Price Management in Wholesale Electricity Markets by Wind/Storage Allocation in Pre-determined Regions

Amin Masoumzadeh, Ehsan Nekouei, *Member, IEEE,* and Tansu Alpcan, *Senior Member, IEEE*

***Abstract*—This paper investigates the impacts of installing regulated wind and electricity storage on average price and price volatility in electricity markets. A stochastic bi-level optimization model is developed which computes the optimal sizing of new wind and battery capacities by minimizing a weighted sum of the average market price and price volatility. A fixed budget is allocated on wind and battery capacities in the upper-level problem. The operation of strategic/regulated generation, storage, and transmission players is simulated in the lower-level problem using a stochastic (Bayesian) Cournot-based game model. Australia's National Electricity Market (NEM), which is experiencing occasional price peaks, is considered as the case study. Our simulation results quantitatively illustrate that the regulated wind is more efficient than storage in reducing the average price, while the regulated storage more effectively reduces the price volatility. According to our numerical results, the storage-only solution reduces the average price at most by 9.4%, and the wind-only solution reduces the square root of price volatility at most by 39.3%. However, an optimal mixture of wind and storage can reduce the mean price by 17.6% and the square root of price volatility by 48.1%. It also increases the consumer surplus by 1.52%. Moreover, the optimal mixture of wind and storage is a profitable solution unlike the storage-only solution.**

***Index Terms*—Electricity market, Bi-level optimization model, Average price, Price volatility, Regulated wind-storage firm.**

NOMENCLATURE

Indices

m	Intermittent generator.
n	Dispatchable generator.
b	Storage.
i, j	Region or state.
t	Load time (hr).
w	Scenario.

Parameters

α_{it}, β_{it}	Intercept and slope of the inverse demand function.
c_{mi}^{ig}	Operation cost of the intermittent generator.
ω_{itw}	Intermittent energy availability coefficient.
c_{ni}^{dg}	Operation&fuel cost of the dispatchable generator.
R_{ni}^{up},R_{ni}^{dn}	Ramping up and down coefficient of the dispatchable generator.
G_{ni}	Inter-temporal energy availability for the dispatchable generator.
c_{bi}^{s}	Operation cost of the storage firm.
η_{bi}^{ch},η_{bi}^{dis}	Charge and discharge efficiencies of the storage.
ζ_{bi}^{ch}, $\zeta_{bi}^{\mathrm{dis}}$	Charge and discharge power rates of the storage.
$Q_{bi}^{\mathrm{s},0}$	The initial state of charge of the storage firm.
$\gamma_{ij}^{\mathrm{tr}}$	Binary parameter to distinguish if the transmission line is strategic (0) or regulated (1).
$c_{i^*}^{\mathrm{ig,reg}}$,$c_{i^*}^{\mathrm{s,reg}}$	Unit operation costs of generation and storage for the wind-storage firm.
I^{ig}, $\overline{I^{\mathrm{ig}}}$	The unit investment cost and the equivalent annual unit cost of wind technology.
I^{s}, $\overline{I^{\mathrm{s}}}$	The effective unit investment cost (including the degradation cost) and the equivalent annual unit cost of storage technology.
$\mathrm{PL}^{\mathrm{ig}}$, PL^{s}	Life spans of wind and storage technologies.
$\overline{\mathrm{B}}$	The equivalent annual budget on wind and storage.
k	The weighting coefficient between the average price and volatility.
Ψ_w	Probability of scenario w.
Q_{mi}^{ig}	Capacity of the intermittent generator.
Q_{ni}^{dg}	Capacity of the dispatchable generator.
Q_{bi}^{s}	Energy capacity of the storage firm.
Q_{ij}^{tr}	Capacity of the transmission line.
P^{cap}	Cap price in the market.
r	Annual discount factor.

Variables

q_{mitw}^{ig}	Generation of the intermittent generator.
q_{nitw}^{dg}	Generation of the dispatchable generator.
q_{bitw}^{s}	Electricity flow of the storage firm.
q_{ijtw}^{tr}	Electricity flow from node j to node i.
q_{bitw}^{ch}	Charge flow of the storage firm.
q_{bitw}^{dis}	Discharge flow of the storage firm.
$q_{i^*tw}^{\mathrm{ig,reg}}$	Intermittent generation of the wind-storage firm.
$q_{i^*tw}^{\mathrm{s,reg}}$	Storage flow of the wind-storage firm.
$q_{i^*tw}^{\mathrm{dis,reg}}$	Storage discharge of the wind-storage firm.
$q_{i^*tw}^{\mathrm{ch,reg}}$	Storage charge of the wind-storage firm.
$Q_{i^*}^{\mathrm{ig,reg}}$	Wind power capacity of the wind-storage firm.
$Q_{i^*}^{\mathrm{s,reg}}$	Storage capacity of the wind-storage firm.

Functions

$P_{itw}(.)$	Wholesale electricity price.
$y_{itw}(.)$	Net electricity demand.
$\mathsf{Var}(.)$	Variance of price over scenarios w.
$\mathsf{E}(.)$	Expectation of price over scenarios w.

I. INTRODUCTION

HIGH price volatility and mean price levels have negative impacts on all parties involved in an electricity market, e.g., generators and consumers. On one hand, high levels of mean wholesale electricity prices lead to higher retail prices, i.e., impose high cost on consumers. For example, the electricity prices have increased in average by 200% in Australia's National Electricity Market (NEM) during 2015-2018, and average household power bills increased almost 16 percent after Hazelwood coal plant closure in Victoria in 2017 [1]. One the other hand, price

We also acknowledge this work was supported in part by the ARC Discovery Project DP140100819. A. Masoumzadeh and T. Alpcan are with the Department of Electrical & Electronic Engineering, University of Melbourne, Australia, and E. Nekouei is with KTH Royal Institute of Technology, Sweden. E-mails: amin.masoumzadeh@unimelb.edu.au, tansu.alpcan@unimelb.edu.au, nekouei@kth.se

volatility imposes large financial risks on the market participants by increasing the future price prediction uncertainty [2], [3]. Extreme levels of price volatility may lead to market suspension, for example, NEM becomes suspended if the sum of spot prices during a period is above the Cumulative Price Threshold.

Recently, limited state (government) intervention has been proposed as a solution which may pave the way towards lower levels of electricity price and volatility in the markets as the private sector is likely to act slowly due to regulatory, institutional, or other barriers [4]. For example, in 2017, South Australia (SA) government took an initiative to improve the SA's electricity market structure by installing 100 MW (125 MWh) electricity storage devices manufactured by Tesla, and the project was delivered successfully over 100 days. Following the success of the SA battery project, Victoria has also secured an agreement to build its own Tesla battery near the town of Stawell [5].

Therefore, the state may intervene by installing state-owned regulated wind and storage capacities, which have short construction periods, to reduce the electricity prices as well as the price volatility [6]. Regulated wind-storage firms, which aim at maximizing the social welfare, can more effectively reduce both average price and price volatility in the market, compared with strategic players which maximize their own profits [7]. Note that average prices and volatility levels after the state (government) intervention still must allow competing firms to make money.

Our goal in this paper is to find the optimal regulated wind and storage capacity balance which, given a limited budget, minimizes a weighted sum of the mean price and the price volatility. We note that the market price in an electricity market is a stochastic process due to the random nature of renewables and stochastic nature of the electricity demand. Thus, it is desirable to simultaneously control both the first moment of the price (its mean) and its second moment (its volatility). Note that minimizing only the mean price (the volatility) can result in increasing volatility (mean). Therefore, our approach can be interpreted as a risk-sensitive solution which aims at minimizing the weighted sum of the mean price and the price volatility. Although regulated storage has other positive effects on the electricity networks, e.g., improving the stability, in this paper we only focus on its effect on the electricity market prices. The model is applied to the five-state NEM market and is calibrated with realistic data from year 2016.

A. Contributions

This paper studies the optimal allocation of storage and wind for minimizing a linear combination of the average price and the square root of price volatility, which have the same scale of \$/MWh in our study. In fact, we propose a bi-level optimization model to optimally allocate regulated wind and storage capacities in a multi-region wholesale electricity market. In the upper level problem, the weighted sum of average price and price volatility is minimized by allocating a fixed budget on regulated wind and storage capacities. In the lower level problem, the non-cooperative market interaction between strategic/regulated generation, storage and transmission players and a regulated wind-storage player is modeled as a stochastic (Bayesian) Cournot-based game. Our bi-level optimization model is converted into an equivalent single level problem, in which the optimal capacities of wind and storage are calculated via a line search algorithm.

The main contributions of this paper can be summarized as :

- proposing a bi-level model which achieves two objectives by optimally allocating the wind and storage capacities. At the upper level, model seeks to ensure the successful day-to-day operation of market by controlling the mean and variance of prices. At the lower level, the regulated wind-storage firm aims at maximizing the social welfare considering the exercise of market power by other players;
- including regulated generation, storage, and transmission players in addition to the strategic players in a multi-region Cournot-based competitive electricity market model. The model consists of non-linear inverse demand functions to ensure accurate relation between demand and price is taken into account. The proof is provided that regulated players aim at maximizing social welfare in our model;
- quantifying the impacts of wind and storage on average price and price volatility, considering a large number of scenarios for the uncertainties, in an analytical game-theoretic market model;
- evaluating the performance of this methodology for the five-node NEM market, using real data from 2016.

B. literature Review

The problem of storage allocation in presence of intermittent renewable energy generation in electricity networks has been studied in [8]–[13] using cost minimization approaches, and in [14]–[19] using profit maximization objectives.

Facilitating the integration of renewable resources, the potential value of energy storage in power systems with renewable generation is evaluated by minimizing the total operation cost in the network in [8]. The optimal operation and sizing of the storage systems is studied by minimizing the cost of the system in [9]. The storage allocation in renewable integrated power systems is studied in [10] and [11] under deterministic and stochastic wind models, respectively. To accommodate the integration of renewable generation, bi-level optimization models are also proposed to determine the optimal allocation and operation of energy storage systems in [12] and of battery energy storage systems in [13], in which the upper level problem minimizes the storage system cost and the lower level problem implements the power flow in the network. Note that these works are based on cost minimization models and do not investigate the market interplay between storage, renewable generators and other firms.

Assuming the storage firms as price takers in the market, the optimal operation of storage firms in renewable integrated systems is determined by maximizing the profit from energy arbitrage and regulation services in [14], by maximizing the energy arbitrage profit in day-ahead and hour-ahead markets in [15], and by maximizing their energy and reserve profit in day-ahead and hour-ahead markets in [16]. Assuming the storage firms as price maker players in the market, the optimal charge/discharge operation of the storage devices, and the optimal operation and size of the storage devices are determined in [17] and [18], respectively, treating the price bids of market participants other than the storage players as exogenous inputs. The market operation behavior of all generation and storage firms are considered endogenously in a single-region electricity market in [19] using a Cournot-based electricity market model.

The impact of the optimal storage allocation on price volatility reduction in a multi-region electricity market model is studied in [7]. However, studying the joint effect of wind and storage allocation on market price characteristics is missing in the literature. As we show in this paper, wind firms are potentially more efficient than storage firms in reducing the average price and the results of [7] are not applicable when it is desirable to reduce the average price in the market. Therefore, different from the existing work, we consider the problem of managing the average price and the price volatility by optimal allocation of wind and storage capacities.

The rest of the paper is organized as follows. Section II illustrates the system model and the proposed bi-level optimization problem. The solution approach for finding the market equilibrium is presented in Section III. Section IV provides the simulation results and Section V presents the concluding remarks.

II. The Problem and Market Model

We consider a regional electricity market including $\{1, ..., N_I\}$ regions (states). Let $\mathcal{N}_i^{\mathrm{ig}}$ be the set of intermittent generation firms located in state i, $\mathcal{N}_i^{\mathrm{dg}}$ be the set of dispatchable generators, such as coal, gas, and hydro power plants, located in state i, $\mathcal{N}_i^{\mathrm{s}}$ be the set of storage firms, such as pump-hydro and battery, located in state i, and $\mathcal{N}_i^{\mathrm{tr}}$ be the set of neighboring states of the state i. Since some parameters such as wind and solar power availabilities, which affect the electricity generation, are stochastic, a scenario-based model including N_W different scenarios is developed to model the intermittent power generation in the electricity network. The strategies of intermittent and dispatchable generators, storage firms, and transmission players as well as the nodal prices are determined by solving a stochastic (Bayesian) Cournot-based game.

In this paper, we present a bi-level optimization framework for optimally allocating a budget on regulated capacities of wind and storage to minimize the weighted sum of average price and price volatility in a single state taking into account the interdependencies to other states in the market. All the market players, which are allowed to be strategic or regulated, with their decision variables, operating limits, and objective functions are introduced in detail in the lower level problem, Section II-B.

Note that the lower level problem in this paper is similar to the one used in [7] but differs in including a regulated wind-storage firm in the market.

A. Upper-level Problem

In the upper-level optimization problem, we minimize the weighted sum of average price and its standard deviation over the operation horizon $\{1, ..., N_T\}$ and scenario set $\{1, ..., N_W\}$ at state $i^* \in \{1, ..., N_I\}$ by allocating a fixed budget on regulated storage and wind generation technologies. The price volatility is measured by the regional price variance [20], i.e., the variance of market price is considered as a measure of price volatility. Market price variance and mean in state i^* under a set of scenarios $\{1, ..., N_W\}$, i.e., $\mathsf{Var}\left(\{P_{i^*tw}\}_w\right)$ and $\mathsf{E}\left(\{P_{i^*tw}\}_w\right)$, are defined as:

$$\mathsf{Var}\left(\{P_{i^*tw}\}_w\right) = \sum_w \left(P_{i^*tw}\left(.\right)\right)^2 \Psi_w - \left(\sum_w P_{i^*tw}\left(.\right) \Psi_w\right)^2 \tag{1a}$$

$$\mathsf{E}\left(\{P_{i^*tw}\}_w\right) = \sum_w P_{i^*tw}\left(.\right) \Psi_w \tag{1b}$$

where Ψ_w is the probability of scenario w, and $P_{i^*tw}\left(.\right)$ represents the market price in state i^* at time t under the scenario w, which is a function of the decision variables, i.e., generation, arbitrage and transmission levels, of all players in the lower level problem. $P_{i^*tw}\left(.\right)$ is a probabilistic function because of the stochastic intermittent generation in our model.

Given that the wind and storage technologies have unequal lifespans, we compare their equivalent annual unit costs and consider the equivalent annual budget in our model. Moreover, battery capacity may be degraded significantly over time. In order to consider the battery degradation cost in our calculations, we equivalently increase the unit cost of battery with respect to the degradation rate and call it the effective unit cost. Considering the relation between the effective unit investment cost, I, and the equivalent annual unit cost, $\overline{I}$, for a technology with lifespan of PL, that is, $I = \sum_{y=1}^{\mathrm{PL}} \frac{\overline{I}}{(1+r)^y}$, the equivalent annual unit costs of wind and storage technologies, $\overline{I^{\mathrm{ig}}}$ and $\overline{I^{\mathrm{s}}}$, become as [21]:

$$\overline{I^{\mathrm{ig}}} = \frac{rI^{\mathrm{ig}}}{1-(1+r)^{-\mathrm{PL}^{\mathrm{ig}}}} \tag{2a}$$

$$\overline{I^{\mathrm{s}}} = \frac{rI^{\mathrm{s}}}{1-(1+r)^{-\mathrm{PL}^{\mathrm{s}}}} \tag{2b}$$

where I^{ig} and I^{s} are the effective unit investment costs, and $\mathrm{PL}^{\mathrm{ig}}$ and PL^{s} are the life spans of wind and storage technologies, respectively. The parameter r represents the discount rate. Note that we include the yearly maintenance costs of technologies as part of their investment costs and do not consider them separately.

Based on the equivalent annual unit costs of wind and storage technologies, $\overline{I^{\mathrm{ig}}}$ and $\overline{I^{\mathrm{s}}}$, $\overline{I^{\mathrm{s}}}Q_{i^*}^{\mathrm{s,reg}}$ and $\overline{I^{\mathrm{ig}}}Q_{i^*}^{\mathrm{ig,reg}}$ represent the investment share from the equivalent annual budget, $\overline{\mathrm{B}}$, on wind and storage, respectively.

Given the equations for price volatility and average price (1a-1b), which are functions of the strategy of all firms, and the equations for the equivalent annual cost of wind and storage technologies (2a-2b), we define the upper level optimization problem as:

$$\min_{Q_{i^*}^{\mathrm{ig,reg}}, Q_{i^*}^{\mathrm{s,reg}}} (1-k)\sqrt{\overline{\mathsf{Var}}\left(\{P_{i^*tw}\}_{tw}\right)} + k\overline{\mathsf{E}}\left(\{P_{i^*tw}\}_{tw}\right) \tag{3a}$$

s.t.

$$\overline{I^{\mathrm{s}}}Q_{i^*}^{\mathrm{s,reg}} + \overline{I^{\mathrm{ig}}}Q_{i^*}^{\mathrm{ig,reg}} = \overline{\mathrm{B}}\$ \tag{3b}$$

where $0 \leq k \leq 1$ represents the weighting coefficient, $Q_{i^*}^{\mathrm{ig,reg}}$ is the regulated wind generation capacity and $Q_{i^*}^{\mathrm{s,reg}}$ is the regulated storage capacity in state i^*. $\overline{\mathsf{Var}}\left(\{P_{i^*tw}\}_{tw}\right)$ is the normalized level of the average of price volatility levels over the horizon $\{1, ..., N_T\}$, i.e., normalized level of $\frac{\sum_t \mathsf{Var}(\{P_{i^*tw}\}_w)}{N_T}$, and $\overline{\mathsf{E}}\left(\{P_{i^*tw}\}_{tw}\right)$ is the normalized level of the average of mean prices over the horizon $\{1, ..., N_T\}$, i.e., normalized level of $\frac{\sum_t \mathsf{E}(\{P_{i^*tw}\}_w)}{N_T}$. The normalized levels of price volatility and mean price, which are between zero and one, indicate their ratio with respect to their base values, i.e., with respect to their amounts when there is no regulated wind and storage firm in the market.

B. Lower-level Problem

In the lower level problem, the strategies of all market players and the nodal market prices are obtained by solving a stochastic Cournot-based game between intermittent generators, dispatchable generators, storage firms, and transmission firms. Following the standard Cournot game models [22], any player in our model maximizes its objective function given the decision variables of other players. Our game model, which considers different wind and solar power availability scenarios with given probabilities, is consistent with the Bayesian game definition. Players maximize their utility functions over a set of scenarios with a given probability distribution in a Bayesian game [23]. Note that the decision variables in the upper level problem, $Q_{i^*}^{\mathrm{ig,reg}}$ and $Q_{i^*}^{\mathrm{s,reg}}$, are the wind and storage capacity amounts of a regulated wind-storage firm in state i^*.

The market price in state i at time t under scenario w is represented in our model by an exponential inverse demand function [7]:

$$P_{itw}\left(y_{itw}\right) = \alpha_{it} e^{-\beta_{it} y_{itw}} \tag{4}$$

where α_{it} and β_{it} are positive real values representing in the price function, and y_{itw} is the net electricity demand in state i at time t under scenario w.

The lower level problem in our bi-level model is developed based on DC Load Flow equations. The equality between electricity supply and demand in each state and at any time, i.e., the the nodal electricity balance, is ensured in our model with the following equations:

$$y_{itw} = \sum_{m \in \mathcal{N}_i^{\mathrm{ig}}} q_{mitw}^{\mathrm{ig}} + \sum_{n \in \mathcal{N}_i^{\mathrm{dg}}} q_{nitw}^{\mathrm{dg}} + \sum_{b \in \mathcal{N}_i^{\mathrm{s}}} q_{bitw}^{\mathrm{s}} + \sum_{j \in \mathcal{N}_i^{\mathrm{tr}}} q_{ijtw}^{\mathrm{tr}} \quad \forall i \neq i^* \tag{5a}$$

$$y_{itw} = \sum_{m \in \mathcal{N}_i^{\mathrm{ig}}} q_{mitw}^{\mathrm{ig}} + \sum_{n \in \mathcal{N}_i^{\mathrm{dg}}} q_{nitw}^{\mathrm{dg}} + \sum_{b \in \mathcal{N}_i^{\mathrm{s}}} q_{bitw}^{\mathrm{s}} + \sum_{j \in \mathcal{N}_i^{\mathrm{tr}}} q_{ijtw}^{\mathrm{tr}} + q_{itw}^{\mathrm{ig,reg}} + q_{itw}^{\mathrm{s,reg}} \quad i = i^* \tag{5b}$$

where q_{mitw}^{ig} is the generation strategy of the mth intermittent generator located in state i, q_{nitw}^{dg} is the generation strategy of the nth dispatchable generator located in state i, q_{bitw}^{s} is the charge/discharge strategy of the storage firm b located in state i, q_{ijtw}^{tr} is the transmission strategy of line between states i and j, and $q_{itw}^{\mathrm{ig,reg}}$ and $q_{itw}^{\mathrm{s,reg}}$ are the wind generation strategy and the storage charge/discharge strategy of the regulated firm in state i^*, respectively, at time t and under scenario w.

In what follows, $P_{itw}\left(.\right)$ refers to the market price in (4).

1) Intermittent Generators: The mth intermittent generator (wind or solar) in state i determines its best response strategy by solving the following profit maximization problem:

$$\max_{\left\{q_{mitw}^{\mathrm{ig}}\right\}_{tw} \succeq 0} \sum_{w=1}^{N_W} \Psi_w \sum_{t=1}^{N_{\mathrm{T}}} \left(P_{itw}\left(.\right) - c_{mi}^{\mathrm{ig}}\right) q_{mitw}^{\mathrm{ig}} \tag{6a}$$

s.t.

$$q_{mitw}^{\mathrm{ig}} \leq \omega_{itw} Q_{mi}^{\mathrm{ig}} \quad \forall t, w \tag{6b}$$

$$P_{itw}\left(.\right) \leq P^{\mathrm{cap}} \quad \forall t, w \tag{6c}$$

where q_{mitw}^{ig} (decision variable) is the generation level of the intermittent generator m in state i at time t under scenario w, Q_{mi}^{ig} is its maximum generation capacity, and c_{mi}^{ig} is its marginal cost of generation. The constraint (6b) limits the electricity generation to the available generation capacity of the firm, considering the energy availability coefficient ω_{itw} in state i at time t under scenario w. The availability coefficient ω_{itw} is the source of stochasticity in our model. The constraint (6c) ensures that the market price is always less than the cap price P^{cap}.

2) Dispatchable Generators: The best response strategy of the nth dispatchable generator in state i is obtained by solving the following profit maximization problem:

$$\max_{\left\{q_{nitw}^{\mathrm{dg}}\right\}_{tw} \succeq 0} \sum_{w=1}^{N_W} \Psi_w \sum_{t=1}^{N_{\mathrm{T}}} \left(P_{itw}\left(.\right) - c_{ni}^{\mathrm{dg}}\right) q_{nitw}^{\mathrm{dg}} \tag{7a}$$

s.t.

$$q_{nitw}^{\mathrm{dg}} \leq Q_{ni}^{\mathrm{dg}} \quad \forall t, w \tag{7b}$$

$$q_{nitw}^{\mathrm{dg}} - q_{ni(t-1)w}^{\mathrm{dg}} \leq R_{ni}^{\mathrm{up}} Q_{ni}^{\mathrm{dg}} \quad \forall t, w \tag{7c}$$

$$q_{ni(t-1)w}^{\mathrm{dg}} - q_{nitw}^{\mathrm{dg}} \leq R_{ni}^{\mathrm{dn}} Q_{ni}^{\mathrm{dg}} \quad \forall t, w \tag{7d}$$

$$\sum_t q_{nitw}^{\mathrm{dg}} \leq G_{ni} \quad \forall w \tag{7e}$$

$$P_{itw}\left(.\right) \leq P^{\mathrm{cap}} \quad \forall t, w \tag{7f}$$

where q_{nitw}^{dg} (decision variable) is the generation level of the dispatchable generator n in state i at time t under scenario w, Q_{ni}^{dg} is its generation capacity, and c_{ni}^{dg} is its marginal cost of generation. The constraint (7b) considers the maximum capacity limit and the constraints (7c-7d) consider the ramping up and down limits, R_{ni}^{up} and R_{ni}^{dn}, respectively. The constraint (7e) considers the inter-temporal energy availability G_{ni}, e.g., the total hydro power generation over a year due to the dam water availability during that period.

3) Storage Firms: The best response strategy of the bth storage firm in state i is the solution of the following arbitrage profit maximization problem:

$$\max_{\substack{\left\{q_{bitw}^{\mathrm{dis}}, q_{bitw}^{\mathrm{ch}}\right\}_{tw} \succeq 0, \\ \left\{q_{bitw}^{\mathrm{s}}\right\}_{tw}}} \sum_{w=1}^{N_W} \Psi_w \sum_{t=1}^{N_{\mathrm{T}}} P_{itw}\left(.\right) q_{bitw}^{\mathrm{s}} - c_{bi}^{\mathrm{s}} \left(q_{bitw}^{\mathrm{dis}} + q_{bitw}^{\mathrm{ch}}\right) \tag{8a}$$

s.t.

$$q_{bitw}^{\mathrm{s}} = \eta_{bi}^{\mathrm{dis}} q_{bitw}^{\mathrm{dis}} - \frac{q_{bitw}^{\mathrm{ch}}}{\eta_{bi}^{\mathrm{ch}}} \quad \forall t, w \tag{8b}$$

$$q_{bitw}^{\mathrm{dis}} \leq \zeta_{bi}^{\mathrm{dis}} Q_{bi}^{\mathrm{s}} \quad \forall t, w \tag{8c}$$

$$q_{bitw}^{\mathrm{ch}} \leq \zeta_{bi}^{\mathrm{ch}} Q_{bi}^{\mathrm{s}} \quad \forall t, w \tag{8d}$$

$$0 \leq Q_{bi}^{\mathrm{s},0} + \sum_{k=1}^{t} \left(q_{bikw}^{\mathrm{ch}} - q_{bikw}^{\mathrm{dis}}\right) \Delta \leq Q_{bi}^{\mathrm{s}} \quad \forall t, w \tag{8e}$$

$$P_{itw}\left(.\right) \leq P^{\mathrm{cap}} \quad \forall t, w \tag{8f}$$

where q_{bitw}^{ch} and q_{bitw}^{dis} (decision variables) are the charge and discharge levels of the storage firm b in state i at time t under scenario w, respectively, q_{bitw}^{s} (intermediate decision variable) is the net charge/discharge level, and c_{bi}^{s} is the marginal cost of charge/discharge. The right hand side of equality (8b) indicates the difference between the net outflow ($\eta_{bi}^{\mathrm{dis}} q_{bitw}^{\mathrm{dis}}$) and inflow ($\frac{q_{bitw}^{\mathrm{ch}}}{\eta_{bi}^{\mathrm{ch}}}$) of electricity considering the charging and discharging efficiencies, η_{bi}^{ch} and η_{bi}^{dis}, respectively. The constraints (8c) and (8d) limit the output/input energy flow of the firm, with power rate coefficients $\zeta_{bi}^{\mathrm{dis}}$ and ζ_{bi}^{ch}, respectively. The parameters ζ_{bi}^{ch} and $\zeta_{bi}^{\mathrm{dis}}$ indicate the percentage of the storage capacity Q_{bi}^{s} that can be charged or discharged during time period Δ, which are considered equal to 10% per hour for pump-hydro and 50% per hour for battery in our study. The constraint (8e) limits the battery's state of charge at time t, i.e., ($Q_{bi}^{\mathrm{s},0} + \sum_{k=1}^{t} \left(q_{bikw}^{\mathrm{ch}} - q_{bikw}^{\mathrm{dis}}\right) \Delta$), to its capacity, assuming that the storage device has the initial state of charge $Q_{bi}^{\mathrm{s},0}$.

4) Transmission Firms: The best response strategy of the transmission line (interconnector) between states i and j is obtained by solving the following profit maximization problem:

$$\max_{\left\{q_{jitw}^{\mathrm{tr}},q_{ijtw}^{\mathrm{tr}}\right\}_{tw}} \sum_{w=1}^{N_W} \Psi_w \sum_{t=1}^{N_{\mathrm{T}}} \left(P_{jtw}\left(.\right) q_{jitw}^{\mathrm{tr}} + P_{itw}\left(.\right) q_{ijtw}^{\mathrm{tr}}\right) \left(1-\gamma_{ij}^{\mathrm{tr}}\right) + \gamma_{ij}^{\mathrm{tr}} \left(\frac{P_{jtw}\left(.\right)}{-\beta_{jt}} + \frac{P_{itw}\left(.\right)}{-\beta_{it}}\right) \quad (9a)$$

s.t.

$$q_{ijtw}^{\mathrm{tr}} = -q_{jitw}^{\mathrm{tr}} \quad \forall t,w \quad (9b)$$

$$-Q_{ij}^{\mathrm{tr}} \leq q_{ijtw}^{\mathrm{tr}} \leq Q_{ij}^{\mathrm{tr}} \quad \forall t,w \quad (9c)$$

$$P_{ktw}\left(.\right) \leq P^{\mathrm{cap}} \quad k \in \{i,j\},\ \forall t,w \quad (9d)$$

where q_{ijtw}^{tr} (decision variable) is the electricity transmitted from state j to state i at time t under scenario w, and Q_{ij}^{tr} is the capacity of transmission line between states i and j. The transmission firm between states i and j is a strategic player when $\gamma_{ij}^{\mathrm{tr}}$ is zero and is a regulated player when $\gamma_{ij}^{\mathrm{tr}}$ is one. It is discussed in [7] that maximizing $P_{jt}\left(.\right) q_{jitw}^{\mathrm{tr}} + P_{itw}\left(.\right) q_{ijtw}^{\mathrm{tr}}$ is equal to maximizing the profit from electricity transmission between states i and j. Besides, it is shown in Appendix A that maximizing $\frac{P_{jtw}(.)}{-\beta_{jt}} + \frac{P_{itw}(.)}{-\beta_{it}}$ is equivalent to maximizing the social welfare (the total surplus of consumers and producers) for the regulated transmission firm. Note that the electricity markets with regulated transmission firms are called *electricity markets with transmission constraints* in the literature, e.g., [24], [25]. The constraint (9b) ensures that electricity does not flow simultaneously in both directions of the line, and the constraint (9c) limits the electricity flow between states i and j to the capacity of the line.

5) Regulated State-owned Wind-Storage Firm: The best response strategy of the state-owned wind-storage firm in state i^*, which is a regulated firm, is determined by solving the following optimization problem:

$$\max_{\substack{\left\{q_{i^*tw}^{\mathrm{ig,reg}}\right\}_{tw}\succeq 0,\\ \left\{q_{i^*tw}^{\mathrm{dis,reg}},q_{i^*tw}^{\mathrm{ch,reg}}\right\}_{tw}\succeq 0,\\ \left\{q_{i^*tw}^{\mathrm{s,reg}}\right\}_{tw}}} \sum_{w=1}^{N_W} \Psi_w \sum_{t=1}^{N_{\mathrm{T}}} \frac{P_{i^*tw}\left(.\right)}{-\beta_{i^*t}} - c_{i^*}^{\mathrm{ig,reg}} q_{i^*tw}^{\mathrm{ig,reg}} - c_{i^*}^{\mathrm{s,reg}} \left(q_{i^*tw}^{\mathrm{dis,reg}} + q_{i^*tw}^{\mathrm{ch,reg}}\right) \quad (10a)$$

s.t.

$$q_{i^*tw}^{\mathrm{ig,reg}} \leq \omega_{i^*tw} Q_{i^*}^{\mathrm{ig,reg}} \quad \forall t,w \quad (10b)$$

$$q_{i^*tw}^{\mathrm{s,reg}} = \eta_{i^*}^{\mathrm{dis,reg}} q_{i^*tw}^{\mathrm{dis,reg}} - \frac{q_{i^*tw}^{\mathrm{ch,reg}}}{\eta_{i^*}^{\mathrm{ch,reg}}} \quad \forall t,w \quad (10c)$$

$$q_{i^*tw}^{\mathrm{dis,reg}} \leq \zeta_{i^*}^{\mathrm{dis,reg}} Q_{i^*}^{\mathrm{s,reg}} \quad \forall t,w \quad (10d)$$

$$q_{i^*tw}^{\mathrm{ch,reg}} \leq \zeta_{i^*}^{\mathrm{ch,reg}} Q_{i^*}^{\mathrm{s,reg}} \quad \forall t,w \quad (10e)$$

$$0 \leq Q_{i^*}^{\mathrm{s,reg},0} + \sum_{k=1}^{t} \left(q_{i^*kw}^{\mathrm{ch,reg}} - q_{i^*kw}^{\mathrm{dis,reg}}\right) \Delta \leq Q_{i^*}^{\mathrm{s,reg}} \quad \forall t,w \quad (10f)$$

$$P_{i^*tw}\left(.\right) \leq P^{\mathrm{cap}} \quad \forall t,w \quad (10g)$$

where $q_{i^*tw}^{\mathrm{ig,reg}}$ (decision variable) is the wind (intermittent) generation level of the regulated firm in state i^* at time t under scenario w, $Q_{i^*}^{\mathrm{ig,reg}}$ is its maximum wind generation capacity, and $c_{i^*}^{\mathrm{ig,reg}}$ is its marginal cost of wind generation. Moreover, $q_{i^*tw}^{\mathrm{ch,reg}}$,$q_{i^*tw}^{\mathrm{dis,reg}}$ (decision variables), and $q_{i^*tw}^{\mathrm{s,reg}}$ (intermediate decision variable) are the charge, discharge and net charge/discharge levels of the regulated firm in state i^* at time t under scenario w, respectively. The constraint (10b) is similar to the constraint in the wind generation problem (6b), and the constraints (10c)-(10f) are similar to the constraints in the storage arbitrage problem (8b)-(8e). It is also shown in Appendix A that maximizing $\frac{P_{i^*tw}(.)}{-\beta_{i^*t}} - c_{i^*}^{\mathrm{ig,reg}} q_{i^*tw}^{\mathrm{ig,reg}} - c_{i^*}^{\mathrm{s,reg}} \left(q_{i^*tw}^{\mathrm{dis,reg}} + q_{i^*tw}^{\mathrm{ch,reg}}\right)$ is equivalent to maximizing the social welfare for the regulated wind-storage firm.

III. Solution Approach

Here, the bi-level storage and wind allocation problem reducing the average price and price volatility is transformed into a single-level Mathematical Problem with Equilibrium Constraints (MPEC).

A. Solution Method for the lower level problem

The regulated wind and storage capacities are the only variables that couple the scenarios in the lower level problem. Therefore, for any regulated wind and storage capacity amounts, each scenario of the lower level problem can be solved autonomously and the market equilibrium can be obtained by solving the KKT equations of all firms. The existence of the Bayes-NE solution at the lower level problem is stated in Proposition 1.

Proposition 1: For any vector of regulated wind and storage capacity amounts, $[Q_{i^*}^{\mathrm{ig,reg}}, Q_{i^*}^{\mathrm{s,reg}}]$, the lower level game admits a Bayes-NE.

Proof: The objective function of any firm in the game is continuous and quasi-concave in its strategy, and their strategy space is non-empty, compact and convex. Therefore, according to Theorem 1.2 in [26], the lower level game admits a Bayes-NE. ■

In the lower level problem, the nodal market prices depend on the regulated wind and storage capacities through the constraints (10b) and (10d-10f). This dependency allows us to minimize the objective function on the upper level problem using the optimal values of regulated wind and storage capacities.

B. Solution Method for the equivalent single level problem

Imposing the KKT conditions of all firms as constraints in the optimization problem (3), we can transform our bi-level problem into the following single-level optimization problem:

$$\min \left(1-k\right) \sqrt{\mathsf{Var}\left(\{P_{i^*tw}\}_{tw}\right)} + k\overline{\mathsf{E}}\left(\{P_{i^*tw}\}_{tw}\right) \quad (11)$$

s.t.

$$(3b)\,, \quad \mathrm{KKT}\left(6a-6c\right), \quad \mathrm{KKT}\left(7a-7f\right), \quad \mathrm{KKT}\left(8a-8f\right), \quad \mathrm{KKT}\left(9a-9d\right), \quad \mathrm{KKT}\left(10a-10g\right)$$

where the optimization variables are the regulated wind and storage capacities, the bidding strategies of all firms, and the set of all Lagrangian multipliers. Note that the feasible region is not necessarily convex or even connected because of the nonlinear complementary constraints. It is possible to write the equivalent single level problem (11) as a Mixed-Integer Non-Linear Problem (MINLP), but the large number of integer variables makes the problem computationally infeasible.

Considering the equality constraint (3b), there is just one decision variable on the upper level problem. We perform a uniform line search on the variable $Q_{i^*}^{\mathrm{ig,reg}}$, i.e., the single decision variable of the upper level problem, with N iterations. We increase the regulated wind capacity by $\Delta Q^{\mathrm{ig,reg}}$ and decrease the regulated storage capacity by $\Delta Q^{\mathrm{s,reg}}$, which is a function of $\Delta Q^{\mathrm{ig,reg}}$, and find the Bayes-NE solution of the lower level game at each iteration. Comparing the average price and price volatility calculated at different iterations, we find the optimal regulated wind and storage allocation, as described in Algorithm 1.

Algorithm 1 The line search (N-step) algorithm for finding the wind-storage allocation.

$\Delta Q^{\mathrm{ig,reg}} = \frac{B}{N I^{\mathrm{ig}}}$
initial point $\leftarrow Q^{\mathrm{ig,reg}} = 0,\ Q^{\mathrm{s,reg}} = \frac{\mathrm{B}}{I^{\mathrm{s}}}$
for iteration = $0 : N$ **do**
  iteration=iteration+1
  $Q^{\mathrm{ig,reg}}_{i^*}(\text{iteration}) \leftarrow Q^{\mathrm{ig,reg}}_{i^*}(\text{iteration}-1) + \Delta Q^{\mathrm{ig,reg}}$
  $Q^{\mathrm{s,reg}}_{i^*} \leftarrow \frac{\mathrm{B} - I^{\mathrm{ig}} Q^{\mathrm{ig,reg}}_{i^*}}{I^{\mathrm{s}}}$
  $\boldsymbol{q}^{\star}(\text{iteration}) \leftarrow$ Lower level problem Bayes–NE
  $\overline{\mathsf{E}}(\text{iteration}), \overline{\mathsf{Var}}(\text{iteration}) \leftarrow (1b, 1a)$ at Bayes–NE
end for
$Q^{\mathrm{ig,reg}*}_{i^*} \leftarrow \underset{Q^{\mathrm{ig,reg}}_{i^*}}{\text{find}} \left(\min((1-k)\sqrt{\overline{\mathsf{Var}}\left(Q^{\mathrm{ig,reg}}_{i^*}\right)} + k\overline{\mathsf{E}}\left(Q^{\mathrm{ig,reg}}_{i^*}\right))\right)$
$Q^{\mathrm{s,reg}*}_{i^*} \leftarrow \frac{\mathrm{B} - I^{\mathrm{ig}} Q^{\mathrm{ig,reg}*}_{i^*}}{I^{\mathrm{s}}}$

When simulating a large number of scenarios is not possible, one can use the scenario reduction methods, e.g., [27], to construct a finite number of scenarios from the available data. However, our solution method enables us to include a large number of scenarios in our simulation.

IV. Case Study and Simulation Results

In this section, we apply our bi-level price management framework to Australia's National Electricity Market (NEM). NEM has a regional pricing mechanism, which sets the marginal value of demand at each state as the regional price, in five states of South Australia (SA), Queensland (QLD), Tasmania (TAS), Victoria (VIC) and New South Wales (NSW). The inverse demand functions in our model are calibrated with historical demand and price data from the year 2016. Different types of electricity generation firms, such as coal, gas, hydro, biomass, and wind, with total generation capacity of 46 GW were active in NEM in 2016 [28]. In our numerical study, we consider 365 scenarios each representing a 24-hour (time-series) wind power availability and electricity demand profiles. The realistic data in different regions of NEM from the year 2016 is used to generate the scenario set (Source of data: AEMO). Note that all the prices are in Australian dollar.

A. Impact of Generation Capacity, Gas Price and Transmission Line on Average Price and Price Volatility in NEM

In this subsection, we first study the average price and price volatility in the NEM by considering two cases. In our primary case, the NEM market is simulated based on the available data in 2016. In our secondary case, the Hazelwood coal power plant in VIC is closed down [29], the gas price in total NEM is increased, and the Basslink transmission line, between VIC and TAS, which was under maintenance in 2016, is restarted in comparison to the primary case. Table I compares the simulated wholesale electricity prices in five regions of NEM in the primary and secondary cases. Our simulation results show that the average price of electricity increases in all regions, about 14.27% in NEM, due to Hazelwood power plant closure and gas price surge. The highest rate of price increment belongs to VIC, about 40.33%, where the coal plant was located, following by its neighboring region SA with 19.80%. According to our numerical results, restarting the Basslink interconnector between VIC and TAS reduces the impacts of coal plant closure and gas price surge on the electricity price in TAS, which increases just by 3.58% in average.

TABLE I: Wholesale electricity prices ($/MWh) in five-state NEM market in primary and secondary cases.

	SA	QLD	TAS	**VIC**	NSW	NEM
Primary Case	108.97	72.32	99.64	**57.48**	58.81	67.27
Secondary Case	130.55	78.94	103.20	**80.66**	61.65	76.87
Change%	19.80	9.16	3.58	**40.33**	4.83	14.27

Our calculation also shows that price volatility increases in NEM after the coal plant closure and gas price surge. The square root of price volatility increases by 17.7% in NEM, where VIC experiences the highest increase rate of 41.5%. Moreover, the Basslink transmission line suppresses the price volatility in TAS after the Hazelwood closure and gas price surge.

B. Managing the Average Price and Price Volatility by Only Regulated Wind or Only Regulated Storage

In this subsection, we study the impact of installing only regulated wind or only regulated storage on the average price and price volatility in VIC, where the coal power plant is closed down. We start our simulations with the equivalent annual budget of 300 m$, and perform the sensitivity analysis with other amounts of the equivalent annual budget, between zero and 300 m$, later. Considering the investment cost of 2400 $/kW and lifespan of 25 years, the equivalent annual unit cost is 96 $/(kW.yr) for wind generation. Also, with the investment cost of 550 $/kWh (which is approximately equal to 600 $/kWh considering the degradation rate of 10% for a Lithium-ion battery [30]) and lifespan of 10 years, the equivalent annual unit cost is 60 $/(kWh.yr) for battery storage [31]. Note that we assume the inflation rate is equal to the interest rate, which leads to discount rate of zero, i.e., $r = 0$, in our study. Therefore, the equivalent annual budget of 300 m$ is almost equivalent to 3125 MW wind capacity or 5000 MWh battery capacity.

Fig. 1 shows the impact of installing only 3125 MW regulated wind on the wholesale electricity prices in VIC. The regulated wind in our model with capacity of 3125 MW generates electricity with average level of 975 MW, i.e., with capacity factor of 31%, in VIC. The generation of the regulated wind firm results in the average peak and off-peak wholesale price reductions of 28 $/MWh and 5 $/MWh, respectively, in VIC. The average wholesale electricity price in VIC decreases from 80.6 $/MWh to 62 $/MWh due to the 3125 MW wind capacity addition.

Fig. 2 shows the impact of installing only 5000 MWh regulated battery on the mean wholesale electricity prices in VIC. According to this figure, the regulated battery in VIC makes profit from electricity arbitrage, i.e., charges at off-peak times, with average peak charge level of 1271 MW, and discharges at peak hours, with average peak discharge level of 1022 MW. The charge/discharge of the installed battery approximately results in the average peak price reduction of 47 $/MWh and the average off-peak price increment of 16 $/MWh in VIC. The average wholesale electricity price in VIC decreases from 80.6 $/MWh to 72.9 $/MWh due to the addition of 5000 MWh regulated battery. This observation confirms that wind power generators are more efficient in average price reduction than storage firms.

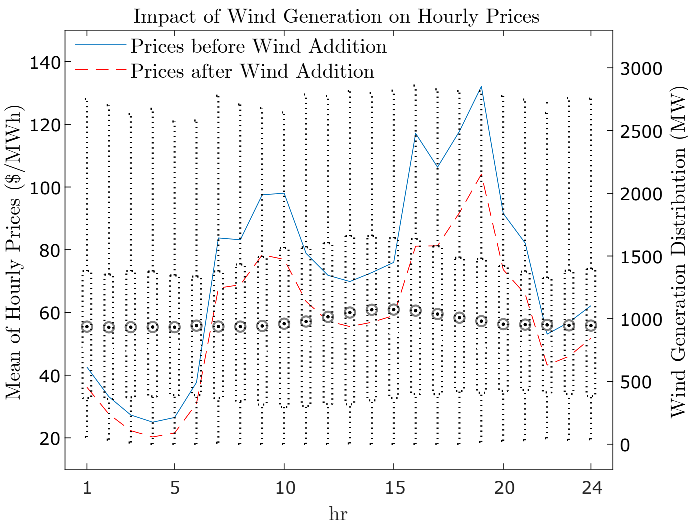

Fig. 1: Mean (over 365 scenarios) wholesale electricity prices in VIC before and after addition of only 3125 MW regulated wind generation capacity (the central marks show the mean levels and the bottom and top edges of the boxes indicate the 25th and 75th percentiles of wind generation).

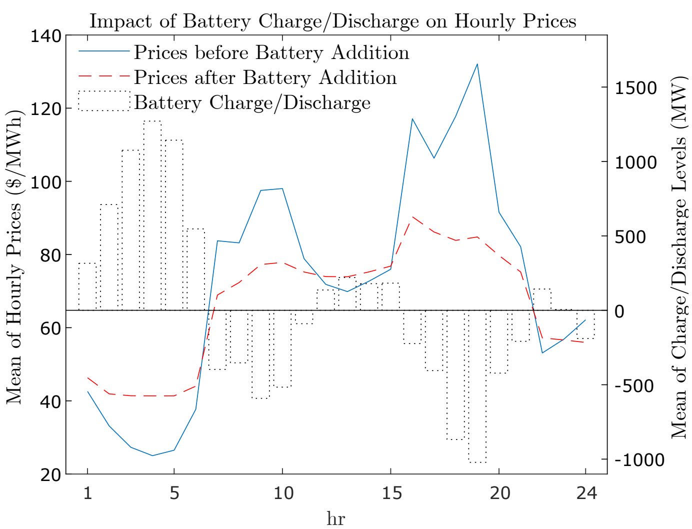

Fig. 2: Mean (over 365 scenarios) wholesale electricity prices in VIC before and after addition of only 5000 MWh regulated battery storage capacity.

Fig. 3a and 3b compare the impact of a regulated wind with that of a regulated storage on the average price and the price volatility, respectively, in VIC when the equivalent annual budget increases from zero to 300 m$. It can be seen that for different levels of budget, i.e., different levels of capacity, the regulated storage is more efficient in reducing the price volatility whereas the regulated wind is more efficient in reducing the average price. Given the equivalent annual budget of 300 m$, the regulated storage and the regulated wind reduce the square root of price volatility in VIC by 71.14 % and 53.55 %, respectively. However, with the same equivalent annual budget, regularized storage and wind firm reduces the average price in VIC by 10.04 % and 29.08 %, respectively. This observation quantitatively shows the effectiveness of storage in price volatility reduction and wind in average price reduction.

Moreover, in addition to mean price and price volatility reduction impacts, the cost analysis of the regulated wind and regulated storage can affect the investment decisions. Fig. 3c indicates the cost analysis of the regulated wind and regulated storage in VIC when the equivalent annual budget varies from zero to 300 m$. The life-time rate of return less than 100 % shows a financially unprofitable investment [21]. Based on this figure, the regulated wind is financially profitable in VIC when the equivalent annual investment cost is less than 300 m$, but the regulated storage makes profit in VIC when the equivalent annual investment cost is less than 100 m$. Thus, the (low) life time rate of return of storage further reduces the desirability of storage only solution for the market intervention. Note that future reduction in battery cost makes the large investments on batteries profitable.

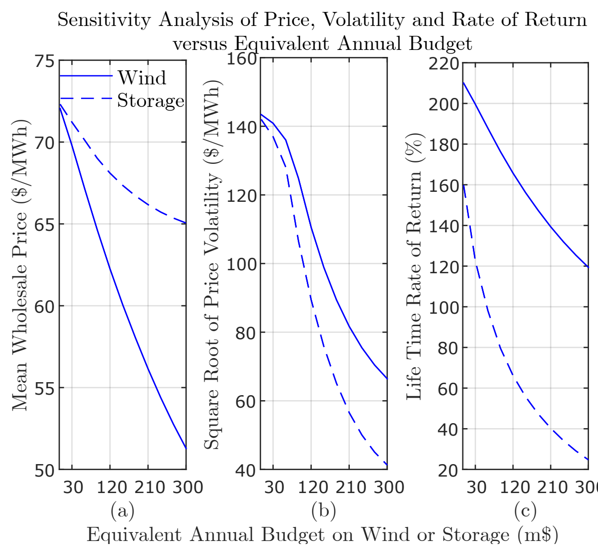

Fig. 3: The mean price, the square root of price volatility, and the life time rate of return for only regulated wind and only regulated battery allocation versus the equivalent annual budget in VIC.

C. Managing the Average Price and Price Volatility by Mixture of Regulated Wind and Storage in VIC

In this subsection, we study the impact of jointly optimal regulated wind and storage allocation on the mean price and price volatility. Fig. 4 illustrates the normalized mean wholesale price as well as the normalized square roof of price volatility for different mixtures of wind and battery allocation with the equivalent annual budget of 300 m$ in VIC. The mean wholesale prices are normalized with base value of 73 $/MWh, which is the average price in the market before adding regulated wind-storage capacities, and the square root of price volatilities are normalized with the base value of 143 $/MWh, which is the square root of price volatility in the market before adding regulated wind-storage capacities. According to Fig. 4, the increase of the regulated wind share, ξ, (or equivalently, the decrease of regulated storage share, 1-ξ) results in relatively lower average prices but higher price volatility levels in the market, and vice versa. Therefore, depending on the importance of average price or price volatility, i.e., the coefficient k, the total budget can be allocated on a mixture of regulated wind and battery capacities.

Fig. 5 shows the budget allocation share between regulated wind (ξ) and regulated battery ($1-\xi$) when the weighting coefficient of price volatility and average price in the upper level problem (3), k, varies from zero to one. The logistic shape of

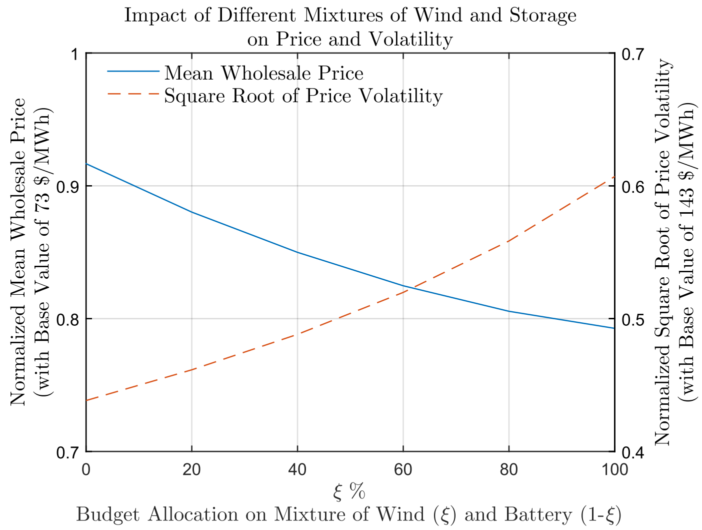

Fig. 4: Normalized mean wholesale price and square root of price volatility for different mixtures of regulated wind and regulated battery with the equivalent annual budget of 300 m$ in VIC.

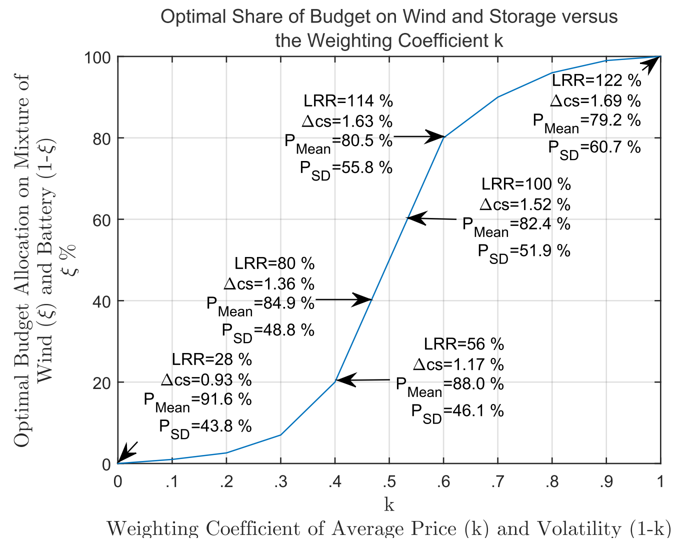

Fig. 5: The budget allocation share between the regulated wind and the regulated battery as a function of the weighting factor k with the equivalent annual budget of 300 m$ in VIC. Life-time Rate of Return (LRR), change of consumer surplus or profit (Δcs), normalized amount of average price ($\mathrm{P_{Mean}}$), and normalized amount of square root of price volatility ($\mathrm{P_{SD}}$) are annotated.

the optimal budget share function with respect to the weighting coefficient k verifies our observations regarding the impacts of wind and storage capacities on the price. The optimal share of regulated wind is more than that of the regulated storage when average price reduction is prioritized, i.e., when $0.5 \leq k \leq 1$. Similarly, when price volatility reduction is more important, i.e., when $0 \leq k \leq 0.5$, the optimal share of regulated battery is more than that of the regulated wind. The decision making on the budget share is highly sensitive with respect to parameter k when the average price and the price volatility are almost equally important, i.e., $0.4 \leq k \leq 0.6$.

Moreover, the annotated data in Fig. 5 is provided to compare the Life-time Rate of Return (LRR), the change of consumer surplus or profit (Δcs), the normalized amount of average price ($\mathrm{P_{Mean}}$), and the normalized amount of square root of price volatility ($\mathrm{P_{SD}}$) when different mixtures of wind and battery are installed in VIC, given the equivalent annual budget of 300 m$. Investing all the budget on battery, we can achieve the minimum square root of price volatility 62.7 $/MWh (43.8 % of its base value), while investing all the budget on wind, we can get the minimum average price 57.5 $/MWh (79.2 % of its base value) and the highest life-time rate of return 122%. Investing the budget on regulated wind is financially more profitable than on regulated battery. It is required to allocate at least 60% of the equivalent annual budget on wind to make the investment on any mixture of wind-storage financially economical, i.e., having the life-time rate of return above 100%. Lastly, the consumer surplus (profit) increases between 0.93% and 1.69% when the regulated wind-storage firm is considered in the market. It can be seen that the mixtures of regulated wind and storage capacities are more effective than storage-only solution in increasing the consumer surplus.

V. Conclusion

Closure of base-load coal power plants, and gas price surge may increase the average price and price volatility in electricity markets. Our study presents an optimization framework which allocates a budget on regulated wind and storage capacities in order to minimize the weighted sum of the average price and the price volatility. Based on our numerical results in NEM, the impacts of regulated wind and storage on average price and price volatility can be summarized as:

- Both storage and wind affect the average price and price volatility in electricity markets. Storage technologies can reduce the price and the price volatility by electricity price arbitrage. Being spread across the network, wind turbines can also decrease the price and volatility in electricity markets. In our model, a single node represents an entire state, and hence, incorporates diversity of wind generation across a large geographic region that counteracts natural intermittency of wind generation.
- Given the equivalent annual budget of 300 m$ to invest on regulated wind-storage capacities in VIC, storage is relatively 47.8% more efficient in price volatility reduction than wind whereas wind is 13.5% more efficient in average price reduction. Based on the importance of average price and price volatility, a mixture of regulated wind and storage capacities can be allocated in a region to reach the desired level of price and volatility in the market.
- When investing on only storage is not economical, the regulated firm can make profit by investing on a mixture of wind and storage capacities. Minimum 60% budget allocation on wind, given the equivalent annual budget of 300 m$ in VIC, makes the investment on any mixture of wind-storage economical.
- The mixtures of regulated wind and storage capacities are relatively more efficient, up to 81.7% in VIC given the equivalent annual budget of 300 m$, than the storage-only solution in increasing the consumer surplus (profit) in our study.
- Wind turbine, with small or large capacity, is already a competent technology which is able to recover its life time cost in the market, but storage technology is economical just in small to medium size. However, the mixture of wind and storage capacities, which can optimally reduce the average price and price volatility, may be competent to make profit in the market. Future technology cost reduction can also make it economical to install larger batteries in the market.

Lastly, our model can be updated to incorporate the decision on the location of wind-storage systems in addition to their capacities. However, this requires updating the solution approach and we plan to study the impact of wind-storage allocation at different regions on regional market prices in our future work.

Appendix A
Regulated Transmission and Regulated Wind-Storage Firms

In this appendix, we show (i) how the objective function of any transmission player in our model is generalized to be either strategic (aims at maximizing its profit) or regulated (aims at maximizing the social welfare), and (ii) how the objective function of the regulated state-owned wind-storage firm is designed, i.e., is equivalent to maximizing the social welfare.

Definition 1: Social Welfare (SW) is equal to the total surplus of consumers and producers in the market. Under any scenario w in our problem, the social welfare can be written as:

$$\mathrm{SW}_w = \sum_{i,t} \int_0^{y_{itw}} P_{itw}\left(.\right) \partial y_{itw} - \mathrm{TC}_{it} = \sum_{i,t} \frac{P_{itw}\left(.\right) - \alpha_{it}}{-\beta_{it}} - \mathrm{TC}_{it}$$

where TC is the total cost of electricity generation, storage, and transmission.

The transmission player maximizes its profit when $\gamma_{ij}^{\mathrm{tr}}$ in (9a) is zero, and equivalently maximizes the social welfare when $\gamma_{ij}^{\mathrm{tr}}$ is one. The derivative of regulated term in (9a), respect to q_{ijtw}^{tr}, given the constraint (9b), that is, $q_{ijtw}^{\mathrm{tr}} = -q_{jitw}^{\mathrm{tr}}$, is:

$$\frac{\partial \left(\frac{P_{jtw}(.)}{-\beta_{jt}} + \frac{P_{itw}(.)}{-\beta_{it}} \right)}{\partial q_{ijtw}^{\mathrm{tr}}} = P_{itw}\left(.\right) - P_{jtw}\left(.\right),$$

which is equal to the derivative of the social welfare function respect to q_{ijtw}^{tr}. It shows that based on the first order optimality conditions, maximizing the regulated term is equivalent to maximizing the social welfare for the transmission player.

Similarly, the derivatives of regulated wind-storage firm's objective function (10a) respect to $q_{i^*tw}^{\mathrm{ig,reg}}$, $q_{i^*tw}^{\mathrm{ch,reg}}$, $q_{i^*tw}^{\mathrm{dis,reg}}$ and $q_{i^*tw}^{\mathrm{st,reg}}$ are equal to the derivatives of social welfare function respect to the corresponding variables. Likewise, it shows that maximizing the objective function (10a) is equivalent to maximizing the social welfare for the regulated state-owned wind-storage firm.

References

[1] C. Latimer, "Victorian power bills soar after hazelwood coal plant closure," March 2018. [Online]. Available: www.theage.com.au

[2] H. Higgs and A. Worthington, "Stochastic price modeling of high volatility, mean-reverting, spike-prone commodities: The Australian wholesale spot electricity market," *Energy Economics*, vol. 30, p. 3172–3185, 2008.

[3] D. Chattopadhyay and T. Alpcan, "A Game-Theoretic Analysis of Wind Generation Variability on Electricity Markets," *Power Systems, IEEE Transactions on*, vol. 29, no. 5, pp. 2069–2077, Sept 2014.

[4] S. Borenstein, "Understanding competitive pricing and market power in wholesale electricity markets," *The Electricity Journal*, vol. 13, no. 6, pp. 49 – 57, 2000.

[5] D. McConnell, "A month in, Tesla's SA battery is surpassing expectations," January 2018. [Online]. Available: http://theconversation.com

[6] D. Wozabal, C. Graf, and D. Hirschmann, "The effect of intermittent renewables on the electricity price variance," *OR spectrum*, pp. 1–23, 2014.

[7] A. Masoumzadeh, E. Nekouei, T. Alpcan, and D. Chattopadhyay, "Impact of Optimal Storage Allocation on Price Volatility in Energy-only Electricity Markets," *IEEE Transactions on Power Systems*, vol. PP, no. 99, pp. 1–1, 2017.

[8] N. Li, C. Uçkun, E. M. Constantinescu, J. R. Birge, K. W. Hedman, and A. Botterud, "Flexible Operation of Batteries in Power System Scheduling With Renewable Energy," *IEEE Transactions on Sustainable Energy*, vol. 7, no. 2, pp. 685–696, April 2016.

[9] A. Berrada and K. Loudiyi, "Operation, sizing, and economic evaluation of storage for solar and wind power plants ," *Renewable and Sustainable Energy Reviews*, vol. 59, pp. 1117 – 1129, 2016.

[10] V. Krishnan and T. Das, "Optimal allocation of energy storage in a co-optimized electricity market: Benefits assessment and deriving indicators for economic storage ventures ," *Energy*, vol. 81, pp. 175 – 188, 2015.

[11] M. Sedghi, A. Ahmadian, and M. Aliakbar-Golkar, "Optimal Storage Planning in Active Distribution Network Considering Uncertainty of Wind Power Distributed Generation," *IEEE Transactions on Power Systems*, vol. 31, no. 1, pp. 304–316, Jan 2016.

[12] L. Zheng, W. Hu, Q. Lu, and Y. Min, "Optimal energy storage system allocation and operation for improving wind power penetration," *IET Generation, Transmission Distribution*, vol. 9, no. 16, pp. 2672–2678, 2015.

[13] J. Xiao, Z. Zhang, L. Bai, and H. Liang, "Determination of the optimal installation site and capacity of battery energy storage system in distribution network integrated with distributed generation," *IET Generation, Transmission Distribution*, vol. 10, no. 3, pp. 601–607, 2016.

[14] R. Walawalkar, J. Apt, and R. Mancini, "Economics of electric energy storage for energy arbitrage and regulation in New York ," *Energy Policy*, vol. 35, no. 4, pp. 2558 – 2568, 2007.

[15] H. Mohsenian-Rad, "Optimal Bidding, Scheduling, and Deployment of Battery Systems in California Day-Ahead Energy Market," *IEEE Transactions on Power Systems*, vol. 31, no. 1, pp. 442–453, Jan 2016.

[16] H. Akhavan-Hejazi and H. Mohsenian-Rad, "A stochastic programming framework for optimal storage bidding in energy and reserve markets," in *Innovative Smart Grid Technologies (ISGT), 2013 IEEE PES*, Feb 2013, pp. 1–6.

[17] H. Mohsenian-Rad, "Coordinated Price-Maker Operation of Large Energy Storage Units in Nodal Energy Markets," *IEEE Transactions on Power Systems*, vol. 31, no. 1, pp. 786–797, Jan 2016.

[18] E. Nasrolahpour, S. J. Kazempour, H. Zareipour, and W. D. Rosehart, "Strategic Sizing of Energy Storage Facilities in Electricity Markets," *IEEE Transactions on Sustainable Energy*, vol. 7, no. 4, pp. 1462–1472, Oct 2016.

[19] W.-P. Schill, C. Kemfert *et al.*, "Modeling strategic electricity storage: the case of pumped hydro storage in Germany," *Energy Journal-Cleveland*, vol. 32, no. 3, p. 59, 2011.

[20] G. Kirchgässner and J. Wolters, *Introduction to modern time series analysis*. Springer Science & Business Media, 2007.

[21] C. S. Park, G. Kim, and S. Choi, *Engineering economics*. Prentice Hall: Upper Saddle River, NJ, USA, 2007, vol. 22.

[22] B. E. Hobbs, "Linear complementarity models of Nash-Cournot competition in bilateral and POOLCO power markets," *IEEE Transactions on Power Systems*, vol. 16, no. 2, pp. 194–202, May 2001.

[23] J. C. Harsanyi, "Games with Incomplete Information Played by "Bayesian" Players, I-III. Part II. Bayesian Equilibrium Points," *Management Science*, vol. 14, no. 5, pp. 320–334, 1968.

[24] W. W. Hogan, "A Market Power Model with Strategic Interaction in Electricity Networks," *The Energy Journal*, vol. 18, no. 4, pp. 107–141, 1997.

[25] E. G. Kardakos, C. K. Simoglou, and A. G. Bakirtzis, "Optimal bidding strategy in transmission-constrained electricity markets ," *Electric Power Systems Research*, vol. 109, pp. 141 – 149, 2014.

[26] D. Fudenberg and J. Tirole, *Game theory*. Cambridge, Mass. : M.I.T. Press, 1991.

[27] M. Daghi, M. Sedghi, A. Ahmadian, and M. Aliakbar-Golkar, "Factor analysis based optimal storage planning in active distribution network considering different battery technologies," *Applied Energy*, vol. 183, pp. 456 – 469, 2016.

[28] W. Gerardi and P. Galanis, "Emissions mitigation policies and security of electricity supply," Jacobs Group (Australia), Tech. Rep., June 2017.

[29] A. Masoumzadeh, E. Nekouei, and T. Alpcan, "Impact of a coal power plant closure on a multi-region wholesale electricity market," in *2017 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe)*, Sept 2017, pp. 1–6.

[30] K. Abdulla, J. de Hoog, V. Muenzel, F. Suits, K. Steer, A. Wirth, and S. Halgamuge, "Optimal operation of energy storage systems considering forecasts and battery degradation," *IEEE Transactions on Smart Grid*, vol. 9, no. 3, pp. 2086–2096, May 2018.

[31] M. Jeppesen, M. Brear, D. Chattopadhyay, C. Manzie, R. Dargaville, and T. Alpcan, "Least cost, utility scale abatement from Australia's NEM (National Electricity Market). Part 1: Problem formulation and modelling," *Energy*, vol. 101, pp. 606 – 620, 2016.