinear single-level into a single-level mixed-integer linear optimization problem. The decomposed and undecomposed models provide the same solutions. The undecomposed and decomposed models take 0.3 s and 2.7 s, respectively, of wall-clock time to solve. This shows that the decomposition algorithm has too much 'overhead' to be applied effectively to a problem of sufficiently small size.

V. CASE STUDY

This section summarizes the results of a more comprehensive case study, which is based on a 150-MW wind generator that participates in the electricity market of Alberta, Canada during the year 2015 (*i.e.*, wind and load data for 2015 are used). We consider a single-bus model for this case study because, by legislation, Alberta's electricity system is meant to be built to be congestion-free.¹ The congestion-free mandate that is imposed on Alberta's electricity system is reflected further in the electricity price being set based on an hourly system marginal price as opposed to using locational marginal pricing. The investment cost of the wind generator is assumed sunk and the wind generator is assumed to have a \$0/MWh marginal operating cost.

We consider two energy-storage technologies: compressedair (CAES) and battery (BES) energy storage. CAES is assumed to have investment costs of \$1250/kW and \$150/kWh, a 20-year lifetime (which is used to annualize the investment cost), a power-to-energy-ratio range of 0.05 h⁻¹–0.25 h⁻¹, and a round-trip efficiency of 0.72 [31]. BES is assumed to have investment costs of \$616/kW and \$291/kWh, a 20year lifetime, a power-to-energy-ratio range of 0.10 h⁻¹– $4.00 h^{-1}$, and a round-trip efficiency of 0.90.² The values of \bar{E}^{ch} , \bar{E}^{dis} , and \bar{E}^{E} are sufficiently large that there are no binding constraints on the amount of energy storage that is built. In selecting these values in this way, the firm is not restricted in investing in energy storage that is economically viable.

We assume three transmission-line types: a 69-kV, 138-kV, or 240-kV line, which correspond to 40-MW, 140-MW, or 400-MW flow limits [32]. The corresponding costs of these configurations are \$0.3 million/km-year, \$0.6 million/km-year, and \$1.1 million/km-year.³ Transmission-investment costs are annualized, which is why they are reported in units of \$/km-year [26].

We consider a base case in which perfectly competitive and price-making behavior are contrasted with one another, considering all 8760 hours of 2015 as operating periods, no uncertainty, and a 1-km transmission line. This base case is contrasted with four sensitivity cases. The models are implemented and solved using the same computational setting that is used for the example that is presented in Section IV.

A. Base-Case Results

With both the perfectly competitive and price-making assumptions, the wind generator does not invest in either energy-

¹cf. decision number 22942-D02-2019 of Alberta Utilities Commission. ²https://atb.nrel.gov/

³https://public.tableau.com/profile/transmissioncost

storage technology. This is due to the high costs of the technologies relative to the profit increases that they yield. In the perfectly competitive case the wind generator builds a 400-MW transmission line, which allows it to sell all of its potential wind production to the market. The transmission line is downsized to 140 MW under the price-making assumption, which results in about 0.1% of potential wind production being curtailed. The strategic behavior that our model captures increases the net profit of the wind generator by about 3.6% compared to the perfectly competitive case.

B. Sensitivity Analyses

We summarize the results of four sensitivity cases.

1) Energy-Storage Costs: This sensitivity case considers up to 70% reductions in the investment costs of the two energystorage technologies. CAES is not built in any of these cases. BES with 24-MW and 72-MWh power and energy capacities is built in the case in which the investment cost is 70% lower than baseline and the wind generator behaves as a price-maker. However, this added energy storage does not result in reduced transmission capacity and increases the net profit of the wind generator by 1% relative to the base case. This result shows that energy storage has limited value to a wind generator in Alberta with a relatively short transmission connector.

2) Transmission-Connector Length: This sensitivity case varies the length of the transmission connector that the wind generator must build up to 30 km. Moreover, we consider basecase and 70%-reduced energy-storage-investment costs. Even with a 30-km connector, no energy storage is built with the baseline energy-storage-investment costs. Table I summarizes the amount of CAES and transmission capacities that are built and resultant firm profits in the case in which the investment cost is 70% lower than baseline and the wind generator behaves as a price-maker. Table II summarizes the same for BES. The tables show that the energy-storage and transmission capacities that are built with connector lengths of up to 25 km are the same. Firm profit decreases as the connector length increases, due to its increased cost.

TABLE I CAES AND TRANSMISSION CAPACITIES BUILT AND PROFIT EARNED IN TRANSMISSION-CONNECTOR-LENGTH SENSITIVITY CASE IN SECTION V-B2 WITH REDUCED ENERGY-STORAGE-INVESTMENT COSTS

| Connector Length (km) | $E^{ch} = E^{dis}$ (MW) | E^E (MWh) | Connector Capacity (MW) | Profit (\$ million) |
|--------------------------|-------------------------|-------------|----------------------------|------------------------|
| 1 | 0 | 0 | 140 | 21.7 |
| 5 | 0 | 0 | 140 | 19.3 |
| 10 | 0 | 0 | 140 | 16.3 |
| 15 | 0 | 0 | 140 | 13.3 |
| 20 | 0 | 0 | 140 | 10.3 |
| 25 | 0 | 0 | 140 | 7.3 |
| 30 | 18 | 237 | 40 | 5.2 |

BES is built in the low-investment-cost case with all transmission-connector lengths. However, with transmission-connectors that are 25-km or shorter the line is not downsized relative to the high-investment-cost case. This implies that energy storage is not being used to alleviate the need to build

TABLE II BES AND TRANSMISSION CAPACITIES BUILT AND PROFIT EARNED IN TRANSMISSION-CONNECTOR-LENGTH SENSITIVITY CASE IN SECTION V-B2 WITH REDUCED ENERGY-STORAGE-INVESTMENT COSTS

| Connector Length (km) | $E^{ch} = E^{dis}$ (MW) | E^E (MWh) | Connector Capacity (MW) | Profit (\$ million) |
|--------------------------------------|--|---|---|--|
| 1 5 10 15 20 25 30 | 24 24 24 24 24 24 24 29 | 72 72 72 72 72 72 72 72 202 | 140 140 140 140 140 140 140 | $21.9 \\19.5 \\16.5 \\13.5 \\10.5 \\7.5 \\5.5$ |

transmission to deliver wind to load. Rather, energy storage is being used to increase the price at which wind energy is sold. The energy-storage units that are built in these low-investmentcost cases yield a variety of profit changes. With a transmission connector of 25 km or less, the BES that is built increases profits by 3% compared to the associated high-investmentcost case. If the transmission connector is 30 km, BES and CAES that are built in the low-investment-cost case increase profits by 16% and 9%, respectively, compared to the highinvestment-cost case.

3) Price Volatility: This sensitivity case examines the impacts of price volatility. More specifically, we examine cases in which the difference between on- and off-peak loads increase, which gives a commensurate increase in energy-price differences. We measure the volatility of prices by their variance. Fig. 1 summarizes the amount of energy-storage and transmission capacities that are built with different price-volatility levels, as well as the resultant firm profits. Cases in which price volatility level) do not see any energy-storage investment. Instead, there are increases in firm profit of up to 17% relative to the base case. This profit increase is because higher price volatility increases revenues that the firm earns during peak-price periods.



Fig. 1. Energy-storage and transmission capacities built and profit earned in price-volatility sensitivity case in Section V-B3.

Fig. 1 shows that relatively high price volatility is needed to justify energy-storage investment. BES investment occurs with

price volatility that is at least 64.4% higher than baseline. Firm profit increases between 20% and 63% relative to the baseline value as a result of BES being built in these cases. A 140-MW transmission connector is built in all of the cases, except with a 97%-120% increase in price volatility. In these cases, a 400-MW transmission connector is built to support the dispatch of the wind and the larger energy storage.

CAES is built with price volatility of at least 97% above baseline. This is due to the higher relative cost (accounting for its operating characteristics) of CAES compared to BES. The profit increase that is earned in these cases is 35%–51% higher than base-case profit. With extremely high price volatility, the capacity of the transmission connector is increased further from 140 MW to 400 MW. These results, in conjunction with those that are presented in Section V-B2, indicate that the energy storage is not being used to alleviate the need for transmission to deliver wind to load. Rather, energy storage is being used to arbitrage price differences, which increases the need for transmission capacity in some cases.

4) Stochasticity: This sensitivity case considers two sets of 45 second-stage scenarios, which are composed of three different wind-generation cases, three cases related to load growth and reductions, and five cases related to offers from rival generators. The wind-generation levels are assumed to be independent of the other random variables. Conversely, generator offers are correlated with loads. We consider one set of scenarios in which loads can decrease either 0.5%, 1.0%, or 1.5% relative to the base-case levels and in which rival generators' offers decrease by either 0.0%, 2.5%, 5.0%, 7.5%, or 10.0% relative to the base case. We consider also another set of scenarios in which loads and rival generators' offers increase by these same amounts relative to the base case. Given the large size of this case study, we capture the year's operations with six representative operating weeks (as opposed to modeling the full year), which are obtained from the full year's data using k-means clustering. We set a tolerance of $\epsilon = 0.1$ in Algorithm 1 and use an optimality gap of 0 when solving the master, sub, and auxiliary problems in Lines 4, 7, and 9 of the algorithm.

Energy storage is not built with the first set of scenarios, in which loads and rival generators' offers decrease relative to the base-case levels. Under this set of scenarios, the same 140-MW transmission corridor is built and the wind generator earns an expected profit of \$32.1 million over the representative year. Table III summarizes the amount of energy storage that is built with the second set of scenarios, in which loads and rival generators' offers increase relative to the base case. A 140-MW transmission corridor is built in the case of using CAES. This means that the CAES is being used primarily to shift wind generation to higher-price periods. If the BES is built, the capacity of the transmission corridor is increased to 400 MW. This is because the BES is used for energy-arbitrage purposes that go beyond shifting the sale of wind generation.

C. Computational Efficiency

To verify the computational efficiency of the multi-cut Benders's algorithm, we examine computation time and solutions

TABLE III ENERGY-STORAGE CAPACITIES BUILT AND FIRM PROFITS UNDER HIGH-LOAD-AND-OFFER SECOND-STAGE SCENARIOS

| Energy-Storage | Energy-Storage | Expected Profit | | |
|----------------|----------------|-----------------|--------------|--|
| Technology | Power (MW) | Energy (MWh) | (\$ million) | |
| CAES BES | 8 48 | 30 297 | 44.8 47.9 | |

that are obtained from the decomposed and undecomposed models. The single-scenario cases that are examined in Sections V-B1–V-B3 take between 3.6 minutes and 4.7 minutes of wall-clock time to solve using the decomposed model. This can be contrasted with solution times of between 1.5 minutes and 2.8 minutes for the undecomposed model, which shows that (as with the example in Section IV) the multicut Benders's algorithm is not beneficial for small problem sizes. The stochastic case, with 45 second-stage scenarios and six representative weeks takes between 50 minutes and 55 minutes of wall-clock time to solve using the decomposed model. Conversely, the undecomposed model with 45 secondstage scenarios cannot be solved. This shows the power of the multi-cut Benders's algorithm in solving large and complex instances of our model.

The solutions that are obtained from applying the multi-cut Benders's algorithm to our case study have optimality gaps of less than 0.001%. Moreover, the installed capacities of the energy storage and transmission connector are less than 1.7% different between the two sets of solutions. This shows that the proposed multi-cut Benders's algorithm provides high-quality near-optimal solutions.

VI. CONCLUSION

This paper proposes an approach to modeling the behavior of a strategic wind firm that co-optimizes the size of transmission and co-located energy storage and its offers into a wholesale market. To this end, we use a stochastic bi-level model, which is solved efficiently using multi-cut Benders's decomposition. Our Alberta-based case study shows that energy storage has limited value for a profit-maximizing wind generator. Energy storage can be justified with sufficiently long transmission corridors, market uncertainty, or price volatility.

Our model neglects some facets of price-making behavior, which we relegate to future research. This includes equilibrium analysis with multiple strategic firms [2], [3] and participation in markets for both energy and ancillary service.

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